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Applications of DEA

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Abstract: ***Data Envelopment Analysis (DEA), an efficiency measurement and benchmarking technique originated in 1978 with the publication of the seminal paper of Charnes et al (1978) has evolved into an important technique over the years. This paper attempts to critically review the various methodological aspects of DEA for application in any domain in the public or private sectors. In specific it reviews some of the important literature available on a) variable selection methods in DEA, b) Sensitivity analysis and ranking of DMUs and c) some of the applications it has been put into over the last four decades. The focus is on specific practical aspects of applying DEA in any particular field.***

Key Words: Efficiency Measurement, Data Envelopment Analysis (DEA), Returns to scale, Decision Making Units (DMU).

I. INTRODUCTION

Data envelopment analysis is a linear programming based technique to measure the relative efficiency of various units called decision making units, DMUs in short. Each unit (DMU) would have used various inputs in different quantities to produce various outputs in different quantities. The method does not require that all of the inputs and outputs to have common units of measurement and any common denominator like money and the efficiency measurement will be in comparison to other units and hence is a relative measure of efficiency. These properties make the method attractive especially in not-for-profit situations where various resources used and outputs produced may not be all in monetary units. As long as the inputs and outputs can be quantified, the method can be used to measure the relative efficiencies (Charnes et al, 1978; Ramanathan, 2003).

Data Envelopment Analysis has emerged as an important benchmarking method for measuring the efficiency of decision making units in both private sector and public not-for –profits sector. This paper reviews three critical areas of applying DEA to measure efficiency for benchmarking of DMUs; the various variable selection methods for applying the technique on data of any particular domain, sensitivity analysis of the results, ranking of decision making units based on DEA results and reviews some of the applications of DEA found in literature.

The first part of the paper critically looks at some of the variable selection methods, the second part looks at various methods available for ranking and the third part of the review looks at some of the areas in which the technique has been applied, followed by references.

II. VARIABLE SELECTION METHODS IN DATA ENVELOPMENT ANALYSIS

In order to measure the efficiency of a DMU as realistically as possible, it is necessary to identify and measure all variables that aid in, facilitate and constrain a DMU in achieving its objectives. However, DEA as a measurer of efficiency will produce higher values of efficiency for all DMUs and identify more number of DMUs as efficient as the number of variables increase, thereby losing its discriminating power in differentiating between efficient and inefficient units. Hence, in applying DEA as a technique of efficiency measurement one has to strike a balance between modeling reality and retaining discriminating power of identifying efficient and inefficient units. Hence, there is a lot of attention in DEA for variable selection and a lot of papers are published under this topic. This section looks at some of the more important ones briefly. One of the important methods of variable reduction widely published in DEA literature is the use of Principal Component Weights instead of variables themselves. Two of the earliest papers in this area are Ueda and Hoshiai (1997) and Adler and Golany (2001). Ueda and Hoshiai (1997) state that more inputs and outputs in DEA will lead to more DMUs becoming efficient and hence the need to select inputs and outputs appropriately by experts who know their characters very well and people who are less familiar with them will have to use tools to assist in selection. As the inputs and outputs are usually correlated, the authors propose the use of Principal Component Analysis as a means of weighting of inputs and outputs to summarise them parsimoniously. Adler and Golany (2001) in a study of deregulated airline networks, use Principal Components analysis to aggregate data to overcome the difficulties of excessive number of inputs and outputs. A new PCA-DEA model has been developed by the authors who argue that there is minimal difference between the efficiency scores obtained by using the original data model and the PCA-DEA model. And that the use of PCA weights leads to reduction in number of variables with minimum loss of information thereby improving the discriminatory power of the DEA model. In a subsequent paper Adler and Golany (2002) further developed the PCA-DEA model and suggested three formulations, the first one for quality or environmental measures, the second model applied to both inputs and outputs separately to increase the discrimination and the third formulation to develop a single set of global weights so that all the DMUs are ranked according to their efficiency levels.

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Pastor et al (2002) discussed the concept of nested radial DEA models (like CCR or BCC models) where the set of constraints of one of the models is contained in the other model, which may be used in certain problems of management operations research and engineering.
In the paper they focused on analyzing the marginal role of a given variable (which they called 'Candidate') with respect to the efficacy measured using a DEA model, which they defined as Efficiency Contribution Measure (ECM) which compares the efficiency scores of the nested DEA models which differ in the candidate. A statistical test was developed to test the significance of the ECM of a candidate. The candidate may be selected based on the result of the significance set. Jenkins and Anderson (2003) question the wisdom of omitting highly correlated variables from analysis and argue that such removal could have a 'major influence on computed efficiency measures'. The paper describes a systematic statistical method to find which of the highly correlated variables to be omitted and which to be retained. A method was introduced which identifies variables that can be omitted with least loss of information, the said multivariate statistical technique, based on partial covariance, measures the proportion of total variance lost by omitting the particular variable.

Cinca and Molinero (2004) argue that the selection of DEA model is problematic and that the estimated efficiency of any DMU will depend on the inputs and outputs included in the model and the total number of inputs and outputs. Stressing the importance of selecting a parsimonious specification and to avoid models that assign high efficiency values to DMUs that operate in unusual ways (mavericks), the paper proposes a new method for model selection. The paper suggests the use of principal component analysis for analyzing the efficiency scores obtained from various model specifications and for producing DMU rankings. Each model (data model) may be used as a variable and each efficiency score of individual DMUs may be taken as observations of the variable for running the PCA.

Cook and Jhu (2007) discuss the problem of classifying particular variables as either inputs or outputs. They argue that certain performance measures can play the roles of either inputs or outputs and called them flexible measures. They suggest both an individual model and an aggregate model as methods for deriving the most appropriate designations for flexible measures and illustrated their application in two problems. Podinovsky and Thanassoulis (2007) name increasing the number of DMUs, decreasing the number of input and output variables and imposing input / output weight restrictions as some of the practical methods of increasing discrimination in DEA efficiency scores. The paper recommends weighting of individual factors to aggregate them as one of the methods of reducing the number of factors.

Wagner and Shimshak (2007) developed a stepwise method to select inputs and outputs for DEA in which variables are added or removed stepwise based on their individual contribution to the efficiency score. The procedure starts with including all inputs and outputs and running the DEA. Then one variable is dropped at a time and efficiency scores are recorded and differences in efficiency score with the drop of each variables. Once all inputs or outputs are dropped, the least influential factor is identified as the one which had least change in average efficiency score of all DMUs. The next iteration starts after removing such factors and the iterations could go on till only one input and one output are left in the end or any other set criteria.

Morita and Avkiran (2009) proposed diagonal layout experiment, a statistical experiment to find an optimal combination of inputs and outputs and demonstrate their model using financial statement data from NIKKEI 500 index. Kao et al (2010) propose another method that of using Independent Component Analysis (ICA) with DEA to overcome the problem of low discrimination of efficiency scores due to use of more factors in DEA. The paper suggests the use of ICA to extract independent components from input variables in the first stage and use of ICs as variables in DEA in the second stage. In the second stage, kurtosis values are used to select the input variables to be used.

Adler and Yazhemsky (2010) use simulation to compare two methods for improving discrimination in DEA, the principal component analysis applied to DEA (PCA-DEA) and Variable Reduction method (VR) based on partial covariance analysis. The paper states that PCA-DEA is a more powerful method and provides more accurate results compared to VR. The paper also states that the method (PCA-DEA) can be used for all basic models of DEA and suggested guidelines to minimize mis-classification in DEA.

Nataraja and Johnson (2011) compare four different methods of variable selection, Efficiency Contribution Measure (ECM), Principal Component Analysis (PCA), a regression-based test and boot strapping for variable selection via Monte Carlo simulation to determine each methods advantages and disadvantages. They state that PCA-DEA performed well with highly correlated variables (greater than 0.8) even for smaller data sets (less than 300 observations). Observed that both ECM and regression based methods did well under low correlations (below 0.2) and larger data sets (more than 300) and argue that boot strapping performed poorly and took considerable time for implementation. The paper also suggests guidelines for choosing the right method among the four.

III. SENSITIVITY ANALYSIS AND RANKING OF DMUS

Efficiency of DMUs as measured by DEA produces an efficiency score between 0 and 1 for each DMU, thus indicating whether a DMU is efficient or not. All the efficient units get a score of 1 which makes it difficult to rank efficient DMUs as whether a DMU is more or less efficient than another. Also efficiency scores are sensitive to which variables are included in the analysis and what model is being used. Hence, it becomes important to understand how strong a DMU is efficient and what happens if some of its input or output values change. Also of interest is to rank DMUs both efficient ones and inefficient ones.

Charnes and Neralic (1990) studied the sensitivity analysis for the additive model of DEA. Sufficient conditions for simultaneous change of all inputs and all inputs of a efficient DMU which still preserves its efficiency are established. Anderson and Peterson (1993) developed a model for ranking efficient DMUs, which later became known as super efficiency model. A modified version of DEA based upon comparison of efficient DMUs relative to a reference is developed which provides a framework for ranking efficient DMUs.

Neralic (1997) studied sensitivity analysis in DEA for arbitrary additive perturbations of all data in the CCR ratio model for which efficiency of an efficient DMU is preserved. Simar and Wilson (1998) developed a general methodology of bootstrapping to analyse the sensitivity of efficiency scores relative to the sampling variations of the estimated frontier. The paper demonstrates the results using data of 19 electric utilities operating in 1978. Zhu (2001) discusses and reviews the use of super-efficiency approach in DEA sensitivity analysis and showed that the super-efficiency score can be decomposed into two data perturbance components of a particular test frontier DMU and the remaining DMUs. The concept of cross efficiency and cross efficiency matrix was first introduced by Sexton et al (1986). The paper defined cross efficiency as the efficiency score derived by calculating the score based on optimal input and output weights of other DMUs. The paper also brought in the concepts of aggressive and benevolent formulations. Doyle and Green (1994) developed the concept of cross efficiency further and coined the term Maverick DMU and Maverick Index. The paper discusses the concept of peer appraisal as opposed to self appraisal which is possible using cross efficiency and discusses the relative merits of both. Friedman and Sinuany-Stern (1997) developed a method for comparison between individual DMUs and the ranking of all DMUs, both efficient and inefficient, with the use of canonical correlation analysis (CCA). Canonical correlation can be used to determine weights for multiple inputs and multiple outputs to form a composite input variable and a composite output variable such that the correlation between the two composite variables is maximized. Sinuany-Stern and Friedman (1998) developed a method using discriminant analysis to provide common weights for multiple inputs and multiple outputs that discriminate optimally between efficient and inefficient DMUs. The method, Discriminant Data Envelopment Analysis of Ratios (DR/DEA), calculates the ratio of weighted outputs and inputs to be used as a metric for ranking DMUs. Friedman and Sinuany-Stern (1998) developed a combined ranking method for ranking DMUs in the DEA context based on three ranking methods, the CCA, the DR/DEA and the ranking based on cross efficiency method (CE/DEA). Adler et al (2002), in a review of various ranking methods, divided the methods into six somewhat overlapping areas. The first area being use of cross efficiency matrix, the second based on super efficiency methods, the third based on number of DMUs for whom a particular efficient DMU is peer to, the fourth using various multivariate statistical techniques, the fifth area on ranking of inefficient DMUs based on proportional measures of efficiency and the sixth one based on combining multiple criteria decision methodologies with DEA. The authors argue that each method may have its usefulness in particular areas, however, none of the methods can be considered as a complete solution for ranking. Cinca and Molinero (2004) recommend the use of PCA of efficiency scores obtained under different data models and use the first PCA factor score for ranking DMUs.

IV. VARIOUS APPLICATIONS OF DEA

The technique of DEA has been used in various practical applications both in the industrial sector and the not-for-profits sector in numerous ways ever since the first paper on DEA (Charnes et al, 1978) was publised. This section looks at some of those applications from both methodological and interpretation perspectives.

Roll et al (1989) in a case study apply DEA to measure the efficiency of maintenance units in Israeli air force. The study discusses the technique for measuring the efficiency in a complex public organization. Huang and McLaughling (1989) applied DEA to evaluate rural primary healthcare programmes which are known to be heterogeneous, based on data from National Evaluation of Rural Primary Health Care Programs in the USA. The study concludes that despite the requirement of homogenous units and need for nonzero values; the method is useful in comparing efficient inefficient classification with other data and assisted in the evaluation. The study used correlation and stepwise regression analysis to identify redundant variables and remove them and classifies variables as discretionary and non-discretionary inputs and outputs. Oral et al (1991) use mathematical programming, similar to DEA to find a self evaluation model for each R&D project, then use cross evaluation model based on cross efficiency matrix and use pair-wise comparison of cross efficiencies to select the most desirable R&D units. Ray (1991) combines DEA with regression to estimate relative efficiency in public school districts of Connecticut. First the efficiencies are measured using the discretionary inputs only. The efficiency scores thus obtained are treated as dependent variables in a second stage regression using nondiscretionary variables. The findings suggest that the variation in performance of schools may be greatly ascribed to the nondiscretionary variables and the variation in managerial efficiency is much less than what the DEA results implied.

Majumdar (1998) evaluates the performance differences between Government owned, mixed sector and private sector enterprises in India for the period from 1973-74 to 1988-89 using DEA. The results shows that the firms in the Government sector were less efficient compared to those in the mixed sector which were less efficient to those in the private sector. The paper also finds that there are inter-temporal efficiency gains in both the state and central Government sectors, with first period of 7 years showing negative growth and the second 7 years showing high positive growth. Pina and Torres (2001) did a study of efficiency with which urban transportation systems are delivered in important cities of the regions of Catalonia in Spain. The methods used are DEA, multiple linear regression, logit and cluster analysis. The study concludes that private management of urban transport service was not more efficient compared to public management and that exogenous factors were not relevant. Worthington and Dollery (2002) compare several approaches for incorporating nondiscretionary inputs in DEA in using the planning and regulatory functions of 173 local governments of NSW. The nondiscretionary inputs used in the study are population growth and distribution, the level of development and non-residential building activity and the proportion of the population with a non-English speaking background. Sathye (2003) uses DEA in a study of 94 banks in India and states that the average efficiency scores were comparable with the world mean efficiency.

The efficiency scores of three groups of banks, publicly owned, privately owned and foreign owned are measured using two models and found that the efficiency of private sector commercial banks are lower than public sector banks and foreign banks.

Khankhoje and Sathye (2008) in a study of the efficiency of rural banks in India to investigate whether the restructuring of regional rural banks (undertaken in 1993-94) has helped improve their production efficiency, measured efficiencies using DEA. The study uses interest income and non-interest income as outputs and interest expense and non-interest expenses as inputs. The efficiency scores are calculated for the years from 1990 to 2002.

Gaspar et al (2009) analyse technical efficiencies of livestock farming systems in Extremadura, Spain using input oriented both constant returns to scale (CRS) model and variable returns to scale (VRS) model. The study uses two models, the first one with four inputs and one output and the second one with four inputs and two outputs including European Union's Common Agricultural Policy (CAP) subsidies. Liu et al (2013) claiming to be the first literature review on DEA applications, covers papers published in journals indexed by Web of Science database from 1978 to 2010. The paper states that one third of the papers are methodological and the other two thirds are embedded in empirical data. The first twenty years were dominated by methodological papers while applications caught up with methodological papers in 1999. The paper also identifies the top five applications as banking, healthcare, agriculture and farming, transportation and education. Khoshnevis and Teirlinck (2018) study the performance of R&D active firms in Belgium with a focus on R&D resources allocation. The study uses both VRS and CRS DEA models to evaluate the efficiencies of the firms along with scale efficiencies and types of RTS. The study highlights the sources of inefficiencies and makes suggestions to improve their efficiencies. The study finds that the size mattered with larger firms having higher average efficiencies and those firms in specialized supplier industries tended to perform better than others and those in science based industries underperformed.

V. CONCLUSIONS

There is a trade-off between capturing the all the details of a production process while trying to measure efficiency and the level of discrimination one can expect to get in comparing various decision making units when one uses DEA. Hence, there are various methods for parsimonious selection of variables while applying DEA. Sensitivity analysis is done to assess the robustness of the DEA results, in terms of classification of DMUs as efficient or inefficient and in setting targets for inefficient DMUs to achieve efficiency. Various methods of ranking exist in literature one could choose from. The method has found use in a wide variety of areas over the last four decades in both private sector and public sector as the various applications presented in this paper suggest. However, its application in the not-for-profits sector has been limited though this was the sector for which Charnes et al (1978) devised the method for.

Note: This study is based on the Research work done for the Ph.D. thesis of the first author, to be submitted to KSRM, KIIT DU.

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