Chapter 2
DEA Conceptual Exposition and Literature Review

2.1 Data Envelopment Analysis Conceptual Exposition

Efficiency is a fundamental concept in the field of economics and has been variously defined in different textbooks. The concept is basically concerned with the economic use of resources (inputs) for production. Given the limited and finite nature of resources available to every productive process, the importance of studying efficiency is self-evident. In the very first sentence of his influential seminal paper, (Leibenstein 1966) goes so far as to state explicitly: 'At the core of economics is the concept of efficiency'.

DEA concerns itself with assessing the efficiency of an individual firm. This firm is the fundamental unit of analysis that, following aggregation, makes up the sample for analysis and is typically defined as the decision making unit (DMU) (Charnes et al. 1978).

In either case, the terminology refers to the organizational entity responsible for controlling the process of production and for making decisions at various levels that may influence the productive process and the level of efficiency associated with it. These include daily operational, short-term tactical and long-term strategic decisions. DEA can be employed to measure the holistic efficiency of a firm by comparing it with other homogeneous units that transform the same group of measurable positive inputs into the same types of measurable positive outputs. In fact, this homogeneity of both the inputs and outputs constitutes a fundamental underlying assumption upon which the reality of DEA efficiency measures is based. In the absence of such an assumption, the relevance of measuring efficiency across any set of DMUs could undoubtedly be called into question.

The conceptual basis of data envelopment analysis (DEA) came from Farrell, but it was initially restricted to the performance evaluation of decision making units (DMUs) with multiple inputs and only a single output.

The basic principle of utilizing DEA to measure the efficiency level of firms within a given sample can be explained through the use of the example data

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Table 2.1 Single input and single output

Terminals	T1	T2	T3	T4	T5	T6	T7	T8
Stevedores	10	20	30	40	50	50	60	80
Throughput	10	40	30	60	80	40	60	100
Productivity (throughput/stevedores)	1	2	1	1.5	1.6	0.8	1	1.3
Efficiency (%)	50	100	50	75	80	40	50	63

presented in Table 2.1 and the conceptual illustration provided in Fig. 2.1. In relation to assessing the validity of the homogeneity assumption, it is critically important that the quality of inputs utilized by the various container terminals across the sample is similar.

Together, Table 2.1 and Fig. 2.1 present a simplified vision of the production process of eight container terminals, with 'Stevedores' being the only input considered and 'throughput' (i.e. containers per unit time) the only output. The productivity of any entity is simply the absolute measure of outputs/inputs and, therefore, in Table 2.1 the productivity of each terminal is represented by the calculated ratio of 'throughput/stevedore'. It should be pointed out that this measure is equivalent to the slope of the line connecting each point to the origin in Fig. 2.1 and corresponds to the number of containers moved per stevedore per unit time. It is clear from Fig. 2.1 that T2 has the highest absolute level of productivity compared with the other points and is, therefore, the most efficient unit in the sample. As such, the line from the origin through T2 is deemed to define the production frontier, at least insofar as current relative information on a limited sample allows. All the other

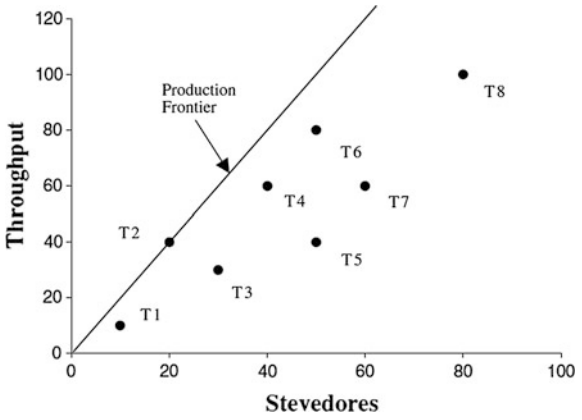

Fig. 2.1 Comparison of efficiencies of container terminals (CCR model). *Source* Drawn by Cullinane (2007)

points are inefficient compared with T2 and are termed to be physically 'enveloped' by the production frontier. In the context of DEA, the relative efficiencies of all units of analysis other than T2 (as shown in the bottom line of Table 2.1) are measured by comparing their productivity with that of T2. The term 'Data Envelopment Analysis' stems directly from this graphical representation of a frontier 'enveloping' data points and of data points being 'enveloped' by a frontier.

The way in which efficiency is calculated in Table 2.1 and Fig. 2.1 is based on an assumption that production exhibits constant returns to scale. In other words, there are no (dis)economies of scale as the level of productive output changes. The DEA model corresponding to this assumption is termed the DEA-CCR model (named in recognition of the large contribution of Charnes et al. 1978). In general, the DEA-CCR model can be distinguished into a parametric production frontier and a non-parametric production frontier; the former requires the production function to be known, whereas the latter does not. DEA utilizes the non-parametric type and applies the concept of 'Pareto optimization' for performance evaluation. Using DEA, it is possible to identify a DMU as an efficient unit or an inefficient unit, and the DEA analysis provides useful guidance regarding how a given DMU's performance might be improved.

Apart from the DEA-CCR model, the DEA-BCC model (similarly named in recognition of Banker et al. 1984[1]) is as well as widely studied and applied. The main difference between the two models and the DEA-BCC model allows for perhaps a more realistic assumption of variable returns to scale, in contrast to the constant returns to scale assumed in the DEA-CCR model.

Accordingly, the production frontier representations associated with these models are different. When either the DEA-BCC model is utilized, Fig. 2.1 shows the piecewise linear production frontier that would be estimated for the same data sample given in Table 2.1. The contrast with the production frontier in Fig. 2.1, where the DEA-CCR model is utilized, can be clearly seen. In Fig. 2.2, the data points defined by T1, T2, T6 and T8 are all located on the estimated production frontier and, therefore, are defined as efficient. In essence, therefore, given the validity of the variable returns to scale assumption, none of these sample data points can dominate each other. The other observations that are 'enveloped' by these efficient units are deemed to be inefficient.

For the DEA-BCC model, in terms of the projection path from each of the data-points that represent the inefficient firms onto the production frontier, the proportionate distance that results from the projection path that impacts directly upon the efficiency estimate derived for a specific inefficient data point. For instance, the inefficient firm located at T3 can be projected to either T3I or T3O under the DEA-BCC model in terms of either the input or output orientation.

[1]Leibenstein, H. (1966), Allocative efficiency versus "X-efficiency". *American Economic Review*, Vol. 56, pp. 392–415.

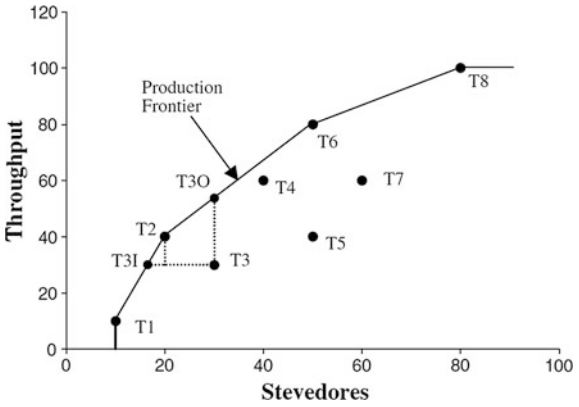

Fig. 2.2 Comparison of efficiencies of container terminals (BCC model). *Source* Drawn by Cullinane and Wang

Ultimately, it is merely this different projection path that yields the different estimates of the relative efficiencies for the inefficient firms.

The basic information derived from the above two DEA models, i.e. the DEA-CCR model and the DEA-BCC model, is whether or not a firm can improve its performance relative to the set of firms to which it is being compared. A different set of firms is likely to provide different efficiency results because of the possible movement of the production frontier.

Because the CCR model gives a value of 1 for all efficient DMUs, it is unable to establish any further distinctions among the efficient DMUs. Andersen and Petersen, therefore, presented a new DEA model, DEA-Super Efficiency model. This model removes an efficient DMU, and then estimates the production frontier again; this provides a new efficiency value for the efficient DMU that had previously been removed. The new efficiency value can thus be greater than 1. However, if an inefficient DMU is removed, the original production frontier does not change. Therefore, the efficiency values of inefficient DMUs do not change in the DEA-Super Efficiency model in Fig. 2.3.

In other words, the two basic models of DEA (i.e. CCR and BCC models) are used to provide the efficiency values for self-appraisal of terminal operational performance. The DEA-Super Efficiency model is used to make further distinctions among the efficient DMUs since they all have efficiency values of 1 in the CCR model. Thus, the varied and complementary information can be extracted from these three models to provide a more complete and comprehensive performance evaluation.

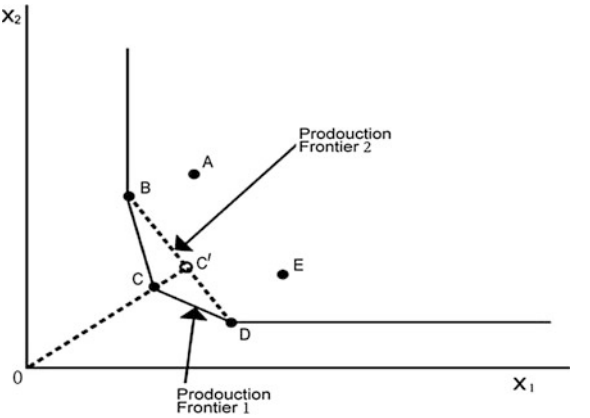

Fig. 2.3 DEA-super efficiency model. *Source* Author of the original source

DEA has become a popular method for general business management because it has a number of advantages[2]: it can evaluate a DMU's performance with multiple inputs and multiple outputs; it allows the units of input and output variables to be different; and it is not necessary to know the type of production function in advance. However, DEA also has several limitations: the DMUs must be homogeneous; to obtain the best results, the number of DMUs must be at least twice the total number of input and output variables; and 'isotonicity' must exist, that is, the output must not decrease while the input increases.

2.2 Economic Meanings of DEA Efficiency

Data envelopment analysis (DEA) is a non-parametric method in operations research and economics for the estimation of production frontiers. DEA basic theory and DEA models are all based on the theory of micro-economics. Therefore, it is necessary to state the concept of DEA efficiency.

The study of DEA efficiency is based on the production function $y = f(x)$. Above all, the production function will be explained as following:

Business firms combine various factors of production in order to produce various goods and services. Although there are thousands of different factors of production, or inputs, for simplicity we often use a model with only two factors, labor and capital. We can then study how the two inputs can be combined to produce an output. The relationship between inputs and output is called the production function. The general equation for the production function is: $Q = f(L, K)$ where Q is output, L is labor, K is capital, and f is the functional relationship between inputs

[2]Lewin, A.Y. and Minton, J.W., 1986, Determining organization effectiveness: another look and an agenda for research, *Management Science*, Vol. 2, No. 5, pp. 514–538.

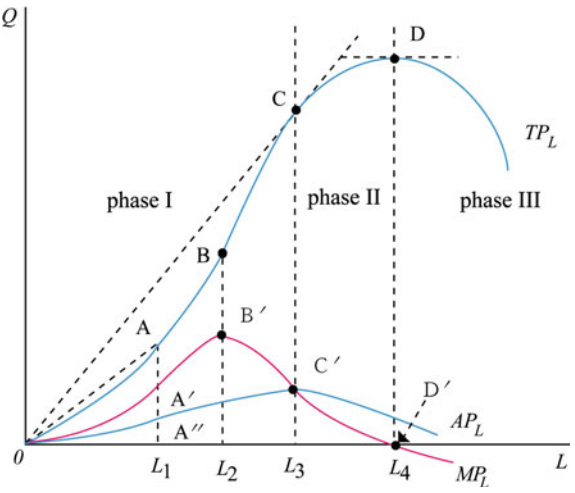

Fig. 2.4 Production function. *Source* Drawn by Samuelson and Nordhaus (2001)

and output. In the short run, we assume that capital cannot be varied; labor is therefore, the only variable factor. To increase output, then, a firm must increase the amount of labor. The relationship between the amount of the variable input (labor) and output can be illustrated with a total product curve such as that the curve of TP_L in Fig. 2.4.

Suppose that the curve is production function of a commercial container terminal. The terminal's capital—the facility—is fixed in the short run. Only the number of equipments can vary. As the amount of equipments increase from zero, the throughput (output) increases. Between zero and L_2, output increases at an increasing rate. As more equipments are invested, total output continues to increase, although marginal product curve is decreased from L_2 to L_4. Beyond that point, investing more equipments reduce output. The reason the total product curve has that particular shape can be seen more clearly in the curve of AP_L and TP_L in Fig. 2.4, which show the average and marginal product curves. The average product of equipments is total output divided by the amount of equipments respectively, such as throughput per yard truck or throughput per crane. The marginal product of equipments is the change in total output brought about by changing the amount of equipments by one unit. Because at least some equipments are needed to handle the containers, the first few equipments invested greatly increase total output (throughput); marginal product is rising. Between L_2 and L_4, the marginal product of equipments falls. Total product continues to rise, but no longer at an increasing rate. The law of diminishing marginal returns[3] which states that we will get less and less extra output when we add additional doses of an input while holding other inputs fixed. In other words, the marginal product of each unit of input will decline

[3]Samuelson & Nordhaus, Microeconomics, *McGraw Hill 2001, 17th ed*, p. 110.

as the amount of that input increases holding all other inputs constant, has taken effect.

At L_3, marginal product equals average product and average product is maximized. As more equipments are invested average product falls. Note that as long as marginal product is positive, more equipments mean more output and the total product curve will have a positive slope. Beyond L_4, marginal product becomes negative and total product falls. The terminal may be so crowded that equipments bump into each other and reduce the amount of work that each does.

Some economists divide the production function of Fig. 2.4 into three stages:

In stage one, from zero to L_2, total product and average product of equipment both rise. In stage two, between L_2 and L_4, total product rises while average product falls. In stage three, beyond L_4, total product and average product both fall (and marginal product is negative).

Moreover, in economics, returns to scale describes what happens as the scale of production increases in the long run, when all input levels including physical capital usage are variable (chosen by the firm). They are different terms and should not be used interchangeably.

The term returns to scale arises in the context of a firm's production function. It refers to changes in output resulting from a proportional change in all inputs (where all inputs increase by a constant factor). If output increases by that same proportional change then there are constant returns to scale (CRS). If output increases by less than that proportional change, there are decreasing returns to scale (DRS). If output increases by more than that proportional change, there are increasing returns to scale (IRS). Thus the returns to scale faced by a firm are purely technologically imposed and are not influenced by economic decisions or by market conditions.

If the production status (x, y) can satisfy the production function $y = f(x)$, then the production status (x, y) is pure technical efficiency. The points (x, y) are in the production frontier.

The scale efficiency is that, on the production function, the amount of input x are exact (not to more and not too less) located on the point between the increasing return to scale and decreasing return to scale. In other words, when the marginal product of input (x) which is the change in total output brought about by changing the amount of input (x) by one unit is maximum, the DMU is scale efficiency. Therefore, in Fig. 2.4, only DMU-B is scale efficiency.

2.3 Literature Review of DEA to Container Terminals

In recent years, DEA has been increasingly used to analyze port production. Compared with traditional approaches, DEA has the advantage that it can cater for multiple inputs to and outputs from the production process. This accords with the characteristics of port production, so that there exists, therefore, the capability of providing an overall summary evaluation of port performance.

Ryon (2005) analyzed the relative efficiencies of the container terminal operation in the port of Busan and Gwangyang using data envelopment analysis (DEA) based on output-orientated measurement with data from 2002 to 2004. The results show that the container terminals of Gamman and Uam are found to be the most efficient terminals in 2002, 2003 and 2004. Gamcheon is found to be the most efficient terminal in 2003 and 2004. Relatively most inefficient terminals include Gwangyang phase 1 and Gwangyang phase 2 terminal based on variable returns to scale assumption.

Roll and Hayuth (1993) probably represents the first work to advocate the application of the DEA technique to the ports context. However, it remains a purely theoretical exposition, rather than a genuine application.

Martinez-Budria et al. (1999) classified 26 ports into three groups, namely high-, medium- and low complexity ports. After examining the efficiency of these ports using DEA-BCC models, the authors conclude that the ports of high complexity are associated with high efficiency, compared with the medium and low efficiency found in other groups of ports.

Tongzon (2001) uses both DEA-CCR and DEA-Additive models to analyze the efficiency of four Australian and 12 other international container ports in 1996. The results suggest that Melbourne, Rotterdam, Yokohama and Osaka are the most inefficient ports in the sample, with enormous scope for improvement found to exist with respect to container berths, terminal area and labor inputs. Clearly, plagued by a lack of data availability and the small sample size (only 16 observations), more efficient ports are naturally identified. Realizing this serious drawback, the author concludes that further work should be done in collecting more observations to enlarge the sample analyzed.

Valentine and Gray (2001) apply the DEA-CCR model to 31 container ports out of the world's top 100 container ports for 1998. The objective of the authors' work is to compare port efficiency with a particular type of ownership and organizational structure to determine if there exists any relationship between them. The authors conclude that cluster analysis is a viable tool for identifying organizational structures and that the ports sector exhibits three structural forms that seem to have a relationship to estimated levels of efficiency.

For the period 1990–1999, Itoh (2002) conducted a DEA window analysis using panel data relating to the eight international container ports in Japan. Tokyo was found to be consistently efficient in terms of its infrastructure and labor productivity over the whole period, while Nagoya performed well during the early part of the period covered by the analysis. At the other extreme, efficiency scores for Yokohama, Kobe and Osaka were found to be low throughout the duration of the period under study.

Barros (2003[4]) applies DEA to the Portuguese port industry in 1999 and 2000. The motivation for the analysis is to determine what relationship exists between the

[4]Barros, C.P., & Athanassiou, M. (2004), Efficiency in European seaports with DEA: Evidence from Greece and Portugal, *Maritime Economics and Logistics*, Vol. 6, No. 2, pp. 122–140.

governance structure that has been established for the Data Envelopment Analysis (DEA) and Portuguese port sector, the incentive regulation promulgated under this structure and the ultimate impact on port efficiency. The author concludes that extant incentive regulation has been successful in promoting enhanced efficiency in the sector, but that this could be improved upon by the implementation of recommendations aimed at redefining the role of Portugal's Maritime Port Agency, the regulatory body responsible for port matters.

This time using data for 1990 and 2000, Barros (2003) again applies DEA to the Portuguese port industry to derive estimates of efficiency that can then be utilized to determine the source of any inefficiency that may be identified. One of the results of the analysis is that while Portuguese ports have attained high levels of technical efficiency over the period covered by the analysis, the sector has generally not kept pace with technological change. The author concludes that the financial aids to investment that form part of the EU's Single Market Program have stimulated greater efficiency in the port sector, particularly as the result of the greater competition that is faced; a feature that is particularly relevant for Portuguese ports located near the border with Spain. Through the application of Tobit regression analysis, it is also found that container ports are more efficient than their multi-cargo counterparts (suggesting that there are dis-economies of scope in cargo handling), that efficiency is positively related to market share and, finally, that greater public sector involvement is negatively related to efficiency.

In yet another extension of this work, Barros and Athanassiou (2004) apply DEA to the estimation of the relative efficiency of a sample of Portuguese and Greek seaports. The broad purpose of this exercise was to facilitate benchmarking so that areas for improvement to management practices and strategies could be identified and, within the context of European ports policy, improvements implemented within the seaport sectors of these two countries. The authors conclude that there are economic benefits from the implementation of this form of benchmarking and go on to evaluate their extent.

Bonilla et al. (2004) apply a version of DEA that includes a statistical tolerance for inaccuracies in input and output data to the investigation of commodity traffic efficiency within the Spanish port system. Their sample comprises 23 ports and annual data are collected for 1995–1998 inclusive. The analysis is unusual in that the sample ports handle a range of cargoes—solid bulk, liquid bulk and general break-bulk—rather than being restricted to a single form of cargo (most usually containers). Given a calculated high level of correlation between prospective input variables, a single input encapsulating infrastructure endowment is incorporated into the analysis. The most and least efficient Spanish ports are identified and, using an 'incidence analysis', the authors conclude by identifying which ports are most sensitive to variations in traffic volumes among the different types of cargo handled.

Given the characteristics of the container port industry and the random effects associated with a single measured value of production for each port or terminal in a sample and the level of measured efficiency associated with it, Cullinane et al. (2004) recognized that the analysis of cross-sectional data will inevitably provide inferior estimates of efficiency than those based on panel data. In seeking to allow

for this potential, they applied alternative DEA approaches based on cross-sectional and panel data analysis, respectively. The authors conclude that by so doing, the development of the efficiency of each container port or terminal in a sample can be tracked over time and that this provides interesting and potentially useful insights for both policy formulations and management.

Recognizing the limitations in assessing the efficiency of ports solely on the basis of capital and labor inputs, Park and De (2004) develop what they refer to as a 'Four-Stage DEA Method'. This involves the disaggregation of the overall efficiency model into its constituent components, so that better insight can be gained into the real sources of efficiency. The model comprises individual DEA components that determine the respective efficiency related to productivity, profitability, marketability and overall. In applying their method to a sample of Korean ports, the authors conclude that improving the marketability of Korean seaports should be the utmost priority of port authorities.

Turner et al. (2004) applied DEA to the determination of changes in infrastructure productivity in North American ports over the period 1984–1997. They then went on to use the productivity estimates as the dependent variable within a Tobit regression model, which sought to determine the causal factors affecting the scores they derived. Perhaps most significantly, the authors conclude that there are significant economies of scale present within the North American sector, both at port and at terminal level—a finding that concurs with the outcomes of most research investigating economies of scale in the port sector. They also find that access to the rail network is a pivotal determinant of container port infrastructure productivity in North America, but that there is no evidence to suggest that specific investment in on-dock rail facilities is a productive use of the land-take involved.

Cullinane et al. (2005) empirically examine the relationship between privatization and relative efficiency within the container port industry. The sampling frame comprises the world's leading container ports ranked in the top 30 in 2001, together with five other container ports from the Chinese mainland. DEA is applied in a variety of panel data configurations to eight years of annual data from 1992 to 1999, yielding a total of 240 observations. The analysis concludes that there is no evidence to support the hypothesis that greater private sector involvement in the container port sector irrevocably leads to improved efficiency.

Using cross-sectional data for 2002, Cullinane and Wang (2006) apply DEA to the derivation of estimates of relative efficiency for a sample comprising 69 of Europe's container terminals with annual throughput of over 10,000 twenty foot equivalent units (TEUs). The sample was distributed across 24 European countries. The main finding is that significant inefficiency pervades the European container handling industry, with the average efficiency of container terminals under study amounting to 0.48 (assuming constant returns to scale) and 0.42 (assuming variable returns to scale). Most of the container terminals under study exhibit increasing returns to scale, with large container terminals more likely to be associated with higher efficiency scores. A further conclusion was that there was significant variation in the average efficiency of container terminals located in different regions,

with those in the British Isles found to be the most efficient and Scandinavia and Eastern Europe the least efficient.

Cullinane et al. (2005) apply both DEA and Stochastic Frontier Analysis (SFA) to the same set of container port data for the world's largest container ports and compare the results obtained. A high degree of correlation is found between the efficiency estimates derived from all the models applied, suggesting that results are relatively robust to the DEA models applied or the distributional assumptions under SFA. High levels of technical efficiency are associated with scale, greater private-sector participation and with transshipment, as opposed to gateway, ports. In analyzing the implications of the results for management and policy-makers, this paper concludes that a number of shortcomings of applying a cross-sectional approach to an industry characterized by significant, lumpy and risky investments are identified and the potential benefits of a dynamic analysis, based on panel data, are enumerated.

Similarly, using the same dataset for the world's most important container ports and terminals, Cullinane et al. (2006[5]) evaluate and compare relative efficiency estimates derived from the two alternative techniques of DEA and the Free Disposal Hull model. The results confirm expectations that the available mathematical programming methodologies lead to different results and the conclusion is drawn that the appropriate definition of input and output variables is a crucial element in meaningful applications of such techniques.

[5]Cullinane, K.P.B., Song, D.-W., & Wang, T.-F. (2006). The application of mathematical programming approaches to estimating container port production, *Journal of Productivity Analysis*, Vol. 24, No. 1, pp. 73–92.

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