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# An Analysis on the Logistics Efficiency of Shanghai Port for Global Supply Chain

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## Abstract

**Purpose:** As China experienced a crisis due to Covid-19, the global supply chain collapsed and affected the world. Therefore, it is time for a change in port operational efficiency, increasing in importance with changes in the global supply chain. This study analyzed Shanghai Port's efficiency, the world's largest port and representative hub port in Northeast Asia, by looking at the relationship between facility factors and cargo throughput to present hub port development's timely implications. **Research design, data and methodology:** This study applied the Charnes, Cooper, and Rhodes (CCR) and Banker, Charnes, and Cooper (BCC) models of the data envelopment analysis (DEA) to construct an analysis from the input-oriented and output-oriented perspectives. **Results:** As a result, Yidong Container Terminal can be considered the most optimized in facilities and operation processes. Yidong and Shengdong Container Terminal should maintain current operating levels, while Pudong Container Terminal should review facility investments. Also, Zhendong, Huang, Mingdong, and Guandong Container Terminal should be reviewed to increase cargo throughput or to adjust current input variables in the current state. **Conclusions:** Therefore, the utilization of the container terminal input variables should be reviewed, and the factors of inefficiency should be improved. Moreover, the strategic focus of container terminal operations should be on increasing annual cargo throughput.

**Keywords:** Container Terminal, DEA, Efficiency, Logistics, Port

**JEL Classification Code:** L52, L98, M11, O25

## 1. Introduction

The COVID-19 pandemic has made the world face unprecedented challenges. First of all, COVID-19 disrupts supply chains and causes changes in consumption patterns, leading to a change in industry and distribution structures. It is not a transitory phenomenon but rather a starting point of reorganizing the international economy and the entire industrial supply chain.

China, an essential country in the global supply chain, has dramatically impacted the world due to COVID-19. Along with changes in the global supply chain, competition among ports is increasing to attract international cargo. In addition, the recent Suez Canal disaster along with COVID-19 has made us aware of the weaknesses in the global supply chain. The Suez Canal is an artery of world trade, connecting the Mediterranean with the Red Sea, and providing an avenue for vessels to pass between Asia and the Middle East and Europe. The main alternative, a passage round the Cape of Good Hope at the southern tip of Africa, takes considerably longer. Therefore, the global supply chain and dependence on China, especially the role and operational efficiency of Shanghai Port, the largest international logistics port, should be carefully examined (BBC NEWS, 03/24/2021).

In a recent study by Kim (2017) on the development strategy of Shanghai Port, Shanghai Port should be competitive in both construction and management.

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However, some limitations suggest general development directions based on secondary data. Therefore, port facilities' efficient operation is required, and it is time to diagnose the operational efficiency of the container terminal for Shanghai Port, which plays an important role. Recently, ports have become larger and more advanced, and port facilities that have been invested in high costs may lead to inefficiencies in their operations.

With the recent rapid growth of the port and shipping industry, China is striving to expand ports in Shanghai, Shenzhen, Ningbo, and Hong Kong to make facilities more advanced. Kim (2016) studied the management and operation of infrastructure processes, focusing on the port industry in China. The Chinese government has been good at planning and investing in national infrastructure. In particular, to overcome inefficiency in the public sector, it is said to be increasing competitiveness in the port industry in partnership with the private sector. Japan is providing political support to attract transshipment cargo and new routes. To become the hub port in Northeast Asia with certainty. Each container terminal must improve operational efficiency and ensure competitiveness to become a hub port in Northeast Asia. In other words, an analysis on a container terminal basis should be conducted to figure out whether the current cargo handling capacity is adequate or needs to be improved.

Port efficiency is one of the most critical factors determining competitive advantage. Port efficiency plays a vital role in enhancing the competitiveness of individual ports and improving export competitiveness by reducing ocean transport costs. This study will analyze Shanghai port efficiency and provide directions for container terminals to be more efficient. Shanghai Port is the world's largest port based on cargo throughput, and there is no port of scale suitable for comparative efficiency analysis in Northeast Asia. Therefore, it would be better to compare and analyze the container terminals of Shanghai port to increase efficiency than to compare them with other ports that do not fit the size for comparative analysis. Various research has been conducted on port efficiency. However, prior studies analyzed the efficiency of large numbers of ports worldwide, and the analysis was conducted on a port basis. Therefore, there is a lack of research focusing on ports analyzing on a container terminal basis. Therefore, it was possible to identify previous studies that may fail to consider the characteristics of the regions and ports, and the selection of inputs may be inappropriate.

In this study, the most influential input and output variables representing the container terminal's operational efficiency are selected. Based on this, the operation efficiency of seven container terminals at Shanghai Port is compared, and the development plan is proposed. The focus of the analysis is the operational efficiency of

individual container terminals (pier) but not the entire port. The CCR and BCC models of the DEA are applied as the analysis method, and results are presented from the input-oriented and output-oriented perspectives. This study will provide timely policy implications at this point.

## **2. Literature Review**

### **2.1. Concept of Efficiency**

In general, the concept of efficiency in economics refers to analyzing the inputs and outputs of a system. The concept can be explained in terms of two aspects: (1) maximizing efficiency by obtaining the maximum output with a given set of inputs; (2) achieving a particular output level with the minimum possible input resources.

A company's efficiency means the minimum cost required to achieve the target, which can be defined as the inputs' output percentage. It is essential how much output can be produced by the input, and high efficiency means to achieve the goal at a minimal cost. This concept helps evaluate the efficiency of single-input and single-output. However, the limitation is that this method cannot measure efficiency in multiple inputs and outputs. The efficiency of producing multiple outputs by using multiple inputs is determined by the proper combination and use of inputs (Charnes, Clark, Cooper, & Golany, 1984).

Charnes, Cooper, & Rhodes (1978) extended the concept of efficiency suggested by Farrell (1957) to the DEA-CCR model, which can handle multiple inputs and outputs. In determining relative efficiency, an analysis method was presented that the best weights should be chosen according to the DMU (decision-making unit). The measurement of efficiency is essential in assessing the performance and competitiveness of an organization in two respects. First, efficiency can be used as an indicator of success to evaluate production organizations. Second, by measuring efficiency and separating the effects of the production environment, the cause of the difference in efficiency can be identified. Therefore, identifying the cause of the difference in efficiency is essential to establish policies and strategies to improve performance.

### **2.2 Previous Studies Review**

This study reviewed previous studies that analyzed the ports and container terminals efficiency in analyzing the efficiency of crucial hub ports in Northeast Asia. The review focused on the input and output variables applied for efficiency analysis in preceding studies. As a result of the review, various inputs and outputs have been applied by different researchers. Table 1 presents the prior studies

on measuring the efficiency of ports using DEA.

Although previous studies tried various methods to measure the competitiveness and efficiency of ports, too many ports have been selected for analysis. Thus, the efficiency analysis concluded that most ports were efficient,

resulting in a lack of operational implications. Some studies questioned the suitability of the input variables. Because DEA presupposes that all analysis targets have similar size and characteristics, input variables such as port depth are meaningless.

**Table 1:** Previous Studies on Port Efficiency

Researcher	DMU	Input Variable	Output Variable	Model
Wang, Nguyen, Fu, Hsu, & Dang (2021)	14 potential port companies of Vietnam	Total assets, Owner's equity, Liabilities, Operation expense	Revenue, Net profit	DEA Malmquist and EBM
Kuo, Lu, & Le (2020)	53 port in Vietnam	Total terminal area, Terminal length, Equipment	Throughput, Vessel calls	DEA
Zarbi, Shin, & Shin (2019)	Top 5 port in Iran	Length of quay wall, Number of quay wall, Number of gantry crane, Size of yard area	Container throughput	DEA
Ahmed & Mohamed (2019)	20 ports of Middle East	Berth length, Terminal area, Port depth	Container throughput	CCR, BCC; SE
Ablanedo-Rosas et al. (2010)	11 ports of China	Return on equity, Total asset turnover, Accounts receivable turnover	Financial ratios	DEA
Chudasama (2010)	12 ports of India	No. of Cranes, No. of Other Equipment, No. of Vessels handled, No. of Berths, Storage Area.	Cargo volume in thousand Tons	CCR, BCC
Cullinane & Wang (2010)	25 ports worldwide	Berth length, Terminal area, Number of C/C	Container throughput	CCR, BCC
Wu & Goh (2010)	35 ports of G7 and developing countries	Terminal area, Berth length, Number of C/C	Container throughput	DEA

### 3. Research Design and Methodology

#### 3.1. Research Methodology

DEA was used as the research methodology. DEA is a nonparametric method that uses input and output variables of the DMU (decision-making unit) to measure relative inefficiency through linear programming. The principles of the DEA model were first introduced in Farrell's (1957) model that measured the technical efficiency (TE) and the allocated efficiency (AE). Charnes, Cooper, & Rhodes (1978) developed the CCR model that assumes a constant return to scale based on Farrell's pioneering work. However, the CCR model was a suitable model for a company only if it operated on an optimal scale. Namely, it fails to consider that companies might not operate optimally due to real competition and financial constraints. Accordingly, Banker, Charnes, & Cooper (1984) proposed a BCC model that complements the CCR model's limitations, taking into account the variable return to scale (VRS).

#### 3.2. Research Model

##### 3.2.1. DEA-CCR Model

Charnes, Cooper, & Rhodes (1978) proposed the CCR

model. This basic DEA model calculates the optimal weights of multiple inputs and outputs by computing all weighted outputs to the sum of all weighted inputs. In other words, the relative efficiency  $h_k$  of DMU ( $k = 1, 2, 3, \dots, n$ ) is measured by selecting  $s$  output variables  $y_{rk}$  ( $r = 1, 2, 3, \dots, s$ ) and  $m$  input variables  $x_{ik}$  ( $i = 1, 2, 3, \dots, m$ ) for  $n$ 's DMU ( $k = 1, 2, 3, \dots, n$ ). Under the constraint that the efficiency condition is  $h_k = 1$  and the ratio of the output to the input is equal to or less than 1, the weighted values  $v_i$  and  $u_r$  of the inputs and outputs are calculated to measure efficiency as follows:

$$(FP_n) \text{ Max } h_n = \frac{u_1 y_{1k} + u_2 y_{2k} + \dots + u_s y_{sk}}{v_1 x_{1k} + v_2 x_{2k} + \dots + v_m x_{mk}} = \frac{\sum_{r=1}^s u_r y_{rk}}{\sum_{i=1}^m v_i x_{ik}} \quad (1)$$

$$\text{Subject to } \frac{u_1 y_{1k^1} + u_2 y_{2k^2} + \dots + u_s y_{sk^n}}{v_1 x_{1k^1} + v_2 x_{2k^2} + \dots + v_m x_{mk^n}}$$

$$= \frac{\sum_{r=1}^s u_r y_{rk^n}}{\sum_{i=1}^m v_i x_{ik^n}} \leq 1 \quad (k = 1, \dots, n)$$

$$v_i \geq \epsilon \geq 0 \quad (i = 1, \dots, m)$$

$$u_r \geq \epsilon \geq 0 \quad (r = 1, \dots, s)$$

where,

$h_n$ : efficiency of DMUK<sup>n</sup>

$v_i$ : weight for the  $i$ -th input variable

$u_i$ : weight for the  $r$ -th output variable

$x_{ik}^n$ : amount of the  $i$ -th input to the DMUK<sup>n</sup>

$y_{rk}^n$ : amount of the  $r$ -th output to the DMUK<sup>n</sup>

$\epsilon$ : non-Archimedean constant

$n$ : number of DMUs

$m$ : number of input variables

$s$ : number of output variables

In a Fractional Linear Programming model such as formula (1), when an infinite optimal solution is calculated, or the number of evaluation targets is large, the maximization problem is difficult to calculate. Therefore, to solve this problem, if the weighted sum of the input of the objective function is fixed to 1, and the constraint expression is transformed into a linear programming problem (CCR Transformation), the following Formula (2) is obtained. Formula (2) presents the CCR transformation that converts the constraint expression to a modified linear planning problem.

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

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

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

$$u_r \geq \epsilon \geq 0, v_i \geq \epsilon \geq 0, \forall r, i$$

### 3.2.2 DEA-BCC Model

Banker, Charnes, & Cooper (1984) recognized the practical limitations of the CRS assumptions of the CCR model. They suggested the DEA model known as BCC, which incorporates variable returns to scale (VRS). The BCC model can estimate the impact of scale size and separate it from the technical efficiency (TE) to measure the pure technical efficiency (PTE) that ignores scale efficiency. It allows us to 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):

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

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

$$v_i \geq \epsilon \geq 0 \quad (i = 1, \dots, m)$$

$$u_r \geq \epsilon \geq 0 \quad (r = 1, \dots, s)$$

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

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

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

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

$$u_r \geq \epsilon \geq 0, v_i \geq \epsilon \geq 0, \forall r, i$$

If the scale index is excluded from the above BCC model, it will be identical with the CCR model. The scale Index is used as an indicator of the economic effects of scale. If the optimal solution is calculated and the measured scale index is  $u_k^*$ , we can think of it as follows:

$$u_k^* = 0: \text{ CRS (Constant Returns to Scale)}$$

$$u_k^* > 0: \text{ DRS (Decreasing Returns to Scale)}$$

$$u_k^* < 0: \text{ IRS (Increasing Returns to Scale)}$$

### 3.2.3. Scale Efficiency

The estimated efficiency calculated by the CCR model and BCC model is and, respectively. If the measure of technical efficiency of a DMU in the CCR model and that in the BCC model is different, scale inefficiency exists. Therefore, scale inefficiency can be expressed as the difference between the efficiency in the BCC model and the efficiency in the CCR model, which is defined as follows:

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

## 3.3. Selection of Samples and Variables

Comparable homogeneous DMUs must exist, and the inputs and outputs must be measurable to use DEA. Besides, management and control should be possible to enable variable selection for actual management improvement. This study reviewed previous studies on the relationship between the number of DMUs and the numbers of inputs and outputs with the DEA model's predictive ability. Most of the studies that used the DEA model complied with the standard that the model is predictive only if the number of DMUs must be at least twice the sum of inputs and outputs (Fitzsimmons & Fitzsimmons, 1994; Banker, Charnes, & Cooper, 1984; Busofance, Dyson, & Thanassoulis, 1991; Park, 2008).

### 3.3.1 Samples

In the Ranking of Container Ports of the World announced in March 2020, the World Shipping Council selected Shanghai Port as the number one port for cargo

throughput in the last 10 years. Therefore, the seven container terminals in Shanghai port were selected as DMUs, and the following Table 2 is shown below.

**3.3.2 Variables**

The selection of inputs and outputs affects the predictive ability of the DEA model’s efficiency analysis results. The selection of inputs and outputs should be appropriate for efficiency analysis and manageability (Kim & Park, 2013). Chen, Dowall, & Song (2010) stated that the association between input and output variables should be considered most important because research on efficiency analysis cannot consider many variables, Therefore, this study first considered variables that were frequently selected as inputs and outputs in previous studies and then screened out an appropriate number of variables that do not violate the number of DMUs. Table 3 summarizes the frequently selected variables in previous studies.

As a result of organizing the frequency of selecting input and output variables in prior studies, the most frequently selected input variables are total area, CY area, CFS area, container freight station, number of berth, and berth length. In contrast, the most frequently selected output variable is annual container throughput. The final selection of the input and output variables considered the predictive ability and the possibility of securing the data when applying the analysis method. This study applies the two inputs and one output derived from previous studies and

found that twice the sum of the inputs and outputs is 6 while the number of DMUs is 7, meaning that the sample size is satisfactory. Port depth is not a sufficient input that affects the output variables because it is an essential condition that all ports in this analysis meet. Besides, the berth number is not proper to be used as an input because it is counted based on vessels with different sizes in each container terminal. The previously published studies, total area, CY area, and CFS area, were applied as area-related variables. CY is the actual operating area. Thus, only the CY area is applied as an area-related input in this study. Besides, while handling equipment must be considered an input variable, the types of handling equipment vary. However, the Container crane (C/C) was selected as an input because it handles equipment that presents common data.

**Table 2:** Selection Result of DMU

Section	Container Terminal	Section	Container Terminal
Total	7	4	Mingdong Container Terminal
1	Pudong Container Terminal	5	Shengdong Container Terminal
2	Zhendong Container Terminal	6	Guandong Container Terminal
3	Hudong Container Terminal	7	Yidong Container Terminal

**Table 3:** Frequency of Variable Selection in Previous Studies

Section	Variable Selection in Previous Studies		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 berth, 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

Recently, ports in the Asian region are contesting investment in logistics infrastructure to construct large-scale ports and expand facilities. Therefore, the selection of facility-related inputs is well-timed. On the other hand, this study selected annual container throughput as the output variable because it is considered the most representative variable for evaluating the logistics facilities' efficiency. with facility-related inputs. Many previous studies have

confirmed that annual container throughput is an unarguably proper output variable in logistics facilities.

Also, the practical feasibility of the inputs and outputs selected based on the literature review was verified. Through interviews with 3 port and shipping logistics experts, the significance of DMU selection and the validity of variable selection was confirmed. The inputs and outputs selected through the above process are shown in Table 4.

**Table 4:** Selection Result of Final Variables

Input Variables	Output Variable
$I_1$ : CY area	$O$ : Annual container throughput
$I_2$ : Number of C/C	

**Table 5:** DEA Input Data

Section		$I_1$	$I_2$	$O$
<b>Shanghai Port</b>	Pudong Container Terminal	500,000 m <sup>2</sup>	11	2,600,000 TEU
	Zhendong Container Terminal	1,080,000 m <sup>2</sup>	26	6,520,000 TEU
	Hudong Container Terminal	980,000 m <sup>2</sup>	17	4,100,000 TEU
	Mingdong Container Terminal	1,126,000 m <sup>2</sup>	26	6,200,000 TEU
	Shengdong Container Terminal	1,486,000 m <sup>2</sup>	34	8,855,000 TEU
	Guandong Container Terminal	1,418,000 m <sup>2</sup>	30	7,555,700 TEU
	Yidong Container Terminal	611,000 m <sup>2</sup>	14	4,000,000 TEU

Note: Input and output variables from the IAPH

**3.3.3 Input Data**

This study collected the DEA input data of the selected DMUs and input and output variables from the IAPH (International Association of Ports and Harbors)’s 2018 report. The DEA inputs are as follows Table 5.

**4. Results**

**4.1 CCR Model Results**

The CCR model assumes a constant return to scale (CRS). In this study, both the input-oriented and output-oriented CCR models were used for the analysis. The excess input and output shortages were computed. This study also analyzed the reference set that inefficient DMUs should benchmark and suggested the target value.

**4.1.1 CRS Efficiency Analysis**

The results of the analysis of the efficiency index showed that Yidong Container Terminal was efficient. On the other hand, 6 container terminals (Pudong, Zhendong, Houdong, Mingdong, Shengdong, Guandong) were inefficient. In particular, Pudong Container Terminal was highly inefficient. Table 6 presents the efficiency index of the CCR model.

**4.1.2 Reference Set**

To improve efficiency, inefficient DMUs should refer to the reference set, reference weight ( $\lambda_i$ ), and reference

The excess input ( $I_1$ ) and target value ( $I'_i$ ) of the input variables and the output shortage ( $O$ ) and target value ( $O'$ ) of output variables of the inefficient DMUs are

count, which can be calculated. Table 7 shows the reference terminal and reference weight ( $\lambda_i$ ) of each container terminal and the reference count of efficient DMUs in the CCR model. The reference terminal to be referenced by inefficient DMU is an efficient virtual unit. As an efficient DMU, Yidong Container Terminal is the most efficient with 6 reference counts.

It is possible to calculate the target value for DMUs to become efficient based on the reference set analysis results by analyzing inefficient DMUs’ excess input and outputs. It is multiplying the reference weight ( $\lambda_i$ ) of the Yidong Container Terminal by the input/output variable and then summing the products to find the input/output target value that meets Pudong’s improvement goal Container Terminal. The ( $\lambda_i$ ) value derived by the CCR-I model was applied to the calculation of the inputs’ target value, while the ( $\lambda_i$ ) value derived from the CCR-O model was applied to the calculation of the target value of the output. Formulas (6) and (7) present the calculation process.

Yidong Container Terminal	Input Target Value	
		(6)
		(7)

$$I_1: 0.65 (\lambda_i) \times 611,000 (m^2) = 397,150 (m^2)$$

$$I_2: 0.65 (\lambda_i) \times 14 (EA) = 9.1 (EA)$$

Yidong Container Terminal	Output Target Value	
		(7)

$$O: 0.7857 (\lambda_i) \times 4,000,000 (TEU) = 3,142,800 (TEU)$$

obtained by the above process, as shown in the following Table 8.

**Table 6:** CRS Efficiency Index

Section	CCR-I	CCR-O	Section	CCR-I	CCR-O
Pudong Container Terminal	0.8273	0.8273	Shengdong Container Terminal	0.9115	0.9115
Zhendong Container Terminal	0.9222	0.9222	Guandong Container Terminal	0.8815	0.8815
Hudong Container Terminal	0.8441	0.8441	Yidong Container Terminal	1	1
Mingdong Container Terminal	0.8411	0.8411	-	-	-

**Table 7:** Reference Set Analysis of CCR Model

DMU	TE	Reference Set		Reference Count	
		CCR-Input ( $\lambda_i$ )	CCR-Output ( $\lambda_i$ )	CCR-I	CCR-O
Pudong Container Terminal	0.8273	Yidong (0.65)	Yidong (0.7857)	Yidong (6 times)	Yidong (6 times)
Zhendong Container Terminal	0.9222	Yidong (1.63)	Yidong (1.7676)		
Hudong Container Terminal	0.8441	Yidong (1.025)	Yidong (1.2143)		
Mingdong Container Terminal	0.8411	Yidong (1.55)	Yidong (1.8429)		
Shengdong Container Terminal	0.9115	Yidong (2.2138)	Yidong (2.4286)		
Guandong Container Terminal	0.8815	Yidong (1.8889)	Yidong (2.1429)		

**Table 8:** Calculation of Target Value for the CCR Model

DMU	Excess Input and Output Shortage			Target Value		
	Input		Output	Input		Output
	$I_1$ (m <sup>3</sup> )	$I_2$ (EA)	$O$ (TEU)	$I'_1$ (m <sup>3</sup> )	$I'_2$ (EA)	$O'$ (TEU)
Pudong Container Terminal	102,850	1.9	542,800	397,150	9.1	3,142,800
Zhendong Container Terminal	84,070	3.18	550,400	995,930	22.82	7,070,400
Hudong Container Terminal	353,725	2.65	757,200	626,275	14.35	4,857,200
Mingdong Container Terminal	178,950	4.3	1,171,600	947,050	21.7	7,371,600
Shengdong Container Terminal	133,368.2	3.007	859,400	1,352,632	30.993	9,714,400
Guandong Container Terminal	263,882.1	3.555	1,015,900	1,154,118	26.445	8,571,600
Yidong Container Terminal	0	0	0	611,000	14	4,000,000

**4.2 BCC Model Results**

The BCC model is based on the assumption of variable returns to scale (VRS). As the CCR model, both input-oriented and output-oriented BBC models were applied to

the efficiency analysis. This study compared the results of efficiency analysis of CRS and VRS to examine scale efficiency (SE), the type of Return to Scale (RTS), excess input, output parameters (output shortage and target value), and the reference set that the inefficient DMUs should benchmark.

**4.2.1 VRS Efficiency Analysis**

In addition to the 1 container terminal (Yidong) identified as efficient DMUs in the CCR model, the BCC model results pointed out 2 more container terminals (Pudong, Shengdong) as efficient DMUs. Namely, In the BCC model, which takes scale efficiency (SE) into account

when measuring technical efficiency (TE), identified a total of three container terminals as efficient DMUs. On the contrary, Zhendong, Hudong, Mingdong, and Guandong were relatively inefficient. In particular, Hudong Container Terminal was highly inefficient. The VRS efficiency index is presented in the following Table 9.

**Table 9:** VRS Efficiency Index

DMU	CRS	VRS		SE		RTS	
	CCR-I,O	BCC-I	BCC-O	BCC-I	BCC-O	BCC-I	BCC-O
Pudong Container Terminal	0.8273	1	1	0.8273	0.8273	IRS	IRS
Zhendong Container Terminal	0.9222	0.9863	0.9875	0.935	0.9339	DRS	DRS
Hudong Container Terminal	0.8441	0.8478	0.8671	0.9956	0.9735	DRS	DRS
Mingdong Container Terminal	0.8411	0.8948	0.9041	0.94	0.9303	DRS	DRS
Shengdong Container Terminal	0.9115	1	1	0.9115	0.9115	DRS	DRS
Guandong Container Terminal	0.8815	0.9549	0.9584	0.9231	0.9198	DRS	DRS
Yidong Container Terminal	1	1	1	1	1	CRS	CRS

**4.2.2 Reference Set**

Table 10 expresses the reference terminal and reference weight ( $\lambda_i$ ) in each container terminal and the reference counts of efficient DMUs in the BCC-I and BCC-O models. Concerning the reference counts of efficient DMUs in BCC-I, Yidong Container Terminal has seven, Shengdong Container Terminal has 5. BCC-O found that Yidong and Shengdong Container Terminal has four reference counts, respectively.

The reference set's analysis results suggest the excess input, output shortage, and target value of inefficient DMUs. The process of calculating the target value of

Zhendong Container Terminal is to multiply the reference weights ( $\lambda_i$ ) of the two reference sets (Yidong, Shengdong), respectively, by the input/output variable, and then sum the products, as presented by formulas (8) and (9) Following the above process, the access input  $I_i$  and the target value  $I'_i$  of input variables of inefficient DMUs are computed by BCC-I, whereas BCC-O calculates output shortage  $O$  and the improvement target value  $O'$  of the output variables of inefficient DMUs. Table 11 shows the calculation as follows:

**Table 10:** Reference Set Analysis of BCC Model

DMU	SE		Reference Set		Reference Count	
	BCC-I	BCC-O	BCC-I ( $\lambda_i$ )	BCC-O ( $\lambda_i$ )	BCC-I	BCC-O
Zhendong Container Terminal	0.935	0.9339	Shengdong (0.5191) Yidong (0.4809)	Shengdong (0.536) Yidong (0.464)	Shengdong (5 times)  Yidong (7 times)	Shengdong (4 times)  Yidong (4 times)
Hudong Container Terminal	0.9956	0.9735	Shengdong (0.0206) Yidong (0.9794)	Shengdong (0.15) Yidong (0.85)		
Mingdong Container Terminal	0.94	0.9303	Shengdong (0.4531) Yidong (0.5469)	Shengdong (0.5886) Yidong (0.4114)		
Guandong Container Terminal	0.9231	0.9198	Shengdong (0.7324) Yidong (0.2676)	Shengdong (0.8) Yidong (0.2)		



$$\begin{aligned}
 & \text{Shengdong Container Terminal} & \text{Yidong Container Terminal} & \text{Input Target Value} \\
 I_1: & [0.5191 (\lambda_i) \times 1,486,000 (\text{m}^2)] + [0.4809 (\lambda_i) \times 611,000 (\text{m}^2)] = 1,065,213 (\text{m}^2) \\
 I_2: & [0.5191 (\lambda_i) \times 34 (\text{EA})] + [0.4809 (\lambda_i) \times 14 (\text{EA})] = 24.382 (\text{EA})
 \end{aligned}
 \tag{8}$$

$$\begin{aligned}
 & \text{Shengdong Container Terminal} & \text{Yidong Container Terminal} & \text{Output Target Value} \\
 O: & [0.536 (\lambda_i) \times 8,855,000 (\text{TEU})] + [0.464 (\lambda_i) \times 4,000,000 (\text{TEU})] = 6,602,280 (\text{TEU})
 \end{aligned}
 \tag{9}$$

**Table 11:** Calculation of Target Value for the BCC Model

DMU	Excess Input and Output Shortage			Target Value		
	Input		Output	Input		Output
	$I_1$ (m <sup>2</sup> )	$I_2$ (EA)	$O$ (TEU)	$I'_1$ (m <sup>2</sup> )	$I'_2$ (EA)	$O'$ (TEU)
Pudong Container Terminal	0	0	0	500,000	11	2,600,000
Zhendong Container Terminal	14,787.5	1.618	82,280	1,065,213	24.382	6,602,280
Hudong Container Terminal	350,975	2.588	628,250	629,025	14.412	4,728,250
Mingdong Container Terminal	118,537.5	2.938	657,653	1,007,463	23.062	6,857,653
Shengdong Container Terminal	0	0	0	1,486,000	34	8,855,000
Guandong Container Terminal	166,150	1.352	328,300	1,251,850	28.648	7,884,000
Yidong Container Terminal	0	0	0	611,000	14	4,000,000

### 5. Conclusions

This study analyzed the container terminal’s operational efficiency at Shanghai Port, which is regarded as the world’s largest port, which plays an essential role in the global supply chain. This research reviewed previous studies to select input and output variables effective for the operational efficiency analysis of container terminals. The selection of variables considered the current situation in major Asian countries that large international logistics ports were built competitively and existing ports were expanded with high-tech facilities. Two container terminal facility-related variables were selected as the input variables. Annual container throughput, an undisputed variable for efficiency indicators, was selected as the output variable.

The analysis results of the CCR model showed that Yidong Container Terminal was efficient. On the other hand, 6 container terminals (Pudong, Zhendong, Houdong, Mingdong, Shengdong, Guandong) were inefficient. In

particular, Pudong Container Terminal showed the highest degree of inefficiency. The BCC model’s analysis results showed that 3 container terminals were efficient, including two additional container terminals (Pudong, Shengdong) and the Yidong Container Terminal identified as efficient DMU CCR model. Contrarily, the BCC model found that the 4 container terminals (Zhendong, Hudong, Mingdong, Guandong) in Shanghai Port were inefficient. Especially, Hudong Container Terminal was the most inefficient.

The analysis results in the BCC model were derived from a comparative analysis with the technical efficiency (TE) index of the CCR model. If the CCR model’s technical efficiency is equal to the technical efficiency (TE) index of the BCC model, the assumption of CRS was adopted. Otherwise, the assumption of VRS was adopted. VRS consists of scale efficiency (SE) and pure technical efficiency (PTE). In this case, it is either IRS or DRS. The results of scale efficiency analysis indicated that Yidong Container Terminal in Shanghai Port have CRS because their efficiency values were found equal in both the CCR and the BCC models. Their efficiency indexes are all equal

to one. In the Yidong Container Terminal, an increase in all inputs leads to the same proportional increase in outputs.

Theoretically, we reviewed the effectiveness of variables from previous studies using DEA for ports and selected optimal variables. In addition, too many ports were selected, and DEA analysis was carried out in previous studies. However, rather than including many DMUs with similarities and less meaning in comparative analysis, the analysis focuses on container terminals within Shanghai Port, the world's largest port. Through this, practical implications were presented by analyzing the operational efficiency of the container terminals of the most representative ports. In particular, we compare and analyze CCR and BCC models and identify that efficient container terminals also have different characteristics and meanings of their efficiency.

In practical terms, in Pudong and Shengdong container terminals, it was inefficient in the CCR model but efficient in the BCC model. Significantly, the Pudong Container Terminal has been shown to have an IRS (Increasing Return to Scale) in terms of scale efficiency. The Pudong Container Terminal is expected to have an EOS (Economics of scale) effect on the scale of investment and facilities. It is estimated that the container terminal facilities in Pudong Container Terminal will significantly increase the operational process's efficiency through the specialization and automation of cargo handling and investment in automation systems. On the other hand, the 4 container terminals (Zhendong, Hudong, Mingdong, Guandong) in Shanghai Port, the world's largest port, were found to have a DRS (decreasing return to scale). In other words, increasing the input facilities may further reduce productivity. Bottlenecks and queues may occur on the container terminals' operational process in the port, resulting in port congestion. Although the cargo throughput of Yidong Container Terminal is currently less than that of the 5 container terminals (Zhendong, Hudong, Mingdong, Shengdong, Guandong) in Shanghai Port, Yidong Container Terminal can be thought of as the most optimized in terms of facilities and operation processes. Comparing the most inefficient Hudong Container Terminal in the BCC model with the efficient Yidong Container Terminal, the similar cargo throughput but larger CY size can be attributed to the inefficiency. Therefore, the utilization of the container terminal input variables should be reviewed, and the factors of inefficiency should be improved.

Moreover, the strategic focus of container terminal operations should be on increasing annual cargo throughput. In conclusion, it was recognized that policy efforts and competition to build a logistics hub port increased in Northeast Asia. The container terminals in Shanghai Port in China were operated as hub ports with

transshipment cargo at the center. This study showed that there are fundamental differences in the inefficiency of container terminals in Shanghai Port. Yidong and Shengdong Container Terminal should maintain current operating levels, while Pudong Container Terminal should review facility investments. Besides, Zhendong, Huang, Mingdong, and Guandong Container Terminal should be reviewed to increase cargo throughput or to adjust current input variables in the current state.

This study selected seven container terminals in Shanghai port as DMUs. And the constraints associated with the DEA model's discrimination capacity limit the number of inputs and outputs to three. Because the static analysis was used in this study, dynamic research that uses time-series data will be needed in the future. Despite these limitations, this study analyzed Shanghai Port's efficiency, the world's largest port and representative hub port in Northeast Asia, by looking at the relationship between facility factors and cargo throughput to present hub port development's timely implications.

## References

- Ablanedo-Rosas, J. H., Gao, H., Zheng, X., Alidaee, B., & Wang, H. (2010). A study of the relative efficiency of Chinese ports: a financial ratio-based data envelopment analysis approach. *Expert Systems*, 27(5), 349-362. <https://doi.org/10.1111/j>
- Ahmed, A. S., & Mohamed, A. E. (2019). Assessing the Middle East top container ports relative technical efficiency. *Pomorski zbornik*, 56(1), 59-72. <https://hrcak.srce.hr/224135>
- Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, 30(9), 1031-1142. <https://doi.org/10.1287/mnsc.30.9.1078>
- BBC NEWS (2021). Egypt's Suez Canal blocked by huge container ship. March 24<sup>th</sup> Edition. <https://www.bbc.com>
- Boussofiane, A., Dyson, R. G., & Thanassoulis, E. (1991). Applied data envelopment analysis. *European Journal of Operations Research*, 52(1), 1-15. [doi.org/10.1016/0377](https://doi.org/10.1016/0377)
- Charnes, A., Clark, C. T., Cooper, W. W., & Golany, B. (1984). A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the U.S. air force. *Annals of Operations Research*, 2(1), 95-112. <https://doi.org/10.1007/BF01874734>
- Charnes, A., Cooper, W. W., & Rhodes, E. L. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, 2(6), 429-444. <https://doi.org/10.1016/>
- Chen, S. H., Dowall, D. E., & Song, D. W. (2010). Evaluating impacts of institutional reforms on port efficiency changes: Ownership, corporate structure, and total factor productivity changes of world container ports. *Transportation Research Part E*, 46(4), 546-561. <https://doi.org/10.1016>
- Chudasama, K. M. (2010). Shipbuilding Infrastructure: An efficiency analysis of Indian shipyards. *IUP Journal of Infrastructure*, 8(3), 7-22.

- Cullinane, K., & Wang, T. (2010). The efficiency analysis of container port production using DEA panel data approaches. *OR Spectrum*, 32(3), 717-738. <https://doi.org/10.1007/1007>
- Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of Royal Statistical Society*, 120(3), 253-290. <https://doi.org/10.2307/2343100>
- Fitzsimmons, J. A., & Fitzsimmons, M. J. (1994). *Service Management for Competitive Advantage*. NY: McGraw-Hill College.
- 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*, 11(8), 5-14. <https://www.koreascience.or.kr>
- Kim, J. H. (2017). Studies on port development strategy in Shanghai, China. *Journal of Distribution Science*, 15(1), 7-14. <https://www.koreascience.or.kr>
- Kim, J. H. (2016). Public private partnerships in Chinese port as infrastructure. *Journal of Distribution Science*, 14(7), 45-52. <https://www.koreascience.or.kr>
- Kuo, K. C., Lu, W. M., & Le, M. H. (2020). Exploring the performance and competitiveness of Vietnam port industry using DEA. *The Asian Journal of Shipping and Logistics*, 36(3), 136-144. <https://doi.org/10.10>
- Wang, C. N., Nguyen, N. A. T., Fu, H. P., Hsu, H. P., & Dang, T. T. (2021). Efficiency assessment of seaport terminal operators using DEA Malmquist and Epsilon-Based Measure models. *Axioms*, 10(2), 48. <https://doi.org/10.3390/axioms10020048>
- Wu, Y. C. J., & Goh, M. (2010). Container port efficiency in emerging and more advanced markets. *Transportation Research Part E*, 46(6), 1030-1042. <https://doi.org/10.1016/>
- Zarbi, S., Shin, S. H., & Shin, Y. J. (2019). An analysis by Window DEA on the influence of international sanction to the efficiency of Iranian container ports. *The Asian Journal of Shipping and Logistics*. 35(4), 163-171. <https://doi.org/10>