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Data Envelopment Analysis Cross Efficiency Evaluation Approach to the Technology Selection

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ABSTRACT

This paper proposes two data envelopment analysis (DEA) cross efficiency models for selecting the most efficient alternatives in manufacturing technology. The cross efficiency evaluation (CEE) method which is developed as a contribution to the classical Data Envelopment Analysis (DEA) is a method successively used in the ranking problems. In its original, the CEE method includes the efficiency evaluations made use for the reusage of optimal weights in the other Decision Making Units (DMUs) obtained for a DMU by the classical DEA. Since the optimal weights in the classical DEA solutions have usually multiple solutions, this reduces the usefulness of CEE method. This study suggests new methods for the second stage of CEE method to remove the question of multiple optimal weights. A numerical example illustrates proposed models, and an application and a comprehensive simulation experiment in technology selection with multi-inputs/multi-outputs shows the usefulness of the proposed approaches.

Keywords: Data envelopment analysis, technology selection, cross efficiency, multiple optimal weights.

1. INTRODUCTION

Technology selection is an important part of management of technology. Selecting the best technology is always a difficult task for decision-makers. Selection of a robot for a specific industrial application is one of the most challenging problems in real time manufacturing environment. It has become more and more complicated due to increase in complexity, advanced features and facilities that are continuously being incorporated into the robots by different manufacturers. Knott and Getto in [1] published one of the preliminary works on robot selection. In this study, the problem of robot selection has been analyzed according to an economical point of view. A similar work has been proposed by Huang and Ghandforoush [2]. The most important disadvantages of the specific approach are the lack of flexibility and reliability, which have reduced the diffusion of economic models. Some mathematical programming approaches have been used for technology selection in the past. Rai et al. [3] addressed application of a fuzzy Goal Programming (GP) concept to model the problem of machine-tool selection and operation allocation with explicit considerations given to objectives of minimizing the total cost of machining operation, material handling and setup. Chan et al. [4] presented a fuzzy GP approach to model the machine tool selection and operation allocation problem of flexible manufacturing systems. Jaganathan et al. [5] proposed an integrated fuzzy analytic hierarchy process (AHP) based approach to facilitate the selection and evaluation of new manufacturing technologies in the presence of intangible attributes and uncertainty. However, there are many models which are based on either mathematical programming principles [6] or regression analysis [7-9]. Multi-criteria decision-making techniques [10-18], in a combination with the ranking methods, give satisfactory

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solutions on decision problems. However, the large number of parameters, which decision makers have to take into consideration, conduces to the complexity of the procedure. The increased expectations for system's production level, as well as the requirements of decision makers, have contributed to the introduction of fuzzy logic and genetic algorithms in decision making [19-25]. For the majority of fuzzy methodologies, the first step is data defuzzification, continuing with the traditional technique of data processing. While researches are based on optimizing selection process and developing a flexible selection system, a combination of two or more methodologies has been proposed, in order to benefit from all of their advantages [26, 27]. Finally, there were many alternative methodologies proposed which are classified in a general category [28-30]. Recently, the concept of graph representation for data processing has been introduced in the field of robot selection by Rao and Padmanabhan [31]. A different aspect of robot selection problem has been presented by Koulouriotis and Ketipi [32] using a fuzzy digraph model. Athawale and Chakraborty [33], in their recent research, presented some multi-criteria decision-making methods applied in robot selection cases and studied their ranking performance, while Koulouriotis and Ketipi [34] presented an early bibliographic overview on robot selection methodologies.

A number of studies have used DEA for robot selection. Khouja [35] 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. Baker and Talluri [11] proposed an alternate methodology for technology selection using DEA. They addressed some of the shortcomings in the methodology suggested by Khouja [35] and presented a more robust analysis based on cross-efficiencies in DEA. Karsak [36] developed a two-phase procedure for the selection of industrial robots that integrated DEA with a fuzzy decision-making algorithm that enabled the decision-maker to fully rank robot alternatives by taking into account both objective and subjective criteria. Karsak [37] considered both quantitative and qualitative criteria expressed as fuzzy numbers or linguistic variables in robot evaluation using a DEA-based methodology. Talluri and Yoon [38] presented a cone-ratio DEA approach for robot selection that made use of weight restriction constraints to incorporate a priori information on the priorities of factors.

Data Envelopment Analysis is a nonparametric efficiency method developed for the first time by Charnes et al. [39] having the purpose to measure the relative efficiencies of similar economical DMUs in respects of goods and services they produced. One of the uses of data envelopment analysis (DEA) is technology 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. As the applications of this so powerful technique are improved, many new problems have arisen [40-43]. These problems which were dependent of each other's and known for a long time are the weak discrimination power, the issue of unrealistic weights distribution and having multiple optimal solutions to weights for the efficient DMUs. The weak discrimination power or the lack of discrimination power appears in the case in which the number of DMUs under evaluation is insufficient in comparison with the total number of inputs and outputs. For the classical DEA models, this mostly results the solutions determining too many DMUs as efficient. The problem of unrealistic weight distribution for DEA occurs when some DMUs are rated as efficient because of input and output weights have the extreme or zero values. Having multiple optimal solutions to weights affects the consistency of operations related to weights to an important extent. The super efficiency and cross efficiency methods are the most frequently studied areas in DEA literature.

The cross efficiency method is a useful technique developed by Sexton et al. [44] so as to rate the DMUs by using the cross evaluation scores computed as related to all DMUs and hence identify the best DMUs [45]. The basic idea of cross evaluation is to use DEA as machinery in peer evaluation instead of self-evaluation. Peer evaluation refers to the assigned score for each DMU that obtained by using the optimal weights of other DMUs. The advantages of cross efficiency method are the ability of rating DMUs and being a useful tool without feeling the need of any expert opinion or prerequisites to work out the unenviable cases such as multiple solutions, solutions with extreme or zero values for the weights in DEA.

Although the cross efficiency method has a widespread usage, it has also some deficiencies arising from the classical DEA. As stated by Doyle and Green [46], the non-uniqueness, i.e., having multiple solutions to optimal weights in DEA decreases the usefulness of cross efficiency method. Sexton et al. [44] and Doyle and Green [46] recommended the use of a secondary objective (model) for the cross efficiency evaluation related to the non-uniqueness of optimal weights in DEA. They proposed the aggressive and benevolent models for the secondary objective. The basic idea in the benevolent approach is to obtain the set of optimal weights maximizing not only the efficiency of a DMU under evaluation but also the average efficiency of other DMUs. In the aggressive models, on the contrary it is searched the set of optimal weights minimizing the average efficiency of other DMUs. In recent days, Liang et al. [47] attempted some new suggestions for the second stage in cross efficiency evaluation. Their suggestions consist of three different models including the minimization of deviations from the ideal point (the minsum efficiency), the minimization of maximum inefficiency amount (the minmax efficiency) and the minimization of absolute deviations from the average efficiency. The first two models of these suggestions are used in the multicriteria DEA approach proposed by Li and Reeves [48] for the problems of ranking the units and unrealistic weight distribution.

In some cases, decision maker must select only one DMU throughout a set of considered DMUs. There have been several studies to extend some integrated DEA models for finding a unique efficient DMU. Ertay and Ruan [49] suggested a cross-efficiency approach to determine the most efficient number of operators. Ertay, Ruan, and Tuzkaya [50] integrated DEA and analytic hierarchy process (AHP) in manufacturing systems and developed a robust layout framework for evaluating facility layout design (FLD) alternatives in a plastic profile production system. Amin et al. [51] proposed an MILP model to deal with the technology selection problem. However, their model designed for single input and multiple outputs. Amin and Toloo [52] formulated a new mixed integer linear programming (MILP) model to find the most efficient unit. Amin [53, 54] explained some drawbacks of previous MILP models and introduced a new mixed integer non-linear programming (MINLP) model to modify these flaws. It was mathematically proved that these models can determine the best efficient unit, however the suggested models were nonlinear in nature. Amin and Emrouznejad [55] formulated an integrated minimax linear programming (LP) model for finding relevant search engines and compared the achieved result with ordered weighted averaging operator. Amin, Gattoufia, and Rezaee Serajib [56] introduced the maximum discrimination between the weights of the criteria and achieved the optimal solution of the proposed corresponding DEA model efficiently without the need of solving the related mathematical models. Foroughi [57] proposed a new integrated maximin MILP model that finds the most efficient unit by maximizing the minimum possible distance between a selected unit and the next ranked unit. It was shown that the suggested approach can also be extended to rank all extreme efficient DMUs. Wang and Jiang [58] clarified that Foroughi's model is very complicated and involves many redundant constraints and proposed a new approach to identify the most efficient DMU. Toloo [59] formulated an MILP model for finding the most efficient unit without explicit input. By excluding the non-Archimedean epsilon, Toloo [60] proposed an approach which finds the most efficient DMU with fewer computations. Toloo [61] proposed an integrated model that is able to determine the most efficient unit under a common condition is developed. This model formulated a minimax mixed integer linear programming (MILP) model for finding the most efficient DMU.

This paper depicts the technology selection process through cross efficiency DEA model. The objective of this paper is to propose new DEA cross efficiency models for selecting the best technologies.

The paper is organized as follows. In Section 2, the basic DEA model and related concepts are given. In Section 3, cross efficiency method is presented and its aggressive formulation is explained. In Section 4, the model in which the input and output components are respectively approximated to the weighted input and weighted sums and the model that the variation of weights is minimized are given for the second stage of cross efficiency evaluation. In Section 5, the basic CCR, aggressive cross efficiency method, Toloo [61] model and proposed models for cross efficiency evaluation are applied to robot selection data and their solutions are compared. In Section 6, for the comparison the models in terms of ranking and discrimination power, a comprehensive simulation experiment is conducted. Lastly, in Section 7, a summary of the research and its results are provided.

2. DATA ENVELOPMENT ANALYSIS

Data Envelopment Analysis (DEA) is a mathematical programming approach that utilizes multiple inputs and outputs to measure relative efficiencies within a group of decision making units (DMUs). Assuming that there are n DMUs to be evaluated in terms of m inputs and s outputs. Let x_{ij} ($i = 1, \ldots, m$) and y_{rj} ($r = 1, \ldots, s$) be the input and output values of DMU_j ($j = 1, \ldots, n$). Then the efficiency of DMU_p can be defined as

$$\theta_p = \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}} \tag{1}$$

where v_i ($i = 1, \ldots, m$) and u_r ($r = 1, \ldots, s$) are respectively the input and output weights assigned to i^{th} input and r^{th} output. Charnes et al. [39] established the following model,

$$\begin{aligned} \max\ \theta_p &= \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}} \\ \text{s.t.}\quad & \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad j = 1, 2, \ldots, n \\ & u_r \ge 0, \quad r = 1, \ldots, s \\ & v_i \ge 0, \quad i = 1, \ldots, m \end{aligned} \tag{2}$$

where DMU_p refers to the DMU under evaluation. This fractional program, well known as CCR model, can be converted into a linear programming problem where the optimal value of the objective function indicates the relative efficiency of DMU_p. Hence the reformulated linear programming problem is as follows:

$$\begin{aligned} \max\ \theta_p &= \sum_{r=1}^{s} u_r y_{rp} \\ \text{s.t.}\ & \\ \sum_{i=1}^{m} v_i x_{ip} &= 1 \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} &\le 0, \\ j &= 1,\ 2,\ \ldots,\ n \\ u_r &\ge 0, \\ r &= 1,\ \ldots,\ s \\ v_i &\ge 0, \\ i &= 1,\ \ldots,\ m \end{aligned} \tag{3}$$

In these models, DMU_p is efficient if and only if $\theta_p^* = 1$; otherwise, it is referred to as non- efficient.

3. CROSS EFFICIENCY EVALUATION

The cross efficiency method was developed as a DEA extension tool that can be utilized to identify best performing DMUs and to rank DMUs using cross efficiency scores that are linked to all DMUs [44]. The idea of the cross efficiency method that alleviates the weak discrimination of the classical DEA model could be explained in two stages. In the first stages, the classical DEA analysis is performed and for each DMU optimal weights of inputs and outputs are calculated. The optimal weights computed by classical DEA have multiple solutions especially for the efficient DMUs and these solutions provide unrealistic weights, i.e., weights with extreme or zero values. In the second stage, these drawbacks are reduced and suitable set of weights preserving the efficiency values obtained by DEA is selected for each DMU.

The first stage is calculated for each DMU optimal weights of inputs and outputs using the classical DEA formulation. Given the results of the first stage, we could use the weights used by the DMU for itself to calculate the peer rated efficiency for each of the other DMUs. The peer evaluation score, $\theta_{p,j}$, is the efficiency score for DMU_j using the weights obtained by DMU_p [45].

$$\theta_{p,j} = \frac{\sum_{r=1}^{s} u_{r,p} y_{rj}}{\sum_{i=1}^{m} v_{i,p} x_{ij}} \tag{4}$$

Since the optimal weights obtained by classical DEA in the first stage are generally multiple solutions, the values $\theta_{p,j}$ will also change depending on these values in the second stage. To reduce this undesirable case, there are some model suggestions preserving the self efficiency scores, $\theta_{p,p}$, obtained for each DMU. The one so-called aggressive efficiency model developed by Sexton et al. [44] and extended by Doyle and Green [46] is given in (5) below. In this approach, the efficiencies of other DMUs are tried to minimize while the efficiency of the DMU under evaluation is preserved. In contrary, it is tried to maximize the efficiencies of other DMUs, in benevolent approach. Since the discrimination of DMUs is an important problem in DEA, the aggressive model seems more convenient than the benevolent model in respect of the discrimination problem.

$$\begin{aligned} \min\ & \sum_{r=1}^{s} \left(u_{rp} \sum_{j=1; j\neq p}^{n} y_{rj} \right) \\ \text{s.t.}\ & \\ & \sum_{i=1}^{m} \left(v_{ip} \sum_{j=1; j\neq p}^{n} x_{ij} \right) = 1 \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \qquad j = 1,\ \ldots,\ n; \\ & j \neq p \\ & \sum_{r=1}^{s} u_r y_{rp} - \theta_{p,p} \sum_{i=1}^{m} v_i x_{ip} = 0 \\ & u_r \ge 0,\ r = 1,\ \ldots,\ s \\ & v_i \ge 0,\ i = 1,\ \ldots,\ m \end{aligned} \tag{5}$$

The second stage is repeated for each DMU_p; $p = 1,\ \ldots,\ n$. The weights $u_{r,p}$ and $v_{i,p}$ obtained from model (5) are used in computing the score $\theta_{p,j}$ for DMU_j by the aid of equality (4). After the computation of all the cross evaluation scores, the cross efficiency score for DMU_k is derived by [45].

$$CE_k = \frac{\sum_{j=1}^{n} \theta_{j,k}}{n} \tag{6}$$

The existence of complete weight flexibility in classical DEA solutions gives rise to obtaining unrealistic (inappropriate) weights for efficient DMUs. DMUs having extreme weights are potential "false positive" candidates. A "false positive" DMU is a DMU evaluated as efficient because of having good values only in a few inputs and outputs in spite of it has very bad values in most of inputs and outputs. Using a measure of false positive index, FPI, Baker and Talluri [11] demonstrated an effective way of measuring false effectiveness. The FPI value for DMU_k is calculated as

$$FPI = \frac{\left(\theta_{kk} - CE_k\right)}{CE_k}. \qquad (7)$$

A high FPI value for an efficient DMU indicates that it has been evaluated as efficient because of having good values only in one or a few inputs and outputs in spite of it has very bad values in most of inputs and outputs in respect of the other units. Such a high FPI value appears in the case in which the difference between the self and peer efficiencies computed for the unit increases. In essence this shows that any unit having high FPI value is not a good unit compared to other units.

4. PROPOSED METHODS FOR TECHNOLOGY SELECTION

4.1. Closing the input and output components to weighted output sum

In the classical DEA it is known that the optimal weights, especially the optimal weights obtained for the efficient units are multiple optimal. In addition, in the case the values of an output (input) variable are greater than the values of other output (input) variables; the weight assigned to this output (input) generally becomes zero or very near zero. In this way, a variable which can be able to affect the performance of a DMU has no (ability of) contribution to the efficiency of DMU under evaluation. To give an importance to each input and each output proportional to their greatness eliminates this drawback [62].

In the proposed approach, closing each weighted output component to weighted output sum it is provided to make a contribution to efficiency account of each output component proportional to the output values, i.e., to the extent that their greatness or smallness, and it is also aimed to obtain more appropriate weights than the classical DEA model. Similarly, it is also provided to make a contribution to efficiency account of each input component proportional to the input values, i.e., to the extent that their greatness or smallness by closing each weighted input component to weighted input sum (i.e., to the value 1, $\sum_{i=1}^{m} v_i x_{ip} = 1$). In the second stage of cross evaluation, a model is given by (8) in which the classical DEA efficiency scores for each unit are preserved and more appropriate weight values are selected for the units for which the optimal weights obtained by classical DEA in the first stage have possibly multiple and inappropriate solutions.

$$\begin{aligned}
\min\ & w_p = z_p \\
\text{s.t.}\ & \\
& \sum_{r=1}^{s} u_r y_{rp} = \theta_p^* \\
& \sum_{i=1}^{m} v_i x_{ip} = 1 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \\
& j = 1,\ 2,\ \ldots,\ n \\
& \sum_{r=1}^{s} u_r y_{rp} - u_r y_{rp} \le z_p, \\
& r = 1, 2,\ \ldots,\ s \\
& 1 - v_i x_{ip} \le z_p, \\
& i = 1, 2,\ \ldots,\ m \\
& u_r \ge 0, \\
& r = 1, 2,\ \ldots,\ s \\
& v_i \ge 0, \\
& i = 1, 2,\ \ldots,\ m \\
& z_p \ge 0
\end{aligned} \qquad (8)$$

where θ_p^* is the efficiency value for DMU_p obtained from the classical DEA given in (3). The z_p variable in the model symbolizes the maximum deviation from the weighted output sum and weighted input sum for the output component and input component, respectively.

4.2. Minimization of Variations for Weights

The optimal weights of inputs and outputs of DMUs and efficiency values of DMUs are obtained by weighted sum of outputs are maximized in classical DEA. In many cases, it is known that multiple optimal solutions are obtained for efficient DMUs. Since multiple optimal solution case causes some problems, the important of acquiring the weights with the unique optimal solution is increased. For this reason, after weighted sum of outputs is maximized in classical DEA, the unique optimal weight can be obtained by minimizing variations of input and output weights. This model serves the same purposes of the model given by (8).

The coefficient of variation (CV), the ratio of sample standard deviation to the sample mean, is the one of methods used in the measuring of variation. It compares the relative dispersion in one type of data with the relative dispersion in another type of data.

Let u_r $\left(r = 1, 2,\ \ldots,\ s\right)$ be the weight on output r and let $\overline{u}$ be the mean of the u_r $\left(r = 1, 2,\ \ldots,\ s\right)$. We define the CV for the weights u_r as

$CV_U = \frac{\sqrt{\sum_{r=1}^{s}\left(u_r - \bar{u}\right)^2 \Big/ \left(s-1\right)}}{\bar{u}}$. Similarly, we can calculate the CV for the weights $v_i \ \left(i = 1, 2, \ . \ . \ . \ , m\right)$ as

$$CV_V = \frac{\sqrt{\sum_{i=1}^{m}\left(v_i - \bar{v}\right)^2 \Big/ \left(m-1\right)}}{\bar{v}} \quad [63].$$

The model (9) preserving the classical DEA efficiency scores for DMUs minimizes the coefficient of variation (CV) for input-output weights. The model (9) used in the stage of cross evaluation can be formulated as follows:

$$\begin{aligned} \min\ & w_p = CV_U + CV_V \\ \text{s.t.}\ & \\ & \sum_{r=1}^{s} u_r y_{rp} = \theta_p^* \\ & \sum_{i=1}^{m} v_i x_{ip} = 1 \\ & \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1,\ 2,\ . \ . \ . \ , n \\ & u_r \ge 0, \quad r = 1, 2, \ . \ . \ . \ , s \\ & v_i \ge 0, \quad i = 1, 2, \ . \ . \ . \ , m \end{aligned} \tag{9}$$

where, θ_p^* is the efficiency value for DMU_p obtained from the classical DEA given in model (3). In the solution of this model, because of the structure of objective functions for the proposed models, a normalized data obtained by dividing each input-output with their highest value is used.

5. A NUMERICAL EXAMPLE: EFFICIENCY EVALUATION OF INDUSTRIAL ROBOTS

This section examines a well-known numerical example to validate proposed models for ranking the decision making units. For this purpose, basic CCR, aggressive cross efficiency, Toloo [61] model and proposed models (model 8 and 9) have been investigated. More recently, Toloo [61] proposed an integrated model that is able to determine the most efficient unit. We use the model (15) in the Toloo [61] study for the comparison of the ranking and discrimination power performances of the models.

Baker and Talluri [11] realized the efficiency evaluation of 27 industrial robots via cross efficiency method. Two inputs and two outputs were chosen to measure the performance of those industrial robots. Output variables: y_1; load capacity, kg, y_2; velocity, m/s; input variables: x_1; cost, \$10,000, x_2; repeatability, mm. The data set and results are reported in the Table 1 and Table 2, respectively.

In the Table 2, it is seen that the classical DEA model (CCR model) determines 9 robots; 1, 4, 7, 10, 13, 14, 19, 20 and 27, as efficient ones. As noted by Baker and Talluri [11], the robots 1, 4, 20 and 27 have high FPI value. For these robots, FPI values are seen as 0.727, 2.247, 1.890 and 0.695 in the fifth columns of Table 2 named as FPI-CCR. The other efficient robots have low FPI values. By examining efficient units with high FPI values, it can be seen that robot 1 produces its second output high, robot 4 uses its second input low, robot 20 uses its first input low and robot 27 produces its second output high. On the contrary, these robots have very bad values at most of inputs and outputs comparing to the other robots. In other words, these robots are considered as efficient ones thanks to only one input or output value. For the robots 1, 4, 20 and 27, model (8) yields FPI values as 0.563, 2.934, 1.615 and 0.408, respectively. Also, model (9) yields FPI values as 0.588, 2.998, 1.678 and 0.399, respectively. The obtained results indicate that models (8) and (9) determine false positive robots similar to the aggressive model.

Baker and Talluri [11] stated that robot 14 is the best DMU with the highest cross efficiency value and the lowest FPI value according to cross efficiency evaluation. For this robot, the aggressive cross efficiency and FPI values are seen as 0.821 and 0.218 in the third and fifth columns of Table 2 named as CE-CCR and FPI-CCR, respectively. This result is supported by proposed models (8) and (9). For robot 14 model (8) yields cross efficiency score as 0.861, FPI value as 0.162. Also, model (9) yields cross efficiency score as 0.849, FPI value as 0.185.

Reference to Table 2 shows that 9 out of 27 industrial robots are efficient according to basic CCR model (DMUs 1, 4, 7, 10, 13, 14, 19, 20 and 27). The number of efficient units are reduced to 3 at the model (8) and model (9) (DMU7, DMU14 and DMU19). In the Table 2, the cross efficiency scores of the proposed models are given. Toloo [61] model gives the DMU14 as most efficient robot, while DMU7 is selected as the efficient with the 1 efficiency score. Toloo [61] model results also supports the idea of Baker and Talluri [11] in terms of the highest efficiency score and lowest FPI value.

Table 1: The data of industrial robots

DMU	y_1	y_2	x_1	x_2
1	1.35	60	7.2	0.15
2	1.1	6	4.8	0.05
3	1.27	45	5	1.27
4	0.66	1.5	7.2	0.025
5	0.05	50	9.6	0.25
6	0.3	1	1.07	0.1
7	1	5	1.76	0.1
8	1	15	3.2	0.1
9	1.1	10	6.72	0.2
10	1	6	2.4	0.05
11	0.9	30	2.88	0.5
12	0.15	13.6	6.9	1
13	1.2	10	3.2	0.05
14	1.2	30	4	0.05
15	1	47	3.68	1
16	1	80	6.88	1
17	2	15	8	2
18	1	10	6.3	0.2
19	0.3	10	0.94	0.05
20	0.8	1.5	0.16	2
21	1.7	27	2.81	2
22	1	0.9	3.8	0.05
23	0.5	2.5	1.25	0.1
24	0.5	2.5	1.37	0.1
25	1	10	3.63	0.2
26	1.25	70	5.3	1.27
27	0.75	205	4	2.03

Table 2: Industrial robot results

DMU	CCR	CE-CCR	Rank	FPI-CCR	CE-Model(8)	Rank	FPI-Model(8)	CE-Model(9)	Rank	FPI-Model(9)	Toloo [61] Model	Rank
1	1	0.579	7	0.727	0.640	7	0.563	0.636	7	0.588	0.901	7
2	0.904	0.483	9	0.872	0.470	11	0.924	0.469	12	0.937	0.613	11
3	0.529	0.306	21	0.729	0.351	20	0.508	0.366	20	0.452	0.301	24
4	1	0.308	20	2.247	0.254	24	2.934	0.255	24	2.998	0.501	20
5	0.592	0.190	26	2.116	0.223	25	1.654	0.221	26	1.737	0.292	26
6	0.482	0.284	22	0.697	0.314	21	0.535	0.329	21	0.482	0.480	21
7	1	0.697	4	0.435	0.761	2	0.314	0.784	2	0.281	1	2
8	0.783	0.562	8	0.393	0.610	8	0.284	0.616	8	0.277	0.621	9
9	0.378	0.266	23	0.421	0.284	22	0.331	0.296	22	0.319	0.370	22
10	1	0.703	3	0.422	0.730	5	0.371	0.739	5	0.364	0.925	5
11	0.671	0.430	12	0.560	0.491	9	0.366	0.510	9	0.323	0.625	8
12	0.102	0.057	27	0.789	0.066	27	0.546	0.069	27	0.514	0.092	27
13	1	0.726	2	0.377	0.743	4	0.347	0.746	4	0.351	0.985	4
14	1	0.821	1	0.218	0.861	1	0.162	0.849	1	0.185	1.087	1
15	0.613	0.365	16	0.679	0.419	16	0.464	0.436	15	0.412	0.565	15
16	0.604	0.351	17	0.721	0.404	17	0.494	0.415	18	0.462	0.512	19
17	0.405	0.196	25	1.066	0.222	26	0.823	0.236	25	0.744	0.295	25
18	0.365	0.258	24	0.415	0.277	23	0.318	0.283	23	0.305	0.355	23
19	1	0.665	5	0.504	0.747	3	0.338	0.759	3	0.327	0.992	3
20	1	0.346	19	1.890	0.382	19	1.615	0.376	19	1.678	0.550	17
21	0.851	0.348	18	1.445	0.398	18	1.141	0.419	17	1.043	0.532	18
22	0.829	0.463	10	0.790	0.452	13	0.834	0.459	13	0.828	0.606	13
23	0.694	0.442	11	0.570	0.488	10	0.421	0.507	10	0.378	0.615	10
24	0.636	0.415	13	0.533	0.457	12	0.391	0.476	11	0.351	0.606	12
25	0.553	0.381	14	0.451	0.420	15	0.320	0.431	16	0.293	0.551	16
26	0.581	0.368	15	0.579	0.423	14	0.373	0.441	14	0.327	0.575	14
27	1	0.590	6	0.695	0.710	6	0.408	0.721	6	0.399	0.911	6

Table 3: Multiple optimal solutions for efficient industrial robots

Efficient DMU	u_1	u_2	v_1	v_2	CV_U	CV_V
1	0.002659800	0.016607001	0.105560	1.59970	1.024	1.239
	0	0.016666670	0.104166660	1.666666870	1.414	1.248
	0	0.016666670	0.108269130	1.469748850	1.414	1.220
	0.014304830	*0.016344810*	*0.108860430*	*1.441365840*	*0.094*	*1.216*
4	1.51030	0.00213490	0.0034160	39.0160	1.410	1.414
	1.51515150	0	0	40	1.414	1.414
	1.50111511	*0.006176016*	*0.00128667*	*39.62943901*	*1.403*	*1.414*
	1.50	*0.0066667*	*0*	*40*	*1.402*	*1.414*
7	0.989640	0.00207230	0.338010	4.05110	1.408	1.196
	0.946814541	0.01063710	0.548704147	0.34280729	1.383	0.327
	0.866580	*0.02668400*	*0.4469200*	*2.13420*	*1.330*	*0.924*
	0.93808855	*0.012382289*	*0.537634401*	*0.53763454*	*1.377*	*0*
10	0.963550	0.00607520	0.328460	4.23410	1.396	1.211
	1	0	0.328947368	4.210526316	1.414	1.209
	0.93023253	0.01162791	0.290697753	6.046506882	1.379	1.284
	0.9120983	*0.014650284*	*0.333766541*	*3.97920605*	*1.370*	*1.195*
13	0.824890	0.001013201	0.077750	15.024	1.411	1.400
	0.83333331	0	0.008928572	19.4285717	1.414	1.413
	0.83043981	0.000347222	0.008680556	19.44444466	1.413	1.413
	0.75471693	*0.009433964*	*0.235849112*	*4.905656338*	*1.379*	*1.284*
14	0.31460	0.020749001	0.0068239	19.4540	1.239	1.413
	0	0.033333335	0.208333328	3.333333731	1.414	1.248
	0.41666667	*0.016666667*	*0.1250*	*10*	*1.305*	*1.379*
	0.0320513	*0.0320513*	*0.2146809*	*2.8255310*	*0*	*1.214*
19	1.31230	0.0606310	0.794940	5.05510	1.289	1.030
	1.64960182	0.050511945	0.815320432	4.671975613	1.330	0.994
	1.08720597	*0.067383821*	*0.760183592*	*5.70854848*	*1.249*	*1.082*
	1.64494028	*0.050651792*	*0.84833970*	*4.051213645*	*1.330*	*0.924*
20	1.250	0	6.250	0	1.414	1.414
	1.20590	0.0235470	6.14780	0.00817660	1.360	1.410
	1.06167528	*0.100439848*	*5.308376422*	*0.075329886*	*1.170*	*1.375*
	1.250	*0*	*0.68493150*	*0.44520550*	*1.414*	*0.300*
27	0	0.004878049	0.250	0	1.414	1.414
	0.00736734	0.004851095	0.1645930	0.168289656	0.291	0.016
	0.32602942	*0.003685258*	*0.188869483*	*0.12045422*	*1.383*	*0.313*
	0.00485990	*0.00486030*	*0.16583750*	*0.16583750*	*0*	*0*

In Table 2, the rank values of DMUs are obtained by the model (8) and (9) are almost same the rank values of DMUs are obtained by the aggressive cross efficiency model in the industrial robot example. Spearman's rank correlation coefficient for model (8) and aggressive cross efficiency model is calculated as $r_s = 0.980$. Also, for model (9) and aggressive cross efficiency model is calculated as $r_s = 0.977$. Moreover, model (8) and model (9) are almost same the rank values with the Toloo

[61] model. Spearman's rank correlation coefficients for model (8) and Toloo [61] model and model (8) and Toloo [61] model are calculated as $r_s = 0.985$ and $r_s = 0.987$, respectively.

The results in the Table 2 show that there is a powerful correlation in the same direction between the proposed models and aggressive cross efficiency model Toloo [61] model in terms of efficiency ranking values of the DMUs.

As mentioned in the above the classical DEA model (CCR model) rates robots; 1, 4, 7, 10, 13, 14, 19, 20 and 27, as efficient ones. The optimal solutions of these robots are multiple optimal. In Table 3, four solutions drawn randomly from the multiple solutions for each of efficient robots are given (There are a lot of efficient units in this example. In order not to occupy too much space, four optimal solutions of efficient DMUs are chosen randomly). For robots 1, 10 and 13, model (8) and (9) have same optimal solutions given in fourth rows (solutions) of each of these DMUs in the Table 3. For robots 4, 7, 14, 19, 20 and 27, the optimal weights are obtained by model (8) and model (9) are given respectively in the third and fourth rows (solutions) of each of these units in the Table 3. It is shown that the variations of the multiple optimal weights obtained by model (8) and model (9) are smaller than the others. Meanwhile, CE-CRR (efficiency score obtained by aggressive cross efficiency models) shown in Table 2 is computed using the solutions in the first row of the Table 3.

6. SIMULATION EXPERIMENT

In the simulation study, the efficiency scores of the CCR model, aggressive cross efficiency CCR model, Toloo [61] model and proposed two models are evaluated according to the formed possible cases for the different number of DMUs ($n = 10, 20, 30, 40, 50, 75, 100$), and of input variables ($i = 1, 2, . . . , 7$), and of output variables ($o = 1, 2, . . . , 7$). Each case is repeated for 1000 times. The input and output variables are generated using Cobb-Douglas production function.

For each case, using the following hypotheses it is tested if the two approaches give the similar rankings to DMUs.

H_0 : The DMU efficiency scores for the proposed model (model 8 or model 9) are uncorrelated to the DMU efficiency scores for the aggressive cross efficiency CCR model (or Toloo [61] model).

H_1 : The DMU efficiency scores for the proposed model (model 8 or model 9) are correlated in the same direction to the DMU efficiency scores for the aggressive cross efficiency CCR model (or Toloo [61] model).

For testing the hypotheses, the Spearman's rho rank correlation coefficients are used. In Tables 4-7, in the column of testing the ranks of methods, the number of cases agreed with the hypothesis H_1 per 1000 repeats and the average value for the Spearman's rank correlations are given.

Later, in order to compare the number of efficient units corresponding to the proposed models and the basic CCR model and Toloo [61] models the following hypotheses are tested.

H_0 : There are no difference in terms of number of efficient units between the efficient units corresponding to the proposed model (model 8 or model 9) and the CCR model (or Toloo [61] model).

H_1 : The number of efficient units for the proposed model (model 8 or model 9) are less than that of the CCR model (or Toloo [61] model).

For testing the hypotheses, the Mann-Whitney statistic is used. In Table 4, in the column of testing the number of efficient units, the number of cases agreed with the hypothesis H_1 per 1000 repeats and the average value for p -values are given. Additionally, all model evaluations are performed on standard commercial processing unit of *2.50 GHz Intel (R) Core (TM) i5-2520 M type CPU with 4.00 GB of RAM.*

Table 4: Results of the hypotheses testing with model (8) and CCR model

			Testing the ranks of methods		***Testing the number of efficient units***	
n	i	o	***Number of accepting*** H_1	$\overline{r}_s$	***Number of accepting*** H_1	$\overline{p}$ ***val.***
10	2	1	995	0.912	1000	0.0001
	1	2	980	0.887	1000	0.0002
	2	2	994	0.918	1000	0.0001
	1	3	990	0.860	998	0.0014
20	3	1	989	0.755	1000	0.0008
	2	3	987	0.709	995	0.0011
	4	1	1000	0.771	1000	0.0007
	2	4	979	0.715	989	0.0025
30	3	2	991	0.708	995	0.0021
	2	5	1000	0.712	1000	0.0009
	4	3	988	0.669	985	0.0077
	3	5	965	0.644	979	0.0093
40	4	3	987	0.602	991	0.0024
	2	5	992	0.635	986	0.0079
	6	3	967	0.587	979	0.0065
	4	4	1000	0.651	991	0.0017
50	3	4	1000	0.541	990	0.0030
	4	6	979	0.469	985	0.0061
	5	3	987	0.521	965	0.0085
	5	5	975	0.465	988	0.0035
75	5	2	985	0.498	988	0.0054
	4	6	986	0.503	975	0.0078
	6	3	967	0.479	968	0.0085
	5	6	965	0.478	979	0.0099
100	3	5	996	0.455	992	0.0015
	4	7	978	0.427	968	0.0058
	6	4	967	0.445	965	0.0065
	7	7	951	0.401	959	0.0072

Table 5: Results of the hypotheses testing with model (9) and CCR model

			Testing the ranks of methods		***Testing the number of efficient units***	
n	i	o	***Number of accepting*** H_1	$\overline{r}_s$	***Number of accepting*** H_1	$\overline{p}$ ***val.***
10	2	1	991	0.908	1000	0.0001
	1	2	985	0.901	999	0.0009
	2	2	999	0.925	1000	0.0001
	1	3	991	0.907	1000	0.0002
20	3	1	995	0.796	993	0.0017
	2	3	992	0.778	995	0.0009
	4	1	995	0.800	1000	0.0005
	2	4	981	0.726	992	0.0021
30	3	2	1000	0.715	995	0.0021
	2	5	1000	0.719	999	0.0007
	4	3	990	0.695	988	0.0062
	3	5	972	0.652	979	0.0065
40	4	3	991	0.632	993	0.0019
	2	5	993	0.642	987	0.0045
	6	3	978	0.601	980	0.0095
	4	4	991	0.629	992	0.0018
50	3	4	995	0.528	991	0.0029
	4	6	978	0.495	986	0.0055
	5	3	986	0.525	969	0.0088
	5	5	986	0.521	983	0.0058
75	5	2	981	0.491	992	0.0045
	4	6	987	0.500	979	0.0088
	6	3	969	0.465	951	0.0098
	5	6	969	0.472	961	0.0094
100	3	5	991	0.451	987	0.0054
	4	7	979	0.438	975	0.0062
	6	4	969	0.432	969	0.0069
	7	7	961	0.415	959	0.0091

Table 6: Results of the hypotheses testing with model (8) and Toloo [61] model

			Testing the ranks of methods		***Testing the number of efficient units***	
n	i	o	***Number of accepting*** H_1	$\overline{r}_s$	***Number of accepting*** H_1	$\overline{p}$ ***val.***
10	2	1	992	0.908	150	0.301
	1	2	991	0.901	105	0.295
	2	2	1000	0.945	120	0.247
	1	3	989	0.907	130	0.245
20	3	1	991	0.796	165	0.294
	2	3	990	0.778	165	0.325
	4	1	991	0.800	155	0.312
	2	4	1000	0.826	140	0.275
30	3	2	995	0.715	165	0.295
	2	5	988	0.719	175	0.289
	4	3	990	0.695	190	0.255
	3	5	988	0.652	140	0.250
40	4	3	985	0.632	185	0.175
	2	5	1000	0.692	190	0.198
	6	3	979	0.601	178	0.164
	4	4	987	0.629	155	0.155
50	3	4	985	0.528	200	0.115
	4	6	979	0.495	185	0.125
	5	3	988	0.525	175	0.145
	5	5	991	0.521	160	0.115
75	5	2	985	0.491	219	0.105
	4	6	989	0.500	241	0.101
	6	3	975	0.465	226	0.092
	5	6	968	0.472	247	0.085
100	3	5	965	0.451	310	0.040
	4	7	978	0.438	305	0.021
	6	4	961	0.432	295	0.055
	7	7	975	0.415	292	0.069

Table 7: Results of the hypotheses testing with model (9) and Toloo [61] model

			Testing the ranks of methods		***Testing the number of efficient units***	
n	i	o	***Number of accepting*** H_1	$\overline{r}_s$	***Number of accepting*** H_1	$\overline{p}$ ***val.***
10	2	1	989	0.908	155	0.278
	1	2	988	0.901	159	0.288
	2	2	977	0.925	161	0.285
	1	3	1000	0.927	158	0.282
20	3	1	990	0.796	201	0.220
	2	3	991	0.778	185	0.235
	4	1	985	0.800	165	0.208
	2	4	991	0.726	159	0.208
30	3	2	1000	0.775	185	0.185
	2	5	989	0.719	195	0.191
	4	3	992	0.695	200	0.141
	3	5	978	0.652	245	0.148
40	4	3	981	0.632	212	0.132
	2	5	986	0.642	209	0.125
	6	3	986	0.601	241	0.114
	4	4	978	0.629	299	0.103
50	3	4	983	0.528	269	0.060
	4	6	982	0.495	252	0.065
	5	3	981	0.525	225	0.090
	5	5	969	0.521	272	0.099
75	5	2	989	0.491	261	0.032
	4	6	981	0.500	285	0.021
	6	3	979	0.465	295	0.015
	5	6	955	0.472	300	0.012
100	3	5	969	0.451	285	0.019
	4	7	971	0.438	351	0.021
	6	4	969	0.432	380	0.036
	7	7	980	0.415	365	0.014

Table 4 and Table 5 show that there is a high correlation in the same direction between the efficiency scores of DMUs assigned by proposed models and the aggressive cross efficiency CCR model in more than 95.1% of the cases and reaches 100% of the case for n =20, $i = 4$, and $o =1$; n =30, $i = 2$, and $o =5$; n =40, $i = 4$, and $o =4$; n =50, $i = 3$, and $o =4$ for proposed model (8) and n =30, $i = 3$, and $o =2$ and n =30, $i = 2$, and $o =5$ for proposed model (9). Similarly, Table 6 and Table 7 show that there is a high correlation in the same direction between the efficiency scores of DMUs assigned by proposed models and the Toloo [61] model in more than 95.5% of the cases and reaches 100% of the case for n =10, $i = 2$, and $o =2$; n =20, $i = 2$, and $o =4$; n =40, $i = 2$, and $o =5$ for proposed model (8) and n =10, $i = 1$, and $o =3$; n =30, $i = 3$, and $o =2$ for proposed model (9).

On the other hand, the number of efficient units for the proposed models are less than that of the basic CCR in more than 95.9% of the cases and reaches 100% of the case for n =10, $i = 2$, and o $=1$; n =10, $i = 1$, and $o =2$; n =10, $i = 2$, and $o =2$; n =20, $i = 3$, and $o =1$; n =20, $i = 4$, and $o =1$; n =30, $i = 2$, and $o =5$ for proposed model 8, and n =10, $i = 1$, and $o =1$; n =10, $i = 2$, and $o =1$; n =10, $i = 1$, and $o =3$; n =20, $i = 4$, and $o =1$ for proposed model (9) according to Table 4 and Table 5, respectively. Similarly, Table 6 and Table 7 show the discrimination power comparison between proposed models and Toloo [61] model. Toloo [61] model is better than the proposed models in terms of the reducing the number of efficient units. Although the proposed models are developed to eliminate multiple optimal solutions at input-output weights and therefore to obtain consistent ranks of DMUs, Toloo [61] model is designed to determine the most efficient unit. However, it is observed that as the sample size increases, difference number of efficient unit between proposed models and Toloo [61] model significantly decreases.

All results of the simulation show that there is statistically a significant correlation and hence a similarity between the ranks obtained by the proposed models and aggressive cross efficiency and Toloo [61] model for each case. In addition, in almost all cases it is observed that the number of efficient units are significantly less than the basic CCR model.

7. CONCLUSION

DEA has previously been used for the selection of technologies. In this study, two proposed model have been applied to robot selection problem. Since the optimal input-output weights obtained by classical DEA are usually not unique, the cross efficiency scores depending on these weights may not be unique either. The purpose of this study is to remove the question of multiple optimal weights and to provide ranking the industrial robots. As a result, two models as named model (8) and model (9) are proposed for the second stage of the cross efficiency evaluation. Provided that the classical DEA efficiencies are preserved, by taking into account the quantities of input and output values (their greatness or smallness), the model (8) chooses the weights with an approximation containing the input-outputs components efficiency evaluation from the optimal weights set obtained by classical DEA. Similarly, provided that the classical DEA efficiencies are preserved, by minimizing the variation of input-output weights the model (9) chooses the weights from the optimal weights set obtained by classical DEA. The results show that there is a high correlation in the same direction between the efficiency scores of DMUs assigned by proposed models and the aggressive cross efficiency CCR model. Additionally, the number of efficient units for the proposed models are statistically significantly less than that of the basic CCR model. An important result indicate that recently proposed by the Toloo [61] model is better than the proposed models in terms of the reducing the number of efficient units. At the same time, there is a high correlation in the same direction between the efficiency scores of DMUs assigned by proposed models and the Toloo [61] model.

Finally, the results of a well-known literature robot selection example and a comprehensive simulation experiment indicate that proposed models are useful for the ranking and discrimination power problems in the DEA.

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