Chapter 3

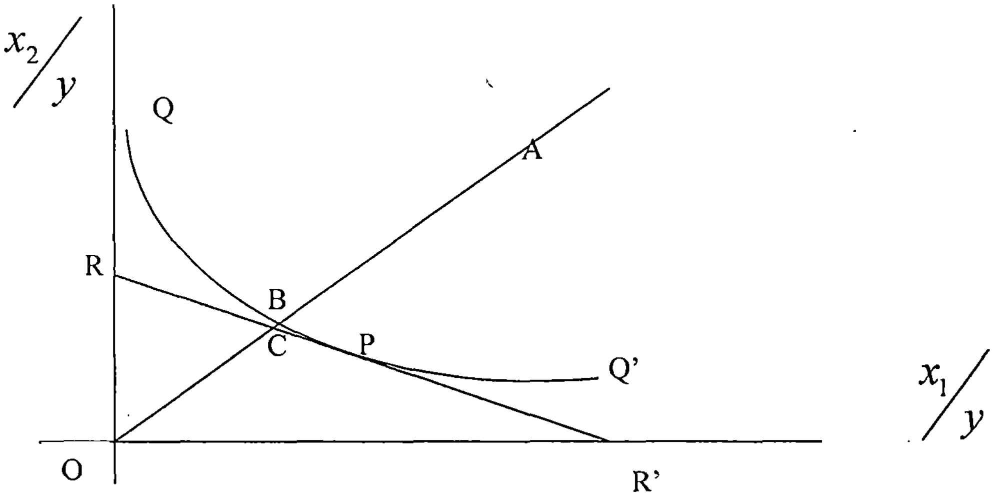
Measurement of Efficiency & DEA: A Review

3.1 Introduction:

Decision making is a very important facet of management. Operations research provides appropriate optimizing tools and techniques which can help managers to take the best decisions. A decision is said to be 'the best', if it helps an economic unit or organization to achieve the optimal level of performance. When an organization operates at this optimal level of performance we define it as 'efficient'. A key factor of business sustainability is the 'efficient performance' of that organization. In this respect, the performance measurement becomes essential to understand the extent of achievement attained by the organization. Any operation at sub-optimal level gives birth to inefficiency that implies wastages of resources and makes the system economically vulnerable. In the long run, this inefficiency does not only make the existence of that particular system/organization at stake but it also reduces the social well-being at macro-economic level. Traditionally, evaluation of performance of any organization suggests measure in the form of a ratio of output and input, like cost per unit, profit per unit etc. these are commonly considered as measure of efficiency. Even the measure of productivity is a ratio like 'output per unit of time' or 'output per worker employed' etc. These measures are known as 'partial productivity' in the literature. But for 'total factor productivity' measure we have to take into account all inputs and all outputs to obtain an output-to-input ratio. There are two difficulties that we face to obtain 'total factor productivity' measures: i) choosing the inputs and outputs to be considered, and ii) what should be the weights to be attributed to different inputs and outputs in order to obtain a single ratio. Further, since the measurement of efficiency involves market-driven factors (economic factors), technical aspect of production process and allocative problems etc, the measurement of efficiency should be of different types. Farrel's (1957) work on 'Measurement of production efficiency' is a pioneering one in this respect. So far the economic activity is concerned; measurement of efficiency implies assessment of performance of industries or individual firms in using real resources to produce goods and services. An efficiency measure should reflect the difference between actual performance and potential performance. Better the utilization of inputs/resources in the production process, the better is the efficiency. Efficiency can be considered in terms of the optimal combination of inputs to achieve a given level of outputs (an input orientation), or the optimal output that could be produced given a set of inputs (an output orientation).

The following figures 3.1 & 3.2 explain the input oriented and output oriented efficiencies. Input oriented efficiency measure is defined as less the input used per unit output (x_1/y or x_2/y) better is the efficiency. Thus, the figure 3.1 shows efficient frontier as convex.

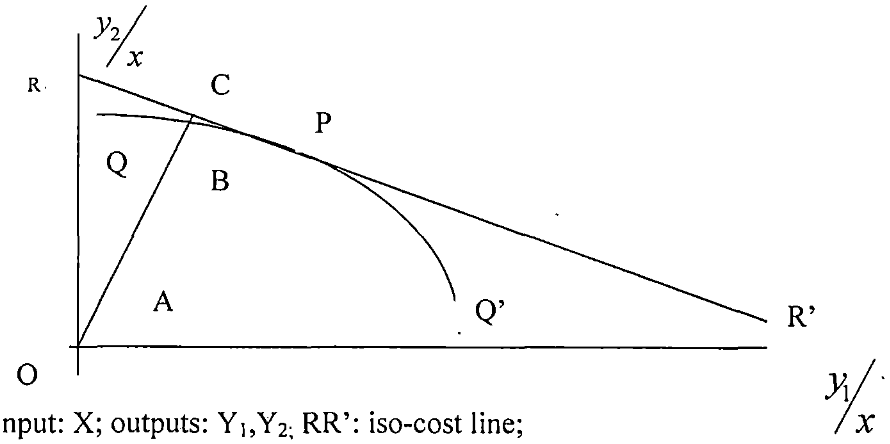
Figure 3.1: Input oriented efficiency



Inputs: X_1, X_2; output: Y; RR': iso-cost line;
QQ': Production possibility frontier; AB: level of inefficiency;
(OB/OA): Technical efficiency; (OC/OB): Allocative efficiency;
(OC/OA): overall economic efficiency or cost efficiency

towards the origin. On the other hand output oriented efficiency measurement is defined as more the produced output per unit of input (y_1/x or y_2/x) better is the efficiency. Hence the figure 3.2 shows that the efficient frontier is concave towards the origin

Figure- 3.2: Output oriented efficiency



Input: X; outputs: Y_1,Y_2; RR': iso-cost line;
QQ': Production possibility frontier; AB: level of inefficiency;
(OA/OB): Technical efficiency; (OB/OC): Allocative efficiency;
(OA/OC): overall economic efficiency or cost efficiency

However, on the basis of Farrel, it has been shown that, in order to attain overall economic efficiency, the firm must be technically efficient, input allocative efficient and output allocative efficient (Kumbhakar & Lovell, 2000).

Technical efficiency (TE) deals with the usage of labour, capital, machinery as inputs to produce outputs relative to the best practice in a given sample of decision making units (DMUs). Given the same technology for all the DMUs no wastage of inputs is considered in producing the given quantity of output. TE is an indicator of how close actual production is to the maximal production that could be produced given the available fixed and variable factors of production. Technical efficiency also, however, may be an indicator of the minimum levels of inputs or factors of production necessary to produce a given level of output relative to the levels of inputs actually used to produce that same level of output. It is almost impossible to obtain an absolute measure of TE, and thus, TE is usually defined relative to some benchmark level. The benchmark is referred to as the "best practice frontier" and represents actual observed achievements in similar operations (Färe and Grosskopf 1998). Hence, TE is thus a relative measure and indicates how close the actual or observed production is to the production corresponding to the "best practice frontier" level of output.

Other than TE there are two more concepts of efficiency in production parlance. They are allocative efficiency (AE) and overall economic efficiency or cost efficiency. AE deals with the minimization of cost of production with proper choice of inputs for a given level of output and a set of input prices, assuming that the organization being examined is already fully technically efficient. Cost efficiency deals with combination of technical and allocative efficiency. An organization will only be cost efficient if it is both technically as well as allocative efficient.

Another simple approach for estimating technical efficiency has been to calculate the ratio of output to input (Dyson et al.). Recognizing that it is usually not possible to actually calculate technical efficiency, a relative efficiency measure is often constructed by dividing the observed output by input of one operating unit to that of a known efficient unit (Dyson et al., Beasley). Alternatively, efficiency has often been calculated by constructing simple output to single input ratios over time and then comparing those ratios over time to determine maximum efficiency. A measure of technical efficiency should indicate whether or not a firm is operating along the frontier. Data Envelopment Analysis (DEA) is such a tool which decides about the benchmarks and improves efficiency. In recent years, there has been a growing interest in using DEA to assess technical efficiency & benchmarking.

3.2 Data Envelopment Analysis

Data envelopment analysis (DEA) is a new technique developed in operations research and management science over the last two decades for measuring productive efficiency. This is a nonparametric technique based only on the observed input output data of firms or decision making units (DMUs). After management has acknowledged the need of 'improved performance" DEA shows the way and provides the methodology of measuring performance improvement. DEA provides measures of competitive efficiency and is relevant in situations that contain a number of comparable units. The first step is to define the units (DMU's), the entities for which the performances are going to be measured. While defining the units, it also requires identifying the authority and limits of DMU's as well as its responsibilities associated with it, and also which resources are parts of it. Then comes the next important part of choosing the outputs through which the performance of the DMU's will be measured. Then the management has to decide upon the inputs, those determine DMU's achievements. The aim is to account for everything that aids or hinders the production of the DMU's. And finally it requires choosing an appropriate DEA model to analyze the performance. The first task of management after the DEA results have been interpreted is to ensure that the messages that emerge are accepted throughout the organization with a view to getting the approach accepted. DEA highlights the reasons for the good and bad aspects of the units performances – i) factors that contribute to it's efficiency rating or detracted from it, ii) a particular DMU's reference set (peer set) – a detailed qualitative and quantitative comparison with the reference DMUs. One of the most powerful pieces of information that is obtained by the DEA analysis is the set of target factor values for those units assessed as inefficient. These reference units can be used for efficiency estimation and performance benchmarking purposes. The input-output combination of the evaluated unit relative to that of the reference unit can be used for evaluating the efficiency of past operations and for assessing potential improvements for future operations. The units that constitute the reference unit are potential benchmark partners. In addition, comparison of the production process of the evaluated unit with that of the benchmark partners exposes causes for past inefficiencies and suggestive remedies could be assessed. An assumption that is implicit in most DEA models is that higher amount of output is preferred over less and for the inputs less is considered better than more. All composite units that are dominated by other units, which produce more output with minimum or less input or alternatively consume less input for equal or more output, can be discarded as decision alternatives. Only non-dominated units have to be considered as potential reference units. The value of its contribution would depend upon how well the analysis is planned and how well the results are integrated with other elements of management information.

Data Envelopment analysis (DEA) was first proposed by Charnes, Cooper and Rhodes (CCR) in1978. It is a nonparametric method which assumes the production function as unknown. Based on Farrell (1957), the idea of the method is to assess efficiency by comparing each individual production unit against all other production units or possible combination of such, within its sample data. DEA involves solving a linear programming problem (LPP) where the solution provides a numerical account of a piecewise linear production frontier. The efficiency of each unit is calculated by comparing output and input use with points on the production frontier (best observed practice). If the production unit is on the frontier it will be assigned an efficiency score of 1, and a unit that is inside the frontier will be allocated an efficiency score smaller than 1. Such production units are often referred to as DMU. Thus a DMU will be defined either efficient or inefficient according as the value is equal to 1 or smaller than 1 respectively. In case the DMU is inefficient, it will be designated a value which will show that how far it is from the frontier in terms of potential reduction (increase) in its input (output) use. In addition to that mentioned above, a DEA study also provides:

- A best practice frontier represented by a piecewise linear observed envelopment surface. The best practice units are those exhibiting the highest input (output) relation.
- Specific objectives or efficient projections onto the frontier for each inefficient DMU.
- An efficient reference set or peer group for each DMU defined by the efficient units closest to it. The peer DMUs are observed to produce the same or highe r level of outputs with the same or less inputs in relation to the inefficient DMU being compared.

Initially, DEA was primarily concerned with evaluating the technical efficiency of DMUs. More recently DEA is being used to assess a wide variety of economic performance measures under various situations which include (i) measuring scale and allocative efficiency, (ii) single and multiple product capacity and capacity utilization, (iii) optimal input utilization, (iv) identification of peer or comparison groups, (v) setting benchmarks for technical change, and (vi) identification of discretionary, non-discretionary, and undesirable inputs and outputs, etc. Thus, DEA can be used to measure performance of the organization as a whole.

In DEA, the organization under study is the DMU. The definition of DMU is very simplified to allow flexibility in using it over a wide range of possible applications. Generically a DMU is regarded as the entity responsible for converting inputs into outputs and whose performances are to be measured. To formally introduce the concepts behind DEA and frontier models, the activities of a firm are defined by a production set defined as $P \equiv \{(x, y) \mid x$ can produce $y\}$, which contains feasible combinations of inputs (x) and outputs (y). The set can further be described in terms of output feasibility sets, or input requirement sets (according as output or input orientation). DEA deals with the pairs of input and output vectors $(\mathbf{x}_j, \mathbf{y}_j)$, $(j = 1, \ldots, n)$ of n DMUs. Under DEA model, all data are assumed to be nonnegative but at least one component of every input and output vector is positive. This implies components are as semi-positive with a mathematical characterization given by $\mathbf{x}_j \geq 0$, $\mathbf{x}_j \neq 0$ and $\mathbf{y}_j \geq 0$ & $\mathbf{y}_j \neq 0$ for some $j = 1, \ldots, n$. Therefore, each DMU is supposed to have at least one positive value in both input and output. A pair $(\mathbf{x}, \mathbf{y})$ of such semi-positive input $\mathbf{x} \in R^m$ and output $\mathbf{y} \in R^s$ is called an activity where components of each such vector pair is a semi-positive orthant point in $(m + s)$ dimensional linear vector space having 'm' dimensional input vectors and 's' dimensional outputs vectors respectively. The set of feasible activities is called the production possibility set and is denoted by P. DEA formulation postulates the following properties of the Production Possibility Set P (Charnes, Cooper & Tone, 2002)

- The observed activities (x_j, y_j) (j = 1,... ,n) belong to P.
- If kth activity (x_k, y_k) belongs to P, then the activity (cx_k, cy_k) belongs to P for any positive scalar 'c'. This property is termed as the constant returns-to-scale assumption.
- For kth activity (x_k, y_k) in P, any semi-positive activity ($\bar{x}$, $\bar{y}$) with $\bar{x} \geq x_k$ and $\bar{y} \leq y_k$ is included in P. That is, any activity with input no less than x in any component and with output no greater than y in any component is also contained in P.
- Any semi-positive linear combination of activities in P belongs to P.

Arranging the data sets in matrices X = (x_j) and Y = (y_j), we can define the production possibility set P satisfying the above four postulates by $P = \{(x, y) / x \geq X\lambda, \ y \leq Y\lambda, \ \lambda \geq 0\}$, where λ is a semi-positive vector in R^n.

The important thing is all the DMU's must be homogeneous i.e. characteristics of each of them must be similar and comparable. For the purpose of securing relative comparisons, a group of DMUs is used to evaluate each other with each DMU having a certain degree of managerial freedom in decision making. For DMU_j (j =1, 2, ..., n) some common input and output items for each of these DMU_j, j = 1,...,n are selected as follows:

1. Inputs, outputs and choice of DMUs should reflect an analyst's or a manager's interest regarding components that will enter into the relative efficiency evaluations of the DMUs.
2. In principle, smaller input amounts and larger output amounts are preferable.
3. The measurement units of the different inputs and outputs need not be same.

Let the input and output data for DMU_j be (x_{1j}, x_{2j}, ..., x_{mj}) and (y_{1j}, y_{2j},...., y_{sj}), respectively. The input data matrix $X_{m \times n}$ and the output data matrix $Y_{s \times n}$ can be arranged as follows,

$$X_{m \times n} = \begin{pmatrix} x_{11} & x_{12} \cdots & x_{1n} \\ x_{21} & x_{22} \cdots & x_{2n} \\ x_{m1} & x_{m2} \cdots & x_{mn} \end{pmatrix}$$

$$Y_{s \times n} = \begin{pmatrix} y_{11} & y_{12} \cdots\cdots & y_{1n} \\ y_{21} & y_{22} \cdots\cdots & y_{2n} \\ y_{s1} & y_{s2} \cdots\cdots & y_{sn} \end{pmatrix}$$

Given the data, one for each DMUj to be evaluated and hence n optimizations are required. The problem can be states as the following fractional programming problem (FP_0) to obtain values for the input "weights" (v_i), (i = l, 2,......, m) and the output "weights" (u_r) {r = l,...,s) as variables:

$$\max_{u,v} \ \theta_0 = \frac{u_1 y_{10} + u_2 y_{20} + \ldots\ldots\ldots + u_s y_{s0}}{v_1 x_{10} + v_2 x_{20} + \ldots\ldots\ldots + v_m x_{m0}}$$

subject to,

$$\frac{u_1 y_{1j} + u_2 y_{2j} + \ldots\ldots\ldots + u_s y_{sj}}{v_1 x_{1j} + v_2 x_{2j} + \ldots\ldots\ldots + v_m x_{mj}} \leq 1 \ (j = 1, 2, \ldots, n)$$

$$v_1, v_2, \ldots\ldots\ldots\ldots v_m >= 0$$

$$u_1, u_2, \ldots\ldots\ldots\ldots u_s >= 0$$

The constraints ensure that the ratio of "virtual output" vs. "virtual input" should not exceed 1 for every DMU. The objective is to obtain such sets of weights (v_i) and (u_r) so that the ratio of a particular DMU (DMU_0) is maximized. By virtue of the constraints, the optimal objective value Θ_0^* could not exceed 1. Mathematically, the non-negativity constraint is not sufficient for the fractional terms in the above expression to have a positive value. In managerial terms it implies that all outputs and inputs have some nonzero worth. This is ensured by assigning positive values to the weights u_r and v_i. The above fractional program (FP_0) may now be replaced by the following linear program (LP_0):

$$\max_{u,v} \theta_0 = u_1y_{10}+u_2y_{20}+..........+u_sy_{s0}$$

subject to,

$$v_1x_{10}+v_2x_{20}+..........+v_mx_{m0}=1$$

$$u_1y_{1j}+u_2y_{2j}+..........+u_sy_{sj} \leq v_1x_{1j}+v_2x_{2j}+..........+v_mx_{mj} \quad j = 1, 2, ...n$$

$$v_1,v_2,............v_m \geq 0$$

$$u_1,u_2,..........u_s \geq 0$$

In vector notation LP_0 can be written as

$$\max_{u,v} \theta_0 = uY_0$$

$$\textit{subject to,}$$

$$vX_0 = 1$$

$$-vX + uY \leq 0$$

$$u \geq 0,\ v \geq 0$$

The primal has *m+s* variables (unknowns) in the form of v_i (I = 1,2....m) and u_r (r = 1,2,....s) and *n+1* constraints. Hence in dual there will be *m+s* constraints and *n+1* variables. Let the dual variables are Θ_B, λ_1, λ_2,......... λ_n. The dual of the above linear programming problem can be obtained as follows:

$$\min_{\theta_B, \lambda} \theta_B$$

$$\textit{subject to,}$$

$$\theta_B x_0 - X\lambda \geq 0$$

$$Y\lambda \geq y_0$$

$$\lambda \geq 0$$

where θ_B is a scalar. The credit of introducing these two primal-dual forms goes to Charnes, Cooper and Rhodes who gave the concept of input oriented DEA model. In DEA literature these are known as CCR-I model.

In case of output oriented model, the objective variable would be the reciprocal of the dual objective θ_B. defining dual objective as η, we have $\eta = \frac{1}{\theta_B}$. Substituting θ_B of the above and assuming $\frac{\lambda}{\theta_B} = \mu$ we get the following form.

$$
\begin{aligned}
&\max \ \eta \\
&\textit{subject to} \\
&\qquad x_0 - X\mu \geq 0, \\
&\qquad \eta y_0 - Y\mu \leq 0, \\
&\qquad \mu \geq 0
\end{aligned}
$$

The above form is also introduced by Charnes, Cooper and Rhodes as the output oriented CCR model in dual form. This is known as CCR-O model in the dual form.

In 1984 Banker, Charnes & Cooper proposed a new model which takes into consideration the variable returns to scale. In literature, this was referred to as BCC model. In this case, the production possibility set P is defined as

$$P = \{(x, y) / x \geq X\lambda, y \leq Y\lambda, \mathbf{e}\lambda = 1, \lambda \geq 0\}$$

where all are same as previous CCR model. '**e**' is a row vector with all the elements equal to 1. Hence a new condition is added in the BCC model that $\mathbf{e}\lambda = \sum_{j=1}^{n} \lambda_j = 1$, together with the condition $\lambda_j \geq 0$ for all j. It enables that the convex combination of vectors to be incorporated in the model. With the introduction of this particular condition, combination of DMUs are now allowed together to find the best practiced DMU. Hence the input oriented BCC model in the dual form becomes

$$\min_{\theta,\lambda} \theta$$

$$\begin{aligned} subject\ to,& \\ &\theta x_0 - X\lambda \geq 0, \\ &Y\lambda \geq y_0, \\ &e\lambda = 1,\ \lambda \geq 0 \end{aligned}$$

To obtain the dual form as shown above, replacing the objective value θ by reciprocal of the dual objective assumed as η and assuming $\frac{\lambda}{\theta} = \mu$, the following formulation could be obtained:

$$\max \eta$$

$$\begin{aligned} subject\ \text{to},& \\ &x_0 - X\mu \geq 0, \\ &\eta y_0 - Y\mu \leq 0, \\ &e\mu=1,\ \mu \geq 0 \end{aligned}$$

This is what is known as output oriented BCC model in the dual form.

Sources of inefficiency of a DMU may be two: One is the inefficient operation of the DMU itself and the other is the non-conducive condition under which a particular DMU operates. CCR and BCC scores could be used to specify actual source of inefficiency. We know CCR model assumes constant return to scale (CRS), whereas BCC assumes variable return to scale (VRS). Though both models indicate the technical efficiency CCR actually gives the global TE. BCC model on the other hand being able to incorporate a convex combination of the observed DMU to form a production possibility set, gives local pure technical efficiency. That is why a DMU is to be considered as operating at most productive scale size if the DMU is fully efficient (score 1) in both under CCR & BCC. If, therefore a DMU is fully efficient under BCC considerations but having low score under CCR then the DMU is actually operating efficiently locally but not globally. For this reason, the scale efficiency of a DMU is indicated by the ratio of two scores. Accordingly,

$$\text{Scale Efficiency } (SE) = \frac{\theta^*_C}{\theta^*_B}$$

Where θ^*_C and θ^*_B are CCR and BCC scores of a DMU. Hence

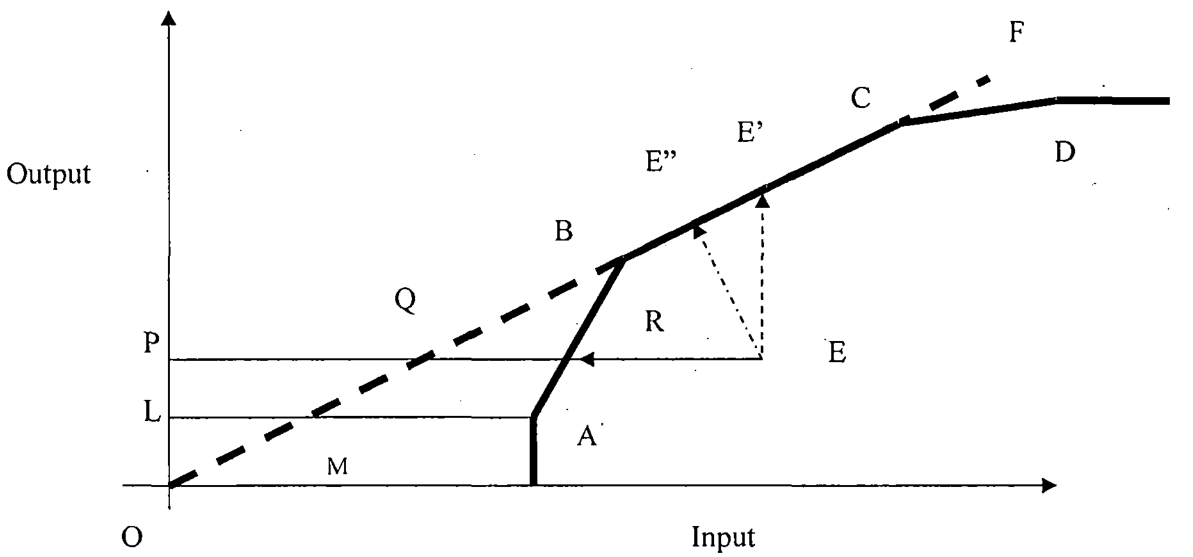
$$\theta^*_C = \theta^*_B * \text{ SE}$$

It implies that,

Technical Efficiency (TE) = Pure Technical Efficiency (PTE) * Scale Efficiency (SE)

This formulation helps to identify the sources of inefficiency – either caused by inefficient operation or by non- conducive conditions displayed by the scale efficiency or by both. This is explained graphically by the Fig- 3.3. In the figure, BCC efficient VRS frontier (ARBCD) and CCR efficient CRS frontier (OQBCF) are shown.

Figure-3.3: Scale Efficiency



DMU 'A' is on BCC efficient frontier but being positioned below the CCR efficient frontier, is CCR inefficient. It, therefore explains that 'A' is operating efficiently locally but not globally due to scale inefficiency which is given by $\frac{\text{LM}}{\text{LA}}$. DMU 'B' and 'C' are operating at the most productive scale size as those are both positioned on CRS as well as VRS frontier.

In case of DMU 'E', which is neither CCR efficient nor BCC efficient, it's CCR score is $\frac{\text{PQ}}{\text{PE}}$ (Technical Efficiency) and BCC score is $\frac{\text{PR}}{\text{PE}}$. Therefore, as we described above, the scale efficiency (SE) is obtained as

$$SE = \frac{PQ/PE}{PR/PE} = \frac{PQ}{PR}$$

Hence, technical efficiency $\frac{PQ}{PE} = \frac{PQ}{PR} * \frac{PR}{PE}$. Thus we can say "Technical Efficiency = Scale Efficiency * Pure Technical Efficiency". It explains how much of the overall inefficiency of DMU 'E' is caused by technical inefficient operation and how much is caused by inefficiency due to scale.

However, many different variations of DEA models, (both CCR & BCC) have already been developed in order to comprehend the specificity of different problems in DEA literature. Model selection for a particular situation is, therefore a difficult task.

3.3 Model Selection:

There exist different models of DEA in the literature. However, experts mention that few important considerations to be taken into account regarding model selection. One of the main purposes of a DEA study is to project the inefficient DMUs onto the production frontiers, e.g., the CCR-projection and the BCC projection, among others.

As shown in Fig-3.3, the inefficient DMU 'E' may be moved towards efficient frontier in two directions. One is along ER and another along EE'. In the first case, it would attain efficient frontier by reducing inputs maintaining the existing output level (input- oriented). On the other hand, it would arrive at efficient frontier position E' by improving the output level while maintaining the present level of input (output - oriented). Recent development of DEA suggests a third choice which opts for maximizing jointly input excesses (s^-) and output shortfalls (s^+). Input excesses (s^-) and output shortfalls (s^+) are defined as follows:

$$s^- = x_0 - X\lambda \text{ and } s^+ = Y\lambda - \eta y_0$$

These are basically surplus and slack variables respectively in output oriented BCC model of dual form. As we know, so far as the technical and mix inefficiency is concerned all models yield the same result if achievement of efficiency is the only objective. However, it is to be noted that the new models incorporating input excesses (s^-) and output shortfalls (s^+) may give different estimates when inefficiencies are present. Another important aspect to be considered at the time of model selection is the number of inputs and outputs associated with the problem. Generally speaking, if the number of DMUs (n) is less than the combined number of inputs (m) and outputs (s),that is if $n < (m + s)$, then a large portion of the DMUs will be identified as efficient. In that case efficiency discrimination among DMUs is to be questionable due to inadequate number of degrees of freedom. Hence, it is suggested that 'n' exceeds 'm + s' by several times. A rough rule of thumb in the envelopment model is to choose n (= the number of DMUs) equal to or greater than max $\{m * s, 3 * (m + s)\}$. Thus, the selection of input and output items along with the number of DMU is crucial for successful application of DEA.

In our present study, the assumption of constant returns to scale, however, is not valid for marine fishery. Hence the frontiers have assumed to be piecewise linear and concave characteristics. Since the BCC model has its production frontiers spanned by the convex hull of the existing DMUs and capture the characteristics of variable returns to scale, we choose to apply BCC model. Further, since our objective is to optimize the output, given the input levels, we select the output oriented model. Specifically our objective is to maximize efficiency score of the DMUs subject to the conditions:

(i) Actual convex combination of inputs < = virtual input ($\because e\lambda = 1 \; \& \; \lambda \geq 0$)

(ii) Maximum virtual output <= actual convex combination of output.

It is, therefore, rational and logical to apply the following specific formulation of BCC output – oriented model in our study,

$$\begin{aligned} & \text{Max} \quad \eta \\ \textit{subject to} & \\ & X\lambda \leq x_0 \\ \eta y_0 - & Y\lambda \leq 0 \\ & e\lambda = 1 \\ & \lambda \geq 0 \end{aligned}$$

Where, η is the efficiency score, **X**= input vectors specified, **Y**= fish production of each maritime state of the corresponding year, $\mathbf{x}_0$ = virtual input combination, $\mathbf{y}_0$= virtual output.

The above model will be used for the determination of efficiency of the different maritime states of India those are considered as DMUs in our present study.

3.4 Conclusion: Advantages and disadvantages of DEA:

The major advantage of DEA methodology is that it uses less or minimal a priori assumptions. It does not also require specifying functional relations between inputs and outputs. DEA estimates inefficiencies in both inputs and outputs for every decision-making unit (DMU). It also identifies the peer (comparison) group or benchmarks of efficient DMU's. It also provides additional information in the form how DMU's can be improved to make them more efficient. DEA identifies the sources of inefficiencies such as purely technical inefficiency or scale efficiency or a combination of both for each DMU. DEA offers a measure that allows for simultaneous consideration of a multiple outputs and a multiple inputs. It still considers the same, even though the relationships between the inputs and the outputs may be multifaceted and involve unknown substitutions. The primary advantage of DEA is that the weights are derived directly from the data without numerous assumptions regarding characteristics of weights. Moreover the weights are chosen in a manner that assigns the best set of weights to each DMU. DEA utilizes techniques such as mathematical programming which can handle large numbers of variables and relations (constraints). This eliminates the difficulties of choosing large number of inputs and outputs, which are generally encountered in application of many other techniques. DEA can also accommodate sensitivity analysis techniques to study the impact of specific decision variables on critical performance measures. Many linkages between DEA and other methodologies have been established in recently developed literature. Among these are: non-linear programming, simulation, multiple criteria decision analysis, multivariate and nonparametric statistics, neural networks and genetic algorithms, fuzzy sets, game theory, integer programming, goal programming, and multi-objective linear programming.

Normally, in many other available mathematical techniques, the efficiency of any decision making unit is supposed to characterize how successful is this unit in utilizing its inputs to produce its outputs. The difficulty that arises is to aggregate all the different inputs of this unit into the one single indicator, say s, and all the different outputs of this unit into the other single indicator, say v, so that the ratio v/s could be considered as the efficiency. This aggregation requires that all inputs and outputs to be expressed in common denominator. This conversion may cause error to a great extent.

A set of common criticism of DEA are

(i) it considers only radial expansions of outputs or radial contractions of inputs,

(ii) it is deterministic and hence does not take into account random error

(iii) measurement error can cause significant problems because the solution to optimization problems is sensitive to changes in data.

However, the most noteworthy limitation of DEA is that the level of significance of the estimates given by DEA can not be tested statistically. All said and done, there are situations, like the present study of measuring performance of maritime states, there is no alternative than to take resort of application of DEA as the best suitable technique that satisfy the objective of the study.