The Efficiency of Baseports in the Philippines based on Data Envelopment Analysis: Benchmarks and Target Improvements

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Abstract: The steady growth of economic activities in the Philippines necessitates the need for efficient ports to accommodate the growing demand for trade. This study applies the Data Envelopment Analysis (DEA) to provide the efficiency scores of the nineteen base ports in the country using data from 2019. An output-oriented analysis approach was applied for the DEA constant return to scale model (DEA-CCR) and DEA variable return to scale model (DEA-BCC) to compute the overall technical efficiency and pure technical efficiency of the ports. The findings show that the ports of Calapan, Tagbilaran, Cagayan de Oro, and Ozamiz demonstrated the best performance in both models. The ports of Lamao, Legazpi, and Masbate achieved pure technical efficiency but are classified as inefficient under DEA-CCR. The other ports were consistently classified as inefficient regardless of the model. The target outputs for the ports were also derived by projecting the efficiency scores of the inefficient DMUs into a hypothetical DMU operating in the established efficiency frontier.

Keywords: Efficiency Measurement, Data Envelopment Analysis (DEA), Maritime Port Operations, Domestic Ports, Public Transportation Management

1. INTRODUCTION

Logistics play a critical role in the development of an archipelagic country like the Philippines. The extensive area of the bays and coastal and oceanic waters gives the maritime sector a vital role in the development and growth of the local economy. For centuries, the Philippine territorial waters are the primary medium for transporting goods in domestic and international trade and play a crucial role in inter-island connectivity.

According to the Philippine Statistics Authority (PSA), almost 99.9 percent of domestic trade commodities were traded through water transportation (coastwise) and the remaining 0.1 percent through air transportation (Philippine Statistics Authority, 2019). The Maritime Industry Authority (MARINA) reports that in 2011-2017, the number of domestic shipping passengers has increased from about 50 million to 72 million, or an average annual growth rate of 6.5%. In the same period, domestic cargo also increased by 5.5% per year, from 74.17 million tons in 2011 to 102.53 million tons in 2017 (Maritime Industry Authority, 2018). The total domestic cargo throughput served by the maritime industry in 2019 reached 104.43 million tons. On the other hand, inter-island shipping had also transported around 83.5 million passengers in 2019 (Maritime Industry Authority, 2020).

The national government recognizes the need for efficient ports and continuously puts efforts into improving the maritime transportation network. One of the ten-year Maritime Industry Development Plan programs aims to improve the efficiencies of port facilities as part of the Philippine Nautical Highway Development. A particular desired outcome of this program is to increase the number of passengers, cargo volume, and the number of ship calls (Maritime Industry Authority, 2018).

As the country's population and economic activities continue to grow, port authorities are tasked with maintaining the flow of goods, improving the efficiency of the port, and making services more competitive to accommodate the growing demand for trade. Since ports are a vital link in the overall trading chain, port efficiency is an essential metric in assessing the international competitiveness and productivity of a nation (Tongzon, 1989; Hung et.al, 2010; Lirn and Guo, 2011; Kutin, et.al, 2017). Port managers need to constantly evaluate the operations and processes related to performance. The efficiency of a distribution center is an important metric in assessing the effectiveness of an island or region in bridging the gap between suppliers and consumers.

A great number of studies have focused on measuring the efficiency of international ports. Most of the international studies concentrated on container ports and do not consider passenger data. However, as of this writing, studies on the efficiency of domestic ports in the Philippines have been rare. The measurement of efficiencies of domestic ports is scarce mainly because of the relatively small trading volumes as compared to the lucrative business done in the container ports. Furthermore, port data in the Philippines is not consolidated and requires significant effort in acquiring. Hence, this paper hopes to contribute to the literature on efficiency measurement and management of local ports and maritime transportation in the Philippines. The researchers also aim to address the research gap between international and domestic ports in the country.

The objective of this study is to apply using a non-parametric technique called the Data Envelopment Analysis (DEA) in measuring and comparing the efficiencies of nineteen ports in the Philippines. DEA Constant Return to Scale (DEA-CCR) and DEA Variable Return to Scale (DEA-BCC) will be applied in this study. The efficiency scores of the ports will be calculated and presented using the DEAP software and DEA Solver LV8.

This study is organized as follows: Section 2 is a review of related literature of studies that used DEA as a measure of the efficiency with variations in types of ports, data requirements, methodologies, and models; Section 3 outlines and defines the DEA CCR and BCC models used in the analysis; Section 4 describes the implemented methodology as well as the definition and the bases of the variables used as inputs and outputs; Section 5 provides the results and analyses for DEA-CCR and DEA-BCC applied to the nineteen ports; Finally, Section 6 summarizes the outcomes, insights and concludes the results of this study.

2. REVIEW OF RELATED LITERATURE

In simple cases where production operations depend on a single input and output, managers can easily measure efficiency by taking the ratio of the output and input. However, ports utilize multiple inputs and cater to different types of services (e.g, passenger, dry cargo, liquid cargo, container, etc.). DEA can effectively assess ports' relative efficiency since it was designed for organizational units with multiple inputs and produce multiple measurable outputs.

One of the pioneering studies in analyzing seaport efficiency using DEA efficiency was done in 1993. Twenty hypothetical seaports were measured using DEA-CCR, the standard DEA model, with three variables as inputs and four as outputs (Roll and Hayuth, 1993). The same process and model were then applied in a study examining 12 international ports and four

Australian container ports in 1996 (Tongzon, 2001). According to the study, the DEA technique can be a significant alternative to classical econometric approaches to extracting efficiency scores from sample observations. Another study also used DEA-CCR, in investigating cross-sectional data for the year 1998 to establish a relationship between ownership type and port efficiency of 31 container seaports (Valentine and Gray, 2001).

DEA-BCC was performed in a study of 26 Spanish seaports that were then grouped into three based on their complexity (Martínez-Budría *et al.*,1999). In this study ports of high complexity presented higher comparative efficiency levels, being closer to the efficiency frontier as compared to the medium and low complexity ports. There are also studies that applied both the DEA-CCR and DEA-BCC models. The efficiency of six seaports from Greece and Portugal was estimated using both models. The researchers were able to conclude that five seaports were efficient except for one, which is the port of Thessaloniki (Barros and Athanassiou, 2004). In addition, sixty-nine container terminal ports with annual throughput of 10,000 TEUs in Europe were studied using both DEA models (Cullinane *et al.*, 2004). The general conclusion from this study is that the efficiency of different container ports can fluctuate over time to different extents. Applying the models in the Asian region, Munisamy and Singh (2011) calculated the technical efficiencies of 69 major container ports and was able to generate efficiency ranking. The study was able to show that the overall technical inefficiency in Asian container ports is due to pure technical efficiency rather than scale efficiency.

More recent studies applied new variations from the standard DEA. The DEA additive models were used alongside the DEA CCR to examine the technical efficiencies of ports in India from 1993 to 2011 (Rajasekar and Deo., 2014). It was concluded that port size is not a related factor for port efficiency. The difference between input and output orientation were also examined in a different study using both DEA-CCR and DEA-BCC. The results from this states that there is no difference in efficiency identification of the decision-making units (Rajasekar and Deo, 2014). The standard DEA model was also used in the analysis of nine Saudi Arabian seaports and their comparison with Jazan port (Esmail, 2016). A comparison was also done in 2018, wherein the efficiency scores of seven Tunisian ports were computed using DEA-CCR, DEA-BCC, and another non-parametric method, the Stochastic Frontier Analysis (Kammoun, 2018).

Another variation of the DEA method is the DEA-Malmquist Productivity Index. A study used the DEA-MPI method in examining four Aegean passenger ports using the data gathered from 2003 to 2010. Two inputs (labor and total expenditures) and three outputs (passenger calls, ship calls, and total income) were set as variables in the study. The research found that the average efficiency scores by year did not follow a specific trend and fluctuated (Güner and Coskun, 2013). Baran and Górecka (2015) made use of DEA-CCR and DEA-BCC models to determine the overall technical efficiency, pure technical efficiency, and scale efficiency of 18 container ports all around the world. They also included the application of Malmquist Productivity Index, which was used to analyze the changes in seaport productivity of four ports from 1996 to 2012. The study indicated that technological progress had more impact on the change in productivity of ports than changes in technical efficiency.

Kutin et al. (2017) applied output-oriented DEA-CCR and DEA-BCC to compare the efficiencies of fifty ASEAN container ports. The study grouped the sample ports into six categories depending on the geographic location[1] of port and the handling equipment used in the dock (e.g., rubber-tired gantry systems, straddle gantry systems, forklift truck systems, etc.). The input parameters considered in the analysis vary depending on the category, but only one output, container throughput in TEUs, was considered. The results revealed that, in general,

[1] Ports located in a riverbank connected to the sea are called “inland seaports” and those located by the seaside are call “seaports”.

ASEAN seaports perform better than ASEAN inland seaports. Analyses also implied that ASEAN ports have relatively good scale efficiencies and can handle an increase in container volume. Hung and Wang (2010) studied the efficiencies of 31 ports in 9 various countries in Asia, ranked among the world's leading 100 ports in 2003. The study used input-oriented DEA to assess the operating performance, review the effect of geographical factors, and determine efficiency rankings of Asian container ports. The results showed that the overall inefficiencies of Asian ports are primarily due to pure technical efficiencies and that port managers should focus efforts on improving management practices.

Using four DEA models–DEA-CCR, DEA-BCC, cross-efficiency in DEA-CCR, and cross-efficiency in DEA-BCC models, Lirn and Gou (2011) benchmarked the efficiencies of ten ports from the ASEAN and VISTA regions. They considered four inputs and one output in all their models. The results showed that the port of Singapore, the port of Ambarli in Turkey, and the port of Durban in South Africa were the most efficient among the sampled ports. The authors suggest that port managers can improve efficiency by balancing the resources it inputs and the output it receives and by adapting an appropriate marketing positioning strategy.

In the local context, the DEA method was also applied in the different fields of study. The efficiencies and productivity change of 78 state universities and colleges were examined using the method and DEA-MPI (Cuenca, 2011). In the field of disaster resilience, the DEA method was applied in various households of Compostela Valley to estimate a composite resilience score in responding to climate-induced calamities such as floods and landslides (Villano *et al.*, 2014). The DEA was also used in the field of public health. Social Hygiene Clinics were evaluated and benchmarked using the basic method (Seposo, *et al.*, 2019).

3. THE ANALYSIS MODEL

3.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is a non-parametric technique (i.e., it does not require assumptions on functional form like regression equations) that can be used to assess the efficiency of an individual firm. This firm—called a Decision-Making Unit (DMU)—is the fundamental unit of analysis and is responsible for decisions that influence the production process and the efficiency level at which the production is carried out (Charnes *et al.*, 1978). DEA measures the efficiency of a particular DMU by comparing it with other homogenous DMUs that utilize the same multiple inputs to produce the same types of outputs. For each DMU, DEA seeks out input and output weights that maximize the corresponding efficiency score. If a DMU obtains an efficiency score greater than or equal to one, it is efficient, whereas it is considered inefficient if it gets less than one. The most efficient DMUs form a frontier that 'envelops' all the relatively inefficient DMUs, hence the term 'Data Envelopment Analysis.'

Charnes, Cooper, and Rhodes (CCR) invented the technique of Data Envelopment Analysis in 1978. It is also commonly known as the DEA-CCR model (Charnes *et al.*, 1978). This method is based on linear programming and converts the input and output variables to measure efficiency. The DEA-CCR model assumes that production follows constant returns to scale (CRS). This means that there are no economies of scale as the level of output changes, specifically, an increase in the input results in a proportional increase in output. Banker, Charnes, and Cooper (BCC) later extended the DEA-CCR method in 1984 to allow a variable returns to scale (VRS) assumption. The model was known as the DEA-BCC (Banker *et al.*, 1984). Since then, DEA has become one of the most common performance evaluation techniques used by experts in the management discipline.

It is important to note that the production frontiers produced by each model are different.

The information that one can infer from both models is limited to whether or not a DMU can improve its performance relative to the set of other DMUs to which it is being compared. In this regard, changing the set of DMUs in the analysis would likely change the relative efficiency results (Cullinane and Wang, 2006).

3.2 Model Specification

DEA models can be classified into whether they are input and output-oriented. The input-oriented DEA model tries to minimize the inputs of a DMU for producing a desired level of output to be achieved. In contrast, the output-oriented DEA model maximizes the outputs while keeping the input at a constant level. In general, input-oriented DEA focuses on operational and managerial issues while output-oriented DEA is more associated with planning and strategy (Cullinane *et al.*, 2005).

This study utilizes the output-oriented formulation of the DEA-CCR and DEA-BCC models because the inputs used in the study (e.g., port area and berth length) are impractical to minimize. The infrastructure properties of these inputs have already been configured at a constant level; hence, it is hard to provide recommendations on port area and berth length reduction. More importantly, port managers are more interested in how much they can increase their productions given the constraints they currently encounter (Kutin *et al.*, 2017).

3.2.1 DEA-CCR

As presented in the previous section, DEA focuses solely on the relative efficiencies of each port by comparing one DMU with all the other DMUs in the dataset considered. DEA can therefore be described as data-oriented, as it derives efficiency evaluations directly from the data, with minimal assumptions. The problem of obtaining the efficiencies can be expressed as a task of fractional programming, but to apply it, DEA consists of solving linear programming tasks for each DMU under evaluation (Martić *et al.*, 2009).

The objective of the linear formulation is to maximize the weighted relative efficiency of one DMU by multiplying a combination of weights to each input and output. This formulation ensures that the DMU is as efficient as possible. Seeking the weights is subject to the constraint that (a) the calculated weighted efficiencies of the other DMUs in the set do not exceed one when using the weights and (b) that each weight is positive (i.e., since they represent the relative importance of an input or output).

Mathematically, we let R be the total number of DMUs in the analysis. For a selected DMU which uses a combination of n inputs and m outputs, let x_{ji} be the observed magnitude of a j-type input for an entity i ($x_{ji} > 0$; $j = 1, 2, 3, \ldots, n$; $i = 1, 2, 3, \ldots, R$) and y_{ki} be the observed magnitude of a k-type output for entity i ($y_{ki} > 0$; $k = 1, 2, 3, \ldots, m$; $i = 1, 2, 3, \ldots, R$). The basic model for computing the relative efficiency score of a selected DMU p, given multiple input and output factors, is given below:

$$maximize\ \theta_p = \sum_{k=1}^{m}(u_k y_{kp}) / \sum_{j=1}^{n}(v_j x_{jp}) \quad (1)$$

subject to

$$\sum_{k=1}^{m}(u_k y_{ki}) / \sum_{j=1}^{n}(v_j x_{ji}) \leq 1, \ \ i = 1, 2, 3, \ldots, i_p, \ldots, R \quad (2)$$

$$u_k \geq \varepsilon, \qquad k = 1,2,3, \ldots, m \tag{3}$$

$$v_j \geq \varepsilon, \qquad j = 1,2,3, \ldots, n \tag{4}$$

where,

- θ_p : relative efficiency of the *p*th DMU
- m : number of outputs
- u_k : weights assigned for output *k*
- n : number of inputs
- v_j : weights assigned for input *j*
- R : number of DMUs
- ε : a small positive value

The objective function in (1) is the relative efficiency of the *p*th DMU expressed as the ratio between the weighted sum of outputs and the weighted sum of inputs. The constraint in (2) indicates that the calculated weights from (1) will produce a value of θ_p such that $0 < \theta_p \leq 1$ for all the other R DMUs. The calculated weights u_k and v_j that satisfy (1)-(4) represents the importance of each input and output for the selected DMU. It also makes sure that the inefficient DMUs are inside the efficiency frontier.

If the efficiency score, θ_p, is equal to one then the selected DMU has the maximum value for θ_p and is operating at the efficiency frontier. This means that there is no way for the DMU to further increase its level of output given its current level of input. However, if the DMU obtained an efficiency score of less than one, the DMU is deemed relatively inefficient. A DMU is relatively inefficient when it can expand any of its outputs without changing any of its inputs and without reducing the level of all its other outputs.

A DMU is said to operate under constant return to scale if an increase in the inputs proportionately increases the outputs. The CCR model calculates the overall technical efficiency wherein the pure technical efficiency and scale efficiency are aggregated (Martić *et al.*, 2009).

3.2.2 DEA-BCC

The DEA-BCC or variable returns to scale model is the most important extension of the CCR model (Banker *et al.*, 1984). It considers the productivity of a DMU at the most productive scale size, which may not be attainable for other smaller DMUs. The DEA-CCR model is only appropriate when all DMUs are functioning at an optimal scale. The consideration of imperfect competition, financial constraints, demand disparity, etc., may cause a DMU to not operate at the optimal level. Therefore, the DEA-BCC efficiency score only measures pure technical efficiency. It is similar to the CCR model but with an additional constraint introduced (Martić *et al.*, 2009)

$$\sum_{c=1}^{R} \lambda_c = 1 \tag{5}$$

where,

- λ : coefficient of linear combination

A DMU operates under variable returns to scale if an increase in the inputs does not proportionately change the outputs. The BCC model ignores the impact of scale size and gives the pure technical efficiency score. This is done by comparing DMUs of the same scale. In most cases, the small units are qualitatively different from large units and a comparison between the two may misrepresent the comparative efficiency.

Again, the DEA model can be output-oriented or input-oriented. In the input-oriented model, an inefficient unit can become efficient by proportionately decreasing the inputs while the outputs remain the same. It contracts the inputs as far as possible while controlling the outputs. Meanwhile, in the output-oriented model, the inefficient unit can become efficient by proportionately increasing the outputs while the inputs remain constant. The orientation of the model determines the projection direction of the inefficient DMUs. For the CCR model, the input and output measurements are always the same. For the BCC model, an input-oriented model must be used to get input interpretations while an output-oriented model must be used separately to get output interpretations.

3.2.3 Scale Efficiency

The technical efficiencies derived from both the DEA-CCR and DEA-BCC models are often used to calculate scale efficiency for each DMU p (Cullinane and Wang, 2006). The scale efficiency is defined as the ratio between the overall technical efficiency score (calculated from DEA-CCR) and the pure technical efficiency score (calculated from DEA-BCC) of each DMU in the analysis. It denotes the optimum degree to which the DMU is efficient, enabling maximum outputs.

$$SE_p = \frac{\theta_{p,CCR}}{\theta_{p,BCC}} \tag{6}$$

where,

SE_p	: Scale Efficiency score
$\theta_{p,CCR}$	: CCR efficiency score
$\theta_{p,BCC}$	: BCC efficiency score

Under the scale efficiency measure, for any DMU p, if $SE_p = 1$, then the DMU p is considered scale efficient. This means that the current size of the operation is already at the optimal point. Changes and modifications on its size will render the DMU less efficient. On the other hand, if $SE_p < 1$, then this indicates that the firm is over/under-dimensioned (Ulas and Keskin, 2015).

4. METHODOLOGY

Given the diversity of ports and complexity of management in the local setting, it is necessary to restrict the scope of analysis to a limited number of ports in the Philippines. In this study, all DMUs are domestic seaports in the Philippines. Table 1 lists the names of the chosen ports along with their locations and respective island group.

The three main island groups of the Philippines (Luzon, Visayas, and Mindanao) were considered for this study. Only the baseports classified by the Philippine Ports Authority (PPA) from the three regions were examined because they are the main hub ports in their respective areas. These ports also hold the regional administration office known as the Port Management Office (PMO). PMOs operate and manage other ports and terminals with areas of jurisdiction separate and independent from the baseport. PMOs serve as the local authority for the area under their control. This study identified six baseports from Luzon, four baseports from Visayas, and nine baseports from Mindanao, putting the total number of DMUs considered in the study at 19.

Table 1. Ports Considered

Port Name	Location / PMO	Island Group
Calapan	Mindoro	Luzon
Lamao	Bataan	Luzon
Legazpi	Bicol	Luzon
Lucena	Quezon Province	Luzon
Masbate	Masbate	Luzon
Puerto Princesa	Palawan	Luzon
Banago	Negros Occidental	Visayas
Dumaguete	Negros Oriental	Visayas
Ormoc	Western Leyte	Visayas
Tagbilaran	Bohol	Visayas
Cagayan De Oro	Misamis Oriental	Mindanao
Dapitan	Zamboanga del Norte	Mindanao
Iligan	Lanao del Norte	Mindanao
Makar Wharf	SOCSARGEN	Mindanao
Nasipit	Agusan del Norte	Mindanao
Ozamiz	Misamis Occidental	Mindanao
Sasa	Davao	Mindanao
Surigao	Surigao	Mindanao
Zamboanga	Zamboanga	Mindanao

The total number of DMUs in the analysis is critical. Using a small sample of DMUs is more likely to skew the results and produce a high proportion of efficient units. Cooper *et.al* (2000) suggest using the following equation for the determination of minimum sample size:

$$N \geq \max\{m \times s, 3(m+s)\} \tag{7}$$

where,

N : minimum sample size of DMUs
m : number of inputs
s : number of outputs

Using (7), it can be verified that the 19 DMUs selected are sufficient for the analysis that utilizes two inputs and three outputs. Since the technical efficiencies derived from DEA are relative, using the maximum available sample size allows for an empirical yet meaningful generalization of the results and improves the accuracy of the efficiency estimates for each DMUs (Cullinane and Wang, 2006).

In terms of the variables, a common feature of port benchmarking studies is the use of operational data (Kutin *et al*., 2017). The inputs and outputs were selected through logical justification and related literature. This study used input variables based on land and facilities available in the port because these are instrumental in reflecting the possible capacity and handling power to move the goods in the port sector. The berth is the area in the port that facilitates the stationing of vessels alongside the pier, quay, or wharf. The port area is considered to be the total area where all activities in the port are done, including waiting areas, storage areas, passenger terminals, etc.

The chosen output parameters consist of cargo throughput, passenger count, and the number of ship calls. These were selected as they are directly affected by the input parameters. They are also consistent with the targets of the maritime industry development plan programs (Maritime Industry Authority, 2018). The output parameters essentially require that the baseport to be analyzed should cater to both passenger and cargo demand.

The data used in this study are secondary in nature. Information regarding the port's berth length and total area were derived through correspondence with each PMO office. The values of cargo throughput, passenger count, dwell time, and ship calls were acquired from the 2019 annual statistics report of the PPA. Further consideration is the availability of the analysis parameters selected for this study as given in Table 2:

Table 2. Compilation of Input and Output Variables

Input	**Output**
Total Berth Length	Cargo Throughput
Total Port Area	Passenger Count
	Ship Call

5. RESULTS AND DISCUSSION

Parameter data were extracted from the 2019 PPA statistical report and consultations and communications with the different port operations divisions of the PMOs. Each DMU was modeled using the output-oriented DEA-CCR and output-oriented DEA-BCC. Their corresponding scale efficiencies were also acquired. Models were implemented using the DEA Solver LV8 (Cooper *et.al*, 2000) and DEAP 2.1 program (Coelli, 2003). Results are consistent in both implementation and yielded the same efficiency scores.

Table 3 shows the DEA-CCR score of each DMU. According to the model, ports that obtained a score of 1.00 will be treated as efficient, and ports with less than 1.00 will be treated as inefficient. The ports deemed to be efficient are Calapan, Tagbilaran, Cagayan de Oro, and Ozamiz. These ports are classified as efficient particularly in terms of input/output configuration as well as the size of operations. The fifteen other ports are found to be inefficient as they have CCR scores of less than one, with Iligan having the lowest score at 0.1359. These ports are experiencing inefficiencies possibly due to managerial underperformance or are not operating at an optimal scale. The average overall technical efficiency is found to be 0.659 or at 65.9% percent level. This means that the overall output can be further expanded by 34.1% for the same set of input quantities if all ports were as efficient as the benchmark ports identified by the DEA.

To better understand the source of inefficiencies, the overall technical efficiency was decomposed into two mutually exclusive and non-additive components: pure technical efficiency and scale efficiency (Kumar and Gulati, 2008).

The pure technical efficiency scores from the DEA-BCC analysis are also shown in Table 3. The average pure technical efficiency is found to be 0.7765 which tells that the ports can further increase the outputs by 22.4% under the efficiency frontier of the output-oriented DEA-BCC model. Seven out of the nineteen ports got a score of 1.0 and are classified as efficient and properly managed. These are Calapan, Lamao, Legazpi, Masbate, Tagbilaran, Cagayan de Oro and Ozamiz. Comparing to the results of the DEA-CCR, the ports of Lamao, Legazpi, and Masbate are considered efficient if the average pure technical efficiency is only considered. Ports with scores equal to one serve as the benchmark ports and depict best practices. The other twelve ports are classified as inefficient as they fall below the BCC frontier. These may imply that these ports have room for improvement in their management strategies.

Table 3. Overall Technical Efficiency Score (CCR), Pure Technical Efficiency Score (BCC), Scale Efficiency (SE), and Return to Scale of each DMU

DMU	CCR score	BCC score	SE score	Return to Scale
Calapan	1	1	1	Constant
Lamao	0.5738	1	0.5738	Increasing
Legazpi	0.7932	1	0.7932	Increasing
Lucena	0.2944	0.3057	0.9630	Constant
Masbate	0.6407	1	0.6407	Increasing
Puerto Princesa	0.6038	0.6726	0.8977	Constant
Banago	0.3141	0.3569	0.8801	Increasing
Dumaguete	0.5525	0.7116	0.7764	Constant
Ormoc	0.5847	0.7208	0.8112	Increasing
Tagbilaran	1	1	1	Constant
Cagayan De Oro	1	1	1	Constant
Dapitan	0.5732	0.8268	0.6933	Increasing
Iligan	0.1359	0.1435	0.9470	Increasing
Makar Wharf	0.902	0.9252	0.9749	Increasing
Nasipit	0.7879	0.8571	0.9193	Increasing
Ozamiz	1	1	1	Constant
Sasa	0.8278	0.8325	0.9944	Increasing
Surigao	0.4499	0.5069	0.8876	Increasing
Zamboanga	0.4822	0.8946	0.5390	Constant
MEAN	0.6587	0.7765	0.86	

In terms of scale efficiency scores, the average scale efficiency is found to be 0.86. Four ports—Calapan, Tagbilaran, Cagayan De Oro, and Ozamiz—were identified to already have the optimal size of operations by having scale efficiency scores equal to one. The other ports got scale efficiency scores less than 1.0 with Zamboanga having the lowest score at 0.539. This means that these ports are experiencing scale inefficiencies. Scale inefficiencies can be furthered characterized by the type of return to scale.

The last column of Table 3 summarizes information about the return to scale property of the DMUs. A port can have increasing returns to scale, constant returns to scale, or decreasing returns to scale. If a port is operating with either increasing or decreasing returns to scale, then it can further improve its efficiency by operating within CCR (Iqbal and Awan, 2015). Increasing returns to scale occur when the increase in outputs is faster than the growth of inputs. Decreasing returns to scale occur when the increase in outputs is slower than the growth of inputs.

Eleven ports are facing increasing returns to scale and eight ports are deemed to have constant returns to scale. For ports that are operating at an increasing returns to scale, reducing their outputs while improving and expanding their inputs will significantly result in a more efficient system. This means that for these ports, demand can be diverted to other servicing ports to improve efficiency. They also have the option to expand their facilities to have a constant return to scale. Returns to scale can also be constant when the growth of inputs and outputs are similar. These ports are at the CCR and BCC efficient frontiers. They are at the highest productivity and have reached their optimal size (Huguenin. 2012).

The ports of Calapan, Tagbilaran, Cagayan de Oro, and Ozamiz are all efficient regardless of the DEA model. This indicates that these ports are properly managed and operating at the optimal scale. CCR and BCC classifications can vary per DMU as with Lamao, Legazpi, and

Masbate. This result is not surprising since the DEA-CCR provides information on the aggregated pure technical and scale efficiency while DEA-BCC only focuses on pure technical efficiency. Contrary to the CCR classification, Lamao, Legazpi and Masbate are efficient ports under the BCC frontier which implies that these ports have a scale problem and the inefficiency due to poor management is eliminated. The other ports that were not mentioned are consistently inefficient. This means that they are located below the efficiency frontiers and that the ports still have room for improvement relative to the efficient ports. Improving management and the scale of operations can be done to achieve an increase in efficiency.

Table 4 presents the calculated weighted output parameters for each model used in the analysis. This gives port managers an idea on where to focus their efforts in improving their port's efficiency. The weighted outputs can be used to identify the most important output parameters in determining each port's efficiency. For example, when considering the DEA-CCR model for baseport Lamao, the total cargo throughput has the most weight, followed by the number of ship calls, while the total passengers have zero weight. This suggests that in the case of baseport Lamao, the most effective way of increasing efficiency is prioritizing to increase the total cargo throughput and then total number of ship calls. On the other hand, using the same model for the case of port Puerto Princesa, the most effective way of increasing their efficiency scores is putting all efforts in increasing annual cargo throughput.

Table 4. Calculated Weighted Output Parameters for each Model

DMU	**CCR (CRS) Model**			**BCC (VRS) Model**		
	u_1 **× Ship Calls/Number of Vessels**	u_2 **× Total Cargo Throughput**	u_3 **× Total Passengers**	u_1 **× Ship Calls/Number of Vessels**	u_2 **× Total Cargo Throughput**	u_3 **× Total Passengers**
Calapan	-	-	1.0000	1.0000	-	-
Lamao	0.3605	0.6395	-	0.3447	0.6553	-
Legazpi	-	1.0000	-	-	1.0000	-
Lucena	0.9075	0.0925	-	0.9305	0.0695	-
Masbate	0.7603	0.2397	-	0.7623	0.2377	-
Puerto Princesa	-	1.0000	-	-	1.0000	-
Banago	0.2913	0.7087	-	0.2670	0.7330	-
Dumaguete	0.7655	0.2345	-	0.8167	0.1833	-
Ormoc	-	0.5073	0.4927	-	0.2406	0.7594
Tagbilaran	-	1.0000	-	0.5498	0.4502	-
Cagayan De Oro	0.0346	0.9654	-	-	0.9471	0.0529
Dapitan	0.7091	0.2909	-	0.6614	0.3386	-
Iligan	-	1.0000	-	-	1.0000	-
Makar Wharf	-	1.0000	-	-	1.0000	-
Nasipit	-	1.0000	-	-	1.0000	-
Ozamiz	0.7878	0.2122	-	0.5942	0.4058	-
Sasa	-	1.0000	-	-	1.0000	-
Surigao	0.6695	0.3305	-	0.6719	0.3281	-
Zamboanga	-	0.7284	0.2716	-	0.3413	0.6587

The next important step for port managers is knowing how much they should increase their outputs to attain the same level of efficiency as the ports in the frontier. Using DEA, target values were also calculated and are presented in Tables 5 and 6. These values were derived by projecting the efficiency scores of the inefficient DMUs into a hypothetical DMU operating in the established efficiency frontier.

Table 5. Target Values for Ports to be CCR (CRS) efficient

DMU	Ship Calls/Number of Vessels			Total Cargo Throughput (tons)			Total Passengers		
	Current	Target	Diff.(%)	Current	Target	Diff.(%)	Current	Target	Diff.(%)
Calapan	**20,155**	**20,155**	**-**	**44,734**	**44,734**	**-**	**5,607,982**	**5,607,982**	**-**
Lamao	792	1,380	74.27	123,571	215,352	74.27	107,421	396,714	269.31
Legazpi	1,417	5,431	283.26	753,360	949,809	26.08	122,040	1,713,061	1,303.69
Lucena	5,803	19,708	239.62	126,285	428,889	239.62	921,793	5,566,599	503.89
Masbate	4,532	7,074	56.08	305,268	476,465	56.08	1,074,532	2,067,418	92.40
Puerto Princesa	1,251	14,900	1,091.06	1,573,430	2,605,929	65.62	188,378	4,700,013	2,394.99
Banago	1,814	5,776	218.42	320,034	1,019,050	218.42	219,498	1,710,896	679.46
Dumaguete	12,119	21,933	80.98	792,993	1,435,175	80.98	2,185,898	6,401,397	192.85
Ormoc	4,931	8,596	74.33	441,251	754,695	71.04	1,486,794	2,542,944	71.04
Tagbilaran	**11,022**	**11,022**	**-**	**1,927,676**	**1,927,676**	**-**	**3,476,726**	**3,476,726**	**-**
Cagayan De Oro	**2,727**	**2,727**	**-**	**6,683,369**	**6,683,369**	**-**	**1,157,292**	**1,157,292**	**-**
Dapitan	4,110	7,170	74.46	360,104	628,223	74.46	866,306	2,126,925	145.52
Iligan	498	4,553	814.33	289,735	2,132,310	635.95	129,690	1,500,249	1,056.80
Makar Wharf	1,226	2,073	69.12	3,594,327	3,984,711	10.86	27,749	827,424	2,881.82
Nasipit	807	4,729	486.03	1,251,555	1,588,426	26.92	415,845	1,528,208	267.50
Ozamiz	**17,192**	**17,192**	**-**	**932,013**	**932,013**	**-**	**3,504,805**	**3,504,805**	**-**
Sasa	777	4,790	516.51	3,880,318	4,687,537	20.80	7,156	1,695,317	23,590.85
Surigao	4,443	9,875	122.26	468,618	1,041,529	122.26	1,061,229	2,967,210	179.60
Zamboanga	10,149	21,845	115.25	2,567,770	5,325,242	107.39	3,322,540	6,890,543	107.39

Table 6. Target Values for Ports to be BCC (VRS) efficient

DMU	Ship Calls/Number of Vessels			Total Cargo Throughput (tons)			Total Passengers		
	Current	Target	Diff.(%)	Current	Target	Diff.(%)	Current	Target	Diff.(%)
Calapan	**20,155**	**20,155**	**-**	**44,734**	**44,734**	**-**	**5,607,982**	**5,607,982**	**-**
Lamao	**792**	**792**	**-**	**123,571**	**123,571**	**-**	**107,421**	**107,421**	**-**
Legazpi	**1,417**	**1,417**	**-**	**753,360**	**753,360**	**-**	**122,040**	**122,040**	**-**
Lucena	5,803	18,981	227.09	126,285	413,061	227.09	921,793	4,867,367	428.03
Masbate	**4,532**	**4,532**	**-**	**305,268**	**305,268**	**-**	**1,074,532**	**1,074,532**	**-**
Puerto Princesa	1,251	10,304	723.66	1,573,430	2,339,401	48.68	188,378	3,275,965	1,639.04
Banago	1,814	5,083	180.21	320,034	896,754	180.21	219,498	1,514,607	590.03
Dumaguete	12,119	17,032	40.54	792,993	1,114,449	40.54	2,185,898	4,140,483	89.42
Ormoc	4,931	7,220	46.42	441,251	612,152	38.73	1,486,794	2,062,644	38.73
Tagbilaran	**11,022**	**11,022**	**-**	**1,927,676**	**1,927,676**	**-**	**3,476,726**	**3,476,726**	**-**
Cagayan De Oro	**2,727**	**2,727**	**-**	**6,683,369**	**6,683,369**	**-**	**1,157,292**	**1,157,292**	**-**
Dapitan	4,110	4,971	20.94	360,104	435,518	20.94	866,306	1,248,318	44.10
Iligan	498	4,968	897.53	289,735	2,018,467	596.66	129,690	1,559,575	1,102.54
Makar Wharf	1,226	2,437	98.76	3,594,327	3,884,859	8.08	27,749	879,459	3,069.34
Nasipit	807	5,196	543.86	1,251,555	1,460,188	16.67	415,845	1,595,035	283.57
Ozamiz	**17,192**	**17,192**	**-**	**932,013**	**932,013**	**-**	**3,504,805**	**3,504,805**	**-**
Sasa	777	4,886	528.88	3,880,318	4,661,128	20.12	7,156	1,709,079	23,783.17
Surigao	4,443	8,765	97.27	468,618	924,431	97.27	1,061,229	2,509,564	136.48
Zamboanga	10,149	12,738	25.51	2,567,770	2,870,157	11.78	3,322,540	3,713,811	11.78

The highlighted ports in each table represent the benchmark ports identified by the DEA model used in the analysis. These ports have the same current and target outputs, which means that they are already operating at the efficiency frontier. It can also be observed that the output parameters with the highest weights presented in Table 4 have the lowest percentage difference between the current and the target output values. This is consistent with the recommendation that port managers focus on these output parameters, i.e., they can reach a more efficient state with the least amount of change.

Combining the data in tables 4, 5, and 6, the port managers can now formulate a strategic plan to increase the efficiency of their respective ports. For example, in the case of baseport Lamao, around 64% of the overall effort to increase port efficiency should focus on reaching the target goal of 215, 352 metric tons of annual cargo throughput, while the remaining 36% should focus on increasing the number of ship calls to from 792 to 1380 in the next year.

Figure 1 is the illustration of CCR and BCC scores as data pairs on a two-dimensional graph. The graph can be interpreted to easily understand the relative role of pure technical efficiency and scale effects in relation to the scores (Baran and Górecka, 2015). The graph is divided into four regions by the vertical and diagonal dashed lines. The vertical line denotes the mean DEA-BCC score (0.7765) and the diagonal line is a line with a slope that represents the average scale efficiency (0.8574).

The first quadrant (upper right) shows that Sasa, Nasipit, Makar Wharf, Ozamiz, Tagbilaran, Cagayan de Oro, and Calapan have high pure technical efficiency and high scale efficiency. This indicate that the resource utilization of these ports, whether in technique or scale, reaches the fittest. These implies that the ports can exploit their facilities well and can also serve large amounts of demand. No further recommendations can be made for these ports, and they simply need to maintain their current operations.

Five ports are located at the second quadrant (upper left) namely: Iligan, Lucena, Banago, Surigao, and Puerto Princesa. This port has a relatively high scale efficiency but relatively low pure technical efficiency. This means that the ports can accommodate a larger number of passengers and cargos with limited performance, but do not efficiently operate their resources. Better port management will help increase their efficiencies. Capacity utilization of the berthing space should be increased as well as the optimization of the ship dwell times. This can be done by implementing route capacity measurements and appropriate time tabling techniques.

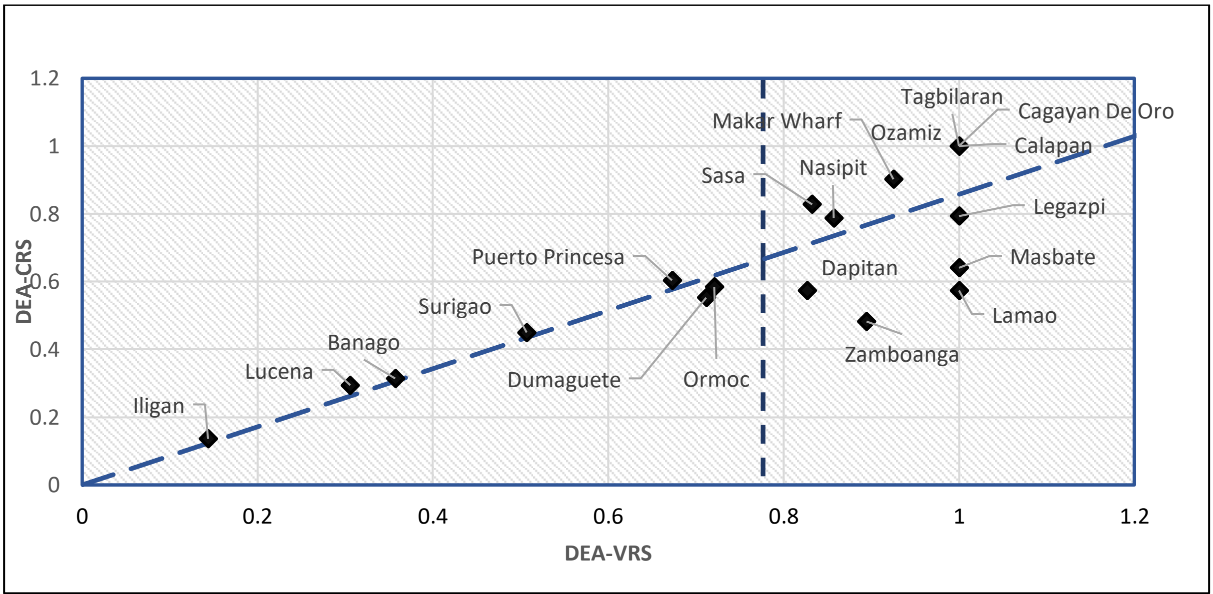

Figure 1. Graphical Illustration of the Efficiency Scores

The ports at the lower-right part are Dapitan, Zamboanga, Masbate, Lamao and Legazpi. They have high pure technical efficiency but low scale efficiency. These ports manage their facilities well, but they are subject to scale effects because of their inability to accommodate the present demand. Mitigating strategies include the expansion of the port and construction of more berthing spaces to increase the ship capacity of the port. On the demand side, passengers and cargo can be diverted to other less congested ports that also provide the same services.

Lastly, the ports on the lower-left part are Dumaguete and Ormoc. They have relatively low pure technical efficiency and low scale efficiency. This means that the ports can only accommodate low demand with inefficient resource utilization. Therefore, these ports need to improve their overall competitiveness and efficiency by upgrading the port and managing their resources better.

6. CONCLUSIONS AND RECOMMENDATIONS

The non-parametric approach called the Data Envelopment Analysis was applied in this study to measure the relative efficiencies of selected nineteen PPA base ports in the Philippines. Six base ports from Luzon, four base ports from Visayas, and nine base ports from Mindanao were identified to be the Decision Making Units (DMU) for this study. The chosen input data were the total port area and the total number of berthing spaces, while the chosen output data were the total passenger count, total cargo throughput, and total number of ship calls. These were extracted from the 2019 port statistics data of PPA and requested from the various port management offices.

The results of the DEA-CCR and DEA-BCC models show that the average efficiency scores are 0.6587 and 0.7765, respectively. The ports of Calapan, Tagbilaran, Cagayan de Oro, and Ozamiz demonstrated the best performance in both models. The ports of Lamao, Legazpi and Masbate achieved pure technical efficiency but are classified as inefficient under DEA-CCR. The other ports were consistently classified as inefficient regardless of the model. The scale efficiencies of the ports were also identified for analysis. The returns-to-scale approach was used to assess whether each port is in increasing, decreasing, or constant returns to scale. Increasing returns to scale was found on eleven ports.

The findings of this study can provide port masters with insights into resource allocation and port operation optimization. For technically inefficient ports, increasing the number of goods and people that use the port thru proper management can be prioritized so that the facilities can be fully utilized. For scale inefficient ports, modernizing the current state of the ports by either increasing labor or improving infrastructure can address the inefficiency.

Possible future development for this study is to acquire more data that can be used as input and/or output variables. The increase of input and output metrics will increase the accuracy of the results. Future studies can explore other input variables such as labor, equipment, and capital, among others. The paper has not used labor as an input variable since it tends to correlate with output negatively. This negative correlation is especially true for ports with low mechanization and automation, which usually have a higher number of employees and relatively low output (Lirn and Guo, 2011). Using port operational data such as loading and unloading efficiency and financial information such as yearly investments, revenues and costs can also help provide a better analysis and efficiency measurement of the DMUs. Acquiring panel data will enable the use of the DEA-Malmquist Productivity Index (DEA-MPI). This method examines the changes in the efficiency of a port between two time periods. Another efficiency measurement such as the Stochastic Frontier Analysis (SFA) can be performed to improve the research.

ACKNOWLEDGEMENTS

The authors would like to thank the Philippine Ports Authority (PPA) for providing data and sufficient information needed for this study.

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