Abstract

It is important to measure efficiency of organizational processes in order to evaluate, control, learn and improve. It is acknowledged that a process is efficient if it produces as much as possible with the inputs actually employed and if the production is at minimum cost. A precise quantification of “relative efficiency”, in the most general of cases, has been provided by the increasingly popular non-parametric technique – data envelopment analysis (DEA).

The applicability of DEA, in so far as the analysis results represent the underlying reality, remains a challenge because of reasons cited below. This research aims at increasing the relevance and usability of DEA.

In its computation of efficiency, DEA is known to be sensitive to the corpus of production units (DMUs) that are being evaluated. There are cases when in the absence of adequate number of “efficient” units, an inefficient unit would be accorded a disproportionately high “efficiency score”. Moreover, a DEA benchmark, may not be a feasible target for an inefficient production unit.

There are several variants of DEA proposed in literature that take into consideration the specific nature of inputs and outputs, in order to come up with an efficiency score or a set of benchmarks. The problem of combining these extensions effectively, though, remains unresolved. Additionally, problems of sensitivity to the DMUs being analysed as well as issues of feasibility of benchmark, have received less attention and, in the opinion of the researcher, has restricted the applicability of DEA.
To address the problems of “sensitivity” and “feasibility” cited above, this research has come up with three separate DEA based models that individually do a reasonably good job. This is borne out by empirical evidence that has been provided in this thesis. While Chapters 2 and 4 take different approaches to increasing the feasibility of benchmarking, Chapter 3 increases the robustness of DEA, reducing the sensitivity to the number of DMUs in general, and number of efficient DMUs in particular.

The individual models provide encouraging results. The three suggested DEA extension models can be separately used, depending upon the nature of the problem in order to arrive at an actionable set of results.

A possible direction for further work would be to combine the extensions into an integrated framework that realizes the benefits of the individual models.

The structure of the thesis is as follows.

In Chapter 1.2, “Theoretical Developments”, we discuss the tools used in this research along with the relevant body of literature that has been surveyed in course of this work.

The next three chapters discuss the primary work that has been done in this research. In Chapter 2, “Alternative Benchmarks”, we discuss a framework built on DEA which can be used to find alternative, more easily achievable benchmarks than conventional DEA approaches.

In the next chapter, “Neural DEA”, this research uses Artificial Neural Network to work around the problem of inadequate numbers of DMUs, making the obtained results less sensitive to data and thereby more meaningful in general. The framework described in this chapter uses DEA as well as ANN in a novel approach to “discover” the true efficiency frontier for benchmarking inefficient DMUs.

In the next chapter, “Time-stepped Benchmarking”, we again focus on feasibility of achieving benchmark targets. Here we formulate and modularize a time-stepped strategy based on DEA to achieve performance improvements in a manner that could be customized and time tabled for greater achievability.

In Chapter 5 we summarize the results of the research and discuss directions and possible ways of extending this research.