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Measuring terminal efficiency: Case of fishing ports in Malaysia

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This study aims to measure the efficiency of a fishing port terminal in utilizing their resources to achieve better productivity and better strategic decisions making by incorporating Data Envelopment Analysis (DEA), using both BBC and CCR indexes for measuring the efficiency level. Based on the CCRI efficiency level of each terminal, four fishing terminals were located at an efficient frontier while another 55.56% of the fishing terminals are inefficient. For BCCI, 66.66% of the DMU is efficient. By looking at the efficiency, this study determines which specific terminals need to augment their inputs or outputs to achieve efficiency level. At the same time, this study is also looking onto other seaport terminals which have similar facilities in term of infrastructures and services like container terminal where both fishing terminal and container terminal have cranes, number of berth and storage capacity.

1. Introduction

Malaysia has a vibrant and thriving fisheries sector. This sector plays a significant role in the national economy include a source of employment, foreign exchange and a source of protein for a rural population where a large portion of fish produced in the country is consumed fresh in the domestic market. The fisheries industry plays a vital role in providing social and economic stability to the users, stakeholders and fishermen as a whole. Fisheries resources in Malaysia waters area are made up of two categories based on the area where the resources are exploited. The inshore waters are waters within 30 nautical miles from the shore while the areas beyond 30 nautical miles are established as deep-sea waters.

Seaport efficiency is often associated with productivity and performance, which interrelated with the use of inputs to produce output levels, as well as technologies adopted by ports (Merk and Dang, 2012). The existing technical efficiency of fisheries has almost exclusively focused on fishing vessel and fleet, and more towards fish resources. On the other hand, since less empirical work had been done pertaining to the case of the fishing port terminal, this study hence aiming to fill in the gap by measuring the efficiency of the fishing port terminal to ensure that there is a long term capability of a terminal to support fishing activities and industry. This is done by estimating the most efficient fishing terminal and its relative differences in equipment, production scale and input utilization. As such, it would be good if this study could reach related stakeholders, like government bodies and terminal operators to monitor and make the necessary adjustment to improve terminal efficiency. On the other hand, this study also intended to measure fishing terminal services and propose some improvements for future purposes.

2. Operation of fishing port terminal

Fish handling operations affect fish quality. Fish is a very perishable food commodity that requires proper handling and preservation to increase its shelf life and retain its quality and nutritional attributes (Emere and Dibal, 2013). Handling techniques took precedence as well as handling equipment that used to unload fish from the vessel to processing facility or markets. Fish as a rapidly

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perishable commodity requires quick transshipment and immediate processing to maintain its quality. The daily routine of the fishing port has been adapted to these requirements (Dopplinger, 1968). The first operation took place is where the fish is taken to the sorting area. Vessels with fishes arrive at the terminal and deliver the catch in the iced boxes in the sorting area of auction through their own gear or conveyor belts (Agerschou, 2004; Dopplinger, 1968). Immediately after the fish being sold (after the auction), the fish are transported where forklifts load the fish boxes onto lorries or refrigerated trucks to processing plants within the harbor or transported to the buyer's place if it is outside the port area.

2.1. Efficiency in fishing terminal

Efficiency can be defined as the degree of a given quality of input that matches the optimal use of resources to produce outputs of a given quality (Bhagavath, 2006). Noura et al. (2010, 2011) described efficiency as an important and complicated subject that had also been widely used in engineering, management and economy. Efficiency is a significant concept for terminals where any resources can be saved and used towards providing additional facilities and services or to upgrade current infrastructure in fishing port or the operational system. The economic efficiency of a production system is made up of two components which are technical and allocative efficiency; technical efficiency is the physical component of the production system that deals with the maximization of output from the physical combination of inputs, while, allocative efficiency is the optimization of the production process which takes into consideration of input-output price relationships. Koopmans (1951) referred to technical efficiency as an input-output vector that is technically efficient if the increase of any output or decreasing of any input is possible only by decreasing some other output or increasing of some other input.

Farrell (1957) also proposed that the efficiency of a firm consists of two components: technical efficiency, which reflects the ability of a firm to obtain maximal output from a given set of inputs, and allocative efficiency, which reflects the ability of a firm to use the inputs in optimal proportions, given their prices and production technology. Ajibefun (2008) and Kasypi (2013) referred to technical efficiency as the ability of a firm to produce the maximum quantity of output given an amount of input and production technology. The distance between its production and the frontier will define how an inefficiency of the fishing terminal is compared with other terminals. In other words, technical efficiency can be referred to as the degree with which a fishing port terminal can reduce its use of inputs to produce a given set of outputs.

Fare et al. (1985) measured the efficiency of a producer by comparing situation which satisfies the procedure's behavioral goal that includes cost, revenue and profit maximization. Cost affects the economy, efficiency, productivity, and profitability. A producer would satisfy when the firm could increase profits by expanding output without additional cost or input. A profit-maximizing firm would not be satisfied with the production of point E (Fig. 1) which is inefficient because the firm could increase profits by expanding output to the level associated with point F without requiring more input. Point H' represents the production frontier while F and G represent efficient points.

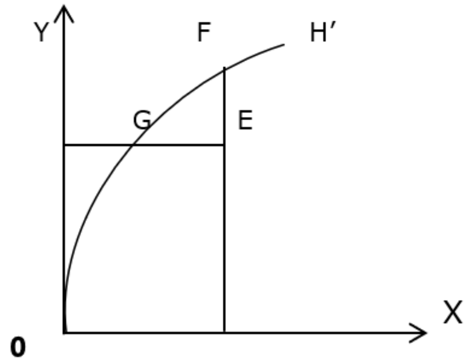

Fig. 1: Technical efficiency and inefficiency

As mentioned previously, even though there are plenty of empirical studies focusing on port performance and efficiency, there is less empirical work on the subject of the fishing terminal. Nonetheless, this study will look into other seaport terminals which have similar facilities in term of infrastructures and services, especially container terminal where both fishing terminal and container terminal have cranes, number of the berth, storage capacity albeit their uses is quite different. Seaport efficiency is often related to productivity and performance (Merk and Dang, 2012). Noura et al. (2010) also mentioned that by making more efficient use of existing facilities; better management, improved maintenance and proper operational, it could improve the capacity of many fishing ports. Fishing port terminal efficiency is an important indicator of the port performance, which stimulates terminal competitiveness among others and boosts port development. Thus, it is vital to support the port and terminal activities, by determining the most efficient port or terminal, the resource utilization and relative differences in technology.

2.2. Previous studies on DEA and fishing terminal

As mentioned earlier, the study related to fishing terminals with DEA was relatively rare in Malaysia. Generally, there is less empirical work on the topic that focuses on fishing terminal efficiency. On the other hand, DEA has been widely used, not only for seaport but also in other sectors such as agriculture and electric sector soon after its introduction in 1978. They recommended it as an excellent methodology of operational research for performance measurements and evaluations.

The performance of port efficiency has been measured by many researchers through DEA as well as in parametric methods. DEA-CCR and BCC models are the most commonly used by researchers to capture both CRS and VRS in their analysis. For instance, Cullinane et al. (2006) measured the efficiency of container ports and found that the CCR model yields the lowest average efficiency compares to the BCC model. Kasypi (2013) measured the efficiency of container terminal operations, involving six terminals in Peninsular Malaysia as DMU over eight years of observations. The result showed 19 out of 48 terminals are CCR efficient while 25 terminals are BCC efficient. Wang et al. (2003) examined the efficiency of the world's leading container ports and analyzed a total of 57 observations. The study employed CCR, BCC input-oriented and FDH models and found only nine terminals are identified to be efficient compared with 23 and 37 efficient terminals of BCC and FDH respectively. Thangasamy and Deo (2013) analyzed the operational efficiency of eight major ports in India from 1993 to 2011. The authors used DEA-Additive CRS and VRS models and the DEA Super Efficiency model for their analysis. The result showed four out of eight ports are efficient throughout the 19 years' observation period for DEA-Additive CRS. DEA-Additive VRS in five efficient ports where the Chennai port appeared to be efficient in the analysis. DEA Super Efficiency model is employed to evaluate higher efficiency and it is found that JPNT port experienced the highest average efficiency value.

The study suggested inefficient ports to improve their equipment and upgrade port infrastructure facilities. Munisamy and Jun (2013) analyzed the technical and scale efficiency of Asian ports. The study obtained data from 69 container ports and found only 21 ports are fully efficient. The study recommended the utilization of new technologies rather than adopting flexibility in management through a combination of production factors and investment. A study was done by Lu and Wang (2013) also found that Chinese container terminals are more efficient than Korean terminals due to its huge investment of equipment, standard infrastructure development and improvement of intermodal transportation. Al-Eraqi et al. (2008) evaluated the location efficiency of Arabian and African seaports using DEA-CCR and BCC models. The study observed 22 seaports in the region of East Africa and the Middle East from 2000 to 2005. The authors found three out of 18 higher productivity ports are efficient under the CCR model while six ports were efficient under the BCC model. Munisamy and Jun (2013) measured the efficiency of 30 container seaports in Latin America over the period 2000 to 2008 by using DEA-CCR and BCC models. The study investigated the changes that occurred in pure technical efficiency, scale efficiency and return to scale, as well as investigating the source of inefficiency of Central America and Caribbean seaports, and identified the seaports operating under VRS. On the other hand, a study by Ebrahimnejad et al. (2014) used the three-stages of DEA to examine the efficiency of coastal container terminals in China. In the study, they used traditional DEA-BCC model (input-oriented) for stage one; in stage two, SFA regression model is employed to decompose slack variables; and for the last stage, the authors compare the adjusted target average input value and actual average input value to exclude environmental variables and statistical noise. Based on those studies, it shows that the CCR model is more inclined towards a lower efficiency as it focuses on purely technical and scales efficiency; different from the BCC model which is determined purely by technical efficiency. Also, the BCC model tends to disregard the impact of the scale size by only comparing DMUs at a given scale of operation.

Martic et al. (2009) described that the results hinge on the input and output choices and the number and homogeneity of the DMUs to be estimated. Golany and Roll (1989) suggested refining the variables list through three stages: (1) judgmental screening; (2) non-DEA quantitative analysis; and (3) DEA based analysis. Almost all of the previous studies widely treat total throughput as dominant indicator for terminal performance measurement as what have been done by Wang et al. (2003), Al-Eraqi et al. (2008), Cullinane et al. (2006), Kasypi (2013), Thangasamy and Deo (2013), and Merk and Dang (2012). Previous studies suggested total throughput is an appropriate output variable for port efficiency benchmarking as it is closely related to the need for cargo-related facilities and services. In other words, total throughput is the measurable benefit generated from inputs and terminal.

Cullinane et al. (2006) pointed out that container port production relies upon the efficient use of labor, land, and equipment. There are a few ways to define labor input. For instance, Thangasamy and Deo (2013) collected a number of employees as labor input in their respective studies. Ebrahimnejad et al. (2014) used staff quantity to represent the labor input. González and Trujillo (2009) employed labor factor by the means of employees of port authorities, which constitute of administrative staff and technical employees. Munisamy and Jun (2013) took total yard equipment as the input factor to indicate labor resources. In terms of land input, Merk and Dang (2012), Cullinane et al. (2006), Lu and Wang (2013), and Al-Eraqi et al. (2008) defined the land resources by using total quay length and terminal area. Cullinane et al. (2006) indicated that total quay length is more appropriate compared to the number of births because the quay can be reconfigured or upgraded in order to meet the market requirements. For the equipment input, Wang et al. (2003) proposed that the number of gantry cranes, number of yard gantry cranes and number of straddle carriers are the most suitable to be enveloped into the model as input variables for container terminal efficiency. On the basis of a terminal depends vitally on the efficient use of infrastructure and equipment, Lu and Wang (2013) incorporated quantities of quay crane, yard crane and yard tractor per berth into their analysis.

There have some arguments about the size of the port or terminal area where the size of port or terminal matters for port efficiency. Merk and Dang (2012) after comparing the efficiency levels among studies world port terminal, suggesting that the size of the port and terminal area are imperative for port efficiency to compare to quay length and handling equipment. Liu (1995) and Notteboom et al. (2000) found that port size is significant for port efficiency where the larger size of ports tends to be more efficient than smaller ports. In similar cases, Kennedy et al. (2011) showed that the numbers of a terminal crane, yard tractor, quality of port infrastructure, quality of cargo handling and incurred port charges are critical factors that contribute the most to seaport operational efficiency. Interestingly, Asil and Fanati Rashidi S (2015) showed no clear relationship between port size and efficiency since there is a strong correlation between volume and efficiency when a terminal area or ship-to-shore gantries are absent. Coto-Millan et al. (2000) also justified that port size is not important when associated with efficiency. Both bigger and smaller ports may achieve efficiency frontier given the utilization of resources and technologies adopted by the ports are the most efficient. Thangasamy and Deo (2013) proved that there is no significant difference between the size and efficiency of the port. Hence, this study will look into the relationship between port size or terminal area to fishing port terminal efficiency.

3. Formulating methodology

Kazan and Baydar (2013) described efficiency as part of productivity. Even though efficiency is a part of productivity, but the term of efficiency and productivity are not exactly the same things. González and Trujillo (2009) denoted that efficiency and productivity are not related even though both terms are occasionally treated as the same. In other words, productivity is a measure of aggregate output over aggregate input. Fig. 2 shows the difference between technical efficiency and productivity. The X and Y axis measure productivity at a particular data point. If a firm operating in point A then shifts to point B is technically efficient, the slope of ray would be greater and yield higher productivity at point B. On the other hand, by shifting to point C, the optimal scale to explore the economic scale gives the maximum points of possible productivity. Collier et al. (2014) concluded that a firm may be technically efficient but there could still be room for productivity improvement.

In DEA, efficiency defined as a ratio of the weighted sum of outputs to the weighted sum of inputs. The ultimate objective of DEA is to determine which DMUs are operating on their efficiency frontier and which ones are not. In other words, the measurement of efficiency using DEA is to identify the best practice of DMU through comparison with other DMUs and identify the inefficiency factors to improve their performance in a competitive environment.

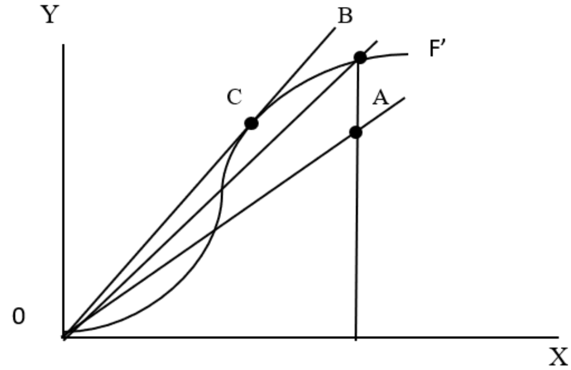

Fig. 2: Productivity, technical efficiency and scale economies (Collier et al., 2014)

DMU that lies on the frontier is considered as efficient. In general, the selection of DMUs is important in terms of their homogeneity as a set of peer entities. Therefore, the peer entities have to perform analogous activities and served equal objectives, under similar market environments while utilizing identical factors. DEA is used to measure the relative productivity of a DMU by comparing it with other homogeneous units transforming the same group of measurable positive inputs into the same types of measurable positive outputs. Fig. 3 (below) illustrates the DMU and homogeneous units.

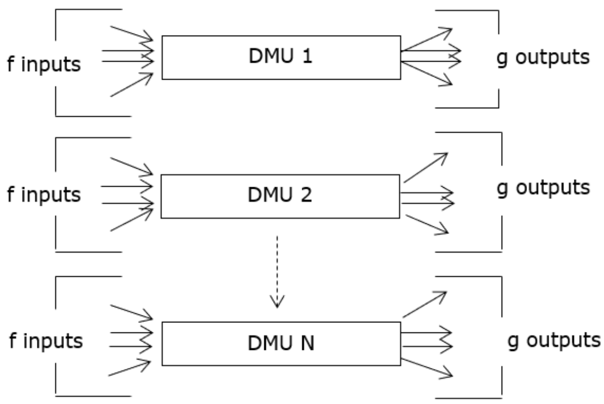

Fig. 3: DMU and homogeneous units

$$\chi = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{fn} & \cdots & x_{fn} \end{bmatrix} \tag{1}$$

$$y = \begin{bmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{fn} & \cdots & y_{fn} \end{bmatrix} \tag{2}$$

Suppose there are the following $DMUs: DMU1, DMU2 \dots and\ DMUn$. Input and output variables for each of these $j = 1,2 \dots n$ DMUs are selected. Each DMU produces g outputs and f inputs. The input and output data for Fig. 3 can be demonstrated by matrixes $X\ and\ Y$ in (1) and (2). Where Xkj refers to kth input data of $DMUj$, while Ykj is the kth of the output of $DMUj$. The efficiency can be expressed as follows:

Equations:

$$Efficiency = \frac{weighted\ sum\ of\ outputs}{Weighted\ sum\ of\ inputs}$$

$$\frac{\sum_{g=1}^{n} u_{rg} y_{rg}}{\sum_{f=1}^{n} v_{if} x_{if}} \quad (3)$$

where; u_rg= weight attached to output g; y_rg= quantity of output g; v_if= weight attached to input f; x_if= quantity of input f.

Generally, the optimal weight may differ from one DMU to another. Hence, the weights in DEA are derived from the data instead of being fixed in advance (Cooper et al., 2007). Vincova (2005) suggested that input and output weights derived by means of an optimizing calculation where DMUs can be categorized into efficient and inefficient. First of all, the fractional programming problem is solved to obtain value for the input weights v_i $(i = 1, \ldots, f)$ and the output weights(u_r) $(r = 1, \ldots, g)$ as variables. Let $DMUj$ assigned as $DMUo$.

$$\max_{v,u} \theta = \frac{u_1 y_{1o} + u_2 y_{2o} + \cdots + u_g y_g}{v_1 x_{1o} + v_2 x_{2o} + \cdots + v_f x_{fo}} \quad (4)$$

subject to:

$$\frac{u_1 y_{1j} + \ldots + u_g y_{gj}}{v_1 x_1 + \ldots + v_f x_{fj}} \leq 1 (j=1,2,\ldots,n)$$
$$V_1, V_2, \ldots, V_f \geq 0$$
$$U_1, U_2, \ldots, U_g \geq 0.$$

The objective here is to acquire weights (v_i) and (u_r) that maximize the ratio of DMUj. It is subject to the constraint that the efficiency score will not exceed 100% and the coefficient values are positive and non-zero. Next, replace the above fractional program by linear program:

$$\max_{\mu,v} \theta = \mu_1 y_{1o} + \cdots + \mu_g y_{go} \quad (5)$$

subject to:

$$v_1 x_{1o} + \cdots + v_f x_{fo} = 1$$
$$\mu_1 y_{1o} + \cdots + \mu_g y_{go} \leq v_1 x_{1j} + \cdots + v_f x_{fj}$$
$$(j = 1,2, \ldots n)$$
$$v_1, v_2, \ldots v_f \geq 0$$
$$\mu_1, \mu_2, \ldots \mu_g \geq 0.$$

Let an optimal solution of (LPo) be $(v = v^*, \mu = \mu^*)$ whereas, the optimal solution of (FPo) also be $(v = v^*, u = \mu^*)$. The above transformation is a result of Charnes-Cooper transformation (Cooper et al., 2007).

3.1. CCR input-oriented model

DEA-CCR efficiency that measures under constant returns to scale (CRS) is introduced by Charnes et al. (1978). CCR model inflicts three restrictions on the frontier technology which include a constant return to scale (CRS), the convexity of the set of feasible input-output combinations and strong disposability of inputs and outputs (Zamorano, 2004). This model assumes a production process that inputs and output are independent of the scale of operation. The CSR model measures the technical efficiency for each of the DMUs. The CCR input-oriented model for envelopment (6) and multiplier models (7) are illustrated by Cooper et al. (2007) as below:

$$min\theta \quad (6)$$

subject to:

$$\sum_{j=1}^{n} x_{ij} \lambda_j \leq \theta x_{i0} \qquad i = 1,2$$
$$\sum_{j=1}^{n} y_{rj} \lambda_j \geq y_{r0} \qquad r = 1,2$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\sum_{j=1}^{n} \geq 0 \;\; (j = 1,2, \ldots n).$$

Where x_{io} y_{r0} is the i^{th} input and r^{th} is the output for a DMUo under evaluation; λ_j is the decision variable that DMUj would place on DMUo in constructing its efficiency reference set while θ is the relative technical efficiency of DMU_o. The optimal value of θ is not greater than 1. The optimal solution θ produces an efficiency score for a particular DMU. The process is repeated for each DMUj. The DMU for which θ< 1 is inefficient, while DMU which θ= 1 are boundary points. In this dual formulation, the authors tend to seek efficiency by minimizing the efficiency of DMU_o subject to two sets of inequality where the first inequality emphasizes that the weighted sum of inputs of the DMUs should be less than or equal to the inputs of DMU_o being evaluated. On the second inequality, the weighted sum of the outputs of the non-focal DMUs should be greater than or equal to the focal DMU. The weights are the λ values. The λ values would be equal to 1 for the efficient DMU, while for DMUs that are inefficient, the λ values will be expressed in their efficiency reference set.

$$\max(\sum_{i=1}^{f} s_i^- + \sum_{r=1}^{g} s_r^+) \quad (7)$$

subject to:

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \qquad i = 1,2, \ldots f;$$
$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \qquad r = 1,2, \ldots g;$$
$$\sum_{j=1}^{n} \lambda_j = 1$$
$$\lambda_j \geq 0, \quad j = 1,2, \ldots n$$
$$s_i^- \geq 0, \quad i = 1,2, \ldots f$$
$$s_r^+ \geq 0, \quad r = 1,2, \ldots g.$$

Cooper et al. (2007) incorporated slack variables s_i^- (input) and s_r^+ (output) into the model (7) to avoid weak efficiency due to non-zero values in their maximal value.

The performance of DMUo is fully efficient if both θ= 1 and all slacks s_i^-= s_r^+= 0. It is also noted that the performance of DMU_o is inefficient only if both θ=1 and $s_i^- \neq 0$ and/or $s_r^+ \neq 0$ for some input and output.

$$min\theta - \varepsilon(\sum_{i=1}^{f} s^{-}_{i} + \sum_{r=1}^{g} s^{+}_{r}) \quad (8)$$

subject to:

$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad i = 1,2, \ldots f;$
$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad r = 1,2, \ldots g;$
$\lambda_j \geq 0, \quad j = 1,2, \ldots n$
$s_i^- \geq 0, \quad i = 1,2, \ldots f$
$s_r^+ \geq 0, \quad r = 1,2, \ldots g.$

Where s_i^- and s_r^+ are slack variables used to convert the inequalities in Eq. 6. The ε> 0 is a non-Archimedean component defined to be smaller than any positive real number. DMU_o is CCR efficient if $\theta^* = 1$, and all slacks $s_i^- = s_r^+ = 0$, otherwise, DMU_o is CCR-inefficient which it means that $\theta^* < 1$.

For this study, the objective function is to maximize the efficiency score h_0 for fishing terminal j_0, subject to constraint, when the same set of u and v coefficients (weight) are applied to all other fishing terminals.

$$\text{Max } h_0 = \sum_{r=1}^{g} \mu_r y_{rj0} \quad (9)$$

Subject to:

$\sum_{i=1}^{f} v_i x_{ijo} = 1$
$\sum_{r=1}^{g} \mu_r y_{rj} - \sum_{i=1}^{f} v_i \, x_{ij} \leq 0 \qquad j = 1, \ldots, n$
$\mu_r, v_i \geq \varepsilon > 0$

3.2. DEA BCC input-oriented model

Another version of DEA method was suggested by Banker et al. (1984) which relaxes the assumption of constant return to scale (CRS) and imposes variable return to scale (VRS) by adding the constraint $\sum_{j=1}^{n} \lambda_j = 1$. This study also used the VRS model because the model isolates pure technical efficiency components and scale efficiency related to the size of the DMUs.

$$min\theta \quad (10)$$

subject to:

$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_o$
$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_0$
$\sum_{j=1}^{n} \lambda_j = 1$
$\sum_{j=1}^{n} \geq 0 \ (j = 1,2, \ldots n).$

Similar to the CCR model, the BCC model also has the same concern of inefficient boundary point when there are non-zero slacks. However, it can be eliminated by citing the slacks and their maximal values:

$$\max(\sum_{i=1}^{f} s^{-}_{i} + \sum_{r=1}^{g} s^{+}_{r}) \quad (11)$$

Subject to:

$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad i = 1,2, \ldots f \ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad r = 1,2, \ldots g;$
$\sum_{j=1}^{n} \lambda_j = 1$
$\lambda_j \geq 0, \quad j = 1,2, \ldots n$
$s_i^- \geq 0, \quad i = 1,2, \ldots f$
$s_r^+ \geq 0, \quad r = 1,2, \ldots g$

The slacks obtained are called DEA slacks, where s_i^- and s_r^+ represent input and output slacks, respectively. It is calculated from a second-stage DEA calculation. DMU is efficient only if θ= 1 and $s_i^- = s_r^+ = 0$ for all i and r. DMU is weakly efficient if θ= 1 and $s_i^- \neq 0$ and (or) $s_r^+ \neq 0$ for some i and r. Eqs. 10 and 11 represent two stages the DEA process involved in the following Eq. 12.

$$min\theta - \varepsilon(\sum_{i=1}^{f} s^{-}_{i} + \sum_{r=1}^{g} s^{+}_{r}) \quad (12)$$

subject to:

$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad i = 1,2, \ldots f;$
$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad r = 1,2, \ldots g;$
$\sum_{j=1}^{n} \lambda_j = 1$
$\lambda_j \geq 0, j = 1,2, \ldots n$
$s_i^- \geq 0, i = 1,2, \ldots f$
$s_r^+ \geq 0, r = 1,2, \ldots g.$

The presence of non-Archimedean ε in the Eq. 12 allows the minimization over θ to anticipate the optimization involving the slacks, s_i^- and s_r^+. Hence, (12) is calculated in a two-stage process with maximal reduction of inputs being achieved first, via (10); then, in the second stage, movement onto efficient frontier is achieved via invoking the slack variables in Eq. 11. Zhu (2014) reminded that it is inappropriate to solve Eq. 12 in a single stage by specifying an ε value in Eq. 12.

From the VRS model, analysis on whether a fishing terminal imposes increasing return to scale, the constant return to scale, or decreasing return to scale becomes possible. There is an increasing return to scale when the value of Zjo is greater than zero ($Zjo > 0$), decreasing return to scale if the value of Zjo is less than zero ($Zjo < 0$), while the value of Zjo is equal to zero ($Zjo = 0$) for constant return to scale. From that, the number of fishing terminal operating at an efficient scale can be estimated.

$$\text{Max } h_0 = \sum_{r=1}^{g} \mu_r y_{rj0} + z_{j0} \quad (13)$$

subject to:

$\sum_{i=1}^{f} v_i x_{ijo} + z_{j0} = 1$
$\sum_{r=1}^{g} \mu_r y_{rj} \qquad j = 1, \ldots, n$
$-\sum_{i=1}^{f} v_i x_{ij} + z_{j0} \leq 0$
$\mu_r, v_i \geq 0.$

4. Data source

This study intends to measure the technical efficiency of the fishing terminal by accessing their input utilization through the given output. Initially, the information regarding the criteria of data was collected through a review of related articles. Besides that, data were collected from fishing port authorities; including terminal operators and fishermen. This study adopts cross-sectional analysis and panel data analysis to capture DMUs performance for single and multiple time periods. The data were refined and the variables were identified based on previously selected references as well as a selection of characteristics of fishing terminals. Statistical summary for collected data for input and output variables are presented in Table 1.

Table 1: Statistical summary of input and output variables of fishing terminals

	Max	Min	Average	Std. Deviation
Tonnage	91490	1812.5	24821.58	28595.51
Revenue	136966339	6770851	53184364.70	51259871.90
Terminal area	330000	5400	115168.33	151921.07
Berth length	500	180	298.33	143.31
Draft	7	3.4	5.36	1.5
Storage area	550	300	443.33	105.30
Average labor	26	15	21	4.55
Gate lane	2	2	2	0
Trolley	16	4	8.33	5.44
Forklift	2	0	1	0.82
Shore to sea crane	6	4	5	0.82
Shore crane	4	2	2.67	0.94
Slider	20	0	7.67	8.81
Fish tray	16	9	11.67	3.09

4.1. Correlation between input and output variables

Correlation test is carried out to measure how well they are related. The most common measure of correlation in statistics is the Pearson Test. The result will be between -1 and 1 which gives the strength of the relationship and whether the relationship is negative or positive. If the coefficient value is closer to zero, the greater the variety of data points would be, which means the variable has no linear relationship or a very weak linear relationship. The relationship is negative when the value is less than zero and vice versa. Pearson correlation test suggests that high correlation ranged from 0.5 to 1.0 or -0.5 to -1.0; medium correlation is range from 0.3 to 0.5 or -0.3 to -0.5; while low correlation range from 0.1 to 0.3 or -0.1 to -0.3.

The correlation between inputs and outputs variable is presented in Table 2. For instance, the correlation coefficient of the gate lane with other input variables is 0 and this signifies that there is no linear relationship between the variables. Besides, the result also shows no linear relationship exists between shore to sea cranes and shore crane. The correlation coefficient of the terminal area indicates a high correlation between berth length, average labor and shore to sea cranes, whereas the correlation between draft and storage area is quite low. The correlation between the terminal area and forklift is close with zero, indicated that the linear correlation is very weak. Berth length correlation coefficient shows a low correlation between all the variables except for terminal area, average labor, number of trolley and shore to sea cranes. The correlation results with linear relationship ranking are shown in Table 3.

4.2. Score result of DEA-CCR (Input-oriented rating)

The finding is shown in Table 4, Fig. 4 and Fig. 5 indicates the scores of efficiency estimated for a fishing terminal using the DEA-CCRI model for the years 2012, 2013 and 2014 respectively. An efficiency score of 1 signifies efficient fishing terminals and vice versa. Based on the CCRI efficiency level of each terminal, the analysis shows that only four fishing terminals were efficient with a score of 1, approximately 44.44% over the analyzed period. It is obvious that about 55.56% of the fishing terminals are inefficient.

Table 2: Correlation between inputs and outputs variables

	Terminal Area	Berth Length	Draft	Storage Area	Avr Labour	Gate Lane	Trolley	Forklift	Shore to Sea Cranes	Shore Cranes	Slider	Fish Tray	Tonnage	Revenue
Terminal Area	1	0.9962	0.1579	0.2584	0.7856	0	-0.4450	0.0126	-0.8723	-0.4890	-0.3629	-0.3695	-0.3452	-0.3476
Berth Length	0.9962	1	0.2419	0.3416	0.8365	0	-0.5123	0.9970	-0.9115	-0.4111	-0.2804	-0.2872	-0.2730	-0.2668
Draft	0.1579	0.2419	1	0.9787	0.7248	0	-0.9397	0.9728	-0.6125	0.7697	0.8474	0.8438	0.7408	0.8399
Storage Area	0.2584	0.3416	0.9787	1	0.8008	0	-0.9801	0.9692	-0.6978	0.7163	0.8063	0.8021	0.6977	0.7915
Avr Labour	0.7856	0.8365	0.7248	0.8008	1	0	-0.9036	0.6287	-0.9878	0.15554	0.2914	0.2846	0.2328	0.2914
Gate Lane	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Trolley	-0.4449	-0.5212	-0.9397	-0.9801	-0.9036	0	1	-0.9011	0.8260	-0.5636	-0.6673	-0.6678	-0.5759	-0.6624
Forklift	0.0126	0.09970	0.9728	0.9692	0.6286	0	-0.9011	1	-0.5	0.8660	0.9271	0.9245	0.8101	0.9079
Shore to Sea Cranes	-0.8723	-0.9116	-0.6125	-0.6978	-0.9878	0	0.8260	-0.5	1	0	-0.1391	-0.1321	-0.0972	-0.1429
Shore Cranes	-0.4890	-0.4112	0.7697	0.7163	0.1555	0	-0.5636	0.8660	0	1	0.9903	0.9912	0.8793	0.9658
Slider	-0.3629	-0.2804	0.8474	0.8063	0.2914	0	-0.6730	0.9271	-0.1391	0.9903	1	0.9999	0.8843	0.9763
Fish Tray	-0.3695	-0.2872	0.8438	0.8021	0.2846	0	-0.6677	0.9245	-0.1321	0.9912	0.9999	1	0.8845	0.9762
Tonnage	-0.3452	-0.2730	0.7408	0.6976	0.2328	0	-0.5759	0.8101	-0.9072	0.8793	0.8843	0.8845	1	0.9326
Revenue	-0.3476	-0.2668	0.8399	0.7915	0.2914	0	-0.6624	0.9079	0.1429	0.9658	0.9762	0.9762	0.9326	1

Table 3: Correlation result with linear relationship ranking

	Terminal Area	Berth Length	Draft	Storage Area	Avr Labour	Gate Lane	Trolley	Forklift	Shore to Sea Cranes	Shore Cranes	Slider	Fish Tray	Tonnage	Revenue
Terminal Area	High	High	Low	Low	High	n/a	Medium	Weak	High	Medium	Medium	Medium	Medium	Medium
Berth Length	High	High	Low	Medium	High	n/a	Medium	Weak	High	Medium	Low	Low	Low	Low
Draft	Low	Low	High	High	High	n/a	High	High	High	High	High	High	High	High
Storage Area	Low	Medium	High	High	High	n/a	High	High	High	High	High	High	High	High
Avr Labour	High	High	High	High	High	n/a	High	High	High	Low	Low	Low	Low	Low
Gate Lane	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Trolley	Medium	High	High	High	High	n/a	High	High	High	High	High	High	High	High
Forklift	Weak	Weak	High	High	High	n/a	High	High	Medium	High	High	High	High	High
Shore to Sea Cranes	High	High	High	High	High	n/a	Medium	Medium	High	n/a	Low	Low	Weak	Low
Shore Cranes	Medium	Medium	High	High	Low	n/a	High	High	n/a	High	High	High	High	High
Slider	Medium	Low	High	High	Low	n/a	High	High	Low	High	High	High	High	High
Fish Tray	Medium	Low	High	High	Low	n/a	High	High	Low	High	High	High	High	High
Tonnage	Medium	Low	High	High	Low	n/a	High	High	Weak	High	High	High	High	High
Revenue	Medium	Low	High	High	Low	n/a	High	High	Low	High	High	High	High	High

Table 4: Efficiency result of using DEA-CCRI

No	Year	Fishing Terminal	Efficiency Score		Rank
1	2012	Chendering (C1)	0.947434	Inefficient	5
2	2012	Kuala Kedah (K1)	0.50266	Inefficient	9
3	2012	Tok Bali (T1)	0.709325	Inefficient	6
4	2013	Chendering (C2)	1	Efficient	1
5	2013	Kuala Kedah (K2)	1	Efficient	1
6	2013	Tok Bali (T2)	1	Efficient	1
7	2014	Chendering (C3)	0.708819	Inefficient	7
8	2014	Kuala Kedah (K3)	0.547525	Inefficient	8
9	2014	Tok Bali (T3)	1	Efficient	1

For the year 2012, all terminals were inefficient with a score of less than 1. Chendering fishing terminal (C1) is considered close to the efficient frontier with a score of 0.94743 while other terminals like Kuala Kedah (K1) and Tok Bali (T1) recorded a much lower value with a score of 0.50266 and 0.70932 respectively. The inefficiency tends to exist due to linear programming nature that seeks to maximize the efficiency score. In 2013, all fishing terminals appeared to be efficient with an efficiency score of 1. For the year 2014, only one fishing terminal is efficient, which is Tok Bali while C3 and K3 were identified as inefficient with inefficiency scores of 0.708819 and 0.547525, respectively. During the analyzed period, K1 was found to have the lowest efficiency score of 0.50266 in the year 2012. This may be connected with low landings of catch. Tok Bali fishing terminal appeared to be efficient in both 2013 and 2014.

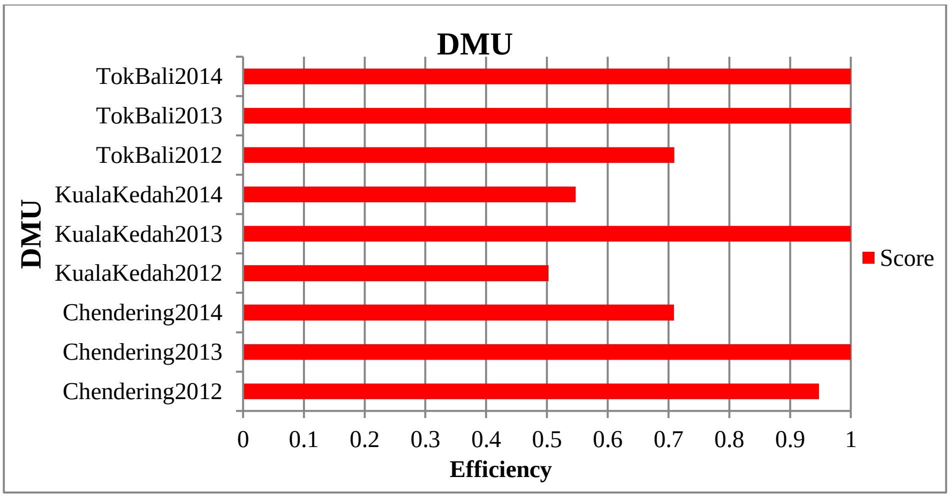

Fig. 4: Efficiency of the fishing terminal for the year 2012 to 2014

It is widely known that Tok Bali is the most efficient fishing terminals in Peninsular Malaysia due to its strategic location at the South China Sea, successful collaboration with investors and effective government plans to establish Tok Bali fishing port as an industrial area and new growth area for investment. Furthermore, the fishing port will be expanding with the completion of Tok Bali Integrated Fisheries Park (TBIFP) and Tok Bali Supply Base (TBSB) projects. TBIFP is expected to drive Tok Bali as main fisheries hub for both local and export markets, reinforcing its potential to draw private investments in the primary processing of fish-based products and supporting industries such as ice-making factories, with the integration of marine eco-tourism and hospitality sectors. The average efficiency score of all fishing terminals is 0.8238. The year in which the efficiency average was at its lowest is 2012 with 0.7198; while 2014 with an average score of 0.7521.

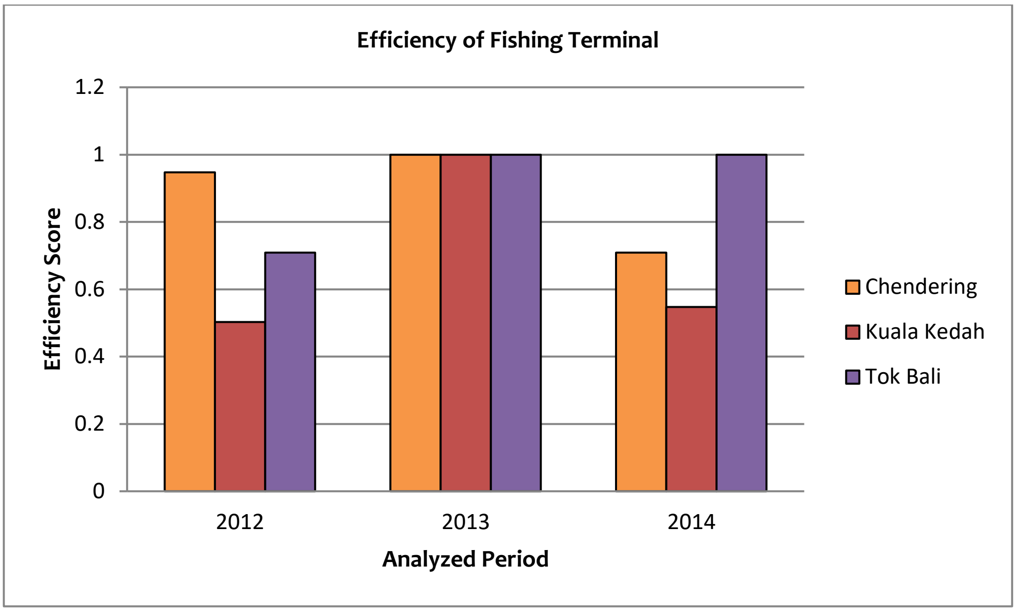

Fig. 5: Efficiency of the fishing terminal for the year 2012–2014

Fig. 6 shows that C1 attained an efficiency of 0.947434 in the year 2012, followed by a constant return to scale in year 2013. Nevertheless, the efficiency drops approximately (29.12%) in the following year due to the excess amount of input variables. Kuala Kedah increased its efficiency by 49.73% from 0.50266 to 1 in the year 2013 and suffered a drop of 45.25% in the year 2014. Tok Bali achieves its efficiency score of 0.709325 in 2012, followed by an increase of 29.07% in 2013.

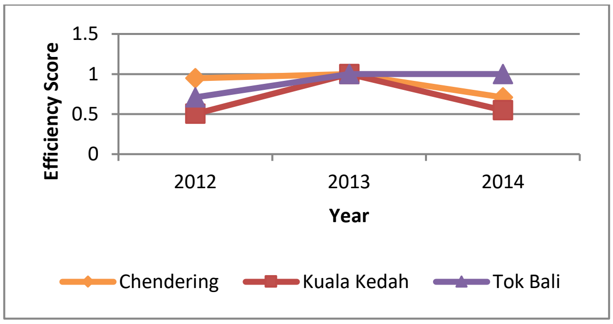

Fig. 6: Efficiency score by DEA-CCRI for fishing terminals

4.2.1. The reference set of best practice

DEA identifies the closest efficient fishing terminals located on the frontier for each inefficient terminal. These efficient terminals are called peers or benchmarks. The benchmarks are created through DEA computations. As shown in Table 5, the inefficient fishing terminals can use a group of efficient terminals as a reference set in order to be at an efficient frontier. The reference set in Table 6 offers two different explanations based on whether the terminal is efficient or inefficient. For the inefficient fishing terminal, the reference set of best practice provides information on which fishing terminal have to set as their reference in order to be efficient.

As shown above, efficient fishing terminals may consider themselves to be on their own benchmarks. For example, the benchmark for T3 is T3 and for K2 is K2. On the other part, for inefficient terminals, their benchmarks stand for one or many efficient terminals. C3 observes three efficient terminals as its benchmark, namely C2, K2, and T2. While the benchmark for T1 is two fishing terminals, T2 and T3. This means that both C3 and T3 must use a combination of three fishing terminals and two fishing terminals respectively in order to achieve the level of efficiency. The values of the combination of efficient terminals to achieve efficiency to each benchmark fishing terminal can be calculated by attained λ (lambda) weights which solved from dual version of linear program. For instance, C3 will attempt to become like C2 more than K2 and T2 given that respective λ weights of C2 is 0.5323 compare to the latter, 0.0485 and 0.0265. In addition, K1 and K3 observe that K2 is efficient, hence K2 is set as benchmark.

Table 5: Benchmarks for input-oriented CCR Model

No.	DMU	Score	Reference Set
1	Chendering 2012 (C1)	0.947434	C2
2	Chendering 2013 (C2)	1	C2
3	Chendering 2014 (C3)	0.708819	C2 and K2 and T2
4	Kuala Kedah 2012 (K1)	0.50266	K2
5	Kuala Kedah 2013 (K2)	1	K2
6	Kuala Kedah 2014 (K3)	0.547525	K2
7	Tok Bali 2012 (T1)	0.709325	T2 and T3
8	Tok Bali 2013 (T2)	1	T2
9	Tok Bali 2014 (T3)	1	T3

Table 6: The reference set of best practice to other DMU

Reference	Frequency to other DMU
Chendering 2013 (C2)	2
Kuala Kedah 2013 (K2)	3
Tok Bali 2013 (T2)	2
Tok Bali 2014 (T3)	1

Table 6 present the frequency of best practice to other DMUs. Under the CRS assumption, fishing terminal that is most frequently used as a benchmark by inefficient terminals is K2 in 2013. Hence, it is identified as the peer for 3 inefficient fishing terminals. This result is quite surprising, yet reasonable. Kuala Kedah fishing terminal are able to utilize minimum input for a given output, given that their inputs is relatively small compare to other fishing terminals. Chendering and Tok Bali were used as a benchmark by 2 inefficient terminals respectively in the same year, while in 2014, only T3 is used as benchmark by inefficient terminals since it is the only efficient fishing terminal. Based in Table 7, it is observed that the terminals that failed to be references in 2012 are C1, K1 and T1; as well as C3 and K3 in year 2014.

4.2.2. Return to scale

The return to scale of an inefficient DMU is determined at its projected point on the efficient frontier. However, it is being argued that the evaluation may not be accurate when there are multiple projection points. Scale inefficiency can be either decreasing return to scale (DRS) or increasing return to scale (IRS). The scale inefficiency falls onto decreasing return to scale if output increases by less than that proportional change in inputs. If output increases by more than proportional change in inputs, then, it is increasing returns to scale. The return to scale can be calculated and examined by summing up lambda (λ)'s weight values. A DMU exhibits increasing return to scale if the total sum of lambda weights $\sum\lambda < 1$ and decreasing return to scale when $\sum\lambda > 1$. DMU is considered for having constant return to scale if $\sum\lambda = 1$. Increasing, Constant and Decreasing Return to Scale under the CRS assumption were shown in Table 7.

Table 7 displays return to scale under constant return to scale assumption. For the fishing terminals that only have one benchmark in their reference set, $\sum\lambda$ is equal to λ weight of that terminal reference. On the other hand, for the fishing terminal that has more than one terminal in its benchmark set, the value of $\sum\lambda$ of that terminal is calculated by adding λ weight of reference terminals. For example, $\sum\lambda$ value of C3 is calculated by adding λ weight of C2, λ weight of K2 and λ weight of T2 (0.532277+0.048549+0.026481= 0.607307). Similar to calculation for T1, $\sum\lambda$= 0.709325 (0.708276+0.001049). As one can see, there are four fishing terminals that demonstrate a constant return to scale, namely C2; K2; T2 and T3 where their $\sum\lambda=1$. There are five terminals namely, C1; C3; K2; T2 and T3 which all identified as BCC inefficient units with their $\sum\lambda$ are 0.947434; 0.607307; 0.50266; 0.547525; and 0.709325 respectively. These inefficient fishing terminals exhibit increasing returns to scale where their $\sum\lambda < 1$. The fishing terminals that operate with IRS could achieve efficiency by increasing their scale of operations to be as efficient as their peer reference of best practice.

Table 7: Increasing, Constant and Decreasing Return to Scale under CRS assumption

DMUs	CRS efficiency score	∑λ	RTS	λj	λj	λj
C1	0.9474	0.9474	IRS	0.9474		
C2	1	1	CRS	1		
C3	0.7088	0.6073	IRS	0.5322	0.0485	0.0264
K1	0.5026	0.5026	IRS	0.5026		
K2	1	1	CRS	1		
K3	0.5475	0.5475	IRS	0.5475		
T1	0.7093	0.7093	IRS	0.7082	0.0010	
T2	1	1	CRS	1		
T3	1	1	CRS	1		

4.2.3. Slack variable analysis

The slack variable analysis provides a reference set of specific recommendations to aid each inefficient fishing terminal to become efficient, by minimizing the input resources to produce a given output. The analysis indicated that the Tok Bali fishing terminal in the year 2013 and 2014; and Chendering and Kuala Kedah fishing terminal in the year 2013 had been relatively efficient. Their ratios of input variables to output variables were appropriate and their input resources utilization is efficient. The constraint is binding when a slack variable associated with constraint is 0 which means the constraint restricts the possible changes of the point. If the constraint is non-binding, the constraint does not restrict the possible changes of the point.

The fishing terminal like C3 was inefficient due to inappropriate application of input resources and excess amount of resources utilized (Table 8). Chendering can improve its efficiency or reduce its inefficiency proportionately by reducing its inputs.

C3 achieved its efficiency score of 0.708819, which implies that Chendering should adjust all input by 29.12% in order to be technically efficient. The result indicates that there is a surplus of almost all its input variables. Chendering would require to reduce its terminal area by 57729.38 square meter; berth length by 73.84 meter; storage area by 55.61 square meter; average labor by 3.28; gate lane by 0.20; forklift by 0.12 unit; shore to sea crane by 0.28 unit; shore crane by 0.15 unit; and fish tray by 1 unit. Nevertheless, despite these inputs reduction, it is unable to push C3 to the frontier target. Therefore, in order to achieve efficiency, the fishing terminal should also increase its tonnage by 3.99%. Hence, the surplus variables should be adjusted accordingly if the terminal would like to reach an efficient state. For other inefficient fishing terminals such as C1, K1 as well as K3, the analysis result shows that there is a shortage in tonnage. These three fishing terminals cannot reduce any inputs but must augment tonnage of fish landing by 47.47%, 90.18% and 67.30% respectively. In contrast, the result founds that there are no slack variables for T1. This finding, therefore, indicates the inappropriate application of input resources and T1 should fully utilize its resources in order to be efficient.

Table 8: Slack variable analysis result for inefficient fishing terminals

	Chendering 2012 (C1)	Kuala Kedah 2012 (K1)	Tok Bali 2012 (T1)	Chendering 2014 (C3)	Kuala Kedah 2014 (K3)
Excess T.A	0	0	0	57729.38	0
Excess B.L	0	0	0	73.84	0
Excess D	0	0	0	0	0
Excess S.A	0	0	0	55.61	0
Excess A.L	0	0	0	3.28	0
Excess G.L	0	0	0	0.20	0
Excess T	0	0	0	0	0
Excess F	0	0	0	0.12	0
Excess S.T.C	0	0	0	0.28	0
Excess S.C	0	0	0	0.15	0
Excess S	0	0	0	0	0
Excess F.T	0	0	0	0.90	0
Shortage T	4201.17	1634.44	0	347.72	1510.39
Shortage R	0	0	0	0	0

Note: Excess - T.A: Terminal Area; B.L: Berth Length; D: Draft; S.A: Storage Area; A.L: Average Labour; G.L: Gate Lane; T: Trolley; F: Forklift; S.T.C: Shore to Sea Crane; S.C: Shore Crane; S: Slider; F.T: Fish Tray; Shortage – T: Tonnage; R: Revenue

4.3. Score result of DEA-BCCI (Input-oriented rating)

DEA-BCCI model measures the pure technical efficiency of a DMU at a given scale of operation where its frontiers establish piecewise linear and concave characteristics which lead to variables return to scale. The basic BCCI model is solved using DEA-Solver. The results of efficiency estimated are presented in Table 9. Based on the BCCI efficiency level of each fishing terminal, the analysis indicates that six out of nine fishing terminals were efficient (score of 1), around 66.66% of the analyzed period.

It is evident that all fishing terminals found to be efficient with a score of 1 (Table 9). This is not surprising as in VRS models; more terminals can find their way to the frontier. Nevertheless, C1, K1 and T1 are classified as inefficient although their BCC-projection is constant. This scenario could happen, when the value could not be computed accurately, mostly when multiple projections occur. The inefficiency may also have influenced by lambda weight value that reflects the different return to scale possibilities.

Table 9: Efficiency results of using DEA-BCCI

No	Year	Fishing Terminal	Efficiency Score		Rank
1	2012	Chendering (C1)	1	Inefficient	1
2	2012	Kuala Kedah (K1)	1	Inefficient	1
3	2012	Tok Bali (T1)	1	Inefficient	1
4	2013	Chendering (C2)	1	Efficient	1
5	2013	Kuala Kedah (K2)	1	Efficient	1
6	2013	Tok Bali (T2)	1	Efficient	1
7	2014	Chendering (C3)	1	Efficient	1
8	2014	Kuala Kedah (K3)	1	Efficient	1
9	2014	Tok Bali (T3)	1	Efficient	1

Details regarding inefficient units are discussed in the next section. Fig. 7 and Fig. 8 are created in order to provide more details on the efficiency scores of fishing terminals.

The results indicated that DEA-BCCI obtained better results compare to DEA-CCRI. The result is predictable as BCCI operates variables returns to scale whereas CCRI operates constant return to scale. VRS efficiency score is generally higher than the CRS efficiency score, particularly for the input approach.

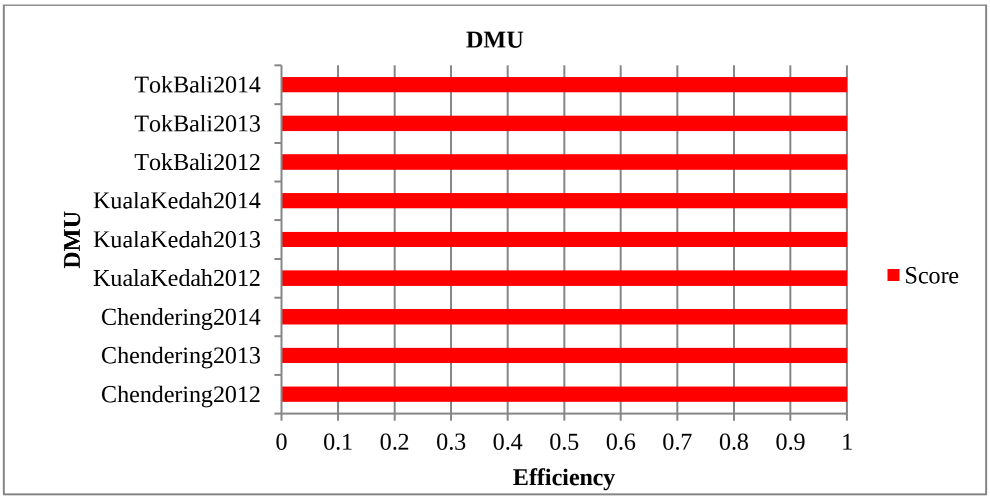

Fig. 7: Efficiency of the fishing terminal for the year 2012 to 2014

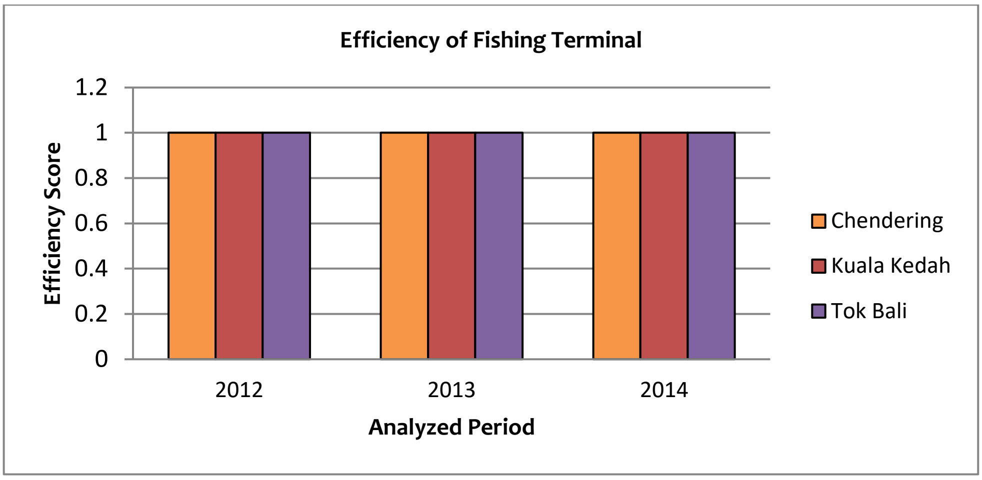

Fig. 8: Efficiency of the fishing terminal for the year 2012-2014

4.3.1. The reference set of best practice

Efficient fishing terminals could be referred to as better performers, however not the best. In order to distinguish the best of them, one may investigate the reference set frequency as an indicator of the best performer. It is necessary to understand the production process of best practices which may help both inefficient and efficient terminals to make improvements. However, one should be cautious that efficient terminals may represent the best existing but not necessarily the best terminal since there is always a possibility that a fishing terminal can be operated more efficiently. Table 10 and Table 11 show some results.

Table 10: Benchmarks for input-oriented BCC model

No.	DMU	Score	Reference Set
1	C1	1	C2 and C3
2	C2	1	C2
3	C3	1	C3
4	K1	1	K2
5	K2	1	K2
6	K3	1	K3
7	T1	1	T3
8	T2	1	T2
9	T3	1	T3

Table 11: The reference set of best practice to other DMU

Reference	Frequency to other DMU
Chendering 2013	1
Chendering 2014	1
Kuala Kedah 2013	1
Tok Bali 2014	1

As can be seen in Table 10, efficient fishing terminals may consider themselves to be their own benchmarks. For example, the benchmark for C2 is C2 and T3 is T3. On the other hand, for inefficient terminals, their benchmarks stand for one or many of the efficient terminals. C1 observes two efficient terminals as its benchmark, namely Chendering 2013 (C2), Chendering 2014 (C3). This means that C1 must use a combination of two fishing terminals in order to achieve efficiency. The values of the combination of efficient terminals to achieve efficiency and reported next to each benchmark fishing terminal can be calculated by attained λ (lambda) weights which solved from the dual version of a linear program. For instance, C1 will attempt to become like C2 more than C3 given that respective λ weights of C2 are 0.840808 compare to the latter, 0.159182. Besides, one can also find that K1 and T1 perceived K2 and T3 as their benchmark respectively based on the way they utilize input and produce enough output.

Table 11 presents the frequency in the reference set for efficient fishing terminals. The reference set provides a basis for what inefficient terminals should do to achieve efficiency. Under the VRS assumption, the result of the frequency of the reference set indicated that C2 and K2 were used as a benchmark in 2013. While in 2014, only C3 and T3 were appointed as references for an inefficient fishing terminal.

4.3.2. Return to scale (RTS)

BCC model assumes that the evaluated decision-making unit characterizes variable return to scale, distinguishing between scale and technical efficiency. This model identifies only isolated technical efficiency for a given scale of operations and exhibit either Increasing Return to Scale (IRS) or Constant Return to Scale (CRS) or Decreasing Return to Scale (DRS) when working in Data Envelopment Analysis Program (DEAP). Return to scale is an important part of DEA which enables us to determine the movement of inefficient fishing terminals at the frontier to steer direction. Increasing, Constant and Decreasing Return to Scale under VRS assumption were shown in Table 12.

Table 12 displays return to scale under variable return to scale assumption. For the fishing terminals that have only one benchmark in their reference set (Table 10). On the other hand, for the fishing terminal that has more than one terminal in its benchmark set, the value of ∑λ of that terminal is calculated by adding λ weight of reference terminals. For detail illustration, ∑λ value of C1, 0.99999, is calculated by adding λ weight of C2 and λ weight of C3 (0.840808+0.159182= 0.99999). As one can see, there are six fishing terminals that demonstrate a constant return to scale, namely C2; C3; K2; K3; T2 and T3 where their ∑λ= 1. For the inefficient terminals, C1, K1 and T1 are identified as BCC inefficient with the value of the index of 0.99999 respectively. The reference units for C1 are C2 and C3 with λ weight are 0.840808 and 0.159182, showing an increasing return to scale where ∑λ< 1. Likewise, for K1 and T1, it shows an increasing return to scale that explains an optimum value of 1 for C1, K1 and T1. Nonetheless, with non-zero optimal sums of slacks, those were inefficient in their RTS status. Yet, the RTS status of these terminals was based on their BCC-projection (i.e., unit B) which is a constant value.

Table 12: Increasing, constant and decreasing return to scale under VRS assumption

DMUs	VRS efficiency score	∑λ	RTS	λj	λj
Chendering 2012 (C1)	1	0.99999	IRS	0.84080	0.15918
Chendering 2013 (C2)	1	1	CRS	1	
Chendering 2014 (C3)	1	1	CRS	1	
Kuala Kedah 2012 (K1)	1	0.99999	IRS	0.99999	
Kuala Kedah 2013 (K2)	1	1	CRS	1	
Kuala Kedah 2014 (K3)	1	1	CRS	1	
Tok Bali 2012 (T1)	1	0.99999	IRS	0.99999	
Tok Bali 2013 (T2)	1	1	CRS	1	
Tok Bali 2014 (T3)	1	1	CRS	1	

4.3.3. Slack variable analysis

In this study, DEA further identifies slack or surplus values. The input reductions are called total inefficiencies which comprise not only the number of proportional reductions but also on "slack", which indicates for those fishing terminals that cannot reach their efficiency frontier regardless of the proportional reductions. The slack value is the amount of the resource that is not being used while the surplus is the extra amount over the constraint that is being produced. It is interesting to investigate the sources of inefficiency through slack variable analysis to identify potential areas of improvement. One can find further details as in section 3.8.2. BCC efficiency analysis classified that six DMUs were relatively efficient for the years 2013 and 2014, namely C2; C3; K2; K3; T2 and T3. It shows that their ratio of input variables to output variables was appropriate and their input resources utilization was applied efficiently. The constraint is binding and the slack or surplus value equal to zero. Table 13 depicts the slack or surplus variables result where three fishing terminals were identified as inefficient due to inappropriate application of input resources and outputs.

Although these three terminals obtained a score of 1, nonetheless it is found that there was such an inefficiency under slack variable analysis with non-zero slacks. C1 was found to have surplus variables and a shortage in the output variable. The result indicates that C1 would need to reduce its draft depth by 0.159182 meters. Nevertheless, despite this input reduction, it is unable to move C1 to the frontier target. Hence, in order to achieve efficiency, the fishing terminal should also enlarge its tonnage by 46.53%. From that, it is expected that the result will yield an output DEA slack after it shifted to VRS frontier by input reduction.

For other inefficient terminals like K1 and T1, the result shows that there is a shortfall in tonnage and revenue. K1 and T1 cannot reduce any input but have to augment tonnage by 278.34% and 145.75% respectively. For other output variables, they must increase their revenue by 98.94% and 39.44%.

Table 13: Slack variable analysis result for inefficient fishing terminals for DEA-BCCI

	Chendering 2012 (C1)	Kuala Kedah 2012 (K1)	Tok Bali 2012 (T1)
Excess T.A	0	0	0
Excess B.L	0	0	0
Excess D	0.159182	0	0
Excess S.A	0	0	0
Excess A.L	0	0	0
Excess G.L	0	0	0
Excess T	0	0	0
Excess F	0	0	0
Excess S.T.C	0	0	0
Excess S.C	0	0	0
Excess S	0	0	0
Excess F.T	0	0	0
Shortage T	4118.15	5044.83	54260.07
Shortage R	0	6699062	38319682

Note: Excess-T.A: Terminal Area; B.L: Berth Length; D: Draft; S.A: Storage Area; A.L: Average Labour; G.L: Gate Lane; T: Trolley; F: Forklift; S.T.C: Shore to Sea Crane; S.C: Shore Crane; S: Slider; F.T: Fish Tray; Shortage–T: Tonnage; R: Revenue

4.3.4. Efficiency and size of the fishing terminal

It is interesting to examine the relationship between efficiency and terminal size under the DEA-BCCI assumption that a larger terminal size tends to score higher efficiency scores. The finding suggested that large fishing terminals are not necessarily more efficient than smaller ones. This result can be seen from Table 13 where Chendering has shown an increasing return to scale in 2012 and non-zero slack in input and output variable. Therefore, it can be concluded that there is no significant relationship between terminal size and efficiency, and that technical efficiency and terminal size are not the main factors of efficiency.

5. Conclusion

The empirical result depicts that there is a shortfall of output under CRS and VRS slack variable analysis. Output augmentation is necessary, however, the input function cannot have reduced, but more to augment the output to be more efficient. This is a challenging task as a fishing port is the only port that depends solely on ocean products. Any shortfall of catch or restriction on fishing fleet could cause a decrease in the fish landing which would eventually affect the performance of fishing port to be less economical. Nevertheless, in this case, the recommendation is hard to be suggested given that this study is conducted under input orientation. The only way left is to upgrade or sustain the existing inputs to increase the catch. On the output side, port management should pay more attention to existing fishing vessel capacity in harvesting fish and the size of the fishing fleet. To overcome a shortfall in revenue, the diversification of port income is necessary. Apart from upgrading the existing facilities, port management may introduce a multi-operation facility by exploring other possibilities such as hosting marine-related activities. This can be done by giving access to the port for other potential users such as eco-fishing tourism, marine transport and supports offshore fish farming. Fishing port like Tok Bali, for example, has the potential to turn into a supply base for offshore support activities. For input reduction, it is hard to provide any recommendation about the reduction of inputs, since it is linked with the depth of berth, terminal size, storage area and cranes. In order to improve its overall performance, new measures could be introduced for income sources, as well as fully utilize the inputs. For those efficient fishing ports, they need to adapt to frequently changing demands of fishermen and customers to stay efficient. On the other hand, it is advisable for inefficient ports to develop better strategies to utilize their input resources effectively.

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Compliance with ethical standards

Conflict of interest

The authors declare that they have no conflict of interest.

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