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A new approach to overall performance evaluation based on multiple contexts: An application to the logistics of China

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ABSTRACT

Data envelopment analysis (DEA) is a useful method for evaluating the performance of decision making units (DMUs). In this paper, we propose a new approach to overall performance evaluation of DMUs based on multiple contexts in the framework of DEA. For a given set of DMUs, an algorithm is performed to identify frontiers of different efficiency levels as evaluation context. An ideal case is supposed in which all evaluation contexts lead to a consistent report on the performance of DMUs. Shannon entropy is employed to measure the entropy deviations of evaluation results from the real case to the ideal case. A constrained optimization model is constructed to integrate the results against multiple evaluation contexts into an overall performance score for each DMU. The proposed approach is applied to evaluate the logistics performance of China. Its comparisons to some previous methods are also illustrated using the empirical application. It is shown that the proposed approach is robust and provides a more comprehensive evaluation for logistics performance.

1. Introduction

Data envelopment analysis (DEA), originated by Charnes, Cooper, and Rhodes (1978), is a useful mathematical programming methodology for evaluating the relative efficiencies of a set of peer decision making units (DMUs) with multiple inputs and multiple outputs. Conventional DEA identifies an efficient frontier spanned by efficient DMUs, and the inefficient DMUs being enveloped are measured according to the distance between their current position and their referent point on the efficient frontier. This original efficient frontier hence establishes an evaluation context.

In the spirit of this, we may consider that not only the original efficient frontier can provide a context for performance evaluation. As revealed in Tversky and Simonson (1993), choices made by decision makers are often influenced by the context in which the alternatives are involved. For example, an alternative may appear superior against a background of worse alternatives but may become inferior when surrounded by some better ones. As such, alterations of the efficient frontier in DEA may influence the evaluation results. If all the DMUs on the original efficient frontier are omitted, the remaining DMUs (if exist) will identify a new sub-efficient frontier. This new frontier provides another context for evaluating the performances of the whole sample. This implies that multiple contexts can be derived if we continue to omit the DMUs on the newly identified sub-efficient frontier until there is no DMU left in the sample (Chen, Morita, & Zhu, 2005; Morita, Hirokawa, & Zhu, 2005; Seiford & Zhu, 2003; Ulucan & Atıcı, 2010). In this sense, DEA appears more talented in performance analysis since it enables a comprehensive evaluation in a multifaceted way then, depending on not only the original efficient frontier spanned by efficient DMUs but also those sub-efficient frontiers spanned by inefficient DMUs.

It is noticed that the identified efficient frontiers correspond to different efficiency levels. If all the identified frontiers render the same evaluation report on the performances of DMUs in the sample, choices made based on each specific context are equally reliable. In general, different frontiers identified in multiple efficiency levels, however, are shaped in distinctive structures. As a result, using different efficient frontiers as evaluation context may lead to distinctive and even inconsistent results. This implies that it may not be reliable to choose any single frontier as evaluation context, because in that way the results might be one-sided. It should be more appropriate to conduct an overall performance evaluation based upon all the identified contexts.

Seiford and Zhu (2003) proposed to discriminate between the DMUs on the same frontier based on another frontier identified as evaluation context (a third option). Indeed, prioritizing DMUs is implicitly in the rationale of the inconsistency induced by different frontiers as evaluation context. In the literature on DEA ranking, a broad family of methods can be classified into several categories. For example, the cross-efficiency method, firstly introduced by Sexton, Silkman, and Hogan (1986), uses a peer-evaluation procedure to evaluate a DMU with the input and output weights of all the other DMUs in the sample. Doyle and Green (1994) extended this method and employed a

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secondary goal to address the non-uniqueness of input and output weights. So far, a number of studies have been carried out on both theory (e.g., Anderson, Hollingsworth, & Inman, 2002; Jahanshahloo, Hosseinzadeh Lotfi, Jafari, & Maddahi, 2011; Liang, Wu, Cook, & Zhu, 2008a; Wang & Chin, 2010) and applications to such as R&D project selection (Oral, Kettani, & Lang, 1991), preference voting (Green, Doyle, & Cook, 1996), Supplier selection (Falagario, Sciancalepore, Costantino, & Pietroforte, 2012), and banking (Zerafat Angiz, Mustafa, & Kamali, 2013). The super-efficiency method, proposed by Andersen and Petersen (1993), evaluates a DMU by removing it away from the reference set and comparing it to the frontier spanned by the remaining DMUs. This technique can further discriminate between efficient DMUs but it often suffers from the issue of infeasibility in computation (Seiford & Zhu, 1999; Thrall, 1996). Modifications to address this problem can be found in the works such as Lovell and Rouse (2003), Ray (2008), Du and Chen (2013), Pourmahmoud, Hatami-Marbini, and Babazadeh (2016), and Aldamak, Hatami-Marbini, and Zolfaghari (2016). The benchmarking method provides another way for differentiating efficient DMUs. It examines their importance as a benchmark or a reference for inefficient DMUs. Typical studies of this method include Sinuany-Stern, Mehrez, and Barboy (1994), Torgersen, Forsund, and Kittelsen (1996), Jahanshahloo, Junior, Hosseinzadeh Lotfi, and Akbarian (2007), and Lu and Lo (2009). The inefficient frontier method, firstly proposed by Yamada, Matsui, and Sugiyama (1994), evaluates DMUs in a pessimistic way by maximizing the input-to-output ratio, which defines an inefficient frontier. Entani, Maeda, and Tanaka (2002) combined the optimistic and pessimistic viewpoints and proposed a new model with interval efficiency. The model was further studied in the works such as Wang and Yang (2007) and Azizi (2011). The statistics method incorporates statistical techniques into DEA. These techniques include canonical correlation analysis (Friedman & Sinuany-Stern, 1997), discriminant analysis of ratios (Sinuany-Stern & Friedman, 1998), and regression analysis for common weights (Wang, Luo, & Lan, 2011). The multi-criteria decision making methods have also been applied to the DEA area. Means such as preferential information (in terms of constraints on the multipliers) (Halme, Joro, Korhonen, Salo, & Wallenius, 1999), multiple objectives (Li & Reeves, 1999), analytical hierarchical process (Sinuany-Stern, Mehrez, & Hadad, 2000), and weighted sum (Hosseinzadeh Lotfi, Rostamy-Malkhalifeh, Aghayi, Beigi, & Gholami, 2013) are incorporated into DEA models. For an overview of ranking methods in DEA, see Adler, Friedman, and Sinuany-Stern (2002) and Aldamak and Zolfaghari (2017). In summary, most categories of the previous methods have not taken multiple evaluation contexts into consideration. In this regard, this paper attempts to fill in the gap and develop a new approach using multiple contexts.

In this study, the performances of DMUs are evaluated against multiple contexts in the framework of DEA. We first identify multiple efficient frontiers as evaluation context and evaluate the performance of DMUs against each context. An ideal case is supposed in which all the contexts render a consistent evaluation report on the performance of DMUs. We then employ Shannon entropy (Shannon, 1948), which is derived from information theory, to measure the entropy deviations of evaluation results from the real case to the ideal case, and based on which we construct a constrained optimization model to integrate the evaluations against multiple contexts into an overall performance evaluation.

The remainder of the paper is organized as follows. The next section presents the proposed approach to overall performance evaluation. An application to the evaluation of the logistics performance of China is provided in Section 3, followed by concluding remarks.

2. Overall performance evaluation

2.1. Identification of multiple evaluation contexts

Suppose there are n peer DMUs $\{DMU_j, j = 1, 2, ..., n\}$ with inputs, $x_{ij}(i = 1, 2, ..., m)$ and s outputs, $y_{rj}(r = 1, 2, ..., s)$. Consider a specific DMU$_o$, $o \in \{1, ..., n\}$. Let $J^1 = \{DMU_j, j = 1, 2, ..., n\}$, i.e., J^1 is the whole set of DMUs in the sample. Let $J^{l+1} = J^l - E^l$ and $E^l = \{DMU_o \in J^l \mid \varphi_o^{l*} = 1\}$, where φ_o^{l*} is the optimal value to the following model (1) when DMU$_o$ is being evaluated. Based upon the original (CCR) DEA model (Charnes et al., 1978), which was developed under the condition of constant returns to scale (CRS), the following output-oriented model (Seiford & Zhu, 2003) is constructed for identifying efficient frontiers of multiple efficiency levels.

$$\begin{aligned} \max_{\lambda_j, \varphi_o^l} \quad & \varphi_o^l \\ s.t. \quad & \textstyle\sum_{j \in C(J^l)} \lambda_j x_j \leqslant x_o, \\ & \textstyle\sum_{j \in C(J^l)} \lambda_j y_j \geqslant \varphi_o^l y_o, \\ & \lambda_j \geqslant 0, \quad j \in C(J^l), \end{aligned} \tag{1}$$

where φ_o^l denote the efficiency of DMU$_o$ evaluated by the l^{th}-level efficient frontier, x_{io} and y_{ro} represent the i^{th} input and the r^{th} output of DMU$_o$, and $j \in C(J^l)$ stands for $DMU_j \in J^l$.

From model (1) it can be concluded that E^l represents the set of DMUs on the l^{th}-level efficient frontier. We start running model (1) with $l = 1$. It follows that if $l = 1$, model (1) is equivalent to the CCR model of output-orientation, and E^1 is the set of efficient DMUs on the original (1st-level) efficient frontier, which represents the highest efficiency level in the sample. For $l = 2$, model (1) identifies the 2nd-level efficient frontier spanned by the DMUs in E^2. Proceeding with l increasing, we can derive a series of efficient frontiers of multiple efficiency levels. Each such efficient frontier provides a context for performance evaluation. The following algorithm is then implemented to identify multiple contexts with model (1).

- *Step 1:* Set $l = 1$.
- *Step 2:* Evaluate the set of DMUs, J^l, by model (1) to derive the l^{th}-level efficient frontier and the set of DMUs, E^l, on this frontier.
- *Step 3:* Remove all the DMUs in E^l from the sample, i.e., $J^{l+1} = J^l - E^l$.
- *Step 4:* If $J^{l+1} \neq \varnothing$, let $l = l + 1$ and go to Step 2, otherwise stop.
- *Stopping rule:* $J^{l+1} = \varnothing$, the algorithm stops.

Suppose we finally identify L efficiency levels according to the algorithm. We summarize the following properties associated with the resulting sets of DMUs in different efficiency levels.

(i) $J^k = \cup_{l=k}^{L} E^l$, and $E^l \cap E^{l'} = \varnothing$ if $l \neq l'$.
(ii) The l^{th}-level efficient frontier spanned by E^l envelops the DMUs in $J^{l'}$ if $l < l'$.
(iii) Against different evaluation contexts, a particular DMU in E^l is not necessarily to be more efficient than the DMUs in $J^{l+l'}$, where $0 < l' \le L - l$.

For a simple illustration of these properties, we employ the sample DMUs with two outputs and a single input of unity exemplified in Seiford and Zhu (2003), with two additional DMUs given in Table 1. Fig. 1 portrays the efficient frontiers of four efficiency levels

Table 1
Sample DMUs.

DMU	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	***12***
Output 1	6	5	2	5.5	4.75	3	1	4	3	1	3	2
Output 2	2	3.5	5	1.5	2.5	3.5	4	1	3	3.5	2	3