A Forgotten Point in Technology Selection

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Abstract

The assumption of classical technology selection models is based on complete homogeneity of technologies. In spite of this assumption in many applications some technologies do not comprehensively consume common inputs to comprehensively supply common outputs. The objective of this paper is to propose a Data Envelopment Analysis (DEA) model for selecting slightly non-homogeneous technologies. A numerical example demonstrates the application of the proposed method.

Keywords: Technology selection, Slightly non-homogeneous technologies, Data envelopment analysis, Interval data, Missing values

1. Introduction

The assumption of classical technology selection models is based on the principle that technologies consume common inputs to produce common outputs. In spite of this assumption in many applications some technologies do not comprehensively consume common inputs to comprehensively produce common outputs. For instance, to select a power plant there are different technologies. Most of inputs and outputs of power plants are common, but there are a few input(s) and/or output(s) for some power plants that may not be common to all. A power plant may consume natural gas, coal, oil, nuclear fuel, falling water, geothermal steam, wind power, solar energy, and biomass. A power plant uses natural gas whereas an input of such kind for the power plant that uses nuclear fuel may be meaningless. It is clear that zero value allocation for this type of input, causes relative efficiency of the power plant that uses nuclear fuel, to increase unrealistically. In other words, to evaluate the relative efficiency of power plants, all the power plants may not have identical functions. In this case, it is not acceptable saying that the power plants which use natural gas, are not comparable with the power plants which do not. Meanwhile, allocating zero value to power plants that do not use natural gas, is not fair. Generally, zero allocation to outputs and inputs of some technologies, makes the efficiency evaluation unfair. That is zero allocation to output, may make a technology inefficient, on the other hand, zero allocation to input, may make a technology efficient, unrealistically.

Some mathematical programming approaches have been used for technology selection in the past. Archer and Ghasemzadeh (1999) suggested an integrated framework to provide decision support for project portfolio selection. Ghasemzadeh and Archer (2000) discussed the implementation of an organized framework for project portfolio selection through a decision support system. Lee and Kim (2000) presented a methodology using Analytic Network Process (ANP) and Zero-One Goal Programming (ZOGP) for information system projects selection problems that have multiple criteria and interdependence property. Lee and Kim (2001) described an integrated approach of interdependent information system project selection using Delphi method, ANP, and Goal Programming (GP). Kim and Emery (2000) addressed the quantitative methodology for determining possible implementable solutions to project selection problems. Also, they presented an application of GP as an aid in project selection. Mohamed and McCowan (2001) addressed the issue of combining both monetary and non-monetary aspects of an investment option. They proposed a method capable of modeling and ranking various investment options, specifically developed for construction projects. The proposed method utilizes interval mathematics and possibility theory to handle the inherent uncertainty associated with investment parameters. Badri et al. (2001) attempted to present a comprehensive model that includes all the suggested factors that appeared in separate studies. Their model is based on GP. Malladi and Min (2005) showed how an Analytic Hierarchy Process (AHP) model could be utilized to select the optimal access technology for a rural community under a multiple number of criteria. Then, they formulated a mixed integer programming problem that would provide the optimal access technologies for a multiple number of homogeneous communities that were pooling resources such as budgets for fixed and variable costs. Finally, they showed how the problem could be extended to the case of heterogeneous communities where the fixed and variable costs vary among communities. Hajeeh and Al-Othman (2005) used AHP to select the most appropriate technology for seawater desalination. Shehabuddeen et al. (2006) focused on the experience of operationalizing of a framework for technology selection. This is achieved through the application of a software tool, which is based on the structure provided by the framework. They illustrated how theoretical concepts presented in the framework relate to "real-life" technology selection considerations. Khouja (1995) proposed a decision model for technology selection problems using a two-phase procedure. In phase 1, Data Envelopment Analysis (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 Multi-Attribute Decision Making (MADM) model is used to rank a technology from those identified in phase 1. Khouja (1995) used MADM, to select a robot from the efficient robots. Baker and Talluri (1997) proposed an alternate methodology for technology ranking using DEA. They addressed some of the shortcomings in the methodology suggested by Khouja (1995) and presented a more robust analysis based on cross-efficiencies in DEA. Talluri et al. (2000) offered a framework, which is based on the combined application of DEA and nonparametric statistical procedures, for the selection of Flexible Manufacturing Systems (FMSs). 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. Yurdakul (2004) introduced a combined model of the AHP and GP, to consider multiple objectives and constraints simultaneously. Parkan and Wu (1999) demonstrated the use of and compare some of the current MADM and performance measurement methods through a robot selection problem borrowed from Khouja (1995). 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 (2006) offered comments on Parkan and Wu (1999) based on an examination of their proposed OCRA method. Since the premise of the OCRA method is that the cost/revenue ratios must be 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. Talluri and Yoon (2000) introduced advanced manufacturing technology selection process. They proposed a combination of a cone-ratio DEA model and a new methodological extension in DEA, while allowing for the incorporation of preferences of decision makers. Farzipoor Saen (2006) proposed an innovative approach for ranking technologies, which is based on the super-efficiency. What is new is the simplification of technology selection & ranking process. Farzipoor Saen (in press) proposed a comprehensive reference that discusses the use of Imprecise DEA (IDEA) in technology selection. Farzipoor Saen (2006) also proposed a model that ranks the most appropriate technologies in the conditions that both ordinal and cardinal factors are present. Sarkis and Talluri (1999) introduced an application of DEA that considers both cardinal and ordinal data, for the evaluation of alternative FMS. The initial DEA model is based on the works of Cook et al. (1996). To improve the discriminatory power of DEA in the presence of both cardinal and ordinal factors, an additional DEA model relying on pairwise comparisons of FMS was proposed. The results of the pairwise comparison model are aggregated through cross-efficiency measures. Bernroider and Stix (2006) proposed a new, conceptual approach, named profile distance method, to support information system selection problems. By combining the basic concept of the popular utility scoring and ranking technique with DEA, they recognized their appealing benefits while making up for a number of their limitations. However, all the aforementioned references relied on the assumption of complete homogeneity of technologies and do not consider the slightly non-homogeneous technologies.

To the author's knowledge, there is not any reference that deals with slightly non-homogeneous technologies on the one hand, and has computational simplicity on the other hand. The objective of this paper is to propose a simple model for selecting technologies in the presence of slightly non-homogeneous technologies.

This paper proceeds as follows. In Section 2, proposed model for selecting technologies is presented. Numerical example and concluding remarks are discussed in Sections 3 and 4, respectively.

2. Proposed model for selecting technologies

For those slightly non-homogeneous technologies (Decision Making Units (DMUs)) lacking one or some feature (input and/or output), the contribution with respected the lacking factor(s) is considered as missing value(s). Fundamental assumptions of the original DEA are that the inputs and outputs are measured with crisp positive values on a ratio scale and all the data required are available. However, in many applications (such as slightly non-homogeneous technology selection problem) the efficiency evaluation of the DMUs has to take into account missing values for some inputs and outputs. Replacement of missing values by approximations in the form of intervals in which the unknown missing values are likely to belong is proposed. The case of missing values in DEA models have been examined in the literature in different ways. To determine the relative efficiency of slightly non-homogeneous technologies, Farzipoor Saen (2006) developed an algorithm that is based on AHP and chance-constrained DEA. Such an algorithm is computational burden. Other approaches use imputation techniques to estimate exact approximations of the missing values (for example, average value of the other DMUs) (Cooper, Seiford and Tone (1999)). Smirlis, Maragos and Despotis (2006) proposed the use of the interval DEA and particularly the approach introduced by Despotis and Smirlis (2002). However, as Wang, Greatbanks and Yang (2005) indicated, their model used variable production frontiers, i.e. different constraint sets, to measure the efficiencies of DMUs, which made them lack of comparability.

In this paper the use of the interval DEA is suggested. The bounds of intervals are constant and can be obtained by various estimation techniques. The interval DEA model provides for the DMUs with missing values a lower and an upper bound of their efficiency score corresponding to their most favorable and unfavorable option.

Suppose that there are n technologies (DMUs) to be evaluated. Each DMU consumes m inputs to produce s outputs. In particular, DMU$_j$ consumes amounts $X_j = \{x_{ij}\}$ of inputs (i=1, …, m) and produces amounts $Y_j = \{y_{rj}\}$ of outputs (r=1, …, s). Unlike the original DEA model, the interval DEA assumes that some of the crisp input x_{ij} and output y_{rj} values are not known and for them, it is only known that they lie within bounded intervals, i.e. $x_{ij} \in [x_{ij}^L, x_{ij}^U]$ and $y_{rj} \in [y_{rj}^L, y_{rj}^U]$, with the upper and lower bounds of the intervals $x_{ij}^L, x_{ij}^U, y_{rj}^L, y_{rj}^U$ to be strictly positive constants.

In order to deal with such a situation, the following pair of linear programming models has been developed to generate the upper and lower bounds of interval efficiency for each DMU (Wang, Greatbanks and Yang (2005)):

$$
\begin{aligned}
&\operatorname{Max}\theta_{jo}^{U} = \sum_{r=1}^{s} u_r y_{rj_o}^{U} \\
&\text{s.t.} \\
&\sum_{i=1}^{m} v_i x_{ij_o}^{L} = 1, \\
&\sum_{r=1}^{s} u_r y_{rj}^{U} - \sum_{i=1}^{m} v_i x_{ij}^{L} \le 0, \qquad j = 1, \cdots, n \\
&u_r, v_i \ge \varepsilon \qquad \forall r, i.
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
&\operatorname{Max}\theta_{jo}^{L} = \sum_{r=1}^{s} u_r y_{rj_o}^{L} \\
&\text{s.t.} \\
&\sum_{i=1}^{m} v_i x_{ij_o}^{U} = 1, \\
&\sum_{r=1}^{s} u_r y_{rj}^{U} - \sum_{i=1}^{m} v_i x_{ij}^{L} \le 0, \qquad j = 1, \cdots, n \\
&u_r, v_i \ge \varepsilon \qquad \forall r, i.
\end{aligned} \tag{2}
$$

where j_o is the DMU under evaluation (usually denoted by DMU$_o$); u_r and v_i are the weights assigned to the outputs and inputs; θ_{jo}^{U} stands for the best possible relative efficiency achieved by DMU$_o$ when all the DMUs are in the state of best production activity, while θ_{jo}^{L} stands for the lower bound of the best possible relative efficiency of DMU$_o$. They constitute a possible best relative efficiency interval $[\theta_{jo}^{L}, \theta_{jo}^{U}]$. ε is the non-Archimedean infinitesimal.

In order to judge whether a DMU is DEA efficient or not, the following definition is given.

Definition 1. A DMU, DMU$_o$, is said to be DEA efficient if its best possible upper bound efficiency $\theta_{jo}^{U*} = 1$; otherwise, it is said to be DEA inefficient if $\theta_{jo}^{U*} < 1$.

Models (1) and (2) are able to handle interval data and estimate the efficiency bounds of the DMUs. Missing values of inputs/outputs can be replaced by estimations in the form of intervals. So intervals $[x_{ij}^{L}, x_{ij}^{U}]$, $[y_{rj}^{L}, y_{rj}^{U}]$ can take the place of any missing input/output values x_{ij} and y_{rj} and thus form an interval data set. The bounds $x_{ij}^{L}, x_{ij}^{U}, y_{rj}^{L}, y_{rj}^{U}$, depending on the particular application, can be estimated by using different techniques: descriptive statistics, regression/extrapolation techniques, distance/proximity measurements, experts opinions, etc. When no estimation can be provided by any technique, the column minimum and maximum for the particular input-output may be used to form such an interval.

3. Numerical example

Assume that there are 12 technologies. Two inputs and 2 outputs are considered. Table 1 shows the data for inputs and outputs. As it is noticed, technology$_2$ lacks one input, technology$_4$ also lacks one input, etc. Hence the comparison of these technologies with the others is not fair. For this, the proposed model is implemented. Based on experts opinions, missing values of inputs/outputs are replaced by estimations in the form of intervals. The exact data are viewed as a special case of interval data with the lower and upper bounds being equal. Therefore, all the input and output data are now transformed into interval numbers and can be evaluated using interval DEA models. Using the interval DEA models (1) and (2), the rating results are obtained that have been shown in Table 2. The non-Archimedean infinitesimal was set to be $\varepsilon = 10^{-10}$.

Table 1. Input and output vectors

Technology No. (DMU)	I_1	I_2	O_1	O_2
1	5	3	8	3
2	-	9	2	4
3	3	4	9	0
4	6	-	3	6
5	2	6	4	-
6	-	2	5	3
7	3	3	4	6
8	-	2	-	2
9	4	0	5	3
10	3	2	2	-
11	2	5	-	4
12	5	9	3	7

It can be seen from Table 2 that, with respect to definition 1, technologies 3, 5, 9, 10, and 11 are efficient and should be considered as the best technologies.

Table 2. The results

Technology No. (DMU)	$[\theta_{jo}^{L}, \theta_{jo}^{U}]$
1	[.83, .83]
2	[.24, .44]
3	[1, 1]
4	[.44, .5]
5	[.65, 1]
6	[.62, .91]
7	[.97, .97]
8	[.27, .85]
9	[1, 1]
10	[.45, 1]
11	[.8, 1]
12	[.53, .53]

4. Concluding remarks

One of the assumptions of all the classical models of technology selection is based on complete homogeneity of technologies, whereas this assumption in many cases cannot be generalized. In other words, some of the criteria are not common for all the technologies occasionally. In this paper a method for selecting slightly non-homogeneous technologies was proposed. Employing the proposed method, practical difficulties for technology selection are largely reduced.

The problems considered in this study are at initial stage of investigation and many further researches can be done based on the results of this paper. Some of them are as follows:

Similar research can be repeated for selecting technologies when there are fuzzy data.

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