

Performance Measurement: From DEA to MOLP

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INTRODUCTION

Data envelopment analysis (DEA) is a non-parametric technique to measure the efficiency of productive units as they transform inputs into outputs. A productive unit has, in DEA terms, an all-encompassing definition. It may as well refer to a factory whose products were made from raw materials and labor or to a school that, from prior knowledge and lessons time, produces more knowledge. All these units are usually named decision making units (DMU).

So, DEA is a technique enabling the calculation of a single performance measure to evaluate a system. Although some DEA techniques that cater for decision makers' preferences or specialists' opinions do exist, they do not allow for interactivity. Inversely, interactivity is one of the strongest points of many of the multi-criteria decision aid (MCDA) approaches, among which those involved with multi-objective linear programming (MOLP) are found. It has been found for several years that those methods and DEA have several points in common. So, many works have taken advantage of those common points to gain insight from a point of view as the other is being used. The idea of using MOLP, in a DEA context, appears with the Pareto efficiency concept that both approaches share. However, owing to the limitations of computational tools, interactivity is not always fully exploited.

In this article we shall show how one, the more promising model in our opinion that uses both DEA and MOLP (Li & Reeves, 1999), can be better exploited with the use of TRIMAP (Climaco & Antunes, 1987, 1989). This computational technique, owing in part to

its graphic interface, will allow the MCDEA method potentialities to be better used.

MOLP and DEA share several concepts. To avoid naming confusion, the word *weights* will be used for the weighing coefficients of the objective functions in the multi-objective problem. For the input and output coefficients the word *multiplier* shall be used. Still in this context, the word *efficient* shall be used only in a DEA context and, for the MOLP problems, the optimal Pareto solutions will be called non-dominated solutions.

BACKGROUND

Ever since DEA appeared (Charnes, Cooper, & Rhodes, 1978) many researchers have drawn attention to the similar and supplementary characteristics it bears to the MCDA. As early as 1993, Belton and Vickers (1993) commented their points of view supplement each other. This is particularly relevant for MOLP. For instance, both MOLP and DEA are methodologies that look for a set of solutions/units that are non-comparable between them, that is, are efficient/non-dominated. This contribution is focused on the synergies between MOLP and DEA.

Taking into consideration the vast literature and to be able to follow the theme's evolution articles should be classified into different categories. The first two categories are those in which DEA is used for MOLP problems and vice versa. Although the differences are often not very clear, these categories can be useful to introduce the theme.

Works in which DEA is used within MOLP are not the object of this article. Some of these works are those of Liu, Huang, & Yen (2000), or Yun, Nakayama, Tanino, and Arakawa (2001).

Within those articles in which MOLP is used in DEA problems a further disaggregation is possible:

1. Models that use MOLP to determine non-radial targets in DEA models. Their own nature makes it imperative that these models use the DEA envelop formulation.
2. Models that, besides the classic DEA objective, use other objectives, generally considered of lesser importance. The majority of the articles concerning this approach use the multipliers formulation.
3. Models in which optimization of more than one DMU is simultaneously attempted.

Papers in Which MOLP is Used in DEA

The first article explicitly written along this line is Golany's (1988). He starts from the assumption that not all DEA efficient solutions are effective, that is, they do not equally cater to the decision maker's preferences. The article assumes that the inputs vector is constant and an outputs vector should be computed so the DMU is both efficient and effective. So, an interactive algorithm (MOLP), based on STEM (Benayoun, Montgolfier, Tergny, & Larichev, 1971) is proposed. This algorithm checks all possible DMU benchmarks and eliminates in succession those that do not conform to the decision maker's interests. In fact, the author uses a multi-objective model in which every output is independently maximized, maintaining all inputs constant.

Joro, Korhonen, and Wallenius (1998) produce a structural comparison between MOLP and DEA. They show that the non Archimedean output-oriented CCR model displays several similarities with the reference point MOLP model. This property is used in the "Value Efficiency Analysis" (Halme, Joro, Korhonen, Salo, & Wallenius, 2002; Joro, Korhonen, & Zionts, 2003) to assist a decision maker to find the most preferred point at the frontier.

Tavares and Antunes (2001) based themselves on a minimizing Chebyshev's distance method to put forward a DEA alternative target calculation.

Lins, Angulo-Meza, and Silva (2004) developed the models MORO and MORO-D. These models are

a generalization of Golany's (1988) model. The multi-objective method allows simultaneously for output maximization and input minimization. Quariguasi Frota Neto and Angulo-Meza (2007) have analyzed the characteristics of the MORO and MORO-D models and used them to evaluate dentists' offices in Rio de Janeiro.

The fuzzy-DEA multidimensional model (Soares de Mello, Gomes, Angulo-Meza, Biondi Neto, & Sant'Anna, 2005) used MORO-D as an intermediary step to find optimistic and pessimistic targets in the fuzzy DEA frontier.

Korhonen, Stenfors, & Syrjanen (2003) minimize the distance to a given reference point to find alternative and non-radial targets. In an empirical way, they show that radial targets are very restrictive.

DEA Models with Additional Objective Functions

The first models of this type were not recognized as multi-objective by their authors and are rarely mentioned as such. They include the two step model (Ali & Seiford, 1993) and the aggressive and benevolent cross evaluation (Doyle & Green, 1994; Sexton, Silkman, & Hogan, 1986). These models are not usually accepted as multi-objective ones. However, as they optimize in sequence two different objective functions, they can be considered as a bi-objective model solved by the lexicographic method (Climaco, Antunes, & Alves, 2003).

Kornbluth (1991) remarked that the formulation of multipliers for DEA can be expressed as multi-objective fractional programming.

A similar approach by Chiang and Tzeng (2000) optimizes simultaneously the efficiencies of all DMUs in the multipliers model. An objective function corresponds to each DMU. The problem is formulated in the fractional form so as to avoid its becoming unfeasible owing to the excessive number of equality restrictions. The authors use fuzzy programming to solve this multi-objective fractional problem. Optimization is carried out in such a manner as to maximize the efficiency of the least efficient DMU. The last two models can also be classified as models in which more than one DMU are simultaneously optimized.

Owing to its importance, Li and Reeves (1999) model is detailed hereafter.

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