International Journal of Applied Industrial Engineering
Volume 8 • Issue 1 • January-June 2021

Multiple Criteria DEA-Based Ranking Approach With the Transformation of Decision-Making Units

Jae-Dong Hong, South Carolina State University, USA

ABSTRACT

Though various ranking methods in the data envelopment analysis (DEA) context have emerged since the conventional DEA was introduced, none of them has not been accepted as a universal or a superior method for ranking decision-making units (DMUs). The DEA-based ranking methods show some shortcomings as the numbers of inputs and outputs for DMUs increase. To overcome such shortcomings, this paper proposes a two-step procedure of ranking DMUs more effectively and consistently. In the first step, the multi-objective programming (MOP) is applied for the multiple criteria DEA to transform the original DMUs into the new simpler DMUs with two inputs and a single output, regardless of the numbers of inputs and outputs that the original DMUs use and produce. With the transformed DMUs, some conventional DEA-based methods for ranking DMUs are applied in the second step. A numerical example demonstrates the efficient performance of the proposed method.

KEYWORDS

Conventional DEA, Data Envelopment Analysis (DEA), Decision-Making Unit, Multiple-Criteria DEA, Multi-Objective Programming Model, Ranking Method

INTRODUCTION

The conventional data envelopment analysis was first introduced in 1978 by Charnes, Cooper, and Rhodes (1978), in evaluating the efficiency of a set of peer organizations called decision-making units (DMUs) that consume multiple inputs to generate various outputs. DEA methods have been widely accepted as an effective technique in identifying and separating efficient DMUs from inefficient ones. But the conventional DEA intrinsically aims to identify efficient DMUs and the efficient frontier, so the use of DEA is not enough for discriminating between efficient DMUs. In terms of ranking DMUs, many authors show that conventional DEA is not an appropriate method in many situations. Consequently, the researchers and practitioners have faced a question, “Which DEA method should we use for ranking DMUs effectively and consistently?” Publication and research work have grown substantially, resulting in significant advancements in its methodologies, models, and real-world applications (see Cook and Seiford, 2009; Chen et al., 2019).

DOI: 10.4018/IJAIE.20210101.oa2

Charnes et al. (1978) demonstrate how to change a fractional linear measure of efficiency into a linear programming (LP) format to measure efficiency scores (ESs) of DMUs. In the conventional DEA (C-DEA), a relative efficiency is defined as the ratio of the sum of weighted outputs to the sum of weighted inputs. The C-DEA solves an LP formulation for each DMU to be rated, and the weights assigned to each linear aggregation are obtained by solving the corresponding LP. The DMUs in the C-DEA to be assessed should be relatively homogeneous. As the whole technique is based on a comparison of each DMU with all the remaining ones, a considerable large set of DMUs is necessary for the assessment to be meaningful (Ramanathan, 2006). The C-DEA eventually determines which of the DMUs make efficient use of their inputs and produce most outputs and which DMUs do not. The significant function that the conventional DEA model can do is to separate efficient DMUs from inefficient DMUs. For the inefficient DMUs, the analysis can quantify what levels of improved performance should be attainable. Also, the study indicates where an inefficient DMU might look for benchmarking help as it searches for ways to improve. Recently, Cao et al. (2020) introduce the concept of the anti-strike ability of a single DMU and provide a new ranking method of DMUs. Shahghobadi (2020) presents a method for performance assessment of units so that a large number of units are not evaluated as efficient, but there is at least one efficient unit. Toloo et al. (2020) contend that the number of performance factors (inputs and outputs) plays a decisive role when applying DEA to real-world applications.

The C-DEA produces a single, complete measure of performance for each DMU. The highest efficiency score among all the DMUs would identify the most efficient DMU(s), and every other DMU would be evaluated by comparing its ratio to the DMU with the highest one. A significant weakness of the C-DEA-based assessment comes out because a considerable number of DMUs out of the set of DMUs to be rated can be classified as efficient, and all efficient DMUs are considered to be equal. The nature of the self-evaluation of C-DEA allows each DMU to be evaluated with its most favorable weights. Thus, to maximize the self-efficiency, the conventional DEA model intentionally ignores unfavorable inputs/outputs. The DEA-based methods are developed to measure the relative efficiency of DMUs with multiple inputs and outputs. If DMUs have a single output and a single input, any DEA ranking method is necessary. As the number of inputs and/or outputs of DMUs to be rated increases, the weaknesses of DEA-related methods become more apparent since the DEA method can overlook the weights assigned to unfavorable inputs or outputs

Since the weakness of C-DEA results from its pure self-evaluation, a DEA extension is suggested by Sexton et al. (1986), which is called the cross-efficiency (CE) DEA method. The CE-DEA with the main idea of using the conventional DEA to add the peer evaluation to the pure self-evaluation enhances the discrimination power, and the efficient DMUs treated equally by the conventional DEA can be ranked by their cross-efficiency scores (CESs). Sexton et al. (1986) construct a CE matrix consisting of two rating results, the self-evaluation and the peer-evaluation. The CE-DEA can provide a full ranking for the DMUs to be evaluated and eliminates unrealistic weight schemes without requiring the elicitation of weight restrictions from application area experts (see Anderson et al., 2002). Due to its enhanced discriminating power, especially for the simple DMUs with few inputs and outputs, There are a significant number of applications using the CE evaluation in the DEA literature (see Gavgani and Zohrehbandian, 2014; Hou et al., 2018; Lee, 2019; Liang et al., 2009; Liu et al., 2019; Wang and Chin, 2010).

There have been some crucial issues facing the CE method application. The first issue is the ratio of self-evaluation to peer-evaluation in computing the CES. Doyle and Green (1994) exclude the proportion of self-evaluation by eliminating the diagonal elements in the CE matrix to compute CESs. Some researchers suggest that the percentage of self-evaluation be 1/N, where N is the total number of DMUs to be evaluated. The second issue is that the non-uniqueness of CESs due to the often-present multiple optimal DEA weights. It implies that the CES produced by the CE method is not unique, but flexible, depending on the optimization software used. They (1994) suggest that secondary goals such as aggressive and benevolent models for the CE evaluation. Later, Wang and

Related Content