CHAPTER 2

Literature Survey

2.1 Measure of Port Efficiency

Attempts to measure port efficiency are not uncommon in literature. The use of surveys to determine the efficiency level of the ports is one common methodology used by the researchers. Clark et al (2004) investigated the determinants of shipping costs to the United States using a huge database of more than 300,000 observations a year on shipments of products from different ports around the World and found that variations in port efficiency are linked to excessive regulation, the prevalence of organized crime, and the general condition of the country's infrastructure. Emphasizing the role of seaport efficiency they showed that shipping costs could be reduced by more than 12%, or the equivalent of 5,000 miles in distance by an improvement in port efficiency from 25th to 75th percentiles. They concluded that the efficiency of ports also had a crucial role besides distance and containerization, in determining the maritime transport costs.

Sanchez et al. (2003) made an extensive survey of 41 Latin American common user ports to examine the determinants of waterborne transport cost, with particular emphasis on the efficiency at port level. They generated a statistically quantifiable measure of port efficiency and estimated a model of waterborne transport cost, including the port efficiency measures generated by them as explanatory variables. They found that such measures are substantial components of these transport costs and have an impact on trade flows that is similar in magnitude to that of distance.

However, the method is not devoid of drawbacks. Firstly, as the survey data depend on perception of the people surveyed, there are possibilities of confusing the observations of port efficiencies with other factors connected with the country of the port’s location. Secondly, a serious drawback in this method is that the existing surveys of port efficiencies have only been conducted at a point in time or for a limited timeframe, and hence there is almost no information available on evolution of port efficiencies over time in these studies.

Alternatively, the method of data envelopment analysis (DEA) was used by most of the recent studies to measure port efficiencies. In this procedure an estimate of the most efficient
production frontier across a group of ports is derived by using data on inputs, outputs and production function theory. Then, for each port, the deviation from this frontier is taken for calculation of port efficiency. The method has its advantage over other traditional approaches in the sense that here multiple inputs and outputs can be considered without any prior information about the production characteristics of ports. In DEA an overall evaluation of port performance as a non-parametric function can be provided. In the port sector DEA was first applied by Roll and Hayuth (1993). DEA-BCC model was used to analyze 26 Spanish ports by Martinez-Budria et al. (1999) who came to the conclusion that larger ports produced higher efficiencies. Tongzon (2001) used the DEA – Additive and DEA – CCR model for analyzing the efficiency level of four Australian and twelve other ports. Tongzon concluded that container handling operation was the most important component of the service offered by port authorities. In 2008 Tongzon pointed out that operational efficiency did not solely depend on a port’s size and function. Wang and Cullinane (2006) in their study using DEA included European container terminals with annual throughput of over 10,000 TEUs from 29 countries. According to their observation most of the terminals covered under the study showed inefficiency. Wang and Cullinane also came to the conclusion that large-scale production tended to be associated with higher efficiency. Yongrok Choi (2011) in a study covering 13 major sea ports in North East Asia including the seven largest container ports, using DEA and its variant models, concluded that self created logistics demand and strategic allowances rather than investment in infrastructure do improve the efficiency of ports. Chudasama (2009) used the technique of DEA to identify the efficient and inefficient major ports of India and the sources of inefficiency for the inefficient ports. Lee et al. applied a new procedure Recursive Data Envelopment Analysis (RDEA) based on DEA to rank 16 international container ports in Asia Pacific region in terms of operational efficiency.

In a limited number of studies, another alternative method of econometric estimation of production/cost functions for ports was used to measure port efficiency. Estache et al. (2002) used one such method for their study and also provided a review of previous analyses using these methodologies.

In their study based on empirical work on trade among 16 Latin-American countries Wilmsmeier et al. (2006) provided empirical evidence that indicators for different port characteristics had a statistically significant and strong impact on international maritime
transport costs. They established that doubling port efficiency in a pair of ports and halving the distance between them had the same impact on international transport costs.

Bhatt and Gaur (2011), with the background of rapid growth, inherent inefficiencies and changing institutional structures in Indian ports measured operational efficiency for the group of container terminals in JNPT- Mundra range of ports through appropriate indicators and DEA. According to their findings, after privatisation of the container terminals the competition of securing the cargo had led to relatively closely matched efficiencies in the performance of the terminals especially on quay side where ships turnaround times and client satisfaction are closely related. However, they found that yard side efficiencies in evacuation of cargo were suffering major differences.

Another straightforward approach was developed and applied by Blonigen and Wilson (2006) to estimate port efficiency by using detailed data on U.S. imports and associated import costs for the period 1991 to 2003, yielding estimates across ports, products, and time. They incorporated these measures into a gravity trade model and estimated that improved port efficiency significantly increases trade volumes. The study provides new measures of ocean port efficiencies through simple statistical tools. This study’s methodology was able to provide such estimates for a much broader sample of countries and years with little cost. It also has the flexibility to quickly provide port efficiency comparisons on a commodity-by-commodity basis. Hadded et al. (2006) developed a spatial CGE\(^2\) model integrated to a transport network system in order to simulate the impacts of increases in port efficiency in a

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\(^2\)CGE Model: Computable general equilibrium (CGE) models are a class of economic models that use actual economic data to estimate how an economy might react to changes in policy, technology or other external factors. The strength of CGE models is their internal consistency; i.e. they allow for consistent comparative analysis of policy scenarios by ensuring that in all scenarios the economic system remains in general equilibrium (however, extensions to model market imperfections are possible). They integrate micro-economic mechanisms and institutional features into a consistent macro-economic framework and consider feedback mechanisms between all markets. All behavioural equations (demand and supply) are derived from microeconomic principles. Since CGE models are calibrated to a base year data set, the data requirement is limited even if the degree of disaggregation is high. This allows for the evaluation of distributional effects, across countries, economic sectors and agents. CGE models are advantageous for analysing general economic policies like public finance, taxation and social policy, and their impact on longer term structural change.
context of trade liberalization while attempting to explain one of the mechanisms that link trade barriers, in the form of port costs, and subsequent growth and regional inequality. They considered role of ports of entry and ports of exit explicitly in order to get the holistic picture in an integrated interregional system. They suggested that in the CGE models formal consideration of nodes in a transportation network was required to get the full implications of transportation costs. They also suggested that in cases where nodal inefficiencies play a key role, it became important to separate out link and node costs. From a policy perspective this separation is even more important.

Using disaggregated Australian import data Pomfret and Sourdin (2010) analysed country-by-country variations in trade costs. They observed trade costs were related to distance and to weight, but simple correlations were weak and there did not exist any simple relationship between the size of the trading partner and trade costs. According to their observation exporting countries’ institutional quality as measured by the Transparency International corruption perceptions index played an important role in determining the trade costs, especially in the case of manufactured goods. They observed that country-specific characteristics influencing trade costs provide a link between institutions and economic development and countries with good institutions would, ceteris paribus, have lower trade costs in the most dynamic segment of international trade, time-sensitive manufactures, and be better able to participate in global value chains and benefit from globalization.

A study conducted by Navigation Economic Technologies, US ARMY CORPS used trade data in their analysis for measuring efficiency of US ports. The costs associated with imports and exports were analyzed and were assumed to be relative to ports efficiency. The other components of the charges on imports and exports were statistically separated and efficiency was evaluated assuming that less cost meant efficient port operations. This methodology is highly dependent on the quality of the data available. They made use of the Census data over a period of 7 years and ran the model for results. Limitations to this methodology were sensitivity to the data and a neglect of value of money over a period of time however the advantage being possibility of analysis of the efficiency over a large period of time.

Stochastic frontier model was used by Coto, Banos and Rodriguez in 2000 to measure efficiency of Spanish Ports. Their focus being on effect of port size and type of management
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on the efficiency of ports, they used regression to analyze the relation by having a dummy variable of autonomous ports as 0 or 1 on number of linear meters of depth over 4 m of quays to indicate the size of port. These indices resulted in a conclusion that efficiency and size are not related and that autonomous ports are less efficient than the rest.

Notteboom, Coeck and Van den Broeck (2000) used a similar study and methodology for measuring efficiency of 36 European container terminals. Their study concluded that hub ports were more efficient than feeder ports. It also came to the conclusion that efficiency and size relationship was a function of type of port and there was no relationship between type of ownership of port or terminal and the efficiency level.

This observation on relationship of ownership and efficiency were contradicted by Jose Tongzon and Wu heng (NUS, Singapore) in 2005. According to their observation private participation in ports was useful for improving efficiency, but complete privatization was not the answer to improve efficiency of a port.

These studies identified Size of the port, Competition – Intra and Inter port, Technology adopted and Management/Institutional structure as some of the factors which had their effect on port efficiency. These factors are again interdependent and region specific. And so while drawing conclusions one should be cautious about selecting comparable terminals and indicators.

In conclusion, we can say that so far, plenty of attempts were made for measuring the efficiency levels of the ports. Although some other measures were also used, the most commonly used measure was DEA. However, comparatively lesser attempts were made to relate the port efficiency with the regional development. In the Indian context very few attempts were made in this regard.

2.2 Data Envelopment Analysis

Data Envelopment Analysis (DEA) was originally developed by Charnes, Cooper and Rhodes (1978) to evaluate non-profit and public sector organizations. Soon its usefulness was recognised by the researchers in a number of fields as an excellent and easily used
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methodology for modelling operational processes for performance evaluations. DEA was extensively applied in performance evaluation and benchmarking of schools, hospitals, bank branches, production plants, etc. (Charnes et al., 1994). Its empirical orientation and the absence of a need for the numerous *a priori* assumptions unlike other approaches resulted in its use in a number of studies involving efficient frontier estimation in the governmental and non-profit sector, in the regulated sector, and in the private sector.

DEA is useful for the following purposes.

1. In DEA service units are compared on the basis of all resources used and services provided, to identify the most efficient units or best practice units and the inefficient units in which efficiency improvements are possible. It can be used as a very powerful benchmarking technique.

2. Another important feature of DEA is that it can calculate the amount and type of cost and resource savings that can be achieved by making each inefficient unit as efficient as the most efficient / best practice unit/s.

3. DEA can be used to identify specific changes in the inefficient service units, which can be implemented by the management to achieve potential savings. These changes would make the efficient units performance approach the best practice unit performance. Besides, the amount of additional service an inefficient unit can provide without employing any additional resource can also be estimated by DEA.

4. DEA provides information about performance of service units which that can be utilised by the management to transfer system and managerial expertise from better-managed, relatively efficient units to the inefficient ones. This in turn may lead to improvement in productivity of the inefficient units, reduction in operating cost and increase in profitability.

The advantage of DEA over other techniques commonly used in service organizations is that the information provided by DEA as mentioned above can identify relationships not identifiable by other techniques. As a result, DEA can help management to improve performance in a much better way than other traditional techniques.
Efficiency can be defined as the ratio of output to input, i.e., output per unit of input. More output per unit of input indicates relatively greater efficiency. A state of absolute or optimum efficiency can be achieved when the greatest possible output per unit of input is achieved. At this stage it is not possible to increase efficiency further unless new technology is introduced or other changes take place in the production process. DEA can be used where there are more than one input and more than one output. So, it is a multi-factor productivity analysis model which can be used to measure the relative efficiencies of a homogenous set of decision making units (DMUs) i.e., that use similar inputs to produce similar outputs. In the presence of multiple input and output factors the efficiency score is defined as:

\[
\text{Efficiency} = \frac{\text{weighted sum of outputs}}{\text{weighted sum of inputs}}
\]

DEA is a linear programming technique based on non-parametric method. Farrell’s (1957) work of measuring technical efficiency was extended by Charnes, Cooper and Rhodes (1978) to introduce the data envelopment model, later on known as the DEA-CCR model, which investigated efficiency based on the assumption of constant returns to scales. Banker, Charnes and Cooper (1984) introduced DEA-BCC model, by extending the CCR model to investigate efficiency assuming variable returns to scales. In DEA, the efficiency of any DMU is demonstrated by its ability to convert inputs into outputs and the value of efficiency is always less than or equal to one. As DEA is based on nonparametric computation, the prior knowledge of weights for inputs and outputs are not required. In DEA, a single virtual output and single virtual input is obtained without estimating the production function. As mentioned above efficiency is measured by the ratio of weighted sum of outputs to weighted sum of inputs.

DEA is useful in identifying possible benchmarks towards which the performance can be targeted by providing the observed efficiencies of individual firms. Benchmark for relatively inefficient firms may be set by the weighted combinations of peers and the peers themselves. The actual levels of inputs used or output of efficient firms can serve as the specific targets for less efficient firms, while the processes of benchmarking firms can be used for the information of managers of firms aiming to improve the performance (SCRCSSP, 1997).

2.2.1 Methodological Frameworks

Measurement of Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency: CCR and BCC DEA models
The technique of DEA can be used to calculate the measures of technical, pure technical, and scale efficiencies for individual decision making units (DMU). In DEA multiple incommensurable inputs and outputs of each decision making unit (DMU) are converted into a scalar measure of operational efficiency, relative to its competing DMUs. At first ‘peer’ DMUs are identified for an individual DMU and then the efficiency of the DMU is estimated by comparing its performance with that of the best practice DMUs chosen from its peers. The efficiency score of the DMU(s) whose performance is/are best amongst its (their) peers is considered as equal to one. The referrals ‘standards’ are constituted by these units which ‘envelop’ the other units and, thus, form the efficient frontier. In DEA, a linear programming problem is solved for each DMU to get information about the peers of the DMU and the efficiency of the DMU relative to its peer group. According to DEA, technical efficiency (TE) can be viewed from two perspectives (i) input oriented TE and (ii) output oriented TE. The first one focuses on the possibility of reducing inputs to produce a given level of output, whereas, the second one considers the possible increase in output level for a given set of input quantities. Output oriented TE ($\theta_o^{\text{output}}$) and input oriented TE ($\theta_o^{\text{input}}$) for a DMU can be defined as

$\theta_o^{\text{output}} = \frac{\text{Actual output}_o}{\text{Maximum possible output}_o}$ in output-oriented context, or

$\theta_o^{\text{input}} = \frac{\text{Minimum possible input}_o}{\text{Actual input}_o}$ in input-oriented context.

It is necessary to find out the divergence between actual production and production on the boundary of the feasible production set to quantify a measure of technical efficiency. The feasible production set summarizes all technically possible ways of transforming inputs into outputs that are available to the organization. For a technically inefficient DMU production occurs within the interior of this production set. A measure of scale efficiency (SE) can be obtained by comparing technical efficiency measures derived under the assumptions of constant returns-to-scale (CRS) and variable returns-to-scale (VRS), a measure of scale efficiency (SE) is obtained. The overall technical efficiency (OTE) which measures inefficiencies due to the input/output configuration and as well as the size of operations is measured by technical efficiency measure under the assumption of constant returns to scale (CRS). The technical efficiency measure under the assumption of variable returns to scale (VRS) represents pure technical efficiency (PTE) which measures inefficiencies due to only managerial underperformance. As mentioned earlier, the measure of scale efficiency (SE) is derived as $SE = OTE / PTE$. 

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In DEA, the observed input-output bundles of the DMUs are used to construct a benchmark technology. For this the following general assumptions about the production technology are made without specifying any functional form. The assumptions are fairly weak in nature and hold for all technologies represented by a quasi-concave and weakly monotonic production function.

(A1) It is assumed that all actually observed input-output combinations are feasible. When an output bundle \( y \) can be produced from the input bundle \( x \), then an input-output bundle \((x, y)\) is feasible. Suppose that we have a sample of \( N \) firms from an industry producing \( m \) outputs from \( n \) inputs. Let \( x_j = (x_{1j}, x_{2j}, \ldots, x_{nj}) \) be the input bundle of firm \( j \) (\( j = 1, 2, \ldots, N \)) and \( y_j = (y_{1j}, y_{2j}, \ldots, y_{mj}) \) be its observed output bundle. Then, by (A1) each \((x_j, y_j)\) \((j = 1, 2, \ldots, N)\) is a feasible input-output bundle.

(A2) The production possibility set is convex. Consider two feasible input-output bundles \((x^A, y^A)\) and \((x^B, y^B)\). Then the (weighted) average input-output bundle \((\bar{x}, \bar{y})\)

where \( \bar{x} = \lambda x^A + (1-\lambda)x^B \) and \( \bar{y} = \lambda y^A + (1-\lambda)y^B \) for some \( \lambda \) satisfying \( 0 \leq \lambda \leq 0 \) is also feasible.

(A3) Inputs are freely disposable. If \((x^0, y^0)\) is feasible, then for any \( x \geq x^0 \), \((x, y^0)\) is also feasible.

(A4) Outputs are freely disposable. If \((x^0, y^0)\) is feasible, then for any \( y \leq y^0 \), \((x^0, y)\) is also feasible.

If additionally we assume that constant returns to scale holds,

(A5) If \((x, y)\) is feasible, then for any \( k \geq 0 \), \((kx, ky)\) is also feasible.

It is possible to empirically construct a production possibility set satisfying assumptions (A1-A5) from the observed data without any explicit specification of a production function. Consider the input-output pair \((\hat{x}, \hat{y})\) where \( \hat{x} = \sum_{i=1}^{N} \mu_i x^i \), \( \hat{y} = \sum_{i=1}^{N} \mu_i y^i \), \( \sum_{i=1}^{N} \mu_i = 1 \), and \( \sum_{i=1}^{N} \mu_j \geq 0(j = 1, 2, \ldots, N) \). By (A1-A2), \((\hat{x}, \hat{y})\) is feasible.

Now, by (A3), if \( x \geq \hat{x}, (x, \hat{y}) \) is also feasibly. Next, by (A4), if \( y \leq \hat{y}, (x, y) \) is feasible. Thus, using (A1-A4), the input-output combination \((\hat{x}, \hat{y})\) is feasible. If, additionally, constant returns to scale are assumed, \((k\hat{x}, k\hat{y})\) is also a feasible bundle for any \( k \geq 0 \). Define \( \tilde{x} = k\hat{x} \) and
\[ \tilde{y} = k\tilde{y} \text{ for some } k \geq 0. \] Then, by construction, \[ \sum_{i=1}^{N} \tilde{y} \leq k \sum_{i=1}^{N} \mu_j y^j \] and \[ \tilde{x} \geq k \sum_{i=1}^{N} \mu_j x^j. \] Next define \[ \lambda_j = k\mu_j. \] Then \[ \lambda_j \geq 0 \text{ and } \sum_{j=1}^{N} \lambda_j = k. \] But \( k \) is only restricted to be non-negative. Hence, beyond non-negativity, there are no additional restrictions on the \( \lambda_j \)'s.

Based on the observed input-output quantities and under the assumptions (A1-A5), the production possibility set or the technology set is defined as follows:

\[
T^C = \{ (x, y) : x \geq \sum_{i=1}^{N} \mu_j x^j ; y \leq \sum_{i=1}^{N} \mu_j y^j ; \mu_j \geq 0 ; (j = 1, 2, ..., N) \}. \tag{2.1}
\]

Here the superscript \( C \) indicates that the technology is characterized by constant returns to scale.

The output-oriented technical efficiency of firm \( t \) producing output \( y^t \) from the input bundle \( x^t \): Assuming that \( y^* \) is the maximum producible output from the same input bundle \( x^t \) and that \( \phi^* \) is the maximum value of \( \phi \) such that \((x^t, \phi^* y^t)\) lies within the technology set, we get \( y^* = \phi^* y^t \). Then the output-oriented technical efficiency of firm \( t \) is defined as

\[
TE_O = TE_O (x^t, y^t) = \frac{y^t}{y^*} = \frac{1}{\phi^*}. \tag{2.2}
\]

In order to evaluate the input-oriented technical efficiency of any firm, we examine whether and to what extent it is possible to reduce its input(s) without reducing the output(s). This is quite straightforward when only one input is involved. In the presence of multiple inputs, a relevant question would be whether reducing one input is more important than reducing some other input. When market prices of inputs are not available, one way to circumvent this problem is to look for \textit{equi-proportionate} reduction in all inputs. This amounts to scaling down the observed input bundle without altering the input proportions. The input-oriented technical efficiency of firm \( t \) is \( \theta^t \) where

\[
\theta^t = \min \theta : (\theta x^t, y^t) \in T^C. \tag{2.3}
\]

Note that \((x^t, \phi^* y^t) \in T^C\). Hence, \((k x^t, k \phi^* y^t) \in T^C\). Setting \( k = \frac{1}{\phi^*} \), we get \((\frac{1}{\phi^*} x^t, y^t) \in T^C\).
Obviously, under CRS, $\theta^* = \frac{1}{\phi^*}$. That is, the input- and output-oriented technical efficiency measures are identical in this case.

### 2.2.2 Use of DEA for measuring Port performances

Traditionally, the performances of ports have been evaluated by the engineering single-port approach of comparing their actual and engineering optimum throughputs, i.e. the maximum throughputs or cargo tonnage that ports can physically handle under certain conditions. The improvement of performance of a port is indicated by the movement of its actual throughput over time. If a port’s actual throughput approaches its optimum throughput over time, it can be concluded that its performance has improved over time. On the contrary, if the actual cargo throughput departs from its optimum throughput over time, the conclusion is that there is a deterioration of its performance over time.

The economic optimum throughput of a port is defined as the throughput that satisfies an economic objective of the port. It may be an (a) economic technically efficient optimum throughput (derived from the port’s economic production function, representing the relationship between a port’s maximum throughput and given levels of its productive resources), (b) cost efficient optimum throughput (rived from the port’s economic cost function, representing the relationship between a port’s minimum costs to be incurred in handling a given level of throughput) or (c) effectiveness optimum throughput (derived from a port’s effectiveness operating objective such as maximizing profit).

From the point of view of technical efficiency, and effectiveness the economic performance of a port may be evaluated by comparing its actual throughput with its economic technically efficient optimum throughput, whereas from the standpoint of cost efficiency and effectiveness this may be done by comparing the port’s actual throughput with its cost efficient optimum throughput and effectiveness optimum throughput, respectively. The single-port approach for evaluating a port’s performance may also be used for comparing the actual values of a port’s performance indicators (i.e. variables whose values are under the control of port management) to their standards i.e., values of the performance indicators that satisfy an economic objective of the port. Thus, the standards may be technically efficient standards, cost efficient standards or effectiveness standards. When the actual values of the
port’s performance indicators approach their respective standards over time, the port’s performance – with respect to its economic objective – is said to be improved over time. On the contrary when the actual values deviate from their respective standards over time the port’s performance – with respect to its economic objective – is said to be deteriorated over time. In case performance indicator standards are not available, a port’s performance can be evaluated just by knowing the actual values of its performance indicators. Specifically, if the direction of movement in these values over time moves the port nearer to (away from) achieving its economic objective, the conclusion is that the port’s performance has improved (deteriorated) over time. Methodologies for selecting performance indicators include the operating objective specification methodology and the criteria specification methodology. The operating objective specification methodology requires the specification of an operating objective for the purpose of then selecting performance indicators. The criteria specification methodology specifies the criteria that selected performance indicators must satisfy. In the literature, multi-port performance evaluations of the technical efficiency of ports generally rely upon frontier statistical models that utilize DEA techniques – non-parametric mathematical programming techniques for deriving the specification of the production frontier model. DEA techniques derive relative efficiency ratings for the ports that are used in the analysis. These ports should be similar; otherwise, the efficiency ratings may be misleading.

While conducting DEA for the port sector one can find different opinions in the literature on choosing the input indicators. According to Dowd and Leschine (1990), and Cullinane and Song (2003) labour information should be included as one of the input indicators. On the other hand, Valentine and Gray (2001) argued against inclusion of it citing the reason that labour information was difficult to obtain and there might be a high potential of measurement error. In views of Notteboom et al. (2000) the number of gantry cranes, and number of dock workers were closely related. Apart from this, Tongzon (2001) and Cullinane and Song (2003) argued in favour of using number of berths as one of the input indicators reflecting the berth side productivity. Cullinane et al. (2002) and Notteboom et al. (2000) argued for total berth length instead of number of berths. Wang et al. (2005) also favoured berth length as in their opinion it was more reasonable because the number of berths could change easily. It was suggested by De Neufville and Tsunokawa (1981), Notteboom et al. (2000) and Wang et al (2005) that information on unloading facilities, such as the number of quay cranes and yard
cranes, should also be considered for input indicators. When considering output indicators, it was argued by most of the authors that container throughput is the most appropriate indicator. A summary of the inputs and outputs taken by various authors in their analysis is given in Table 2.1 below.

<table>
<thead>
<tr>
<th>Author</th>
<th>DMU</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Model</th>
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<tbody>
<tr>
<td>Hayuth and Roll (1993)</td>
<td>All world (20)</td>
<td>-Manpower</td>
<td>-cargo throughput</td>
<td>DEA-CCR</td>
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<td>-Capital</td>
<td>- level of service</td>
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<td>-Cargo uniformity</td>
<td>-user satisfaction</td>
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<td>- ship calls</td>
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<tr>
<td>Martinez-Budria et al.</td>
<td>Spanish ports (26)</td>
<td>-Labour expenditure</td>
<td>-Total cargo moved through the docks</td>
<td>DEA-BCC</td>
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<td>(1999)</td>
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<td>-Depreciation charges</td>
<td>-Revenue earned from the rent of port facilities</td>
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<td></td>
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<td>-other expenditures</td>
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<tr>
<td>Tongzon (2001)</td>
<td>Australia (4), International container ports (12)</td>
<td>-Cranes</td>
<td>-Cargo throughput</td>
<td>DEA-CCR DEA-ADDITIVE</td>
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<td>-Number of container berths</td>
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<td>-Number of employees</td>
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<td>Barros (2003)</td>
<td>Portugeese ports (10)</td>
<td>-Number of employees</td>
<td>-Number of ships</td>
<td>DEA- Malmquist Tobit</td>
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<td>- Book values of assets</td>
<td>-Tons of moved freight</td>
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<td>-Tons of liquid bulk</td>
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<td>-Number of cranes</td>
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<td>5) Wang et al. (2005)</td>
<td>Largest container ports (25) plus mainland China (5)</td>
<td>-Berth length</td>
<td>- TEUs handled</td>
<td>DEA-CCR &amp; BCC</td>
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<td>-Terminal area</td>
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<td>-Number of berth cranes</td>
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<td>-Number of yard cranes</td>
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<tr>
<td>Author(s)</td>
<td>Description</td>
<td>Metrics</td>
<td>DEA Method(s)</td>
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<td>Wang and Cullinone (2006)</td>
<td>European container terminals (104)</td>
<td>- Number of straddle carriers</td>
<td>DEA-CCR &amp; BCC</td>
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<td>Rios &amp; Macada (2006)</td>
<td>Container terminals Brazil (15), Arzentina (6), Uruguay (2)</td>
<td>- Total berth length - Terminal area - Equipment cost</td>
<td>DEA-BCC</td>
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<td>Yen-Chun Jim Wu &amp; Chia-Wen Lin (2008)</td>
<td>Largest container ports over the period 2002-05 (from 22 countries)</td>
<td>- Terminal area - Total quay length - Number of quayside gantry cranes - Number of yard gantries - Number of straddle carriers</td>
<td>DEA-CCR &amp; BCC</td>
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<td>Koster, Balk &amp; van Nus (2009)</td>
<td>Terminals of two large container operators, APMT (39 terminals) and European terminals of PSA (seven terminals).</td>
<td>- Number of quayside gantry cranes - Total quay length (in meters) - Terminal area (in hectare)</td>
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<td>Jie Wu et al. (2010)</td>
<td>Global container ports (77)</td>
<td>- Capacity of cargo handling equipment - Number of berths - Terminal area - Storage capacity</td>
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<td>Cullinone &amp; Wang (2010)</td>
<td>Leading container ports (25)</td>
<td>- Terminal area - Terminal length - Number of quayside gantry cranes - Number of yard gantries - Number of straddle carriers</td>
<td>DEA</td>
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<td>Yongrok Choi (2011)</td>
<td>Major sea ports in N-E Asia: China (9), Korea (3), Taiwan (1)</td>
<td>- Quay length - Terminal area - Number of cranes</td>
<td>DEA-CCR &amp; BCC &amp; DEA-Malmquist</td>
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<td>Guner et al. (2012)</td>
<td>Turkish passenger</td>
<td>- Total expenditure - Labour - Passenger calls</td>
<td>DEA-CCR</td>
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<table>
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<th>Ports (6)</th>
<th>Number of Cruise</th>
<th>Labour</th>
<th>Fixed Assets</th>
<th>Annual Expenses</th>
<th>Total Revenue</th>
<th>OCER</th>
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<td>Chih-Ching Yang (2013)</td>
<td>International Commercial ports Taiwan (4) for 7 years treating each port-year as a DMU</td>
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</table>

Source: Collection from relevant papers

2.3 Principal Component Analysis

Principal Component analysis is used to uncover the latent structure (dimension) of a set of variables (Gorsuch, 1983, Rummel, 1970). It reduces attribute space from a larger number of variables to a smaller number of factors and as such is a ‘non-dependent’ procedure. Factor analysis could be used for any of the following purposes (Hair et al, 1998):

- To reduce a large number of variables to a smaller number of factors for modelling purposes, where the large number of variables precludes modelling all the measures individually.
- To select a subset of variables from a larger set based on which original variables have the highest correlations with the principal component factors.
- To create a set of factors to be treated as uncorrelated variables as one approach to handling multi-collinearity in such procedures as multiple regression.
- To validate a scale or index by demonstrating that its constituent items load on the same factor, and to drop proposed scale items which cross-load on more than one factor.
- To establish that multiple tests measure the same factor, thereby giving justification for administering fewer tests.
- To identify clusters of cases and/or outliers.
- To determine network groups by determining which sets of people cluster together (using Q-mode factor analysis).

While using multivariate analysis, the number of variables increases. Univariate techniques are limited to a single variable, but multivariate techniques can have tens, hundreds or even thousands of variables. If one has few variables, they may all be distinct and different. When more and more variables are added, more and more overlaps i.e., correlation is likely among
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the variables. As the variables become correlated, the problem becomes how to manage these variables – grouping highly correlated variables together, labelling or naming the groups, and perhaps even creating a new composite measure that can represent each group of variables. Factor analysis provides the tools for analysing the structure of the interrelationships among a large number of variables by defining sets of variables that are highly interrelated, known as factors. These groups of variables (factors), that are by definition highly inter-correlated, are assumed to represent dimensions within data. If one is only concerned with reducing the number of variables, then dimensions can guide in creating new composite measures. On the other hand, if one has a conceptual basis for understanding the relationships among variables, then the dimensions may actually have meaning for what they collectively represent. In the latter case, these dimensions may correspond to concepts that cannot be adequately described by a single measure. Factor analysis presents several ways of representing these groups of variables for use in other multivariate techniques.

2.4 System Dynamics

System Dynamics, developed by Forrester (1961, 1968) identifies cause-effect relationships and structures them in a feedback control framework to understand the dynamic behaviour of the system. The approach professes causality doctrine associated with determinism. System Dynamics is a methodology that has ability to capture and model dynamic complexity of complex systems. Dynamic complexity refers to state where cause and effect are subtle and where effects over time interventions are not obvious (Senge, 1990). According to Coyle (1977) a System Dynamics study aims at the following objectives: Explaining the systems behaviour in terms of structure and policies, and suggesting changes in structure, policies or both, which will lead to an improvement in behaviour. In terms of practical system-dynamics work, and as a conceptual framework, it is useful to look at systems in the light of how much certain knowledge about their workings it is possible to acquire and how far it is possible to exert actual and direct control over what goes on.

Causal loop diagrams: Model boundary charts and subsystem diagrams show the boundary and architecture of the model but don’t show how the variables are related. Causal loop diagrams (CLDs) are flexible and useful tools for diagramming the feedback structure of systems in any domain. Causal diagrams are simply maps showing the causal links among
variables with arrows from a cause to an effect. Causal loop diagrams emphasize the feedback structure of a system (Sterman, 2000).

Positive feedback loops generate growth, amplify deviations, and reinforce change. Negative loops seek balance, equilibrium, and stasis. Negative feedback loops act to bring the state of the system in line with a goal or desired state. They counteract any disturbances that move the state of the system away from the goal (Sterman, 2000).

System dynamics is an approach to understanding the behaviour of complex systems over time. It deals with internal feedback loops and time delays that affect the behaviour of the entire system. What makes using system dynamics different from other approaches to studying complex systems is the use of feedback loops and stocks and flows.

The use of system dynamics for giving decision support to transport policy makers has been presented in Schade and Rothengatter (2001) and Schade (2004). According to Schade and Rothengatter, this tool is able to handle a high complexity of interactive subsystems such that it is appropriate to analyse long-term impact mechanism within the transport sector and between other sectors of the economy.

Causal thinking is the key to organizing ideas in a system dynamics study. Instead of ‘cause’, ‘affect’ or ‘influence’ can be used to describe the related components in the system. Some influences can be logically deduced such as food intake increases weight or say if there is smoke there is fire or say use of seatbelts reduces highway fatalities. However unidirectional linear causality is not enough to describe the dynamics of a system. It requires identifying feedback loops that govern the dynamics of a system. A feedback can be said “that an initial cause ripples through a chain of causation ultimately to re-affect itself”. Thus one key element of System Dynamics is to identify closed, causal feedback loops. The most important causal influences will be exactly those that are enclosed within feedback loop.

Causal loop diagrams represent the feedback structure of systems. It captures the causes of dynamics. For example, we know the better salary leads better performance while better performance also results in higher salary. That is, in “Salary vs Performance” dynamics it can be represented as:

- Salary → Performance
- Performance → Salary
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The causal loop diagram can be shown as given in figure 1a below.

**Figure 2.1: Salary – Performance Loop**

Adding a ‘+’ or a ‘-’ sign at each arrowhead conveys more information. For example;

- A ‘+’ sign is used if the cause increase, the effect increases and if the cause decrease, the effect decreases
- A ‘-’ sign is used if the cause increases, the effect decreases and if the cause decreases, the effect increases

Since it is established that salary leads to better performance and better performance leads to higher salary, the above diagram can be shown as (Figure 1b).

**Figure 2.2: Salary – Performance Loop with signs**
The signs establish the polarity of the loop. The polarity results in positive or negative feedback loop. Positive feedback loops have the following characteristics:

- Have an even number of ‘–’ signs
- Some quantity increase, a “snowball” effect takes over, and that quantity continues to increase
- The “snowball” effect can also work in reverse
- Generate behaviors of growth, amplify, deviation, and reinforce

The notation used is to place symbol in the center of the loop

Negative feedback loops have the following characteristics:

- Have an odd number of “–” signs
- Tend to produce “stable”, “balance”, “equilibrium” and “goal-seeking” behavior over time
- Notation: place symbol in the center of the loop

Thus the causal loop diagram for salary – performance dynamics would be as shown in figure 1c below:

**Figure 2.3: Salary – Performance Positive Loop**

There are systems which have more than one feedback loop within them. A particular loop in a system of more than one loop is most responsible for the overall behavior of that system. The dominating loop might shift over time. When a feedback loop is within another, one loop must dominate. A stable condition will exist when negative loops dominate positive loops. A example of negative loop is the example of “usage versus maintenance”. More we use a machine more is the maintenance required for that machine. More we maintain the machine less it is available for usage. Figure 1d shows the negative loop arising out of the nature of dynamics between usage of a machine and its maintenance.
2.5 Chapter Summary

Factors and variables affecting Port Performance – Findings from Literature Review

The review of literature reveal that factors affecting Port efficiency emerging through these studies are Size, Competition – Intra and Inter port, Technology adopted and Management/Institutional structure. These factors are again interdependent and region specific. The important findings may be drawn on comparable terminals and indicators. These are summarized below.

i. The operational performance of a port is generally measured in terms of the speed with which a vessel is dispatched, the rate at which cargo is handled and the duration that cargo stays in port prior to shipment or post discharge (KekChoo Chung, 1993). The performance parameter that indicates this aspect is the turn round time (TRT).

ii. Container terminal efficiency declines as the terminal becomes more congested (Farrel, 2009). The performance parameter that manifests congestion is the pre berthing delay (PBD).

iii. The number of berths and the capital deployed are the most sensitive measures impacting performance of most container ports (Yan and Liu, 2010).

iv. Vessel turnaround time is highly correlated with crane allocation as well as the number of containers loaded and discharged (Yan and Liu, 2010). The average output per ship berth day (AOPSBD) is the parameter that reflects the impact of crane and moves per crane on vessel turnaround time.
v. Variations in port efficiency are linked to excessive regulation, the prevalence of organized crime, and the general condition of the country's infrastructure (Clark et al, 2004). They found that besides distance and containerization, the efficiency of ports is also important in determining maritime transport costs.

*The pre berthing delay and post operation time prior to departure or the non-working time reflect the delay owing to regulations and other factors. These time durations are reflected in TRT.*

vi. Larger ports produced higher efficiencies (Martinez-Budria et al. 1999, Tongzon 2008).

*Port’s size is reflected in terms of number of berths and/or cargo throughput per annum of the port.*

vii. Large-scale production tended to be associated with higher efficiency (Wang and Cullinane 2006).

*Cargo throughput and vessels handled reflect scale of production for ports.*

viii. Investment in infrastructure does not improve efficiency, rather self-created logistics demand and strategic allowances do improve the efficiency (Yongrok Choi 2011).

*The difference in efficiency between public and private or between any ports handling similar cargo under similar economic environment is expected to indicate the impact of difference in strategies of the ports, on the efficiency.*

ix. Privatization may or may not have effect efficiency of the ports and terminals (Bhatt and Gaur, 2011; Güner et al, 2014, Baird (2000)).

*The difference in efficiency between public and private ports is expected to indicate the impact of privatization on the efficiency.*

**Research Gap**

The literature survey reveals that different discrete analytical tools have been used by the researchers to draw conclusion on factors and dimensions affecting port performance and their relationships. It is felt that a well-defined analytical framework is required to define the causality amongst the factors and their variables. The causal model will enable the port managers to take the right decision. In this paper an analytical framework has been described to arrive at a causal model for decision making by port managers.
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So far as port efficiency is concerned, plenty of attempts were made for measuring the efficiency levels of the ports. Although some other measures were also used, the most commonly used measure was DEA. However, comparatively lesser attempts were made to relate the port efficiency with the regional development. In the Indian context very few attempts were made in this regard. In none of the previous DEA study turn round time (TRT) per thousand TEU, which has direct impact on logistics cost, has been taken as output.

From the literature it is clear that whereas a number of studies and surveys provided evidence that privatization generally led to improved performance over public-sector operations, a number of economists argued against the strength of the opinion in favour of private ownership and suggested that principal–agent problems may also arise in the private sector as a result of capital market imperfections. Thus, the question of the relative efficiency of alternative forms of ownership was an empirical one. So, in the Indian context there is a need to find out the reality. In the Indian context, although Bhatt and Gour tried to find out the effect of privatization on the performance of the container terminals they kept the scope of their study limited to the group of container terminals in JNPT- Mundra range of ports. So, from that point of view a study on major container handling ports of India is felt very much needed. The relative position of Indian ports with regard to the regional ports leads to the fact that conclusion of Sashikumar (1998) continues to hold good till date and thus calls for further in-depth study of Indian ports.