PERFORMANCE EVALUATION OF POWER DISTRIBUTION SECTOR OF SRI LANKA BASED ON DATA ENVELOPMENT ANALYSIS

K.V.R.Perera

109241R



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Department of Electrical Engineering

University of Moratuwa Sri Lanka

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Kankanamalage Varuni Randima Perera

109241R



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Degree Master of Science

Supervised by: Dr.K.T.M.Udayanga Hemapala

Department of Electrical Engineering

University of Moratuwa Sri Lanka

February 2015

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.

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ABSTRACT

Performance Evaluation of Power Distribution Sector of Sri Lanka Based on Data Envelopment Analysis

Performance benchmarking is very important for any type of organization. Results of such benchmarking studies allow the organization or the unit to compare themselves with the best organization or unit and to develop strategic plans for improvements in their performance. There are several methods and techniques for the measurement of the relative efficiency of organizations or units in relation to an efficient frontier or best practice. Each technique is either based on linear programming or econometrics. Data Envelopment Analysis (DEA), Parametric Programming Analysis (PPA), Partial Factor Productivity (PFP), Corrected Ordinary Least Squares (COLS) and Stochastic Frontier Analysis (SFA)

The algorithm which can be followed by top managers of any organization to evaluate and improve relative performance is discussed. Relative performance of 20 areas within Distribution Division 02 (DD2) of Ceylon Electricity Board is evaluated using Data Envelopment Analysis (DEA). Relative efficiency scores and methods to improve efficiencies can be identified for each area.

This paper studies how to carry out DEA analysis to evaluate CRS, VRS and scale efficiency scores and slack analysis in order to find efficient input targets and output targets. Then DEA analysis was carried out with different models and yustified the selected base model for the analysis. This paper also discusses the classification of DMUs according to the sensitivity analysis.

Generally, the study concludes that DEA analysis can be carried out to evaluate the performance of an organization, department or branch whether it is a public sector or private sector. The evaluation can be carried out once a year or once in two years in order to identify their position and utilized resources can also be reduced according to the results of the analysis.

Key words: Data Envelopment Analysis, Performance, Electricity Distribution Sector, Efficiency Score

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List of Abbreviations

Abbreviation	Description
CEB	Ceylon Electricity Board
СР	Central Province
CRS	Constant Returns to Scale
DD2	Distribution Division 02
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
DRS	Decreasing Return to Scale
EP	Eastern Province
ERS	Efficiency Reference Set
IRS	Increasing Return to Scale
LV	Low Voltage
MV	University of Moratuwa, Sri Lanka.
NIRS (O)	ENeurboicasing Reput to Scalertations
O&M	Woperation and Maintenance
RTS	Return To Scale
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index
VRS	Variable Returns to Scale
WPN	Western Province North

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1 INTRODUCTION

1.1 Background

Performance benchmarking is very important for any type of organization. Results of such benchmarking studies allow the organization or the unit to compare themselves with the best organization or unit and to develop strategic plans for improvements in their performance.

Benchmarking studies allow identifying areas within the organization where performance is lacking and direct those particular sections to further analysis in order to identify methods and practices to implement or to identify mitigating factors to improve their performance. After identifying strengths and weaknesses properly an organization or unit can prepare and implement an enhanced corporate plan in order to have a better position in the market compared to other competitors.

Performance evaluation is everyymuch/important in Srider to knaintain the quality of electricity provided to consumers. Although the method of evaluating performance benchmarking is different in each country their use is common in most of the countries. The top managers in distribution utilities use the results of performance evaluation to get a proper idea about their operational performance compared to other units. Other than that by performance evaluation they also expect to know whether they provide a uniform quality of service to consumers, predict the problems they have to face in future and how to handle capital expenditure.

Not having a proper benchmarking method or a data base of performance indicators for electricity distribution utilities in Sri Lanka is a main handicap for their top management. The top managers in electricity distribution utilities don't have a proper method to identify which divisions or units need improvements, to observe progress or to compare their divisions with other divisions. They are lack of this important management tool of performance benchmarking. As managers it is very important to having a clear idea of their units or divisions performance in order to direct staff under him to achieve organization's targets.

There are various methods to evaluate relative performance of organizations or units. Each technique is based on either linear programming or econometrics. Often it is argued that an average benchmark should be employed instead of a frontier benchmark. But the frontier approach can be considered superior for several reasons. Most importantly, if the objective of the regulator is to maximize efficiency then there is no alternative to the frontier approach. Second, as the comparators are real companies there is no a priori reason to believe that the frontier cannot be reached by any firm. Last, frontier benchmarking allows the regulator to increase the stiffness of the regulation over time by employing safety margins in the early stages of regulation without the need to compromise on his general commitment to frontier benchmarking.

Table 1.1. Overview of benchmarking methods			
Category	Etyperonic Theses	fechniquertations	Main purpose
Programming techniques	Linear programming	Data Envelopment Analysis (DEA)	Firm-level efficiency
		Parametric Programming Analysis (PPA)	Firm-level efficiency
	Index approach	Partial Factor Productivity (PFP)	Industry-level efficiency
		Total Factor Productivity (TFP)	Industry-level efficiency
Econometric (parametric approach)	Determinist	Corrected Ordinary Least Squares (COLS)	Firm-level efficiency
	Stochastic	Stochastic Frontier Analysis (SFA)	Firm-level efficiency
Process approaches	Engineering Economic Analysis	Engineering Economic Analysis	Firm-level efficiency
	Process approach	Process Benchmarking	Firm-level efficiency

Table 1.1 gives a broad overview of benchmarking methods [1]

2

1.2 Motivation

Evaluating the performance and having a clear idea regarding their position is very much vital for any type of organization. It may be a private sector organization, public sector organization or may be different departments or branches within same organization. Presently there is not any proper method of finding performance within regions, provinces, or areas in Ceylon Electricity Board (CEB). In my research relative performance of 20 areas within Distribution Division 02 (DD2) of CEB is evaluated using Data Envelopment Analysis (DEA). Relative efficiency scores and methods to improve efficiencies can be identified for each area.

1.3 Objective of the Study

The main objective of this study is to evaluate relative efficiencies of each area in DD2 using DEA and to identify best performing areas within DD2. Then identify ways to improve each area's performance, if it is not one of the top performing areas. A common algorithm which can be followed by any type of organization in order to evaluate their performance is proposing to find the performance of each area of DD2.

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1.4 MethodologyElectronic Theses & Dissertations

- Literature Review.lib.mrt.ac.lk
- Studying Data Envelopment Analysis
- Algorithm to be followed
- Input output variable selection
- Data collection
- DEA analysis to evaluate CRS, VRS efficiencies and scale efficiency
- Slack Analysis and finding efficient input targets and output targets
- DEA analysis with different models
- Justification of the selected base model
- Sensitivity based classification of DMUs

2 DATA ENVELOPMENT ANALYSIS

2.1 Introduction to DEA

DEA is a commonly used benchmarking technique which is developed by Charnes, Cooper and Rhodes in 1978 in order to evaluate performance of nonprofit and public sector organizations [2].

DEA can be considered as a non parametric programming technique which creates an efficiency frontier by optimizing the weighted output to input ratio of each DMU. This is subject to the condition that this ratio can be equal to 01, but never exceed 01 for any DMU considered. DEA is a linear programming type technique and it is based on an optimization platform [1].

DEA evaluates the relative efficiencies considering the input and output variables used for the analysis. It also identifies most efficient units and inefficient units which need improvements UThise can be obtained by analyzing the ainputs used and the outputs produced by an information of the analysis. The second by analyzing the ainputs used and the outputs produced by an information of the cost to be reduced in order to become efficient as other units.

The exact changes which need to be done to inefficient units can also be identified by DEA analysis. The managers can implement them to get savings and to enhance performance. By implementing these changes the unit or organization can achieve the best practice or most efficient unit's performance. Other than that the managers can identify the amount of output or service they can provide without increasing the amount of resources. Also by DEA analysis managers receive some important information like which units or organizations can be used to transfer systems, managerial expertise, practices from most efficient units to inefficient units. By this it can be increased the performance and productivity of inefficient units by reducing their operating costs and resources and then by increasing profitability.

2.2 The Mathematical Formulation of DEA

In order to obtain highest possible value for efficiency rating θ for the DMU being considered the set of values for the coefficients u's and v's are evaluated using linear programming technique [2].

In the model,

j	= number of DMUs considered for DEA
$\mathbf{DMU}_{\mathrm{j}}$	= DMU number j
θ	= relative efficiency rating of the DMU being evaluated by DEA
y _{rj}	= amount of r^{th} output produced by $j^{th} DMU$
\mathbf{x}_{ij}	= amount i th input consumed by j th DMU
i	= number of inputs used by the DMUs
r	= number of outputs generated by the DMUs
u _r	= coefficient or weight assigned by DEA to output r
vi	= coefficient or weight assigned by DEA to input i Electronic Theses & Dissertations

It is required to collect data for outputs y_{rj} and inputs x_{ij} for a particular time period for each DMU considered for the analysis in order to carry out Data Envelopment Analysis. Here x_{ij} is the amount of ith input consumed by jth DMU and y_{rj} is the amount of rth output produced by jth DMU.

If the value obtained for the efficiency rating θ for a particular DMU is less than 100%, then that DMU is called relatively inefficient. That means it has the capability to produce the same level of output with lesser amount of inputs.

Objective Function [2]

Maximize
$$\theta = \frac{u_1 y_{1o} + u_2 y_{2o} + \dots + u_r y_{ro}}{v_1 x_{1o} + v_2 x_{2o} + \dots + v_m x_{mo}} = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}$$
 (2.1)

Here the efficiency rating θ is maximized for the DMU O.

The above mentioned objective function is subjected to the constraint that when same set of u and v values are applied to all the DMUs being considered the efficiency rating θ is always less than or equal to unity [6].

DMU=Decision Making Unit

.....

$$DMU1: \frac{u_1y_{11} + u_2y_{21} + \dots + u_ry_{r1}}{v_1x_{11} + v_2x_{21} + \dots + v_mx_{m1}} = \frac{\sum_{r=1}^{s} u_ry_{r1}}{\sum_{i=1}^{m} v_ix_{i1}} \le 1$$
(2.2)

$$DMU2: \frac{u_1y_{11} + u_2y_{22} + \dots + u_ry_{r2}}{v_1x_{12} + v_2x_{22} + \dots + v_mx_{m2}} = \frac{\sum_{r=1}^{s} u_ry_{r2}}{\sum_{i=1}^{m} v_ix_{i2}} \le 1$$
(2.3)

$$DMUo: \frac{u_1y_{1o} + u_2y_{2o} + \dots + u_ry_{ro}}{v_1x_{1o} + v_2x_{2o} + \dots + v_mx_{mo}} = \frac{\sum_{r=1}^{s} u_ry_{ro}}{\sum_{i=1}^{m} v_ix_{io}} \le 1$$
(2.4)

$$DMU_{j} : \underbrace{\bigcup_{u_{2}y_{2j} + \dots + u_{r}y_{rj}}^{s} \bigcup_{u_{2}y_{2j} + \dots + u_{r}y_{rj}}^{s} \bigcup_{u_{2}y_{2j} + \dots + u_{r}y_{rj}}^{s} \bigcup_{i=1}^{s} v_{i}x_{ij}}_{i=1} \leq 1$$

$$(2.5)$$

$$u_1,\ldots,u_s>0$$
 and $v_1,\ldots,v_m\geq 0$

In order to run DEA on a standard linear program package it can be algebraically reformulated as follows.

Maximize
$$\sum_{r=1}^{s} u_r y_{ro}$$
 (2.6)

Subject to

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \, j = 1, \dots, n$$
(2.7)

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

$$u_r, v_i \ge 0$$
(2.8)

Assume that there are n DMUs.

Then the dual linear program of above model can be interpreted as follows.

Minimize θ

Subject to

$$\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta x_{io} \qquad i = 1, 2, \dots, m ; \qquad (2.9)$$

$$\sum_{j=1}^{n} \lambda_{j} y_{rj} \ge y_{ro} \qquad r = 1, 2, \dots, s ; \qquad (2.10)$$

$$\lambda_j \ge 0$$
 $j = 1, 2, \dots, n$. (2.11)
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Here the meaning of equation 2.9 is weighted sum of inputs of other DMUs is less than or equat to the input in to efficiencly rating of the DMU being considered. The equation 2.10 shows that weighted sum of outputs of other DMUs is greater than or equal to the output of the DMU being considered. Here the weights are the λ values. This model is referred to as "envelopment model".

2.3 Orientations in DEA

In performance evaluation DEA basically comprises of 03 orientations. According to the type of organization, their service or main task, the most appropriate orientation can be selected. There are mainly three orientations in DEA called input-oriented, output-oriented or base oriented models.

In **input-oriented models** a given amount of outputs have to be produced consuming smallest possible amount of inputs. That is outputs are uncontrollable and inputs are controllable.

Only the fixed factors of production are used as variables in DEA analysis in order to measure the capacity. For the judgment of capacity utilization input oriented model is not relevant as fixed factors of production cannot be reduced. It can be evaluated the reduction of input levels while keeping outputs produced and output levels fixed by doing some modifications the traditional input oriented DEA model.

In **output-oriented models** the DMU will produce maximum number of outputs with given amount of inputs. Here the inputs are uncontrollable and outputs are controllable. As an example the services like government hospitals, schools can be considered. Within the limited allocated budget highest possible service has to be given to the public. In output-oriented DEA model the linear programming is configured in order to determine organization's output at a fixed input level if it is operating efficiently as other units or organizations along the best practice frontier.

In **base oriented models** the DMUs are expected to utilize minimum level of inputs to produce maximum level of outputs. That means both inputs and outputs are controllable. Figure 2.1 depicts the projection of an inefficient unit on the frontier with the three possible orientation of a DEA moder [3].

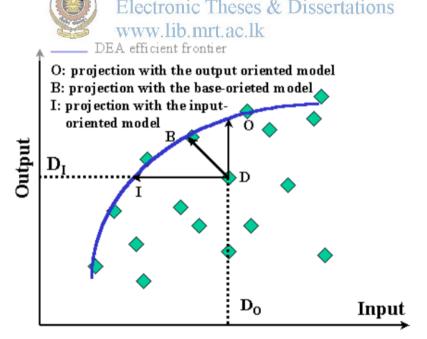


Figure 2.1 Projection of an inefficient unit on the frontier

2.4 Returns to Scale Versions

The surface of the envelopment may be differ depending on the scale assumptions that emphasize the model. There are two basic scale assumptions which are used generally called constant returns to scale (CRS), and variable returns to scale (VRS). Variable returns to scale include both increasing and decreasing returns to scale. In CRS outputs will change by the same proportion as inputs are changed. The meaning is doubling of all inputs will double outputs. In variable returns to scale the production technology may exhibit increasing, constant and decreasing returns to scale.

Figure 2.2 depicts the effect of scale assumption [4]. Considering both scale assumptions CRS and VRS, four points namely A, B, C & D are used to demonstrate the efficient frontier and outputs produced for a fixed input. Each frontier demonstrates the maximum amount of outputs produced for a fixed input level. In Constant Returns to Scale the frontier is depicts by point C for all the points along frontier with all other points falling below the frontier. Therefore the points below the frontier show capacity traderutifizational In WRS Schelffonkier is demonstrated by three points A. B. C. & D. and it shows capacity underutilization. It can be noted that the output produced in VRS is lower than the output produced in CRS for a fixed input level.

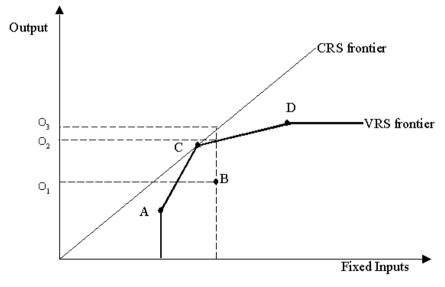


Figure 2.2 Effect of scale assumption

The ratio of actual output produced to frontier level of output is considered as the measure of capacity utilization. Under both assumptions point C has 100% capacity utilization. The measure of capacity utilization is lower for all the points in CRS than VRS except for point C. For point B the ratio O_1 over O_3 is less than the ratio of O_1 over O_2 . Therefore it can be concluded that if a CRS frontier is considered the output produced is greater than and inputs utilized is lower than that of a VRS frontier.

2.5 Basic DEA Model Classifications

The exact type of model which is suitable for a particular application can be selected considering the scale and orientation of the model. If the scale of economies doesn't change when the scale of operation increases or decreases, the CRS type model can be selected for such kind of situations. In VRS type models the scale of economies changes when scale of operation increases or decreases. Figure 2.3 depicts the basic DEA models based on returns to scale and model orientation. These models will be referred as "Envelopment Models."

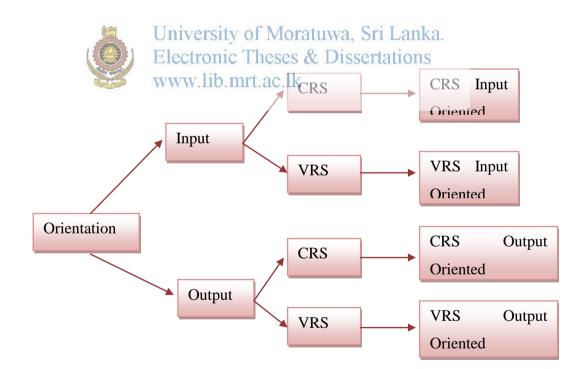


Figure 2.3 Basic models based on returns to scale and model orientation

3 ALGORITHM FOLLOWED

DEA compares decision making units considering resources used and services provided, and identifies the most efficient units or best practice units. Also it identifies the inefficient units in which real efficiency improvements are possible. Here the unit may be a separate organization or may be several branches or departments within same organization.

DEA calculates the amount and type of cost and resource savings that can be achieved by making each inefficient unit as efficient. Specific changes in the inefficient service units can also be identified, where management can implement. DEA also estimates the amount of additional services an inefficient unit can provide without using additional resources. Management receives information about performance of decision making units which can be used to transfer systems and managerial expertise from better managed, relatively efficient units to the inefficient units. By the productivity of the inefficient units can be improved, while Electronic Theses & Dissertations reducing operating costs and increasing profitability.

Figure 3.1 shows the algorithm to be followed by top managers of any organization to improve relative performance. That may be a private sector organization or government sector organization. Private sector organizations like banks, insurance companies, manufacturing companies, fast food restaurants, business firms and retail stores can follow this algorithm to find relative efficiencies of their units. Other than that government organizations like schools, universities, educational institutes, hospitals and government agencies can also follow this algorithm suitably.

By following this algorithm any company can know where they stand in relation to other companies. The other companies can be used as evidence of problem areas, and provide possible solutions for each area. Also it allows organizations to understand their own administrative operations better, and marks target areas for improvement. It is an ideal way to learn from other companies who are more successful in certain areas.

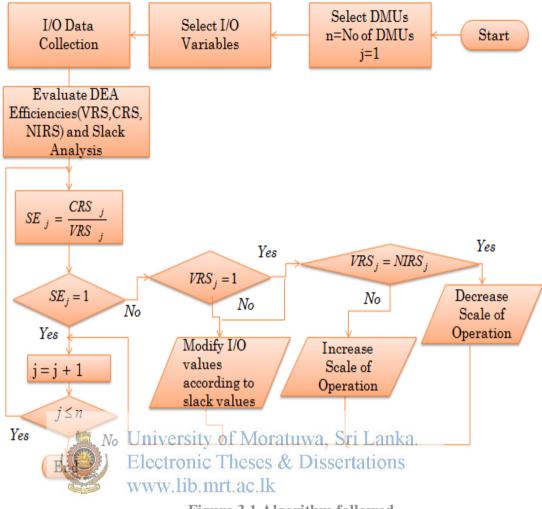


Figure 3.1 Algorithm followed

First select set of DMUs for the DEA analysis. They may be number of organizations or same departments or branches within same organization. All the units must perform same task with same inputs and outputs in order to compare their relative efficiencies. Then it is needed to select suitable input variables and output variables. Selection of input output variables are more significant as it directly affects the efficiency of each unit. Normally, inputs are defined as resources utilized by the DMUs or conditions affecting the performance of DMUs, while outputs are the benefits generated as a result of the operation of the DMUs. However, sometimes it may become difficult to classify a particular factor as input or output, especially when the factor can be interpreted either as input or as output.

After selecting suitable variables, then data has to be collected for the analysis. It is important to collect accurate and timely data as the results of whole analysis depends upon these values.

Next step is to find Constant Return to Scale (CRS), Variable Return to Scale (VRS) and NIRS (Non Increasing Return to Scale) efficiencies for each DMU using DEA. Slack analysis also has to be carried out in order to find efficient input values and output values for inefficient units. Then scale efficiency is found by dividing CRS efficiency by VRS efficiency. If scale efficiency for DMU j is equal to one, then the scale efficiency for j+1th DMU can be found. If scale efficiency is not equal to one and VRS efficiency is not equal to one, then input and output variables have to be changed according to the values obtained from slack analysis. If scale efficiency is not equal to one and VRS efficiency is equal to one, then compare NIRS efficiency with VRS efficiency. If NIRS efficiency is equal to VRS efficiency, scale of operation has to be decreased. Otherwise scale of operation has to be increased.

The algorithm showed by figure 3.1 can be used to find the performance of electricity distribution sector as well. In my research this algorithm has been Electronic Theses & Dissertations followed upper to find relative efficiency scores of 20 areas in Distribution Division 02 (DD2) of Ceylon Electricity Board. DD2 consists of three provinces namely Western Province North (WPN), Central Province (CP) and Eastern Province (EP). 06 areas from WPN, 10 areas from CP and 04 areas from EP were selected for the analysis.

DD2 is managed by one Additional General Manager (AGM) and most of the rules and practices are same in all areas under DD2. Therefore areas in DD2 can be considered as homogeneous units which perform similar nature of work and their objective is same. The performance of each area is defined by same set of input output variables. Therefore those 20 areas can be selected as the Decision Making Units (DMUs) for the DEA analysis.

4 EVALUATING DEA EFFICIENCY SCORES

4.1 Selection of Input & Output Variables

4.1.1 Introduction

Selection of suitable input and output variables are very significant in DEA analysis. The criteria of selection of these inputs and outputs are quite subjective. A DEA study should start with an exhaustive, initial list of inputs and outputs that are considered relevant for the study. At this stage, all the inputs and outputs that have a bearing on the performance of the DMUs to be analyzed should be listed. Screening procedures, which may be quantitative or qualitative may be used to pick up the most important inputs and outputs and, therefore reducing the total number to a reasonable level.

Normally, inputs are defined as resources utilized by the DMUs or conditions affecting the performance of DMUs while outputs are the benefits generated as a result of the operation of the DMUs However Dometimes it may become difficult to classify a particular Wactor like input of a butput, especially when the factor can be interpreted either as input or as output.

For a meaningful study, it is important to restrict the total number of inputs and outputs to reasonable levels. Some rules of thumb specified above can help to determine the appropriate number of inputs and outputs. Usually, as the number of inputs and outputs increases, there will be more number of DMUs that will get an efficiency rating of 1, as they become too specialized to be evaluated with respect to other units. In other words, as mentioned earlier, it is possible for DMUs to concentrate on a few inputs and/or outputs and score highest efficiency ratings, leading to large number of DMUs with unit efficiency ratings.

Factors to be considered when selecting input and output variables

- Availability of data
- Relevant to electricity distribution
- Accuracy
- Common usage in available literature
- Represent activity levels of the utilities
- Bearing on the costs

Table 4.1 shows some input and output variables which can be selected for DEA analysis considering the availability of data in DD2.

Input Variables	Output Variables
No of Substations	Sales
MV & LV Network Length	No of Consumers
No of Employees	Revenue Collection
No of New Connections University of Moratuwa, Cost WWW lib.mrt.ac.lk SAIDI & SAIFI	Sri Lanka. ertations

 Table 4.1 Input output variables

4.1.2 Correlation analysis

The strength between two numerical variables is measured by correlation. Here the target is not to use one variable to predict another variable. But it shows the strength of the linear relationship between two variables.

Table 3.2 shows a guild line to correlation analysis. When correlation coefficient $r = \pm 1$ it indicates that there is a perfect positive or negative correlation between those two variables. If the value of r=0 that means there is no any relationship between the two variables. All other values of r fall between -1 & 1 and the value indicates the strength of the relationship between two variables

Table 4.2 below may be used as a guideline as to what adjective should be used for values of r obtained after calculation to describe the relationship [5].

Exactly -1	A perfect negative linear relationship
-0.7	A strong negative linear relationship
-0.5	A moderate negative relationship
-0.3	A weak negative linear relationship
0	No linear relationship
0.3	A weak positive linear relationship
0.5	A moderate positive relationship
0.7	A strong positive linear relationship
Exactly +1	A perfect positive linear relationship

Table 4.2 Guideline to correlation analysis

Table 4.3 shows the resul	Its of correlation	analyzic corriad	out for available	voriables
1 able 4.5 shows the result	its of conclation	i allarysis carrieu	out for available	variables.

UTable 13.3 Resplose sorrelation analysis.											
1000	No of Subs	Elect MV Line Length W	TONI LV Line Length	No of	Ses 0&M Cosk	Connections	ertat SAIDI	ions _{SAIFI}	Sales	No of Consumers	Revenue Collection
No of Subs	1.000										
MV Line Length	0.657	1.000									
LV Line Length	0.648	0.896	1.000								
No of Employees	0.403	0.309	0.296	1.000							
O&M Cost	0.099	-0.101	-0.102	-0.081	1.000						
New Connections	0.768	0.829	0.754	0.342	-0.210	1.000					
SAIDI	-0.219	0.203	0.107	0.122	-0.349	-0.037	1.000				
SAIFI	-0.222	0.257	0.182	0.078	-0.507	-0.041	0.755	1.000			
Sales	0.602	-0.120	-0.086	0.171	0.323	0.087	-0.428	-0.487	1.000		
No of Consumers	0.664	0.615	0.658	0.369	0.289	0.772	-0.220	-0.364	0.435	1.000	
Revenue Collection	0.615	-0.101	-0.068	0.168	0.347	0.109	-0.427	-0.507	0.996	0.473	1.000

Revenue collection and Sales have the highest correlation of 0.996 while LV line length and MV line length have the second highest correlation. No of new connections is highly correlated with no of substations, MV line length and LV line length. No of consumers and no of new connections are also highly correlated having correlation coefficient of 0.772. Also the SAIFI and SAIDI are having a strong correlation with the value 0.755. It is important not to consider highly correlated variables in DEA analysis. Therefore above mentioned highly correlated variables were not used in the analysis simultaneously.

Number of new connections and number of substations are having a correlation coefficient of 0.768. In urban areas, there are more transformers nearby to cater required load. New houses, shops, industries are established rapidly in those areas and new electricity connections have to be provided to them. But in rural areas number of substations are less and they are located far away from each other as load requirement is minimum. On the other hand customers in rural areas doesn't apply for new electricity connections frequently as they don't trend to construct new buildings, shops, industries in a hurry. Therefore it can be noted a high correlation between number of transformers and number of new connections in a particular area.

MV line length and LV line length are having a correlation coefficient of 0.896. If the size of the area is huge in order feed transformers, it is required to draw lengthy HV feeders. Although the existing transformers are slightly loaded in order to provide electricity to whole area, it is mandatory to install new transformers when the distance from existing transformer exceeds 1.8km due to low voltage issues. At Electronic Theses & Dissertations the same time if the size of the area is large, LV feeder length will be lengthier. It can be assumed that, there exists a direct relation between MV line length and LV line length due to above explained matters.

Number of new connections and MV line length have a correlation coefficient of 0.829. But it is difficult to identify a clear reason for the higher correlation exist between these two variables.

Number of new connections and LV line length have a correlation coefficient of 0.754. If the size of the area is large LV line length is higher. But that doesn't mean that consumers in that area apply for more number of new electricity connections. In urban areas although the LV feeder length is shorter, there may be more number of new service connections. Therefore a clear reason for the higher correlation exists between these two variables cannot be identified.

Number of new service connections and number of consumers have a correlation coefficient of 0.772. Number of new service connections provided per year will be added to the existing customer base. Every new service connection means addition of a customer. On the other hand it can be assumed that in a particular area if the number of consumers is high, that area may be an urban, congested area where number of new service connections is high. But if the size of area is high and scale of operation is high there may be more number of customers. Anyhow a direct correlation between number of new service connections provided and number of consumers can be identified.

SAIDI and SAIFI have a correlation coefficient of 0.755. SAIDI means System Average Interruption Duration Index and SAIFI means System Average Interruption Frequency Index. If SAIDI value is high that means average time taken to restore supply when a breakdown occurs is high. If SAIFI value is high that means average number of breakdowns are higher in that particular area. If any area maintaining a reliable power supply by carrying out maintenance work of MV, LV lines and substations properly and construction of a higher quality and construction of the same service connection with a higher quality and carrying out sway deave clearing according to a proper schedule that area time they can restore supply of a breakdown within minimum time period by giving a lower value for SAIDI as well. If any area having more number of breakdowns, they are unable to restore supply within shortest time period as available staff and vehicles are limited. Then both SAIDI and SAIFI value goes high. Therefore it can be noted a direct correlation between SAIDI and SAIFI.

Sales and revenue collection has a correlation coefficient of 0.996. The value of sales is the amount of electricity consumed in rupees and revenue collection is the money received through cash counters. Suppose in a particular area every consumer pay their electricity bills without any arrears before receiving their next month bill. Most of the places monthly electricity consumption has a same pattern. Then it can be assumed that sales of a particular month almost equal to the revenue collection of that month. Anyhow if consumers pay their electricity bills without arrears, then sales and revenue collection must be same. Therefore a very high correlation between sales and revenue collection can be identified.

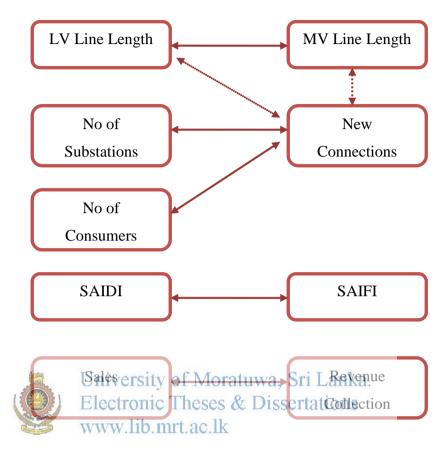


Figure 4.1 Correlated input output variables

MV line length and LV line length have a higher correlation. Therefore it is required to remove one variable out of them from the analysis. In Distribution Division 02 (DD2) there are 03 provinces called Western Province North (WPN), Central Province (CP) and Eastern Province (EP). Each province has a Planning Branch, Construction Branch and Distribution Maintenance Branch. The decisions to draw MV lines were taken by Planning Branch or in some cases by Commercial Branch. Construction of new MV lines are carrying out by Construction Branch while DM branch carryout the routine maintenance work of MV lines. Therefore it can be seen that designing, construction and maintenance of MV lines are not handled by areas. But constructions of LV lines are carried out by respective areas although the most of

the decisions are taken by Planning Branch regarding LV lines. The routine maintenance of LV lines is totally carried out by respective areas. Therefore it is more appropriate to select LV line length for the analysis rather than MV line length.

No of new connections has a higher correlation with both number of substations and number of consumers. Therefore no of new connections is removed from the analysis.

SAIDI and SAIFI have a higher correlation. If SAIDI value is high in a particular area that means time taken to restore supply is higher. Houses, shops, commercial buildings are not having electricity supply for hours. In customer point of view they are really unsatisfied and have a huge loss. For the utility also not providing electricity supply causes a loss. If SAIFI value is high that means there are frequent breakdowns. There may be long duration breakdowns as well as very short period breakdowns. Frequent breakdowns cause a huge loss to customers who are having sensitive electrical equipments. But that kind of customers are limited. Therefore it is reasonable to select SAIDI value for the analysis rather than SAIFI value.

University of Moratuwa, Sri Lanka.

Sales and revenue <u>Edilection has heigher</u> correlation (ilf) sales increase, revenue collection increases automatically as accepted on sales. In order to get correct sales figures it is required to provide accurate bills to consumers within correct time period. Sales can be increased by having proper MV planning proposals to install gantries, primaries grid substations and MV lines, in order to cater existing and future load requirements. Other than that system augmentation jobs has to be carried out to install new distribution substations, to draw new LV lines and for phase conversions to meet the new load additions. Therefore it can be seen that sales figure is more relevant for the analysis rather than revenue collection.

4.1.3 Input and output variables used in literature

Table 4.4 shows the input and output variables used in literature. Although data are available province wise for distribution loss, system peak load, it's hard to find area wise details.

Inputs	Outputs
No of substations	Sales
MV &LV network length	No of consumers
No of employees	Size of service area
Distribution loss	Distribution system peak load
Transformer capacity	
O&M cost	

Table 4.4 Input output variables used in literature

4.1.4 Selection of input and output variables for the analysis

Correlation analysis and variables used in literature were considered when selecting input and output variables for the analysis. As sales and revenue collection are highly correlated only sales were used for the analysis. Out of MV line length and LV line length, only LV line length was selected as they have the second highest correlation. LV line length reveals the extension of the electricity network and it also relates to the no of breat downs occurring within that area As no of new connections is highly correlated with novofy substations. MYkline length, LV line length and No of consumers it is not selected for the analysis. Out of SAIDI and SAIFI, only SAIDI was used for the analysis as they are highly correlated. Table 4.5 shows the selected 5 input variables and 2 output variables for the analysis.

Table 4.5 Selected in	nput output	variables for	the analysis
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Inputs	Outputs
No of substations	Sales
LV line length	No of consumers
No of employees	
O&M cost	
SAIDI	

Following assumptions were made when collecting data for input and output variables

- All the employees in a unit og organization are considered to be homogenous. That is whether he is an engineer or meter reader, he is considered as a single employee
- The O&M cost includes both labor and non-labor costs
- All consumers are considered homogenous. That means they are not categorized according to the tariff.
- SAIDI was calculated considering total customer interruption durations per year
- Substations are not differentiated based upon their category (ordinary or bulk) or capacity.
- Sales for all categories of consumers are considered

4.1.5 Selection of DMUs

Homogeneity and number of DMUs are considered when selecting DMUs for the DEA analysis All the selected DMUs must be homogenous units. They should perform similar nature of work and objective of each unit should be same. The input and output variables which describes the performance of the DMUs should be same, but the quantity and value of variables may be different. According to the objective of the DEA study the number of DMUs to be compared has to be decided. But there are some facts to be considered when selecting DMUs for a DEA study.

If the number of DMUs is high, then the probability of capturing high performance units that determine the efficiency frontier will also be high. A large number of DMUs will also enable a sharper identification of typical relations between inputs and outputs. In general, as the number of DMUs increases, more inputs and outputs can be incorporated in a DEA analysis. However, the DEA analyst should be cautious not to increase the number of units unnecessarily. The most important consideration in the selection of the number of DMUs should be the homogeneity of the DMUs. One should not relax this and include heterogeneous units which are not comparable with the rest just for the sake of increasing the number of DMUs. In this research, 20 areas in Distribution Division 02 (DD2) were considered for the analysis. DD2 consists of three provinces namely Western Province North (WPN), Central Province (CP) and Eastern Province (EP). 06 areas from WPN, 10 areas from CP and 04 areas from EP were selected for the analysis.

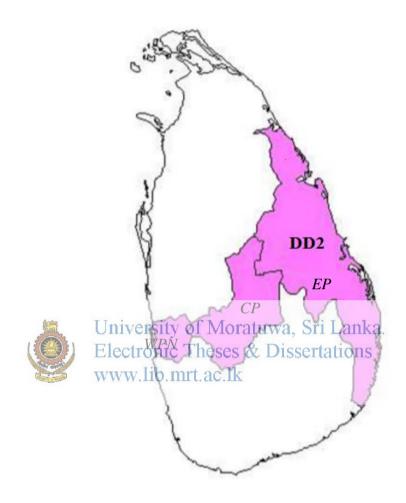


Figure 4.2 Distribution Division 02

DD2 is managed by one Additional General Manager (AGM) and most of the rules and practices are same in all areas under DD2. Therefore areas in DD2 can be considered as homogeneous units which perform similar nature of work and their objective is same. The performance of each area is defined by same set of input output variables. Table 4.6 shows the selected DMUs for the DEA analysis.

Province	Area
	Kelaniya
	Negombo
	Gampaha
WPN	Veyangoda
	Ja-Ela
	Diulapitiya
	Kandy City
	Peradeniya
	Katugastota
	Galagedara
	Kundasale
	Kegalle
СР	Mawanella
	Matale
	Dambulla
	Nawalapitiya
	Trincomalee
FD	Ampara
University of Morat	uKatmushai Lanka.
Electronic Theses &	
www.lib.mrt.ac.lk	

Table 4.6 Selected DMUs for the analysis

4.2 DEA Analysis

4.2.1 Input oriented CRS efficiency score

Out of two orientations input oriented and output oriented, input oriented model was selected for the analysis. In input oriented models inputs are controllable while outputs are uncontrollable. The manager of a distribution utility has to meet customer requirements with available resources. In this situation it can be assumed that outputs are fixed or uncontrollable to the utility manager. But he can reduce the resources used by implementing managerial techniques. In this analysis sales and number of consumers are selected as output variables and those cannot be increased as per utility's requirements. It is out of the control of utility. Variables like O&M cost, No of employees and SAIDI have been selected as input variables. The controls of those variables are on the hand of utility managers and inputs can be considered as

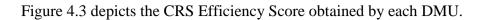
controllable variables. Therefore it is reasonable to select input oriented model for the analysis rather than output oriented model.

Out of two return to scale versions CRS and VRS, CRS model was selected first for the analysis. It provides an overall efficiency score and can be considered as a long run measure of efficiency.

DEA model was solved using DEA Frontier Software. Efficiency scores for the Input Oriented CRS (Constant Returns to Scale) model were obtained and are listed in table 4.7.

DMU No.	DMU Name	CRS Efficiency	Sum of lambdas	RTS
1	Kelaniya	1.0000	1.000	Constant
2	Negombo	0.9988	0.954	Increasing
3	Gampaha	1.0000	1.000	Constant
4	Veyangoda	0.9819	0.921	Increasing
15	Ulai Etarsity of	Moggewa	, Sr00 0an	k Constant
	EDiulapitiya T	nes@.8083Di	SS@:65801	Increasing
	KandyGitynt	ac110000	1.000	Constant
8	Peradeniya	1.0000	1.000	Constant
9	Katugastota	0.9153	0.753	Increasing
10	Galagedara	1.0000	1.000	Constant
11	Kundasale	0.7646	0.863	Increasing
12	Kegalle	1.0000	1.000	Constant
13	Mawanella	1.0000	1.000	Constant
14	Matale	0.9043	0.727	Increasing
15	Dambulla	0.6906	0.650	Increasing
16	Nawalapitiya	0.9114	0.851	Increasing
17	Trincomalee	0.8433	0.833	Increasing
18	Ampara	0.8121	0.919	Increasing
19	Kalmunai	1.0000	1.000	Constant
20	Batticaloa	1.0000	1.000	Constant

Table 4.7 Efficiency scores for input oriented CRS model



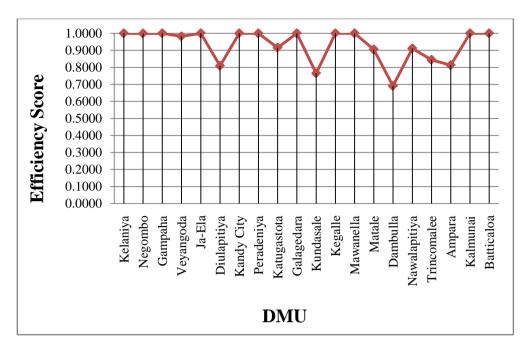


Figure 4.3 CRS efficiency score plot

It can be noted that out of 20 DMUs, 10 DMUs obtained efficiency score 1.0. Dambulla area has the lowest efficiency score and Kundasale and Divulapitiya areas have relatively lower efficiency scores compared to other DMUs. As Constant WWW.lib.mrt.ac.lk Returns to Scale version was considered for the analysis the analysis doesn't provide a short run efficiency measurement. The DMUs which have lower efficiency scores have to alter their scale of operation in order to reach efficiency frontier. DMUs can be ranked according to the obtained results. Table 4.8 shows the rank of each DMU according to the results obtained for DEA analysis.

Rank	Efficiency Score	DMU
1	1.0000	Kelaniya
1	1.0000	Gampaha
1	1.0000	Ja-Ela
1	1.0000	Kandy City
1	1.0000	Peradeniya
1	1.0000	Galagedara
1	1.0000	Kegalle
1	1.0000	Mawanella
1	1.0000	Kalmunai
1	1.0000	Batticaloa
11	0.9988	Negombo
12	0.9819	Veyangoda
13	0.9153	Katugastota
14	0.9114	Nawalapitiya
15	0.9043	Matale
16	0.8433	Trincomalee
Univer		Sri Amplara
Electro	nic Theses & Dis	sertDiulapitiya
19	0.7646	Kundasale
20 W.1	0.6906	Dambulla

Table 4.8 Ranks of DMUs

4.2.2 Efficiency reference set

Conner 2

Efficiency Reference Set (ERS) indicates the relatively efficient DMUs against which the inefficient DMUs were most clearly determined to be inefficient [2]. Table xx indicates ERS values for each inefficient DMU. It can be noted that Negombo area was found to have operating inefficiencies in direct comparison to Kelaniya, JaEla and Batticaloa. The value in parenthesis in table xx represents the relative weight assigned to each efficiency reference set (ERS) member to calculate the efficiency score (θ). If a DMU's efficiency score is 100%, then that DMU is its own ERS and we generally don't report it as an ERS which is the reason DMUs like Kelaniya, Gampaha, JaEla have not reported ERS in the table 4.9.

Table 4.9 ERS values of DMUs

DMU	Efficie	Efficiency Reference Set (ERS)
	ncy	
Kelaniya	1.0000	
Negombo	0.9988	Kelaniya (0.046), JaEla (0.710), Batticaloa (0.198)
Gampaha	1.0000	
Veyangoda	0.9819	Kelaniya (0.038), Gampaha (0.050), JaEla (0.074), Kegalle (0.208), Kalmunai (0.245), Batticaloa (0.306)
Ja-Ela	1.0000	
Diulapitiya	0.8083	JaEla (0.185), Kegalle (0.226), Mawanella (0.046), Batticaloa (0.201)
Kandy City	1.0000	
Peradeniya	1.0000	
Katugastota	0.9153	Kegalle (0.077), Mawanella (0.264), Kalmunai (0.337), Batticaloa (0.074)
Galagedara	1.0000	
Kundasale	0.7646	Gampaha (0.233), Peradeniya (0.004), Mawanella (0.291), Batticaloa (0.334)
Kegalle	1.0000	
Mawanella	1.0000	
Matale	0.9043	JaEla (.002), Kegalle (0.140), Mawanella (0.12), Kalmunai (0.445)
Dambulla	0.6906iv	ClaElay (0.021), raKesalle S(0.050), Mawanella (0.028), Kalmunai (0.079), Batticaloa (0.473)
Nawalapitiya	0.9114C	Regatle (0.174), Mawanella (0.037), Kalmunai (0.367),
Trincomalee	0.8433	Kelaniya (0.132), JaEla (0.60), Kegalle (0.170), Batticaloa
	0.0101	(0.471)
Ampara	0.8121	Batticaloa (0.919)
Kalmunai	1.0000	
Batticaloa	1.0000	

4.2.3 VRS efficiency score

Variable Return to Scale Efficiency can be identified as technical efficiency or managerial efficiency. For a given scale of operation management practices and work can be measured by VRS efficiency score. It totally depends on managerial performance.

By adding single additional formulae the DEA analysis changes to VRS. In CRS model it is assumed that scale of economies don't change as size of the DMU increases. But after adding below mentioned equation to the DEA formulae it allows

the existence of economies and diseconomies of scale. The additional constraint equation is,

$$\sum_{j=1}^n \lambda_j = 1$$

Efficiency scores for the Input Oriented VRS (Variable Returns to Scale) model were obtained and are listed in table 4.10.

DMU No	DMU Name	Input Oriented VRS Efficiency
1	Kelaniya	1.000
2	Negombo	1.000
3	Gampaha	1.000
4	Veyangoda	1.000
5	Ja-Ela	1.000
6	Diulapitiya	1.000
7	Kandy City	1.000
S ATTACZ	~	ratuwa, Soo Lanka.
Ele	Kangastotaleses	& Dissections
20 WV	VGalagedara.ac.ll	1.000
11	Kundasale	0.818
12	Kegalle	1.000
13	Mawanella	1.000
14	Matale	1.000
15	Dambulla	1.000
16	Nawalapitiya	0.991
17	Trincomalee	0.943
18	Ampara	0.872
19	Kalmunai	1.000
20	Batticaloa	1.000

Table 4.10 VRS efficiency scores

It can be noted that most of the DMUs have obtained efficiency scores of 1.0. DMUs like Ampara, Kundasale, Trincomalee and Nawalapitiya have obtained lower efficiency scores. That means compared to other DMUs they are technically inefficient. Managerial efficiency or managerial performance is less compared to

others. Their efficiency score can be increased by implementing best management practices in order to reduce the inputs used and increase the outputs.

4.2.4 Slack analysis

n

Slack analysis was carried out for input oriented VRS model. Technically inefficient DMUs are using excessive resources for producing given level of output. In order to find out amount of resources which have been used in excess, slack analysis has to be carried out. For this purpose Input oriented VRS model has been used.

In DEA after solving dual linear program it is required to solve a second stage linear programming model to find slack values.

In order to find slack values second stage linear program is formulated as follows [6]

$$Maximize \sum_{i=1}^{m} s_i^{-} + \sum_{r=1}^{s} s_r^{+}$$
(3.1)

$$\lambda_j \ge 0 \qquad \qquad \mathbf{j} = 1, \dots, \mathbf{n} \tag{3.4}$$

Here, the symbol $s_r^+ \theta^*$ denotes the efficiency score obtained from previous DEA analysis. Here s_r^+ and s_i^- represents output and input slacks respectively.

It should be noted that (-) sign on s indicates a reduction of outputs produced and (+) sign on s indicates increment of outputs produced.

Table 3.11 indicates the input slack values and output slack values obtained for each DMU. If each DMU can change their input and output values according to the slack values they can score higher efficiency values. It can be noted that the DMUs which have 100% efficiency scores don't have slacks. Only the DMUs which have efficiency scores below 100% have slacks. By changing inputs and outputs according to the slack values obtained, DMUs can reach their efficiency target.

As an example it can be noted that Katugasthota area needs to reduce its SAIDI value by 0.173. As there are not any input slacks to be reduced, it is required to increase its sales by 83.929 million.

Ν	DMU		In	Output Slacks				
0	Name	No of	LV line	No of	O&M	SAIDI	Sales	No of
		subs	length	emplo	Cost			consu
				yees				mers
1	Kelaniya	0.000	0.000	0.000	0.000	0.000	0.000	0.000
2	Negombo	0.000	0.000	0.000	0.000	0.000	0.000	0.000
3	Gampaha	0.000	0.000	0.000	0.000	0.000	0.000	0.000
4	Veyangoda	0.000	0.000	0.000	0.000	0.000	0.000	0.000
5	Ja-Ela	0.000	0.000	0.000	0.000	0.000	0.000	0.000
6	Diulapitiya	0.000	0.000	0.000	0.000	0.000	0.000	0.000
7	Kandy City	Unive	rsity of 1	Moratu	0.009 wa, Sri	L <u>0.000</u> Lanka.	0.000	0.000
8	Peraceniya	Electr	ongoophe	s&&&	D9ssert	aticops	0.000	0.000
9	Katugastot	W:000 .	lib. ADDt. a	C.0.000	0.000	0.000	0.000	0.000
10	Galagedara	0.000	0.000	0.000	0.000	0.000	0.000	0.000
11	Kundasale	0.000	224.978	0.000	39.970	0.000	0.000	0.000
12	Kegalle	0.000	0.000	0.000	0.000	0.000	0.000	0.000
13	Mawanella	0.000	0.000	0.000	0.000	0.000	0.000	0.000
14	Matale	0.000	0.000	0.000	0.000	0.000	0.000	0.000
15	Dambulla	0.000	0.000	0.000	0.000	0.000	0.000	0.000
16	Nawalapiti	1.970	0.000	0.000	8.464	0.000	829.372	0.000
17	Trincomale	16.754	378.996	0.000	18.355	0.000	0.000	0.000
18	Ampara	64.414	752.993	7.072	29.637	0.000	212.445	0.000
19	Kalmunai	0.000	0.000	0.000	0.000	0.000	0.000	0.000
20	Batticaloa	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4.11 Input and output slack values

4.2.5 Efficiency targets for inputs & outputs

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In DEA analysis for an input oriented model the efficiency targets for inputs and outputs can be calculated as follows [6].

Target value for inputs = input value * optimal efficiency score - slack value

$$x_{io} = \theta^* x_{io} - s_i^{-*}$$
 $i = 1,...,m$ (3.5)

Target value for outputs = output value + slack value

$$\tilde{y}_{ro} = y_{ro} + s_i^{+*}$$
 r = 1,....,s (3.6)

Table 4.12 indicates the input targets and output targets for each DMU.

Ν	DMU		Efficien	Efficient Output				
0	Name	No of	LV line	No of O&M		SAID	Sales	No of
		subs	length	employ	Cost	Ι		consum
1	Kelaniya	624.96	1424.35	182.00	293.10	1.61	8194.67	116428.
2	Negombo	51714ve	191529.36	M08.001	W243.4911	Lanka	1. 6494.36	93349.0
3	Gampaha	410.38tr	011489.3610	C. 244.08	Dissearta	tic28S	2614.42	107199.
4	Veyangoda	367.68V.	105.32104.2	10.65.00	230.60	1.40	2337.54	89901.0
5	Ja-Ela	479.04	818.75	211.00	280.47	1.33	7995.18	89486.0
6	Diulapitiya	328.32	1681.55	147.00	191.74	1.30	2308.98	63239.0
7	Kandy City	180.00	437.32	189.00	195.38	1.03	2617.64	41054.0
8	Peradeniya	346.00	2031.30	189.00	303.50	1.61	1406.48	99570.0
9	Katugastota	194.00	872.30	142.00	202.23	1.42	789.31	54390.0
10	Galagedara	186.00	1066.00	248.00	173.14	0.70	811.77	59286.0
11	Kundasale	342.95	1584.39	196.44	175.91	0.90	1550.61	82278.0
12	Kegalle	268.00	2297.39	133.00	280.56	2.11	1577.18	85974.0
13	Mawanella	138.00	1004.62	200.00	193.16	0.97	671.14	53452.0
14	Matale	188.00	779.83	128.00	275.17	2.15	1017.29	52721.0
15	Dambulla	441.00	1866.20	180.00	176.29	0.98	1407.27	71774.0
16	Nawalapitiy	311.26	1376.25	154.63	217.75	1.45	2016.12	77299.0
17	Trincomale	446.44	1913.53	172.63	188.39	1.13	2865.65	93471.0
18	Ampara	490.94	2105.49	209.14	157.03	0.75	1993.82	113540.
19	Kalmunai	237.00	550.34	154.00	299.46	1.94	1217.01	72613.0
20	Batticaloa	547.00	2296.57	202.00	154.07	0.76	2211.11	123513.

Table 4.12 Efficient input and output targets

4.2.6 Scale efficiency

n

In CRS model it is assumed that the size of the organization or unit is not relevant to evaluate its relative efficiency score. That is in CRS model it is assumed that smaller organizations can produce outputs with same ratio of input to output like larger units or organizations. This assumption can be considered correct here as there are not economies or diseconomies of scale available. As an example if the inputs are doubled then outputs will also be doubled. But this assumption is not correct for the DMUs which have economies or diseconomies of scale. The organizations which have increasing return to scale that is economies of scale present then doubling all inputs lead to more than doubling of outputs. That is because managers can spread the overheads more effectively or they can obtain profits by purchasing materials in bulk scale. On the other hand if the DMU has decreasing returns to scale that is if diseconomies of scale present then doubling of all inputs will lead to less than doubling of outputs. Therefore all organizations must ensure that they are operating at optimal size without being too small or too large. Otherwise they will have increasing returns to scale or decreasing returns to scale instead of having constant University of Moratuwa, Sri Lanka. returns to scale. **Electronic Theses & Dissertations**

A DMU is said to be scale efficient if it is operating in its optimal size and it is said to be scale inefficient if it is operating below or beyond its optimal size.

$$Scale \ Efficiency = \frac{CRS \ Efficiency}{VRS \ Efficiency}$$
(3.7)

If **Scale Efficiency = 1**, DMU is apparently operating at optimal scale.

If **Scale Efficiency** <1, DMU appears to be either too small or too large relative to its optimum size.

In order to determine whether the DMU is too small or too large it is required to run a 3^{rd} variant of DEA subject to non increasing return to scale (NIRS). The NIRS constraint can be indicated as follows.

$$\sum_{j=1}^{n} \lambda_j \le 1 \tag{3.8}$$

Then compare Variable Return to Scale Efficiency (VRS) and Non Increasing Returns to Scale Efficiency (NIRS) in order to determine scale efficiency.

If VRS Efficiency Score = NIRS Efficiency Score

Then DMU is said to be in the region of decreasing returns to scale (DRS) and it is too large relative to its optimal size. That means if all the inputs are doubled then the outputs produced will not be doubled and it will increase by an amount which is less than doubling.

If VRS Efficiency Score > NIRS Efficiency Score

Then DMU is said to be operating in the region of increasing returns to scale (IRS) and it is too small relative to its optimal size. That means doubling all inputs will lead to more than doubling of outputs.

DMU			Scale Efficiency	RTS	
Kelaniya Univ	ersitoot	M0.636uv	ra, <u>1</u> 500La	Constant	
Negembo Elec	roaisesTh	eseso o D	iscentatic	Indreasing	
Gampaha WWV	v.lib999rt.	ac.11000	1.000	Constant	
Veyangoda	0.982	1.000	0.982	Increasing	
Ja-Ela	1.000	1.000	1.000	Constant	
Diulapitiya	0.808	1.000	0.808	Increasing	
Kandy City	1.000	1.000	1.000	Constant	
Peradeniya	1.000	1.000	1.000	Constant	
Katugastota	0.915	1.000	0.915	Increasing	
Galagedara	1.000	1.000	1.000	Constant	
Kundasale	0.765	0.818	0.934	Increasing	
Kegalle	1.000	1.000	1.000	Constant	
Mawanella	1.000	1.000	1.000	Constant	
Matale	0.904	1.000	0.904	Increasing	
Dambulla	0.691	1.000	0.691	Increasing	
Nawalapitiya	0.911	0.991	0.919	Increasing	
Trincomalee	0.843	0.943	0.894	Increasing	
Ampara	0.812	0.872	0.932	Increasing	
Kalmunai	1.000	1.000	1.000	Constant	
Batticaloa	1.000	1.000	1.000	Constant	

4.2.7 Summary of results and recommendations

 Table 4.13 Summary of efficiency scores

Table 3.13 summarizes the CRS Efficiency, VRS Efficiency, Scale Efficiency and Return to Scale for each DMU. Return to Scale indicates whether a DMU is operating at increasing return to scale (IRS), decreasing return to scale (DRS) or constant return to scale (CRS). A DMU is said to be scale efficient if it is able to produce similar proportionate increase in input.

It can be seen that Ten DMUs out of twenty are found to be scale efficient that means they are operating in constant returns to scale (CRS). On the other hand DMUs like Negombo, Veyangoda, Kundasale etc are operating in Increasing Return to Scale (IRS). They need to increase its scale of operation in order to reach efficiency frontier. In this analysis there are not DMUs which are operating in Decreasing Return to Scale (DRS). DMUs like Kelaniya, Jaela, Kegalle etc exhibit CRS characteristic which means they have the optimal scale size.

Figure 4.2 depicts the technical efficiency (VRS) and Scale efficiency for all the DMUs being considered. It can be noted that although most of the DMUs are technically efficient their overall efficiency is low as they are not operating at their optimal scale of operation.

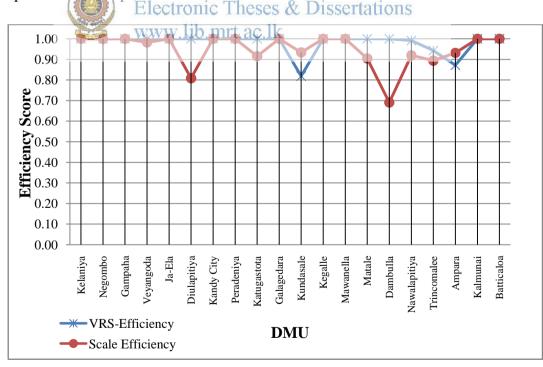


Figure 4.4 VRS and Scale efficiency score plot

Table 4.14 shows the DEA results and recommendations for each area in order to reach efficiency frontier.

DMU	DEA Result	Recommendation
Kelaniya	Technical efficiency and scale efficiency is 1.0	As the area is efficient compared to 20 areas in DD2 it is not required to change the system in short run. But after carrying out a DEA analysis with all the areas in CEB a long run improvement can be done.
Negombo	Technical efficiency 1 but scale efficiency is less than 1. RTS increasing.	Scale of operation has to be increased.
Gampaha	Technical efficiency and scale efficiency is 1.0	As the area is efficient compared to 20 areas in DD2 it is not required to change the system in short run. But after carrying out a DEA analysis with all the areas in CEB a long run improvement can be done.
Veyangoda	Technical efficiency 1 but scale efficiency ses lessywthanib.mrt.RTSk increasing.	Scale of operation has to be increased.
Ja-Ela	Technical efficiency and scale efficiency is 1.0	As the area is efficient compared to 20 areas in DD2 it is not required to change the system in short run. But after carrying out a DEA analysis with all the areas in CEB a long run improvement can be done.
Diulapitiya	Technical efficiency 1 but scale efficiency is less than 1. RTS increasing.	Scale of operation has to be increased.
Kandy City	Technical efficiency and scale efficiency is 1.0	As the area is efficient compared to 20 areas in DD2 it is not required to change the system in short run. But after carrying out a DEA analysis with all the areas in CEB a long run improvement can be done.
Peradeniya	Technical efficiency and scale efficiency is 1.0	As the area is efficient compared to 20 areas in DD2 it is not required to change the system in short run. But

Table 4.14 Summary of recommendation

		after carrying out a DEA analysis with
		all the areas in CEB a long run
		improvement can be done.
Katugastota	Technical efficiency 1	Scale of operation has to be increased
	but scale efficiency is	
	less than 1. RTS	
	increasing.	
Galagedara	Technical efficiency	As the area is efficient compared to 20
	and scale efficiency is	areas in DD2 it is not required to
	1.0	change the system in short run. But
		after carrying out a DEA analysis with
		all the areas in CEB a long run
		improvement can be done.
Kundasale	Technical efficiency	LV line length has to be reduced by
	and scale efficiency is	224.97km and O&M cost has to be
	less than 1. RTS	reduced by 39.97M. Scale of operation
	increasing.	has to be increased.
Kegalle	Technical efficiency	As the area is efficient compared to 20
Regalle	2	-
	and scale efficiency is 1.0	areas in DD2 it is not required to
	1.0	change the system in short run. But
		after carrying out a DEA analysis with
		all the areas in CEB a long run
11 21		improvement can be done.
Mawanella	Technicalersitefficiency	As the area is efficient compared to 20
	and scale efficiency is	areas in DD2 it is not required to
Alter spint	www.lib.mrt.ac.lk	change the system in short run. But
	w w w.mo.mit.ac.ik	arter carrying out a DEAL analysis with
		all the areas in CEB a long run
		improvement can be done.
Matale	Technical efficiency 1	Scale of operation has to be increased
	but scale efficiency is	
	less than 1. RTS	
	increasing.	
Dambulla	Technical efficiency 1	Scale of operation has to be increased
	but scale efficiency is	
	less than 1. RTS	
	increasing.	
Nawalapitiya	Technical efficiency	No of substations has to be reduced by
	and scale efficiency is	1.97 and O&M cost by 8.46M. Scale
	less than 1.RTS	of operation has to be increased.
	increasing.	· ·
Trincomalee	Technical efficiency	No of substations has to be reduced by
	and scale efficiency is	16.75 and LV line length by 378.99km.
	less than 1. RTS	O&M cost has to be reduced by
	increasing.	18.35M. Scale of operation has to be
	g.	increased.
	l	11111040004.

Ampara	Technical efficiency and scale efficiency is less than 1. RTS increasing.	No of substations has to be reduced by 64.41, LV line length by 752.99km, No of employees by 7.0, and O&M cost by 29.63. Scale of operation has to be increased.
Kalmunai	Technical efficiency and scale efficiency is 1.0	As the area is efficient compared to 20 areas in DD2 it is not required to change the system in short run. But after carrying out a DEA analysis with all the areas in CEB a long run improvement can be done.
Batticaloa	Technical efficiency and scale efficiency is 1.0	As the area is efficient compared to 20 areas in DD2 it is not required to change the system in short run. But after carrying out a DEA analysis with all the areas in CEB a long run improvement can be done.



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5 DEA ANALYSIS WITH DIFFERENT MODELS

5.1 Preparation of Different Models

Other than the base model DEA analysis was carried out for several models in order to analyze the variation of the results for different input output combinations and to justify the selected base model for the analysis. Table 5.1 shows the different models formed with different input output combinations.

Model 1 is the base model selected for previous analysis. There are 7 input output variables from model 1 to 6. Model 1,2,3,4 & 6 have five input variables and two output variables. Model 5 has four input variables and three output variables. From model 7 to 13 there are only 6 input output variables. In each model one variable is excluded from the base model. Out of the variables selected for the base model most important and strengthen variables can be identified by this analysis.

	Table 5.1 Different DEA models University of Moratuwa, Sri Lanka. (())) Electronic Theses & Dissertations													
	Model ww	w ¹	il^2 n	n3	ac411	~ 5	6	7	8	9	10	11	12	13
	No of subs	1	1	1	1	1	1	0	1	1	1	1	1	1
	LV line length	1	0	1	0	1	1	1	0	1	1	1	1	1
Inputs	MV line length	0	1	0	0	0	0	0	0	0	0	0	0	0
Inputs	No of employees	1	1	1	1	1	1	1	1	0	1	1	1	1
	O&M Cost	1	1	1	1	1	1	1	1	1	0	1	1	1
	SAIDI	1	1	0	1	0	1	1	1	1	1	1	1	0
	SAIFI	0	0	1	1	0	0	0	0	0	0	0	0	0
	Sales	1	1	1	1	1	1	1	1	1	1	0	1	1
Outputs	No of consumers	1	1	1	1	1	0	1	1	1	1	1	0	1
	New Connections	0	0	0	0	1	1	0	0	0	0	0	0	0

5.2 Efficiency Scores for Different Models

5.2.1 CRS efficiency score

Input oriented CRS efficiency scores for each model were obtained and are list in table 5.2. It can be noted that for some models efficiency score has slightly changed

and for other models it has dropped significantly. There are some DMUs like Kelaniya, Jaela which were able to stay at same efficiency score for all the models.

Here the variation of CRS efficiency score were obtained for each model. It provides an idea about how the overall efficiency or long run measure of efficiency varies for each model.

	Model	1	2	3	4	5	6	7	8	9	10	11	12	13
	Kelaniya	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Negombo	0.962	0.962	0.962	0.962	0.962	0.951	0.958	0.962	0.962	0.902	0.855	0.941	0.962
	Gampaha	1.000	1.000	1.000	1.000	0.991	0.719	0.954	1.000	1.000	0.913	1.000	0.453	0.991
	Veyangoda	0.981	1.000	0.982	0.982	0.981	0.653	0.861	0.954	0.957	0.945	0.959	0.381	0.981
	Ja-Ela	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Diulapitiya	0.813	0.820	0.808	0.813	0.808	0.616	0.683	0.813	0.812	0.753	0.744	0.422	0.808
	Kandy City	1.000	1.000	1.000	1.000	1.000	0.934	0.807	1.000	1.000	1.000	0.803	0.871	1.000
	Peradeniya	0.983	0.954	0.984	0.984	0.983	0.634	0.824	0.954	0.923	0.931	0.983	0.244	0.983
T OC	Katugastota	0.915	0.889	0.915	0.859	0.915	0.663	0.717	0.859	0.895	0.872	0.915	0.244	0.915
Efficiency Scores of	Galagedara	1.000	1.000	1.000	0.997	1.000		A .	0.997		0.881	1.000	0.261	1.000
DMUs	Kundasale UN	1 V.632	50.729	8.744	6.94	9.932	0.631	0.579	0.729	0.728	0.634	0.726	0.222	0.732
0	Ele	cimo	11iQ	Too	S.008	Não I	0.128	senta	tio	10.996	1.000	1.000	0.353	1.000
	Matvaneila WW	1.000	1000	11:000	d.000	1.000	0.853	0.673	1.000	1.000	1.000	1.000	0.291	1.000
	Matale	0.904	0.859	0.904	0.859	0.912	0.735	0.721	0.859	0.861	0.904	0.887	0.324	0.904
	Dambulla	0.691	0.683	0.691	0.683	0.691	0.592	0.649	0.683	0.685	0.662	0.686	0.280	0.691
	Nawalapitiya	0.911	0.870	0.911	0.868	0.911	0.624	0.781	0.868	0.884	0.886	0.911	0.225	0.911
	Trincomalee	0.834	0.834	0.834	0.834	0.867	0.856	0.816	0.834	0.827	0.794	0.819	0.459	0.834
	Ampara	0.766	0.766	0.766	0.766	0.766	0.714	0.745	0.766	0.763	0.715	0.766	0.292	0.766
	Kalmunai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.451	1.000
	Batticaloa	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.503	1.000

Table 5.2 CRS efficiency scores for different models

5.2.2 VRS Efficiency Score

Input oriented VRS efficiency scores for each model were obtained and are list in table 5.3. It can be noted that for some models efficiency score has slightly changed and for other models it has dropped significantly. There are some DMUs like Kelaniya, Jaela, Kandy City and Batticaloa which were able to stay at same efficiency score for all the models.

Here the variation of VRS efficiency score were obtained for each model. It provides an idea about how the technical efficiency or managerial efficiency varies for each model. For a given scale of operation work, management practices are measured by VRS efficiency score.

	Model	1	2	3	4	5	6	7	8	9	10	11	12	13
	Kelaniya	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Negombo	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.906	0.910	1.000	1.000
	Gampaha	1.000	1.000	1.000	1.000	1.000	0.856	0.962	1.000	1.000	1.000	1.000	0.856	1.000
_	Veyangoda	1.000	1.000	1.000	1.000	0.997	0.928	0.995	0.986	0.961	0.949	0.997	0.908	0.997
_	Ja-Ela	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
_	Diulapitiya	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
_	Kandy City	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
_	Peradeniya	1.000	1.000	1.000	1.000	1.000	0.773	0.863	1.000	1.000	1.000	1.000	0.736	1.000
Efficiency	Katugastota	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.950	0.962	1.000	1.000	1.000
- Scores of	Galagedara	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.895	1.000	1.000	1.000
DMUs	Kundasale	0.753	0.750	0.774	0.774	0.747	0.736	0.720	0.750	0.727	0.645	0.752	0.710	0.747
_	Kegalle	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.994	1.000
_	Mawanella	1.000	1.000			1.000	1.000	1.000	1.000	1.000	1.00 0	1.000	1.000	1.000
_	Matale U	11000	115000	1.000	1.000	1ato	171000	Bopo	1.000	0,926	1.00 0	1.000	1.000	1.000
_	Danbula } E1	0,983	01972	0:982	<u>6.979</u>	0.982	0983	0.988	0.979	0.937	0.754	0.983	0.983	0.982
	Navolapitiya	0.984	1 1 1 1	1.1.4.1.	$\alpha \alpha$	0.984	0.942	0.984	0.957	0.885	0.92 3	0.984	0.911	0.984
	Trincomalee	0.921	0.921	0.921	0.921	0.955	0.955	0.921	0.921	0.837	0.80 6	0.906	0.885	0.921
	Ampara	0.773	0.773	0.773	0.773	0.773	0.764	0.771	0.773	0.764	0.74 2	0.773	0.763	0.773
	Kalmunai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	Batticaloa	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 5.3 VRS efficiency scores for different models

5.3 Analysis With Base Model & Different Models

5.3.1 Efficiency scores of base model and model 2

In base model LV line length is considered as an input variable. In model 2 instead of LV line length MV line length is considered as an input variable.

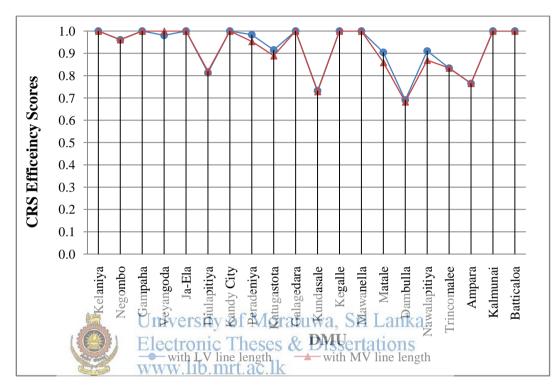


Figure 5.1 CRS efficiency scores of base model and model 2

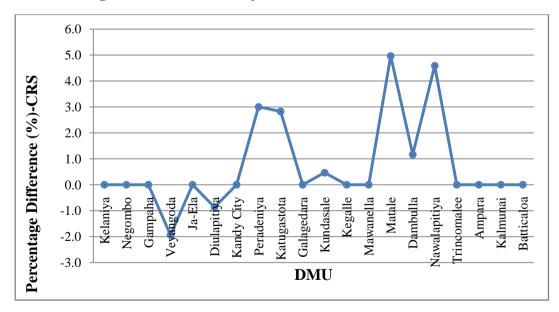


Figure 5.2 Percentage difference of model 2 with base model -CRS

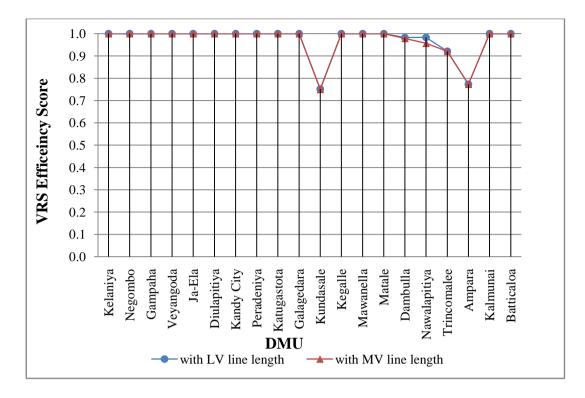


Figure 5.3 VRS efficiency scores of base model and model 2

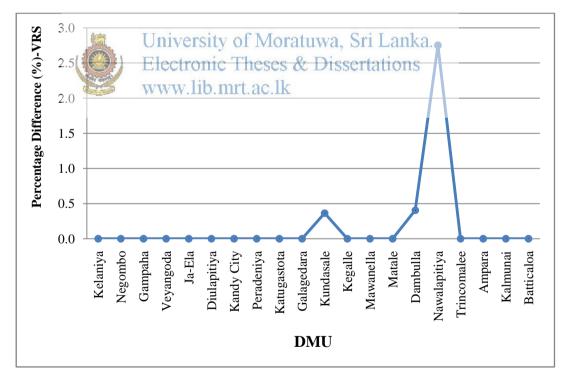


Figure 5.4 Percentage difference of model 2 with base model -VRS

Figure 5.1 shows the CRS efficiency scores of base model and model 2 and figure 5.2 shows the percentage difference with base model. It can be noted that both efficiency scores are almost same for the two models. From the figure 5.2 it can be clearly identified that the percentage difference with base model is almost zero.

Figure 5.3 shows the VRS efficiency scores of base model and model 2 and figure 5.4 shows the percentage difference with base model. Same as CRS efficiency score, VRS efficiency score of model 2 has a very slight variation which is almost equal to zero compared to base model.

It can be concluded that as MV line length and LV line are highly correlated, it is sufficient to select only one variable out of them for the DEA analysis. The reason of having a high correlation between these two variables and the reason to select LV line length for the analysis instead of MV line length was discussed in chapter 4.

5.3.2 Efficiency scores for base model and model 3

In base model SAIDI is considered as an input variable. In model 3 instead of SAIDI, SAIFI is considered last invitable oratuwa, Sri Lanka.

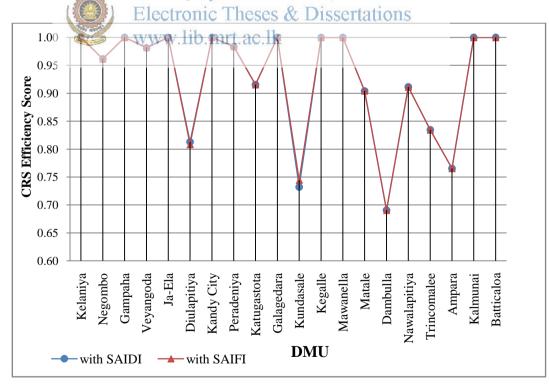


Figure 5.5 CRS efficiency scores of base model and model 3

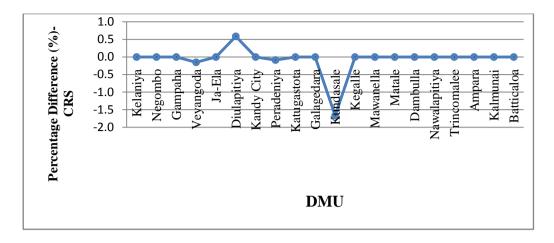


Figure 5.6 Percentage difference of model 3 with base model -CRS

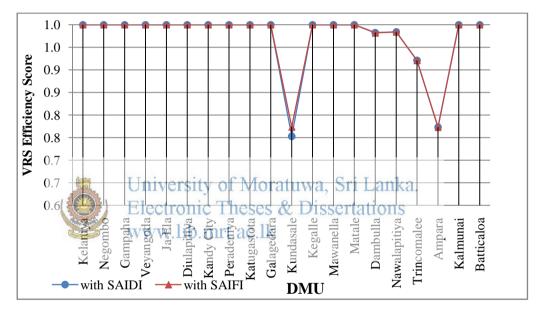


Figure 5.7 VRS efficiency scores of base model and model 3

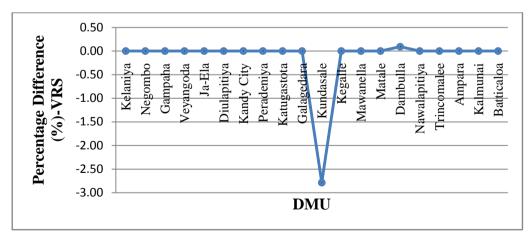


Figure 5.8 Percentage difference of model 3 with base model -VRS

Figure 5.5 shows the CRS efficiency scores of base model and model 3 and figure 5.6 shows the percentage difference with base model. It can be noted that both efficiency scores are almost same for the two models. From the figure 5.6 it can be clearly identified that the percentage difference with base model is almost zero.

Figure 5.7 shows the VRS efficiency scores of base model and model 3 and figure 5.8 shows the percentage difference with base model. Same as CRS efficiency score, VRS efficiency score of model 3 has a very slight variation which is almost equal to zero compared to base model.

SAIDI means System Average Interruption Duration Index and SAIFI means System Average Interruption Frequency Index. If SAIDI value is high that means average time taken to restore supply when a breakdown occurs is high. If SAIFI value is high that means average number of breakdowns are higher in that particular area. If any area having more number of breakdowns, they are unable to restore supply within shortest time period as available staff and vehicles are limited. Then both SAIDI and SAIFI value goes high. Therefore it can be noted a direct correlation between SAIDI and SAIFI

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It can be concluded that as SAIDT and SAIFI are highly correlated, it is sufficient to select only one variable out of them for the DEA analysis. The reason of having a high correlation between these two variables and the reason to select SAIDI for the analysis instead of SAIFI was discussed in chapter 4.

5.3.3 Efficiency scores of model 4 and model 5

In model 4 reliability indices are considered as input variables for the analysis and in model 5 reliability indices are not considered as input variables for the analysis. SAIDI and SAIFI have been used with other 3 inputs in model 4. In model 5, any variable like SAIDI or SAIFI to interpret the reliability of DMUs have not been selected for the analysis.

Reliability is a very important parameter to obtain a decision about distribution utility's performance. Suppose any area is maintaining higher no of sales and consumers utilizing lesser resources and having a very low O&M cost. But the reliability of electricity supply in that area is very low. Then that area cannot be named as a high performing area.

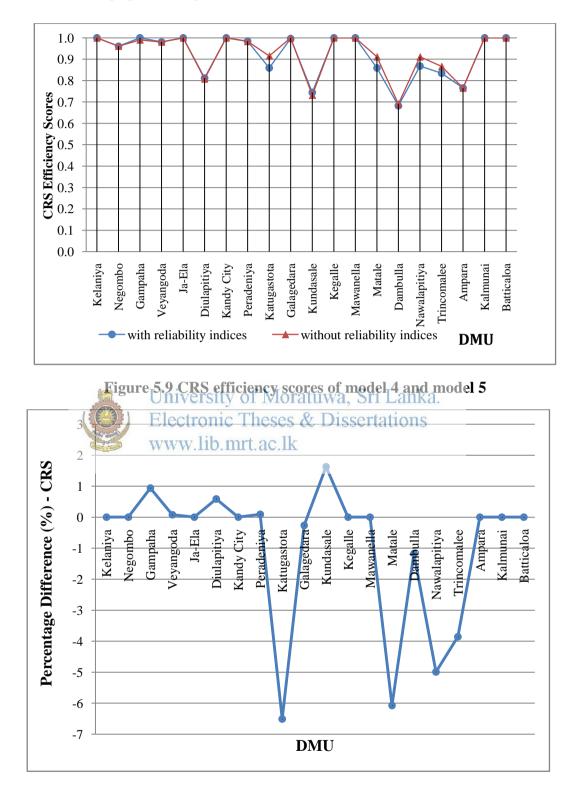


Figure 5.10 Percentage difference of model 4 with model 5 -CRS

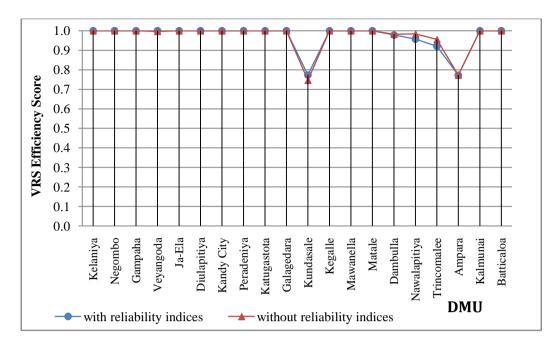


Figure 5.11 VRS efficiency scores of model 4 and model 5

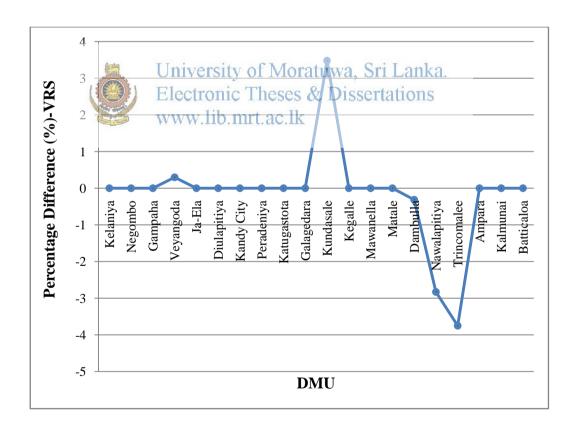


Figure 5.12 Percentage difference of model 4 with model 5 -VRS

Figure 5.9 shows the CRS efficiency scores of model 4 and model 5 and figure 5.10 shows the percentage difference of model 5 compared to model 4. It can be noted that the efficiency score obtained without considering reliability indices is higher for some DMUs. But when reliability indices are considered for the analysis efficiency score has dropped down. The same pattern can be noted for VRS efficiency scores as well. Therefore it can be concluded that it is necessary to consider reliability indices for the analysis.

5.3.4 Efficiency scores for base model, model 6 & 12

In base model new connections are not considered as an output variable. Sales and number of consumers are considered as output variables. In model 6 sales and number of new connections are considered as output variables. Here instead of number of consumers, number of new connections has been used for the analysis. In model 12 only sales has been considered as an output variable. Number of consumers and number of new connections have not been considered for the analysis as output variables.

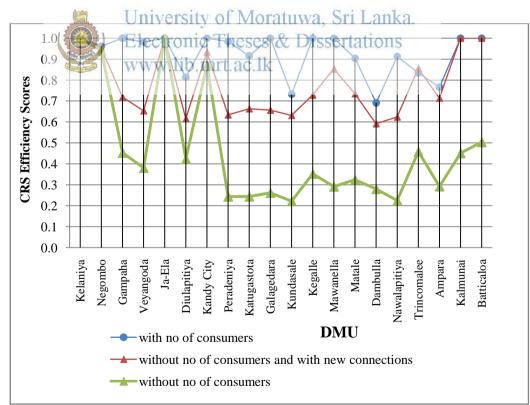


Figure 5.13 CRS efficiency scores of base model, model 06 & 12

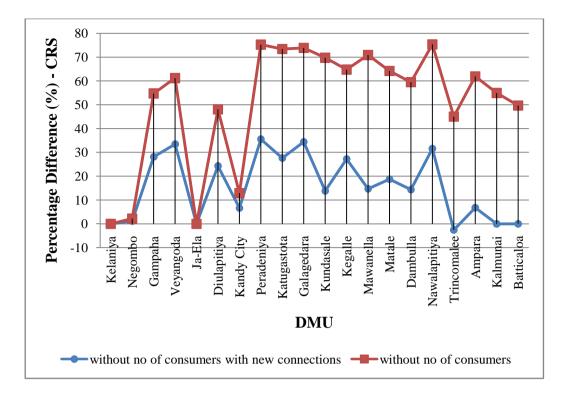


Figure 5.14 Percentage difference of model 6 &12 with base model –CRS

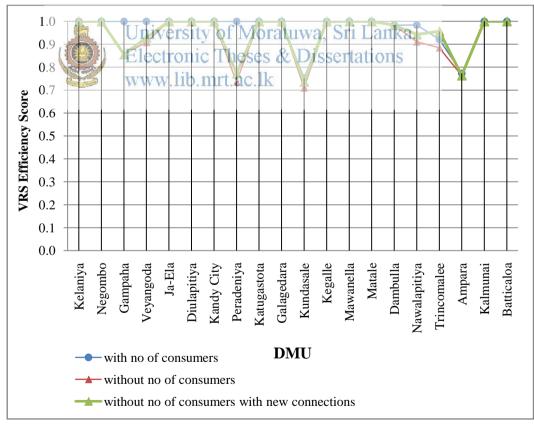


Figure 5.15 VRS efficiency scores of base model, model 6 & 12

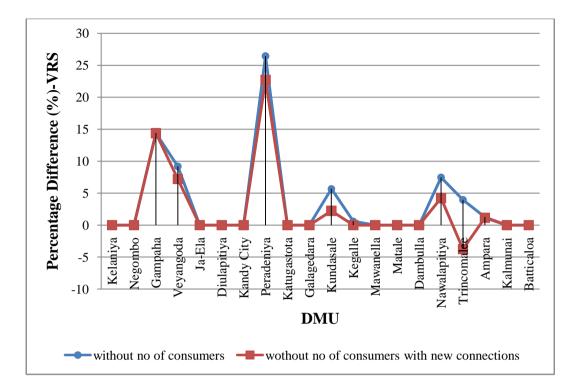
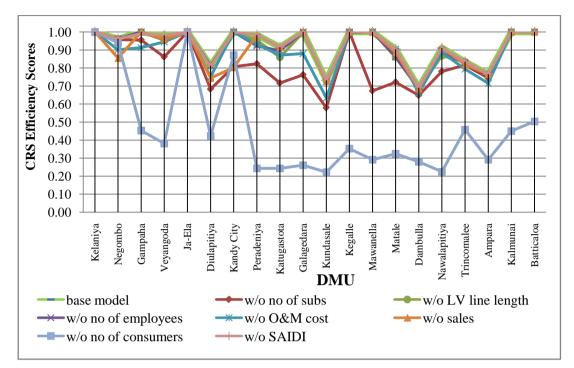


Figure 5.16 Percentage difference of model 6 & 12 with base model –VRS Figure 5.13 depicts the CRS efficiency score obtained for base model, model without number of consumers but with memory connections and for the model without both number of consumers and new connections. Figure 5.14 depicts the percentage variation of two models compared to base model. It can be noted that efficiency score drops significantly when number of consumers are removed from the model. For some DMUs difference is around 80%. Therefore it can be concluded that as an output variable number of consumers is a very important variable for the analysis.

It can be noted that when number of new connections is considered for the analysis instead of number of consumers the difference has become lower. That is because number of new connections and number of consumers have a correlation. When a correlated output variable is used for the analysis the efficiency score has increased compared to the score obtained from the model without both number of consumers and new connections. Figure 5.15 depicts the VRS efficiency score obtained for base model, model without number of consumers but with new connections and for the model without both number of consumers and new connections. Figure 5.16 depicts the percentage variation of two models compared to base model. It can be noted that for model 6 and model 12 VRS efficiency score has dropped down. But efficiency scores have not dropped down significantly as like in CRS models. Percentage difference of the VRS efficiency scores obtained for the model without number of consumers and model without number of consumers but with new connections are almost same. Analyzing VRS efficiency scores also it can be concluded that no of consumers is a very significant and strong output variable for the analysis.



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5.3.5 Analysis with different models upon exclusion of variables from base model

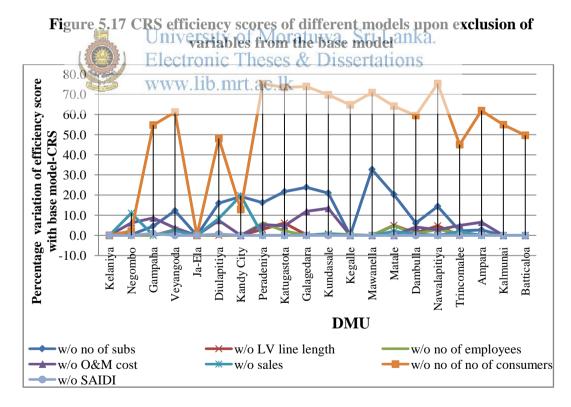


Figure 5.18 Percentage differences of models upon exclusion of variables from base model - CRS

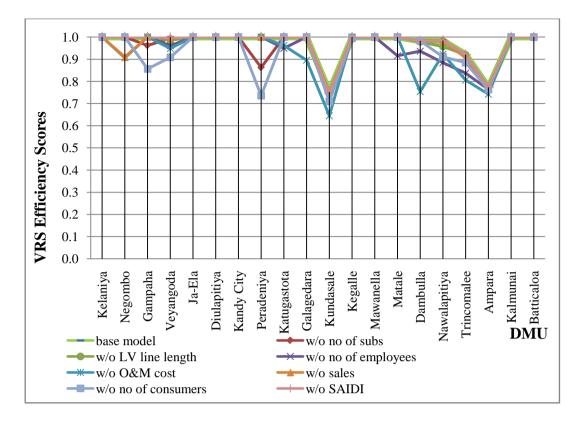


Figure 5.19 VRS efficiency scores of different models upon exclusion of

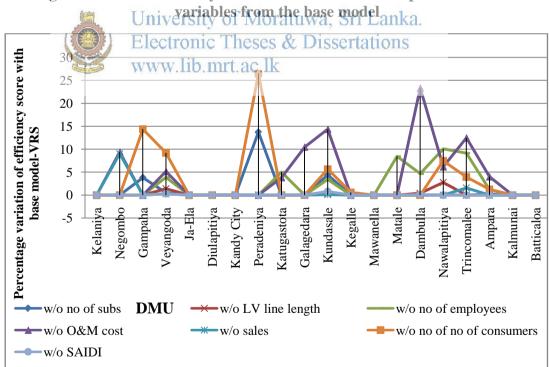


Figure 5.20 Percentage differences of models upon exclusion of variables from base model - VRS

Figure 5.17 depicts the CRS efficiency scores upon exclusion of one variable from the base model at a time and figure 5.18 depicts the percentage difference of each model compared to base model.

It can be observed in figure 5.17 that when variables are removed from the base model the efficiency scores never increase. They always remain same or decreases upon removal of variables from the model. It can be noted that when No of consumers, No of substations and O&M cost are removed from the base model, the efficiency score becomes much lower.

In figure 5.18 it can be observed that there is only plus variation of the efficiency scores of all the DMUs. All the efficiency scores are less than or equal to the base model efficiency score. The model without number of consumers has the highest variation and models without number of substations and without O&M cost have the second and third highest variations respectively. Therefore those input/output variables are more significant for the analysis. The models without number of employees and without sales also have a considerable variation with respect to the base model.

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Figure 5.19 depicts the VRS efficiency scores upon exclusion of one variable from the base model at a time and figure 5.20 depicts the percentage difference of each model compared to base model. It also shows the same pattern as observed for CRS efficiency scores. However when number of consumers is removed from the model for some DMUs CRS efficiency score has dropped to a value around 0.2 while VRS efficiency score has dropped to a value around 0.65. That is for some DMUs the variation of CRS efficiency score is around 80% compared to base model whilst for VRS efficiency score it is around 30%. From figure 5.18 and 5.20 it can be observed that for all the models the variation with CRS efficiency score is higher than with VRS efficiency score.

Therefore it can be concluded that when variables are removed from the base model the overall efficiency has dropped more than the technical efficiency. Although the technical efficiency or managerial efficiency of DMUs drop slightly when variables are removed from the base model their overall efficiency or long run measure of efficiency drops significantly. Also it can be concluded that number of consumers is the most significant variable for the analysis as it shows the highest variation.

5.4 Conclusion of DEA Analysis With Different Models

DEA analysis was carried out for 13 different models and analyzed the results obtained. After the analysis obtained results can be summarized as follows.

- As efficiency scores obtained for two models with MV line length and LV line length are almost same, it is sufficient to select only one variable out of MV line length and LV line length for the DEA analysis.
- As efficiency scores obtained for two models with SAIDI and SAIFI are almost same, it is sufficient to select only one variable out of SAIDI and SAIFI.
- Although it indicates a high efficiency score without reliability indices, with reliability indices the score has become lower. Therefore it is essential to University of Moratuwa, Sri Lanka.
 construct reliability indices for the analysis Electronic fineses & Dissertations www.lib.mrt.ac.lk
- Efficiency score drops significantly when number of consumers is removed from the model. Therefore it can be concluded that as an output variable number of consumers is a very important variable for the analysis. As number of consumers and number of new connections are correlated, it is reasonable to select number of consumers for the analysis.
- When variables are removed from the base model the overall efficiency has dropped more than the technical efficiency. Although the technical efficiency or managerial efficiency of DMUs drop slightly when variables are removed from the base model their overall efficiency or long run measure of efficiency drops significantly. Also it can be concluded that number of consumers is the most significant variable for the analysis as it shows the highest variation.

5.5 Justification of The Selected Base Model

The selected base model for the analysis can be justified from the results of the analysis done after running different DEA models. Table 5.4 depicts the justification of the selected base model.

Input Variables	Results obtained	Output	Results obtained			
	from analysis	Variables	from analysis			
No of substations	Significant variable	Sales	Significant variable			
LV line length	Select only one out	No of	Select only one out			
MV line length	of both	No of new	of both			
No of employees	Significant variable					
O&M cost Significant variab						
SAIDI	Select only one out					
SAIFI	of both					

Table 5.4 Justification of the selected base model

University of Mera	
Input Variables onic Theses	Output Variables
No of substations lib.mrt.ac.lk	Sales
LV line length	No of consumers
No of employees	
O&M cost	
SAIDI	

Number of substations, number of employees, O&M cost, and sales were identified as significant variables because when they are removed from the model efficiency score varies considerably. Out of MV line length and LV line length it is enough to select only one variable for the analysis and therefore only LV line length was selected. SAIDI and SAIFI were considered as reliability indices as both the variables seems to be correlated and efficiency scores are same for both cases only SAIDI was selected for the analysis.

6 SENSITIVITY BASED CLASSIFICATION OF DMUS

6.1 Introduction

Sensitivity analysis in DEA is defined as the effect on DEA efficiency upon the inclusion or exclusion of one or more variables from the model, but not with respect to parametric variation of input or output variables. The sensitivity study on DEA is normally done with two approaches. One approach is based on the removal of one or more DMUs from the basic model and then it compares the DEA efficiencies. Another approach is based on the removal of one or more variables from the model to determine changes in DEA efficiencies. In this work, the sensitivity analysis based on the second approach is considered. Thus, one of the inputs or outputs is removed from the basic model to construct the new model. Comparisons of efficiencies from the base model with the structure perturbed model show the impact of the input/output parameter on efficiency.

University of Moratuwa, Sri Lanka. The decision pased on the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification of the utilities about the results of such analysis can provide classification based on the sensitivity analysis is made.

6.2 Classification of DMUs Based On Sensitivity Analysis

The classification used in this work is an adaptation of ideas presented by Norman and Stoker in their book [12]. Five distinct patterns are obtained from sensitivity analysis and are defined as follows:

- Robustly efficient DEA efficiency score stays at one or decrease very slightly (up to 0.9) when the variables are removed from the model one at a time.
- Marginally efficient Efficiency score is 01 for the base model and remains at 01 in some situations, but drops significantly in other situations.

- Marginally inefficient DEA efficiency score is below 1 but above 0.8 for the base model and stays in that range during the sensitivity analysis
- Significantly inefficient DEA efficiency score is below 1 but above
 0.8 and drops to much lower values during the sensitivity analysis.
- Distinctly inefficient DEA efficiency is significantly low (below 0.8) in all the situations

6.3 Results and Discussion

The sensitivity analysis is carried out by eliminating one parameter at a time and its impact on the DEA efficiency is analyzed. The result of such analysis is given in Table 6.1. Table 6.1 displays the DEA efficiency in the basic model and the efficiency when specific input / output is eliminated. The DMUs are classified based on the above mentioned patterns.

For example. Kegalle has the DEA efficiency score of 1.0 in the base model and remains at 10 when five parameters, namely no of substations, LV line length, O&M cost SAIDI and Sales are eliminated from the base model. But it reduces to 0.9963 when no of employees are removed and to 0.3526 when the number of consumers is removed from the base model. As per the specification given for the marginally efficient DMU, this DMU has a CRS efficiency score 1.0 in the base model, remains in 1.0 in most of the cases and reduces to 0.3526 when number of consumers is eliminated. So this DMU is classified as marginally efficient. It is observed from the above analysis that number of consumers is of critical importance in deciding the efficiency of this DMU.

Similarly, the DMU JaEla also has efficiency score 1.0 in the base model and remains at 1.0 for all the situations. This can be classified as the robustly efficient DMU. If the DMU Dambulla is considered the efficiency scores are below 0.7 for all the situations. Therefore as per the classification given above that DMU can be named as distinctly inefficient DMU.

	DMU	Base CRS	CRS w/o No of substations	LV line	CRS w/o no of employees	0&M	CRS w/o SAIDI	CRS w/o sales	CRS w/o no of consumers
1	Kelaniya	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2	Negombo	0.9616	0.9576	0.9616	0.9616	0.9016	0.9616	0.8553	0.9405
3	Gampaha	1.0000	0.9545	1.0000	1.0000	0.9134	0.9906	1.0000	0.9057
4	Veyangoda	0.9810	0.8613	0.9541	0.9573	0.9452	0.9810	0.9594	0.3809
5	Ja-Ela	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
6	Diulapitiya	0.8131	0.6834	0.8131	0.8124	0.7527	0.8083	0.7445	0.4224
7	Kandy City	1.0000	0.8070	1.0000	1.0000	1.0000	1.0000	0.8032	0.8713
8	Peradeniya	0.9833	0.8237	0.9538	0.9228	0.9310	0.9833	0.9833	0.2436
9	Katugastota	0.9153	0.7168	0.8593	0.8949	0.8717	0.9153	0.9153	0.2438
10	Galagedara	1.0000	0.7619	0.9973	1.0000	0.8806	1.0000	1.0000	0.2615
11	Kundasale	0.7322	0.5788	0.7288	0.7260	0.6338	0.7322	0.7263	0.2217
12	Kegalle	1.0000	1.0000	1.0000	0.9963	1.0000	1.0000	1.0000	0.3526
13	Mawanella	1.0000	0.6733	1.0000	1.0000	1.0000	1.0000	1.0000	0.2914
14	Matale	0.9043	0.7212	0.8594	0.8613	0.9043	0.9043	0.8865	0.3242
15	Dambulla	0.6906	0.6486	0.6826	0.6851	0.6621	0.6906	0.6857	0.2800
16	Nawalapitiya	0.9114	0.7806	0.8681	0.8839	0.8861	0.9114	0.9114	0.2250
17	Trincomalee	0.8345	0.8160	0.8345	0.8267	0.7936	0.8345	0.8188	0.4587
18	Ampara	0.7655	0.7447	0.7655	0.7628	0.7154	0.7655	0.7655	0.2919
19	Kalmunai 🔙	1.000	nit/000sit	1.0000	01420000W	1.0000	110009	1.0000	0.4507
20	Battical	1.000 0	1,0000 lectronic	1.0000 2 Thes	es & Di	1.0000 SSC1121	1.0000	1.0000	0.5034

 Table 6.1 Results of sensitivity analysis

Figure 6.1 exhibits the sensibility profile of typical robustly efficient DMUs. Among the 20 DMUs, 2 of them have been identified as robustly efficient DMUs.

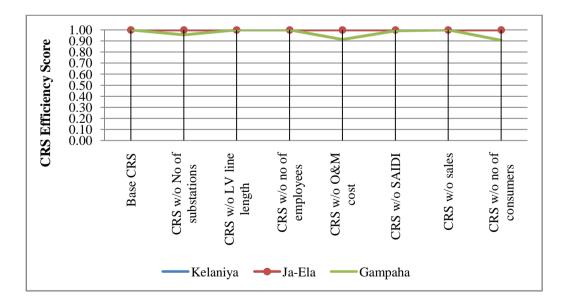


Figure 6.1 Sensitivity profile of robustly efficient DMUs

Figure 6.2 shows the sensitivity profile of typical marginally efficient DMUs. Here, the DMUs have 1.0 efficiency score in the base model, remain at1.0 for most of the situations, but when they drop, they significantly reduce to even 0.26. Six DMUs lie in this category. Efficiency score of Kandy City drops to 0.80, Galagadara area drops to 0.26, Kegalle area drops to 0.35, Mawanella area drops to 0.29, Kalmunai area drops to 0.45 and Batticaloa area drops to 0.5. Out of these 06 DMUs in 05 number of DMUs efficiency score reduce significantly when number of consumers is removed from the model. Therefore number of consumers can be considered as a critical factor for this model.

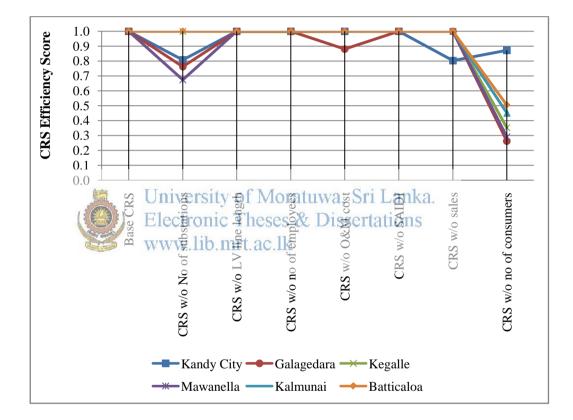


Figure 6.2 Sensitivity profile of marginally efficient DMUs

Figure 6.3 shows the sensitivity profile of typical marginally inefficient DMU. It looks clear that Negombo is the only DMU which is found as marginally inefficient during the sensitivity analysis. This DMU has the DEA efficiency score of 0.96 in the base model, reduces slightly for some situations and remains in the efficiency score range of 0.85 and 0.96. It is obvious from figure 6.3 that the critical factor for this DMU is the sales.

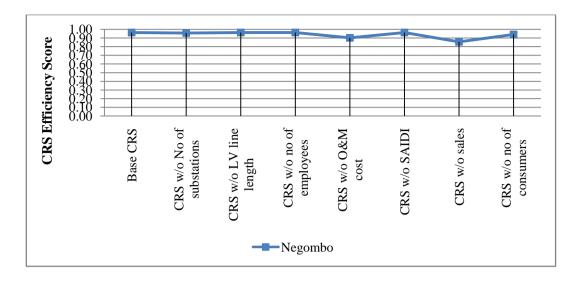


Figure 6.3 Sensitivity profile of marginally inefficient DMUs

Figure 6.4 shows the sensitivity profile of significantly inefficient DMUs. Normally, these DMUs have DEA efficiency score below 1.0 and above 0.8. They remain in that level in some situations but when they drop, they significantly drop to a low value. While referring to the figure, it can be identified that 7 of the DMUs lie in this category. In all the DMUs efficiency score drops significantly when number of University of Moratuwa, Sri Lanka, consumers is reduced from the model. That variable is very much significant for the model.

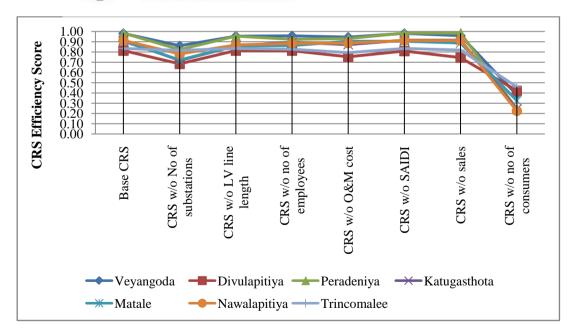


Figure 6.4 Sensitivity profile of significantly inefficient DMUs

Figure 6.5 shows the sensitivity profile of distinctly inefficient DMUs. Three DMUs out of twenty were found to be in this category. These DMUs do not have good efficiency score in the base model and for every parameter elimination their efficiency score reduces without any control.

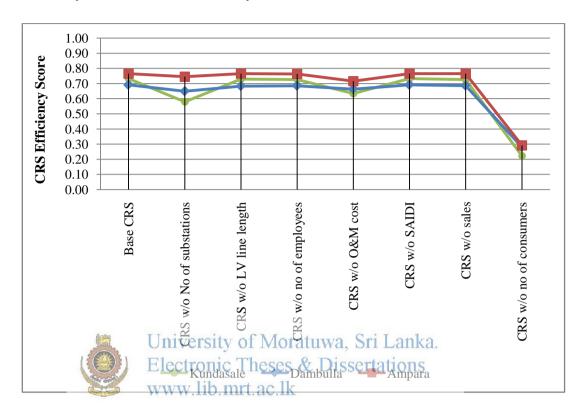


Figure 6.5 Sensitivity profile of distinctly inefficient DMUs

Sensitivity based classification is important when improving the performance or increasing the efficiency scores of DMUs. That is for a particular unit or to an organization it is essential to know its strength and weaknesses in order to achieve their targets.

In distinctly inefficient DMUs the efficiency score is below 0.8 for all the cases including base model. That kind of DMUs needs special attention to improve their performance. At the same time marginally efficient DMUs are very sensitive to changes in some variables only. Therefore it is required to identify important variables for these kinds of DMUs and prevent them from becoming inefficient. Marginally inefficient DMUs are low sensitive to the changes in variables. They can be made efficient only by long term proposals.

	DMU Name	Classification of DMU
1	Kelaniya	Robustly Efficient
2	Negombo	marginally Inefficient
3	Gampaha	Robustly Efficient
4	Veyangoda	Significantly Inefficient
5	Ja-Ela	Robustly Efficient
6	Diulapitiya	Significantly Inefficient
7	Kandy City	Marginally efficient
8	Peradeniya	Significantly Inefficient
9	Katugastota	Significantly Inefficient
10	Galagedara	Marginally efficient
11	Kundasale	Distictly Inefficeint
12	Kegalle	Marginally efficient
13	Mawanella	Marginally efficient
14	Matale	Significantly Inefficient
15	Dambulla	Distictly Inefficeint
16	Nawalapitiya	Significantly Inefficient
Uh7i	Teinsignalef M	Significantly Snefficiente
E18	Ampara These	Distictly Inefficeintons
	Kalmunai ac	Marginally efficient
20	Batticaloa	Marginally efficient

Table 6.2 Classification of DMUs

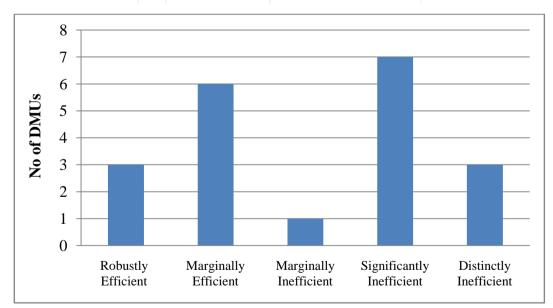


Figure 6.6 Plot of amount of DMUs for each category

Table 6.2 shows the classification of all the DMUs based on sensitivity analysis. Kelaniya, Gampaha and Je-ela DMUs are robustly efficient while DMUs like Kandy City, Galagedara and Batticaloa are marginally efficient. There is only one marginally inefficient DMU and that is Negombo area. DMUs like Divulapitiya, Veyangoda and Peradeniya are significantly inefficient while DMUs like Dambulla, Kundasale and Ampara are distinctly inefficient.

Figure 6.6 indicates the amount of DMUs available for each category after classification. It can be noted that most of the DMUs are significantly inefficient. There are 03 nos of robustly efficient DMUs and 06 nos of marginally efficient DMUs, 7 nos of significantly inefficient DMUs and 3 nos of distinctly inefficient DMUs. There is only one DMU which is marginally inefficient.



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7 CONCLUSION & RECOMMENDATIONS

7.1 Conclusion

In this thesis, I have developed a DEA model to evaluate the performance of electricity distribution sector of Sri Lanka. For this study 20 areas of Distribution Division 02 of Ceylon Electricity Board were selected.

Chapter 2 presents a brief introduction about Data Envelopment Analysis and the mathematical modeling of DEA. In performance evaluation DEA basically comprises of 03 orientations. According to the type of organization, their service or main task, the most appropriate orientation can be selected. Then it discussed about these 03 orientations exists in DEA, namely input orientation, output orientation and base orientation. The surface of the envelopment may be differing depending on the scale assumptions that emphasize the model. There are two basic scale assumptions which are used generally called constant returns to scale (CRS), and variable returns to scale (VRS). The opapter describes about these two return to scales in detail. The exact type of model which its snitable for a particular application can be selected considering the scale and orientation of the model. Finally chapter 02 describes the basic DEA model classifications based on returns to scale and model orientation.

Chapter 3 describes the algorithm followed by top managers of any organization to improve relative performance. That may be a private sector organization or government sector organization. By following this algorithm any company can know where they stand in relation to other companies. The other companies can be used as evidence of problem areas, and provide possible solutions for each area. This algorithm can be used to find the performance of electricity distribution sector as well. In my research this algorithm has been followed in order to find relative efficiency scores of 20 areas in Distribution Division 02 (DD2) of Ceylon Electricity Board.

In chapter 04 efficiency scores for selected 20 DMUs were evaluated using DEA. Input output variables were selected for the analysis based on literature review and correlation analysis. CRS efficiency scores were found for each DMU and it can be noted that out of 20 DMUs, 10 DMUs obtained efficiency score 1.0. Dambulla area has the lowest efficiency score and Kundasale and Divulapitiya areas have relatively lower efficiency scores compared to other DMUs. Then VRS efficiency scores were found for each DMU and it can be noted that most of the DMUs have obtained efficiency scores of 1.0. DMUs like Ampara, Kundasale, Trincomalee and Nawalapitiya have obtained lower efficiency scores. That means compared to other DMUs they are technically inefficient. Their efficiency score can be increased by implementing best management practices in order to reduce the inputs used and increase the outputs.

Slack analysis was carried out find out the amount of resources or inputs to be reduced for inefficient DMUs in order to reach efficient frontier. Technically inefficient DMUs are using excessive resources for producing given level of output. In order to find outpart of resources which have been used in excess, slack analysis have been used.

Scale efficiencies for each DMU were evaluated and it can be seen that ten DMUs out of twenty are found to be scale efficient that means they are operating in constant returns to scale (CRS). On the other hand DMUs like Negombo, Veyangoda, Kundasale etc are operating in Increasing Return to Scale (IRS). They need to increase its scale of operation in order to reach efficiency frontier. In this analysis there are not DMUs which are operating in Decreasing Return to Scale (DRS). DMUs like Kelaniya, Jaela, Kegalle etc exhibit CRS characteristic which means they have the optimal scale size. Finally from the DEA analysis it can be concluded that although most of the DMUs are technically efficient their overall efficiency is low as they are not operating at their optimal scale of operation.

In chapter 5 DEA analysis was carried out considering different DEA models. Other than the base model DEA analysis was carried out for 13 models in order to analyze the variation of the results for different input output combinations and to justify the selected base model for the analysis. The conclusion of the DEA analysis with different models can be summarized as follows.

- As efficiency scores obtained for two models with MV line length and LV line length are almost same, it is sufficient to select only one variable out of MV line length and LV line length for the DEA analysis.
- As efficiency scores obtained for two models with SAIDI and SAIFI are almost same, it is sufficient to select only one variable out of SAIDI and SAIFI.
- Although it indicates a high efficiency score without reliability indices, with reliability indices the score has become lower. Therefore it is essential to consider reliability indices for the analysis.
- Efficiency score drops significantly when number of consumers is removed from the model. Therefore it can be concluded that as an output variable number of consumers is a very important variable for the analysis. As number of consumers and number of new connections are correlated, it is reasonable to select number of consumers for the analysisity of Moratuwa, Sri Lanka.
- When variables are removed Trons the basis model the overall efficiency has dropped more than the technical efficiency. Although the technical efficiency or managerial efficiency of DMUs drop slightly when variables are removed from the base model their overall efficiency or long run measure of efficiency drops significantly. Also it can be concluded that number of consumers is the most significant variable for the analysis as it shows the highest variation.

Then selected base model for the analysis was justified from the results obtained from the DEA analysis with different models.

In chapter 06 sensitivity analysis was carried out by removing one or more variables from the model to determine changes in DEA efficiencies. Thus, one of the inputs or outputs is removed from the basic model to construct the new model. Comparisons of efficiencies from the base model with the structure perturbed model show the impact of the input/output parameter on efficiency. The DMUs were classified as robustly efficient, marginally efficient, marginally inefficient, significantly inefficient and distinctly inefficient based on the results obtained from this analysis. There are 03 nos of robustly efficient DMUs and 06 nos of marginally efficient DMUs, 7 nos of significantly inefficient DMUs and 3 nos of distinctly inefficient DMUs. There is only one DMU which is marginally inefficient.

7.2 Recommendations

From the results obtained from DEA analysis recommendations can be carried out for each area in order to improve their efficiency scores if they have not reached the efficiency frontier. As a case study each area from three different situations were selected to present how to implement those recommendations in practical.

DMU	CRS	VRS	Scale	RTS
	Efficiency	Efficiency	Efficiency	
Kelaniya	1.0	1.0	1.0	Constant
Veyangoda	0.982	1.0	0.982	Increasing
Kundasale	0.765	0.818	0.934	Increasing

Kelaniya Area : University of Moratuwa, Sri Lanka. Electronic Theses & Dissertations

It can be noted that in Kelaniya area both VRS and Scale efficiency score is one. That means it has a technical efficiency score of 01 and it is operating at its optimal size. The management of Kalaniya area has utilized their resources in an optimal manner to produce maximum output. At the same time they have an optimal scale of operation. That means they have the optimum no of consumers and a geographical area. Therefore it is not required to change the system in short run. But after carrying out a DEA analysis with all the areas in CEB a long run system improvement can be obtained.

Veyangoda Area :

Veyangoda area has a VRS efficiency score of one, but its scale efficiency score is less than one. That means Veyangoda area is technically or managerially efficient. The management of Veyangoda area has utilized their resources in an optimal manner. But their overall efficiency score is less than one due to not operating in an optimal scale. The Return to Scale (RTS) obtained from DEA analysis is Increasing RTS. That means the scale of Veyangoda area is small and it has to be increased. The scale of operation can be increased by demarcating new area boundaries by considering no of consumers and geographical area. The other surrounding areas their consumers, geographical area and main incoming feeders have to be considered when demarcating new area boundaries.

Kundasale Area :

It can be noted that in Kundasale area both VRS efficiency score and scale efficiency score is less than 01. That means Kundasale area is technically or managerially inefficient. At the same time it is not operating at its optimal scale also. By the slack analysis carried out for VRS model it can be obtained slack values for each area. For Kundasale area in order to reach efficiency frontier LV line length has to be reduced by 224.97 km and O&M cost has to be reduced by 39.97M. Some locations can be identified in distribution system where there are two LV lines have been drawn unnecessarily without having enough loading. That sort of unnecessary lines can be removed to reduce LV feeder length. If there are two parallel roads nearby where two LV lines been drawn on those roads separately, and if all the service www.lib.mrt.ac.lk connections can be provided by a single LV line that additional line can be removed. LV line length can be reduced practically by above mentioned two methods. O&M cost can be reduced by avoiding unnecessary purchasing of office equipments, materials, stationary items, and unnecessary usage of water, telephones, internet, fuel, hiring vehicles etc. By reducing the input variables as per the results obtained from slack analysis the technical efficiency score can be increased.

In this case scale efficiency score is also less than 01 and it has a RTS of increasing. That means Kundasale area is not operating at its optimal scale and the scale has to be increased. The scale of operation can be increased by demarcating new area boundaries by considering no of consumers and geographical area. The other surrounding areas their consumers, geographical area and main incoming feeders have to be considered when demarcating new area boundaries. Finally as a general recommendation it can be suggested to use Data Envelopment Analysis to evaluate performance of any kind of organization whether it is a private sector organization or government sector organization. Private sector organizations like banks, insurance companies, manufacturing companies, fast food restaurants, business firms and retail stores can use DEA to evaluate relative performance of their organizations or units. Other than those government organizations like schools, universities, educational institutes, hospitals and government agencies can also follow up this method. Performance can be evaluated once a year or once in two years and annual strategic plans can be implemented based on these results. It is also recommended to implement this method for electricity distribution utilities like Ceylon Electricity Board (CEB) and Lanka Electricity Company (LECO). In CEB this method can be implemented to evaluate performance not only in distribution, but also in generation and transmission too.



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Reference List:

[1] Tooraj Jamasb, David Newbery, Michael Pollitt, Thomas Triebs, *International Benchmarking and Regulation of European Gas Transmission Utilities* [On line] Available: <u>http://www.springer.com/978-0-387-75447-5</u>,

[2] H.D.Sherman, J Zhu (2006). *Improving Service Performance Using Data Envelopment Analysis (DEA)* [On line] Available: http://www.springer.com/978-0-387-33211-6.

[3] Kamel Bala, Prof.Wade D.Cook, Moez Hababou, Hans J.Tuenter. (*Tutorial in DEA*) [On line] Available: <u>http://moezh.tripod.com/DEAtutorial</u>

[4] S.Pascoe, J.E.Kirkley, D.Gréboval, C.J.Morrison-Paul. *Measuring and assessing capacity in fisheries. Appendix D, Data Envelopemnt Analysis,* FAO Fisheries Technical Paper. No. 433/2. Rome, FAO. 2003. 130p.

University of Moratuwa, Sri Lanka. [5] Bruce Raner, *ThecGorridationeGoefficientsSDefinitions* [On line] Available: <u>http://www.envtat1.com/res/TheCorrelationCoefficientDefined.html</u> WWW.ID.IIII.ac.IK

[6] Ozcan, Y.A (2008). An assessment using Data Envelopment Analysis [On line] Available: <u>http://www.springer.com/978-0-387-75447-5</u>

[7] S.P Pokharel, R Shrestha ."Performance Evaluation of Electric Distribution Centers using Data Envelopment Analysis", *North American Power Symp. (NAPS), IEEE conf.*, Arlington, TX, 2010, pp. 1-7.

[8] Chyan Yang, Wen-Min Lu ."Assessing the Performance and Finding the Benchmarks of the Electricity Distribution Districts of Taiwan Power Company", *Power Systems*, IEEE Transactions on, volume 21, issue 2, pp.853-861, May 2006.

[9] T Thakur. "Performance Evaluation of Indian Electric Power Utilities Based on Data Envelopment Analysis", *Power Electronics, Drives and Energy Systems, IEEE conf.*, New Delhi, December 2006, pp. 1-4

[10] Vinod Kumar Yadav, Yogesh K.Chauhan, N.P.Padhy, H.O.Gupta. "A Novel Power Sector Restructuring Model Based On Data Envelopment Analysis", *Int. Journal of Electrical Power and Energy Systems*, volume 44, issue 1, pp 629-637, January 2013.

[11] A Pahwa, Fen Xiaoming, D Lubkeman. "Performance Evaluation of Electric Distribution Utilities Based on Data Envelopment Analysis", *Power Engineering Society Summer Meeting*, 2002 IEEE, volume 2, Chicago, IL, USA, July 2002.

[12] M.Norman and B.Stocker, Data Envelopment Analysis: The Assessment of Performance. NewYork: Wiley,1991.

[13] Monthly Progress Reports of DD2 from January 2013 to December 2013. University of Moratuwa, Sri Lanka. Electronic Theses & Dissertations

[14] Monthly Revenue Collection Reports of DD2 from January 2013 to December 2013.

[15] Monthly Expenditure Reports of DD2 from January 2013 to December 2013.

DMU	No of subs	MV line length (km)	LV line length (km)	No of employees	O&M Cost (M.Rs)	New Connections	SAIDI	SAIFI	sales (M.Rs)	no of consumers	Revenue collection (M.Rs)
Kelaniya	625	345.67	1424.35	182	293.10	3951	0.0138	0.0263	8195	116428	7940
Negombo	517	310.40	1529.36	208	243.499	2946	0.0190	0.0482	6494	93349	6355
Gampaha	411	338.41	1489.36	244	311.23	on 3035	0.0124	0.0228	2614	107199	2581
Veyangoda	368	277.39	1532.04	165	230.60	ati 2604	0.0332	0.0388	2338	89901	2306
Ja-Ela	479	225.35	818.75	211	280.45	ert 2444	0.0251	0.0322	7995	89486	7729
Diulapitiya	328	298.19	1681.55	147	191.745	iss 1910	0.0238	0.0500	2309	63239	2236
Kandy City	180	140.80	437.32	189	195.3	D 1013	0.0592	0.0891	2618	41054	2101
Peradeniya	346	641.00	2031.30	189	303.50	0862 20	0.1325	0.0822	1406	99570	1896
Katugastota	194	228.00	872.30	142	202.28	ses	0.2357	0.1348	789	54390	802
Galagedara	186	173.20	1066.00	248	173.A	he tæ	0.2232	0.2142	812	59286	804
Kundasale	419	529.40	2210.60	240	263.75		0.0474	0.0654	1551	82278	1468
Kegalle	268	375.60	2297.39	133	280.555		0.0460	0.1025	1577	85974	1573
Mawanella	138	206.60	1004.62	200	193.1	tro	0.0389	0.1065	671	53452	682
Matale	188	292.00	779.83	128	275.12		0.0435	0.0962	1017	52721	1215
Dambulla	441	579.50	1866.20	180	176.29	E 第64	6890.0	0.2062	1407	71774	1345
Nawalapitiya	316	410.00	1388.42	156	228.21	2742	0.1441	0.1531	1187	77299	1183
Trincomalee	491	723.41	2430.17	183	219.16	00533	0.0766	0.1313	2866	93471	2458
Ampara	637	1097.65	3278.70	248	214.11	9994 ann	0.1746	0.1664	1781	113540	1780
Kalmunai	237	215.94	550.34	154	299.46	2541	0.0046	0.0188	1217	72613	1224
Batticaloa	547	661.50	2296.57	202	154.07	8502	0.0240	0.0236	2211	123513	2503

Appendix A : Data Utilized for the Study