Proceedings of the 9th WSEAS International Conference on Applied Mathematics, Istanbul, Turkey, May 27-29, 2006 (pp272-276)

Technologies Ranking by Super-Efficiency Analysis

REZA FARZIPOOR SAEN
Department of Industrial Management
Islamic Azad University - Karaj Branch
Karaj, P. O. Box: 31485-313
Islamic Republic of IRAN

Abstract: Ranking of technologies is an important phase for technology transfer. Data Envelopment Analysis (DEA) techniques generally do not rank the efficient technologies. This paper proposes an innovative approach, which is based on the super-efficiency. The implication here is that the use of DEA in two-phase model of Khouja for robot selection may be unnecessary and the application of super-efficiency model could suffice to rank the technologies for the purposes of identifying the best performing technologies. A numerical example demonstrates the application of the proposed method.

Key-words: Data envelopment analysis, Technology ranking, Super-efficiency

1 Introduction

As we move toward the factory of the future, managers are called on to make decisions in technical areas such as manufacturing technology selection. Even for managers with high technical competency, the number of available technologies and their wide range of performance and cost is overwhelming. In today's highly competitive environment, an effective technology selection tool is very important to the success of any company. Selecting the right technology is always a difficult task for the R&D manager. Technologies have varied strengths and weaknesses which require careful assessment by the purchasers. Technology selection models help decision maker choose between evolving technologies. Some mathematical programming approaches have been used for technology selection in the past.

Khouja [14] proposed a decision model for technology selection problems using a two-phase procedure. In phase 1, Data Envelopment Analysis (DEA)[1] is used to identify technologies that provide the best combinations of vendor specifications on the performance parameters of the technology. In phase 2, a Multi-Attribute Decision Making (MADM) model is used to select a technology from those identified in phase 1. Khouja [14] used MADM, to select a robot from the efficient robots. Baker and Talluri [4] proposed an alternate methodology for technology selection using DEA. They addressed some of the shortcomings in the methodology suggested by Khouja [14] and presented a more robust analysis based on cross-efficiencies in DEA. Talluri et al. [20] proposed a framework, which is based on the combined application of DEA and nonparametric statistical procedures, for the selection of flexible manufacturing systems. The strengths of this methodology are that it incorporates variability measures in the performance of alternative systems, provides decision maker with effective alternative choices by identifying homogeneous groups of systems, and presents graphic aids for better interpretation of results. However, in these papers, selection processes and computations are burdensome.

Yurdakul [25] introduced a combined model of the Analytical Hierarchy Process (AHP) and Goal Programming (GP), to consider multiple objectives and constraints simultaneously. Liu and Hai [15], to decide the total ranking of the suppliers, compared the weighted sum of the selection number of rank vote, after determining the weights in a selected rank. They presented a novel weighting procedure in place of pairwise comparison of AHP for selecting suppliers. They provided a simpler method than AHP that is called voting analytic hierarchy process, but which do not lose the systematic approach of deriving the weights to be used and for scoring the performance of suppliers. Although their approach are innovative, but possible limitations include subjectivity of AHP and lack of attention to inputs in technology selection.

Parkan and Wu [17] demonstrated the use of and compare some of the current MADM and performance measurement methods through a robot selection problem borrowed from Khouja. Particular emphasis were placed on a performance measurement procedure called Operational Competitiveness Rating (OCRA) and a MADM tool called Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). But, Wang [24] offers comments on Parkan and Wu [17] based on an examination of their proposed OCRA method. Since the premise of the OCRA method is that the cost/revenue ratios must be

[1] Since the DEA models have become common knowledge, the readers are directed to the references.

known, costs and revenues cannot be measured in any units other than dollar value in any practical cases. This property makes the OCRA method faulty. Further, it is shown that the invalid weighting approach used in the OCRA method provides an illusion to management that a cost category with large cost/revenue ratio is more important than a cost category with small ratio. The conclusion is that a performance analysis using the OCRA method can be invalid.

This paper proposes an innovative approach, which is based on the super-efficiency. What is new in this paper is the simplification of technology selection & ranking process. The implication here is that the use of DEA in two-phase model of Khouja for robot selection may be unnecessary and the application of super-efficiency model could suffice to rank the robots for the purposes of identifying the best performing robots. To the author's knowledge, there is not any reference that discusses the use of super-efficiency in technology ranking.

This paper proceeds as follows. In Section 2, a review of super-efficiency models and selected model which can evaluate the efficiency of technologies in input and output orientation, simultaneously, is presented. Numerical example and concluding remarks are discussed in Sections 3 and 4 respectively.

2 Super-efficiency analysis techniques

DEA proposed by Charnes et al. [6] (CCR model) and developed by Banker et al. [5] (BCC model) is an approach for evaluating the efficiencies of Decision Making Units (DMUs). Outcome of DEA models is an efficiency score equal to one to efficient DMUs and less than one to inefficient DMUs. So, for inefficient DMUs a ranking is given but efficient DMUs can not be ranked. One problem that has been discussed frequently in the technologies ranking literature, has been the lack of discrimination in DEA applications, in particular when there are insufficient DMUs or the number of inputs and outputs is too high relative to the number of DMUs. The research on ranking efficient DMUs can be divided into the following streams [1]:

In the first stream, the research was pioneered by Sexton et al. [19]. In their research, the ranking of DMUs was based on a cross-efficiency. In the second stream, the ranking of DEA-efficient DMUs is based on benchmarking, an approach initially developed by Torgersen et al. [23]. They concluded that a DMU was highly ranked if it was chosen as a reference by many other inefficient DMUs. In the third stream, researchers like Fridman and Sinuany-Stern [8], who initiated the research in this direction, used multivariate statistical tools such as canonical correlation analysis and discriminate analysis to rank both efficient and inefficient DMUs. To increase discrimination between efficient DMUs, Farzipoor et al. [7] introduced the correlation coefficient threshold that beyond which omission of one or more input vectors have no statistically significant effect on the efficiency mean. The threshold identification in terms of some of the DEA models was performed.

The last, yet the most popular, research stream in ranking DMUs is called super-efficiency. An advantage of super-efficiency method is the capability to rank both efficient and inefficient DMUs. Here is presented a concise review:

The research in this area was first developed by Andersen and Petersen [3]. They proposed the idea of modifying the envelopment Linear Programming (LP) formulation so that the corresponding column of the DMUs being scored is removed from the coefficient matrix. Thrall [21] pointed out that the model developed by Andersen and Petersen (AP) may result in instability when some inputs are close to zero. Then, to avoid this problem, MAJ [16] and slack-based measure (SBM) [22] models were proposed. Jahanshahloo et al. [10] presented a method for ranking extreme efficient decision making units in DEA models with constant and variable returns to scale. They exploited the leave-one-out idea and l_1-norm. Jahanshahloo et al. [11] using Monte Carlo method, developed a method which is able to rank all efficient (extreme and non-extreme) DMUs. Jahanshahloo et al. [12] introduced a method for ranking of DMUs using Common Set of Weights (CSW). Jahanshahloo and Afzalinejad [9] suggested a ranking method which basically differs from previous methods. In this ranking method, DMUs are compared against a full-inefficient frontier. This method can be used to rank all DMUs to get analytic information about the system, and also to rank only efficient DMUs to discriminate between them. Amirteimoori et al. [2] described a new DEA ranking approach that uses l_2-norm. Jahanshahloo et al. [13] showed that the technique used for rendering MAJ model unit-invariant causes the ranking to change when some inputs of some inefficient DMUs change, without causing any change in the new Production Possibility Set (PPS). They modified MAJ model so that this problem will not occur. Saati et al. [18] suggested a modification for MAJ model and proved that the modified version is always feasible and the ranking lies in (0,1]. Unlike the previous models, this model is both input and output oriented, simultaneously.

In this section, the model which can evaluate the efficiency of technologies in input and output orientation, simultaneously, is presented [18]. Suppose that there are n technologies (DMUs) for ranking, and each DMU consumes m inputs to produce s outputs. In particular, DMU$_p$ consumes x_{ip} (i=1, …, m), the amount of input i, to produce y_{rp} (r=1, …, s), the amount of output r. In the model formulation, X_j and Y_j (j=1, …, n) denote the nonnegative vectors of input and output values for DMU_j, respectively. This model by decreasing inputs and increasing outputs of the DMU under consideration by equal sizes, project it on the frontier. The simultaneously changes in input and output are equal in size because otherwise due to giving different preferences to them, the problem becomes a multi objective programming one and hence yielding a complex situation.

Omitting the column corresponding to DMU_p, the DMU under consideration, the ranking model is obtained as follows:

$$\begin{aligned} \min \quad & \varphi = w_p + 1 \\ s.t. \quad & \sum_{\substack{j=1 \\ j\neq p}}^{n} \lambda_j X_j \leq X_p + w_p \qquad (1) \\ & \sum_{\substack{j=1 \\ j\neq p}}^{n} \lambda_j Y_j \geq Y_p - w_p \\ & \lambda_j \geq 0 \qquad j = 1,\dots,n \end{aligned}$$

where w_p is a free variable and **1** is a vector of ones.

Since the inputs and outputs are not homogeneous and scale of objective function in proposed model is depended on the units of measurement of input and output data, unit independence is obtained by normalization, e.g. dividing each input and output to the largest of them as one of the techniques for normalization.

3 Numerical example

For illustration purposes, the technology ranking approach proposed in this paper is used for robot ranking. The data set for this example was taken from Khouja [14] and contains specifications on 27 industrial robots. The performance measures utilized were cost, repeatability, load capacity, and velocity. Cost and repeatability were used in some sense as inputs for the DEA model. Load capacity and velocity were considered as outputs. Table 1 depicts the robot attributes and the DEA efficiency scores. CCR model [6] identified robots 1, 4, 7, 10, 13, 14, 19, 20, and 27 to be efficient with a relative efficiency score of 1. For those robots, increasing velocity cannot be done unless load capacity is decreased or repeatability or cost is increased. The same argument holds true for increasing the load capacity of those robots. In other words, those robots provide the best combination on technology specifications. The problem now becomes selecting a robot from those nine. To select a robot from the top nine robots in Table 1, model (1) is used.

Table 1. Related attributes for 27 robots

Robot No. (DMU)	Inputs		Outputs		
	Cost (10000$)	Repeatability (mm)	Load Capacity (kg)	Velocity (m/s)	Efficiency
1	7.2	.15	60	1.35	1
2	4.8	.05	6	1.1	.9
3	5	1.27	45	1.27	.53
4	7.2	.025	1.5	.66	1
5	9.6	.25	50	.05	.59
6	1.07	.1	1	.3	.48
7	1.76	.1	5	1	1
8	3.2	.1	15	1	.78
9	6.72	.2	10	1.1	.38
10	2.4	.05	6	1	1
11	2.88	.5	30	.9	.67
12	6.9	1	13.6	.15	.1
13	3.2	.05	10	1.2	1
14	4	.05	30	1.2	1
15	3.68	1	47	1	.61
16	6.88	1	80	1	.61
17	8	2	15	2	.41
18	6.3	.2	10	1	.37
19	.94	.05	10	.3	1
20	.16	2	1.5	.8	1
21	2.81	2	27	1.7	.85
22	3.8	.05	.9	1	.83
23	1.25	.1	2.5	.5	.69
24	1.37	.1	2.5	.5	.64
25	3.63	.2	10	1	.55
26	5.3	1.27	70	1.25	.58
27	4	2.03	205	.75	1

Table 2 shows the normalized data set of nine efficient robots. In Table 3, the ranking results by using model (1), have been displayed. The robots have been ranked in decreasing order of their objective values. As Table 3 shows, robot 27 received the highest objective value and is the first candidate for selection. Therefore, the best choice for decision maker is robot 27.

In comparison with the two-phase model of Khouja, this example demonstrated a straightforward process for technology selection and ranking. Consequently, applying the super-efficiency model could suffice to rank the robots for the purposes of identifying the best performing technologies.

Table 2. Normalized data

Robot No. (DMU)	Inputs		Outputs	
	Cost	Repeatability	Load	Velocity
1	1	0.073892	0.292683	1
4	1	0.012315	0.007317	0.488889
7	0.244444	0.049261	0.02439	0.740741
10	0.333333	0.024631	0.029268	0.740741
13	0.444444	0.024631	0.04878	0.888889
14	0.555556	0.024631	0.146341	0.888889
19	0.130556	0.024631	0.04878	0.222222
20	0.022222	0.985222	0.007317	0.592593
27	0.555556	1	1	0.555556

Table 3. Final solution

Robot rank	Robot No.	Objective Value
1	27	1.576883
2	20	1.130326
3	7	1.04829
4	14	1.019749
5	13	1.003261
6	10	1.003173
7	1	1.00162
8	4	1.001199
9	19	1.000746

4 Concluding remarks

Ranking of technologies is an important phase for technology transfer. DEA techniques generally do not rank the efficient technologies. This paper introduced the use of a super-efficiency model which removes the ranking difficulties about computational burdensome of Khouja [14], Baker and Talluri [4], Talluri et al. [20], Yurdakul [25], Liu and Hai [15], and Parkan and Wu [17].

Following research issues can be studied in future researches: similar research can be repeated for the cases of qualitative data, imprecise data, stochastic data and generally, technology selection under uncertainty.

References:

[1] N. Adler, L. Fridman, Z. Sinuany-Stern, Review of Ranking Methods in Data Envelopment Analysis Context, *European Journal of Operational Research,* Vol. 140, No. 2, 2002, pp. 249-265.

[2] A. Amirteimoori, G. R. Jahanshahloo, S. Kordrostami, Ranking of Decision Making Units in Data Envelopment Analysis: A Distance-Based approach, *Applied Mathematics and Computation,* Vol. 171, No. 1, 2005, pp. 122-135.

[3] P. Andersen, N. C. Petersen, A Procedure for Ranking Efficient Units in Data Envelopment Analysis, *Management Science,* Vol. 39, No. 10, 1993, pp. 1261-1264.

[4] R. C. Baker, S. Talluri, A Closer Look at the Use of Data Envelopment Analysis for Technology Selection, *Computers & Industrial Engineering,* Vol. 32, No. 1, 1997, pp. 101-108.

[5] R. D. Banker, A. Charnes, W. W. Cooper, Some Methods for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis, *Management Science,* Vol. 30, No. 9, 1984, pp. 1078-1092.

[6] A. Charnes, W. W. Cooper, E. Rhodes, Measuring the Efficiency of Decision Making Units, *European Journal of Operational Research,* Vol. 2, No. 6, 1978, pp. 429-444.

[7] R. Farzipoor Saen, A. Memariani, F. Hosseinzadeh Lotfi, The effect of correlation coefficient among multiple input vectors on the efficiency mean in data envelopment analysis, *Applied Mathematics and Computation,* Vol.162, No.2, 2005, pp.503-521.

[8] L. Fridman, Z. Sinuany-Stern, Scaling Units via the Canonical Correlation Analysis and the Data Envelopment Analysis, *European Journal of Operational Research,* Vol. 100, No. 3, 1997, pp. 629-637.

[9] G. R. Jahanshahloo, M. Afzalinejad, A Ranking Method Based On a Full-Inefficient Frontier, *Applied Mathematical Modelling,* Vol. 30, No. 3, 2006, pp. 248-260.

[10] G. R. Jahanshahloo, F. Hosseinzadeh Lotfi, N. Shoja, G. Tohidi, S. Razavyan, Ranking Using l_1-norm in Data Envelopment Analysis, *Applied Mathematics and Computation,* Vol. 153, No. 1, 2004, pp. 215-224.

[11] G. R. Jahanshahloo, F. Hosseinzadeh Lotfi, H. Zhiani Rezai, F. Rezai Balf, Using Monte Carlo Method for Ranking Efficient DMUs, *Applied Mathematics and Computation,* Vol. 162, No. 1, 2005, pp. 371-379.

[12] G. R. Jahanshahloo, A. Memariani, F. Hosseinzadeh Lotfi, H. Z. Rezai, A Note on Some of DEA Models and Finding Efficiency and Complete Ranking Using Common Set of Weights, *Applied Mathematics and Computation,* Vol. 166, No. 2, 2005, pp. 265-281.

[13] G. R. Jahanshahloo, L. Pourkarimi, M. Zarepisheh, Modified MAJ Model for Ranking Decision Making Units in Data Envelopment Analysis, *Applied Mathematics and Computation,* Vol. 174, No. 2, 2006, pp. 1054-1059.

[14] M. Khouja, The Use of Data Envelopment Analysis for Technology Selection, *Computers & Industrial Engineering,* Vol. 28, No. 1, 1995, pp. 123-132.

[15] F. F. Liu, H. L. Hai, The Voting Analytic Hierarchy Process Method for Selecting Supplier, *International Journal of Production Economics,* Vol. 97, No. 3, 2005, pp. 308-317.
[16] S. Mehrabian, M. R. Alirezaee, G. R. Jahanshahloo, A Complete Efficiency Ranking of Decision Making Units in DEA, *Computational Optimization and Applications (COAP),* Vol. 14, No. 2, 1999, pp. 261-266.
[17] C. Parkan, M. Wu, Decision-Making and Performance Measurement Models with Applications to Robot Selection, *Computers & Industrial Engineering,* Vol. 36, No. 3, 1999, pp. 503-523.
[18] S. Saati, M. Zarafat Angiz, A. Memariani, G. R. Jahanshahloo, A Model for Ranking Decision Making Units in Data Envelopment Analysis, *Ricerca Operativ,* Vol. 31, No. 97, 2001, pp. 47-59.
[19] T. R. Sexton, R. H. Silkman, A. J. Hogan, *Data Envelopment Analysis: Critique and Extensions, in RH Silkman (Ed.) Measuring Efficiency: An Assessment of Data Envelopment Analysis,* Jossey-Bass, 1986.
[20] S. Talluri, M. M. Whiteside, S. J. Seipel, A Nonparametric Stochastic Procedure for FMS Evaluation, *European Journal of Operational Research,* Vol. 124, No. 3, 2000, pp. 529-538.
[21] R. M. Thrall, Duality Classification and Slacks in Data Envelopment Analysis, *Annals of Operations Research,* Vol. 66, 1996, pp. 109-138.
[22] K. Tone, A Slack-Based Measure of Super-Efficiency in Data Envelopment Analysis, *European Journal of Operational Research,* Vol. 143, No. 1, 2002, pp. 32-41.
[23] A. M. Torgersen, F. R. Forsund, S. A. C. Kittelsen, Slack-Adjusted Efficiency Measures and Ranking of Efficient Unit, *Journal of Productivity Analysis,* Vol. 7, No. 4, 1996, pp. 379-398.
[24] S. Wang, Comments on Operational Competitiveness Rating Analysis (OCRA), *European Journal of Operational Research,* Vol. 169, No. 1, 2006, pp. 329-331.
[25] M. Yurdakul, Selection of Computer-Integrated Manufacturing Technologies Using a Combined Analytic Hierarchy Process and Goal Programming Model, *Robotics and Computer-Integrated Manufacturing,* Vol. 20, No. 4, 2004, pp. 329-340.