Chapter 35

Mismanagement or Mismeasurement:
The Application of DEA to Generate Performance Values and Insights from Big Data

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ABSTRACT

Data Envelopment Analysis (DEA) is a well-known frontier valuation method to assess the performance of set of Decision Making Units (DMUs). It derives an overall performance for each DMU based on its efficiency relative to others. All DMUs use the same production function that transfers multiple-input into multiple-output of qualitative and quantitative values. Such big data necessitates the provision of a general framework to guide both researchers and practitioners in the analytical evaluation process for better insights. This chapter proposes a new roadmap to guide future research to implement rigorous and relevant DEA applications. This roadmap consists of five phases: Understand, Prepare, Analyze, Implement, and Monitor (AIM-UP). This roadmap could be used to evaluate the efficiency of resource utilization and the effectiveness of production by the operating processes. Finally, three case studies are used to illustrate DEA implementation, and an up-to-date review of DEA applications is conducted.

What we have to learn to do, we learn by doing. (Aristotle)

INTRODUCTION

Data Envelopment Analysis (DEA) is an increasingly popular management tool to assess the relative productive efficiency (performance) of a set of decision making units (DMUs). It generates insights

from big data to speak for themselves about the relationship between inputs and outputs with minimal assumptions unlike traditional approaches (Charnes et al., 1985). The new DEA modeling and analytical capabilities have been found extremely attractive by researchers and professionals leading to a large number of real life applications with positive impacts and values. Although the DEA method can be viewed as a production frontier approach, DEA is widely used for conducting performance evaluation and benchmarking best-practices to discover insights from peers (Cook, Tone and Zhu, 2014). Measuring the performance has never been a simple task; any change in the dataset or computed DEA model would lead to a significant difference in the generated results (Emrouznejad and De Witte, 2010). The availability of DEA software made the generation of DEA results a simple and fast process, with much focus on the DEA modeling process that is an essential step to design before the generation of the analysis. Due to DEA being a young field and attractive for applications; one can easily notice a faster growth in applications than theoretical research since its inception in the early 1980s. Unfortunately, in the literature, one can easily find a number of misguided applications with misguided insights that motivated us to develop this general framework to guide the DEA community; researchers, practitioners, and reviewers. Few published academic frameworks exist, and there are a few emerging guidelines to clarify rules and set academic standards for performance measurement, selection of DEA models, determination of the number of DMUs and their relationships to the number of inputs and outputs and their definitions (Cook, et al., 2014; Osman et al., 2011; Emrouznejad and De Witte, 2010; Brown, 2006; Dyson et al., 2001).

Cook et al (2014) provided some clarifications and directions on the use of DEA. They addressed several issues such as model orientation, input and output selection, the use of mixed and raw data, and the number of DMUs in relation to the total number of input and output variables. Osman et al. (2011) validated the previous practical recommendations on the number of DMUs in relation to the total number of input and output variables to find that the numbers of DMUs should be much greater than 3 to 5 times the total sum of the number of inputs and outputs. This number of DMUs was shown to depend on the types of orientation of the DEA models, and the desired spread of the bell-normality shape of the final-value scores from the perspective of the evaluator. They called for more research on such rule of thumb assumptions related to the number of DMUs and homogeneity of data and working environment.

Emrouznejad and De Witte (2010) proposed COOPER-framework that helps researchers to measure effectively the performance of a set of DMUs. Their framework involves six interrelated phases: (1) Concepts and objectives, (2) On structuring data, (3) Operational models, (4) Performance comparison model, (5) Evaluation, and (6) Results and deployment. Also, they proposed the following process to assess the performance of any DMU; select homogeneous DMUs, identify appropriate inputs and outputs, run/ compute a suitable model, interpret the results and suggest a proper solution to improve the efficiency of each DMU. Dyson et al. (2001) argued that the practical application of DEA presents a range of procedural issues to be examined and solved. Accordingly, they highlighted some of these issues (pitfalls) and suggested protocols to avoid these pitfalls. These issues include homogeneity of DMUs under assessment, the selection of input/output variables, the measurement of those selected variables and the weights attributed to them. Brown (2006) demonstrated these pitfalls and protocols by using DEA in the financial services sector. Given these guidelines, so far there is neither a comprehensive framework nor general guidelines to enhance DEA practice.

Based on published literature, in this chapter, we build a phase-by-phase roadmap – a process oriented framework- to measure the performance of a DMU(s). The roadmap consists of the five phases: *Understand Prepare, Analyze, Implement, and Monitor* (AIM-UP). The roadmap could be used to measure the performance of an Organization, People, Technology, and Service, etc. The roadmap begins with

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