Data Envelopment Analysis and its Application in Education

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Data Envelopment Analysis (DEA) is a relatively new nonparametric approach for evaluating the performance of complex entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. In a relatively short period of time Data Envelopment Analysis (DEA) has grown into a powerful, quantitative, analytical tool for measuring efficiency of decision making units. DEA has been successfully applied in many different fields in worldwide. This paper provides introduction to DEA and describes the application of Data Envelopment Analysis in education.

1. Introduction

Data Envelopment Analysis (DEA) is a relatively new "data oriented" mathematical approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. Since DEA was first introduced in 1978, researches in a number of fields have in a short period of time recognized that DEA is an excellent and easily used methodology for modeling operational processes for performance evaluations. In [31] is given survey and analysis of the 30 years of scholarly literature in DEA up to the year 2007.

This paper is in 8 parts of which this is the first. Data Envelopment Analysis (DEA) as a tool for determining the relative efficiency is presented in Section 2. The history of DEA has been mentioned briefly in Section 3. DEA methodology is described in Section 4. Strenghts and limitations of DEA are presented in Section 5. Literature search for application of DEA in education is overviewed in Section 6, while conclusions are given in Section 6. Bbibliography citations are presented in the final section.

2. Efficiency and data envelopment analysis

Fried, H. O., Lovell, C.A.K., and Schmidt, S.S., in [34] explain that the interest in measuring efficiency has two reasons. First of all, they are success indicators, performance measures, by which production units are evaluated. Second, only by measuring efficiency and productivity, and separating their effects from the effects of the production environment can we explore hypotheses concerning the sources of efficiency or productivity differentials. Identification of sources is essential to the institution of public and private policies designed to improve performance.

Productivity efficiency has two components. The purely technical, or physical, component refers to the ability to avoid waste by producing as much output as input usage allows, or by using as little input as output production allows. Thus the analysis of technical efficiency can have an output augmenting orientation or an input-conserving orientation. The allocative, or price component refers to the ability to combine inputs and outputs in optimal proportions in light of prevailling prices.

Koopmans in [48, p.60] provided a formal definition of technical efficiency: a producer is technically efficient if an increase in any output requires a reduction in at least one other output or an increase in at least one input, and if reduction in any input requires an increase in at least one other input or a reductionin at least one output. Thus a technically inefficient producer could produce the same outputs with less of at least one input, or could use the same inputs to produce more of at least one output.

Debreu in [29] and Farrell in [33] introduced a measure of technical efficienncy. Their measure is defined as one minus the maximum equiproportionate reduction in all inputs that still allows continued production of given outputs. A score of unity indicates technical efficiency because no equiproportionate input reduction is feasible, and a score less than unity indicates the severity of technical inefficiency.

Following work by Dantzig [27] and Farrell [33], Charnes, Cooper, and Rhodes [16] developed mathematical programming technique, Data Envelopment Analysis (DEA).

DEA is a non-parametric linear programming technique that computes a comparative ratio of outputs to inputs for each unit, which is reported as the relative efficiency score. The efficiency score is usually expressed as either a number between 0-1 or 0-100%.

100% efficiency is attained for any Decision Making Unit (DMU) only when:

(a) None of its outputs can be increased without either
- increasing one or more of its inputs or
- decreasing some of its other outputs

(b) None of its inputs can be decreased without either
- Decreasing some of its outputs or
- Increasing some of its other inputs.

A decision-making unit (DMU) with a score less than 100% is deemed inefficient relative to other units.

Thanassoulis, E., in [63] points out that DEA is one of the methods of performance measurement which support type of information such as:
- identification of good operating practices for dissemination;
- most productive operating scale sizes;
- the scope for efficiency savings in resource use and/or for output augmentation;
- most suitable role model operating units an inefficient unit may emulate to improve its performance;
- the marginal rates of substitution between the factors of production and;
- Productivity change over time by each operating unit and by the most efficient of the operating units at each point in time.

3. Data envelopment analysis

History

The term 'Decision Making Unit' (DMU) was used for the first time in the CCR model proposed in Charnes, Cooper and Rhodes [16]. The term DEA (Data Envelopment Analysis) was introduced in their report [18], Rhodes [58] and appeared in Charnes, Cooper and Rhodes' subsequent paper [19].

In their originating study, Charnes, Cooper and Rhodes [16] described DEA as a 'mathematical programming model applied to observational data [that] provides a new way of obtaining empirical estimates of relations – such as the production functions and/or efficient production possibility surfaces – that are cornerstones of modern economics.'

DEA originated from efforts to evaluate results from an early 1970' project called "Program Follow Through" – a huge attempt by the U.S. Office (now Department) of Education to apply principles from the statistical design to experiments to a set of matched schools in a nationwide study. The purpose of the study was to evaluate educational programs designed to aid disadvantaged students in U.S. public schools. The data base was sufficiently large that issues of degrees of freedom, etc., were not a serious problem despite the numerous input and output variables used in the study. Nevertheless, unsatisfactory and even absurd results were secured from all of the statistical-econometric approaches that were tried. While trying to respond to this situation, Rhodes called Cooper's attention to Farrell's seminal article, [33]. Charnes, Cooper and Rhodes extended Farrell's work and succeeded in establishing DEA as a basis for efficiency analysis. Details of the project are described in Charnes, Cooper and Rhodes [20].

A brief history of DEA can be found in [21].

4. DEA methodology

Data Envelopment Analysis estimates a piece-wise linear production function relative to which the efficiency of each firm or decision-making unit (DMU) can be measured. The simplest variant of DEA is a constant returns to scale model in which n decision making units produce s distinct output types using m distinct inputs. The quantities of outputs and inputs which the kth decision-making unit produces and consumes respectively are denoted by Y_{rk}, $r=1,\ldots,s$ and X_{ik}, $i=1,\ldots,m$. The kth decision making unit then chooses its vector of input weights, v_{ik}, $i=1,\ldots,m$, and output weights, u_{rk}, $r=1,\ldots,s$, with the aim of maximizing its weighted sum of outputs subject to a number of constraints. These are that: (i) the chosen weights are such that, when applied to the output and input vectors of any decision-making unit, the ratio of weighted output to weighted input should not exceed unity, (ii), the weighted sum of inputs should be non-negative, and (iv) the weight attached to each input should be non-negative. Now this is a fairly simple linear programming problem. The complete specification of a DEA involves the simultaneous solution of n such programmes – one for each decision – making unit.

The above arguments may be represented by a suite of linear programming problems. Formally, for each k,

$$\max h_k = \sum_{r=1}^{s} u_{rk} Y_{rk} \tag{1}$$

subject to,

$$\sum_{r=1}^{s} u_{rk} Y_{rj} - \sum_{i=1}^{m} v_{ik} X_{ij} \le 0,\ j=1,\ldots,n \tag{2}$$

$$\sum_{i=1}^{m} v_{ik} X_{ik} = 1 \tag{3}$$

$$u_{rk} \ge 0,\ r=1,\ldots,s \tag{4}$$

$$v_{rk} \ge 0,\ i=1,\ldots,m \tag{5}$$

The optimal value of h_k is the efficiency score of the kth decision –making unit. It must lie between zero and one; if h_k=1, then k i tecnically efficient and lies on the efficiency frontier. As specified above, the DEA problem is one of output maximisation. The corresponding input minimisation problem can be constructed by analogous means.

In [44] is given a simple example of five universities (A, B, C, D, E) producing two outputs, y_1 (for example, the number of graduates achieving 'good' degrees) and y_2 (for example, the number of graduates going into employment) using the input x (for example, the number of undergraduates). Fig. 1 plots the ratio of output y_1 to x against the ratio of output y_2 to x, and the piecewise linear boundary which joins up universities A, B, C and D is the production frontier. All DMUs on the frontier are efficient since none can produce more of both outputs (for a given input level) than any other unit on the frontier. In contrast, university E, which lies inside the frontier, is inefficient, and the ratio OE/OE' measures university E's efficiency relative to the other DMUs in the data set.

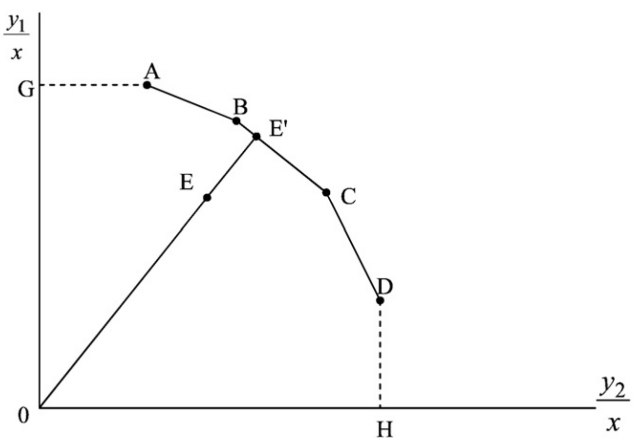

Fig.1. *Diagrammatic representation of an output-oriented DEA*

The CRS assumption can be relaxed and the DEA model can be easily modified to incorporate variable returns to scale (VRS), see Banker, Charnes, & Cooper [7]. While choice of orientation does not affect efficiencies under CRS, it does under the assumption of VRS, see Coelli, Rao, & Battese [24], although it has been shown only to have a slight influence in many cases, see Coelli & Perelman [23].

Basic DEA models and extensions to DEA models can be found in [15], [22], [25], [26].

DEA was initially been used to investigate the relative efficiency of not-for-profit organizations, only to quickly spread to profit-making organizations. DEA has been successfully applied in such diverse settings as schools, hospitals, courts, the US Air Force, rate departments and banks. Charnes et al. [15] have compiled an extensive discussion of efficiency models across a variety of industries.

5. Strenghts and limitations of DEA

A few of the characteristics that make DEA a powerful tool are:

- It is based on a distance function approach and hence can handle multiple outputs and multiple inputs;
- It doesn't require an assumption of a functional form relating inputs to outputs.
- DMUs are directly compared against a peer or combination of peers.
- Inputs and outputs can have very different units. For example X1 could be in units of lives saved and X2 could be in units of dollars without requiring an a priori trade off between the two.

The same characteristics that make DEA a powerful tool can also create problems. An analyst should keep these limitations in mind when choosing whether or not to use DEA.

- Since DEA is an extreme point technique, noise (even symmetrical noise with zero mean) such as measurement error can cause significant problems.
- DEA is a good at estimating "relative" efficiency of a DMU but it converges very slowly to "absolute" efficiency. In other words, it can tell you how well you are doing compared to your peers but not compared to e "theoretical maximum".
- Since DEA is a nonparametric technique, statistical hypothesis tests are difficult and are the focus of ongoing research.
- Since a standard formulation of DEA creates a separate linear program for each DMU, large problems can be computationally intensive.

6. Applications of DEA in education – literature search

Economists typically view educational outcomes as a function of a variety of school inputs, including school expenditures, pupil/teacher ratios, teacher experience, the prior attainment of pupils, peer group pressures and family background, see Hanushek [38, 39]. There has been limited success in finding a causal link between school inputs and educational outcomes. Early work on the education production function concluded that 'teachers and schools differ dramatically in their effectiveness' but that there is 'no strong or systematic relationship between school expenditures and student performance', see Hanushek [39].

For application of DEA in the context of the evaluation of education providers in the primary and secondary sectors see Bessent and Bessent [11], Bessent et al. [10], Bradley et al. [12], Chalos and Cherian [14], Davutyan et al. [28], Fare et al. [32], Ganley and Cubbin [36], Jesson et al. [40], Lovell et al. [50], Kirjavainen and Loikkanen [46], Mancebon and Mar Molinero [52], Mayston and Jesson [53], Norman and Stoker [55], Ray [57], Smith and Mayston [61] and Thanassoulis and Dunstan [62].

Steve Bradley, Geraint Johnes and Jim Millington in [12] calculate the technical efficiencies, based upon multiple outputs – school exam performance and attendance rates – of all secondary schools in England over the period 1993-1998. They estimate models to examine the determinants of efficiency in a particular year, and the determinants of the change in efficiency over the period. Their results suggest that the greater the degree of competition between schools the more efficient they are. The strength of the effect has also increased over time which is consistent with the evolution of the quasi-market in secondary education. Competition is also found to be an important determinant of the change in efficiency over time.

Nurhan Davutyan, Mert Demir and Sezgin Polat in [28] used Data Envelopment Analysis and econometric methods to evaluate the system's efficiency. They identify scale diseconomies and relate them to underlying structural characteristics of the system. Selected suggestions on improving performance are offered. The roles of heterogeneity and centralization are also highlighted. Heterogeneity is modeled as an undesirable measure. The linkage between indicators of centralization and scale diseconomies was found to be statistically significant. The authors believe this to be the first study that investigates the impact of systemic characteristics such as heterogeneity and centralized structure on educational outcomes for Turkey.

The higher education has characteristics which make it difficult to measure efficiency: it is non-profit making; there is an absence of output and input prices; and higher education institutions (HEIs) produce multiple outputs from multiple inputs.

Studies which examine the efficiency of the higher education sectors of various countries such as the UK, the USA, Canada, Finland, Israel, Australia and China have fallen into two main groups:

1. those which have examined the efficiency of a particular department, programme or activity, see (Beasley [8], [9]; Coelli et al., [24]; Haksever & Muragishi [37]; Johnes, [43]; Johnes & Johnes [41], [42]; Korhonen, Tainio & Wallenius [49]; Madden, Savage & Kemp [51]; Tomkins & Green [66], and
2. those which have examined the performance of the entire HEI, see (Ahn et al., [2]; Ahn & Seiford [1]; Athanassopoulos & Shale [5]; Avkiran [6]; Breu & Raab [13]; El Mahgary & Lahdelma [30]; Johnes [44]; Ng & Li [54]).

Ahn and Seiford in [1] used DEA to determine the relative efficiency of 153 doctoral-degree granting institutions of higher learning (IHLs). Of these, 104 were public and 49 were private. The purpose of the study was to determine the effect of different sets of output variables on the relative efficiencies of public and private institutions. Public IHLs are often funded based on an enrollment-related output measure. For this reason, Ahn and Seiford predicted that public IHLs would be more efficient when enrollment-related outputs were considered and private IHLs would be more efficient when less closely monitored outputs were considered. This hypothesis was tested using multiple variable sets. In one trial, faculty salaries, physical investment, and overhead expenses were used as input variables. Undergraduate full-time equivalent students (FTEs) and graduate FTEs were used as output variables. Using these enrollment-related output variables, public IHLs were found to be more efficient than private IHLs. A second trial used faculty salaries, physical investment, overhead expenses, undergraduate FTEs and graduate FTEs as inputs. Undergraduate degrees, graduate degrees, and grants were used as output variables. Using these less closely monitored output variables, private universities were found to be more efficient.

The purpose of the paper [44] is to examine the possibility of measuring efficiency in the context of higher education. The paper begins by exploring the advantages and drawbacks of the various methods for measuring efficiency in the higher education context. The ease with which data envelopment analysis (DEA) can handle multiple inputs and multiple outputs makes it an attractive choice of technique for measuring the efficiency of higher education institutions (HEIs), yet its drawbacks cannot be ignored. Thus, a number of extensions to the methodology, designed to overcome some of the disadvantages, are presented. The paper ends with an application of DEA to a data set of more than 100 HEIs in England using data for the year 2000/01. Technical and scale efficiency in the English higher education sector appear to be high on average. The Pastor, Ruiz, and Sirvent [56] test for comparing nested DEA models is useful in reducing the full model to a smaller 'significant' set of inputs and outputs. Thus, the quantity and quality of undergraduates, the quantity of postgraduates, expenditure on administration, and the value of interest payments and depreciation are significant inputs to, and the quantity and quality of undergraduate degrees, the quantity of postgraduate degrees and research are significant outputs in the English higher education production process. The possibility of differences in the production frontier (and hence the distribution of efficiencies) of three distinct groups of HEIs is explored using a test proposed by Charnes, Cooper, and Rhodes [17] but no significant differences are found. Bootstrapping procedures, however, suggest that differences between the most and least efficient English HEIs are significant.

Little work has been done on measuring the efficiency in producing any of the outputs of higher education institutions in China. For recent studies see (Ng & Li, [54]; Johnes and Yu in [45]).

Ng and Li in [54] used DEA in an attempt to examine the effectiveness of the education reforms of the mid-1980s in China by focusing on the research performance of 84 key Chinese HEIs from 1993 to 1995. Using research staff and funding as inputs, and publications data as outputs, the authors find mean research efficiency in the Chinese higher education sector to be around 76–80% over the three year period. Variations in efficiency levels between the three geographical regions of China (coastal, central and western) are also found, but these results are mixed: the HEIs in the central zone perform best, on average, in 1993 and 1995, but it is the western zone which has the highest mean efficiency in 1994.

Two alternative approaches have been taken in a small number of empirical studies:

1. to evaluate the performance of all departments within one university, see (Arcelus & Coleman [4]; Friedman & Sinuany-Stern [35], Sinuany-Stern et. al. [60]), and
2. to analyse the performance of higher education sectors across states or countries, see (Breu & Rabb [13]; Kocher, Luptácik & Sutter [47]).

The validity of these approaches seems particularly questionable on the grounds that the DMUs in each case are clearly not a homogenous set of producing units.

Sinuany-Stern et al. in [60] used DEA to determine the relative efficiency of 21 departments at Ben-Gurion University. Operational expenditures and faculty salaries were used as inputs. Grant money, number of publications, number of graduate students and number of credit hours offered were used as outputs. Fourteen of the departments were found to be inefficient. Sinuany-Stern et al. in this paper also tested the effects of variations in inputs and outputs on efficiency scores. In one trial, one output was deleted from the original model. The output was chosen for deletion because no departments were relatively inefficient in that output. In this trial, two additional departments became inefficient. The DEA model was run again with the two inputs combined. Again, two additional departments became inefficient.

Technical efficiency scores in the department level analyses tend to be lower, on average, than those computed in HEI level studies. Mean technical efficiencies computed from department level studies vary as follows: 50 to 60% for UK economics departments, see Johnes & Johnes [41], [42]; around 70% in UK departments of chemistry and physics, see Beasley [8]; 65 to 82% in Australian departments of economics, see Madden et al., [51]; 72% in economics research units in Finland, see Korhonen et al., [49]; and 82 to 87% in the administration sector of Australian universities, see Coelli et al., [24]. Evidence from HEI level studies suggests that mean technical efficiency varies from around 70 to 80%, see Ahn & Seiford [1], Ng & Li [54], to well over 90%, see Ahn et al., [2]; Athanassopoulos & Shale, [5]; Avkiran, [6]; Breu & Raab, [13]; Johnes [43], [44]. The single cross country study suggests, not surprisingly given the disparate nature of the DMUs, that mean technical efficiency is low (23% or 37% depending on whether CRS or VRS are assumed).

University research and its transfer to industry has been a topic of interest in the management of technology literature over decades. Universities provide education as well as innovations resulting from their research. Several researches focused on efficiency of university research transfer, see Anderson, T.R., Daim, T. U., Lavoie, F. F., [3], Siegel and Phan [59], Thursby and Kemp [64], Thursby and Thursby [65].

A data envelopment analysis approach in [3] is used as a productivity evaluation tool applied to university technology transfer. The methodology included weight restrictions providing a more comprehensive metric. The results include an examination of efficiency targets for specific universities as well as peer count of inefficient universities. Evidence of significant efficiency in university technology transfer is found in many leading universities. An examination of differences between public versus private universities and those with medical schools and those without indicated that universities with medical schools are less efficient than those without.

Applications of DEA in the context of education are surveyed in Table 1.

Author (s) (Date)	Country/ Region	Sample	Method	Inputs	Outputs
Anderson et al. (2007)	USA	54 Universities	DEA and regression analysis	Total Regression Spending	• Licensing Income Licensing and Options Executed • Startup Companies • Patents Filed • Patents Issued
Bessent et al. (1982)	Houston	Schools	DEA	• Mean ITBS score at 2nd grade • Mean ITBS score at 5th grade • %Non-minority • %Playing full lunch price • Attendance rate • Number of professionals employed per pupil • Federal expenditure per pupil • Number of special programmes in school • %Teachers with masters degree • Teachers >3 years experience • Teacher attendance rate	• Mean ITBS score at 3rd grade • Mean ITBS score at 6th grade
Bredley et al. (2001)	England	2657 secondary schools	DEA and regression analysis	• The proportion of pupils ineligible for free school meals • The proportion of qualified teachers	• The proportion of 5+GCSEs grades A*-C (EXAM) • Attendance rate
Chalos and Cherian (1995)	Illinois	School districts in Illinois	DEA	• %Pupils not low income • %Pupils non-minority • Pupil attendance rate • Operating expenditure per pupil • %Teachers with masters degree	• Mean mathematics IGAP score level 6 • Mean mathematics IGAP score level 8 • Mean verbal IGAP score level 6 • Mean verbal IGAP score level 8
Davutyan et al. (2010)	Turkey	Turkish secondary education in 81 Turkish provinces	DEA and econometric methods	• TCHR[1] • CLSRM[2] • ENTGRD[3] • SDQNT[4] • SDVRBL[5]	• STDNT[6] • QNT[7] • VRBL[8]

Fare et al. (1989)	Missouri	40 school districts in St. Louis	variable returns to scale specification and jackknifing to provide statistical inference	• Number of 8th graders taking BEST test • Net current expenditure • Net assessed valuation • Number of 8th grade teachers	BEST 8th grade test results in each of : • Reading • Mathematics • Economics and Government
Ganley and Cubbin (1992)	England	All English LEAs	DEA	• Secondary school teaching expenditure per pupil • %Children with non-manual head or household • %Children living in houses with all standard amenities • %Ethnicity	• %≥5graded O-level/CSE results • %≥6 draded results at O-level/CSE • %≥1 graded results at O level/CSE
Jesson et al. (1987)	England	All English LEAs	DEA	• Secondary school teaching expenditure per pupil • %Children with non-manual head of household • %Children not from one-parent families • %Ethnicity	• %≥5 higher grade O-level/CSE passes • %≥3graded O-level/CSE results
Johnes and Yu (2008)	China	109 Chinese regular universities	Output oriented DEA with variable returns to scale, (Four models)	• STAFF[9] • STAFFQ[10] • FUNDS[11] • BOOKS[12] • BLPG[13] • PG[14]	• RES[15] • RESPP[16] • REPUT[17]
Krijavainen and Loikkanene (1998)	Finland	291 of 450 senior secondary schools	Use Tobit to explain DEA efficiencies; adopt a jackknifing approach to test robustness of DEA results	• Teaching hours per week • Non-teaching hours per week • Experience of teachers • Education of teachers • Admission level • Educational level of pupils' parents	• Number of students passing grade • Number of graduates • Score in compulsory subjects (matriculation exam.) • Score in additional subjects (matriculation exam.)
Mancebon and Mar Molinero (1998)	Hampshire, Southampton	All primary schools	Uses OLS to explain the DEA efficiences	• Teacher-pupil ratio • %Non on free school meals	• %Successful in SAT2 English • %Sucessful in SAT2 science

Mayston and Jesson (1998)	England	All English LEAs	DEA	• %Children from high socio-economic group households • %Children not from one-parent families • %Children with head of household unemployed	• %≥5 higher grade O-level/CSE • %≥6 higher grade O-level/CSE • %≥1 higher grade O-level/CSE
Ng and Li, (2000)	China	84 Chinese HEIs	DEA	• Research staff • Funding	• publications
Norman and Stoker (1991)	England	One (unnamed) English LEA	DEA	• Running costs • %Children with English as first language • %Children with no referral to counseling • %Children with above average scores in aptitude tests	• Exam results • %Pupils entering employment of higher education on leaving
Thanassoulis and Dunstan (1994)	England	Schools in one (unnamed) British LEA	DEA	• Mean verbal reasoning score on entry • %Pupils not on free school meals	• Mean GCSE score • %Pupils not unemployed after GDSE

Table 1. *Applications of DEA in the context of education*

[1] Number of teachers in each province
[2] Number of classrooms in each province
[3] Average score of students from each province in the high school entrance examination
[4] Standard deviation of the above-mentioned quantitative examinations scores
[5] Standard deviation of the above-mentioned verbal examinations scores
[6] Number of high school students in each province
[7] Average (quantitative examination) score of students from each province in the university entrance examination
[8] Average verbal examination score of students from each province in the university entrance examination
[9] Staff time is measured using a measure of the full-time staff to student ratio (STAFF)
[10] The quality of the staff input is reflected by the percentage of the faculty with the associate professor position of higher (STAFFQ)
[11] Research funding is measured using research expenditure (FUNDS)
[12] Index of library books
[13] Index of the area of the buildings
[14] Index measuring the proportion of all students who are postgraduates
[15] Index of the total number of research publications
[16] Index of research publications per member of academic staff (RESPP)
[17] Index of the prestige of the HEI

7. Conclusion

This paper introduces Data Envelopment Analysis and presents literature survey of DEA in the context of education. It is hoped that these findings will asiist researches in better understanding the status of this methodology in education, and in continuing to move the field forward in the future.

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