BENCHMARKING OF ELECTRICITY DISTRIBUTION LICENSEES OPERATING IN SRI LANKA

Lilantha Neelawala

108889U

Dissertation submitted in partial fulfillment of the requirements for the

Degree Master of Science in Electrical Installations

Department of Electrical Engineering

University of Moratuwa

Sri Lanka

September 2013

DECLARATION

"I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

Also, I hereby grant to University of Moratuwa the non-exclusive right to reproduce and distribute my dissertation, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books)".

UOM Verified Signature

Signature of the candidate : Date: 17/02/2014

(Lilantha Neelawala)

The above candidate has carried out research for the Masters Dissertation under my supervision.

UOM Verified Signature

Signature of the supervisor : Date: 17/02/2014

(Dr. K.T.M. Udayanga Hemapala)

ABSTRACT

Electricity sector regulators are practicing benchmarking of electricity distribution companies to regulate allowed revenue to each company. Mainly this is done by using the relative efficiency scores produced by frontier benchmarking techniques. Some of these techniques, for example Corrected Ordinary Least Squares method and Stochastic Frontier Analysis have econometric approach to estimate efficiency scores, while method like Data Envelopment Analysis uses Linear Programming to compute efficiency scores. Using the relative efficiency scores, the efficiency factor (X-factor) which is a component of the revenue control formula is calculated. The approach used by the regulators to derive X-factor by the relative efficiency scores is varying among regulators.

In electricity distribution industry in Sri Lanka the allowed revenue for a particular distribution licensee is calculated according to the allowed revenue control formula as specified in the tariff methodology of Public Utilities Commission of Sri Lanka. This control formula contains the X-factor as well, but it has been kept zero, since there were no relative benchmarking studies carried out by the utility regulator to decide on X-factor.

In order to produce a suitable benchmarking methodology this dissertation focuses on prominent benchmarking techniques used in international regulatory regime and analyses the applicability to Sri Lankan context, where only five Distribution Licensees are operating at present. The main challenge was to produce robust efficiency scores using frontier techniques for lower sample size (i.e. five) where in contrast many countries have large number of distribution companies or licensees (i.e. large sample size).

Importantly this discussion gives directing signals to the utility regulator on possibility to control allowed revenue of Distribution Licensees according to their efficiencies.

Key words: Data Envelopment Analysis, Corrected Ordinary Least Squares, Distribution Licensees.

ACKNOWLEDGEMENT

Foremost, I pay my sincere gratitude to Dr. K.T.M. Udayanga Hemapala who encouraged and guided me to conduct this investigation and on perpetration of final dissertation.

I extend my sincere gratitude to Dr. J.P. Karunadasa, Head of the Department of Electrical Engineering and all the lectures and visiting lectures of the Department of Electrical Engineering for the support extended during the study period.

Also, I pay my sincere gratitude to Roland Goerlich - Analyst, E-Control Austria and Roar Amundsveen – Adviser, Energy and Regulation Department, Section for Economic Regulation, Norwegian Water Resources and Energy Directorate (NVE) for their continuous support by answering my queries on benchmarking.

Further I Extend my sincere gratitude to Mr. Damitha Kumarasinghe – Director General, Mr. Gamini Herath – Deputy Director General, Mr. Nalin Edirisinghe – Director (Licensing) and Mr. Kanchana Siriwardena – Director (Tariff & Economics) of PUCSL for supporting me during the study period.

I would like to take this opportunity to extend my sincere thanks to following experts who gave their support to conduct my work. Tore Langset – Energy Department, Norwegian Water Resources and Energy Directorate (NVE). Göran Ek - Department of tariff regulation, Energy Markets Inspectorate, Sweden. Prof dr. Nevenka Hrovatin - Academic Unit for Economic Theory and Policy, Faculty of Economics, University of Ljubljana, Slovenia. Aleksander Selcan, Economic Regulation Sector, Energy Agency of the Republic of Slovenia. Jelena Zorić - Assistant Professor, Faculty of Economics, University of Ljubljana, Slovenia. Leonardo Lupano - Deputy Director, Sustainable Energy, AF Mercados Energy Markets International S.A, SPAIN. Denise Laurent - Dutch Competition Authority (NMa), Netherlands. Samuli Honkapuro - Researcher, D.Sc., LUT Energy, Laboratory of Energy Markets and Power Systems, Lappeenranta University of Technology, Finland. Konrad Godzisz - Counselor of the President, Tariff Department, Energy Regulatory Office, Poland. Su Wu - Principal Economic Advisor, Regulatory Development Branch, Australian

Competition and Consumer Commission. Prof. Dr. Massimo Filippini - Department of Technology, Management and Economics, Swiss Federal Institute of Technology, Switzerland. Dr. Chris Tofallis - Statistical Services Consulting Unit, University of Hertfordshire, United Kingdom. Mr. Rishi Maharaj - Assistant Executive Director, Economics and Research, Regulated Industries Commission, Republic of Trinidad & Tobago. Bríd O'Donovan - Electricity Distribution & Interconnection Commission for Energy Regulation, Ireland. Matti Supponen - DG Energy, Electricity & Gas Unit, European Commission. Peter Dane - Manager International Benchmarking, Association of Dutch Water Companies. Keith Smith – Librarian, Information Management and Technology, Ofgem. Emma Davis - Assistant Librarian, Information Management and Technology, Ofgem. Erika Toth - International Affairs Officer, Hungarian Energy Office. Aivars Berzins - Head of Electricity Division, The Public Utilities Commission, Latvia. The Australian Energy Regulator (AER). Sumith Gamage - Design Team Manager, Customer Service Branch, ActewAGL, Australia. Dave Jacobson – South Dakota Public Utilities Commission. Raminta Starkeviciute - High-level Administrator, Council of European Energy Regulators (CEER). Michelle Smith - Administrative Officer, Office Of The Tasmanian Economic Regulator (OTTER).

My thanks extends to Banxia Software for providing the demonstration version of Frontier Analyst®

It is a great pleasure to remember the kind co-operation extended by the colleagues in the post graduate program, friends and specially my wife Wimali Nawarathna who helped me to continue the studies from start to end and to my 2 year old son, Abinada who did not destroy my laptop during the this period.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

Abbreviation	Description
CAPEX	Capital Expenditure
CEB	Ceylon Electricity Board
COLS	Corrected Ordinary Least Squares
DEA	Data Envelopment Analysis
DL	Distribution Licensee
GWh	Giga Watt Hours
HV	High Voltage
LECO	Lanka Electricity Company (Private) Limited
LKR	Sri Lanka Rupee
LV	Low Voltage
MV	Medium Voltage
MWh	Mega Watt Hours
O&M	Operations and Maintenance
OLS	Ordinary Least Squares
OPEX	Operational Expenditure
PPI	Partial Performance Indicators
PUCSL	Public Utilities Commission of Sri Lanka
SFA	Stochastic Frontier Analysis

1 INTRODUCTION

1.1 Background

In electricity regulatory regime, relative benchmarking of electricity distribution licensees (or electricity distribution companies) carried out by regulators. Benchmarking studies results relative efficiency scores of distribution licensees, for example operating within a country. In case of Sri Lanka there are five DLs, namely CEB Region 1, CEB Region 2, CEB Region 3, CEB Region 4 and LECO.

The Distribution Allowed Revenue is the revenue that a Distribution Licensee (DL) is allowed to collect from the distribution users due to the use of the distribution system, excluding allowed Charges (connection, reconnection, meter testing, etc) that are separately regulated[13].

For each DL, the Distribution Allowed Revenue shall be calculated based on a forecasted cash flow for DL for the tariff period, considering following factors [13] including efficient operational expenditure.

- Initial Regulatory Asset Base (the value of the assets belonging to the Licensee to provide the distribution service).
- Rolling forward of the initial regulatory asset base, considering the forecasted capital expenditure for the period
- Depreciation of existing non-depreciated assets
- Return on capital
- Efficient operational expenditure
- Taxes

The OPEX component of the base allowed revenue will be adjusted at a rate defined by an Efficiency Factor (OPEXX) per year. OPEXX (%) will be fixed by the PUCSL before the start of the tariff period [13]. In successive Tariff Periods, the Commission may revise the methodology for computing the efficient OPEX to be included in the distribution Allowed Revenue [13].

1.2 Identification of the Problem

In electricity distribution industry in Sri Lanka the allowed revenue for a particular distribution licensee is calculated according to the allowed revenue control formula as specified in the tariff methodology of Public Utilities Commission of Sri Lanka. The control formulae provide the allowed revenue (AR) for year Y as follows.

$$AR_y = AR_{y-1} \times (1 - \overbrace{X}^{\text{X - Efficiency Factor}}) \times \left[a \times (1 + SLCPI) + (1 - a) \times \left(\frac{FX_y}{FX_{y-1}} + PPIUS \right) \right] \ldots \times \left[b \times (1 + Dcust) + c \times (1 + DkWh) + d \right] - Diff_y \quad \text{------(1)}$$

[Please refer Appendix for more information on allowed revenue control formula]

There is a factor defined as X-factor (efficiency factor), which is in the control formulae as indicated above.

A relative OPEX efficiency score obtained from a benchmarking study is an input to formulate X – factor. PUCSL can decide on X-factor using the result of a benchmarking study.

At present PUCSL take X-factor as **zero** due to the fact that there is no benchmarking study has been done on DLs to obtain relative OPEX efficiency scores. Without these relative efficiency scores (percentage values like 100% for one DL , 60% for another and etc.) X-factor cannot be obtained.

Therefore the electricity sector regulator - PUCSL requires a suitable methodology to benchmark Distribution licensees in Sri Lanka.

1.3 Motivation

The outcome of this project is to develop a suitable methodology to benchmark distribution licensees in Sri Lanka which facilitate PUCSL to regulate allowed revenue for each DL according to the relative OPEX efficiencies of each DL. This would eventually benefit the electricity consumers and the economy of the country.

1.4 Objective of the Study

The objective of this study is to analyse and identify relative efficiencies with respect to efficient operational expenditure of electricity distribution licensees of Sri Lanka. Reader should note that there were no previous benchmarking has been carried out on distribution licensees in Sri Lanka.

Therefore this study would helpful in following aspects of electricity regulations.

- The regulator can set differentiated price caps based on the companies' efficiency performance estimated from a benchmarking analysis. [11]
- Regulator can decide which companies deserve closer examination, so that scarce investigative resources are allocated efficiently [12]
- Regulator can decide on X-factor [13] using the results of benchmarking. The X-factor (efficiency factor) is in the control formulae on distribution allowed revenue.

1.5 Methodology

To complete the project in timely, the work flow was arranged in following manner,

An extensive literature survey was carried out to identify how regulators in worldwide practice the benchmarking of DLs in regulatory business. Benchmarking techniques were studied and Data requirement was identified during the literature review. Then,

- Required data was collected from utilities and the regulator.
- Selected benchmarking techniques were applied on DLs and results were obtained for different data combinations (inputs / Outputs).
- Results were evaluated and came up with suitable methodology for obtaining relative OPEX efficiencies of DLs in Sri Lanka.

Following figure 1-1 illustrates the methodology followed in carrying out this study.

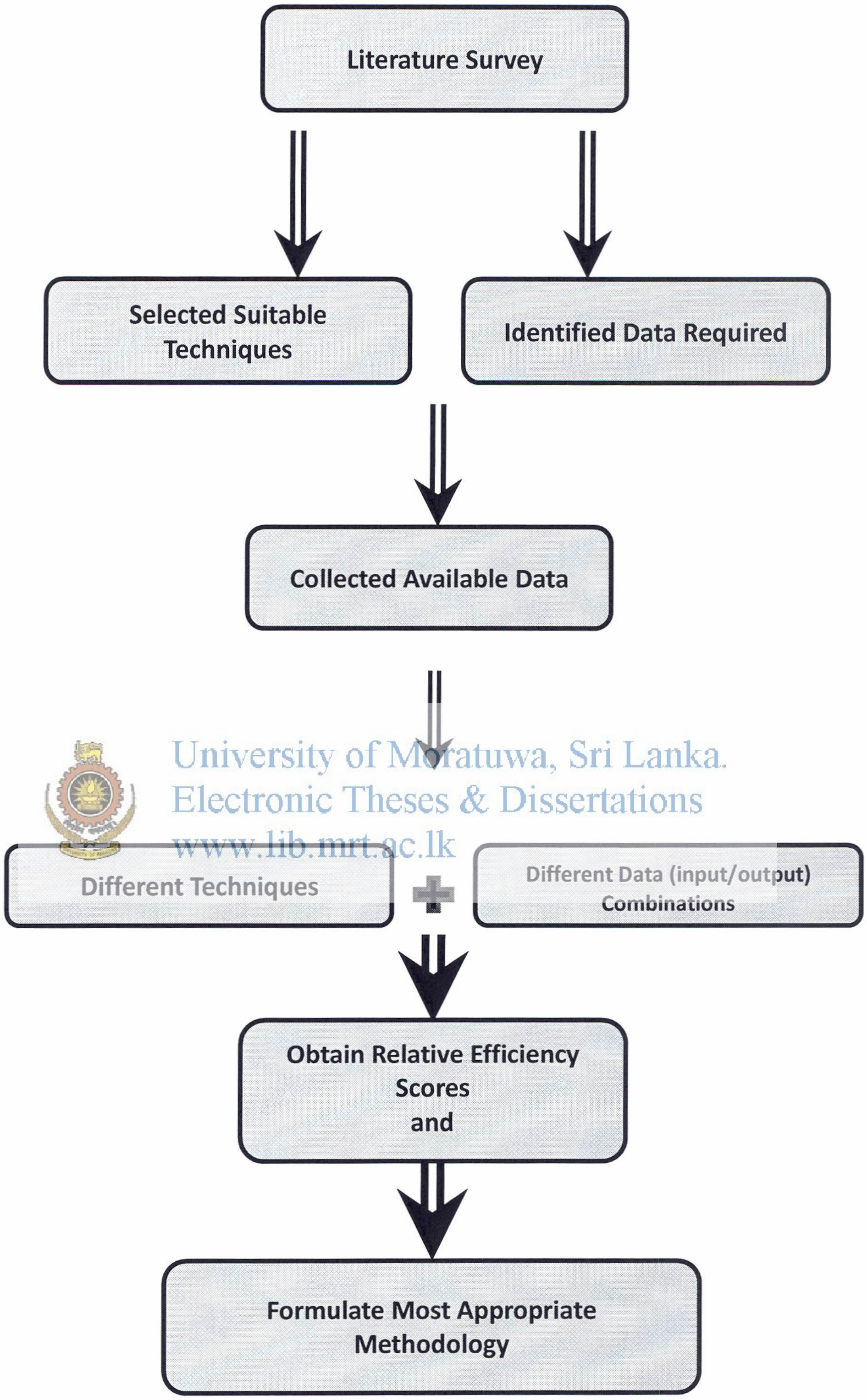

Figure 1-1: Methodology followed

2 PROMINENT BENCHMARKING TECHNIQUES

2.1 Introduction

Regulators have adopted a variety of approaches to incentive regulation. The most widely discussed and adopted schemes are based on price cap, revenue cap, and targeted-incentive regulation models. In practice, most incentive schemes use a combination of different models. A common feature of the incentive based regulation models is the use of some form of benchmarking of utilities. Within this context benchmarking can broadly be defined as comparison of some measure of actual performance against a reference or benchmark performance.

In assessing the most appropriate benchmarking methodology, following principles [1] have to be considered.

- **Practical application**: It should be straightforward to implement the technique in practice, given the available data. Some of the more sophisticated techniques based on econometric methods may be inappropriate when there is only a relatively small sample of firms.

- **Robustness**: The model selected must be robust to changes in assumptions and methodologies. In particular, the ranking of firms, especially with respect to the '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 process is both fully transparent and verifiable.

- **Ability to capture business conditions adequately**: The approach taken should be able to capture the particular characteristics of the industry concerned. For example, some allowance should be made for topology of the network (e.g. via the inclusion of network length).

- **Restrictions**: The restrictions placed on the relationship between the chosen performance measure and variables should be minimized.

- **Consistency with economic theory**: The approach taken should ideally conform to
Economic theory.

- **Regulatory burden**: The burden placed on both the regulator and regulated companies in terms of data collection and analysis should not be overly burdensome.

Some prominent benchmarking methods are given in table 2-1.

Approach	Technique
Linear Programming	Data Envelopment Analysis
Econometric	Corrected Ordinary Least Squares
Econometric	Stochastic Frontier Analysis

Table 2-1 : Prominent Benchmarking Methods

Following Table 2-2 gives an overview of the frequency with different input and output variables are used in 20 international studies [5]. As shown in the table, the most frequently used inputs are operating costs, number of employees, transformer capacity, and network length, whilst the most widely used outputs are units of energy delivered, number of customers, and the size of service area.

Variable	Frequency
Units Sold	*14*
Network size, LV MV HV Line lengths	*15*
No of customers	*12*
Transformer capacity	*12*
Service Area	*8*
OPEX	*7*
Maximum demand	*5*

Table 2-2 : Input Output Variables Used in International Studies

2.2 Partial Performance Indicators (PPIs)

It measures compare the ratio of a single output to a single input across firms and over time (for example labor productivity). However, partial productivity measures can be highly misleading as they are often significantly impacted by capital substitution effects (where capital is substituted for labour, therefore improving labour productivity)[1].

PPIs used in isolation cannot easily take into account differences in the market or operating environment that impact upon a business. For example, a utility may have a relatively high or low unit cost simply because it faces input prices or serves customers that are different from those for utilities operating in other regions. Because of this, they may present problems in providing a meaningful comparison of businesses in different operating environments.[8] Therefore less useful for the regulator.

The use of a matrix of partial performance measures to compare performance of utilities, grouped by scale of operation (such as a composite scale variable), customer type or density, network density, capital density, or a combination of these, often leads to the identification of different best and worst performers in the different dimensions.[8]

2.2.1 Advantages

- Easy to compute and understand
- Can be used to cross check DEA and COLS results for plausibility and transparency
- Can be used to compare certain aspects of efficiency and productivity performance.
- Analysis can help identify trends, determine baselines and establish target performance.

2.2.2 Disadvantages

- Does not allow for evaluation of uncertainty associated with calculating benchmark
- Although can control for some differences in operating environment, many it cannot control for
- The restriction to some of the factors used in production means that the approach can be misleading.
- Can give misleading information regarding the overall economic performance of energy utilities producing multiple outputs and multiple inputs.
- Cannot give an overall measure of potential for cost improvement.

2.2.3 Example for PPIs

- MWh delivered/OPEX
- Customers served/OPEX
- Tree cutting cost per network kilometer.
- Fault costs per network kilometer

A weighted-average performance indicator to combine a set of core performance measures also raises some potential problems because the choice of weights may be arbitrary and the overall indicator may fail to account for differences in the operating environment.

These problems suggest a need for a method to derive comprehensive performance measures that can capture all the information on the inputs used and outputs produced and that can adjust for differences in non-controllable factors that may affect utility performance. [8]

2.3 Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric method that uses linear programming to determine (rather than estimate) the efficiency frontier of the sample. The approach works by solving individual linear programming problems for each firm or observation, in which the firm's inputs and outputs are assigned a set of weights in order to maximize the ratio of weighted outputs to inputs (subject to the constraint that all efficiency scores are less than one).Under this approach, an efficient firm is one where no other firm– or linear combination of other firms - can produce more of all the outputs using less of any input. This means that the efficiency frontier is constructed from the 'envelope' of these linear combinations of input and output combinations.[1]

A key step in DEA is the choice of appropriate input and output variables. The variables should, as far as possible, reflect the main aspects of resource-use in the activity concerned. Misspecification of variables can lead to wrong results, potentially with less efficient firms defining the frontier. DEA can also account for factors that are beyond the control of the firms and can affect their performance, e.g. environmental variables.

DEA is a widely used model, requiring few assumptions about the functional form of cost functions, and it is easy to apply and interpret. Care needs to be taken in the specification of the variables for use in the model, in particular for small samples of firms, but provided this is done, it is a valuable benchmarking tool.
There is a problem involving degrees of freedom, which is compounded in DEA because of its orientation to relative efficiency. In the "envelopment model," the number of degrees of freedom will increase with the number of units (DLs) and decrease with the number of inputs and outputs [21].

2.3.1 Input output variables

Inputs :

- O&M expenditure
- Line length
- Transformer capacity
- Customer density

- Line loss
- Average hours outages per customer
- Labor hours

Outputs:

- Energy delivered
- Total customers
- Peak demand
- Revenue received
- Network length
- Service area
- Feeding power of de-centered generation

Other factors :

- Customer mix
- Temperature
- Humidity
- Salinity
- Topology

2.3.2 Advantages of DEA

- Multi-dimensional method
- Inefficient firms are compared to actual firms (or linear combinations of these) rather than to some statistical measure
- Does not require the specification of a cost or production function.
- It does not require functional relationships between input and output factors
- DEA can be implemented on a small dataset, where regression analysis tends to require larger minimum sample size in order to stand up to statistical testing.

2.3.3 Disadvantages

- The results could be influenced by random errors, measurement errors or extreme events
- Less information about statistical significance of the results[2]
- In case of small samples and high number of input or/and output variables – danger of over- specification of model and "made-up" results for efficiency scores [2]. As more variables are included in the model, the number of firms on the efficient frontier increases.
- The efficiency scores tend to be sensitive to the choice of input and output variables and, in some circumstances, inappropriate choices may lead to relatively inefficient firms defining the frontier.[1]

2.3.4 DEA Linear Programming Model

The DEA takes the following model [10]

$$\max \frac{\sum_{k=1}^{s} v_k y_{kp}}{\sum_{j=1}^{m} u_j x_{jp}}$$

$$s.t \quad \frac{\sum_{k=1}^{s} v_k y_{ki}}{\sum_{j=1}^{m} u_j x_{ji}} \le 1 \quad \forall i$$

$$v_k, u_j \ge 0 \quad \forall k, j,$$

where

k = 1 to s,

j = 1 to m,

i = 1 to n,

y_{ki} = amount of output k produced by DMU i,

x_{ji} = amount of input j utilized by DMU i,

v_k = weight given to output k,

u_j = weight given to input j.

$$\max \sum_{k=1}^{s} v_k y_{kp}$$

$$s.t \quad \sum_{j=1}^{m} u_j x_{jp} = 1$$

$$\sum_{k=1}^{s} v_k y_{ki} - \sum_{j=1}^{m} u_j x_{ji} \le 0 \quad \forall i$$

$$v_k, u_j \ge 0 \quad \forall k, j.$$

2.4 Corrected Ordinary Least Squares (COLS)

The most commonly used deterministic approach is corrected ordinary least squares (COLS), the standard regression technique, with the efficiency measures computed from the residuals. With this approach, the frontier is estimated (rather than calculated) using statistical techniques. A functional form for the production / cost function is specified (see below), and this is estimated using ordinary least squares (OLS) techniques. The calculated line of best fit is then shifted to the efficient frontier by adding the absolute value of the largest negative estimated error to that of the other errors (for a cost function). This is therefore a 'corrected' form of OLS is used, COLS, rather than the standard form. [1]

Given a vector of outputs $Y = (y_1, y_2, y_3 \ldots)$, a vector of input prices $w=(w_1, w_2, w_3 \ldots)$, and a vector of environmental variables $z= (z_1, z_2, z_3 \ldots)$, a benchmark cost function reflects the annualized costs of an efficient business at a given point in time as a function of Y,W,Z, [8].

The following five steps are required for the 'benchmark cost function' approach:

(1) The selection of variables which reflect:

- Outputs produced by the businesses;
- Input prices paid by those businesses; and
- Environmental conditions that affect the production costs.

Collectively, these variables capture all factors that systematically affect the costs of the businesses and that are beyond management control.

(2) The selection of the type of cost function (the 'functional form');

(3) The selection of an estimation method that sets out a way to estimate the specified cost function that best fits the available data;

(4) The compilation of data in relation to costs, outputs, prices, and environmental variables for a set of comparable businesses; and

(5) The estimation process and the interpretation of the residual (the difference between the estimated and actual costs) for each business as a measure of the inefficiency of that business.

A variety of function forms have been used in the empirical studies, ranging from the simple Cobb-Douglas function to the more complex 'flexible' functional forms such as the translog function. The Cobb-Douglas function assumes a (first-order) log-linear functional form; that is, the logarithm of the benchmark cost is assumed to be linear in the logarithm of the output quantity and input price variables specified. For example, with two output variables and two input prices, a log-linear cost function[8] is:

$$\ln \hat{C}(y_1, y_2, w_1, w_2) = a + b_1 \ln y_1 + b_2 \ln y_2 + c_1 \ln w_1 + c_2 \ln w_2$$

The figure 2-2 illustrates a COLS model with a single cost input C and one output Y. The efficient cost equation (COLS line) is estimated using Ordinary Least Squares (OLS) regression and then shifted by AC to on which the most efficient firm C lies. The efficiency score for an inefficient firm B is calculated as EF/BF. [1]

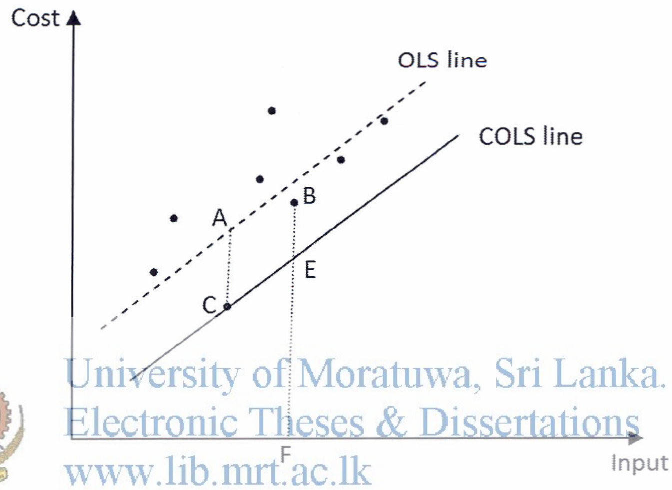

Figure 2-1 : COLS Procedure

2.4.1 Variables used

Dependent variables:

- Total cost
- OPEX.

Input Variables:

- Price of capital
- Price of labor
- Price of input power
- O&M cost.

Output Variables:

- Electricity delivered (kWh)
- Customers served
- Network length.

Other variables:

- Load factor
- Size of service area
- Average temperature
- Average precipitation

2.4.2 Key Assumptions

- The COLS method requires specification of a cost or production function and therefore involves assumptions about technological properties of the firms' production process.

- It is assumed that all deviations from the frontier are due to inefficiency. There are therefore no measurement errors.

2.4.3 Advantages

- Easy to implement
- Allows statistical inference about which parameters to include in the frontier estimation.
- Requires no assumptions about the distribution of the inefficiency scores.

2.4.4 Disadvantages

- The estimated parameters may not make engineering sense
- The method makes no allowance for stochastic errors and relies heavily on the position of the single most efficient firm in the sample

- Similar to DEA, COLS assumes that all deviations from the frontier are due to inefficiency.

- It is not possible to identify firms to which inefficient firms are being compared in the same sense as DEA. All firms are being compared to a frontier defined by one frontier firm. However there may be no 'nearby' frontier firms.

- Requires large data volume in order to create robust regression relationship

- Sensitive to data quality (the company setting frontier could be an outlier)

2.5 Stochastic Frontier Analysis (SFA)

Stochastic frontier analysis (SFA) is similar to COLS described above, in that it requires the specification of a production function based on input variables. The difference is that it does not assume that all errors are due to inefficiency, so errors in parameters are incorporated into the model[8].

The underlying functional form is typically Cobb-Douglas or Translog[1]. A model of the form described under COLS is estimated with two error functions. The first of these will be assumed to have a one-sided distribution. The second error term have a symmetric distribution with mean zero. The Cobb- Douglas stochastic frontier model takes the form of[37];

$$\ln q_i = \beta_0 + \beta_1 \ln x_i + v_i - u_i$$

Where q_i is an output x_i is an input and v_i, u_i are error terms. Perhaps due to the complexities of implementing SFA in practice and the lack of transparency associated with the results, regulators have tended not to rely on SFA in setting X factors. SFA is theoretically the most appealing technique but the hardest to apply.
Regulators have therefore traditionally been reluctant to use SFA techniques in setting X factors[1]. This is because in small samples the technique is either difficult to implement or gives rise to high efficiency scores.

2.5.1 Advantages

- SFA reduces reliance on measurements of a single efficient firm.
- Can incorporate tailored business conditions
- The mean of the efficiency term can be explained by the inclusion of environmental variables in the analysis. Such inclusion handles environmental variables in a statistically robust way.

2.5.2 Disadvantages

- Requires a functional form to be specified
- A statistical distribution also needs to be specified for the inefficiency factor
- Can be difficult to implement in practice due to the length of the algorithms required

- Suffers from a lack of transparency in the derivation of results, again due to the complexity of algorithms required.
- Even if there are no errors in efficiency measurements, some inefficiency may be wrongly regarded as noise.
- Complex functional forms and stochastic errors appear to bias estimates of inefficiency downwards. Some inefficiency would be classified as noise.
- Estimation of the parameters with SFA is more complex than with COLS.
- In practice the technique may not be implementable and give rise to all firms being100% efficient.

3 INTERNATIONAL PRACTICES

Models to obtain relative efficiency scores, practiced by some of the leading regulators who are using benchmarking to control allowed revenue for DLs are discussed below. Further some of the methods used to derive X factor by using relevant relative efficiency scores are also described to highlight the importance of obtaining relative efficiency scores.

3.1 Austria

E-control is the energy regulator for Austria. Three different approaches are applied, two data envelopment analyses (DEAs) with different output variables and a modified ordinary least squares estimation. This has been preferred over the stochastic frontier analysis (SFA) due to the small sample- 20 electricity distributors. The Austrian efficiency benchmarking is based on around 20 DSOs. Table 3-1 displays the variables have been used in the benchmarking models [6].

DEA (I)	DEA (II)	MOLS
Input		
TOTEX	TOTEX	TOTEX
Output		
P_{MV}	P_{MV}	P_{MV}
P_{LV}	P_{LV}	P_{LV}
l_T	l_{HV}	l_T
	l_{MV}	
	l_{LV}	

P- load, l- line length, T- total

Table 3-1 : Variables and Techniques Used by Austrian Regulator

The overall efficiency score of an individual DSO, *ES*, is the weighted sum of all three approaches.

$$ES = 0.4 \cdot DEA(I) + 0.2 \cdot DEA(II) + 0.4 \cdot MOLS$$

The price cap formulae is,

$$C_t = C_{t-1} \cdot [(1 - X) \cdot (1 + \Delta NPI_t)] \cdot (1 + k \cdot \Delta M_t)$$

With as the total costs in period t, the efficiency factor X, as the change in the network operator's price index to account for inflation, k the quantity-cost factor, and the change in the amount of electricity distributed to end-users. The efficiency factor X incorporates the frontier shift due to technological change, Xgen (% p.a.), as well as the individual efficiency scores ES (%) determined via benchmarking. The yearly cost adjustment factor X (% p.a.) is calculated as,

$$X = 1 - (1 - X_{gen}) \cdot \sqrt[5]{ES} .$$

3.2 Finland

Regulation is done by Energy Market Authority (EMA), and 88 distribution network operators involved in the distribution business.

EMA uses both DEA as well as SFA for the efficiency benchmarking of distribution network operators [6]. The input and output factors of the current DEA model are:

Input factor(s): the overall costs to the customers, which are composed of the sum total of controllable operational costs, depreciations and outage costs.

Output factors: the total length of the electricity network, number of users of the network operator and the value of energy distributed to consumption. Formula for DEA model used by EMA is,

$$DEA(-Score) = \frac{\text{u1 x } Energy + \text{u2 x } Networklenghth + \text{u3 x Customers}}{\text{v1 x (OPEX + SLD + DCO)}}$$

with

OPEX: controllable operational costs

SLD: straight-line depreciations

DCO: disadvantage to the customer caused by electricity supply outages

u1-3, v: internal weight factors

The enterprise specific efficiency-figures are therefore calculated as the average of the figures calculated with DEA and SFA with the following formula[6]:

$$EFent,i = \frac{DEAi + SFAi}{2}$$

EFent,i = Enterprise-specific efficiency figure for network operator i

DEAi = Efficiency figure calculated for network operator i with the DEA model
SFAi = Efficiency figure calculated for network operator i with the SFA model

"As both methods used in the efficiency measurement are input-oriented, the result of the above formula indicates how much the network operator should reduce costs that are used as input so that the network operator would achieve a cost level complying with efficient operations. Therefore, the efficiency target of network operator i (ETi) can be presented with the following formula" [6].

$$ETi = 1 - Efent,i$$

3.3 Germany

Efficiency benchmarking is done using DEA and SFA with following variables [6]. Number of connection points across all three considered voltage levels (high, medium, low)

- Circuit of cables (high)
- Circuit of lines (high)
- Circuit of cables (medium)
- Circuit of lines (medium)
- Total network length (low)
- Area supplied (low voltage level)
- Annual peak load (high/medium)
- Annual peak load (medium/low)
- Number of transformer stations across all three considered voltage levels.
- Installed capacity of distributed generation across all three considered levels.

To determine the actual efficiency score (ES), a best off approach is applied with a minimum of 60%.

$$ES = \max(DEA\ I, DEA\ II, SFA\ I, SFA\ II, 0.6)$$

3.4 Norway

The regulatory tasks are ensured by the Norwegian Water Resources and Energy Directorate (NVE). The NVE uses DEA scores to set firm specific efficiency requirements and revenue caps for regional electricity transmission and distribution utilities [6].

Cost norm is calculated based on the relative efficiency scores found by DEA. Norway is the only country where the regulator has systematically examined the effects of environmental factors on the performance of the quality of service and reflected these in the efficiency benchmarking models.

Output variables of the Norwegian DEA model

Variable	*Unit of measurement*
Energy delivered	MWh
Customers (except outages)	No. of customers
Cottage customers	No. of customers
High voltage lines	Kilometres
Network stations (transformers)	No. of stations
Interface	Cost weighted sum of equipment in the interface between the distribution network and the transmission network
Forest	Proportion (0-100) of area with high-growth forest × HV-lines through air (kilometres)
Snow	Average precipitation as snow (mm) × HV-lines through air (kilometres)
Coast/wind	[Average wind speed (m/s) / average distance to coast (meters)] × HV-lines through air (kilometres)

Table 3-2 : Variables of Norwegian DEA Model

3.5 UK

Ofgem, the gas and electricity regulator has used COLS method in distribution price control reviews 2005/06 and 2009/10 [7]. UK consists of 14 distribution network operators. The table 3-3 summarizes the benchmarking methods used by selection of European countries.

Country	Benchmarking Method	Variables	
		Input	Output
Finland	DEA	OPEX	Energy Delivered No. of Customers Network Length Interruption Period
Netherlands	DEA	OPEX CAPEX	Delivered Energy No. of Customers Peak Demand Network Length No. of Transformers
Norway	DEA	Working Hours Network Loss Capital Stock Goods Services	Delivered Energy No. of Customers Network Length
Sweden	DEA	OPEX CAPEX Grid Losses	Delivered Energy No. of Customers Network Length Maximum Power Climate Factor No. of Substations per installed capacity
UK	COLS	OPEX	Delivered Energy No. of Customers Network Length

Table 3-3 : Benchmarking Methods by Selection of European Countries

4 SELECTION OF VARIABLES

4.1 Factors to consider in Selecting Variables

There are number of variables that can be considered when implementing any benchmarking technique as described in section 2. In regulators point of view, following factors has to be considered when selecting variables.

- Quality of the data
- Availability
- Ease of collection.
- Relevance to the business – i.e. electricity distribution business
- International Practices/ Reviews
- Use of statistical indicators (such as correlation)
- Non redundant – to minimize overlapping
- High discriminating power - To limit the analysis to lower number of parameters, since there are only five DLs operating in Sri Lanka.
- Reflecting the scale of operation.
- Cost drivers – variables having major influence on the cost of operation.

Therefore the regulator must take care to keep the number of variables to minimum while those variables are strong cost drivers (i.e. OPEX). Relevant data should be accurate and importantly be practical to collect from the DLs timely.

4.2 Selected Variables

In search of quality, feasible data several reports were analyzed. These include published reports by PUCSL[9,13,23,24] and Licensees[25,26,27,28,29,30,31,32,33,34,35].
Following set of variables found to be in par with factors considered in section 4.1. Further, following variables are used in prominent benchmarking methods by international regulators as described in sections 2.3.1 and 2.4.1.

- Energy Sold (GWh)
- Total number of consumers - This is the number of consumer accounts or the number of consumer connection points

- No. of new connections provided
- No. of employees
- Total distribution lines length (km) – This includes MV and LV network length
- No. of substations
- Authorized operation area (km^2) –This is a constant for each licensee.
- Operational Expenditure (LKR Million)

Note that, in international benchmarking practices, the use of supply/service quality as a variable is rare. Most of the countries reviewed separately run a quality-of-service reward/penalty regime [8 ,pp145]. In Sri Lanka, the supply/service quality is to be determined according to the drafted Electricity Distribution performance regulations, where penalties have been introduced for underperformance [39].

4.3 Justification of Selected Variables

4.3.1 Cost Drivers

Cost is clearly depending on scale of the operation. Accurate data on following scale variables can be timely obtained from DLs,

- Energy distributed – Production of the distribution business
- Number of Consumer Accounts
- Network Length (MV and LV line lengths) – A main cost driver, regarding distance as a main cost driver
- Number of Distribution substations

Since data on above mentioned variables can be timely obtained, regulator can timely perform benchmarking exercise to figure out allowed revenue for each year.

4.3.2 Dispersion of Consumers

Distribution line length per consumer can be taken as indication of how extent the consumer concentration is. It is also an indication of the extent of rural electrification efforts taken by the DLs. For each DL this value is different. For example, DL5 is having a lower value indicating higher concentration of consumers, whereas DL4 is having a larger value as indicated in table 4-1.

Further , the number of consumers per area (km^2) is a another indication of the consumer concentration. The reciprocal, km^2 per consumer indicates the dispersion.

DL	Distribution Line length per Consumer (m)	Area per Consumer (m^2)
DL1	30.8	**21,425**
DL2	23.4	10,614
DL3	28.8	13,085
DL4	31.3	7,940
DL5	8.8	727

Table 4-1 : Dispersion of Consumers in each DL

4.3.3 Correlation

In Sri Lanka there are only five distribution licensees. If too many explanatory variables are applied to a sample of only few observations (i.e. the number of Distribution Licensees), then the results would be left with 100% efficient DLs. Therefore it is necessary to combine several parameters into one single parameter in order to preserve sufficient degrees of freedom. It is important to not to consider highly correlated variables simultaneously, in a benchmarking method.

To assess the correlation of two variables, the linear correlation coefficient can be used. This provides a measure of strength and the direction of a linear relationship between two variables. If variables X and Y have a strong positive linear correlation, then correlation coefficient is close to +1. The correlation coefficient can be written as,

$$\frac{E(XY) - E(X)E(Y)}{\sqrt{E(X^2) - (E(X))^2}\sqrt{E(Y^2) - (E(Y))^2}}. \quad \text{-------------------------}(4.3)$$

where E(X) is the expectation of X.

Therefore correlation coefficients were calculated using past data from year 2006 to 2011 for each DL. The results are given in table 4-2.

Correlation Coefficients	Energy Delivered	No. of Consumer Accounts	No. of new connections	No. of employees	Network Length	LV distribution substations
Energy Delivered	1.0000	**0.9683**	0.8755	**0.9552**	0.7498	0.8245
Number of Consumer Accounts		1.0000	0.8769	0.8635	0.6750	0.7069
No. of new connections			1.0000	0.8635	0.7313	0.6198
No. of employees				1.0000	0.6750	0.6758
Network Length					1.0000	0.7069
LV distribution substations						1.0000

Table 4-2 : Correlation Coefficients

For example, Correlation Coefficient of energy delivered and No of consumer accounts is 0.9683, which is the highest correlation coefficient, while energy delivered and no. of employees is having the second highest. For further verification figures 4-1 and 4-2 were plotted.

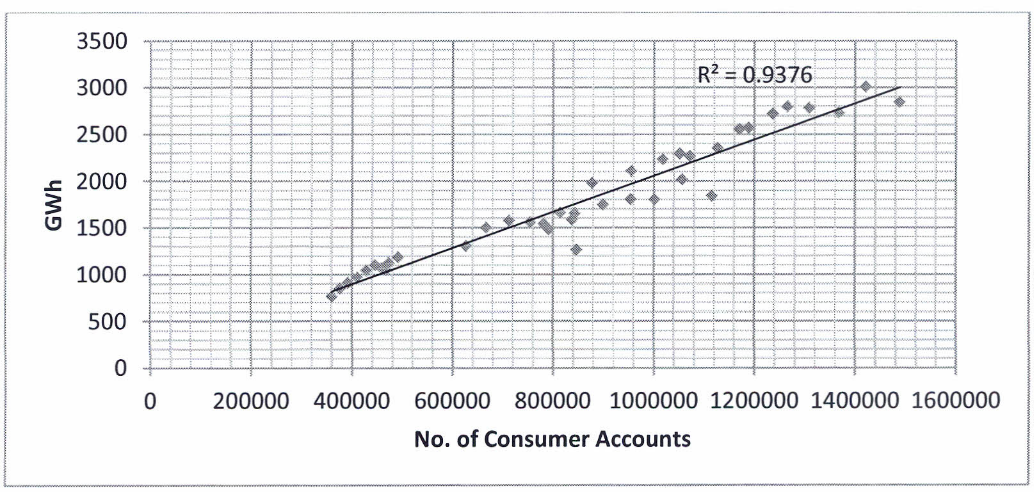

Figure 4-1 : Energy Delivered vs. Number of Consumers

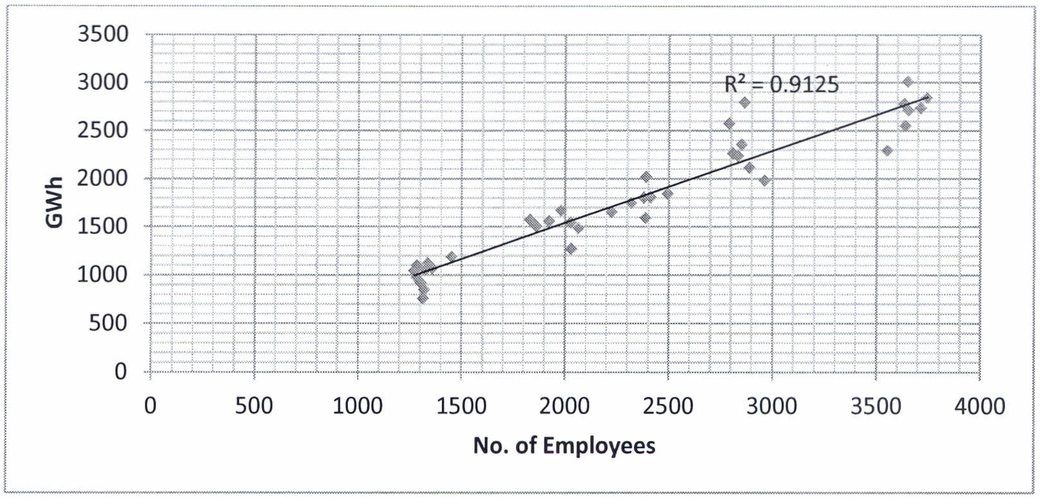

Figure 4-2 : Energy Delivered vs. Number of Employees

The Energy delivered and Number of employees indicated higher correlation (see figure 4-2). It can be concluded that from the selected set of variables, energy delivered and the number of consumers are having the acceptable correlation where when implementing benchmarking techniques like DEA or COLS it is sufficient to account for one variable from energy delivered and number of consumers. Since Energy delivered (output) is highly correlated with no.of Employees (input) are highly correlated it is justifiable taking no. of employees as another input variable.

4.3.4 Input, Output and Environmental Variables

To assess the efficiency on the basis of OPEX as required by revenue control formula, Operational Expenditure (OPEX) taken as the main input variable. Energy delivered can be taken as the main output produced.

Number of new connection provided taken as an output, while number of employees were taken as input variable. Number of employees includes management and operational staff. Demand for new connections depends on the conditions of the authorized area of operation of DLs. This is not under the direct control of the management of the DL. To provide the demanded connection the DL has to input its resources. Table 4-5 depicts the variation between DLs [23]. This reflects the variation in demand for new connections that is varying according to the area of operation.

DLs need to meet this demand. Therefore DLs need to input their resources accordingly.

As given in the table 4-3, DL1 is giving 40 new connections per day (on average) whereas DL5 is only providing 6 new connections per day (on average). Obviously DL1 needs to input more resources than DL5 to cope with the demand for new connections. The demand for connection is out of the control of the DL's management. In some areas, lot of infrastructure developments, resettlements and rural developments are going on due to ending of the war with terrorists. This has caused high demand for new connections. Therefore, when evaluating the overall performance, the number of new service connections provided by respective DLs has to be considered.

Licensee	Average No. of New Connections provided per day (for year 2012)
DL1	40
DL2	31
DL3	33
DL4	14
DL5	6

Table 4-3: Average No. of New Connections Provided by each DL

Network length and substations can be considered as input or output either. One can argue that poles and wires are capital inputs to the service [8].Viewing the network length as an output runs the risk that a network that increases its length of lines is rewarded even if there is no impact on real world delivering of services to the customers [8]. In international regulatory practice network length has been considered as both input and output. Hence both scenarios were taken into consideration.

5 SELECTION OF BENCHMARKING TECHNIQUES AND MODELS

Chapter 2 described prominent benchmarking techniques which are practicing by international regulators. Advantages and disadvantages each techniques were also elaborated.

5.1 Comparison of Benchmarking Methods

The evaluation of prominent benchmarking techniques done in Chapter 2 revealed that each technique have pros and cons relative to each other. Summarization of characteristics of these techniques is given in table 5-1.

For example, it can be seen that DEA is easy to implement on smaller samples compared to SFA which is very difficult to implement with smaller samples.

Characteristic	Method			
	PPI	DEA	COLS	SFA
Easiness to compute and understand (verifiability and transparency)	Very Easy	Easy	Easy	Difficult
Accommodate differences in operating environments	No	Yes	Yes	Yes
Describe overall economic performance of DLs	No	Yes	Yes	Yes
Extension to multiple outputs / inputs	No	Easy	Difficult	Difficult
Inefficient firms are compares with actual firms or linear combinations of those rather than to statistical measure	No	Yes	No	No
Requirement to specify cost function (Strong assumption required)	No	No	Yes	Yes
Requirement of functional relationship with inputs and outputs	No	No	Yes	Yes
Ability to implement in smaller sample	Easy	Easy	Difficult	Very Difficult
Results can influenced by random errors	Yes	Yes		No
Information about statistical significance of the results	No	No	Yes	Yes
Data volume requirement	Low	Low	High	High

Table 5-1: Characteristics of Benchmarking Methods

5.2 Feasible Methods and Models

Results from application of benchmarking method will directly impact the allowed revenue of each DL. If the method itself is complicated and harder to understand then there would be a doubt in the minds of DLs about the efficiency results. From the table 5-1, it can be seen that DEA, COLS, and PPI fulfill the following desirable characteristics.

- Easiness to compute
- Easiness to understand
- Transparency.
- Ability to implement in smaller sample.

However, PPI has to be avoided since it is not a multi-dimensional (cannot extend to multiple inputs and outputs) method where several inputs and outputs are not being taken into consideration at once. SFA is inherently difficult to understand.

If a benchmarking method requires higher number of data points then it will be harder to implement with a smaller sample like five, as in the case where only five DLs in Sri Lanka. DEA can be easily implemented with five DLs, but care has to be taken to verify the results with other methods. A rule of thumb (from international practices)is that for *m* number of inputs and *n* number of outputs, there has to be *n* x *m* number of DLs[10][22]. Otherwise all the DLs would get closer to 100% efficiency and discrimination could be difficult.

In other words, with small sample and high number of input / output variables there is a danger of receiving made-up results for efficiency scores [2]. When more variables are included in the model, the number of DLs on the efficient frontier increases. The selected input / output variables are listed under section 4.2.

Feasibility of COLS has to be decided by practically implementing the COLS method with Cobb-Douglas cost function (refer section 2.4 on cost function) with same set of variables, and also COLS implementation can be used to verify the results from DEA. Implementation is given in the section 6.1.

To verify the results (efficiency scores) at least two different benchmarking methods must be used. Selected methods should have different characteristics so that the regulator can convince the DLs about the efficiency scores. In this case DEA and COLS are feasible to implement considering the characteristics summarized in the table 5.1.

5.3 Availability of data

This is another constraint when selecting a benchmarking technique. Four DLs out of five DLs, the TL and the bulk generation are still operating under one management. Therefore those four DLs are not having separate annual reports where audited data can be extracted. Therefore it is difficult to find reliable past data of OPEX. Hence panel data could not be used where majority does not having reliable OPEX data. This restricted the usage of econometric methods like SFA to benchmark only five DLs. Once PUCSL begins the regulatory accounting on DLs, reliable Opex and Capex data can be easily obtained for strong benchmarking studies.

6 IMPLEMENTATION OF BENCHMARKING TECHNIQUES

6.1 DEA

6.1.1 Mathematical DEA Model

With reference to the facts discussed in section 2.3 , the usual measure of efficiency is,

$$\text{efficiency} = \frac{\text{output}}{\text{input}}$$

With multiple inputs and outputs, a common measure for efficiency is,

$$\text{Efficiency} = \frac{\text{weighted sum of outnuts}}{\text{weighted sum of inputs}}$$

Efficiency of the DL, **P**

$$\textbf{Efficiency of P} = \frac{\mathbf{u1 \times Y1 + u2 \times Y2 + \ldots\ldots\ldots.}}{\mathbf{v1 \times X1 + v2 \times X2 + \ldots\ldots\ldots}}$$

Where,

u1 - weight given to Output 1

v1 – weight given to Input 1

Y1 – Amount of Output 1 from P

X1 – Amount of Input 1 from P

Now each DL allowed to adopt a set of weights which shows it in the most favorable light in comparison to the other DLs. Under these circumstances, efficiency of a target unit **P** can be obtained as a solution to the following problem:

Maximize the efficiency of DL **P**,

Subject to the efficiency of all other DLs being < =1.

The variables of the above problem are the weights and the solution produces the weights most favorable to unit j0 and also produces a measure of efficiency.

$$Maximize\ Efficiency\ of\ \boldsymbol{P}, \qquad \frac{\sum u_i Y_{i_p}}{\sum v_i X_{i_p}},$$

$$Y_{i_p}, X_{i_p} - amount\ of\ output, input\ i\ from\ DL\ \boldsymbol{P}$$

$$Subjected\ to, \qquad \frac{\sum u_i Y_{i_j}}{\sum v_i X_{i_j}} \leq 1\ for\ all\ other\ DL\ \boldsymbol{j}$$

$$u_i, v_i \geq 0$$

The solution to above maximization problem is the maximum efficiency that is attained by DL **P**, with respect to all other DLs considered. For example if you are maximizing the efficiency of DL1 (with respect to DL2, DL3, DL4 and DL5), then those corresponding weights must not exceed other DLs , i.e. DL2, DL3, DL4, DL5 efficiencies beyond 100%.

For example, consider following input / output configuration.

Output 1 : Energy Delivered to customers by DL (say ENERGY)

Output 2 : Network route length maintained by DL (say LENGTH)

Input 1 : Operational Expenditure by DL (say OPEX)

[Note : subscripts denoted the respective DL. That is, $LENGTH_{DL1}$ means network route length maintained by DL1]

Maximize efficiency of DL1

i.e. Maximize :

$$\frac{\mathrm{v1} \times \mathrm{ENERGY_{DL1}} + \mathrm{v2} \times \mathrm{LENGTH_{DL1}}}{\mathrm{u1} \times \mathrm{OPEX_{DL1}}} \text{---------}(6.1)$$

Subjected to:

$$\frac{\mathrm{v1} \times \mathrm{ENERGY_{DL1}} + \mathrm{v2} \times \mathrm{LENGTH_{DL1}}}{\mathrm{u1} \times \mathrm{OPEX_{DL1}}} \leq 1$$

$$\frac{\mathrm{v1} \times \mathrm{ENERGY_{DL2}} + \mathrm{v2} \times \mathrm{LENGTH_{DL2}}}{\mathrm{u1} \times \mathrm{OPEX_{DL2}}} \leq 1$$

$$\frac{\mathrm{v1} \times \mathrm{ENERGY_{DL3}} + \mathrm{v2} \times \mathrm{LENGTH_{DL3}}}{\mathrm{u1} \times \mathrm{OPEX_{DL3}}} \leq 1$$

$$\frac{v1 \times ENERGY_{DL4} + v2 \times LENGTH_{DL4}}{u1 \times OPEX_{DL4}} \leq 1$$

$$\frac{v1 \times ENERGY_{DL5} + v2 \times LENGTH_{DL5}}{u1 \times OPEX_{DL5}} \leq 1$$

$$u1 , v1 , v2 \geq 0$$

It can be seen that above constraints are formulated such that weights v1, v2 and u1 given to outputs and input must not lead to efficiencies of greater than 1 for any DL.

Above non linear model can be converted into a linear model as illustrated in section 2.3.4. That is,

Maximize :

$$v1 \times ENERGY_{DL1} + v2 \times LENGTH_{DL1} \text{ -------------------------- (6.2)}$$

Subjected to :

$$u1 \times OPEX_{DL1} = 1 \text{ -------------------------- (6.3)}$$

$$\left.\begin{aligned}
&v1 \times ENERGY_{DL1} + v2 \times LENGTH_{DL1} - u1 \times OPEX_{DL1} \leq 0\\
&v1 \times ENERGY_{DL2} + v2 \times LENGTH_{DL2} - u1 \times OPEX_{DL2} \leq 0\\
&v1 \times ENERGY_{DL3} + v2 \times LENGTH_{DL3} - u1 \times OPEX_{DL3} \leq 0\\
&v1 \times ENERGY_{DL4} + v2 \times LENGTH_{DL4} - u1 \times OPEX_{DL4} \leq 0\\
&v1 \times ENERGY_{DL5} + v2 \times LENGTH_{DL5} - u1 \times OPEX_{DL5} \leq 0
\end{aligned}\right\} \text{--- (6.4)}$$

$$u1 , v1 , v2 \geq 0 \text{ -------------------------- (6.5)}$$

By solving above linear programming problem, the weights $u1 , v1 , v2$ can be obtained. Then using the equation (6.1) the corresponding maximum efficiency of DL1 with respect to DL2, DL3, DL4 and DL5 can be calculated.

For the same input / output variables (i.e. ENERGY, LENGTH and OPEX) the corresponding weights for maximum efficiency of DL2 relative to DL1, DL3, DL4 and DL4 can be obtained by solving following linear programming problem.

Maximize :

$$v1 \times ENERGY_{DL2} + v2 \times LENGTH_{DL2}$$

Subjected to :

$$u1 \times OPEX_{DL2} = 1$$

$$v1 \times ENERGY_{DL1} + v2 \times LENGTH_{DL1} - u1 \times OPEX_{DL1} \leq 0$$

$$v1 \times ENERGY_{DL2} + v2 \times LENGTH_{DL2} - u1 \times OPEX_{DL2} \leq 0$$

$$v1 \times ENERGY_{DL3} + v2 \times LENGTH_{DL3} - u1 \times OPEX_{DL3} \leq 0$$

$$v1 \times ENERGY_{DL4} + v2 \times LENGTH_{DL4} - u1 \times OPEX_{DL4} \leq 0$$

$$v1 \times ENERGY_{DL5} + v2 \times LENGTH_{DL5} - u1 \times OPEX_{DL5} \leq 0$$

$$u1, v1, v2 \geq 0$$

Therefore by solving linear programming problems (five separate linear programming problems) corresponding to maximizing efficiency of each DL, the relative efficiency of each DL for given input / output variables can be calculated.

6.1.2 Input and Output Variables

Factors to be considered when selecting the input and output variables and justifications for selected variables were discussed in Chapter 4. Accordingly following variables were selected when implementing DEA.

(1) Energy Sales – Amount of energy (GWh) distributed to the consumers by DL during the year concerned. This was taken as the main output variable, since the energy sales is the main production of the electricity distribution business.

(2) New Connection given – That is the number of new service connections provided by the Dl during the year concerned. This is an output of the distribution business.

(3) No. of Employees – Total number of employees employed by the DL. This is taken as an input to the distribution business.

(4) OPEX – The operational expenditure is taken as the main input to the distribution business.

(5) Total Network Length – This is the total route length of the electrical distribution lines. In one hand this can be taken as an output, because this amount of line length has to be maintained by the DL. On the other hand this can be taken as input, because this is a capital input to the distribution business.

(6) No. of Substations – In one view this is taken as an output, as it consumes input resources by DL to maintain. In another view this can be taken as an input as it is a capital input to the distribution business.

(7) Area per Consumer – As described in section 4.3.2 this variable is an indication of the extent of dispersion of the consumers. Generally if the dispersion is greater, then the input resource requirement would be greater per consumer. Hence this is taken as an output to the DEA model.

(8) Network Line Length per Consumer – This is the electricity distribution route length per consumer. As described in section 4.3.2, lower value for this indicates higher concentration of consumers. Further, this is an indication of the extent of rural electrification. To implement this factor in DEA model, it is taken as an output to the DEA model.

Note that, if '*Total Network Length*' is to be taken as an input, then '*No. of Substations*' has to be taken as input also. On the other hand if *Network Length* is to be taken as an output, then '*No. of Substations*' has to be taken as output also.

6.1.3 Implementation of Different Models

For each models given in tables 6-1, 6-3, 6-5, 6-7, 6-9 and 6-11, the efficiency scores were obtained. Note that every possible input output configurations (models) were taken into consideration when obtaining results. For example, as given in table 6-11 for '3- variable models' there is 8 models. As described in section 6.1.2 Energy Sales and OPEX present in each model since those are the main output and input variables respectively. If a variable to a model is taken as output then it is indicated as '**O**' while inputs represented as '**I**'.

Implementation in MS Excel is illustrated below. Here we have considered the 3-variable model. In figure 6-1, the initial values before solving the maximization problem is given. Figure 6-2 represents the implementation of constraints in the model.

	A	B	C	D	E	F	G	H
1	Distribution Licensee	Energy Delivered (GWh) as an Output	Network Length (km) as an Output	OPEX (LKR Million) as an Input	Weighted Output	Weighted Input	Efficiency	Weighted Output - Weighted Input
2	DL1	2,797	38,967	3664.6	41764.35	3664.60	11.40	38099.75
3	DL2	2,844	34,856	4801.5	37699.69	4801.50	7.85	32898.19
4	DL3	1,846	32,196	2624.2	34041.93	2624.20	12.97	31417.73
5	DL4	1,269	26,497	2135.9	27766.45	2135.90	13.00	25630.55
6	DL5	1,184	4,340	1531.5	5524.07	1531.50	3.61	3992.57
7								
8	Weights	V1	V2	U1				
9		1.00000	1.00000	1.00000				

Figure 6-1 : Implementation of DEA 3-Variables model in MS Excel (Initial values)

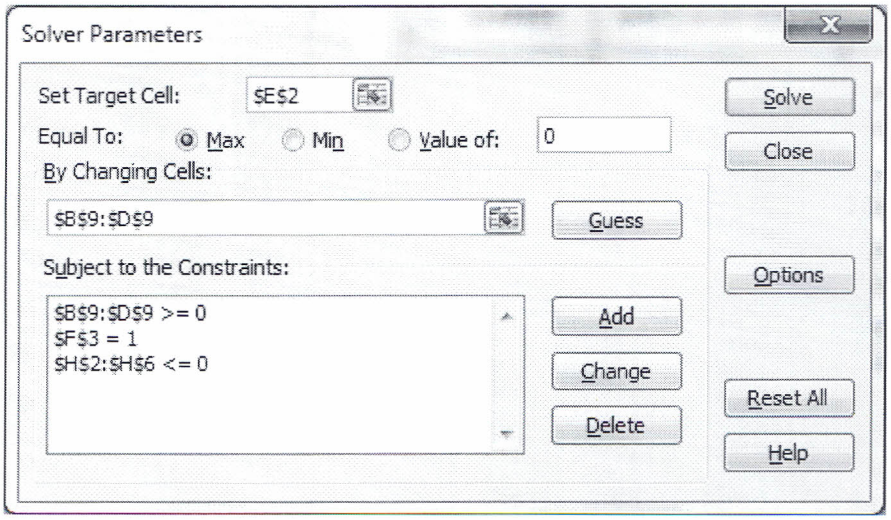

Figure 6-2 : Implementation of Constraints in MS Excel to Maximize Efficiency of DL1

In figure 6-2 the target cell E2 represents the weighted output of DL1 that is to be maximized, that is, the condition described in equation (6.2) in section 6.1.1.

$$v1 \times ENERGY_{DL1} + v2 \times LENGTH_{DL1}$$

This is done by changing the cells B9, C9 and D9 that is the corresponding weights of Energy Delivered, Network Length and OPEX. Note that in the excel sheet the cells B9, C9 and D9 are rounded up to five decimal places.

The constraint **B9:D9 >= 0** represents the weights described in equation (6.5) in section 6.1.1, that is.

$$v1\,, v2, u1 \;\geq 0$$

The constraint **F3 = 1** represents the condition described in equation (6.3) in section 6.1.1, that is,

$$u1 \times OPEX_{DL1} \;= 1$$

The constraint **H2:H6 <=0** represents the conditions described in equations (6.4) in section 6.1.1, that is,

$$v1 \times ENERGY_{DL1} + v2 \times LENGTH_{DL1} - u1 \times OPEX_{DL1} \;\leq 0$$

$$v1 \times ENERGY_{DL2} + v2 \times LENGTH_{DL2} - u1 \times OPEX_{DL2} \leq 0$$

$$v1 \times ENERGY_{DL3} + v2 \times LENGTH_{DL3} - u1 \times OPEX_{DL3} \leq 0$$

$$v1 \times ENERGY_{DL4} + v2 \times LENGTH_{DL4} - u1 \times OPEX_{DL4} \leq 0$$

$$v1 \times ENERGY_{DL5} + v2 \times LENGTH_{DL5} - u1 \times OPEX_{DL5} \leq 0$$

	A	B	C	D	E	F	G	H
1	Distribution Licensee	Energy Delivered (GWh) as an Output	Network Length (km) as an Output	OPEX (LKR Million) as an Input	Weighted Output	Weighted Input	Efficiency	Weighted Output - Weighted Input
2	DL1	2,797	38,967	3664.6	1.00	1.00	1.00	0.00
3	DL2	2,844	34,856	4801.5	1.01	1.31	0.77	-0.30
4	DL3	1,846	32,196	2624.2	0.66	0.72	0.93	-0.05
5	DL4	1,269	26,497	2135.9	0.46	0.58	0.79	-0.13
6	DL5	1,184	4,340	1531.5	0.42	0.42	1.00	0.00
7								
8		V1	V2	U1				
9	Weight	0.00035	0.00000	0.00027				

Figure 6-3 : Results for Maximizing the Efficiency of DL1

In the same manner figures 6-4 and 6-5 represent the corresponding constraints of the maximization problem relevant to DL2 and results after solving the problem respectively.

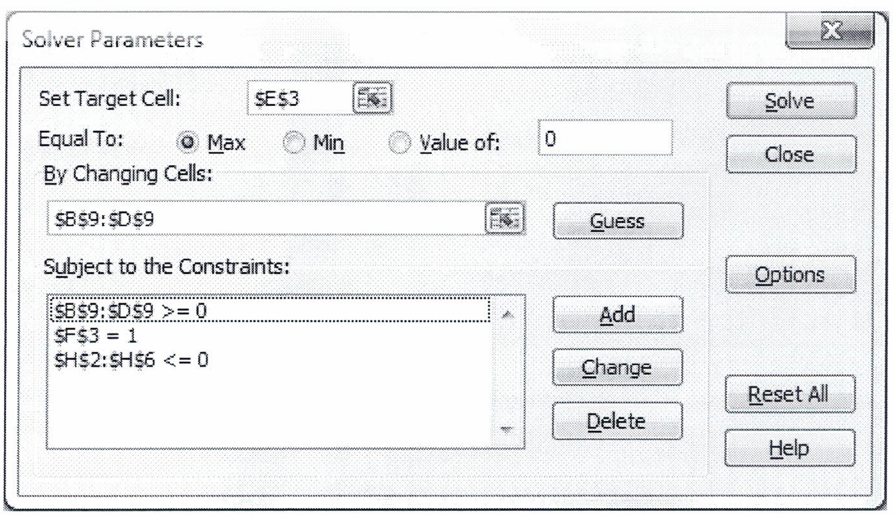

Figure 6-4 : Implementation of Constraints in MS Excel to Maximize Efficiency of DL2

	A	B	C	D	E	F	G	H
1	Distribution Licensee	Energy Delivered (GWh) as an Output	Network Length (km) as an Output	OPEX (LKR Million) as an Input	Weighted Output	Weighted Input	Efficiency	Weighted Output - Weighted Input
2	DL1	2,797	38,967	3664.6	0.76	0.76	1.00	0.00
3	DL2	2,844	34,856	4801.5	0.77	1.00	0.77	-0.23
4	DL3	1,846	32,196	2624.2	0.51	0.55	0.93	-0.04
5	DL4	1,269	26,497	2135.9	0.35	0.44	0.79	-0.09
6	DL5	1,184	4,340	1531.5	0.32	0.32	1.00	0.00
7								
8		V1	V2	U1				
9	Weight	0.00027	0.00000	0.00021				

Figure 6-5 : Results for Maximizing the Efficiency of DL2

In figure 6-5, it can be observed that the maximum efficiency that DL2 has attained is 77%, but all other DLs have attained efficiency of more than DL2 even with the maximum supportive weights to the DL2 itself.

Figures 6-6 and 6-7 represent the corresponding constraints of the maximization problem relevant to **DL3** and results after solving the problem respectively.

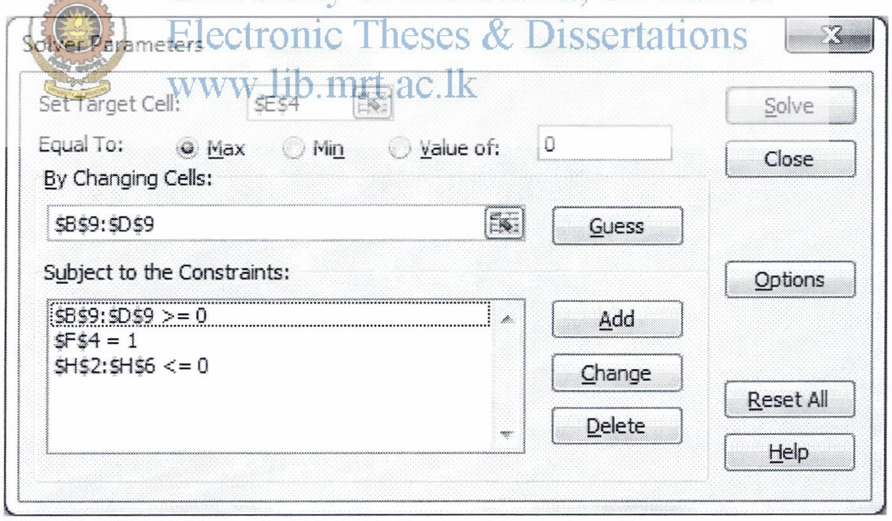

Figure 6-6 : Implementation of Constraints in MS Excel to Maximize Efficiency of DL3

	A	B	C	D	E	F	G	H
1	Distribution Licensee	Energy Delivered (GWh) as an Output	Network Length (km) as an Output	OPEX (LKR Million) as an Input	Weighted Output	Weighted Input	Efficiency	Weighted Output - Weighted Input
2	DL1	2,797	38,967	3664.6	1.27	1.40	0.91	-0.13
3	DL2	2,844	34,856	4801.5	1.17	1.83	0.64	-0.66
4	DL3	1,846	32,196	2624.2	1.00	1.00	1.00	0.00
5	DL4	1,269	26,497	2135.9	0.80	0.81	0.98	-0.02
6	DL5	1,184	4,340	1531.5	0.23	0.58	0.39	-0.36
7								
8		V1	V2	U1				
9	Weight	0.00010	0.00003	0.00038				

Figure 6-7 : Results for Maximizing the Efficiency of DL3

In figure 6-7 it can be observed that efficiency score of DL3 attained 100%. Figures 6-8 and 6-9 represent the corresponding constraints of the maximization problem relevant to **DL4** and results after solving the problem respectively.

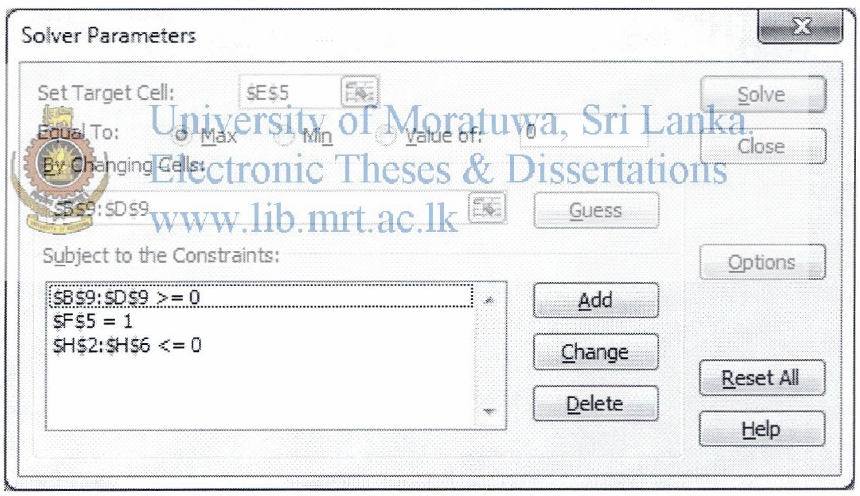

Figure 6-8 : Implementation of Constraints in MS Excel to Maximize Efficiency of DL4

	A	B	C	D	E	F	G	H
1	Distribution Licensee	Energy Delivered (GWh) as an Output	Network Length (km) as an Output	OPEX (LKR Million) as an Input	Weighted Output	Weighted Input	Efficiency	Weighted Output - Weighted Input
2	DL1	2,797	38,967	3664.6	1.51	1.72	0.88	-0.20
3	DL2	2,844	34,856	4801.5	1.37	2.25	0.61	-0.88
4	DL3	1,846	32,196	2624.2	1.23	1.23	1.00	0.00
5	DL4	1,269	26,497	2135.9	1.00	1.00	1.00	0.00
6	DL5	1,184	4,340	1531.5	0.21	0.72	0.29	-0.51
7								
8		V1	V2	U1				
9	Weight	0.00004	0.00004	0.00047				

Figure 6-9 : Results for Maximizing the Efficiency of DL4

Figures 6-10 and 6-11 represent the corresponding constraints of the maximization problem relevant to **DL5** and results after solving the problem respectively.

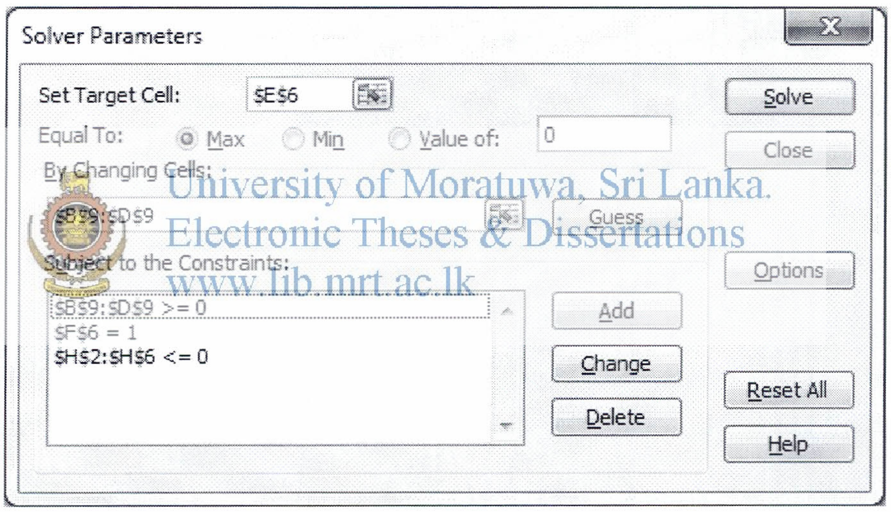

Figure 6-10 : Implementation of Constraints in MS Excel to Maximize Efficiency of DL5

	A	B	C	D	E	F	G	H
1	Distribution Licensee	Energy Delivered (GWh) as an Output	Network Length (km) as an Output	OPEX (LKR Million) as an Input	Weighted Output	Weighted Input	Efficiency	Weighted Output - Weighted Input
2	DL1	2,797	38,967	3664.6	2.36	2.39	0.99	-0.03
3	DL2	2,844	34,856	4801.5	2.40	3.14	0.77	-0.73
4	DL3	1,846	32,196	2624.2	1.56	1.71	0.91	-0.15
5	DL4	1,269	26,497	2135.9	1.07	1.39	0.77	-0.32
6	DL5	1,184	4,340	1531.5	1.00	1.00	1.00	0.00
7								
8		V1	V2	U1				
9	Weight	0.00084	0.00000	0.00065				

Figure 6-11 : Results for Maximizing the Efficiency of DL5

By solving the five maximization problems with respect to DL1, DL2, DL3, DL4 and DL5 the resulting efficiency scores corresponding to the 3-variable model (i.e. model-4 in table 6-11) has obtained. Here Maximum efficiency of each DL is taken as the result. Results are as follows,

- ✓ DL1 with 100% efficiency
- ✓ DL2 with 77% efficiency
- ✓ DL3 with 100% efficiency
- ✓ DL4 with 100% efficiency
- ✓ DL5 with 100% efficiency

The same result is given in the model-4 under the table 6-11.

6.1.3.1 Models with Eight Variables

Here all eight variables discussed in section 6.2.1 were taken into consideration. Hence this has considered total influence from all 8 variables. Note that there are two combinations since '*Total Network Length*' and '*No. of Substations*' can also be considered as inputs to the DEA model.

Model	Energy Sales	New Connections given	Area per Consumer	Network Line Length per Consumer	Total Network Length	No. of Substations	No of Employees	OPEX	DL1	DL2	DL3	DL4	DL5
1	O	O	O	O	O	O	I	I	100	79.3	100	100	100
2	O	O	O	O	I	I	I	I	100	100	100	100	100

Table 6-1 : DEA Efficiency Scores of 8 Input/output Variables Models

	DL1	DL2	DL3	DL4	DL5
DEA Efficiencies of 8-Variables Models					
Maximum	100.0	100.0	100.0	100.0	100.0
Minimum	100.0	79.3	100.0	100.0	100.0
Average	100.0	89.7	100.0	100.0	100.0

Table 6-2: Maximum, Minimum and Average Efficiency Scores of 8 Variables Models

From the results depicted in table 6-1, it can be seen that with respect to the Model 1, DL2 indicates an efficiency score of 79.3% while all other DLs are 100% efficient. With respect to the Model 2 all DLs attained 100% efficiency. In average the efficiency of DL2 is 89.7% as given in table 6-2.

6.1.3.2 Models with Seven Variables

Model	Energy Sales	New Connections given	Area per Consumer	Network Line Length per Consumer	Total Network Length	No. of Substations	No of Employees	OPEX	DL1	DL2	DL3	DL4	DL5
1	O	O	O	O	O	O		I	100	100	100	100	100
2	O	O	O	O	O		I	I	100	77.8	100	100	100
3	O	O	O	O		O	I	I	100	79.3	100	100	100
4	O	O	O		O	O	I	I	100	79.3	100	100	100
5	O	O		O	O	O	I	I	100	79.3	100	100	100
6	O		O	O	O	O	I	I	100	79.3	100	100	100
7	O	O	O	O	I		I	I	100	86.4	100	100	100
8	O	O	O	O		I	I	I	100	97.5	100	100	100
9	O	O	O	O	I	I		I	100	100	100	100	100
10	O		O	O	I	I	I	I	100	100	100	100	100
11	O	O		O	I	I	I	I	100	100	100	100	100
12	O	O	O		I	I	I	I	100	100	100	78.4	100

Table 6-3 : DEA Efficiency Scores of 7 Input/output Variables Models

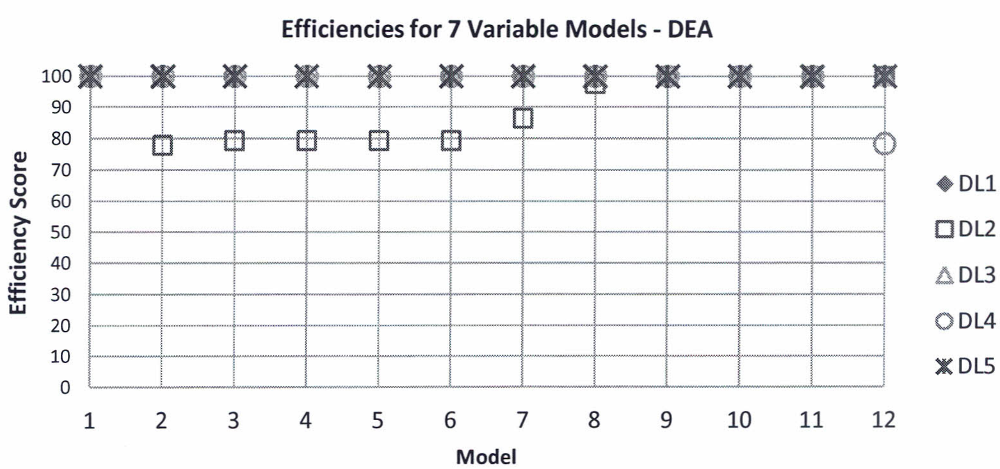

Figure 6-12 : Efficiencies for 7-Variables Models

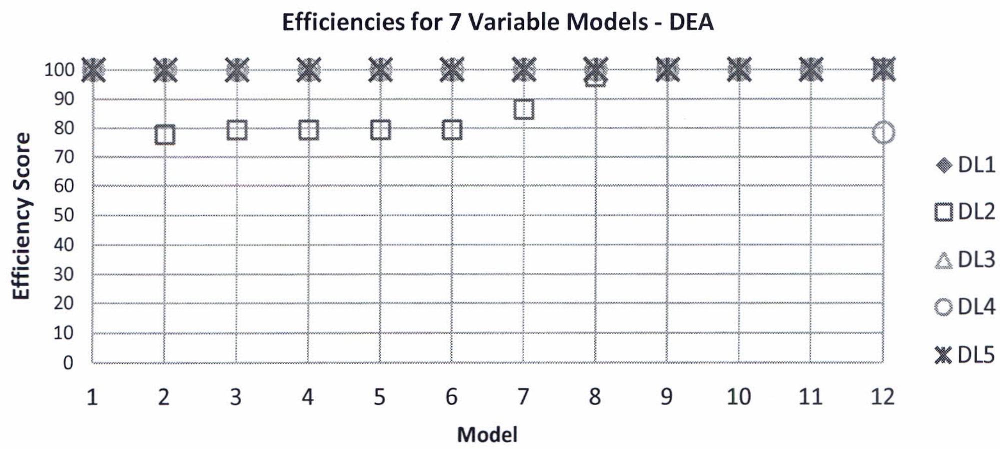

Figure 6-13 : Efficiencies for 7-Variables Models

DEA Efficiencies of 7-Variables Models					
	DL1	**DL2**	**DL3**	**DL4**	**DL5**
Maximum	100.0	100.0	100.0	100.0	100.0
Minimum	100.0	77.8	100.0	78.4	100.0
Average	100.0	89.9	100.0	98.2	100.0

Table 6-4 : Maximum, Minimum and Average Efficiency Scores of 7 Variables Models

From table 6-3 and figure 6-12 it can be seen that in five instances out of 12 models, the efficiency score of DL2 is less than 80%. DL4 has got efficiency score of less than 100% at one instant only. DL1, DL3 and DL5 attained 100% in every model.

6.1.3.3 Models with Six Variables

Model	Energy Sales	New Connections given	Area per Consumer	Network Line Length per Consumer	Total Network Length	No. of Substations	No of Employees	OPEX	DL1	DL2	DL3	DL4	DL5
1	O			O	O	O	I	I	100	79.3	100	100	100
2	O		O		O	O	I	I	100	79.3	100	100	100
3	O		O	O		O	I	I	100	79.3	100	100	100
4	O		O	O	O		I	I	100	77.8	100	100	100
5	O		O	O	O	O		I	100	77.4	100	100	100
6	O	O			O	O	I	I	100	79.3	100	100	100
7	O	O		O		O	I	I	100	79.3	100	100	100
8	O	O		O	O		I	I	100	77.8	100	100	100
9	O	O		O	O	O		I	100	77.4	100	100	100
10	O	O	O			O	I	I	100	78	100	100	100
11	O	O	O		O		I	I	100	77.8	100	100	100
12	O	O	O		O	O		I	100	77.4	100	100	100
13	O	O	O	O			I	I	100	77.8	100	100	100
14	O	O	O	O		O		I	100	77.3	100	100	100
15	O	O	O	O	O			I	100	77.4	100	100	100
16	O	O	O	O	I			I	100	83	100	100	100
17	O	O	O		I		I	I	100	86.4	100	77.7	100
18	O	O		O	I		I	I	100	86.4	100	100	100
19	O		O	O	I		I	I	100	83.4	100	100	100
20	O	O	O	O		I		I	100	97.5	100	100	100
21	O	O	O			I	I	I	100	97.5	100	78.4	100
22	O	O		O		I	I	I	100	97.5	100	100	100
23	O		O	O		I	I	I	100	97.5	100	100	100
24	O			O	I	I	I	I	100	100	100	100	100
25	O		O		I	I	I	I	100	100	92.1	78.4	100
26	O		O	O	I	I		I	100	100	100	100	100
27	O	O			I	I	I	I	100	100	100	78.4	100
28	O	O		O	I	I		I	100	100	100	100	100
29	O	O	O		I	I		I	100	100	100	78.4	100

Table 6-5 : DEA Efficiency Scores of 6 Input/output Variables Models

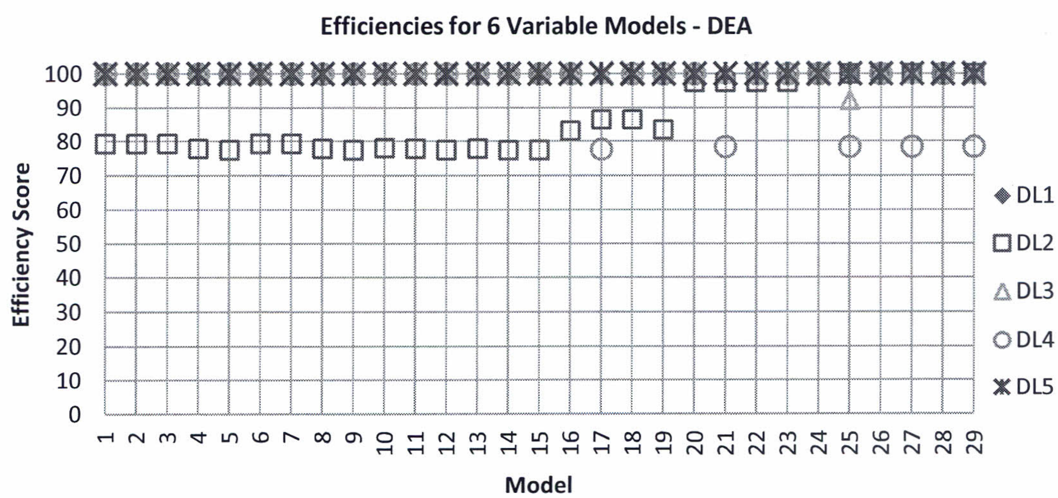

Figure 6-14 : Efficiencies for 6-Variables Models

DEA Efficiencies of 6-Variables Models					
	DL1	DL2	DL3	DL4	DL5
Maximum	100.0	100.0	100.0	100.0	100.0
Minimum	100.0	77.3	92.1	77.7	100.0
Average	100.0	86.3	99.7	96.3	100.0

Table 6-6 : Maximum, Minimum and Average Efficiency Scores of 6 Variables Models

From table 6-5 it can be seen that in 15 models out of 29, the efficiency of DL2 is less than 80%, where all other DLs have attained 100% in those 15 models. The average efficiency of DL2 is 86.3%.

6.1.3.4 Models with Five Variables

Model	Energy Sales	New Connections given	Area per Consumer	Network Line Length per Consumer	Total Network Length	No. of Substations	No of Employees	OPEX	DL1	DL2	DL3	DL4	DL5
1	O	O	O	O				I	100	77.3	100	100	100
2	O		O	O	O			I	100	77.4	100	100	100
3	O	O		O	O			I	100	77.4	100	100	100
4	O	O	O		O			I	100	77.4	100	100	100
5	O			O	O	O		I	100	77.4	100	100	100
6	O	O			O	O		I	100	77.4	100	100	100
7	O	O	O			O		I	100	77.3	100	90.2	100
8	O				O	O	I	I	100	79.3	100	100	100
9	O	O				O	I	I	100	79.3	100	85.2	100
10	O	O	O				I	I	100	77.8	100	77.7	100
11	O			O	O		I	I	100	77.8	100	100	100
12	O			O		O	I	I	100	79.3	100	100	100
13	O		O	O			I	I	100	77.8	100	100	100
14	O		O			O	I	I	100	79.3	100	90.2	100
15	O	O		O		O		I	100	77.3	100	100	100
16	O	O			O		I	I	100	77.8	100	100	100
17	O	O		O			I	I	100	77.8	100	100	100
18	O		O	O		O		I	100	77.0	100	100	100
19	O		O		O	O		I	100	77.4	100	100	100
20	O		O		O		I	I	100	77.8	100	100	100
21	O		O	O	I			I	100	77.0	100	100	100
22	O	O		O	I			I	100	83.0	100	100	100
23	O	O	O		I			I	100	83.0	100	77.7	100
24	O			O	I		I	I	100	83.4	100	100	100
25	O	O			I		I	I	100	86.4	100	77.7	100
26	O		O		I		I	I	100	83.4	92.1	77.7	100
27	O	O	O			I		I	100	97.5	100	78.4	100
28	O	O				I	I	I	100	97.5	100	78.4	100
29	O			O		I	I	I	100	97.5	100	100	100
30	O		O			I	I	I	100	97.5	92.1	78.4	100
31	O	O		O		I		I	100	97.5	100	100	100
32	O		O	O		I		I	100	97.5	100	100	100
33	O			O	I	I		I	100	100	100	100	100
34	O	O			I	I		I	100	100	100	78.4	100
35	O				I	I	I	I	100	100	91.9	78.4	100
36	O		O		I	I		I	100	100	92.4	78.4	100

Table 6-7: DEA Efficiency Scores of 5 Input/output Variables Models

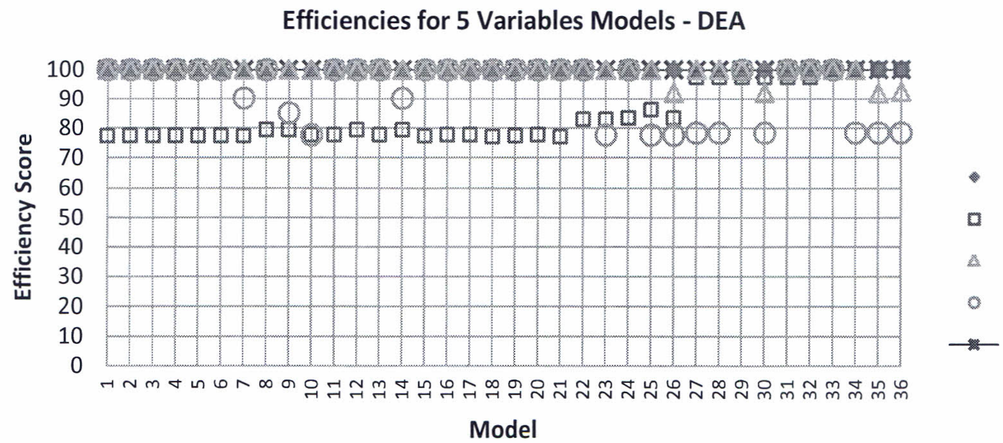

Figure 6-15 : Efficiencies for 5 - Variables Models

DEA Efficiencies of 5-Variables Models					
	DL1	DL2	DL3	DL4	DL5
Maximum	100.0	100.0	100.0	100.0	100.0
Minimum	100.0	77.0	91.9	77.7	100.0
Average	100.0	84.4	99.1	93.0	100.0

Table 6-8 : Maximum, Minimum and Average Efficiency Scores of 5 Variables Models

According to table 6-7, the efficiency of DL2 is less than 80% in 21 models out of 36 models, with respect to the models with five variables where DL1, DL3 and DL5 have attained 100% efficiency score in those 21 models. In 10 models out of all 36 models, the DL4 has ended up with efficiency scores less than 80% where DL1, DL3 and DL5 have attained 100%. Table 6-8 depicts the average efficiency scores of 5 variables models where DL2 ended up with 84.4% average efficiency.

6.1.3.5 Models with Four Variables

Model	Energy Sales	New Connections given	Area per Consumer	Network Line Length per Consumer	Total Network Length	No. of Substations	No of Employees	OPEX	DL1	DL2	DL3	DL4	DL5
1	O	O	O					I	100	77.3	98.1	77.7	100
2	O	O		O				I	100	77.3	100	100	100
3	O	O			O			I	100	77.4	100	100	100
4	O	O				O		I	100	77.3	98.1	85.2	100
5	O	O					I	I	100	77.8	100	77.7	100
6	O		O	O				I	100	77	100	100	100
7	O		O		O			I	100	77.4	100	100	100
8	O		O			O		I	100	77	100	90.2	100
9	O		O				I	I	100	77.8	92.1	77.7	100
10	O			O	O			I	100	77.4	100	100	100
11	O			O		O		I	100	76.8	100	100	100
12	O			O			I	I	100	77.8	100	100	100
13	O				O	O		I	100	77.4	100	100	100
14	O				O		I	I	100	77.8	100	100	100
15	O					O	I	I	100	79.3	91	77.3	100
16	O	O			I			I	100	83	100	77.7	100
17	O	O				I		I	100	97.5	100	78.4	100
18	O		O		I			I	100	77	92.1	77.7	100
19	O		O			I		I	100	97.5	92.1	78.4	100
20	O			O	I			I	100	76.8	100	100	100
21	O			O		I		I	100	97.5	100	100	100
22	O				I	I		I	100	100	91.9	78.4	100
23	O				I		I	I	100	83.4	91	76.9	100
24	O					I	I	I	100	97.5	91.9	78.4	100

Table 6-9: DEA Efficiency Scores of 4 Input/output Variables Models

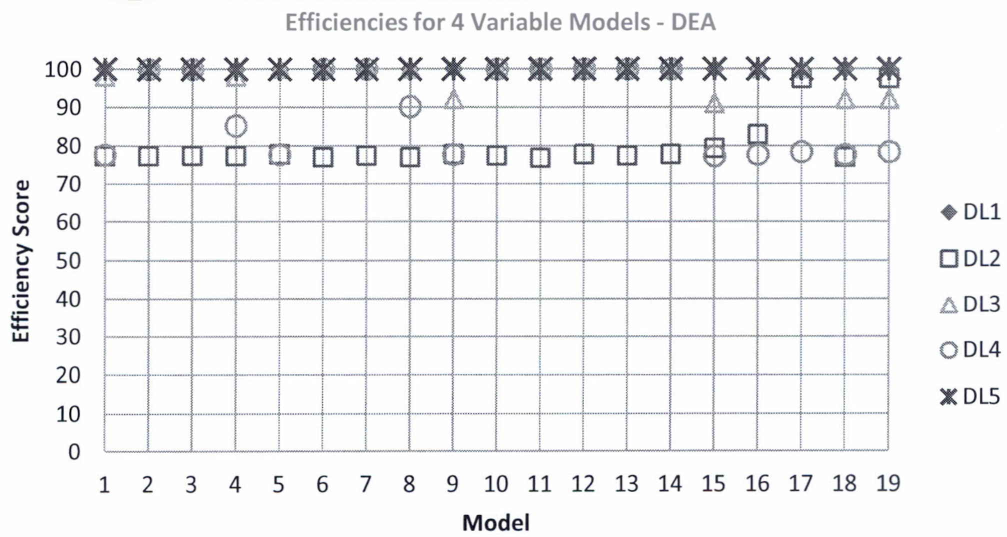

Figure 6-16 : Efficiencies for 4 – Variables Models

DEA Efficiencies of 4-Variables Models					
	DL1	DL2	DL3	DL4	DL5
Maximum	100.0	100.0	100.0	100.0	100.0
Minimum	100.0	76.8	91.0	76.9	100.0
Average	100.0	82.2	97.4	88.8	100.0

Table 6-10 : Maximum, Minimum and Average Efficiency Scores of 4 Variables Models

6.1.3.6 Models with Three Variables

Model	Energy Sales	New Connections given	Area per Consumer	Network Line Length per Consumer	Total Network Length	No. of Substations	No of Employees	OPEX	DL1	DL2	DL3	DL4	DL5
1	O	O						I	100	77.3	100	77.7	100
2	O		O					I	100	77	92.1	77.7	100
3	O			O				I	100	76.8	100	100	100
4	O				O			I	100	77.4	100	100	100
5	O					O		I	98.8	76.6	91	77.3	100
6	O				I			I	98.8	76.6	91	76.9	100
7	O					I		I	100	77.5	91.5	76.9	100
8	O						I	I	100	77.8	91	76.9	100

Table 6-11 : DEA Efficiency Scores of 3 Input/output Variables Models

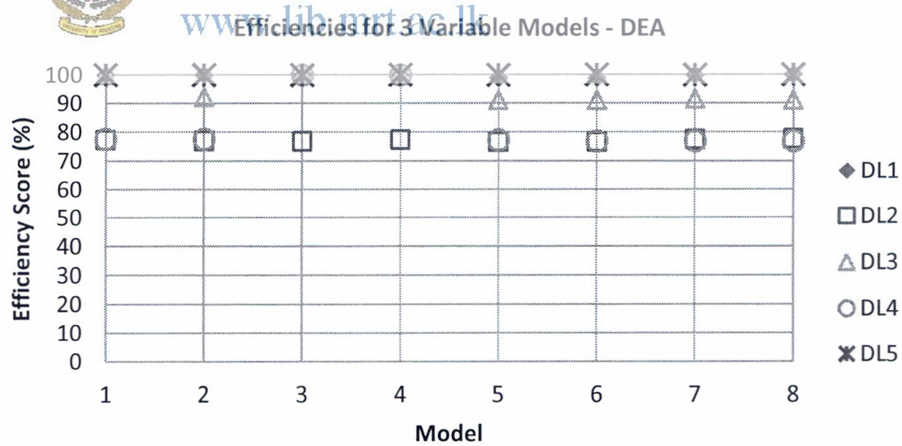

Figure 6-17 : Efficiencies for 3-Variables Models

DEA Efficiencies of 3-Variables Models					
	DL1	**DL2**	**DL3**	**DL4**	**DL5**
Maximum	100.0	77.8	100.0	100.0	100.0
Minimum	98.8	76.6	91.0	76.9	100.0
Average	99.7	77.1	94.6	82.9	100.0

Table 6-12 : Maximum, Minimum and Average Efficiency Scores of 3 Variables Models

6.1.3.7 Conclusion on Results from DEA

According to table 6-13 and figure 6-17 it can be seen that the discrimination between each DL's efficiency scores decreases with the number of variables considered.

DEA Average Efficiencies of Different Models					
Model	**DL1**	**DL2**	**DL3**	**DL4**	**DL5**
8-Variables	100.0	89.7	100.0	100.0	100.0
7-Variables	100.0	89.9	100.0	98.2	100.0
6-Variables	100.0	86.3	99.7	96.3	100.0
5-Variables	100.0	84.4	99.1	93.0	100.0
4-Variables	100.0	82.2	97.4	88.8	100.0
3-Variables	99.7	77.1	94.6	82.9	100.0

Table 6-13 : Average Efficiency Scores by Model

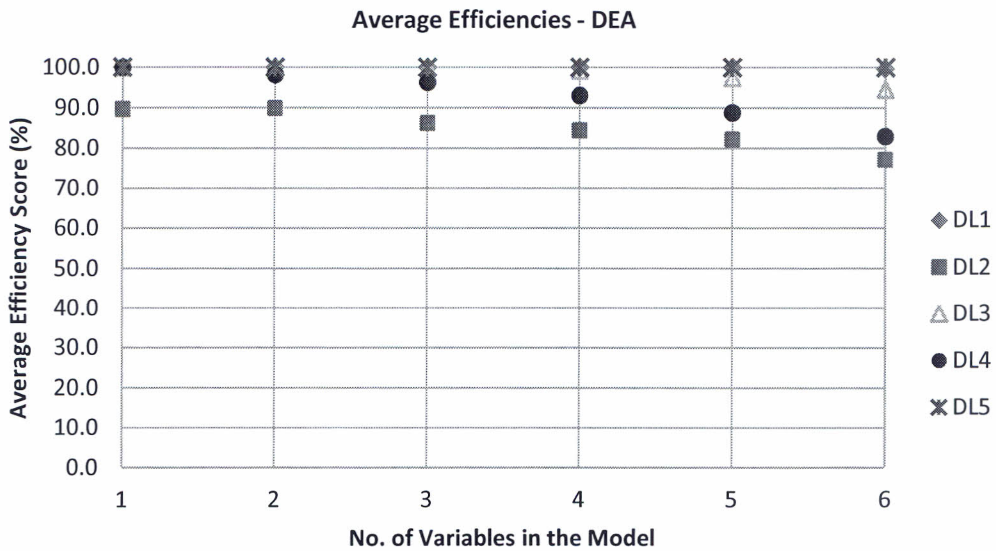

Figure 6-18 : Average Efficiencies of DEA models

It is observed that DL2 is the lowest performer while DL5, DL1, DL3 and DL4 are ranked highest to lower according to the average efficiency scores. Even when considering 8 variables models as given in section 6.1.3.1, it can be observed about 10% gap of efficiency with respect to all other DLs. Therefore it possible to take the 8 variables models as the base and take these efficiency values to calculate the X factor. Note that the implementation is done using data corresponding to year 2011. The DL2 have high degree of freedom to improve its efficiency score since the model contains 8 variables.

If all DLs get closer to 100%, when implementing the DEA method with 8-variables models with current values for respective variables (i.e. According to the year of implementation, thus values for the variables may get changed.), then the reduced variables models (starting from 7-variables to 3 variables) can be considered. This would allow higher discrimination between efficiency scores as it is observed in figure 6-17.

6.2 COLS

Implementation of COLS method has done according to the description given in section 2.4. Therefore it is required to select suitable variables for 'benchmark cost function'. Variables should represent,

- ✓ Output produced by the business
- ✓ Input prices paid
- ✓ Environmental conditions that effect the production cost

In Sri Lanka, OPEX of DLs mainly consists of expenses for human resource. It is about 50 % to 60% of their respective OPEX. Therefore cost per employee must be used as the main input price of the cost function.

Energy Sold (GWh) reflect the main output produced by the distribution business. Therefore it is included in the cost function.

Five DLs have their designated area of operation. Accordingly the customer densities they have to be dealt with differ to each other. The table 6-14 illustrates the differences in customer densities as at year 2011.

DL	Customer Density (Consumer Accounts per km^2)
1	47
2	94
3	76
4	126
5	1375

Table 6-14 : Differences in Customer Densities

Therefore the analysis must account for these differences in their business which is out of their (DLs) control. For this reason the customer density has to be included in the cost function. This variable is to capture the heterogeneity dimension of the distribution business [19]. Further, the consumer density also can be accommodated in the model by using the consumers per unit network length, i.e. number of consumers per kilometer of line length. The table 6-15 indicates the extent of heterogeneity. DL5 has a higher number since its area of operation is highly populated.

Licensee	Consumers per Unit Length of Network (Cons./km)
DL1	32.48
DL2	42.71
DL3	34.66
DL4	31.97
DL5	113.14

Table 6-15 : Consumers per Unit Length of Network

Note that to estimate the coefficients of the cost function we have only five data points. Therefore only one variable from each category, i.e. output, input prices and environmental conditions were used.

6.2.1 COLS using Four Variables

The selected cost function is,

$$\ln(OPEX) = a + b\ln(Energy\ Output) + c\ ln\ (Cost\ per\ employee) + d\ln(Cust.Density) \quad --- (6.2)$$

As described, the customer density can be Consumers per area or consumers per network length. By performing linear regression analysis coefficients of the cost function, i.e. ***a, b, c*** and ***d*** were determined. The implementation was done by using the Regression analysis provided in MS Excel. For example let's consider the following cost function given in equation 6.2.

In table 6-16 the actual values to be assigned to each variable are given. The relevant logarithmic values are given in table 6-17. The regression analysis has carried out using the logarithmic value.

	Energy Sales	Consumer Density-Area	OPEX	Cost per Employee
Unit	GWh	Cons/km^2	LKR Mil.	LKR'000
DL1	2,797	46.68	3,665	843
DL2	2,844	94.22	4,802	819
DL3	1,846	76.43	2,624	766
DL4	1,269	125.94	2,136	789
DL5	1,184	1375.47	1,532	418

Table 6-16 : Actual values of Input / Output Variables

Licensee	Ln(Energy Sales)	Ln(Consumer Density-Area)	Ln(OPEX)	Ln(Cost per Employee)
DL1	7.9364	3.8432	8.2065	6.7373
DL2	7.9529	4.5456	8.4767	6.7077
DL3	7.5207	4.3363	7.8725	6.6413
DL4	7.1463	4.8358	7.6666	6.6704
DL5	7.0765	7.2265	7.3340	6.0343

Table 6-17: Logarithmic Values

Coefficients a, b, c and d in equation (6.2) obtained by regression analysis are given in table 6-18.

Coefficients	
a (Intercept)	-13.09194597
b (Coefficient of Energy Sold)	1.009356796
c (Coefficient corresponds to Cost per Employee)	1.773929147
d (Coefficient corresponds to Customer Density)	0.357535018

Table 6-18 : Coefficients Estimated by Regression Analysis

The residuals given in table 6-19 are the corresponding difference between actual values of ln(OPEX) and predicted values of ln(OPEX) for each DL.

Observation	*Predicted ln(OPEX)*	*Residuals*
DL1	8.244317783	-0.037843
DL2	8.459445417	0.0172382
DL3	7.830716933	0.0418144
DL4	7.682969517	-0.016326
DL5	7.338886142	-0.004883

Table 6-19 : Predicted ln(OPEX) and the Difference with Actual

The maximum negative residual corresponds to DL1 having a value of -0.037843. According to the description given in section 2.4, the efficient cost equation (COLS line) is estimated using Ordinary Least Squares (OLS) regression and then shifted by the relevant amount of residual to on which the most efficient firm (that is DL1 in this case) is positioned. Here the shifting is done in parallel to the OLS line (as described in figure 2-1). Therefore coefficients of the COLS line are as follows. Note that only the value of intercept is decreased by the value equal to -0.37483.

Coefficient	Value
a (Intercept)	**-13.12978928**
b (Coefficient of Energy Sold)	1.009356796
c (Coefficient corresponds to Cost per Employee)	1.773929147
d (Coefficient corresponds to Customer Density)	0.357535018

Table 6-20 : Coefficients of the Efficient ln(OPEX) Line

Now corresponding efficient OPEX for each DL can be calculated using the coefficients of the efficient OPEX line (i.e. COLS line). Results are given in table 6-21.

	Efficient OPEX	Actual OPEX	Efficiency
DL1	3,665	3,665	100.0
DL2	4,544	4,802	94.6
DL3	2,423	2,624	92.3
DL4	2,090	2,136	97.9
DL5	1,482	1,532	96.8

Table 6-21 : COLS Efficiencies

Efficiency scores with respect to all models given in table 6-22 and 6-24 can be estimated in similar manner.

Model No.	Cost Function
1	$\ln(OPEX) = a + b.\ln(Energy\ Output) + c.\ln\ (Cost\ per\ employee) + d.\ln(Cust.per\ Area)$
2	$\ln(OPEX) = a + b.\ln(Energy\ Output) + c.\ln\ (Cost\ per\ employee) + d.\ln(Cust.per\ Line\ length)$
3	$\ln(OPEX) = a + b.\ln(Energy\ Output) + c.\ln\ (Total\ work\ Length) + d.\ln(Cust.per\ Area)$
4	$\ln(OPEX) = a + b.\ln(Energy\ Output) + c.\ln\ (Total\ work\ Length) + d.\ln(Cust.per\ Line\ length)$
5	$\ln(OPEX) = a + b.\ln(Energy\ Output) + c.\ln\ (Total\ work\ Length) + d.\ln(Cost\ per\ Employee)$

Table 6-22: Cost Function used with Four Variables

Model	Energy Sales	Network Length-Total	Consumer Density- Line	Consumer Density-Area	Cost of Employee	Efficiency Score				
	GWh	km	Cons/km	Cons/sqkm	LKR'000	DL1	DL2	DL3	DL4	DL5
1	X			X	X	100.0	94.6	92.3	97.9	96.8
2	X		X		X	100.0	97.8	96.1	99.3	98.6
3	X	X		X		95.7	97.2	100.0	95.6	97.1
4	X	X	X			89.0	85.0	100.0	83.6	89.6
5	X	X			X	100.0	77.8	85.9	87.6	88.3
					Average	96.9	90.5	94.9	92.8	94.1
					Maximum	100.0	97.8	100.0	99.3	98.6
					Minimum	89.0	77.8	85.9	83.6	88.3

Table 6-23 : COLS with Four Variables

The average results indicate more than 90% efficiencies for all DLs. Further, efficiency scores of all DLs lie in a band of 90.5% to 96.9%. Hence discrimination is lower. Therefore analysis carried out for 2-variable models also. Models and respective results are indicated in tables 6-24 and 6-25 respectively.

6.2.2 COLS Using Three Variables

Model No.	Cost Function
1	$\ln(\text{OPEX}) = a + b.\ln(Energy\ Output) + c.ln\ (Cost\ of\ employee)$
2	$\ln(\text{OPEX}) = a + b.\ln(Energy\ Output) + c.\ln(Cust.per\ Line\ length)$
3	$\ln(\text{OPEX}) = a + b.\ln(Energy\ Output) + c.\ln(Cust.per\ Area)$
4	$\ln(\text{OPEX}) = a + b.\ln(Energy\ Output) + c.ln\ (Total\ Network\ Length))$

Table 6-24 : Cost Functions Used with Three Variables

Model	Energy Sales	Network Length-Total	Consumer Density- Line	Consumer Density-Area	Cost per Employee	Efficiency Score				
	GWh	km	Cons/km	Cons/sqkm	LKR'000	DL1	DL2	DL3	DL4	DL5
1	X				X	100.0	76.6	94.6	85.4	88.8
2	X		X			100.0	74.8	93.5	81.6	90.3
3	X			X		100.0	74.7	93.4	79.7	91.9
4	X	X				100.0	76.4	96.1	84.0	89.8
					Average	100.0	75.6	94.4	82.7	90.2
					Maximum	100.0	76.6	96.1	85.4	91.9
					Minimum	100.0	74.7	93.4	79.7	88.8

Table 6-25 : COLS with Three Variables

It can be seen that the average efficiency scores are dispersed than 4-variable models' average. Efficiency scores are stretched out in a band of 75.6% to 100%. Hence discrimination is higher. Note that in each model in table 6-25, DL2 is the lowest performer. Efficiency score of DL2 always ended up below 77%.

6.3 PPI

PPI assumes linear relationship between input and output. As explained in section 2.2 it cannot measure the overall performance of the business. These partial indications can be misleading; therefore care should be taken to identify misleading information.

PPIs were calculated for each DL by taking the OPEX and number of employees as inputs. Line lengths and number of substations were not taken into account, since those can be considered input or output either. On the other hand OPEX and number of employees can only be considered as inputs to the system while energy delivered to consumers, number of consumers can only be taken as outputs from the system. Table 6-26 depicts the results from PPIs.

Partial Performance Indicator		DL1	DL2	DL3	DL4	DL5
Energy Sales/OPEX	kWh/LKR	0.763	0.592	0.703	0.594	**0.773**
No. of Consumers/OPEX	Nos/LKR Mil	345	310	**425**	397	321
Energy Sales/ Employee	MWh	**976**	760	740	625	816
No. of Consumers / Employee	Nos	442	398	**447**	417	338
Corresponding Relative Efficiencies						
Energy Sales/OPEX	%	98.8	76.6	91.0	76.9	100.0
No. of Consumers/OPEX	%	81.2	72.9	100.0	93.3	75.4
Energy Sales/ Employee	%	100.0	77.8	75.8	64.0	83.6
No. of Consumers / Employee	%	98.7	88.9	100.0	93.2	75.6
Average	%	94.7	79.1	91.7	81.8	83.6

Table 6-26 : Efficiency Scores from PPIs

Efficiencies obtained by PPIs are not used to directly conclude the relative efficiency score of a particular DL but to qualitatively verify the results obtained from DEA and COLS. It can be seen that DL1, DL3, DL5, DL4 and DL2 are having the efficiencies from highest to lowest respectively.

7 ANALYSIS OF RESULTS AND RECOMMENDATIONS

7.1 Interpretation of Relative Efficiency Scores.

In DEA 3- variable technique we have used 8 different input/output combinations (8 models) and relative efficiency scores calculated under each model.

Model	Energy Sales	New Connections given	Area per Consumer	Network Line Length per Consumer	Total Network Length	No. of Substations	No of Employees	OPEX	Relative Efficiency Score (%)				
									DL1	DL2	DL3	DL4	DL5
1	O	O						I	100	77.3	100	77.7	100
2	O		O					I	100	77	92.1	77.7	100
3	O			O				I	100	76.8	100	100	100
4	O				O			I	100	77.4	100	100	100
5	O					O		I	98.8	76.6	91	77.3	100
6	O				I			I	98.8	76.6	91	76.9	100
7	O					I		I	100	77.5	91.5	76.9	100
8	O						I	I	100	77.8	91	76.9	100

Table 7-1 : Relative efficiency scores of each models under the DEA 3- variable Method

Let us consider the model-4 given under the DEA 3-variable method given in table 7-1. In the model-4 'Energy Sales' and 'Total Network Length' are taken as outputs of the electricity distribution business while OPEX is taken as the input. In this aspect we look at how efficiently (relatively) a DL has used its OPEX to provide electrical energy to its consumers and also to maintain the total network length owned by that DL.

In that case all DLs except DL2 have obtained relative efficiency score of 100%. DL2 has obtained a score of 77.4%. This means only relative to each other, DL2 is efficient only about 77.4%. This does not imply that all other DLs are 100% efficient in are strictly efficient. It is possible that DLs with 100% score could be operated more efficiently.

DEA compares each DL with all other DLs, and identifies those DLs that are operating inefficiently compared with other DLs' actual operating results. It achieved this by locating the best practice or relatively efficient DLs. This can be graphically illustrated in following manner according to the ratios given in table 7-2.

	Unit of Measure	DL1	DL2	DL3	DL4	DL5
Energy sales per OPEX	GWh/LKR Million	0.76	0.59	0.70	0.59	0.77
Total network length per OPEX	km/LKR Milllion	10.63	7.26	12.27	12.41	2.83

Table 7-2 : Energy Sales per OPEX and Total Network Length per OPEX

The relevant ratios of 'Energy sales per OPEX' and 'Total network length per OPEX' for each DL are given in the table 7-4. In figure 7-1, points A, B, C, D and E represent DL5, DL1, DL3, L4 and DL2 respectively. These points have been plotted according to the respective (Energy delivered per OPEX) and (Network length per OPEX) ratios. The 100% efficient boundary is demarcated by the line connecting ABCD. That is it is the line that efficient DLs (i.e. DL1, DL3, DL4, DL5) those are using lesser inputs (OPEX) to produce outputs (Energy and Network Length) are located. The target '*efficient reference point*' for DL2 (i.e. point E) is given by the point E* which is the intercept of line AB and extended line OE.

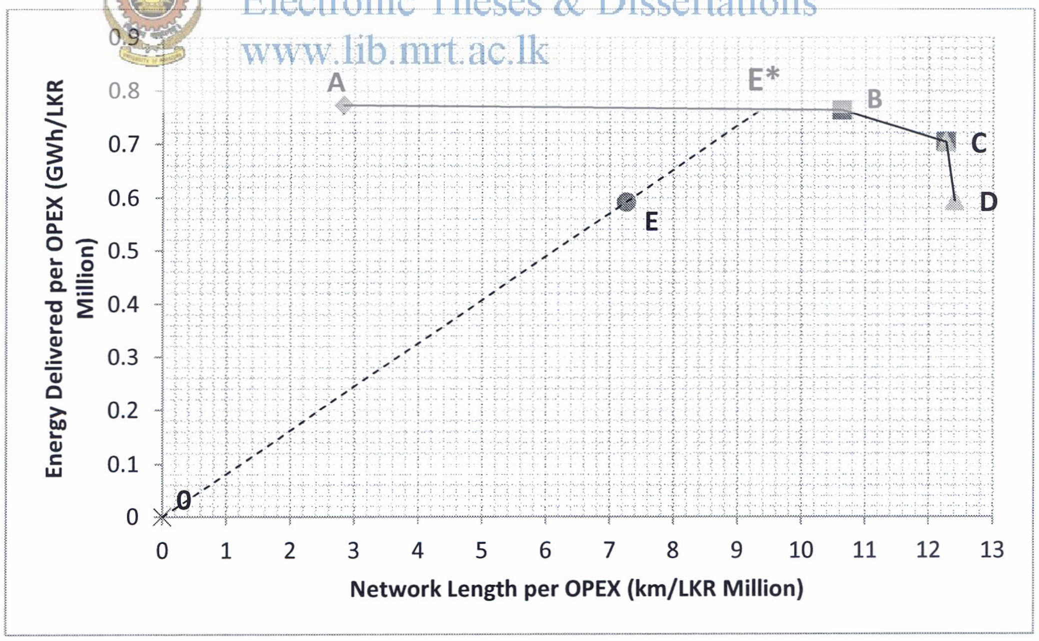

Figure 7-1 : Graphical representation of DEA implementation

In other words this efficient reference point is the point E*, against which the DL2 was found to be most directly inefficient. That is DL2 (point E) was found to have inefficiencies in direct comparison to DL1 (point B) and DL5 (point A). The efficiency of DL2 can be obtained by the ratio of ***OE/OE**** which is equal to 77.4%. The respective (Energy delivered per OPEX) and (Network length per OPEX) ratios for E* are 0.76 and 9.376 as graphically indicated in the figure 7-1. DL2 (point E) can approach the point E* to become 100% relatively efficient, by increasing the respective output/input ratios. In this case, DL2 can reduce its OPEX by 22.6% while keeping the actual outputs in same level, to be 100% relatively efficient. In that manner, the relative efficiency scores are calculated for DEA 3-variable models as given in the table 7-1.

Under the chapter 4, it has explained reasons for selecting these 8 variables (energy sold, No. of new connections given, OPEX, No. of employees, No. of substations, Network line length, Area per consumer and Network line length per consumer). Since these input / output data can be timely obtained, regulator can timely perform benchmarking. The output variable 'Energy Sales' is the main output of the distribution business and the OPEX is the main input of the business. Therefore in every model (in table 7-1) these main two variables have included.

In model-1, the 'no. of new connections given' is included, since it is another output by the DL. As indicated in table 4-3 the number of new connections given per day is varying among DLs. Hence in this model it assesses how efficiently a DL uses OPEX to provide the energy demand while fulfilling the demand for new connections to its system.

In model-2, the variable 'Area per consumer' is included and in model-3 , the variable 'Network line length per consumer' is included. Importance of these two variables is that it accounts the dispersion of consumers. Customer dispersion for each DL is given in the table 4-1. Each DL has to use their input resources differently according to how extent these dispersions are. Further this is an indication of the rural electrification efforts. This effect (requirement of higher OPEX to maintain geographically dispersed consumers) is captured in these two models by using those two variables as outputs. Efficiency score is an indication of how efficiently a DL uses its OPEX to cater the energy demand relative to other DLs who are catering its energy demand having different consumer dispersions.

In model-6 and model-7, the 'No. of substations' and 'Total Network line length' are considered as inputs to the system. In this case these two inputs are considered as capital inputs to the system. Therefore in model-6, the efficiency scores reflect how efficiently a DL (relative to other DLs) caters the demanded energy using the OPEX and the 'Total network length'. Accordingly, in model-7 the efficiency scores indicate how efficiently a DL supply its energy demand using the OPEX and the substations its possess.

In model-8, the efficiency score of a DL indicates how efficiently that DL supply the demanded energy by using the OPEX and 'number of employees' as inputs.

One setback of these 3-variable models is that we cannot assess the effect on efficiency score from the all 8 variables we are considering, at once. Therefore possible combinations of 3 variables selected out from the 8 variables (as indicated in table 6-11) have considered capturing the overall effect on efficiency. This allows capturing overall relative efficiency of each DL. For example the DL4 is operating with 100% relative efficiency under the model-4 but only 77% efficient under model- 1. The average efficiency score of 3 variable models is taken as the final efficiency score.

According to the average efficiency scores (see table 6-12) obtained by DEA 3-variable models, DL5 is the efficient performer with 100% relative efficiency. DL5 is 100% efficient means that it is relatively efficient only, and not strictly, efficient. That is, no other unit is clearly operating more efficiently than this DL5, but it is possible that all DLs, including DL5, can be operated more efficiently. Therefore, the efficient DL (DL5 in 3-variables models) represents the best existing (but not necessarily the best possible) practice with respect to efficiency.

7.2 Appropriateness of DEA 3-variable models

It can be pointed out that considering the small sample size (5 DLs) DEA is theoretically more appealing than COLS technique, because COLS require to estimate number of coefficients leading to unsatisfactory results purely because low sample size.

As explained in section 5.2, if a benchmarking method requires higher number of data points then it will be harder to implement with a smaller sample like five, as in the case where only five DLs in Sri Lanka. DEA A rule of thumb (from international practices)is that for *m* number of inputs and *n* number of outputs, there has to be *n* x *m* number of DLs[10][22]. Otherwise all the DLs would get closer to 100% efficiency and discrimination could be difficult (see figure 7-2 given below). In other words, with small sample and high number of input / output variables there is a danger of receiving made-up results for efficiency scores [2].

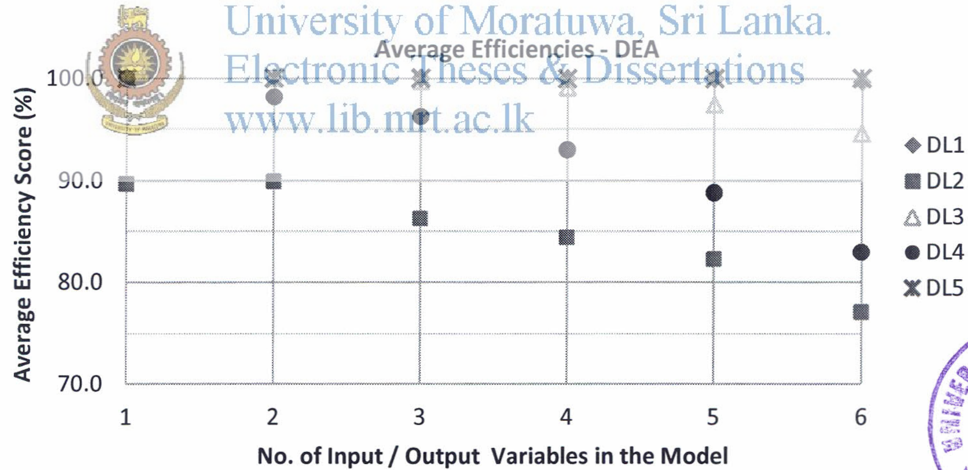

Figure 7-2 : Increase of Discrimination with reduction of Variables in DEA

When more variables are included in the model, the number of DLs on the efficient frontier increases. To avoid lower discrimination of efficiency scores (Since we have only 5 DLs) the 3-variable models are the most suitable in our context (verified by the average efficiency scores given in table 6-13). If we had higher number of DLs we could have gone for DEA models with more than 3 variables while having acceptable discrimination.

7.2.1 Robustness of the Results

The models selected must be robust to changes in techniques implemented. In particular, the ranking of firms, especially with respect to the 'best' and 'worst' performers, and the results must show reasonable stability and the different approaches should have comparable results. COLS and DEA are the main two different techniques used to measure the overall efficiency. Therefore robustness of the results obtained using those two techniques has to be analyzed.

As indicated in table 6-23, we selected COLS- 3 variable models over 4- variables models; because 4-variables models results indicated average efficiency scores of all DLs lie in a band of 90.5% to 96.9% (i.e. low discrimination). In COLS 3-variable technique, indicated higher discrimination and the efficiency scores for all DLs lie in a band of 75.6% to 100% as indicated in section 6.2.2.

Since we have incorporated more variables (from 8 variables to 3 variables) in DEA, direct comparison with COLS results is not possible. The COLS method adopted used 3 variables including OPEX, as given in table 6-25. Results from COLS method with 3-variables including OPEX can be compared with 3 variables model in DEA. This is because both methods used 3 variables as input and output; hence the degree of freedom is the same.

It can be seen that the results produced by DEA and COLS are robust for DL1, DL2, DL3 and DL4 as the differences are very low. For DL5 there is a considerable difference, but the efficiency score for DL5 is beyond 90% for both techniques. It is important to note that operation conditions of DL5 are extensively different than remaining four DLs with respect to consumer density, authorized area of operation and energy demand per consumer.

	Average Efficiency Score				
	DL1	DL2	DL3	DL4	DL5
DEA (3-variables)	99.7	77.1	94.6	82.9	100.0
COLS (3-variables)	100.0	75.6	94.4	82.7	90.2
Difference	-0.3	1.5	0.2	0.3	9.8

Table 7-3 : Average Efficiency Scores

According to the results given in table 7-3 we can conclude that average efficiency score given by DEA 3-variable models are robust and reliable.

7.3 Ranking of DLs According to Overall Efficiency

Since Sri Lanka is in the initial stage of electricity regulation (Electricity Act came into force in 2009), it is more important to peruse underperforming DL to obtain at least the next level of efficiencies performing by peer DLs. Further, according to the efficiency scores the regulator can decide which companies deserve closer examination, so that scarce investigative resources are allocated efficiently [12]. Table 7-2 depicts the ranking of each DL according to each technique used and also verification by using PPIs. DL2 is lowest and DL4 is second lowest in each case. Average efficiency results shown in table 7-1 indicate that DL2 and DL4 are having efficiency scores of nearly 76% and 83% respectively, while all other DLs are having scores greater than 90%.

Rank	Ranking		
	DEA	COLS	PPI
1	DL5	DL1	DL1
2	DL1	DL3	DL3
3	DL3	DL5	DL5
4	**DL4**	**DL4**	**DL4**
5	**DL2**	**DL2**	**DL2**

Table 7-4: Ranking of DLs

As it is explained in section 6.1.3.7, the DL2 is the lowest performer while DL5, DL1, DL3 and DL4 are ranked highest to lower according to the average efficiency scores. Even when considering 8 variables models in DEA as given in section 6.1.3.1, it can be observed about 10% gap of efficiency with respect to all other DLs. Therefore it can be recommended that DL2 deserve closer supervision while DL4 also require close supervision of the electricity regulator (i.e. PUCSL) as they are under performing relative to other three DLs.

7.4 Influence on X- Factor

Regulator can officially obtain data for relevant variables and perform DEA analysis as indicated in section 6 and use the average results from the DEA method which using 3 variables models to obtain efficiency scores. Verify those DEA results with efficiency sores obtained by COLS method using 3 variables method described in section 6.2.2, and verify the rankings with PPIs as given in section 6.3. Then the average efficiency scores given by DEA 3 variables models can be used to decide on X- factor to persuade most underperforming DLs.

The regulator can decide on how to determine the X-factor (the translation of efficiency scores into X-factors), and the method of determining the X-factor may vary among the regulators [40, 41]. For example X-factor can be calculated as (1-Efficiency Score). In such method and according to the average efficiency scores obtained under DEA 3-variable models (refer table 7-1), the X-factor of DL2 is (1-0.771) i.e., 0.229 as the average efficiency score of DL2 is 77.1% (refer table 6-12). While DL1, DL3, DL4, DL5 are having X- factors of 0.003, 0.054, 0.171 and 0.00 respectively. On another hand, if the regulator wants DL2 to catch up 20% of the frontier (100% efficient firm, i.e. DL5) over next year then it would be required to catch up, *(1-0.771) x 0.2 = 0.0458* . Thus the X-factor would be 0.0458 per year [42]. It is important to note that the relative efficiency scores resulted from this benchmarking exercise give an indication to the regulator (PUCSL) on how these DLs are operating relative to each other and what would be the required improvements in efficiency so that regulator has a firm foundation to make a decision on X-factor.

8 CONCLUSION

The relative efficiencies of five Distribution Licensees operating in Sri Lanka were analyzed using prominent benchmarking techniques. International practices in electricity distribution regulatory regime were considered when performing this benchmarking study. Techniques like Data Envelopment Analysis (DEA), Corrected Ordinary Least Squares method (COLS) and Partial Performance Indicators method (PPI) were utilized with several input output models in order to assess the efficiency in several angles. Care was taken to address the heterogeneity of the operating conditions such as consumer density, authorized area of operation of each DL which is out of the management control.

The efficiency scores obtained with respect to various possible models were scrutinized and came up with a suitable methodology to obtain efficiency scores considering the data availability and low number of distribution licensees. The proposed methodology use DEA with 3 input/ output variables and get the average efficiency scores as the final score. That is to have higher discrimination in the efficiency scores.

In parallel these efficiency scores verified by the average results obtained by COLS method (3 variables including OPEX). Further, the ranking of Distribution Licensees are also verified with respect to DEA , COLS and PPIs. It was revealed that for each method DL2 is the lowest ranked and DL4 is the next lowest ranked. DL1, DL3 and DL5 showed up more than 90% average efficiency for DEA and COLS.

Considering the fact that Sri Lanka is in its early stage in regulatory implementations, it is recommended to persuade underperforming DL. These efficiency scores would make a strong platform to the regulator when making the decision on X-factor in order to control the allowed revenue of Distribution Licensees.

The Electricity regulator can use the proposed methodology to start the evaluation of the efficiencies in order to begin incorporating efficiencies of distribution licensees in the electricity distribution revenue control formula. This would definitely encourage Distribution Licensees to minimize their inefficiencies in operations and maintenance. Further, the possible reduction in allowed revenue eventually would pass down to the consumers.

9 REFERENCES

[1] Final report titled "Background to work on assessing efficiency for the 2005 price control review" prepared for Ofgem by Cambridge Economic Policy Associates (CEPA), 2003

[2] Benchmarking in ERRA (Energy Regulators Regional Association) Countries, Issue Paper 2002, ERRA Licensing and Competition committee.

[3] International benchmarking and regulation of European gas transmission utilities, final report prepared for Council of European Energy Regulators (CEER), ToorajJamasb, David Newbery, Michael Pollitt, ThomasTriebs.

[4] Benchmarking Analysis in electricity distribution, Massimo Filippini Mehdi Farsi Aurelio Fetz, Center for Energy Policy and Economics Department of Management, Technology and Economics, Swiss Federal Institute of Technology ETH Zentrum, WEC, 8092 Zurich, Switzerland

[5] Benchmarking and regulation: international electricity experience, T. Jamasb, M. Pollitt, Utilities Policy 9 (2001) 107–130,2001

[6] Cost Benchmarking in Energy Regulation in European Countries, Final report,study for the Australian Energy Regulator,WIK Consult GmbH

[7] Incentive Regulation and Benchmarking of Electricity Distribution Networks: From Britain to Switzerland, Report Prepared forSwiss State Secretariat for Economic Affairs, *Tooraj Jamasb,* Faculty of Economics, University of Cambridge, *Michael Pollitt-* Judge Business School, University of Cambridge, 13 February 2007

[8] Benchmarking OPEX and CAPEX in Energy Networks, ACCC/AER Working paper series, working paper No.06, May 2012.

[9] Decision on Electricity Tariffs 2011 , published by Public Utilities Commission of Sri Lanka

[10] Data envelopment analysis : Models and extensions, Srinivas Talluri; Decision Line, May 2000.

[11] Benchmarking and regulation in the electricity distribution sector, Mehdi Farsi, Aurelio Fetz, Massimo Filippini; CEPE working paper no. 54, Jan 2007.

[12] Benchmarking of electricity networks: Practical problems with its use for regulation, Graham Shuttleworth, NERA Economic Consulting, Stratford Place, London W1C 1BE, January 2005

[13] Tariff Methodology; Public Utilities Commission of Sri Lanka, December 2010 – Distribution allowed revenue

[14] Monitoring performance of electricity utilities, Indicators and benchmarking in sub Saharan Africa; The World Bank 2009.

[15] Concept Paper; Performance benchmarks for electricity distribution companies in South Asia, Nov 2004; USAID SARI/Energy program, www.sari-energy.org (South Asia Regional Initiative for Energy)

[16] Sources from Public Utilities Commission of Sri Lanka

[17] Explanatory Notes to the System Charges Order 2006 [SNT-VO 2006] by Energie-Control Austria

[18] Presentation on "Benchmarking and the regulation of electricity distribution companies", Massimo Fillipini http://www.aeee.es/archivos/documentosCientificos/CONGRESOS%20AEEE/2012%20-%20VII%20CONGRESO%20AEEE%20-%20PAMPLONA/Massimo%20Filippini.pdf

[19] Efficiency and Regulation of the Slovenian Electricity Distribution Companies, Prof. Dr. Massimo Fillippini, Prof. Dr. Nevenka Hrovatin, Jelena Zoric, CEPE working paper Nr. 14, April 2002.

[20] Assessing the Performance and Finding the Benchmarks of the Electricity Distribution Districts of Taiwan Power Company, Chyan Yang, Wen-Min Lu, IEEE Transactions on Power Systems, Vol 21, No.2, May 2006.

[21] Sensitivity and Stability Analysis in DEA: Some Recent Developments,W. W. Cooper, Shanling Li, L. M. Seiford, Ph.D., kaoru tone, R. M. Thrall, J. Zhu, Journal of Productivity Analysis, 15, 217–246, 2001

[22] Frontier Analyst FAQs – Getting the best, http://www.banxia.com/frontier/resources/frequent-questions.

[23] Performance Report of Distribution Licensees 2012, Public Utilities Commission of Sri Lanka.

[24] Performance Report of Distribution Licensees 2011, Public Utilities Commission of Sri Lanka.

[25] Statistical Digest 2011, Ceylon Electricity Board.

[26] Statistical Digest 2010, Ceylon Electricity Board.

[27] Statistical Digest 2009, Ceylon Electricity Board.

[28] Statistical Digest 2008, Ceylon Electricity Board.

[29] Statistical Digest 2007, Ceylon Electricity Board.

[30] Statistical Digest 2006, Ceylon Electricity Board.

[31] Annual Report and Accounts 2010, Ceylon Electricity Board.

[32] Annual Report 2009, Ceylon Electricity Board.

[33] Annual Report 2008, Ceylon Electricity Board.

[34] Annual Report 2011, Lanka Electricity Company (Private) Limited.

[35] Annual Report 2010, Lanka Electricity Company (Private) Limited.

[36] Annual Report 2009, Lanka Electricity Company (Private) Limited.

[37] An Introduction to Efficiency and Productivity Analysis, Second Edition, Thimothy J. Coelli, D.S. Prasada Rao, Christopher J O' Donnell and George E. Battese, pp243

[38] International benchmarking and regulation: an application toEuropean electricity distribution utilities, Tooraj Jamasb, Michael Pollitt, Energy Policy 31 (2003) -pg1609–1622.

[39] Electricity Distribution Performance Regulation – Final Draft, Public Utilities Commission of Sri Lanka, February 2012.

[40] Regulatory Practices in Other Countries Benchmarking opex and capex in energy networks , Australian Competition & Consumer Commission, May 2012.

[41] Strategic behavior under regulatory benchmarking, Tooraj Jamasba,, Paul Nillesenb, Michael Pollittc, Energy Economics 26 (2004) 825– 843.

[42] Performance Measurement and Regulation of Network Utilities, by Tim Coelli, Denis Anthony Lawrence, pp55.

10 APPENDIX

The Revenue Control Formula imposed by PUCSL explained under the section 3.1.2.8 of Tariff Methodology (December 2011).

$$AR_y = AR_{y-1} \times (1-X) \times \left[a \times (1+SLCPI) + (1-a) \times \left(\frac{FX_y}{FX_{y-1}} + PPIUS \right) \right] \dots$$
$$\times \left[b \times (1+Dcust) + c \times (1+DkWh) + d \right] - Diff_y$$

where:

$$Diff_y = \left[AREV_{y-2} \times (1-(AL_{y-2} - ACL_{y-2})) - AR_{y-2} \right] \times (1+r_{y-1})$$

AR_y	Allowed base revenue in year *"y"* (LKR)
AR_{y-1}	Allowed base revenue in year *"y-1"* (LKR)
a	share of local costs in total costs of TL to be approved by the Commission based on the filing by TL.
$SLCPI_{y-1}$	accumulated change in Sri Lanka Consumer Price Index (%) of year *"y-1"*
FX_y/FX_{y-1}	Average change in the LKR:USD exchange rate of year "y-1"
PPIUS	Accumulated change in the Producer Price Index of USA (%) of year "y-1"
X	Efficiency factor (%) is the translation of OPEXX in terms of total revenues
$Diff_y$	Interim adjustment factor to compensate differences between actual distribution revenues and allowed distribution revenues (LKR) of the year "y-2"
$AREV_{y-2}$	Actual distribution revenue based on invoicing (LKR) of the year "y-2"
AR_{y-2}	Allowed revenue (LKR) of the year "y-2"
r_{y-1}	Average reference Interest rate of year "y-1" to be defined by the Commission
b	Allowed revenue coefficient to adjust for increases in the number of customers
Dcust	Percentage of customers in excess (negative if in deficit) of the level forecast at the time of setting tariff for the period
c	Allowed revenue coefficient for energy increase
d	1-b-c
DkWh	Percentage of energy distributed in excess (negative if in deficit) of the level forecast at the time of setting the tariff for the period
AL_{y-2}	Aggregated allowed level of energy losses for year *"y-2"* (%)
ACL_{y-2}	Aggregated actual level of energy losses for year *"y-2"* (%)