Analysis of the Operational Efficiency of International Logistics Hub Ports

Yong-Jeong Kim
Senior Researcher
Sogang Business Research Institute, Sogang University
Baekbeom-ro 35, Mapo-Gu, Seoul, 04107, Korea

Silvana Trimi*
Associate Professor
College of Business Administration, University of Nebraska-Lincoln
730 N. 14th Street, Lincoln, NE 68588-0405 USA

Sang-Gun Lee
Professor
Sogang Business School, Sogang University,
Baekbeom-ro 35, Mapo-Gu, Seoul, 04107, Korea

Abstract

The COVID-19 pandemic has created unprecedented challenges for the world and has significantly disrupted global supply chains, including maritime transportation. It is imperative to continue making major changes in the role and efficiency of international logistics ports to support global supply chains, especially for the post-pandemic period. This study explores the key factors that affect the efficiency of international logistics hub ports. Specifically, we applied two different models of data envelopment analysis (DEA) to evaluate 21 container terminals of four international hub logistics ports in Northeast by examining the relationships between ports' facility factors and annual cargo volume. The models delineated efficient container terminals from inefficient ones, as well as the effect of different economies of scale. The study results provide strategic insights to government policy makers for making investment decisions to enhance the competitiveness of international hub ports/infrastructures and port managers for improving the operational efficiencies of container terminals.

Keywords: COVID-19, Logistics, Hub Port, Container Terminal, Efficiency, DEA

1. Introduction

The COVID-19 pandemic has created unprecedented challenges for every person and organization in the world. COVID-19 has disrupted supply chains that caused changes in people's consumption patterns, leading to new challenges to industries and their distribution structures (Andrew et al., 2020). China, a central player in the global supply chain, was reeling soon after the wide spread of COVID-19 around the world, impacting the economy of almost every country (Al-Mansour and Al-Ajimi, 2020). Not many people would have imagined that a single vessel stuck at the Suez Canal would disrupt one of the most vital maritime trade routes for that long (USA TODAY, 04/07/2021). The Suez Canal disaster in March 2021, climate change, and political instabilities at different parts of the world, in addition to the pandemic crisis, are reminders of the fragility of global supply chains. These are not transitory phenomena, but rather triggers of disruptions and reorganizations in the global economy and the entire industrial supply chain. Consequently, the global supply chain and its dependence on Northeast Asia, especially the role and operational efficiency of international logistics ports in this area, should be carefully examined (The Economist, 03/26/2021).

For the last two decades, global sourcing and overseas production by multinational firms have grown exponentially, with the support of the World Trade Organization (WTO), Free Trade Agreements (FTAs), and Regional Economic Integration (REI). Ports play a vital role for international trade and operations of global supply chain (Bachkar and Lam, 2021). The number, size, and competition among container ports have consistently risen and so has the volume of trade, and therefore, the demand for efficient operation of container terminals (Pancapakesan et al., 2021). To achieve economies of scale, ports and vessels are becoming increasingly larger. The increased size of vessels requires special routes, ports, and dock facilities (Lee et al., 2020; Wu and Goh, 2010). Upscaling these maritime facilities is very costly, thus negatively affecting the existing port facilities. Asian ports handle an enormous amount of transportation to support the manufacturing hub of the world. In Northeast Asia, China is continuously expanding hub ports and upgrading their facilities in Shanghai, Shenzhen, Ningbo, and Hong Kong. Japan has always been a stable place that attracts cargo transshipment and for creating new routes. Japan has been expanding and modernizing logistics facilities through artificial intelligence (AI)-supported container terminals and other advanced digital technologies (Itoh, 2002). South Korea has also been making significant national efforts to develop itself as a regional logistics hub in Northeast Asia.

There have also been several important studies that dealt with maritime transportation outside of Asia. Turner et al. (2004) studied the measurement of port infrastructure productivity growth in North America from 1984 to 1997 and the exploration of several causal relationships between infrastructure productivity and industrial structure. The study supported the existence of economies of scale in container ports. Chang and Tovar (2014) measured technical efficiency of port terminals in Peru and Chile to evaluate the influence of certain specific explanatory variables that may contribute to reducing inefficiency. The study found that the higher the containerization index, the greater the occupancy rate and the higher the bulk rate, thus resulting in the improved efficiency of terminals. The authors also found that the inefficiency of terminals was lower when they were in the private ownership. According to studies by Ferreira et al. (2018) and Saeedi et al. (2019), economic globalization has stimulated the development of ports and shipping companies in most parts of Europe, Asia, Africa and North America.

Previous studies explored the various aspects of port efficiency (Ahmed and Mohamed, 2019; Chudasama, 2010; Cullinane and Wang, 2010; Ha, 2009; Kim et al., 2011; Koo et al., 2011; Lee et al., 2015; Lee and Park, 2013; Na and Qing, 2010; Park et al, 2017; Ryoo, 2005; Song and Sin, 2005; Wu and Goh, 2010). However, most of them focused on efficiency on either a single port or on the general port basis. In this research, we focus on comparing the efficiency of competing ports (rather than efficiency of a singular port), and we conduct analyses on the container terminal basis (rather than the overall port). Most of the previous studies neglected the influence of the unique characteristics of the regions and ports under analysis, and therefore, their selection of inputs might be inappropriate. In this study we analyze the input and output coefficients of ports that are similar in size, geography/region, and competitive goals. Ports analyzed in this study are all from Northeast Asia that have the same basic goal of becoming the preeminent transshipment cargo hub port in the region. The focus of the analysis is the operational efficiency of individual container terminals (piers) and not the entire port, unlike previous studies. Thus, our sample includes 21 container terminals (piers) from four representative ports in Northeast Asia: Busan North Port, South Korea; Busan New Port, South Korea; Hong Kong Port; and Shanghai Port, China. The results of the study provide strategic insights for port management and expansion decisions by government agencies and port authorities.

This study applied the Data Envelopment Analysis (DEA) models proposed by Charnes, Cooper and Rhodes (CCR) (1978) and Banker, Charnes, and Cooper (BCC) (1984). The DEA model has been widely used in logistics research. For example, Rajak et al. (2021) evaluated the efficiency of sustainable transportation systems from the perspective of supply chains. Hassan and Oukil (2021) designed an efficient system of product handling equipment for supply chains and logistics facilities. Vishnu et al. (2020) evaluated the operational efficiency of logistics firms.

The rest of this paper is organized as follows. In Section 2 we review literature to identify the key variables used to measure port efficiency. In Section 3, we present the research methodology used in the study, as well as the sample characteristics and measuring variables. Section 4 presents the results of the study, followed by Section 5 which discusses the finding of the study. Section 6 concludes the study by providing implications of the study results, as well as limitations and future research needs.

2. Literature Review

2.1 Organizational Efficiency

When assessing the performance or competitiveness of an organization, efficiency measurement is important in two respects. First, efficiency can be used as an indicator of the organization's success in terms of its sustainability (Anthony and Dearden, 1976). Second, the assessment process can help the organization identify the critical success factors (CSFs) of efficiency improvement. Identifying CSFs for the causes of difference in efficiency is essential for establishing goals and strategies of the organization (Lee and Oh, 2010).

In economics, the concept of efficiency refers to the analysis of system inputs and outputs for two basic goals (Cabral, 2000; Church and Ware, 2000; Holmstrom and Tirole, 1989; Schmalensee, 1989; Tirole, 1989): (1) maximizing output with a given amount of input available, and (2) achieving a specific level of output with the minimum possible amount of input. High efficiency means achieving a certain goal at a minimal cost. Thus, a firm's efficiency (or productivity) can be measured by output as a percentage of input, or the minimum cost required to achieve a target (Park, 2008). While these definitions are useful to evaluate the efficiency of single-input and single-output systems, they are not appropriate to measure the efficiency of systems with multiple inputs and outputs. When a system produces multiple outputs with multiple inputs, the efficiency needs to be determined by using the combination of inputs (Charnes et al., 1985). Charnes et al. (1978) did exactly that by applying the concept of efficiency suggested by Farrell (1957) in the DEA-CCR (Data Envelopment Analysis by Charnes, Cooper and Rhodes) model. They presented an analytical method where, to determine the relative efficiency, the best weights are chosen according to the judgement of the decision-making unit (DMU).

2.2 Efficiency Measurement

To build the theoretical support for our study, we reviewed previous studies that analyzed the efficiency of ports and container terminals based on DEA. The purpose of the review (summarized in Table 1) was to identify input and output variables used for efficiency analysis in these studies.

Table 1: Previous studies on port efficiency using DEA

Researcher	Port and terminal	Input variables	Output variables	DEA model
Ryoo (2005)	9 terminals of Busan	Number of employees	Container throughput	CCR BCC; SE
Song & Sin (2005)	60 ports of the world	Berth length, Total area, Number of G/C, CFS area, Average work time	Container throughput	CCR, BCC
Lee & Seo (2006)	17 terminals of Korea	Handling capacity, Berth length, Total area, Number of C/C	Container throughput	CCR, BCC Malmquist
Kim et al. (2007)	20 ports of Chinese	Number of employees, Number of berths, Number of C/C	Container throughput	CCR, BCC
Lee et al. (2008)	24 ports of Korea, Chinese and Japan	Number of berths, Berth length, Port depth, Number of C/C, Total area	Container throughput	CCR, BCC Malmquist
Ha (2009)	12 ports of Northeast Asia	Number of berths, Port depth, CFS area, Number of C/C	Container throughput	CCR, BCC Malmquist
Ablanedo-Rosas et al. (2010)	11 ports of Chinese	Return on equity, Total asset turnover, Accounts receivable turnover	Financial ratios	CCR, BCC
Chudasama (2010)	12 ports of India	Number of cranes and other equipment, Number of vessels handled, Number of berths, Storage area.	Cargo volume in thousand tons	CCR, BCC
Cullinane & Wang (2010)	25 ports of the world	Berth length, Terminal area, Number of C/C	Container throughput	CCR, BCC
Na & Qing (2010)	9 ports of Korea and Chinese	Handling capacity, Berth length, Terminal area, Number of C/C	Container throughput	CCR, BCC Malmquist
Wu & Goh (2010)	35 ports of G7 and emerging country	Terminal area, Berth length, Number of C/C	Container throughput	CCR, BCC
Kim et al. (2011)	27 ports and 57 terminals of Korea	Berth length, Number of berths, Port depth	Container throughput	CCR, BCC
Koo et al. (2011)	27 ports of Korea, Chinese and Japan	Number of berths, Berth length, Port depth, Total area, Number of C/C	Container throughput	CCR, BCC
Lee et al. (2012)	10 ports of Asia	Number of berth, Berth length, Port depth, Number of C/C, Total area	Container throughput	CCR, BCC
Kim et al. (2013)	12 terminals of Busan and Gwangyang	Number of C/C, Number of T/C, Number of Y/T, Number of R/S	Container throughput	AHP/DEA-AR

Lee & Park (2013)	28 ports of the world	Number of berths, Number of C/C, CFS area, Storage	Container throughput, Throughput per berth length	CCR, BCC
Lee et al. (2015)	16 ports of Northeast Asia	Number of berths, Berth length, Terminal area, Number of C/C	Container throughput	CCR, BCC
Lee et al. (2015)	22 ports of Northeast Asia	Number of berths, Berth length, Port depth, Total area, Number of C/C	Container throughput	CCR, BCC
Park (2016)	33 ports and 68 terminals of the world	Berth length, Total area, Number of G/C, Yard cranes, CFS area	Container throughput	CCR, BCC
Park et al. (2017)	25 ports of ASEAN	Total Area, Number of berths, Berth length, Number of C/C	Container throughput	CCR, BCC Shannon's Entropy (SBM)
Ahmed & Mohamed (2019)	20 ports of Middle East	Berth length, Terminal area, Port depth	Container throughput	CCR BCC; SE

Note: C/C (Container Crane), G/C (Gantry Crane), T/C (Transfer Crane), Y/T (Yard Tractor), R/S (Reach Stacker), CFS (Container Freight Station)

The key to efficiency analysis with the DEA model is two-fold: finding input/output variables and selecting the appropriate analysis targets (Charnes et al., 1997). While previous studies attempted to measure the efficiency of ports with a variety of methods, the types of ports they selected for analysis were varied widely. Therefore, the input variable suitability for some of these DEA studies is questionable, since analyzed ports were quite different. For example, using the input variable of Port Depth for all ports could be meaningless as some of them were not at all similar in size and characteristics. Measuring port size with either the total number of berths or vessel size accommodated makes the efficiency analyses conclusion of these studies to have limited value in terms of operational implications because their variables do not affect the efficiency of ports that exceed a certain number of berths or vessel size. Also, most of the studies used only the total number of berths, which is not a reasonable input variable. Some of the studies used the total area of berths (instead of numbers) as an input variable since the number of berths is considered replaceable by the lengths of berths. We believe that the CY (container yard) area is a more realistic input variable than the number of berths or total area, thus, in this study we used it as an input variable. In order to accurately compare and determine the efficiency of ports and identify factors for efficiency, we considered port size, region/geography, and competitive strategies. Our sample included ports from two countries in the same region, South Korea and China. Both countries strive to have preeminent hub ports in Northeast Asia.

3. Methodology

3.1 Research Methodology

This study used DEA (data envelopment analysis) as the research methodology. DEA is a nonparametric method that uses input and output variables of the decision-making unit (DMU) to measure relative inefficiency through linear programming.

The principles of DEA were first introduced by Farrell (1957) when the study measured technical efficiency (TE) and allocated efficiency (AE). Based on Farrell's pioneering work, Charnes et al. (1978) developed the CCR model which assumes constant returns to scale (CRS). However, the CCR model is suitable only for a situation where the organization is operating at the optimal scale. Therefore, Banker et al. (1984) proposed the BCC model that overcomes the limitations of the CCR model by accounting for variable returns to scale (VRS). Park (2008) developed the efficiency and productivity analysis system (EnPAS) as a tool for easy applications of DEA.

3.2 Research Model

3.2.1 DEA-CCR model

Charnes et al. (1978) proposed the CCR model, a basic DEA model to determine the optimal weights of multiple inputs and outputs by computing the ratio of the sum of all weighted outputs to the sum of all weighted inputs. In short, the relative efficiency h_k of DMU $(k = 1,2,3,\cdots,n)$ is measured by selecting s output variables

$y_{rk}\,(r = 1,2,3,\cdots,s)$ and m input variables $x_{ik}\,(i = 1,2,3,\cdots,m)$ for n's DMU $(k = 1,2,3,\cdots,n)$. Under efficiency condition constraints, where $\hbar_k = 1$ and the ratio of output to input is less than or equal to 1, the weighted values v_i and u_r of the inputs and outputs are calculated to measure efficiency as shown in the following linear fractional planning model.

$$(FP_n) Max\hbar_n = \frac{u_1y_{1k}+u_2y_{2k}+\cdots\cdots+u_sy_{sk}}{v_1x_{1k}+v_2x_{2k}+\cdots\cdots+v_mx_{mk}} = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \quad (1)$$

$$Subject\ to \frac{u_1y_{1k^1}+u_2y_{2k^2}+\cdots\cdots+u_sy_{sk^n}}{v_1x_{1k^1}+v_2x_{2k^2}+\cdots\cdots+v_mx_{mk^n}} = \frac{\sum_{r=1}^{s} u_r y_{rk^n}}{\sum_{i=1}^{m} v_i x_{ik^n}} \le 1 \ \ (k = 1,\cdots,n)$$

$$v_i \ge \epsilon \ge 0 \ \ (i = 1,\cdots,m)$$

$$u_r \ge \epsilon \ge 0 \ \ (r = 1,\cdots,s)$$

where $\hbar_n$: efficiency of DMUk^n
v_i: weight for the *i-th* input variable
u_r: weight for the *r-th*output variable
x_{ik^n}: amount of the *i-th* input to the DMUk^n
y_{rk^n}: amount of the *r-th* output to the DMUk^n
ϵ: non-archimedian constant
n: number of DMUs
m: number of input variables
s: number of output variables

Maximization of a linear fractional planning model, as expressed by formula (1), is difficult to solve if the optimization of an infinite number is required or an extremely large number of subjects needs to be evaluated. Therefore, to solve such problems, the sum of the weighted inputs of the objective function is set to 1. Formula (2) presents the transformed CCR model with the converted constraint in the modified linear programming formulation.

$$(LP_n)\ Max\hbar_n = \sum_{r=1}^{s} u_r y_{rk} \quad (2)$$

$$s.t. \sum_{r=1}^{s} u_r y_{rk^n} - \sum_{i=1}^{m} v_i x_{ik^n} \le 0 \ \ (k = 1,\cdots,n)$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1$$

$$u_r \ge \epsilon \ge 0,\ v_i \ge \epsilon \ge 0,\ \forall_{r,i}$$

3.2.2 DEA-BCC model

Banker et al. (1984) recognized the practical limitations of the CRS (constant returns to scale) assumption of the CCR model. Thus, in BCC, the model incorporates the notion of variable returns to scale (VRS). The BCC model can estimate the impact of scale size and separate it from technical efficiency (TE) to measure pure technical efficiency (PTE) (which ignores scale size efficiency). The BCC model can identify whether the cause of inefficiency is due to pure technical factors or the impact of scale size. The BCC model is shown in Formula (3):

$$(FP_n)\ Max\hbar_n = \frac{\sum_{r=1}^{s} u_r y_{rk} + u_k}{\sum_{i=1}^{m} v_i x_{ik}} \quad (3)$$

$$s.t. \frac{\sum_{r=1}^{s} u_r y_{rk^n}}{\sum_{i=1}^{m} v_i x_{ik^n}} \le 1 \ \ (k = 1,\cdots,n)$$

$$v_i \ge \epsilon \ge 0 \ \ (i = 1,\cdots,m)$$

$$u_r \ge \epsilon \ge 0 \ \ (r = 1,\cdots,s)$$

To convert the linear fraction programming model shown in Formula (3) into a general linear programming problem, we set the sum of weighted inputs (the denominator of the objective function) to 1, as shown in Formula (4).

$$(LP_n)\ Max\hbar_n = \sum_{r=1}^{s} u_r y_{rk} + u_k \quad (4)$$

$$s.t. \sum_{r=1}^{s} u_r y_{rk^n} - \sum_{i=1}^{m} v_i x_{ik^n} + u_k \le 0 \ \ (k = 1,\cdots,n)$$

$$\sum_{i=1}^{m} v_i x_{ik} = 1$$

$$u_r \geq \epsilon \geq 0,\ v_i \geq \epsilon \geq 0,\ \forall_{r,i}$$

If the scale index u_k is excluded from the above BCC model, it will be identical to the CCR model. The scale index u_k is used as an indicator of the economies of scale. If the optimal solution and the measured scale index is u_k^*,

$u_k^* = 0$:CRS (Constant Returns to Scale)
$u_k^* > 0$:DRS (Decreasing Returns to Scale)
$u_k^* < 0$:IRS (Increasing Returns to Scale)

3.2.3 Scale efficiency

The efficiency calculated by the CCR model and BCC model is h_{CCR}^* and h_{BCC}^*, respectively. If the scale index u_k is excluded from the above BCC model, calculated efficiency will be identical to that of the CCR model. If the measure of DMU technical efficiencies (TE) in the CCR model and BCC model are different, scale inefficiency exists. Thus, scale inefficiency can be obtained from the ratio between the efficiencies in the BCC model and the CCR model as follows:

$$SE(\text{Scale Efficiency}) = \frac{h_{CCR}^*}{h_{BCC}^*} \qquad (5)$$

Generally, the measure of efficiency in the CCR model (h_{CCR}^*) is less than or equal to that of the BCC model (h_{BCC}^*), and, thus, the value for scale efficiency is less than or equal to 1. Figure 1 illustrates the CCR and BCC frontiers. Point A on the BCC frontier is a technically efficient DMU that indicates Increasing Returns to Scale (IRS). Scale efficiency (SE)=LM / LA, the representation of $h_{CCR}^*(A)$, indicates scale inefficiency. DMU F is beyond both CCR and BCC frontiers, indicating that it is inefficient in respect to both technical and scale. As a result, point F is moved to F' on the BCC frontier or to Q on the CCR frontier so that technical efficiency is achieved. Thus, the DMU reference for achieving scale efficiency includes B and C. Both DMU B and C are located on the CCR and BCC frontiers and can be seen as the points where both technical and scale efficiencies are achieved.

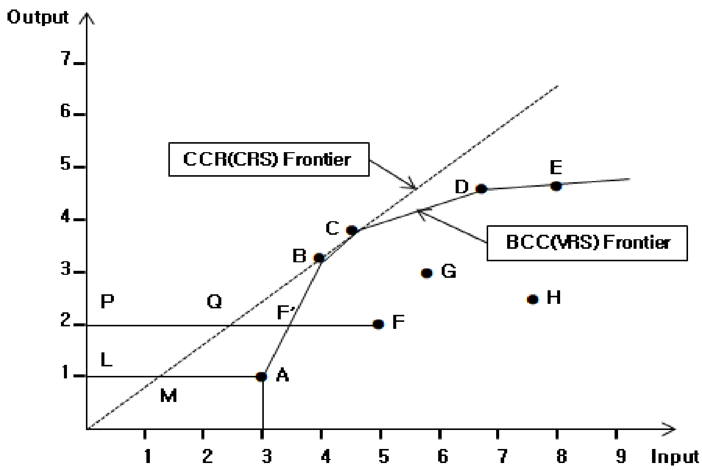

Fig. 1. CCR, BCC efficiency frontiers

3.3 Selection of Samples and Variables

To apply DEA, inputs and outputs must be measurable and DMUs should be homogeneous and comparable. Thus, we need to carefully select and manage model variables. To ensure the predictive ability of DEA models, previous studies suggested that the number of DMUs should be at least twice the sum of inputs and outputs (Banker et al., 1984; Busofance et al., 1991; Fitzsimmons and Fitzsimmons, 1994; Park, 2008).

3.3.1 Samples

To conduct port efficiency analysis, this study selected four top international trade ports based on the Ranking of Container Ports of the World, published by the World Shipping Council (03/26/2020). As previously mentioned, to control for size, unit of analysis was container terminals, not the overall port.

We selected 21 container terminals from the four ports that are currently competing to become the preeminent transshipment cargo hub port in Northeast Asia (Busan North Port, South Korea; Busan New Port, South Korea; Hong Kong Port; Shanghai Port, China) as shown in Table 2.

Table 2: Research sample DMUs

Section	Port / Container terminal	
1	Busan North Port	Jasungdae Pier
2		Shinsundae Pier
3		Gamman Pier
4		Shingamman Pier
5	Busan New Port	New Pier 1
6		New Pier 2
7		New Pier 3
8		New Pier 4
9		New Pier 5
10	Hong Kong Port	Modern Terminals
11		Goodman DP World
12		HIT Terminals
13		COSCO-HIT Terminal
14		ACT Terminal
15	Shanghai Port	Pudong
16		Zhendong
17		Hudong
18		Mingdong
19		Shengdong
20		Guandong
21		Yidong

3.3.2 Variables

As the selection of inputs and outputs affects the predictive ability of the DEA model, it should be managed carefully to support the purpose of analysis (Kim and Park, 2013; Lee et al., 2004; Park, 2008). Because efficiency analysis can accommodate only a limited number of variables into consideration, it is important to consider the strength of association between input and output variables (Lee et al., 2004; Lee et al., 2009). Thus, in this study, we first considered those variables that are most frequently selected as inputs and outputs by previous studies (see Table 3). Then, we selected an appropriate number of variables that would not violate the constraints for the number of DMUs as it should be twice that of input variables (see Table 4).

Table 3: List of the variables employed by previous studies and their selection frequency

Variable Type	Variable selection		Frequency
Input variables	Equipment-related	Number of C/C, Number of T/C, Number of Y/T, Number of R/S	16
	Berth-related	Number of berths, Berth length, Quay length	15
	Area-related	Total area, CY area, CFS area, Terminal area	12
	Depth-related	Port depth	7
	Employee-related	Number of employees	2
	Others	Wages, Salary, Selling cost, Capital amount, Terminal Handling Charge, Freight	
Output variables	Cargo volume-related	Total cargo volume, Container throughput	16
	Sales-related	Sales	2

Note: C/C (Container Crane), T/C (Transfer Crane), Y/T (Yard Tractor), R/S (Reach Stacker), CY (Container Yard), CFS (Container Freight Station)

Table 4: Most frequently used variables

Input variables	Output variables
Port depth, Berth length, Number of berths, Total area, CY area, CFS area, Number of equipment	Container throughput, Sales

As seen in Table 3, the most frequently selected input variables were: total area, CY area, CFS area, number of berths, and berth length; and the most frequently selected output variable was annual container throughput. Based on previous studies, this study derived 9 variables: seven input and two output variables (see Table 4). Since the number of DMUs (i.e., 21) is greater than twice the sum of inputs and outputs (18), the size of our sample is satisfactory for the predictability of the DEA model.

Among the selected variables for our model (Table 4), port depth as an input does not affect the output variables because it is a basic condition that all ports in our sample meet. The number of berths is not a proper input either because it is measured based on the number of vessels of different sizes. Therefore, we replaced the number of berths with berth length. As for total area, all previous studies applied both CY area and CFS area as area-related variables. However, we considered CY and CFS as the actual areas of operation and, consequently, they are the variables that more accurately measure the operational area than total pier (terminal) area. Also, because different ports measure the CFS area of container terminals with different units, CFS is deemed inappropriate to use as an input. Thus, the only area-related input that we used in this study is CY area.

Another input variable for efficiency is handling equipment. However, the types of handling equipment vary considerably. There was no definitive data for the status of common handling equipment in each container terminal in our sample. The only handling equipment data available from all our sample ports was container crane (C/C; G/C: Q/C), which was used as an input variable for equipment handling.

As for the output variable, this study selected only (annual) container throughput because it is considered the most representative measure for evaluating the efficiency of logistics facilities with facility-related inputs. Many previous studies confirmed that the annual container throughput is an inarguably proper output variable in the field of logistics facilities.

Finally, we verified the practical feasibility of the input and output variables selected based on literature review. The verification process involved interviews with four port and shipping logistics experts (one expert at the Busan Port Authority, one executive of Busan New Port Company, one freight forwarding manager, and one professor specializing in maritime transportation). The significance of DMU selection and the validity of selected variables were also confirmed. The final input and output variables selected through the above process are shown in Table 5.

Table 5: Selected input and output variables of the study

Input variables	Output variable
I_1: Berth length I_2: CY area I_3: Number of C/C	O_1: Annual container throughput

3.3.3 Input data

This study collected DEA input data from the selected DMUs and analytical data on inputs and outputs utilized the International Association of Ports and Harbors' (IAPH) database. The annual container throughputs for three container terminals (HIT, COSCO-HIT, ACT terminal) at the Port of Hong Kong were combined and presented together as an integrated output. The data of these three container terminals at the Port of Hong Kong was analyzed as a whole. The DEA inputs are shown in Table 6.

Table 6: DEA input data

Section		I_1	I_2	I_3	O_1
Busan North Port	Jasungdae Pier	1,447m	335,000㎡	14	1,926,000TEU
	Shinsundae Pier	1,500m	804,000㎡	15	1,954,000TEU
	Gamman Pier	1,400m	384,000㎡	13	1,171,000TEU
	Shingamman Pier	826m	153,000㎡	7	970,000TEU
Busan	New Pier 1	1,200m	282,000㎡	11	2,477,000TEU

New Port	New Pier 2	2,000m	525,000㎡	19	4,938,000TEU
	New Pier 3	1,100m	346,000㎡	12	2,770,000TEU
	New Pier 4	1,150m	213,000㎡	12	2,061,000TEU
	New Pier 5	1,400m	154,000㎡	11	2,269,000TEU
Port of Hong Kong	Modern Terminal	2,322m	926,100㎡	30	7,000,000TEU
	Goodman DP World	305m	167,000㎡	4	1,200,000TEU
	HIT Terminals	3,687m	1,110,000㎡	48	10,090,000TEU
	COSCO-HIT Terminal	640m	300,000㎡	9	
	ACT Terminal	740m	285,400㎡	8	
Port of Shanghai	Pudong Terminal	900m	500,000㎡	11	2,600,000TEU
	Zhendong Terminal	1,565m	1,080,000㎡	26	6,520,000TEU
	Hudong Terminal	1,250m	980,000㎡	17	4,100,000TEU
	Mingdong Terminal	2,068m	1,126,000㎡	26	6,200,000TEU
	Shengdong Terminal	3,000m	1,486,000㎡	34	8,855,000TEU
	Guandong Terminal	2,600m	1,418,000㎡	30	7,555,700TEU
	Yidong Terminal	1,641m	611,000㎡	14	4,000,000TEU

4. Results

4.1 The CCR Model Results

The CCR model assumes constant returns to scale (CRS). In this study, we used both the input-oriented and output-oriented CCR models for the analysis and computed the excess inputs and output shortages. We also analyzed the reference set to find out which of the DMUs were efficient, by comparing them with the suggested benchmark value.

4.1.1 The CRS efficiency analysis

The results of the efficiency index analysis (Table 7) indicated that only four of the container terminals, Busan New Port (Pier 2, Pier 5), the Port of Hong Kong (Goodman DP World), and the Port of Shanghai (Zhendong), were efficient. The other 15 container terminals, Busan North Port (Jasungdae, Shinsundae, Gamman, and Singamman), Busan New Port (Pier 1, Pier 3, and Pier 4), the Port of Hong Kong (Modern and HIT), and the Port of Shanghai (Pudong, Houdong, Mingdong, Shengdong, Guandong, and Yidong), were found to be inefficient. It should be noted here that all 4 container terminals at Busan North Port were the most inefficient ones.

Table 7: CRS efficiency index

Section		CCR-I	CCR-O
Busan North Port	Jasungdae Pier	0.5796	0.5796
	Shinsundae Pier	0.4342	0.4342
	Gamman Pier	0.3395	0.3359
	Shingamman Pier	0.5842	0.5842
Busan New Port	New Pier 1	0.8934	0.8934
	New Pier 2	1	1
	New Pier 3	0.9202	0.9202
	New Pier 4	0.8789	0.8789
	New Pier 5	1	1
Port of Hong Kong	Modern Terminal	0.951	0.951
	Goodman DP World	1	1
	HIT Terminals	0.7013	0.7013
	COSCO-HIT Terminal		
	ACT Terminal		
Port of Shanghai	Pudong Terminal	0.7879	0.7879
	Zhendong Terminal	1	1
	Hudong Terminal	0.8269	0.8269
	Mingdong Terminal	0.7949	0.7949
	Shengdong Terminal	0.8681	0.8681
	Guandong Terminal	0.8395	0.8395
	Yidong Terminal	0.9524	0.9524

4.1.2 Reference set

In order to improve efficiency, inefficient DMUs should examine the reference set, reference weight (λ_i), and reference count. Table 8 shows the reference terminal and reference weight for each container terminal, and the reference count of efficient DMUs in the CCR model. The terminal referenced by inefficient DMUs is an efficient virtual unit. Goodman DP in the Port of Hong Kong is the most efficient DMU with 11 reference counts, followed by New Pier 2 and New Pier 5 at Busan New Port with 8 and 4 reference counts, respectively.

Table 8: Reference set analysis of CCR model

DMU		TE	Reference Set (λ_i: Input / Output)	Reference count
Busan North Port	Jasungdae Pier	0.5796	New Pier 2 (0.3341/0.5765), New Pier 5 (0.1217/0.21)	New Pier 2: (8 times) New Pier 5: (4 times) Goodman DP: (11 times) Zhendong: (1 time)
	Shinsundae Pier	0.4342	Goodman (1.6283/3.75)	
	Gamman Pier	0.3395	New Pier 2 (0.2009/0.5918), Goodman (0.149/0.439)	
	Shingamman Pier	0.5842	New Pier 2 (0.1241/0.2124), New Pier 5 (0.1575/0.2696)	
Busan New Port	New Pier 1	0.8934	New Pier 2 (0.4415/0.4942), New Pier 5 (0.1308/0.1464)	
	New Pier 3	0.9202	New Pier 2 (0.4137/0.4496), Goodman (0.606/0.6585)	
	New Pier 4	0.8789	New Pier 2 (0.2493/0.2836), New Pier 5 (0.3659/0.4163)	
Port of Hong Kong	Modern Terminal	0.951	New Pier 2 (0.576/0.6057), Goodman (3.463/3.6414)	
	HIT Terminals	0.7013	New Pier 2 (1.3273/1.8927),	

	COSCO-HIT Terminal		Goodman (2.9467/4.202)	
	ACT Terminal			
Port of Shanghai	Pudong Terminal	0.7879	Goodman (2.1667/2.75)	
	Hudong Terminal	0.8269	Goodman (2.919/3.5299), Zhendong (0.0916/0.1108)	
	Mingdong Terminal	0.7949	Goodman (5.1667/6.5)	
	Shengdong Terminal	0.8681	Goodman (7.3792/8.5)	
	Guandong Terminal	0.8395	Goodman (6.2964/7.5)	
	Yidong Terminal	0.9524	Goodman (3.3333/3.5)	

Analyzing excess inputs and output shortages can be used to calculate the target values that inefficient DMUs need to attain to become efficient. For example, for New Pier 3 at Busan New Port, we calculated the input/output target value that meets the improvement goal by multiplying the reference weights (λ_i) of the two reference sets (New Pier 2 at Busan New Port and the Port of Hong Kong's Goodman DP) by the input/output variable, and subsequently summing the products. The λ_i value derived by the CCR-I model was applied to the target input value calculation, while the λ_i value derived from the CCR-O model was applied to the target output value calculation. Formulas (6) and (7) present the calculation process.

New pier Goodman DP Input target value

$$0.4137 \times \begin{bmatrix} 2{,}000 \\ 525{,}000 \\ 19 \end{bmatrix} + 0.606 \times \begin{bmatrix} 305 \\ 167{,}000 \\ 4 \end{bmatrix} = \begin{bmatrix} 1{,}012.23 \\ 318{,}394.5 \\ 10.284 \end{bmatrix} \quad (6)$$

New pier 2 Goodman DP Output target value

$$0.4496 \times [4{,}938{,}000] + 0.6585 \times [1{,}200{,}000] = [3{,}010{,}325] \quad (7)$$

The excess input (I_i) and target value (I_i') and the output shortage (O_i) and target value (O_i') for inefficient DMUs, obtained by the above process, are shown in Table 9.

Table 9: Target input and output values for the CCR model

DMU		Excess input and output shortage				Target value			
		Input			Output	Input			Output
		I_1	I_2	I_3	O_1	I_1'	I_2'	I_3'	O_1'
Busan North Port	Jasungdae Pier	608.42	140855.7	6.313	1397247	838.58	194144.3	7.687	3323247
	Shinsundae Pier	1003.368	532073.9	8.487	2546000	496.632	271926.1	6.513	4500000
	Gamman Pier	952.755	253644.5	8.587	2278108.4	447.245	130355.5	4.413	3449108.4
	Shingamman Pier	357.3	63592.5	2.91	690553.6	468.7	89407.5	4.09	1660553.6
Busan New Port	New Pier 1	133.88	30069.3	1.173	295541.2	1066.12	251930.7	9.827	2772541.2
	New Pier 2	0	0	0	0	2000	525000	19	4938000
	New Pier 3	87.77	27605.5	1.716	240324.8	1012.23	318394.5	10.284	3010324.8
	New Pier 4	139.14	25768.9	3.238	284001.5	1010.86	187231.1	8.762	2345001.5
	New Pier 5	0	0	0	0	1400	154000	11	2269000
Port of Hong Kong	Modern Terminal	113.785	45379	5.204	360626.6	2208.215	880721	24.796	7360626.6
	Goodman DP World	0	0	0	0	305	167000	4	1200000
	HIT Terminals	1513.656	506468.6	27.995	4298552.6	3553.344	1188931.4	37.005	14388553
	COSCO-HIT Terminal								
	ACT Terminal								
Port of Shanghai	Pudong Terminal	239.156	138161.1	2.333	700000	660.844	361838.9	8.667	3300000
	Zhendong Terminal	0	0	0	0	1565	1080000	26	6520000
	Hudong Terminal	216.351	393599	2.942	858296	1033.649	586401	14.058	4958296

	Mingdong Terminal	492.157	263161.1	5.333	1600000	1575.843	862838.9	20.667	7800000
	Shengdong Terminal	749.344	253673.6	4.483	1345000	2250.656	1232326.4	29.517	10200000
	Guandong Terminal	679.598	366501.2	4.814	1444300	1920.402	1051498.8	25.186	9000000
	Yidong Terminal	624.344	54338.9	0.667	200000	1016.656	556661.1	13.333	4200000

4.2 The BCC Model Results

As previously mentioned, the BCC model assumes variable returns to scale (VRS). Like the CCR model, BBC models apply both the input-oriented and output-oriented data to analyze the efficiency. To examine the scale size efficiency (SE), we compared the results of the efficiency analysis of CRS and VRS for the type of returns to scale (RTS), excess inputs, output parameters (output shortage and target value), and compared the efficiency with the reference set that the inefficient DMUs should benchmark.

4.2.1 Comparison of CRS and VRS efficiency analysis

In the previous section, the CCR model identified four container terminals as efficient DMUs: Busan New Port Pier 2, Busan New Port Pier 5, Port of Hong Kong Goodman DP World, and Port of Shanghai Zhendong.

The BCC model, which takes scale efficiency (SE) into account when measuring technical efficiency (TE), identified nine container terminals as efficient DMUs, the above four, plus five additional terminals: Shingamman of Busan North Port, Modern and HIT of the Port of Hong Kong, and Shengdong and Yidong of the Port of Shanghai. Busan North Port terminals (Jasungdae, Shinsundae, and Gamman), Busan New Port terminals (New Pier 1, New Pier 3, and New Pier 4), and Port of Shanghai terminals (Pudong, Hudong, Mingdong, and Guandong) were identified as relatively inefficient DMUs. The three container terminals at Busan North Port showed particularly high degrees of inefficiency compared to other ports' container terminals. The VRS efficiency index is presented in Table 10.

Table 10: VRS efficiency index

DMU		CRS	VRS		SE		RTS	
		CCR-I,O	BCC-I	BCC-O	BCC-I	BCC-O	BCC-I	BCC-O
Busan North Port	Jasungdae Pier	0.5796	0.5857	0.581	0.9896	0.9976	IRS	IRS
	Shinsundae Pier	0.4342	0.4462	0.4717	0.9731	0.9205	DRS	DRS
	Gamman Pier	0.3395	0.4198	0.3398	0.8087	0.9991	IRS	DRS
	Shingamman Pier	0.5842	1	1	0.5842	0.5842	IRS	IRS
Busan New Port	New Pier 1	0.8934	0.9033	0.901	0.989	0.9916	IRS	IRS
	New Pier 2	1	1	1	1	1	CRS	CRS
	New Pier 3	0.9202	0.921	0.9239	0.9991	0.996	DRS	DRS
	New Pier 4	0.8789	0.885	0.8832	0.9931	0.9951	IRS	IRS
	New Pier 5	1	1	1	1	1	CRS	CRS
Port of Hong Kong	Modern Terminal	0.951	1	1	0.951	0.951	DRS	DRS
	Goodman DP World	1	1	1	1	1	CRS	CRS
	HIT Terminals	0.7013	1	1	0.7013	0.7013	DRS	DRS
	COSCO-HIT Terminal							
	ACT Terminal							
Port of Shanghai	Pudong Terminal	0.7879	0.8605	0.8696	0.9156	0.906	DRS	DRS
	Zhendong Terminal	1	1	1	1	1	CRS	CRS
	Hudong Terminal	0.8269	0.9191	0.9226	0.8997	0.8963	DRS	DRS
	Mingdong Terminal	0.7949	0.9159	0.9196	0.8679	0.8644	DRS	DRS
	Shengdong Terminal	0.8681	1	1	0.8681	0.8681	DRS	DRS
	Guandong Terminal	0.8395	0.9639	0.9653	0.8709	0.8697	DRS	DRS
	Yidong Terminal	0.9524	1	1	0.9524	0.9524	DRS	DRS

4.2.2 Reference set

Reference set analyses results with BCC models are shown in Table 11. As seen, in the BCC-I model, based on reference counts, Hong Kong Goodman DP has 8 efficient DMUs, Yidong Containers Terminal at the Port of Shanghai has 5, New Pier 2 at Busan New Port has 2, and New Pier 5 at Busan New Port and Zhendong Container Terminal at the Port of Shanghai each has 4 reference counts. While the BCC-O model found that Goodman DP has 8 reference counts, Yidong Container Terminal at the Port of Shanghai has 6, New Pier 2 at Busan New Port and Zhendong Container Terminal at the Port of Shanghai have 5 each, and New Pier 5 at Busan New Port has 3.

Table 11: Reference set analysis of the BCC model

DMU		SE		Reference Set (λ_i: Input / Output)	Reference count	
		BCC-I	BCC-O		BCC-I	BCC-O
Busan North Port	Jasungdae	0.9896	0.9976	New pier 2 (0.0943/0.4802), New pier 5 (0.3495/0.2997), Goodman (0.5562/0.2202)	Shingamman: (1 time) New Pier 2: (4 times) New Pier 5: (4 times) Goodman DP: (8 times) Zhendong: (4 times) Shengdong: (2 times) Yidong: (5 times)	New Pier 2: (5 times) New Pier 5: (3 times) Modern: (1 time) Goodman DP: (8 times) Zhendong: (5 times) Shengdong: (2 times) Yidong: (6 times)
	Shinsundae	0.9731	0.9205	Goodman (0.7307/0.0962), Zhendong (0/0.1635), Yidong (0.2693/0.7402)		
	Gamman	0.8087	0.9991	Shingamman (0.3656/0), New pier 2 (0/0.5929), New pier 5 (0.0515/0), Yidong (0/0.0107), Goodman (0.5828/0.3964)		
Busan New Port	New Pier 1	0.989	0.9916	New pier 2 (0.2559/0.3317), New pier 5 (0.2996/0.2892), Goodman (0.4444/0.3791)		
	New Pier 3	0.9991	0.996	New pier 2 (0.4102/0.4294), Modern (0.0063/0.0333), Goodman (0.5835/0.5373)		
	New Pier 4	0.9931	0.9951	New pier 2 (0.0793/0.1482), New pier 5 (0.5282/0.5423), Goodman (0.3925/0.3095)		
Port of Shanghai	Pudong	0.9156	0.906	Goodman (0.6398/0.5431), Zhendong (0.1553/0.2026), Yidong (0.205/0.2543)		
	Hudong	0.8997	0.8963	Goodman (0.3444/0.2658), Zhendong (0.4223/0.4715), Yidong (0.2333/0.2626)		
	Mingdong	0.8679	0.8644	Zhendong (0.4641/0.4357), Shengdong (0.2122/0.3386), Yidong (0.3236/0.2257)		
	Guandong	0.8709	0.8697	Zhendong (0.1666/0.1438), Shengdong (0.6459/0.7137), Yidong (0.1875/0.1415)		

The analysis results of the reference set provide the excess input, output shortage, and target values of inefficient DMUs. The process of calculating the target value (e.g., for New Pier 4 at Busan New Port in 2018) is multiply the respective reference weights (λ_i) of the reference sets (e.g., Busan New Port: New Pier 2, New Pier 5; and the Port of Hong Kong's Goodman DP) by the input/output variable, and subsequently summing the products as shown in formulas (8) and (9).

$$\begin{array}{ccccccc} & \text{New Pier 2} & & \text{New Pier 5} & & \text{Goodman} & \text{Input target value} \\ 0.0793 \times & \begin{bmatrix} 2{,}000 \\ 525{,}000 \\ 19 \end{bmatrix} & + 0.5282 \times & \begin{bmatrix} 1{,}400 \\ 154{,}000 \\ 11 \end{bmatrix} & + 0.3925 \times & \begin{bmatrix} 305 \\ 167{,}000 \\ 4 \end{bmatrix} = & \begin{bmatrix} 1{,}017.793 \\ 188{,}522.8 \\ 8.887 \end{bmatrix} \end{array} \quad (8)$$

$$\begin{array}{ccccccc} & \text{New Pier 2} & & \text{New Pier 5} & & \text{Goodman} & \text{Output target value} \\ 0.1482 \times & [4{,}938{,}000] & + 0.5423 \times & [2{,}269{,}000] & + 0.3095 \times & [1{,}200{,}000] = & [2{,}333{,}690] \end{array} \quad (9)$$

After completing the above calculations, the access input (I_i) and target value ($I_i^{'}$) of inefficient DMUs are computed by the BCC-I model, whereas output shortage (O_i) and the improvement target value ($O_i^{'}$) of the inefficient DMUs are calculated by the BCC-O model, as shown in Table 12.

Table 12: Calculation of target values by the BCC model

DMU		Excess input and output shortage				Target value			
		Input			Output	Input			Output
		I_1	I_2	I_3	O_1	$I_1^{'}$	$I_2^{'}$	$I_3^{'}$	$O_1^{'}$
Busan North Port	Jasungdae	599.459	138784.1	6.139	1389487	847.541	196215.9	7.861	3315487
	Shinsundae	835.215	517430.8	8.307	2188260	664.785	286569.2	6.693	4142260
	Gamman	848.16	222804.6	7.543	2275220	551.84	161195.4	5.457	3446220
Busan New Port	New Pier 1	133.218	27299.3	1.065	272049.4	1066.782	254700.7	9.935	2749049
	New Pier 3	87.004	27366.07	1.683	228237.2	1012.996	318633.9	10.317	2998237
	New Pier 4	132.207	24477.2	3.113	272690.3	1017.793	188522.8	8.887	2333690
Port of Shanghai	Pudong	125.412	100174.4	1.533	389872	774.588	399825.6	9.467	2989872
	Hudong	101.213	323854.9	1.376	343540	1148.787	656145.1	15.624	4443540
	Mingdong	174.056	111723.2	2.188	541867	1893.944	1014277	23.812	6741867
	Guandong	93.883	163702.1	1.083	271689.5	2506.117	1254298	28.917	7827390

5. Discussions

This study analyzed the efficiency of container terminals in international logistics hub ports that are direct competitors in Northeast Asia: two ports in Busan, South Korea; the Port of Hong Kong; and the Port of Shanghai, China. Based on previous studies, we identified the most widely used input and output variables for analyzing the efficiency of container terminals. In addition, we also considered the unique characteristics of the Northeast Asia region. Several countries in this region are competing for dominance in maritime transportation and logistics services (Yang and Chen, 2016). These countries are investing heavily in constructing new international logistics ports, expanding and modernizing the existing ports and developing supporting infrastructures. Thus, we selected three container terminal related variables as the inputs and annual container throughput, the undisputed efficiency measure, as the output variable.

The results of the BCC model were derived from a comparative analysis with the technical efficiency (TE) index of the CCR model. If the technical efficiency of the CCR model is equal to the technical efficiency (TE) index of the BCC model, the CRS (constant return scale) assumption should be adopted. Otherwise, the VRS (variable return scale) assumption should be used. VRS consists of scale efficiency (SE) and pure technical efficiency (PTE) or Increasing Returns to Scale (IRS) and Decreasing Returns to Scale (DRS), respectively. Scale inefficiency can be obtained as the difference between efficiencies derived by the BCC model and the CCR model. Our analysis results showed that the efficiency indexes of all inefficient container terminals, except for those at the Busan North Port, had insignificant differences from the efficiency indexes of efficient container terminals (0.8605-0.9653).

Container terminals at the Busan North Port, Jasungdae (0.587/0.581), Shinsundae (0.4462/0.4717), and Gamman (0.4198/0.3398) had significantly poor efficiency measures. This can be attributed to the fact that most container cargos are now directed to the Busan New Port because of its modern operational systems. Although the Busan North Port continues its operations, its primary focus is now on operating its terminals for international passenger and international cruise services rather than container terminals.

Listed in the descending order, efficient container terminal reference counts were: (1) By the BCC-I model - Goodman DP (11 times), New Pier 2 (8 times), and New Pier 5 (5 times); by the CCR-I model - Goodman DP (8 times), Yidong (5 times), New Pier 2 (4 times), New Pier 5 (4 times), and Zhendong (4 times); (2) By the BCC-O model - Goodman DP (8 times), Yidong (6 times), New Pier 2 (5 times), Zhendong (5 times), and New Pier 5 (3 times).The results of scale efficiency (SE) analysis indicated that New Pier 2 and New Pier 5 at the Busan New Port, Goodman DP at the Port of Hong Kong, and Zhendong at the Port of Shanghai had CRS (constant return to scale) as their efficiency values were found to be equal in both the CCR and BCC models, and their efficiency indexes were all equal to one, indicating that these four container terminals produced proportional increase in output when inputs were increased. However, container terminals at Busan Ports (Jasungdae, Gamman, Singamman, New Pier 1, and New Pier 4) had IRS (increasing return to scale) ($h_{CCR}^{*} < h_{BCC}^{*}$), which means that outputs at these five container terminals were proportionally greater than the changes in inputs.

Opposite was true for most of the container terminals at the Port of Shanghai and the Port of Hong Kong, which had DRS (decreasing return to scale) ($h^*_{CCR} > h^*_{BCC}$), which indicatesdiseconomies of scale where outputs increased by a smaller proportion than increases in inputs.

6. Conclusions

Northeast Asia is the center of global manufacturing and as such the role of hub ports in this region is critical to ensure efficient global supply chains and world trade. However, the significance of the hub ports in this region for international maritime transportation also heightens the competition among the ports. The main competing ports in Northeast Asia are Busan New and Old Ports in South Korea, the Port of Hong Kong, and the Port of Shanghai in China. The operational efficiency of container terminals is the fundamental factor of ports' competitiveness. In this study, we analyzed the efficiency of the four competing ports in Northeast Asia, identifying the differences between efficient and inefficient ports to delineate critical success factors of international hub ports.

As competition among hub ports has increasingly centered on transshipment of cargos, so have the size of ports and vessels. To achieve the economies of scale, hub ports require special routes, terminal facilities, advanced technologies, and supporting inland infrastructures. To gain competitive advantage enormous amounts of investment are required for upscaling/modernizing the existing facilities and/or constructing new international hub ports based on long-term economic policies of the government (Yang and Chen, 2016). The investment decisions in hub ports are complex as they are not based just on economic cost-benefit analysis but many conflicting objectives of various stakeholders.

This study has some limitations, which can be motivations for future research. Due to the difficulty of collecting common data for the 21 sample container terminals and discrimination capacity constraints of the DEA model, this study focused on only four input and output variables. Our study is based on static analysis. Future studies should conduct dynamic analysis of time series data if available from DMUs. Despite these limitations, this study analyzed the efficiency of major international logistics hub ports in Northeast Asia by examining the relationship of facility factors and the cargo throughput. The study results provide new insights to government policy makers for enhancing the competitiveness of international maritime transportation and to the managers of ports for strategic choices to improve operational efficiencies of container terminals to support global logistics.

References

Ahmed A., Mohamed, E. (2019), "Assessing the Middle East top container ports relative technical efficiency", *Journal of Maritime and Transportation Sciences*, Vol. 56 No. 1, pp. 59-72.

Al-Mansour, J.F., Aj-Ajmi, S.A. (2020), "Coronavirus 'COVID-19'–supply chain disruption and implications for strategy, economy, and management", *The Journal of Asian Finance, Economics and Business*, Vol.7 No. 9, pp. 659-672.

Andrew, M., John, N., Kevin, M. (2020), "Changes in consumer decision-making resulting from the COVID-19 pandemic", *Journal of Customer Behavior*, Vol. 19 No. 4, pp. 299-321.

Anthony, R., Dearden, J. (1976), *Management Control Systems*, Richard D. Irwin, Homewood, Illinois.

Bachkar, K., Lam, N.C. (2021), "A conceptual model for benchmarking transshipment ports: the case of Tangier-Med and Algeciras Bay", *International Journal of Logistics Systems and Management*, Vol. 40 No. 4, pp. 525-540.

Banker, R.D., Charnes, A., Cooper, W.W. (1984), "Inefficiencies in data envelopment analysis", *Management Science*, Vol. 30 No. 9, pp. 1031-1142.

Busan Port Authority [online]www.busanpa.com.

Cabral, L. (2000), *Introduction to Industrial Organization*, MIT Press, Cambridge, MA.

Chang, V., Tovar, B. (2014), "Drivers explaining the inefficiency of Peruvian and Chilean ports terminals", *Transportation Research Part E*, Vol. 67, pp. 190-203.

Charnes, A., Clark, C.T., Cooper, W.W., Golany, B. (1985), "A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the U.S. air force", *Annals of Operations Research*, Vol. 2 No. 1, pp. 95-112.

Charnes, A., Cooper, W.W., Lewin, A.Y., Seiford, L.M. (1997), "Data envelopment analysis theory, methodology and application", *Journal of the Operational Research Society*, Vol. 48 No. 3, pp. 332-333.

Charnes, A., Cooper, W.W., Rhodes, E.L. (1978), "Measuring the efficiency of decision-making units", *European Journal of Operational Research*, Vol. 2 No. 6, pp. 429-444.

Chudasama, K.M. (2010), "Shipbuilding infrastructure: an efficiency analysis of Indian shipyards", *IUP Journal of Infrastructure*, Vol. 8 No. 3, pp. 7-22.

Church, J., Ware, R. (2000), *Industrial Organization: A Strategic Approach*, Irwin McGraw-Hill, Boston.

Cullinane, K., Wang, T. (2010), "The efficiency analysis of container port production using DEA panel data approaches", *OR Spectrum*, Vol. 32 No. 3, pp. 717-738.

Farrell, M.J. (1957), "The measurement of productive efficiency", *Journal of Royal Statistical Society*, Vol. 120 No. 3, pp. 253-290.

Ferreira, D.C, Marques, R.C., Pedro, M.I. (2018), "Explanatory variables driving the technical efficiency of European seaports: an order-α approach dealing with imperfect knowledge", *Transportation Research Part E*, Vol. 119, pp. 41-62.

Fitzsimmons, J.A., Fitzsimmons, M.J. (1994), *Service Management for Competitive Advantage*, McGrow-Hill, MA.

Ha, M.S. (2009), "A comparative analysis of terminal efficiency on Northeast Asia and America container ports", *Journal of Korea Port Economic Association*, Vol. 25 No. 3, pp. 229-250.

Hassan, M.M.D., Oukil, A. (2021), "Design of efficient systems of commercial material handling equipment for supply chain and logistics facilities using DEA", *International Journal of Logistics Systems and Management,* Vol. 39 No. 2, pp. 241-272.

Holmstrom, B.R., Tirole, J. (1989), *The Theory of the Firm. Handbook of industrial organization*, Elsevier, Amsterdam, North-Holland.

International Association of Ports and Harbors[online] www.iaphworldports.org.

Itoh, H. (2002), "Efficiency changes at major container ports in Japan: a window application of data envelopment analysis", *Review of Urban and Regional Development Studies*, Vol. 14 No. 2, pp. 133-152.

Kim, H.S., Park, J.R. (2013), "An analysis of the operational efficiency of the major airports worldwide using DEA and Malmquist Productivity Indices", *Journal of Distribution Science*, Vol. 11 No. 8, pp. 5-14.

Kim, J.Y., Chin, H.I., Kim, S.M. (2011), "An analysis of efficiency of container terminal companies in Gwangyang, Busan and Incheon port", *Journal of Korea Port Economic Association,* Vol. 27 No. 4, pp. 187-205.

Koo, J.S., Lee, J.S., Jeon, D.H. (2011), "A comparative study of efficiency among Korea, Chinese and Japanese ports", *Journal of Shipping and Logistics,* Vol. 27 No. 3, pp. 457-474.

Lee, C.B., Kwon, A.L., Kim, B.K., Lee, J.Y. (2015), "A study on relative efficiency analysis of Northeast Asian ports by employing AHP/DEA-AR model", *The Journal of Korea Research Society for Customs*, Vol. 16 No. 1, pp. 271-293.

Lee, D., Kwak, K.S., Nam, K.C., An, Y.M. (2015), "A comparative analysis of terminal efficiency in Northeast Asia container ports", *Journal of Korean Navigation and Port Research*, Vol. 39 No. 1, pp. 55-60.

Lee, G.W., Jun, C.Y., Min, H., Lee, M.K. (2020), "Assessing the impact of containership size on port demand and infrastructure development: a case study of the Busan hub port", *International Journal of Logistics Systems and Management,* Vol. 37 No. 1, pp. 55-78.

Lee, J.D., Oh, D.H. (2010), *Data Envelopment Analysis,* IB BOOK, Seoul.

Lee, J.G., Hong, S.J., Lim, C.W. (2009), "A study on efficiency of major airports in Asian: using DEA and super efficiency", *Journal of the Aviation Management Society of Korea,* Vol. 7 No. 3, pp. 3-12.

Lee, S.M., Park, J.M. (2013), "An efficiency analysis of container terminal using network DEA", *Journal of Industrial Economics and Business*, Vol. 26No. 5, pp. 2117-2141.

Lee, Y.H., Kim, D.H., Kim, E.J. (2004), "Operational efficiency analysis using DEA approach for the major airports in Asia", *Korean Society of Transportation,* Vol. 22 No. 4, pp. 7-18.

Na, J.M., Qing, C.L. (2010), "A comparative study on relative efficiency and competitiveness of productive structure in the major port of China-Korea: focus on the DEA", *Journal of Northeast Asian Studies,* Vol. 15 No. 2, pp. 47-70.

Panchapakesan, A., Abielmona, R., Petriu, E. (2021), "Improving shipping container damage claims prediction through level 4 information fusion", *International Journal of Logistics Systems and Management,* Vol. 40 No. 4, pp. 489-509.

Park, M.H. (2008), "Development of DEA efficiency and Malmquist productivity analysis system", *Productivity Review,* Vol. 22 No. 2, pp. 241-265.

Park, S.Y., Kim, S.Y., Park, H. (2017), "Efficiency analysis of ASEAN ports using DEA and Shannon's entropy", *Journal of Korea Port Economic Association*, Vol. 33 No. 4, pp. 1-16.

Rajak, S., Parthiban, P., Dhanalakshmi, R. (2021), "A DEA model for evaluation of efficiency and effectiveness of sustainable transportation systems: a supply chain perspective", *International Journal of Logistics Systems and Management,* Vol. 40 No. 2, pp. 220-241.

Ryoo, D.K. (2005), "Efficiency measurement of container terminals in Korea using DEA", *Journal of Shipping and Logistics*, Vol. 47, pp. 21-38.

Saeedi, H., Behdani, B., Wiegmans, B., Zuidwijk, R. (2019), "Assessing the technical efficiency of intermodal freight transport chains using a modified network DEA approach", *Transportation Research Part E,* Vol. 126, pp. 66-86.

Schmalensee, R. (1989), *Handbook of Industrial Organization*, Elsevier, Amsterdam, North Holland.

Song, J.Y., Sin, C.H. (2005), "An empirical study on the efficiency of major container ports with DEA model", *Journal of Korean Navigation and Port Research,* Vol. 29 No. 3, pp. 195-201.

The Economist (2021), Why the Suez Canal and other choke-points face growing pressure, *https://www.economist.com/the-economist-explains/2021/03/26/why-the-suez-canal-and-other-choke-points-face-growing-pressure* (Accessed 26 March 2021).

Tirole, J. (1989), *The Theory of Industrial Organization*, MIT Press, Cambridge, MA.

Turner, H., Windle, R., Dresner, M. (2004), "North American containerport productivity: 1984-1997", *Transportation Research Part E*, Vol. 40, pp. 339-356.

USA TODAY (2021), Suez Canal blockage: investigators analyzing Ever Given's black box that could hold key to costly grounding, *https://www.msn.com/en-us/news/world/suez-canal-blockage-investigators-analyzing-ever-given-s-black-box-that-could-hold-key-to-costly-grounding/ar-BB1foO2Z* (Accessed 7 April 2021).

Vishnu, M., Jayakrishnan, D., Ramanan, T.R. (2020), "A DEA approach for evaluation of operational efficiency: case study of a logistics firm", *International Journal of Logistics Systems and Management,* Vol. 36 No. 4, pp. 517-530.

World Shipping Council, [online] www.worldshipping.org.

Wu, Y.C.J., Goh, M. (2010), "Container port efficiency in emerging and more advanced markets", *Transportation Research Part E*, Vol. 46, pp. 1030-1042.

Yang, Y.C., Chen, S.L. (2016), "Determinants of global logistics hub ports: comparison of the port development policies of Taiwan, Korea, and Japan", *Transport Policy*, Vol. 45, pp. 179-189.