Chapter-1

INTRODUCTION

1.1 Introduction
1.2 Motivation
1.3 Objective if the Study

1.INTRODUCTION

1.1 INTRODUCTION

With the opening of the Indian power sector for the independent power producers (IPPs), India embarked upon the path of sector reforms and restructuring since the year 1991. Nearly fourteen years later, the reforms have not yet been able to check the ever-widening demand supply gap; in the year 2003-04, there still existed a peak deficit of 12.6% and average deficit of 7.5% at the all India level (Thakur et al, 2005). The contribution of IPPs is still not significant, with the private sector contributing only 11%, 0.4% and 12% of the total share in generation, transmission and distribution. Thus, the major players in the Indian electricity sector continue to be the SEBs. These SEBs were established for the rationalization of power development at the state level (for Generation, Transmission and Distribution activities), and were statutorily required to function as autonomous corporations by the Electricity (Supply) Act of 1948. The electricity sector in India like other infrastructure sectors had overriding declared social objectives, the pursuance of which led to sacrifice of sector efficiencies. Even though the country witnessed an impressive growth for installed capacity (8.65 %) during the last four decades, the power sector has been delivering unsatisfactory performance in terms of reliable access to electricity and has been unable to meet the growing demand. Tariff policies with free power sops for farmers and irrational subsidies for domestic consumers have affected the financial credibility of the power utilities.

However, it must be admitted that SEBs were not entirely responsible for the debacle; in the beginning SEBs were not expected to view every aspect of developmental activities exclusively from the point of view of profits or returns on investment. The general perception therefore, has been that the SEBs have not been performing adequately well, as reflected in their poor financial performances and widening targets due to increasing shortfalls. Presently, the main focus of ongoing reforms is to make SEBs efficient and commercialize entities. This presents a case for the review of the performances of these utilities, so that lessons from failures be taken note of, and effective steps be taken to mitigate shortcomings. This paper attempts to explore the performances of the SEBs by employing Data Envelopment Analysis (DEA) to delineate and identify the underlying causes of the inadequate sector performances, if any. The objective of the present analysis is to develop a benchmark based on the comparison of the operations of similar SEBs and analyze the inefficiencies of the existing utilities in the policy context of making them efficiency.

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 or areas

1.3 Objective of the Study

The main objective of this study is to evaluate relative efficiencies of each Distribution utility using DEA and to identify best performing areas . Then identify ways to improve each area's performance, if it is not one of the top performing areas.

Chapter-2

REVIEW OF LITERATURE

2.1 Review of literature

2.2 Brief scenario of electricity industry

2.3 Performance of the Electrical Utilities

2.1 Review of Literature :

Managers are often under great pressure to improve the performance of their organizations. To improve performance, one needs to constantly evaluate operations or processes related to producing products, providing services, and marketing and selling products. Performance evaluation and benchmarking are a widely used method to identify and adopt best practices as a means to improve performance and increase productivity, and are particularly valuable when no objective or engineered standard is available to define efficient and effective performance. For this reason, benchmarking is often used in managing service operations, because service standards (benchmarks) are more difficult to define than manufacturing standards (Joe Zhu).

Many empirical applications exist for DEA in many different sectors, like education , banking and economics , manufacturing , logistics , telecommunications , healthcare , and athletics . The versatility of DEA as a decision analysis tool comes from its ability to assign every unit in a dataset its own production function; it does not need to discover a universal relationship between all units in a sample. Comparing the efficiency of a single unit to other units in the dataset, DEA can evaluate the efficiency of that single unit. After completing this process for every unit in the dataset, all units are classified into either an efficient group, which possess 100% efficiency scores, or an inefficient group, which possess less than 100% efficiency scores (Ali Emrouznejad, Rajiv Banker).

DEA is a powerful tool for processing and benchmarking data, using efficiency calculation as the basis. Data Envelopment Analysis (DEA) as a concept was introduced in 1978 by Charnes, Cooper and Rhodes to evaluate non-profit and public sector organizations [A.Charnes et. al.,]. Sherman and Zhu also applied the concepts of DEA to management problems [H.D. Sherman]. However, the scope of DEA is not limited to management and banking problems, but can also be extrapolated to engineering related problems, optimization of electricity usage being one. Gupta et al. have obtained the data for usage of electricity in Uttarakhand, and have done analysis through DEA analysis [V.Yadav et. al.,]. The results revealed that there are several inefficient divisions in the state. The concept of twostage DEA has been introduced in [T.R.Sexton] and [C.Kao], where the methodology has been applied to Taiwan Life insurance companies and Major League Baseball season respectively. As a part of this project, the two-stage DEA methodology is applied to the electrical utility data of Uttarakhand. Most of the DEA studies are focus on measurement of efficiencies, in this work along with the efficiencies, the slacks the input efficiencies as well as the output efficiencies are also calculated using the different models that are put to use.

Performance evaluation and benchmarking positively force any business unit to constantly evolve and improve(Joe Jhu) in order to survive and prosper in a business environment facing global competition. Through performance evaluation, one can

(i) reveal the strengths and weaknesses of business operations, activities, and processes;
(ii) better prepare the business to meet its customers' needs and requirements; and
(iii) identify opportunities to improve current operations and processes, and create new products, services and processes.

2.2 Brief Scenario of Indian Electricity utility:

Electricity is one of the most vital infrastructure inputs for economic development of a country. The demand of electricity in India is enormous and is growing steadily. The vast Indian electricity market, today offers one of the highest growth opportunities for private developers. Since independence, the Indian electricity sector has grown manifold in size and capacity. The generating capacity under utilities has increased from a meagre 1362 MW in 1947 to 112058 MW as on March, 2004. Electricity generation, which was only 4.1 billion KWh in 1947 has risen to a level of over 558.134 billion KWh in 2003-2004. In its quest for increasing availability of electricity, the country has adopted a blend of thermal, hydel and nuclear sources. Out of these, coal based thermal power plants and in some regions, hydropower plants have been the mainstay of electricity generation. Oil, natural gas and nuclear power accounts for a smaller proportion. Thermal plants at present account for 70 percent of the total power generation, hydroelectricity plants contribute 26 per cent and the nuclear plants account for the rest. Of late, emphasis is also being laid on development of non-conventional energy sources i.e. solar, wind and biomass.

The structure, ownership pattern and regulatory setup of the Indian power sector have witnessed radical changes especially in the past few years as part of the ongoing reform program with the establishment of independent regulators, corporatisation, unbundling and the advent of privatization in some States To have an easy access and control, the Indian Power Sector is divided into five regions viz., Northern, Eastern, Western, Southern and North-Eastern Regions. Each state has its own utility previously known as State Electricity Boards. With the introduction of new Electricity Act 2003, Indian power sector is undergoing drastic reformation such as envisaging new National Electricity Policy (NEP), Rationalization of Tariffs, Restructuring of the SOEU's and the provision for new regulatory regime. Each state has the freedom to set up its own regulation and there will be State Electricity Regulatory Commission and each SERC will be centrally coordinated by CERC.

As on March 2005, twenty two states namely, Orissa, Haryana, Andhra Pradesh, Uttar Pradesh, Karnataka, West Bengal, Tamil Nadu, Punjab, Delhi, Gujarat, Madhya Pradesh, Maharashtra, Rajasthan, Himachal Pradesh, Assam, Chatisgarh, Uttaranchal, Goa, Bihar, Jharkhand, Kerala and Tripura have either constituted or notified the constitution of SERC. Eighteen SERCs viz. Orissa, Andhra Pradesh, Uttar Pradesh, Maharashtra, Gujarat, Haryana, Karnataka, Rajasthan, Delhi, Madhya Pradesh, Himachal Pradesh, West Bengal, Punjab, Tamil Nadu, Assam, Uttaranchal, Jharkhand and Kerala have issued tariff orders.

Over the past years, financial performance of SOEU's have deteriorated, resulting in large accumulated losses. There is now a movement towards estimating and monitoring AT&C (Aggregate commercial and technical) losses in the country. The aggregate technical & commercial (AT&C) losses are in the range of 50%. High technical losses in the system are primarily due to inadequate investments over the years for system improvement works, which has resulted in unplanned extensions of the distribution lines, overloading of the system elements like transformers and conductors, and lack of adequate reactive power support. The commercial losses are mainly due to low metering efficiency, theft & pilferages. One must also give due weight to the fact that in the pursuit of the social objective, utilities may not have encouragement to innovate and look for improvements. However, the financial and operational performances suggest the necessity for a detailed technical and financial appraisal of the SOEU's in order to reveal the underlying inefficiencies and the extent of scope for improvement in the new reformed regime.

2.3 PERFORMANCE OF THE STATE ELECTRICAL UTILITIES:

Over the past years the financial performances of SEBs have deteriorated resulting in large accumulated losses. Commercial losses were estimated at about Rs. 260,000 million (Rs. 45=1 US $ approximately) during the year 2000-01. Gross subsidy, was estimated to go up to Rs. 380,000 million in 2000-2001 (Planning Commission, 2002). The tariff structures have been flawed, so that, for the entire country on the average, the tariffs imposed cover up only about 69% of the cost of power supply (year 2000-01). Both the agriculture and residential customers are heavily subsidized. Over time, the problems related to cost recovery have intensified, the SEBs showed an average rate of return (excluding subsidies) of –33.8 % in 1999-2000 (Annual Report, 2002). The operational performances of SEBs have also shown a decline with time . Mounting T&D losses over years have hampered the viability of the Indian Power Sector. These losses stood at 32% (Planning Commission, 2002) during 2002, while the unofficial estimates put T&D losses into a higher range of 40-50%. Commercial losses comprise 2/3rd of the total loss in distribution (Ghosh, 2002). These losses are due to rampant theft and pilferage of electricity, meter tampering, unauthorized connections and unmetered supply.

Chapter-3

METHODOLOGY

3.1 History of data envelopment analysis
3.2 Data envelopment analysis
3.3 Terms Used in Data Envelopment Analysis
3.4 Methods employed in DEA

3.DATA ENVELOPMENT ANALYSIS

3.1 HISTORY OF DATA ENVELOPMENT ANALYSIS:

In microeconomic production theory, a firm's input and output combinations are depicted using a production function. Using such a function, one can show the maximum output which can be achieved with any possible combination of inputs, that is, one can construct a production technology frontier **(Sieford & Thrall 1990).**

Building on the ideas of Farrell (1957), the seminal work "Measuring the efficiency of decision making units" by Charnes, Cooper & Rhodes (1978) applies linear programming to estimate an empirical production technology frontier for the first time. In Germany, the procedure was used earlier to estimate the marginal productivity of R&D and other factors of production (Brock Hoff 1970). Since then, there have been a large number of books and journal articles written on DEA or applying DEA on various sets of problems.

Other than comparing efficiency across DMUs within an organization, DEA has also been used to compare efficiency across firms. There are several types of DEA with the most basic being CCR based on Charnes, Cooper & Rhodes, however there are also DEA which address varying returns to scale, either CRS (constant returns to scale, VRS (variable), non-increasing returns to scale or the non-decreasing returns to scale by Ylvinger (2000). The main developments of DEA in the 1970s and 1980s are documented by Sei ford & Thrall (1990).

3.2 DATA ENVELOPMENT ANALYSIS:

Data Envelopment Analysis (DEA) is a methodology based upon an interesting application of linear programming. It was originally developed for performance measurement. It has been successfully employed for assessing the relative performance of a set of firms that use a variety of identical inputs to produce a variety of identical outputs. The principles of DEA date back to Ferrell (1957). The recent series of discussions on this topic started with the article by Charnes et al. (1978). A good introduction to DEA is available in Norman and Stoker (1991). Cooper et al. (2000) provide recent and comprehensive material on DEA.DEA is a nonparametric method in operations research and economics for the estimation of production frontiers. It is used to empirically measure productive efficiency of decision making units (DMUs). Although DEA has a strong link to production theory in economics, the tool is also used for benchmarking in operations management, where a set of measures is selected to benchmark the performance of manufacturing and service operations. In benchmarking, the efficient DMUs, as defined by DEA, may not necessarily form a "production frontier", but rather lead to a "best-practice frontier" (Cook, Tone and Zhu, 2014). DEA is referred to as "balanced benchmarking" by Sherman and Zhu (2013).

Data Envelopment Analysis is a linear programming-based technique for measuring the performance efficiency of organizational units which are termed Decision-Making Units (DMUs). This technique aims to measure how efficiently a DMU uses the resources available to generate a set of outputs (Charnes et al. 1978). Decision-making units can include manufacturing units, departments of big organizations such as universities, schools,

bank branches, hospitals, power plants, police stations, tax offices, prisons, defence bases, a set of firms or even practising individuals such as medical practitioners. As we shall see later in this book, DEA has been successfully applied to measure the performance efficiency of all these kinds of DMUs. Most of these DMUs are non-profit organizations, where the measurement of performance efficiency is difficult.1 Note that the efficiency of commercial organizations can be assessed easily by their yearly profits, or their stock market indices. However, such measurable factors are not applicable to non-profit organizations. The problem is complicated by the fact that the DMUs consume a variety of identical inputs and produce a variety of identical outputs. For example, schools can have a variety of inputs, which are the same for each school—quality of students, teachers, grants, etc. They have a variety of identical outputs number of students passing the final year, average grade obtained by the students in their final year, etc. The performance of DMUs is assessed in DEA using the concept of efficiency or productivity, which is the ratio of total outputs to total inputs. Efficiencies estimated using DEA are *relative*, that is, relative to the best performing DMU (or DMUs if there is more than one best-performing DMUs). The best-performing DMU is assigned an efficiency score of unity or 100 per cent, and the performance of other DMUs vary, between 0 and 100 per cent relative to this best performance.

Non-parametric approaches have the benefit of not assuming a particular functional form/shape for the frontier, however they do not provide a general relationship (equation) relating output and input. There are also parametric approaches which are used for the estimation of production frontiers (see Lovell & Schmidt 1988 for an early survey). These require that the shape of the frontier be guessed beforehand by specifying a particular function relating output to input. The relative strengths from each of these approaches can be combined in a hybrid method (Tofallis, 2001,) where the frontier units are identified by DEA, then fitted to a smooth surface. This allows a best-practice relationship between multiple outputs and multiple inputs to be estimated.

"The framework has been adapted from multi-input, multi-output production functions and applied in many industries. DEA develops a function whose form is determined by the most efficient producers. This method differs from the Ordinary Least Squares (OLS) statistical technique that bases comparisons relative to an average producer. Like Stochastic Frontier Analysis (SFA), DEA identifies a "frontier" which are characterized as an extreme point method that assumes that if a firm can produce a certain level of output utilizing specific input levels, another firm of equal scale should be capable of doing the same. The most efficient producers can form a 'composite producer', allowing the computation of an efficient solution for every level of input or output. Where there is no actual corresponding firm, 'virtual producers' are identified to make comparisons" (Berg 2010).

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."

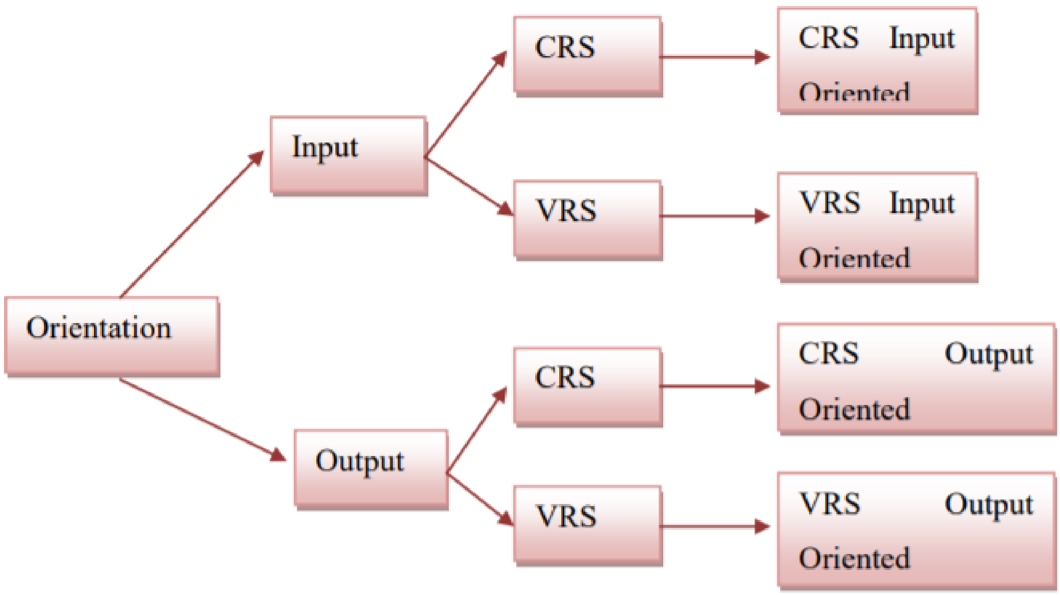

Fig .3.1 Basic DEA Model Classifications

<u>The most of important advantages of the DEA can be listed follows</u>: -

a) The main strength of DEA is its objectivity, i.e., DEA provides efficiency ratings based on numerical data, and not by using subjective opinions of people. Based on the principles of frontier analysis one can say that DEA is very effective evaluation tool that makes maximum possible objective use of the available data.

b) DEA can handle multiple inputs and outputs simultaneously.

c) DEA is non-parametric in the sense that it doesn’t required mathematical form of production function relating inputs and outputs.

d) Excessive use of inputs and shortage of outputs can identify by DEA application through the results of inefficiency.

e) DEA application can be applied easily with inputs and outputs having different units of measurement. For example: one input (number of employees) was measured in number units, while the other input (capital employed) was measured in money units

f) It can identify the nature of returns to scale at each part of efficient frontier.

i) It can use dummy variables too. On other hand, DEA does have certain limitations, which have been listed below.

LIMITATIONS OF DEA:

a) It’s a good at estimating relative efficiency of a DMU with respect to peers, but it converges very slowly to absolute efficiency (theoretical frontier.

b) Very small inputs and very large outputs can affect the results.

c) Limited numbers of the DMUs too affects the results

d) Results are sensitive to the selection of inputs and outputs.

e) It is a deterministic method and does not consider statistical noise.

f) Application of DEA requires solving a separate linear program for each DMU. Hence, the application of DEA to problems that have many DMUs can be computationally intensive. However, this is not a very serious problem, considering the computational power of present-day computers, and the number of DMUs that are considered in normal DEA problems.

3.3 TERMS USED IN DATA ENVELOPMENT ANALYSIS

3.3.1 Efficiency

3.3.2 DMU

3.3.3 Weights

3.3.4 Virtual input and virtual output

3.3.5 CRS

3.3.6 VRS

3.3.7 Input and output slacks

3.3.8 Efficiency frontier

3.3.9 Technical and scale efficiencies

3.3.10 Slack movement

3.3.11 RTS

3.3.12 Input and output oriented envelopment

3.3.13 input and output factors

3.3.1 EFFICIENCY

The basic efficiency measure used in DEA is defined as weighted sum of all the outputs considered in a particular DMU to the weighted sum of inputs

$$\text{Efficiency} = \frac{\text{weighted output}}{\text{weighghted input}}$$

3.3.2 DMU (Decision-making Units) :

Data Envelopment Analysis is a linear programming-based technique for measuring the performance efficiency of organizational units which are termed Decision-Making Units (DMUs). This technique aims to measure how efficiently a DMU uses the resources available to generate a set of outputs (Charnes et al. 1978). Decision-making units can include manufacturing units, departments of big organizations such as universities, schools, bank branches, hospitals, power plants, police stations, tax offices, prisons, defence bases, a set of firms or even practising individuals such as medical practitioners. As we shall see later in this book, DEA has been successfully applied to measure the performance efficiency of all these kinds of DMUs. Most of these DMUs are non-profit organizations, where the measurement of performance efficiency is difficult.1 Note that the efficiency of commercial organizations can be assessed easily by their yearly profits, or their stock market indices. However, such measurable factors are not applicable to non-profit organizations. The problem is complicated by the fact that the DMUs consume a variety of identical inputs and produce a variety of identical outputs. For example, schools can have a variety of inputs, which are the same for each school—quality of students, teachers, grants, etc. They have a variety of identical outputs— number of students passing the final year, average grade obtained by the students in their final year, etc. The performance of DMUs is assessed in DEA using the concept of efficiency or productivity, which is the ratio of total outputs to total inputs. Efficiencies estimated using DEA are relative, that is, relative to the best performing DMU (or DMUs if there is more than one best-performing DMUs). The best-performing DMU is assigned an efficiency score of unity or 100 per cent, and the performance of other DMUs vary, between 0 and 100 per cent relative to this best performance.

3.3.3 WEIGHTS

Weights depends on scale assigned to the inputs and outputs

3.3.4 VIRTUAL INPUT AND VIRTUAL OUTPUT

The inputs and outputs multiplied by their respective weights gives virtual inputs and virtual outputs

3.3.5 Constant Returns to Scale (CRS):

Increase in inputs results in proportional increase in output in case of Constant Returns to Scale.

3.3.6 Variable Returns to Scale (VRS):

Increase in input does not result in proportional increase in output in case of Variable Returns to Scale.

- IRS: increasing returns to scale i.e., if the input is reduced by 10% and the output is reduced by less than 10% it is said to be IRS.
- DRS: decreasing returns to scale i.e., if the input is reduced by 10% and the output is reduced by more than 10% it is said to be DRS.

CRS: constant returns to scale i.e., if the input is reduced by 10% and output is also reduced by 10% it is said to be CRS

3.3.7 INPUT AND OUTPUT SLACKS:

Over the past years, DEA has been applied to profit-making organizations also. This is partly because profit per se is not a good indication of the potential for improvement within an organization, and because other factors are necessary for a holistic assessment of performance.

Input Target = Actual Input ´ Relative Efficiency/100

The difference between actual input and input target is Input Slack

Input Slack = Actual Input –Input Target

Output Target= $\frac{\text{Actual Output}}{\text{Relative Efficiency}/100}$

Slack Output = Output Target- Actual Output

3.3.8 Efficiency Frontier:

Efficiency Frontier, as the line joining the more efficient firms and the vertical and horizontal lines connecting them to the two axes. The efficiency frontier is indicated in Figure 1.1. It represents a standard of performance that the firms not on the frontier should try to achieve. Firms on the frontier (Firms A and C here) are considered 100 per cent efficient.

Such an analysis using the efficiency frontier is often termed Frontier Analysis (Farrell 1957).3 This efficiency frontier forms the basis of efficiency measurement. The efficiency frontier envelops the available data. Hence, the term Data Envelopment Analysis. In the DEA literature, Firms A and C are called efficient firms while Firms B and D that do not lie on the efficiency frontier are called inefficient firms. Firms A and C lie on the efficiency frontier, and hence are the most efficient. Note that this does not mean that their performance cannot be improved. It may or may not be possible. The available data does not give any idea regarding the extent to which their performance can be improved. These are the best firms with regard to the data we have. As no other firm shows better performance, we should assume that their performance is the best achievable. We rate the performance of all other firms in relation to this best achieved performance. Thus, we consider relative efficiencies, not absolute efficiencies

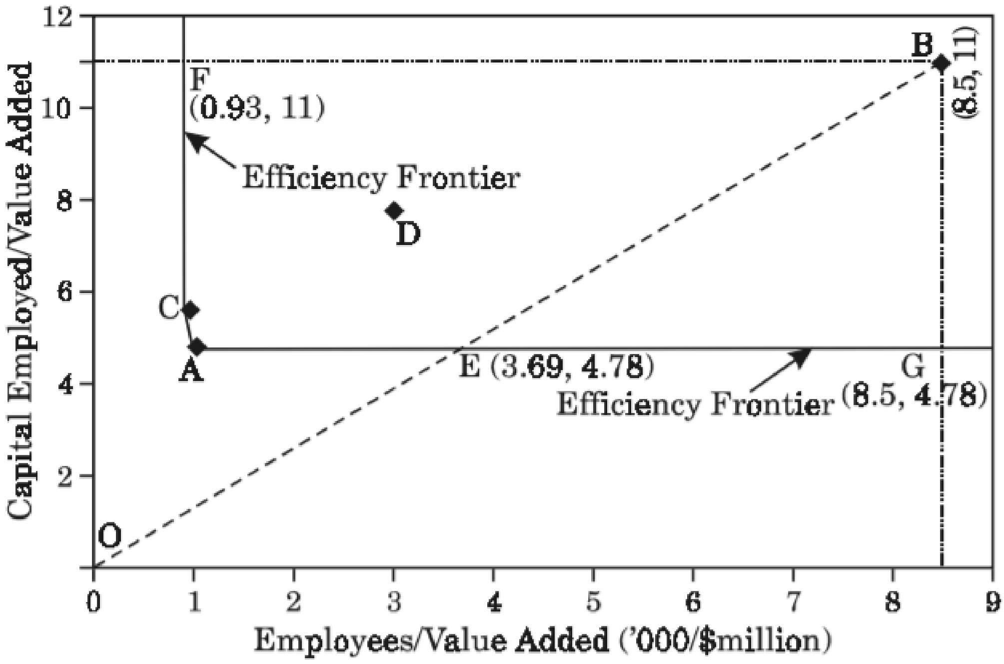

Fig 3.2 Frontier analysis in DEA

Strongly and Weakly Efficient DMUs .In the previous section, it was claimed that the DMUs lying on the efficiency frontier are efficient. However, further distinction among these efficient units is possible. Consider the firm corresponding to the point E in Figure. This firm is considered efficient because it lies in the efficiency frontier, but is weakly efficient as it has a positive slack in one of its inputs (thousand employees). Firm A is strongly efficient as it has no slack. Firm C is also strongly efficient

3.3.9 Technical and Scale Efficiencies

Given the fact that firms are assigned different efficiencies in case of CRS and VRS assumptions, i.e., using CCR models and BCC models, we can distinguish two different kinds of efficiencies—Technical and Scale Efficiencies.

The CCR model (without the convexity constraint) estimates the gross efficiency of a DMU. This efficiency comprises technical efficiency and scale efficiency.

Technical efficiency describes the efficiency in converting inputs to outputs, while scale efficiency recognizes that economy of scale cannot be attained at all scales of production, and that there is one most productive scale size, where the scale efficiency is maximum at 100 per cent.

The BCC model takes into account the variation of efficiency with respect to the scale of operation, and hence measures pure Technical Efficiency.

The CCR model (without the convexity constraint) estimates the gross efficiency of a DMU. This efficiency comprises technical efficiency and scale efficiency. Technical efficiency describes the efficiency in converting inputs to outputs, while scale efficiency recognizes that economy of scale cannot be attained at all scales of production, and that there is one *most productive scale size*, where the scale efficiency is maximum at 100 per cent.

Technical Efficiency

Technical Efficiency describes the efficiency in converting inputs to outputs. Technical Efficiency is defined in terms of equi-proportional increases in outputs that the DMU could achieve while consuming the same quantities of its inputs if it were to operate on the Constant Returns to Scale (CRS) production frontier

Scale Efficiency (SE):

Finally, DEA can also be used to calculate Scale Efficiency. Scale Efficiency recognizes that economy of scale cannot be attained at all scales of production thus concept of Most Productive Scale Size (MPSS) came into the picture and it has been discussed into the details in coming points. Scale Efficiency would be calculated as the ratio of overall Technical Efficiency to Pure

Technical Efficiency. If Scale Efficiency equals one, the power plant is operating at CRS; otherwise it would be characterized by VRS

3.3.10 Slack Movement

Absolute value of Slack Movement is the s- (input slack) or s+ (output slack) in the LP equations. Positive values indicate increase, and negative values indicate decrease.

Benchmarking Models Benchmarking models deals with multiple performance measures and provides an integrated benchmarking measure which are needed to improve their performance. Inefficiency of other models in tackling multiple measures had given raise to benchmarking model. In nutshell, benchmarking is a process of defining valid measures of performance comparison among peer DMUs. In other words, DEA can be considered as benchmarking tool.

3.3.11 Return to Scales (RTS)

Return to Scale look at what happens when you increase all inputs by a multiplier of m. Suppose our inputs are capital or labour, and we double each of these (m = 2), we want to know if our output will more than double, less than double, or exactly double. This leads to the following situations: 1. When our inputs are increased by m, our output increases by more than m. It is termed as Increasing Returns to Scale 2. When our inputs are increased by m, our output increases by exactly m. It is termed as Constant Returns to Scale 3. When our inputs are increased by m, our output increases by less than m. It is termed as Decreasing Returns to Scale

3.3.12 Input and Output Oriented Envelopment DEA Programs

Let us study the two envelopment versions, one involving q and the other involving f. The version involving q aims to produce the observed outputs with minimum inputs. That is why inputs are multiplied by efficiency, according to its constraint rules. Because of this characteristic, this version is often referred to as an input-oriented envelopment DEA program.

The other version is referred to as an output-oriented envelopment DEA program as it aims to maximize output production, subject to the given resource level.

Note that the dual of the output maximizing multiplier program is the input-oriented envelopment program. Similarly, the dual of the input minimizing multiplier program is the output-oriented envelopment program.

Let us examine the behaviour of the input and output oriented envelopment DEA programs more closely, using data regarding the Firms A, B, C, and D. For simplicity, let us consider only one input (capital employed) and only one output (value added). When the values are plotted in a graph (see Figure 4.1), we observe that Firm A has the maximum output (value added) for a given input (capital). Hence, Firm A is the most efficient, and

acts as a peer for all other (inefficient) firms.

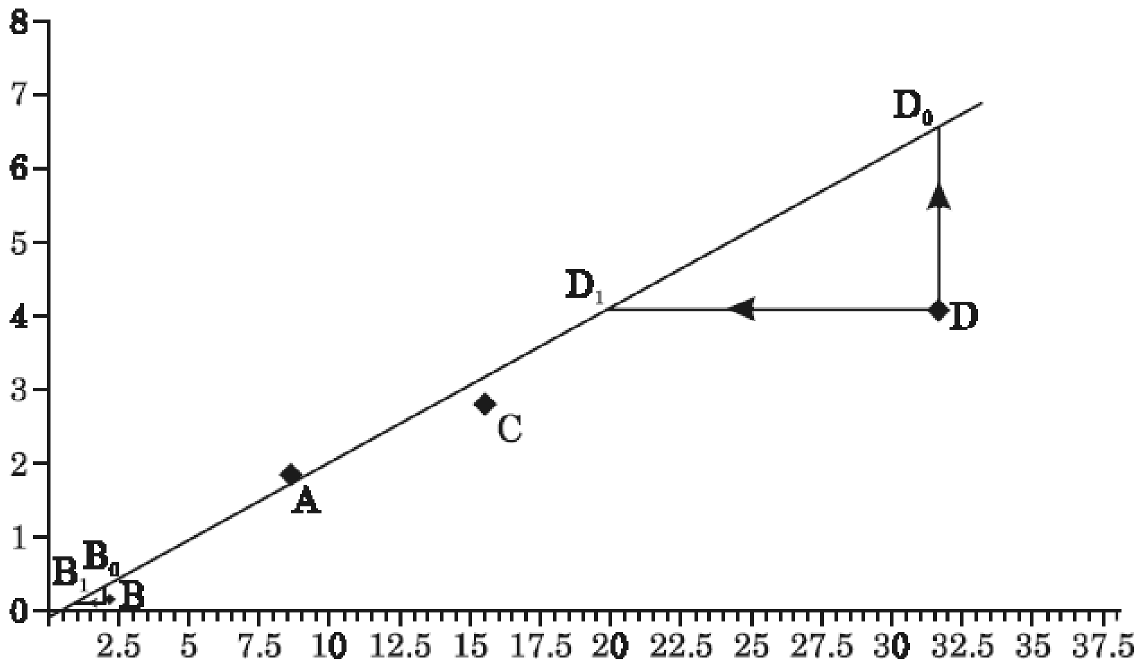

Fig 3.3

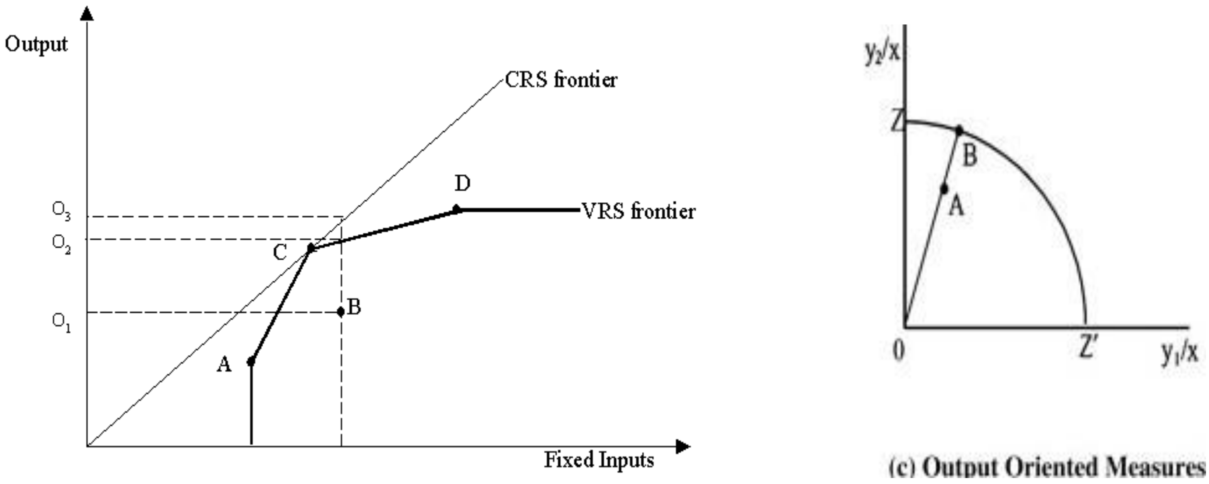

Fig 3.3 Input and Output oriented model graphs

3.3.13 INPUT AND OUTPUT FACTORS:

This project uses samples of 4 discoms in Telangana and Andhra Pradesh states. Each of the DISCOM is treated as decision making unit (DMU) under DEA analysis. The data of Inputs and outputs are collected from years 2010 to 2017.

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, 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. 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

3.3.14 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.

3.4 Methods employed in Data Envelopment Analysis:

3.4.1 TECHNIQUES:

Data envelopment analysis (DEA) is a linear programming methodology to measure the efficiency of multiple decision-making units (DMUs) when the production process presents a structure of multiple inputs and outputs.

"DEA has been used for both production and cost data. Utilizing the selected variables, such as unit cost and output, DEA software searches for the points with the lowest unit cost for any given output, connecting those points to form the efficiency frontier. Any company not on the frontier is considered inefficient. A numerical coefficient is given to each firm, defining its relative efficiency. Different variables that could be used to establish the efficiency frontier are: number of employees, service quality, environmental safety, and fuel consumption. An early survey of studies of electricity distribution companies identified more than thirty DEA analyses—indicating widespread application of this technique to that network industry. (Jamasb, T. J., Pollitt, M. G. 2001). A number of studies using this technique have been published for water utilities. The main advantage to this method is its ability to accommodate a multiplicity of inputs and outputs. It is also useful because it takes into consideration returns to scale in calculating efficiency, allowing for the concept of increasing or decreasing efficiency based on size and output levels. A drawback of this technique is that model specification and inclusion/exclusion of variables can affect the results." (Berg 2010)

Under general DEA benchmarking, for example, "if one benchmarks the performance of computers, it is natural to consider different features (screen size and resolution, memory size, process speed, hard disk size, and others). One would then have to classify these features into “inputs” and “outputs” in order to apply a proper DEA analysis. However, these features may not actually represent inputs and outputs at all, in the standard notion of production. In fact, if one examines the benchmarking literature, other terms, such as “indicators”, “outcomes”, and “metrics”, are used. The issue now becomes one of how to classify these performance measures into inputs and outputs, for use in DEA." (Cook, Tone, and Zhu, 2014)

Data Envelopment Analysis (DEA) is a methodology based upon an interesting application of linear programming. It was originally developed for performance measurement. It has been successfully employed for assessing the relative performance of a set of firms that use a variety of identical inputs to produce a variety of identical outputs. The principles of DEA date back to Farrel (1957). The recent series of discussions on this topic started with the article by Charnes et al. (1978). A good introduction to DEA is available in Norman and Stoker (1991). Cooper et al. (2000) provide recent and comprehensive material on DEA.

Efficiency Frontier, as the line joining the more efficient firms and the vertical and horizontal lines connecting them to the two axes. The efficiency frontier is indicated in form of a graph. It represents a standard of performance that the firms not on the frontier should try to achieve.

3.4.2 Mathematical Programming Aspects of DEA

Performance evaluation for the case of two inputs and one output was more complicated than in the case of single input–output. Graphical analysis was used for analysing this case. However, graphical models cannot be used if we consider a greater number of inputs and outputs. Hence, a general mathematical formulation is needed to handle the case of multiple inputs and multiple outputs. Note that the techniques of frontier analysis has been described by Farrell in 1957, but a mathematical framework to handle frontier analysis could be established only after 20 years. This mathematical formulation was provided by Charnes et al. (1978). This seminal paper provided the fundamentals of the mathematical aspects of frontier analysis.

The three basic, efficient and mostly used models in Data Envelopment Analysis are:

1.The first model is the CCR DEA model. For example, the input-oriented envelopment CCR DEA model does not have any convexity constraint involving $\sum_{n=1}^{N} \lambda_n$=1. Let the optimal objective function value be denoted as p.

2. The second model is the BCC DEA model. For example, the input oriented envelopment BCC DEA model has the additional constraint, $\sum_{n=1}^{N} \lambda_n$=1 . Let the optimal objective function value be denoted as q. We have seen earlier that the ratio p/q is the scale efficiency of the reference DMU. If the scale efficiency is 1, i.e., if p = q, then the reference DMU exhibits CRS.

3. The third model which uses time series analysis is Malmquist Productivity Index.

<u>Time Series Analysis using DEA :</u>

So far, we have compared the performance of a number of DMUs that operate at a particular point in time. This kind of analysis is normally referred to as a cross-sectional analysis. In contrast, one can think of comparing performance of DMUs over time. This type of analysis is generally referred to as a time series analysis. In practice, DMUs are observed over multiple time periods; the variations of efficiency of DMUs over time can help in making important conclusions.

3.4.3 Mathematical Formulation

Let us use x and y to represent inputs and outputs, respectively. Let the subscripts i and j to represent particular inputs and outputs respectively. Thus, xi represents the ith input, and yj represent the jth output of a decision-making unit. Let the total number of inputs and outputs be represented by I and J respectively, where I, J > 0.

In DEA, multiple inputs and outputs are linearly aggregated using weights. Thus, the virtual input of a firm is obtained as the linear weighted sum of all its inputs.

Virtual Input=$\sum_{i=1}^{I} u_i x_i$

where $u_i$is the weight assigned to input $x_i$during the aggregation

Similarly, the virtual output of a firm is obtained as the linear weighted sum of all its outputs.

Virtual Output $=\sum_{j=1}^{J} v_j y_j$

where $v_j$is the weight assigned to output $y_j$during the aggregation

Given these virtual inputs and outputs, the Efficiency of the DMU in converting the inputs to outputs can be defined as the ratio of outputs to inputs

Efficiency$=\frac{\text{Virtual Output}}{\text{Virtual Input}}=\frac{\sum_{j=1}^{J} v_j y_j}{\sum_{i=1}^{I} u_i x_i}$

Obviously, the most important issue at this stage is the assessment of weights. This is a tricky issue as there is no unique set of weights. For example, a school that has a good reputation of teaching humanities will like to attach higher weights to its humanities' output. A school that has a higher percentage of socially weaker groups in its students would like to emphasize this fact, assigning a greater weight to this input category. Thus, the weights assigned should be flexible and reflect the requirement (performance) of the individual DMUs

This issue of assigning weights is tackled in DEA by assigning a unique set of weights for each DMU. The weights for a DMU are determined, using mathematical programming, as those weights which will maximize its efficiency subject to the condition that the efficiencies of other DMUs (calculated using the same set of weights) is restricted to values between 0 and 1. The DMU for which the efficiency is maximized is normally termed as the reference or base DMU or the DMU under the assessment.

Note that these mathematical programs are fractional programs. It is generally difficult to solve fractional programs. If they are converted to simpler formulations, such as the linear programming (LP) formats then they can be solved easily. The simplest way to convert these fractional programs to linear programs is to normalize either the numerator or the denominator of the fractional programming objective function.

The weighted sum of inputs is constrained to be unity in this linear program. As the objective function is the weighted sum of outputs that has to be maximized, this formulation is referred to as the Output Maximization DEA program. An analogous LP formulation is possible by minimizing the weighted sum of inputs, setting the weighted sum of outputs equal to unity. That is the Input Minimization DEA program.

Because of the nature of the formulations, the optimal objective function value of the input minimization DEA program for Firm A will be the reciprocal of the optimal objective function value (i.e., the value of efficiency) of the output maximization DEA program for Firm A.

These were the original models introduced by Charnes et al. in 1978. Immediately after, the authors made a minor modification (Charnes et al. 1979). In a conventional LP, the decision variables are non-negative—they can be either zero or positive. However, the authors chose to define the decision variables of the DEA programs (i.e., the weights) to be strictly positive. They replaced the non-negativity constraints

$$u_1, u_2, u_3 \geq 0$$

by the strict positivity constraints

$$v_1, v_2, v_3 \geq 0$$

General Form of CCR DEA Models

A general output maximization CCR DEA model can be represented as follows

Max z= $\sum_{j=1}^{J} v_j y_j$

Subject to $\sum_{i=1}^{I} u_i x_i = 1$

$$\sum_{j=1}^{J} v_j y_j - \sum_{i=1}^{I} u_i x_i \leq 0 \; n = 1,2,K,N$$

3.4.4 CCR Model

Charnes, Cooper and Rhodes suggested the CCR formulation. It assumes a constant return to scale hypothesis. CCR model presented here is the input-oriented model whose objective is to minimise inputs while producing at least the given output level. The evaluated relative efficiency (CRS) of the CCR model is a technical efficiency score. In addition, the efficiency scores of all DMUs are between 0 and 1 in DEA models. This model assumes a constant return to scale (CRS) assumption. It assigns best set of weights/ coefficients to each unit(Charnes, A).

Now, the efficiency of each of the DMU_j (Decision Making Unit), with j = 1, 2,..n is to be measured so that we can determine relative efficiency and identify inefficient units. If there are 'n' DMUs, we need 'n' optimizations, one for each DMU using following notations. DMUo: DMU which will be evaluated in a particular trial, with o=1, 2,..n.

v_i =Coefficient for input i, with i = 1,2,…..m

u_r =Coefficient for output r, with r = 1,2,…..s

The DEA model can be presented to maximize the efficiency of DMUo, θ_0,by writing the objective function of oth DMU as given below.

$$\theta_{CCR}(k_0) = \frac{u_1 y_{1K_0} + u_2 y_{2K_0} + \cdots + u_n y_{nK_0}}{v_1 x_{1K_0} + v_2 x_{2K_0} + \cdots + v_m x_{mK_0}}$$

The model will be subjected to the constraints;

1. Efficiency of all other DMUs will be less than or equal to 1

$$\frac{u_1y_{1j}+u_2y_{2j}+\cdots+u_sy_{sj}}{v_1x_{1j}+v_2x_{2j}+\cdots+v_mx_{mj}} \leq 1 \ (j=1,2,\ldots.n)$$

2. Non negativity constraints. The model will take fractional programming form as given below.

$$v_1, v_2, \ldots \ldots \ldots v_m \geq 0$$
$$u_1, u_2, \ldots \ldots \ldots u_s \geq 0$$

The fractional programming model can be converted into a linear programming model. This is done by scaling each of the inputs to 1 and rewriting the constraints as mentioned below

$$\begin{aligned}
&\textit{Objective function} \qquad\qquad (\text{for } o^{th} \text{ DMU})\\
&Max\ \theta_o = u_1y_{1o} + u_2y_{2o} + \ldots\ldots + u_sy_{so}\\
&\textit{Subject to}\\
&v_1x_{1o} + v_1x_{1o} + \ldots\ldots\ldots + v_mx_{mo} = 1\\
&u_1y_{1j} + u_2y_{2j} + \ldots\ldots + u_sy_{sj} \leq v_1x_{1j} + v_1x_{1j} + \ldots\ldots + v_mx_{mj}\\
&\qquad\qquad (j = 1, 2, \ldots\ldots, n)\\
&v_1, v_2, \ldots\ldots, v_m \geq 0\\
&u_1, u_2, \ldots\ldots, u_s \geq 0
\end{aligned}$$

The presented model finds the best set of weights or coefficients pertaining to each input and output variable while maximum rating of efficiency is assigned to oth DMU. After solving linear programming model for DMUo, the oth DMU will be efficient only if the model results in:

1) The optimal efficiency of oth DMU is equal to 1

2) All slacks are zero. The efficient DMUs will form efficient frontier.

The DMU's efficiencies are plotted in a curve called efficiency frontier. The DMU_1 and DMU_5 are said to be efficient as they give efficient or maximum output to less or reasonable input.

All the other DMU's are said to be inefficient and the efficient DMU's are set as target to these inefficient DMU's to improve their performance.

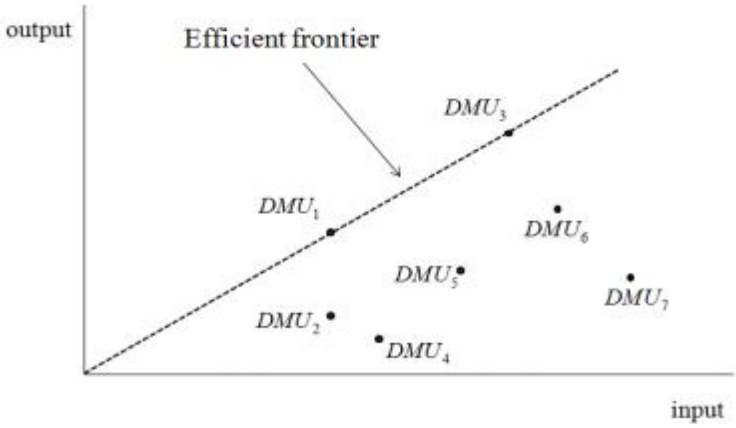

Fig 3.4 efficiency frontier in CCR model

3.4.5 Variable Returns to Scale Envelopment DEA Programs

Thus, the DEA envelopment program for considering variable returns to scale is the following

Min θ_m

Such that

$Y_\lambda \geq Y_m$

$X_\lambda \geq \theta X_m$

$\sum_{n=1}^{N} \lambda_n = 1$

$\lambda \geq 0$

As mentioned earlier, this modification was first suggested by Banker et al. (1984). Hence, the foregoing DEA model is termed the BCC (Banker, Charnes and Cooper) model. In general, DEA programs incorporating the additional convexity constraint to take into account variable returns to scale are called BCC DEA models or VRS DEA models. In contrast, CCR DEA models are also called CRS DEA models

3.4.5 BCC Model:

Banker et al. developed the BCC model that produces variable returns to scale (VRS) efficiency frontier to measure the technical efficiency and evaluates both technical efficiency and scale efficiency (SE). Banker et al. (1984) reported a Linear programming model to generate BCC efficiency factor of the DMUs as follows (Banker, R.D):

The BCC model (to be solved for each DMU)

$$\text{Max } \theta_{BCC}(K_0) = \sum_{j=1}^{n} u_j y_{jK_0} + \mu(K_0)$$

$$\sum_{i=1}^{m} v_i x_{iK_0} \leq 1$$

$$\sum_{j=1}^{n} u_j y_{jK_0} + \mu(K_0) - \sum_{i=1}^{m} v_i x_{iK_0} \leq 0$$

K_0=1,...,K. $u_j \geq 0$, j=1,...,n, vj ≥0, i=1,...,m, and μ(K_0) is unrestricted.

Here μ(ko) indicates the returns to scale (RTS) at particular points on the efficient frontier. It can hold positive, negative or zero value representing that the corresponding DMU presenting increasing, decreasing or constant

Figure 2 provides a representation of the VRS frontier along with the CRS frontier for a set of four DMUs A, B, C, and D.

The DMU_1, DMU_2 and DMU_3 are said to be efficient. These DMU's are benchmarked and set as the target for the remaining inefficient DMU's.

Pure Technical Efficiency Pure Technical Efficiency measures the increase in outputs that the DMU could achieve if it were to use the Variable Returns to Scale (VRS) technology

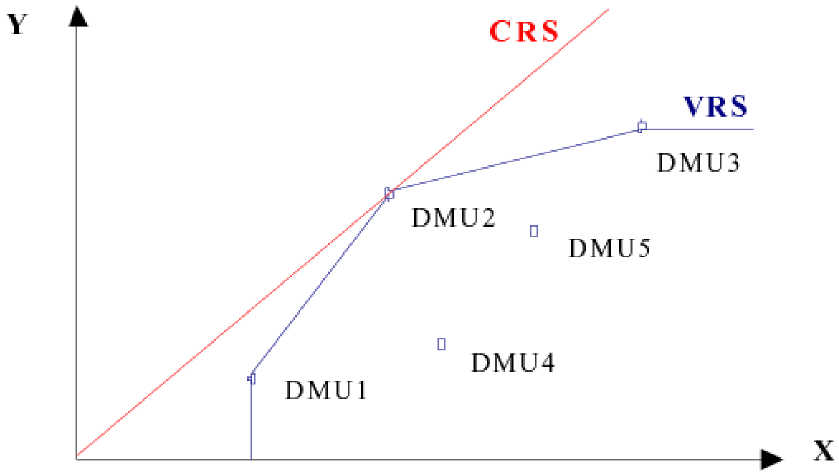

Fig 3.5 BCC model

3.4.6 Malmquist Productivity Index Approach

The Malmquist productivity index (MPI) deals with panel data. It evaluates the total factor productivity change of a DMU between two periods, named period 1 (the “from” period) and period 2 (the “to” period). Malmquist Total Factor productivity index measures the productivity change and decompose this change into Technical change and Technical Efficiency change. This index is named after Malmquist, who proposed to construct input quantity index as a ratio of distance function. Afterwards, Fare et al. [29] constructed a Malmquist productivity index directly from input and output data using DEA. MPI is defined as the product of efficiency change (catch-up) and technological change (frontier-shift).

- Let is the frontier at (t + 1). If there is a technical progress, will shift upwards from . M represents achievement at time (t + 1), while N represents the achievement at time t.

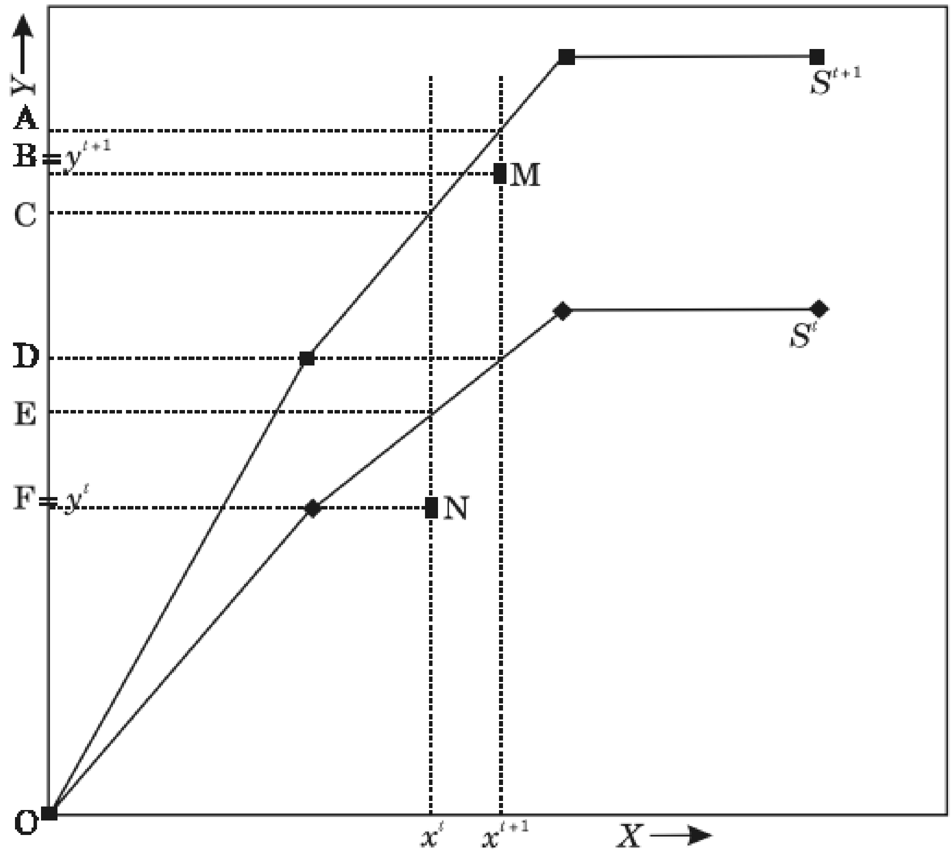

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Fig 3.6 Malmquist Productivity Index

The efficiency change reflects to what extent a DMU improves or worsens its efficiency, while technological change reflects the change of the efficiency frontiers between two periods. These indices may be either input or output-oriented for either the period s or period t technologies [30]. The input-based Malmquist productivity index can be formulated

$$M^{t+1}(x^{t+1}, y^{t+1}, x^{t}, y^{t}) = \left[\frac{D^{t}(x^{t+1}, y^{t+1})}{D^{t}(x^{t}, y^{t})} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t}, y^{t})} \right]^{½}$$

Where Di is the input distance function and M^{t+1} $(x^{t+1},y^{t+1},x^{t+1},y^{t})$ is the productivity of most recent production unit i.e. B (t+1) using period t+1 technology relative to the earlier production unit i.e. B (t) with respect to t technology .

M = ΔTECH × ΔEFF

$$\Delta\text{EFF}=\frac{D_i^{t+1}(x^{t+1},y^{t+1})}{D_i^{t}(x^{t},y^{t})}$$

$$\Delta\text{TECH}=\left[\frac{D_i^{t}(x^{t+1},y^{t+1})}{D_i^{t+1}(x^{t+1},y^{t+1})}\times\frac{D_i^{t}(x^{t},y^{t})}{D_i^{t+1}(x^{t},y^{t})}\right]^{\frac{1}{2}}$$

$D^{t+1}(x^{t+1},y^{t+1})$= DEA efficiency using x^{t+1} inputs and y^{t+1} outputs

Similarly, $D^{t}(x^{t},y^{t})=\frac{OF}{OE}$

$$D^{t+1}(x^{t},y^{t})=\frac{OF}{OC}$$

In practice, this DEA-MPI has proven to be a good tool for measuring the productivity change of DMUs over time, and has been successfully applied in many fields.

The Malmquist Productivity Index gives the data regarding efficiency change, technology change, Pure efficiency change, Scale efficiency change and total factor of productivity change.

Efficiency change:

The efficiency change obtained from Malmquist Productivity Index gives the change in efficiency of a firm with time series

Technological change:

The Technological Change obtained from Malmquist Productivity Index gives the factor with which the technology of converting inputs to outputs have changed.

Scale efficiency change:

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 returns to scale. 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 (K.V.R.Perera.,) .

$$\text{Scale Efficiency} = \frac{CRS\ EFFICIENCY}{VRS\ EFFICIENCY}$$

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

<u>Total factor of production change:</u>

Gives the total factor of change of production of a firm over years

<u>Advantages of Malmquist Productivity Index</u>:

- The socio-economic growth and change in significance of companies over years can be found.
- as it is Consumes less time and space.
- Can be easily evaluated by the companies simple.
- Comparison with their own self over years

Chapter-4

VARIABLES AND DATA

4.1 Variables and data

4.2 Model and application

4.3 DEAP

4.4 Efficiency change

4.5 Observation

4.VARIABLES AND DATA

4.1 VARIABLES AND DATA:

In this project to compare DISCOMs according to their academic productivity in respects of their population and average wealth invested, five variables are used. Total expenditure (TotEx) which is the investment done on distribution and Power Purchase Cost which is the expenditure on purchase of power, Employee cost i.e., one of the most important aspect while the Total Energy Sales and Revenue from sale of power are output.

The inputs and outputs of our project are taken from TSNPDCL, TSSPDCL, APCPDCL, APEPDCL for the years of 2010 to 2017.

4.2 MODEL AND APPLICATION:

For the study of time series analysis in our project Malmquist Productivity Index is used. That is the companies are compared with their own selves for 7 years. The data used for computing efficiency changes of the respective DISCOMs are given in below tables.

Name of the DMU: TSNPDCL					
	PARAMETERS				
Year	**Revenue from sale of power (Cr)**	**Energy Sold (MU)**	**Employee cost (Cr)**	**Total Expenditure (Cr)**	**Power Purchase Cost (Cr)**
2010-11	2566.28	9102.33	402.14	4510.79	3595.7
2011-12	2875.56	10243.93	345.24	5429	4433.36
2012-13	2893.8	9671.61	432.89	8803.11	5300.44
2013-14	3547.21	10287	491.46	6325.36	5250.89
2014-15	3506.47	11104.79	725.19	7429.22	5983.73
2015-16	3661.43	11565.77	692.7	8627.57	7031.76
2016-17	4070.21	12902.78	694.3	9178.36	7576.17

Table 4.1 Data of TSNPDCL

Name of the DMU: TSSPDCL (or APCPDCL)					
	PARAMETERS				
Year	**Revenue from sale of power (Cr)**	**Energy Sold (MU)**	**Employee cost (Cr)**	**Total Expenditure (Cr)**	**Power Purchase Cost (Cr)**
2010-11	9860.07	28740.93	6097.83	12025.92	10173.27
2011-12	9532.35	31597.2	830.52	15124.26	12765.67
2012-13	11185.62	30634.6	766.15	23721.06	15235.31
2013-14	14120.49	31859.73	852.71	17985.74	15255.57
2014-15	13556.15	28724.72	1028.86	17557.23	14925
2015-16	15463.6	29083.93	1719.81	19198.01	16720.06
2016-17	15935.51	30844.18	1386.87	22760.89	19212.94

Table 4.2 Data of TSSPDCL

Name of the DMU: APEPDCL					
	PARAMETERS				
Year	**Revenue from sale of power (Cr)**	**Energy Sold (MU)**	**Employee cost (Cr)**	**Total Expenditure (Cr)**	**Power Purchase Cost (Cr)**
2010-11	3291.52	10334.24	451.98	4454.82	3589.41
2011-12	3863.01	11725.82	433.92	5489.83	4537.43
2012-13	5108.6	11903.93	537.24	6771.96	5406.72
2013-14	6762.7	12900.32	509.48	6486.5	5493.77
2014-15	6989.18	14155.76	971.61	8682.95	6835.22
2015-16	8866.87	15533.6	841.73	9338.73	7548.31
2016-17	8720.3	17088.37	822.66	9161.61	7371.19

Table 4.3 Data of APEPDCL

Name of the DMU: APCPDCL					
	PARAMETERS				
Year	**Revenue from sale of power (Cr)**	**Energy Sold (MU)**	**Employee cost (Cr)**	**Total Expenditure (Cr)**	**Power Purchase Cost (Cr)**
2010-11	4858.47	14446	742.55	6801.67	5061.12
2011-12	5972.36	16388.21	564.13	7917.72	6339
2012-13	6535.12	16444.84	576.21	12902.63	7902.72
2013-14	7327.44	18024.46	854.11	9961.31	8083.16
2014-15	1092.38	26361.61	1813.16	16288	13016.49
2015-16	11910.76	28709.57	1508.85	18356.01	14920.49
2016-17	12731.28	30734.43	1346.66	18535.28	15076.12

Table 4.4 Data of APCPDCL

The above given tables are data collected from the DISCOMS of Andhra Pradesh and Telangana of respective years 2010-2017. The data collected is of seven years. A time series analysis is performed on these four distribution companies and the results are analysed.

The Malmquist Productivity Index is used in the case of time series technique. The Malmquist productivity index compares a firm or DMU with its own self and gives the changes in the firm with in the given period of time.

The analysis of Malmquist Productivity index is done by using DEAP software.

4.3 DEAP:

The software used for evaluating the performance of Distribution Utilities is DEAP. DEAP is the method which gives the evaluation results which is easily adoptable by the user.

It consists of three files. They are:

4.3.1 Data file

The program requires that the data be listed in a text file and expects the data to appear in a particular order. The data must be listed by observation (i.e., one row for each firm). There must be a column for each output and each input, with all outputs listed first and then all inputs listed (from left to right across the file).

The data used for this project are given above of TSNPCL, TSSPDCL, APEPDCL, APSPDCL in tables 4.1, 4.2, 4.3, 4.4 respectively

The data considered is named as firm 1, firm2, firm3, firm 4 for DISCOMS TSNPCL, TSSPDCL, APEPDCL, APSPDCL respectively.

4.3.2 Instruction file

The instruction file is a text file which is usually constructed using a text editor or a word processor. The easiest way to create an instruction file is to make a copy of the DBLANK.INS file which is supplied with the program (by using the FILE/COPY menus in FILE MANAGER in WINDOWS or by using the COPY command at the DOS prompt). We then edit this file (using a text editor or word processor) and type in the relevant information.

4.3.3Output file

As noted earlier, the output file is a text file which is produced by DEAP when an instruction file is executed. The output file can be read using a text editor, such as NOTEPAD or EDIT, or using a word processor, such as WORD or WORD PERFECT. The output may also be imported into a spreadsheet program, such as EXCEL or LOTUS, to allow further manipulation into tables and graphs for subsequent inclusion into report documents.

By following the above steps, the output obtained is given below:

EG1-out - Notepad

File Edit Format View Help

MALMQUIST INDEX SUMMARY

year = 2

firm	effch	techch	pech	sech	tfpch
1	1.000	0.770	1.000	1.000	0.770
2	0.949	0.708	1.000	0.949	0.671
3	1.201	0.745	1.201	1.000	0.895
4	1.000	1.071	1.000	1.000	1.071
mean	1.033	0.812	1.047	0.987	0.839

year = 3

firm	effch	techch	ch	sech	tfpch
1	1.000	1.637	[illegible]	1.000	1.637
2	1.054	1.867	1.000	1.054	1.969
3	1.000	2.007	1.000	1.000	2.007
4	0.983	1.378	1.000	0.983	1.355
mean	1.009	1.705	1.000	1.009	1.721

year = 4

firm	effch	techch	pech	sech	tfpch
1	1.000	0.854	1.000	1.000	0.854
2	1.000	0.763	1.000	1.000	0.763
3	1.000	0.872	1.000	1.000	0.872
4	1.017	0.941	1.000	1.017	0.957
mean	1.004	0.855	1.000	1.004	0.858

year = 5

firm	effch	techch	pech	sech	tfpch
1	0.938	1.208	1.000	0.938	1.133
2	1.000	1.253	1.000	1.000	1.253
3	0.882	1.012	0.947	0.931	0.892
4	0.954	1.100	1.000	0.954	1.049
mean	0.943	1.139	0.986	0.955	1.074

year = 6

firm	effch	techch	pech	sech	tfpch
1	1.067	1.016	1.000	1.067	1.083
2	1.000	0.990	1.000	1.000	0.990
3	1.134	1.074	1.056	1.074	1.218
4	1.048	1.038	1.000	1.048	1.088
mean	1.061	1.029	1.014	1.047	1.092

year = 7

firm	effch	techch	pech	sech	tfpch
1	1.000	0.831	1.000	1.000	0.831
2	0.908	0.810	0.973	0.933	0.735
3	0.898	0.828	0.939	0.956	0.744
4	1.000	0.842	1.000	1.000	0.842
mean	0.950	0.828	0.978	0.972	0.786

MALMQUIST INDEX SUMMARY OF ANNUAL MEANS

year	effch	techch	pech	sech	tfpch
2	1.033	0.812	1.047	0.987	0.839
3	1.009	1.705	1.000	1.009	1.721
4	1.004	0.855	1.000	1.004	0.858
5	0.943	1.139	0.986	0.955	1.074
6	1.061	1.029	1.014	1.047	1.092
7	0.950	0.828	0.978	0.972	0.786
mean	0.999	1.023	1.004	0.995	1.022

MALMQUIST INDEX SUMMARY OF FIRM MEANS

firm	effch	techch	pech	sech	tfpch
1	1.000	1.016	1.000	1.000	1.016
2	0.984	1.002	0.996	0.989	0.986
3	1.013	1.027	1.020	0.993	1.040
4	1.000	1.049	1.000	1.000	1.049
mean	0.999	1.023	1.004	0.995	1.022

Fig 4.2 Output obtained

4.4 Results and Observation:

The Malmquist productivity index for four firms over seven years of time period gave the result of efficiency change, Pure efficiency change, Scale efficiency change, Total factor of production change as given in fig 6.2

The change in efficiency, scale, total factor of production, technology which are above 1 are considered to be desirable or advantageous. The figure above 1 gives the positive change or improvement for a given firm over a period of time.

<u>Year 2:</u>

Considering the changes for year 2, the change of efficiency is satisfactory for the firms 1,3 and 4 where as it is inefficient in case of firm 2. The technology change is excellent for firm 4 whereas lagging in case of remaining firms i.e., technology used to convert inputs to outputs is satisfactory for firm 4.

Pure efficiency change is satisfactory for firm 3 as compared to other firms. The pure efficiency change i.e., converting of inputs to outputs are desired to be done more efficient. Scale efficiency change is very less for firm 2 i.e., the economy of scale for the firm 2 is poor. The total factor of productivity is satisfactory for firm 4 whereas all the other three firms need to improve their performance.

<u>Year 3:</u>

Considering the changes for year 3, the change of efficiency is satisfactory for the firm's 1,2 and 3 where as it is inefficient in case of firm 3. The technology change is excellent for firm 3 whereas satisfactory in case of remaining firms i.e., technology used to convert inputs to outputs is satisfactory for firm 3.

Pure efficiency change is satisfactory for all the firms. The pure efficiency change i.e., converting of inputs to outputs are desired to be done more efficient. Scale efficiency change is very less for firm 4 i.e., the economy of scale for the firm 4 is poor.

The total factor of productivity is satisfactory for firm 3 whereas all the other three firms are satisfactory. The total factor of productivity is satisfactory for firm 3 whereas all the other three firms are satisfactory.

Year 4:

Considering the changes for year 4, the change of efficiency is satisfactory for the firm 4 whereas firms 1,2 and 3 are improvable. The technology change is satisfactory for firm 2 whereas satisfactory in case of remaining firms i.e., technology used to convert inputs to outputs is satisfactory for firm 2.

Pure efficiency change is satisfactory for all the firms. The pure efficiency change i.e., converting of inputs to outputs are desired to be done more efficient. Scale efficiency change is satisfactory for firm 3 i.e., the economy of scale for the firm 3 is good. The total factor of production is poor for firm 2 where as satisfactory in case of remaining firms.

Year 5:

Considering the changes for year 5, the change of efficiency is satisfactory for the firm 2 whereas firms 1,3 and 4 are improvable. The technology change is satisfactory for all the firms i.e., technology used to convert inputs to outputs is satisfactory all firms.

Pure efficiency change is satisfactory for all the firms except firms i.e., converting of inputs to outputs are desired to be done more efficient. Scale efficiency change is satisfactory for firm 2 i.e., the economy of scale for the firm 3 is poor. The total factor of production is poor for firm 3 whereas satisfactory in case of remaining firms.

Year 6:

Considering the changes for year 6, the change of efficiency is satisfactory for the firm 3 whereas firms 1,2 and 4 are improvable. The technology change is satisfactory for all the firms except firm 2 i.e., technology used to convert inputs to outputs is satisfactory all firms.

Pure efficiency change is satisfactory for all the firms except firms i.e., converting of inputs to outputs are desired to be done more efficient. Scale efficiency change is satisfactory for all the firms i.e., the economy of scale for the firms are good. The total factor of production is poor for firm 2 whereas satisfactory in case of remaining firms.

Year 7:

Considering the changes for year 7, the change of efficiency is satisfactory for the firm's 1,4 whereas firms 2,3 are improvable. The technology change is unsatisfactory for all the firms i.e., technology used to convert inputs to outputs is unsatisfactory all firms.

Pure efficiency change is satisfactory for the firm's 1,4 i.e., converting of inputs to outputs are desired to be done more efficient. Scale efficiency change is satisfactory for the firm's 1,4 i.e., the economy of scale for the firms are good. The total factor of production is poor for all the firms whereas satisfactory in case of remaining firms.

The firm 1(TSNPDCL) has good improvement in technological change and total factor of productivity change and a satisfactory efficiency change, Pure efficiency change and scale efficiency change.

The firm 2(TSSPDCL) has poor efficiency change, pure efficiency change, scale efficiency change and total factor of productivity change and a satisfactory technical efficiency change.

The firm 3 (APEPDCL) has good improvement in efficiency change, pure efficiency change technological change and total factor of productivity change and a poor Scale efficiency change.

The firm 4(APSPDCL) has good improvement in technological change and total factor of productivity change, efficiency change, Pure efficiency change and scale efficiency change

5.CONCLUSION

Thus, the performance analysis of electrical distribution utilities has been compared with their own selves to find the change in their performance over years. Every firm has a excellent improvement and also some unsatisfactory improvement with time. The respective firms need to concentrate on lagging aspects ans plan how to improve more and how to serve public satisfactorily.

The efficiency change, Technological change, Pure Efficiency change, Scale efficiency change and total factor of Productivity change of electrical utilities are evaluated and the results are compared.

It is the fact that performance depends on human capital and economic support but your competitiveness varies and depends on whom you compete. In this perspective competing with own self and improving the DMU from year to year is mandatory. The above results can easily be energized to other areas such as economics. Any firm in market positions itself according to its self-scale.

REFERENCES

1.Banker, R.D., Charnes, A. and Cooper, W.W. (1984) 'Some models for estimating technical and scale inefficiencies in data envelopment analysis', Management Science, Vol. 30, No. 9, pp.1078–1092.

2.Charnes, A., Clark, T., Cooper, W.W. and Golany, B. (1985) 'A development study of data envelopment analysis in measuring the efficiency of maintenance units in the US Air Force', Annals of Operations Research, Vol. 2, No. 1, pp.95–112.

3.Charnes, A., Cooper, W.W. and Rhodes, E. (1978) 'Measuring the efficiency of decision making units', European Journal of Operational Research, Vol. 2, No. 6, pp.429–444.

4.Cooper, W.W., Seiford, L.M. and Tone, K. (2000) Data Envelopment Analysis: A Comprehensive Text with Models, Applications, Reference and DEA-Solver Software, Kulwer Academic Publishers, Boston.

5. Ramnathan. R., An Introduction to Data Envelopment Analysis A Tool for Performance Measurement

6. Sonal Singhal, Shrey Jain, Nithin B, Bhawna Rawat Performance evaluation of Uttarakhand Electric Utility Data using Slack Based Measure and TwoStage DEA Modelling

7.Joe Jhu, Quantitative Models for Performance Evaluation and Benchmarking Data Envelopment Analysis with Spreadsheets Second Edition

8. Ali Emrouznejad, Rajiv Banker Data envelopment analysis and its applications.; Proceedings of the 13th International Conference of DEA

9. K.V.R.Perera., Performance evaluation of power distribution sector of sri lanka based on data envelopment analysis.

10. Seema Saxena , Tripta Thakur ., Performance evaluation of Indian electrical distribution utilities in the post Electricity Act 2003 era.

11. Performance Evaluation of Indian Electric Utility: An Intercountry Comparison Using DEA .,Vinod Kumar Yadav, Narayana Prasad Padhy and Hari Om Gupta.

12. Performance Evaluation of Electric Distribution Centers using Data Envelopment Analysis Shiva P. Pokharel, and Rabin Shrestha..

13. Measurement of Relative Efficiency of State Owned Electric Utilities in INDIA Using Data Envelopment Analysis R.Meenakumari.

14. Approach on Performance Evaluation and Index Selection for Electricity Distribution Utilities Ming Zhou, Member, IEEE, Weijun Zhai, and Gengyin Li, Member, IEEE