A Review of Benchmarking Approaches for Productivity and Efficiency Measurement in Electricity Distribution Sector

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***Abstract*—Benchmarking in recent years has become an important tool to set performance benchmarks for production entities thus comparing measures of actual performance against a reference performance. It identifies the key potential areas where a particular production entity is not performing well and suggests future directions for further detailed analysis to identify the underlying contribution causes or mitigating factors to improve performance of production entity. Many researchers had previously used benchmarking studies to assess how well the production entities are doing. This paper compares various benchmarking methodologies employed for productivity and efficiency measurement in electricity distribution utilities.**

***Index Terms*—benchmarking, efficiency, productivity, production, data envelopment analysis, stochastic frontier analysis, corrected ordinary least squares, malmquist index**

I. Introduction

In recent years, benchmarking methods have become well-established and informative tools in the assessment of utility operating performance. Benchmarking methods initially have been developed to benchmark the performance of non-profit entities such as schools and hospitals. In these cases the benchmarking results do not have usually economical effects [1]. Following the wave of liberalization and privatization of electricity sector introduced during the last decades in several countries around the world, new regulatory tools as well as redesign of the existing ones have been developed to mitigate the main difficulties faced by the utility regulators and policy makers. Within the framework of regulatory process, an important role is played by the comparison of regulated utilities in order to evaluate industry's "best-practice" or efficient frontier and benchmark the utilities against it. Benchmarking techniques can be used to assess the production efficiency of electricity distribution utilities for the purpose of measuring utility performance and identifying potential areas for further improvement. The benchmarks are intended to provide a means for improvements in electricity distribution operations and delivery services to consumers [2].

II. Overview of Benchmarking

Efficiency improvement and productivity analysis in electricity distribution utilities has come on demand, as many countries moved towards deregulation of the electricity sector in the last few decades. A widely favored approach in assessing potentials for efficiency improvement is to establish benchmarks for efficient operation. Benchmarking is defined as the continuous and systematic process of comparison of some measure of actual performance against a reference performance, thus identifies the most efficient firms or "best-practice" in the sector and measures the relative performance of less efficient firms against the best-practice frontier [3]. The performance assessment of a firm can be regarded in three main aspects: efficiency, productivity and quality. The key issues in assessing the most appropriate benchmarking methodology are discussed below [4]:

- Robustness: The benchmarking process and the resulting performance assessment must be robust as viewed by operators and peer reviewers. In particular, the ranking of firms, especially with respect to 'best' and 'worst' performers and the results over time should demonstrate reasonable stability, and the different approaches should have comparable means, standard deviations and distributional properties.
- Transparency and Verifiability: In order to ensure accountability and confidence in the price control, it is important that the benchmarking methodologies must be transparent and verifiable.
- Reasonableness of data requirements: It should be straightforward to implement the technique in practice; given the available data and the

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necessary sufficient data must exist to populate any benchmarking methodology.

- Adaptability
- Restrictions: The restrictions must be minimum on the relationship between the chosen performance measure and variables.
- Consistency with economic theory: The benchmarking methodology selected must be consistent with economic theory.
- Regulatory Burden: The burden placed on the regulator and regulated companies in terms of data collection and analysis should not be overly burdensome.

III. BENCHMARKING APPROACHES

There exists wide range of methods to measure the relative efficiency of firm in relation to a sample's efficient frontier. These include linear programming methods, statistical techniques and process approaches. The choice of the benchmarking technique used by individual utilities depends at least partly on the data available and purpose of the benchmarking exercises and can have impact on the determination of efficiency scores [5].

Programming techniques does not require specification of a production or cost function and correlate outputs to inputs without emphasized to econometric estimation. In this technique, the efficiency frontier is calculated from the data. Data envelopment analysis (DEA) and Free Disposal Hull (FDH) are two widely used programming technique, which calculates the efficiency in a given set of decision-making units. Index approaches used to determine efficiency (total factor productivity and partial) also calculate efficiency scores, and so are included in programming technique category, although they do not involve in the calculation of efficiency frontier.

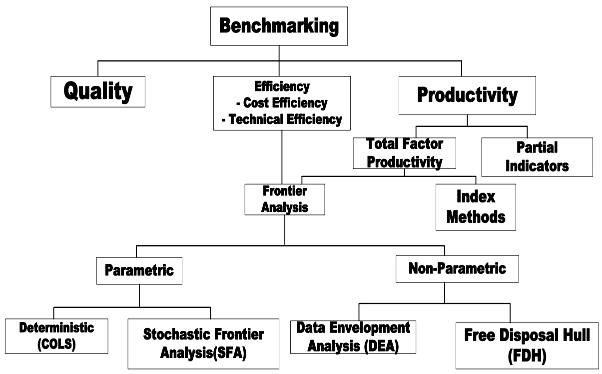

Figure 1. Benchmarking approaches

Econometric techniques, in contrast, require specific assumption about the relationship between the inputs and outputs, and estimate the parameters of a functional form representing this. Econometric methods can be further categorized as deterministic or stochastic. The deterministic frontier approach assumes that all the deviation from an estimated frontier is mainly due to technical inefficiency, with no role played by random factors. Unlike the deterministic frontier approach, a stochastic production frontier approach, however, incorporates both noise and inefficiency component into the model specification [6].

Process benchmarking involves assessing business processes and plans for individual companies to determine the scope for performance improvement using bottom-up techniques. It is also possible to use engineering data to calculate what costs should be for a particular company, based on its own individual characteristics. A possible taxonomy of benchmarking techniques is illustrated in Fig. 1.

A. *Programming Techniques*

Data Envelopment Analysis

Data envelopment analysis is a non-parametric approach that uses piecewise linear programming to determine (rather than estimate) the efficient or best practice frontier of a sample [7], [8]. In this framework, efficiency is defined as the ratio of a linear combinations of inputs, where weights are chosen in order to maximize efficiency for each unit, subject to the constraint that all efficiency scores are less than or equal to one. A firm is labeled as efficient when no other firm, or linear combination of other firms, produces more of all outputs using less of any input. For every inefficient firm, DEA identifies a set of corresponding efficient units or "best-practice" frontier that can be utilized as benchmarks (peers) for efficiency improvement This means the utilities that construct the frontier envelop the inefficient utilities of the sample. DEA is the most widely used benchmarking technique in electricity supply industry because it is a relative simple and intuitive technique that can be easily implemented with small (or limited) data sets.

DEA models can be input and output oriented, and within this framework, one can take either a constant returns to scale (CRS) or variable returns to scale (VRS). In output-oriented models, the output has to be adjusted in order to maximize efficiency for a given level of input [9]. Conversely, in input-oriented models, the input has to be adjusted in order to maximize efficiency for a given level of output. An input-oriented DEA model is widely used by utility regulators in electricity supply industry, as electricity derived demand that is beyond the utility control has to be essentially met by utilities. The efficiency of each firm versus the best-practice frontier is calculated on a scale ranging between 0 and1, with firms on the frontier getting unit scores [10].

The determination of the efficiency score of the i^{th} firm in a sample of N firms in the constant returns to scale model is equivalent to the optimization of the form specified in Eq. (1) where θ is a scalar equal to efficiency score and λ represents N×1 vector of constants. Assuming that the firm use E inputs and M outputs, X and Y represent E×N input and M×N output matrices respectively. x_i and y_i represents input and output column vectors for i^{th} firm respectively. The linear programming problem must be solved N times, once for each firm in the sample. To determine efficiency measures under the Variable returns to scale assumption, a convexity constraint $\sum \lambda = 1$ is added which ensures that the firm is compared against other firms with similar dimension [11].

$$\min_{\theta,\lambda} \theta_{,s.t} \quad \begin{array}{l} -y_i + Y\lambda \geq 0, \\ \theta x_i - X\lambda \geq 0, \\ \lambda \geq 0 \end{array} \qquad (1)$$

The efficiency score for i^{th} firm is calculated by comparing it to a linear combination of sample firms that produce as much as possible output with the minimum feasible combination of inputs. θ measures how much quantity of input needs to be reduced to bring the firm onto the best practice frontier of sample. Fig. 2 illustrates the key features of input-oriented model with Constant returns to scale. The figure shows three firms (G, H, R) that use two inputs (capital K, labour L) for a given output Y. The vertical and horizontal axis represent the capital and labour input per unit of output respectively and the line PP shows the relative price of the two inputs.

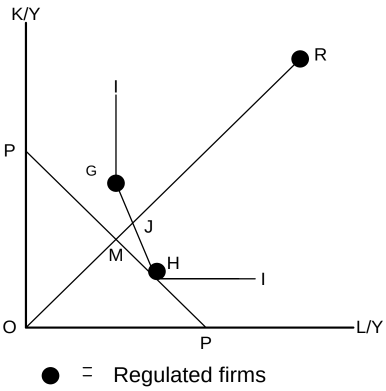

Figure 2. Input-oriented model

The figure illustrates that firms G and H form the best-practice efficient frontier producing the given output with lesser inputs and envelops the less efficient firm R. The technical efficiency of firm R relative to the efficient frontier is determined from OJ/OR, whereas the allocative efficiency is measured as OM/OJ. The ability of the firm to minimize inputs level to produce a given level of outputs is measured as technical efficiency, while the allocative efficiency reflects the firm's ability to optimize the use of inputs given the price of inputs. The ratio OM/OR measures the overall efficiency of firm R [12].

As with all other benchmarking methods, the selection of the input and output variables is of fundamental importance in DEA, since the choice of feasible input-output combinations can significantly reflects the results. In principle, the input and output variables should, as far as possible, capture the relevant aspects of production, including quality of service. Moreover, an incorrect specification of variables and other covariates can lead to perverse results, potentially inefficient utilities defining the best-practice frontier. In addition to inputs and outputs, however, utility performance can significantly differ due to operating or environmental condition factors which are beyond the utility's control [13]. There are a variety of approaches for accounting environmental variables into the DEA analysis. One such approach is simply to incorporate these environmental variables as additional inputs or outputs.

Free Disposal Hull (FDH) Approach

Deprins *et al*. [14], propose the elimination of the convexity assumption, leading to non-convex Free Disposal Hull (FDH) estimation methodology. FDH approach is a more general version of DEA model and stressed on the assumption that true production sets connecting the DEA vertices are not included in the frontier but are composed only of DEA vertices and, free disposal hull (FDH) points interior to these vertices. Because the FDH frontier is either congruent with or interior to the DEA frontier, FDH efficiencies tend to be considerably higher than those for DEA with many more self-efficient firms [15].

Formally, let $Y_0 \subset R_+^{\,p+q}$ denote the data set, whose typical element -- called an observation is – $(x^k, u^k), x^k \in R^q, u^k \in R^p, k = 1,....,n,$ with x^k a vector of inputs, u^k a vector of outputs, and n the number of observations. The free disposal hull of Y_0 is the set defined as

$$Y_{FDH} = \left\{ \begin{array}{l} \begin{bmatrix} u \\ x \end{bmatrix} \in R_+^{\,p+q} \left| \begin{bmatrix} u \\ x \end{bmatrix} = \begin{bmatrix} u^k \\ x^k \end{bmatrix} + \sum_{j=1}^{q} \mu_j \begin{bmatrix} 0^p \\ e_j^{\,q} \end{bmatrix} - \sum_{i=1}^{p} v_i \begin{bmatrix} e_i^{\,p} \\ 0^q \end{bmatrix}, \right. \\ (x^k, u^k) \in Y_0 \cup \left\{ \begin{bmatrix} 0^p \\ 0^q \end{bmatrix} \right\}; \mu_j \geq 0,\ v_i \geq 0,\ j = 1,....,p\ ,\ i = 1,....,p \end{array} \right\} \qquad (2)$$

where $e_i^{\,p}$ is the i^{th} column of the p-dimensional identity matrix, $e_j^{\,q}$ is the j^{th} column of the q-dimensional identity matrix, 0^p and 0^q are, respectively, the p and q – dimensional null vectors. This set is generated as the union of all orthants, positive in x and negative in u, whose origin is an observation.

Here, no convexity assumption is made, nor is it assumed that the boundary be representable by a continuous parametric function. Instead we only assume, in the terms of the Shephard [1970], free disposability of input and output points [16]. Hence, "free disposal hull" terminology used here to designate the constructed set.

However, a key drawback to FDH approach is ignoring the random error. Nevertheless, FDH approach permits efficiency to vary over time and makes no assumption as to the type of the distribution of the inefficiency component, and thus the measured distance between the estimated observation and the frontier is wholly considered as inefficiency [17].

B. Parametric Programming Approaches (PPA)

In line with DEA, this approach also uses linear programming approach to derive the efficiency frontier. Unlike DEA, the frontier assumes a particular functional form, in common with COLS and other parametric methodologies. The translog production function may be preferred to the popular Cobb-Douglas functional form because of the latter's restrictive elasticity of substitution and scale properties.

Total and Partial Factor Productivity Indices

The Index approach to productivity measurement is designed to compare the efficiency with which firms deploy their inputs. Productivity of firms can be compared using partial productivity or total factor productivity measures. Both these methods essentially construct ratios of real output to real input measures. Different indices use different methods to weight inputs and outputs and thus give the methods their distinct features.

Partial Factor Productivity (PFP)

Measuring productivity is quite simple when only a single output is produced with single input. Partial factor productivity measures account for ratio of single output to single input across firms and over time (for example labour productivity). However being commonly used, partial productivity measures can potentially mislead and misrepresent the performance of a firm thus limiting its application [18].

Total Factor Productivity (TFP)

A total factor productivity (TFP) index measures change in total output relative to the change in the usage of all inputs and provide a more informative measure of performance. Total factor productivity (TFP) measures account for the use of a number of factor inputs in production and therefore can be used to compare firms at a specified date and also to compare a particular firm's performance over time [8]. Total factor productivity (TFP) index is defined as

$$\ln TFP_{st} = \ln \frac{output\ \ Index_{st}}{Input\ \ Index_{st}} \tag{3}$$

In most empirical calculations, where TFP indices are calculated, the Tornqvist index formula is commonly used for purposes of output and input indices calculations. The Tornqvist index is defined, in its logarithmic from as

$$\ln Q_{st} = \sum_{i=1}^{N} \left(\frac{\omega_{is} + \omega_{it}}{2} \right) (\ln x_{it} - \ln x_{is}) \tag{4}$$

where, Q_{st} is the Tornqvist index from period s to period t, ω_{is} is the cost share of the i^{th} input in the t^{th} period, x_{it} is the quantity of the i^{th} input in the t^{th} period.

Malmquist Index of Productivity

The Malmquist approach is the most commonly used approach for output comparisons and productivity measures can be tracked over time. This approach is based on the output distance function concept. In contrast to other index approaches, the Malmquist index approach measures productivity with reference to a particular production function [19].

Index Definition

This approach gives a relationship between the inputs and outputs with reference to a particular production function and there is a tradeoff between the output variables i.e. each set of inputs can be used to produce a range of outputs.

A distance function allows one to describe, how far away a given set of inputs and outputs is from the production frontier. Following Fare *et al.* [20], the Malmquist (output-oriented) TFP change index between period s (the base period) and period t is given by

$$m_o(y_s, x_s, y_t, x_t) = \left[\frac{d_o^s(y_t, x_t)}{d_0^s(y_s, x_s)} \times \frac{d_o^t(y_t, x_t)}{d_0^t(y_s, x_s)} \right]^{1/2} \tag{5}$$

where, notation $d_o^s(y_t, x_t)$ represents the distance from the period t observation to the period s technology. A value of M_0 greater than one will indicate positive TFP growth from period s to period t while a value less than on indicates a TFP decline. Note that equation (3) is, in fact, the geometric mean of two TFP indices. The first is evaluated with respect to period s technology and the second with respect to period t technology.

C. Econometric Approaches

Econometric benchmarking method estimates a production (or cost) frontier function from the firm relevant data. Depending on the approach, all the deviations from the frontier are attributed to technical inefficiency (deterministic frontier approach); or to a combination of inefficiency and statistical noise term (stochastic frontier approach (SFA)) [21].

Deterministic Statistical Approach

The most commonly used deterministic frontier approach is corrected ordinary least squares (COLS), the standard regression technique, which estimates (rather than calculate) the 'best-practice" or efficient frontier from residuals. A functional form for the production (or cost) function is shown in Fig. 3, and ordinary least squares (OLS) technique is used to estimate such production (or cost) function. The calculated line of best fit is then shifted to the efficient frontier by an amount corresponding to the absolute value of the largest negative (positive) estimated error to that of estimated intersect (for a cost function). This is therefore a 'corrected' form of OLS is used, COLS, rather than the standard form. The correction reflects the assumption that error terms must be greater than zero and ensures that the function passes through the most efficient unit and bounds the other units. The distance measured from the frontier for the inefficient utilities are then calculated as the exponential of their corrected residuals [22].

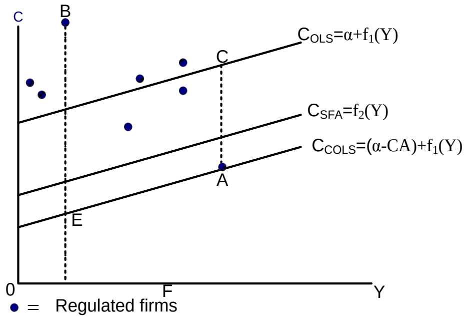

Figure 3. COLS model

Fig. 3 illustrates a COLS model with a single cost input C and one output Y. The cost equation $C_{OLS} = \alpha + f1(Y)$ is estimated using OLS regression and then shifted by CA to $C_{COLS} = (\alpha - CA) + f_1(Y)$ on which the most efficient firm A lies. The efficiency score for an inefficient firm B is calculated as EF/BF. In contrast to DEA, the method estimates the efficiency scores of the firms on a 0 to 1 scale.

Stochastic Frontier Approach

Stochastic frontier analysis (SFA) is another parametric approach that estimates the efficient frontier and efficiency scores of the firms. In SFA model, the production process is subject to two economically distinguishable random disturbances: a symmetric term contributing statistical noise, v_i and an asymmetric term technical inefficiency term, u_i. As with COLS, this method requires a functional form of cost (or production) function involving key assumptions about the firm's production technologies. Aigner *et al.* [22] had estimated a parametric production function of Cobb's-Douglas form, using data on a sample of N firms. The model is defined by

$$\ln(y_i) = x_i\beta - u_i \qquad i=1, 2\ldots\ldots\ldots\ldots, N \quad (6)$$

where $\ln(y_i)$ is the logarithm of the (scalar) output for the i-th firm; x_i is a (K+1)-row vector; β is a (K+1) column vector of unknown parameters to be estimated and u_i is a non-negative random variable, associated with technical inefficiency in production of firms in the industry involved.

The stochastic frontier production function proposed by Aigner *et al.* [23] and Meeusen *et al.* [24] in which an additional random error term, v_i, is added to the non-negative random variable u_i, is modeled as

$$\ln(y_i) = x_i\beta + v_i - u_i \qquad i=1, 2\ldots\ldots\ldots\ldots, N \quad (7)$$

The random error term v_i, allows to encompass random effect of measurement error in output, observation, statistical noise, exogenous shocks and effect of stochastic factors that are beyond the firm control e.g. natural disaster, weather, luck, strike etc., together with the combined effects of unspecified input variables in the production function. The model is called as stochastic frontier production function because the upper limit is determined by the stochastic (random) variable, $\exp(x_i\beta + v_i)$. The random error, v_i, can assume either positive or negative value and so the stochastic frontier outputs vary relative to the deterministic part of the frontier model $\exp(x_i\beta_i)$, depending on favorable or unfavorable external events. The SFA model defined by eq. (6) permits the estimation of standard errors and tests of hypotheses using traditional maximum-likelihood (ML) approach [25].

IV. Key Findings of Different Approaches

The above discussion on the different approaches has shown there to be advantages and disadvantages to each, and a comparison of these is given in Table I.

V. Empirical Electricity Distribution Benchmarking Studies

A number of empirical studies have been undertaken in electricity distribution activities for performance assessment in India and around the world. The interest in benchmarking, by the policy makers and by electricity distribution companies, arises from the widespread trend of Performance-Based Regulation (PBR) in which the efficient distribution companies are rewarded and the inefficient or least efficient companies must implement cost cuttings. A summary review of some of the previous empirical studies is given in Table II.

VI. Conclusions

Benchmarking is not an exact science but provides relative measures of overall performance within the industry, pinpoint areas where improvements can be made, set challenging yet achievable goals, and identify best practices. Experience tells us that it can be used to establish an indication of the performance of the firms or utilities, but uncertainty must be handled carefully. The frontier techniques or approaches recommended above for benchmarking the state electricity distribution utilities has their own strengths and weakness and their choice will depend on the features of the data to which they are applied. With this study, the findings about benchmarking approaches in the literature and the application notes of benchmarking approaches in the service are presented and thus the trends of benchmarking approaches for performance assessment through the years are clearly observed.

TABLE I. Comparison of Various Benchmarking Approaches

Key Characteristics	Strengths	Weakness
Data Envelopment Analysis		
Non-parametric approach that calculates, rather than estimates, the frontier using linear programming techniques	1. No imposition of prior set of input and output weights on the data required. 2. No specification of cost (or production) function is required. 3. Can incorporate uncontrollable (or unpredictable) factors, e.g. environmental. 4. Can calculate technical and allocative efficiency.	1. Sensitive to choice of input and output variables 2. No allowance for stochastic factors and measurement errors

	5. With panel data, can extend to calculate Malmquist productivity indices.	
Total Factor Productivity		
Non-parametric approach that calculates changes in the use of efficiency with which multiple inputs are transformed into multiple outputs.	1. Simple to apply and interpret.	1. Unable to distinguish scale effects from efficiency differences.
Econometric Frontier Approaches (COLS & SFA)		
Statistical approach that estimates a production function, and shifts this to reflect the efficiency of the most efficient firm to determine the frontier.	1. Straightforward to carry out and interpret. 2. Allows statistical interpretation of relationships. 3. The impact of measurement errors and other random effects is taken into account in arriving at efficiency scores.	1. Requires specification of a cost or production function. 2. Relies heavily on position of frontier firm. 3. Requires specification of a cost or production function. 4. Difficult to implement of small samples.

TABLE II. SUMMARY OF ELECTRICITY DISTRIBUTION BENCHMARKING STUDIES

Author and Year	Country and Sample	Methods	Inputs	Outputs	Main Conclusions
Agrell *et al.* (2013)	1998-2002 data on 111 distribution companies in Norwegian power distribution sector	DEA, Modified OLS and SFA	1. Labor Cost 2. Capital Cost	1. Electricity Delivered (GWh)	The purpose of this study is to analyze the cost efficiency of electricity distribution systems in order to enable regulatory authorities to establish price- or revenue cap regulation regimes.
Filippini and Wetzel (2013)	1996-2011 data on 28 electricity distribution companies in New Zealand	SFA frontier panel data model	1. Variable Cost 2. Total Cost 3. Capital Stock (MW)	1. Electricity Delivered (MWh) 2. Number of Consumers	The study found that ownership separation of electricity generation and retail operations from the distribution network has a positive effect on the cost efficiency of distribution companies in New Zealand. The estimated effect of ownership separation suggests a positive average one-off shift of 23 percent in the level of cost efficiency in the short run and 15 percent in the long-run.
Leticia, Humberto and Emili (2012)	1988-2010 data on Spanish electricity distribution comapnies	Translog Input-oriented distance function, Malmquist Index Approach	1. Labor Cost 2. Capital Cost	1. Electricity Sold (GWh)	The study observed that the sector has not increased its productivity over the period under consideration.
Fujii, Kaneko and Afrizal (2011)	2002-2005 data on 22 regional electricity distribution companies in Indonesia	DEA	1. Number of employees. 2. Distribution line length (km). 3. Transformer MVA capacity.	1. Electricity Delivered (MWh) 2. Number of Consumers	This study evaluates the changes in operational performance of regional electricity distribution in Indonesia. The study found that the efficiency improvement slowed in 2005 due to low revenues in real prices as compared to 2004. Further , authors found that main variables that improve electricity distribution efficiency are system loss and company location.
Reyes and Tovar (2009)	1996-2006 data on 14 Peru electricity distribution companies	Malmquist Index	1. Number of employees. 2. Distribution line length (km). 3. Losses	1. Electricity Delivered (MWh) 2. Number of Consumers	The study analyzes the evolution of productivity of the electricity distribution companies in Peru, to assess whether reforms have improved the efficiency in this sector and suggests that improvements in the efficiency and productivity of electricity distribution in Peru have occurred, and that there is a relationship between the restructuring of distribution sector and the enhancement of productivity.
Sadjadi and Omrani (2008)	2004 data on 38 Iranian electricity distribution companies	DEA and SFA	1. Number of employees. 2. Distribution line length	1. Electricity Delivered (MWh) 2. Number of	The paper presented a new robust DEA model where the output parameters are subject to uncertainties. The study

			(km). 3. Transformer MVA capacity.	Consumers	implemented the results obtained from the proposed methods and compared them with other traditional DEA and SFA ones using data gathered from an Iranian energy organization. The preliminary results indicate that the robust DEA approach can be relatively more accessible method for ranking strategies.
Yu, Jamasb and Pollitt (2007)	1990/91 – 2003/04 data on 14 electricity distribution networks in UK	DEA	1. Operational costs 2. Total operational costs 3. Duration of energy interruptions 4. Losses	1. Electricity Delivered (MWh) 2. Number of Consumers 3. Length of lines (km)	The main aim of the study was to present an approach to measure and incorporate service quality and energy losses in analysis of technical and allocative efficiency of the utilities. The study found that efficiency measures improved during the first (1990/91-1994/95) and second (1995/96-1999/00) distribution price control reviews and exhibited a slight decline during the third (2000/01-2004/05) review period. The results suggest that the utilities may not be sufficiently incentivized to achieve socially optimal input bundles under the current incentive scheme.

REFERENCES

[1] S. Honkapuro, J. Lassila, S. Viljainen, K. Tahvanainen, and J, Partanen, "Effects of benchmarking of electricity distribution companies in Nordic countries-comparison between different benchmarking methods," in *Proc. Nordic Distribution and Asset Management Conference*, 2004.

[2] T. Thakur, S. G. Deshmukh, and S. C. Deshmukh, "Efficiency evaluation of the state owned electric utilities in India," *Energy Policy*, vol. 34, no. 17, pp. 2788-2804, Nov. 2006.

[3] T. Jamsab and M. Pollitt, "Benchmarking and regulation: international electricity experience," *Utilities Policy,* vol. 9, no. 3, pp. 107-130, Sep. 2000.

[4] OFGEM, "Background to work on assessing efficiency for the 2005 distribution price control review: Final report," Sep. 2003.

[5] T. Jamsab and M. Pollitt, "Benchmarking and regulation of electricity transmission and distribution utilities: Lessons from international experience," *Working Paper in Economics,* University of Cambridge, Jan. 2001.

[6] V. Irastorza, "Benchmarking for distribution utilities: A problematic approach to defining efficiency," *The Electricity Journal*, vol. 16, no. 10, pp. 30-38, Dec. 2003.

[7] M. J. Farrell, "The measurement of productive efficiency," *Journal of the Royal Stastical Society*, Series A, CXX, part 3, pp. 253-290, 1957

[8] R. Fare, S. Grosskopf, and J. Logan, "The relative performance of publicly-owned and privately-owned electric utilities," *Journal of Public Economics*, vol. 26, no. 1, pp. 89-106, Feb. 1985.

[9] T. Thakur, S. G. Deshmukh, and S. C. Deshmukh, *Performance Evaluation of Electric Supply Utilities in India*, New Delhi, India: Indiacore Publications, 2010.

[10] T. Jamsab and M. Pollitt, "International benchmarking and regulation: An application to European electricity distribution utilities," *Energy Policy*, vol. 31, no. 15, pp. 1609-1622, Dec. 2003.

[11] T. Jamsab, N. Paul, and M. Pollitt, "Strategic behaviour under regulatory benchmarking," *Energy Economics,* vol. 26, no. 5, pp. 825-843, Sep. 2005.

[12] K. Kinnunen, "Pricing of electricity distribution: An empirical efficiency study in Finland, Norway and Sweden," *Utilities Policy*, vol. 13, no. 1, pp. 15-25, Mar. 2005.

[13] S. J. Sadjadi and H. Omrani, "Data envelopment analysis with uncertain data: An application for Iranian electricity distribution companies," *Energy Policy*, vol. 36, no. 1, pp. 4247-4254, Nov. 2008.

[14] D. Deprins, L. Simar, and H. Tulkens, "Measuring labor efficiency in post offices," in *The Performance of Public Enterprise: Concepts and Measurements*, M. Marchand, P. Pestieau and H. Tulkens eds. Elsevier, pp. 345-367.

[15] H. Tulkens, "On FDH efficiency analysis: Some methodological issues and applications to retail banking, courts, and urban transit," *Journal of Productivity Analysis*, vol. 4, no 1-2, pp. 183-210, June 1993.

[16] R. W. Shephard, *Theory of Cost and Production Functions*, Princeton: Princeton University Press, 1970.

[17] P. Molyneux and M. Iqbal, *Banking and Financial Systems in the Arab World*, New York: Pagrave Macmillan, 2005.

[18] R. J. Windle and M. E. Dresner, "Partial productivity measures and total factor productivity in the air transport industry: Limitations and uses," *Transportation Research Part A: Policy and Practice*, vol. 26, no. 6, pp. 435-445, Nov. 1992.

[19] T. Coelli, D. Prasad Rao, and G. E. Battese, *An Introduction to* Efficiency *and Productivity Analysis*, Massachusetts, USA: Kluwer Academic Publishers, 1998.

[20] R. Fare, S. Grosskopf, M. Norris, and Z. Zhang, "Productivity growth, technical progress, and efficiency changes in industrialized countries," *American Economic Review*, vol. 84, no. 1, pp. 66-83, Mar. 1994.

[21] S. C. Kumbhakar and C. A. K. Lovell, *Stochastic Frontier Analysis*, Cambridge: Cambridge University Press, 2003.

[22] A. Yatchew, "Nonparametric regression techniques in economics," *Journal of Economic Literature*, vol. 36, no. 2, pp. 669-72, June 1998.

[23] D. J. Aigner and S. F. Chu, "On estimating the industry production function," *American Economic Review*, vol. 58, no. 4, pp. 826-839, Sep. 1968.

[24] W. Meeusen and J. van den Broeck, "Efficiency estimation from Cobb's Douglas production functions with composed error," *International Economic Review*, vol. 18, no. 2, pp. 435-444, June 1977.

[25] P. H. L. Nillesen and M. G. Pollitt, "Ownership unbundling in electricity distribution: Empirical evidence from New Zealand," *Review of Industrial Organization*, vol. 38, no. 1, pp. 61-93, Jan. 2011.

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