EVALUATION EFFICIENCY OF INDONESIAN SEAPORTS: DATA ENVELOPMENT ANALYSIS

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ABSTRACT

As Indonesia is an archipelago country, sea transportation plays an important role. The state-owned enterprises known as PELINDO I-IV, are the main seaport operators in Indonesia. This study measured the efficiency of 10 PELINDO container terminals/ports using Data Envelopment Analysis (DEA). The results reveal that only three container terminals/ports performed efficiently. The yard crane is determined to be the main influential variable. This study demonstrates that some smaller ports such as Palembang, with smaller output or container throughputs, can become more efficient than larger ports. Overall, Terminal Petikemas Surabaya (TPS) achieved the highest technical efficiency.

Keywords: efficiency, data envelopment analysis, container, port, terminal, Indonesian seaports.

1. INTRODUCTION

Indonesia is the world's largest archipelago country, with more than 16,000 islands BPS (2018). Due to this geographical condition, sea transportation is important for the logistic and economic activities of the country. To develop the economic activity of the country, the Indonesian government has established and expanded 24 ports spread throughout Indonesia which are called *tol laut* in Indonesia, or "sea toll". The concept of sea toll is for improving the performance of sea transportation through the improvement of domestic and international shipping networks. Consequently, the realization of a logistic system, which is internationally connected will improve international competitiveness, and national integration will improve the domestic logistic system (Bappenas, 2015).

The government collaborates with PELINDO in port expansion**.** PELINDO is the state-owned enterprise which runs the main ports in Indonesia**.** About 73 out of 111 commercial seaports are operated by PELINDO**.** The operational area of PELINDO is divided into four regions **(i.e.** PELINDO I, II or IPC, III, IV) and extends from Sumatra to Papua shown in Figure 1 (Ray, 2008)**.**

The volume of containers increased from 14.93 to 16.05 (million TEU) in the year 2017 to 2018 IPC (2019). It shows that national trade in manufactured products is growing and containerization has increased. In this situation, the ports need to continue the improvement of operations and provide a better quality of service. Because seaports are an important connection in the logistics chain, the level of port performance has a significant effect on the country's productivity and competitiveness. To remain competitive and increase customers, the port managers need to understand which critical factors influence decision making on the port choice by a shipping company or forwarder.

Figure 1. Map of operational area of PELINDO
Source: https://yourfreertemplates.com/free-indonesia-map-template/ (modify)

Based on previous studies, several key factors influence port competitiveness. For example, Lirn et al. (2004) found that the equipment handling system is the most important factor for port choice by global carriers. Also, Da Cruz et al. (2013), found that facilities and equipment are the most important factors for port selection by stakeholders. Other studies on port competitiveness were carried out by Tongzon and Heng (2005), by Tongzon (2009) and by Yeo et al. (2008). Port performance is reported to be the most important factor in port competitiveness. The port manager or stakeholders could achieve competitiveness by improving the performance of critical factors (e.g. facilities, equipment and port efficiency) that influence port competitiveness. Improving the performance of facilities and equipment can be done by measuring the utilization of facilities and equipment. The aim of this study is to evaluate efficiency of container ports and terminals in Indonesia by applying the data envelopment analysis (DEA) model. The advantages of applying DEA, is that it can measured the performance of port operation by comparing with another port and DEA can provide information on how to improve the performance of an inefficient port. DEA can identify which factors affect port performance and can determine whether each port has reached optimal operation. DEA also can be used to rank efficient port**.** Therefore, this study could provide information on the factors affecting the efficiency of port performance by comparison with ports in the same region and ports in the other regions.

The paper is organized into five sections as follows: the first section is the Introduction, which discusses the background and objectives of the study. Section two is the Literature Review: a brief overview of measurement efficiency, along with common methods and variables used for measuring port performance. The third section is methodology, which explains data, variables and the DEA method used to estimate the efficiency frontier. The fourth section, is results and discussion: discussion and analysis of result. The last section summarizes the findings.

2. LITERATURE REVIEW

Port efficiency is the capability of a port or terminal to fit the optimum number of inputs to a given output level De Oliveira & Cariou (2015). Measuring efficiency of a container port or terminal provides a detailed source of the effects of inefficiency and can outline overall performance at the ports and terminals Tongzon & Heng (2005).

Regarding the port efficiency literature, three common methods were used to evaluate container port/terminal efficiency: free disposal hull (FDH), data envelopment analysis (DEA), and stochastic frontier analysis (SFA). Wang (2004) studied efficiency measurements of the container port and investigated three types of approach measurement, namely DEA, FDH and SFA models. Cullinane et al (2005) studied port efficiency of 57 container ports by comparing two methods, i.e. DEA and FDH. They found that DEA has potential for assessment efficiency of the Decision-Making Unit (DMU). Wu and Goh 2010 studied port efficiency using DEA and found that DEA methods appeared most appropriate for their study.

Roll and Hayuth (1993) analysed port performance through the application of DEA using multiple inputs and outputs. They argued that DEA is a useful tool for detecting weaknesses and could lead to possible improvements of an inefficient port. Also, DEA provides more in-depth insight into port performance. da Cruz & Ferreira (2016) used the DEA approach to assess the competitiveness of Iberian seaports as well as for finding reasons for inefficient ports. Based on their study, they found that the most efficient port is a port which can use a better input to produce output. Also, they found that an inefficient port has issues with the handling system.

There are three required elements for measuring efficiency: decision making unit (DMU), output variables, and input variables (Charnes, Cooper, & Rhodes, 1978). The container throughputs, financial indicators, resource usages, and port infrastructure facilities are commonly used in analysing the port performance. Barros and Athanassiou (2015) used the number of workers and capital as input variables. Numbers of ships, movement of freight, amount of cargo and containers are used as output variables. In another study, Barros (2006) measures an Italian seaport based on three input variables, namely employee numbers, investment values and operation costs. Output variables are as follows: liquid bulk, dry bulk, numbers of ships, numbers of passengers and numbers of containers. Park and De (2004), measured port efficiency using four factors which are profitability, market, productivity and technical efficiency using different types of variable. Revenue and customer satisfaction are used for measuring the port efficiency on marketability, while berth capacity, cargo handling, and customer satisfaction are used as variables on technical efficiency.

Rios & Macada (2006) used five input variables as follows: the number of cranes, number of berths, number of employees, terminal area and the amount of yard equipment. They focus mainly on the berth area and yard area as the input variables. The average number of containers handled per hour/ship and the total of containers handled in TEU are used to represent the speed of port operations as the two output variables. Cullinane, Song and Wang (2005) used gantry cranes and straddle carriers as an input variable, and container throughput as the output variable. They argued that container throughput is the most important output variable which is affected by the facilities and equipment used in port/terminal operation. Cullinane et al (2006) evaluated the technical efficiency of the container port. They argued that labour, land and equipment are vital variables for port production. Therefore, they used the total quay length, the terminal area, the number of quayside cranes, the number of yard cranes and the number of straddle carriers as the input variables. Container throughput was used as an output variable as it was considered the most acceptable indicator for measuring port output.
Liu (2010) evaluated the elements that influence port efficiency and found that the number of container throughputs was an important variable for port efficiency. Nyema (2014) assessed variable influences on port containers and found that inadequate infrastructure (e.g., quay or yard crane) and limited storage capacity influenced port efficiency. Bichou (2009) measured port efficiency with regard to port equipment technology and handling systems. The author found that handling configurations have a direct effect on port efficiency.

In addition to regular DEA study, slack variable, return to scale and sensitivity analysis are methods that provide further insight from regular DEA study. Barros and Athanassiou (2015) seek out the variables which needs to be adjusted in order to achieve better performance or efficiency on the port operation by using a slack variable. The author found that some inefficient ports need to increase the number of containers handled and reduce the amount of input usage. Wu and Goh (2010) carried out a sensitivity analysis by using three inputs (terminal area, quay length and numbers of equipment) and one output (numbers of container throughputs) based on DEA-CCR. They found that equipment is a significant factor that affected most of the seaport operations. Lu & Park (2013) used sensitivity analyses to determine the critical factors of terminal productivity. They found that the number of yard tractors and terminal cranes makes significant contribution to port production. They mention that sensitivity could provide useful information on how to improve efficiency of an inefficient terminal.

3. METHOD

In our study, we performed an analysis of PELINDO container ports/terminals with five different DEA models using Excel Solver. Initially, we start with applied DEA CCR and BCC to find out which ports are efficient and inefficient, then we implemented the slack variable to identify areas of improvement for inefficient ports based on DEA-CCR. Additionally, this study can identify which input or output variables are more critical to the model by using the sensitivity analysis based on the DEA-CCR model. Furthermore, super efficiency is used to rank efficient ports. In the end, the return to scale is used to determine whether each port has reached its optimal operation. All input and output variables of the DEA models are selected based on the literature review and data availability.

3.1 Input and Output Variable

In this study, the container throughput is used as an output variable, since it is closely related to the facilities needed for storage and loading or unloading of the containers. The input is applied to the basic facility and equipment in port operations. Assigned to the container port production characteristics, the quay length and quay crane are the most appropriate input factors for berth production. The yard area, yard crane, straddle carrier, forklift and truck are vital input factors for yard production. The output and input variables are summarized in Table 2.

Table 2. Input and Output Variables

Variable		**Description**	**Unit**
Input	Quay length	Total berth / quay length	Meter
	Quay crane	Number of quay cranes	Unit
	Yard area	Yard area in square meters	$Meter^2$
	Yard crane	Number of yard cranes	Unit
	Yard tractor	Number of yard tractors (e.g. straddle carrier, reach stacker)	Unit
	Vehicle	Number of trucks	Unit
Output	Container throughput	Total container throughput	TEUs

3.2 The Sample Size and Data Collection

The sampling framework in this study focuses on 10 container terminals/ports located in Indonesia (see Table 3). Regarding the data collection methods, this study used secondary data. The dataset was obtained from the container terminals/ports only for a cross-section of the year 2018. The secondary data are taken from different sources, such as container terminal/port operator websites and annual reports. Also, data obtained through interactions with the authorized port personnel via telephone conversations and email were used.

Table 3. Sampled Ports

ID	DMU	Input variable (x_i)						Output variable (y_r)
		x_1	x_2	x_3	x_4	x_5	x_6	y_1
		Quay Length	Container Yard	Quay Crane	Yard Crane	Yard Tractor	Vehicle	Container Throughput
J1	Terminal Teluk Lamong (TTL)	950	188600	10	20	10	47	636886
J2	Terminal Petikemas Surabaya (TPS)	1450	39700	12	28	4	73	1458180
J3	Berlian Jasa Terminal Indonesia (BJTI)	1620	59683	25	21	8	53	1224892
J4	Terminal Petikemas Bitung (TPB)	720	102000	4	8	3	27	280761
J5	Jambi Port	102	33869	2	3	2	9	48976
J6	Teluk Banyur Port	345	62520	4	3	5	15	84659
J7	Pontianak Port	435	73906	5	8	7	19	297318
J8	Palembang Port	266	54328	2	4	7	13	171594
J9	Panjang Port	301	75000	3	5	2	15	116407
J10	Terminal Petikemas Semarang (TPKS)	600	18720	6	29	5	41	675021

3.3 Data Analysis

Data envelopment analysis (DEA) is used to measure the efficiency of physical amounts of equipment and facilities at ports/terminal by using cross-sectional data from the year 2018. The output-oriented DEA objective function is used to maximise the output while using the amount of the current input since the investment in equipment in the container terminal is high. The explanation of the five different models used in this study are as follows:

3.3.1 DEA-CCR model

The DEA-CCR model developed by Charnes et al. (1978) is used to measure efficiency. The CCR models assume a constant return to scale (CRS), and the overall combination of observations can be scaled up or down proportionally. That means an increase in input will also increase output proportionally. The fractional programming problem of the output oriented CCR model can be formulated as:

$$Min\,\eta = \sum_{i=1}^{m} v_i x_{ijo}$$

$$s.t.\ \sum_{r=1}^{s} u_r y_{rjo} = 1$$

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0; \quad \forall j$$

$$u_r, v_i \geq 0 \quad \forall r, \quad \forall i \tag{1}$$

Where, n = the number of ports (n = 10)
m = the input variables (m = 6)
s = the output variable (s = 1)
x_{ij} = the value of input variables i for port j, (j = 1, 2, 3, …., n)
y_{rj} = the value of output variable r for port j, (j = 1, 2, 3, …., n)

v_i = the weight given to input i, (i = 1, 2, 3, …., m)
u_r = the weight given to output r, (r = 1, s)
x_{ijo} = the value of input variables i for the current port analyzed
y_{rjo} = the value of output variable r for the current port analyzed
η = the relativity efficiency of the current port analyzed 'o'

The DEA output-oriented models give the score efficiency of a port from 1 to infinity. In addition, whether it is output oriented or input oriented, DEA always calculates a ratio of the maximum of weight output to weight inputs and thus produces an efficiency score less than or equal to one. Hence, the efficiency score (θ) of the currently analysed port 'o' can be written as follows (Charnes et al., 1978):

$$\theta = 1/\eta \tag{2}$$

3.3.2 Slack Variable

In addition, DEA provides information on slack variable. Slack variable is the additional information related to the input surplus and output shortfall for inefficient ports to become efficient ports. The slack variable of the DEA-CCR output-oriented model can be formulated as follows (Cooper, Seiford, & Tone, 2006):

$$s_i^- = x_{ijo} - \sum_{j=1}^{n} \lambda_j x_{ij},$$
$$s_r^+ = \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} - \eta y_{rjo} \tag{3}$$

Where, $\sum_{j=1}^{n} \lambda_j x_{ij}$ = input target value for the current port analyzed
$\sum_{j=1}^{n} \lambda_j y_{rj}$ = output target value for the current port analyzed
y_{rjo} = actual output value for the current port analyzed
x_{ijo} = actual input value for the current port analyzed
s_i^- = the input surplus for the current port analyzed
s_r^+ = the output shortfall for the current port analyzed

3.3.3 Sensitivity of Efficiency

Sensitivity analysis is used to estimate the responses of efficiency value when the output and input variables of ports are deleted or added to the consideration. This is generally realized by removing output or input variables from the variable combination of DEA-CCR one by one (Cooper et al., 2006).

3.3.4 DEA-BCC Model and Return to Scale

The DEA-BCC model was developed by Banker et al (1984). It is used to analyse scale efficiencies by introducing a new variable (u_o) on the DEA-CCR form. The dual linear programming problem of the BCC output oriented model can be formulated as follows (Banker, Charnes, & Cooper, 1984):

$$Min\, \eta = \sum_{i=1}^{m} v_i x_{ijo} + u_o$$
$$s.t. \ \sum_{r=1}^{s} u_r y_{rjo} = 1$$
$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} + u_o \geq 0 \quad j = 1, \dots, n$$
$$u_r, v_i \geq 0\,, \quad u_o = any\ value \tag{4}$$

Scale efficiency (SE) expresses how close the port is to the optimal scale. Scale efficiency can be written as follows (Cooper et al., 2006):

$$SE = \theta CCR / \theta BCC \tag{5}$$

Where,

θ CCR = efficiency score of CCR model

θ BCC = efficiency score of BCC model

The scale efficiency score is between 0 and 1. When scale efficiency score is precisely one, it means the port operates at optimal scale. The larger the scale efficiency score, the closer the port is to operating at optimal scale. The smaller the scale efficiency score, the more is lost by not operating at optimal scale. Inappropriately, scale efficiency score does not give information about how to rescale the port operation for a port with a score less than one: whether the port needs increasing (decreasing) due to the port being at too small (large) a scale. Therefore, return to scale is used to analyse the rescaling of port operations. The return to scale can be determined by the summation of lambda j ($\sum\lambda_j$) in the DEA-CCR model or with the following conditions (Cooper et al., 2006):

- If the $\sum\lambda_j = 1$, then it is assumed constant return to scale (CRS)
- If the $\sum\lambda_j \geq 1$, then it is assumed decreasing return to scale (DRS)
- If the $\sum\lambda_j \leq 1$, then it is assumed increasing return to scale (IRS)

Increasing return to scale means the value increase in input is greater than the proportional increase in output. Decreasing return to scale means the increase in output is less than the proportional increase in input value.

3.3.5 DEA Super Efficiency Model

DEA super efficiency is used to rank efficient ports and discriminatory efficiency value. The DEA-BCC and CCR cannot differentiate efficiency value of efficient ports. The score of the super efficiency output-oriented model might be lower or higher than one. The lower score of the super efficiency output-oriented model indicates that a port has operated highly efficiently. The super efficiency output oriented model introduced by Andersen and Petersen based on DEA-CCR or constant return to scale can be formulated as (Andersen & Petersen, 1993):

$$\begin{aligned} & Max\ \theta \\ s.t.\ & \sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j x_{ij} = x_{ijo}, \qquad i = 1, \dots, m \\ & \sum_{\substack{j=1 \\ j\neq 0}}^{n} \lambda_j y_{rj} = \theta\, y_{rjo} \qquad r = 1, \dots, s \\ & \lambda_j \geq 0 \qquad\qquad j = 1, \dots., n, j \neq 0 \end{aligned} \tag{6}$$

4. RESULT AND DISCUSSION

4.1 Technical Efficiency and Slack Variable

The DEA-CCR output-oriented model is applied to evaluate the technical efficiency of the 10 container terminals/ports in Indonesia. The efficiency score is between 0 (technically inefficient) and 1 (technically efficient). The full score indicates that the port performance has achieved optimal operation with the current number of outputs. From the result of the DEA-CCR model, we found that three ports are technically efficient with score equal to one (i.e. TPS, BJTI, TPKS. These ports performed appropriately and fully utilized their resources. The other seven container terminals are technically inefficient with efficiency scores less than 1: TTL, TPB, Panjang, Palembang, Teluk Banyur, Pontianak, and Jambi Port (see Table 4). Slack variable is then used for investigating the causes of inefficiency in those seven ports (see Table

5). Evaluation shows that surplus yard areas are a major cause of port inefficiency. Moreover, surplus value is also obtained on quay length and the number of vehicles operated in each port. This result shows that all inefficient port/terminals have the ability to handle more outputs with the current number of inputs. Therefore, those inefficient ports need to adjust the levels of certain resources as indicated by the slack variables.

Table 4. Efficiency value of DEA-CCR, BCC, Scale Efficiency and Return to Scale

ID	DMU	θ CCR	θ BCC	SE = θ CCR / θ BCC	∑λ	RTS
J1	Terminal Teluk Lamong (TTL)	0.67	0.7	0.96	0.65	IRS
J2	Terminal Petikemas Surabaya (TPS)	1	1	1	1	CRS
J3	Berlian Jasa Terminal Indonesia (BJTI)	1	1	1	1	CRS
J4	Terminal Petikemas Bitung (TPB)	0.67	0.83	0.81	0.30	IRS
J5	Jambi Port	0.46	1	0.46	0.11	IRS
J6	Teluk Bayur Port	0.48	1	0.48	0.14	IRS
J7	Pontianak Port	0.75	0.94	0.80	0.29	IRS
J8	Palembang Port	0.81	1	0.81	0.15	IRS
J9	Panjang Port	0.44	1	0.44	0.19	IRS
J10	Terminal Petikemas Semarang (TPKS)	1	1	1	1	CRS

Table 5. Slack Variable

DMU / ID		Input surplus (S_i^-)						Output shortfall (S_r^+)
		Quay Length (meter)	Yard Area (meter^2)	Quay Crane (unit)	Yard Crane (unit)	Yard Tractor (unit)	Vehicle (unit)	Container Throughput (TEUs)
Terminal Teluk Lamong (TTL)								
J1	Actual value	950	188,600	10	20	10	47	636,886
	Target value	950	26454.5	8.2	18.05	2.72	47	943644.84
	Slack	0	162145.5	1.8	1.95	7.28	0	0
Terminal Petikemas Bitung (TPB)								
J4	Actual value	720	102,000	4	8	3	27	280,761
	Target value	433.3	12411	4	8	1.32	20.79	421310.6
	Slack	286.7	89589	0	0	1.68	6.21	0
Jambi Port								
J5	Actual value	102	33869	2	3	2	9	48,976
	Target value	102	2928.33	0.91	3	0.48	5.77	106814
	Slack	0	30940.67	1.09	0	1.52	3.23	0
Teluk Bayur Port								
J6	Actual value	345	62,520	4	3	5	15	84,659
	Target value	231.43	8526.13	3.57	3	1.14	7.57	174984.6
	Slack	113.57	53993.87	0.43	0	3.86	7.43	0
Pontianak Port								
J7	Actual value	435	73,906	5	8	7	19	297,318
	Target value	435	13466.6	4.78	7.36	1.56	19	396404.5
	Slack	0	60439.4	0.22	0.64	5.44	0	0

Palembang Port								
J8	Actual value	266	54,328	2	4	7	13	171,594
	Target value	217	6,205	2	4	0.66	10.4	210655.3
	Slack	49.35	48122.5	0	0	6.34	2.6	0
Panjang Port								
J9	Actual value	301	75,000	3	5	2	15	116,407
	Target value	287	8,691	3	5	0.98	12.94	267420.9
	Slack	13.55	66308.5	0	0	1.02	2.06	0

4.2 Sensitivity

Sensitivity analysis is used to estimate the sensitive variable that has the biggest effect on the efficiency of ports/terminals. The sensitive variable can be estimated by deleting or adding an input or output variable from the set consideration. Table 6 summarizes the results of sensitivity analysis. Berth length is a critical factor which affects the efficiency of port operations of Jambi, Terminal Teluk Lamong (TTL) and Terminal Petikemas Semarang (TPKS). Vehicle is the critical factor to the efficiency of TTL and Pontianak. Quay crane is the critical factor that affects efficiency of Palembang, Panjang and TPB. The yard crane is determined to be the main influential variable that affects the efficiency of port/terminal operations, since yard crane is the critical indicator of five ports. Sensitivity analysis results shows different factors that affect efficiency of each port. In order to achieve a high level of container throughputs, the port manager needs to invest more on suggested critical factors.

Table 6. Summary of Results of Sensitivity Analysis

ID	DMU	Score efficiency	Sensitivity					
		θ CCR	Quay Length	Yard Area	Quay Crane	Yard Crane	Yard Tractor	Vehicle
J1	Terminal Teluk Lamong (TTL)	0.67	0.66	0.67	0.67	0.67	0.67	0.66
J2	Terminal Petikemas Surabaya (TPS)	1	1	1	1	1	1	1
J3	Berlian Jasa Terminal Indonesia (BJTI)	1	1	1	1	1	1	1
J4	Terminal Petikemas Bitung (TPB)	0.67	0.67	0.67	0.60	0.58	0.67	0.67
J5	Jambi Port	0.46	0.30	0.46	0.46	0.43	0.46	0.46
J6	Teluk Bayur Port	0.48	0.48	0.48	0.48	0.27	0.48	0.48
J7	Pontianak Port	0.75	0.75	0.75	0.75	0.75	0.75	0.70
J8	Palembang Port	0.81	0.81	0.81	0.77	0.71	0.81	0.81
J9	Panjang Port	0.44	0.44	0.44	0.43	0.39	0.44	0.44
J10	Terminal Petikemas Semarang (TPKS)	1	0.98	1	1	1	1	1

4.3 Pure Technical Efficiency

The DEA-BBC or pure technical efficiency measures efficiency of the port/terminal by comparing with another port/terminal at the same level of resource scale. According to the results of the DEA-BCC model (see Table 4), we found that seven container terminals/ports are efficient and three container terminals/ports are inefficient. TTL, TBP and Pontianak are the three ports which are considered to be inefficient using both DEA-CCR and DEA BCC models, while TPS, TPKS, BJTI achieved port efficiency with DEA-BCC and CCR models. TPB and Pontianak are at the same level of input scale as TPKS, but the ratios of output and input of TPB and Pontianak are less than TPKS. While TTL which has the same level of resource as TPKS and TPS, but the average productivity of TTL is less than BJTI and TPS. This implies that BJTI, TPS, and TPKS ports have better management of their resources than TTL, TBP and Pontianak Port.

In the DEA-BCC model (pure technical efficient), we also found that four ports became efficient in the DEA-BCC model with efficiency scores equal to one, i.e. Jambi, Teluk Banyur, Palembang and Panjang. These four ports have a number of resources at minimum level. These ports are efficient since they do not use excessive input, but they are still not performing similarly to those ports that operate at CRS.

4.4 Scale Efficiency and Return to Scale

Scale efficiency (SE) is used to measure the ability of a port to operate at optimal scale or at the level of CRS frontier production. The scale efficiency can be derived from the efficiency score of the DEA-CCR model divided by the efficiency score of the DEA-BCC model.

Based on the SE result shown in Table 4, three container terminals/ports have score scale efficiency equal to one (i.e. TPS, TPKS and BJTI) and seven container terminals/ports have score less than one (i.e. TTL, TPB, Pontianak, Palembang, Panjang, Teluk Banyur and Jambi). For those ports/terminals at the efficient scale level, it indicates that they operate at optimal level as planned. For those ports/terminals at inefficient scale, it indicates that they did not achieve optimal scale. The inefficient terminals/ports with higher scale efficiency scores ranging between 0.80 to 0.90 (i.e. TTL, TPB, Pontianak and Palembang), means these ports are close to achieving optimum scale. But ports with scale efficiency scores lower, at between 0.44-0.48 (i.e. Panjang, Teluk Banyur and Jambi), need extra effort to achieve optimal scale.

Since all seven inefficient ports do not exhibit CRS, they might exhibit an increasing return to scale or decreasing return to scale. In order to analyse the return to scale of these ports we use the summation of lambda in the DEA-CCR model. Based on the return to scale, seven inefficient scale terminals/ports are in the state of increasing return to scale (IRS) with the sum lambda value less than one ($\sum\lambda_j \leq 1$) (see Table 4). Ports that experience increasing returns to scale, indicate that the scale of production is below the optimal level and the output that they handle is too low. These ports have lost by not operating at optimal scale. In order to move the operation to CRS frontier production and attain significant efficiency, they need to expand production levels by increasing the number of outputs or container throughput.

4.5 Super Efficiency

Super efficiency is used in ranking the port efficiency. The port with a lower score refers to the port with a higher level of efficiency. The value of super efficiency ranges from 0.42 to 2.29 is shown in Table 7. The results reveal that Terminal Petikemas Surabaya (TPS) has the lowest score (0.42). It indicates that TPS achieved the highest technical efficiency. It is due to the fact that TPS reached highest productivity using less input than the other ports.

Also, this result showed that some smaller ports with smaller outputs are relatively more efficient than some larger ports with larger output. For example, if we compare between Palembang and Terminal Teluk Lamong (TTL), TTL has a larger input and output than Palembang (see Table 3). Palembang ranks fourth and TTL ranks sixth (see Table 7). It indicates that a smaller port could become more efficient than a larger port when it can manage resources well.

Table 7. Summary of Results of Super Efficiency

ID	DMU	Efficiency score (θ)	Rank
J2	Terminal Petikemas Surabaya (TPS)	0.42	1
J3	Berlian Jasa Terminal Indonesia (BJTI)	0.86	2
J10	Terminal Petikemas Semarang (TPKS)	0.89	3
J8	Palembang Port	1.22	4
J7	Pontianak Port	1.33	5
J1	Terminal Teluk Lamong	1.48	6
J4	Terminal Petikemas Bitung (TPB)	1.5	7
J6	Teluk Bayur Port	2.07	8
J5	Jambi Port	2.18	9
J9	Panjang Port	2.29	10

5. CONCLUSION

In this study the technical efficiency of 10 container terminals/ports located in Indonesia were evaluated by applying data envelopment analysis (DEA-CCR) output-oriented models. Based on the result it was revealed that three terminals/ports are efficient (i.e. TPS, TPKS, BJTI) and seven ports are inefficient: TTL, TPB, Palembang, Panjang, Pontianak, Jambi, Teluk Banyur. As demonstrated by slack variable, the reason the seven ports are at the level of inefficiency is because they have surplus resources or facilities compared to the number of container throughputs. There is some room for improvement to achieve higher efficiency by increasing the numbers of container throughputs or reconfiguring their inputs. This can be done by focusing mainly on the critical resources. The yard crane is considered to be the main influential resource that affects most of the inefficiency of port/terminals.

Pure technical efficiency could be separated between technical efficiency and scale efficiency. In this study we found that Palembang, Panjang, Pontianak, Jambi, Teluk Banyur are pure technically efficient. They have fewer resources, their scale of production is too low while their return to scale is in the level IRS. Another finding is that TTL, TPB and Pontianak are technically inefficient. While they have a large number of inputs, they utilise their resources less and their production is still low compared to BJTI, TPS, and TPKS, since their returns to scale are in the level IRS. Those terminals or ports which are in the level IRS need to expand their scale of production by increasing their production or increase container throughput.

In addition, this study demonstrates the point that some smaller ports with smaller output or container throughputs, such as Palembang, can be more efficient than some larger ports with more container throughputs (e.g. Terminal Teluk Lamong). Overall, Terminal Petikemas Surabaya (TPS) achieved the highest technical efficiency with the scale of production at optimum.

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