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Rationalization in Korea container terminal using DEA cross-efficiency and cluster analysis

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ABSTRACT

Ports and container terminals today are interchanges for maritime and land transport as well as important facilities that serve as communication channels for nations, regional economies, and forelands. They also act as suppliers providing cargo handling and international logistics services at the national level. Traditionally, the port industry was less competitive than other industries. However, competition among terminals is intensifying due to recent environmental changes, and the excessive competition between Korean container terminals has produced negative effects. Therefore, it is necessary to establish terminal rationalization plans to resolve excessive competition among container terminals at the national level. This study examined the direction for terminal rationalization at the national level to alleviate excessive competition among container terminals based on the theory of supply base rationalization. Data envelopment analysis (DEA) cross-efficiency and cluster analysis were combined to provide rationalization plans based on efficiency measurement. This study is significant as it presents a strategic analytical tool to establish terminal rationalization plans at the national level and also proves its applicability.

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1. Introduction

Ports today can be defined as an interchange of maritime and land transport and a venue of total logistics activities such as loading and unloading of cargo, storage, vessel arrival and departure, and various other activities. The role of ports has been changed due to many factors thus far. The increase in world population, advancement of the port and oil industries, and development of specialized ports have accelerated their growth and development. Consequently, ports are serving as communication channels for nations, regional economies, and the forelands.

The port industry was traditionally perceived as less competitive than other industries. However, competition among terminals is becoming more intense due to various environmental changes, such as the change in the logistics structure such as the combined transport system, enlargement of ship size, and excess supply of ports. This competition has both positive and negative effects.

Adequate competition may lead to increased competitiveness of ports, prevention of monopoly, and improved service due to innovation (De Langen & Pallis, 2006). However, excessive competition may result in decreased profitability and deteriorated service quality due to reduced investment (Figueiredo De Oliveira & Cariou, 2015).

Excessive competition has negative effects on container terminals in Korea. When Busan Port Jaseongdae (JASU) opened in 1982, competition increased due to various environmental changes such as rising cargo volume, facility supply of new terminals, and an proliferation of terminal operating companies. In particular, over-supply issues were arising since the mid-2000s when the growth of cargo volume began slowing down, and competition for cargo inducement became fiercer among terminal operating companies (Ha, Choi, & Kim, 2013). However, excessive competition truly began with the opening of the New Port in 2006, which became a serious competitor of the North Port. As large vessels could berth in Busan New Port, it came to be highly preferred by shipping companies, and consequently, a huge volume that had been previously handled in the North Port was transferred to the New Port. In response, operating companies in the North Port began charging lower cargo

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handling fees to secure cargo volume and avoid losing cargo volume to its competitor.

External environmental changes along with supply also intensified competition. To deal with the long-term depression of the liner shipping market, shipping companies are striving to reduce navigation expenses with the economy of scale by enlarging the size of container ships. Accordingly, terminal operating companies are also extending facilities to accommodate large vessels. Since the mid-1990s, strategic alliances began to be formed among large container shipping companies. Mergers and acquisitions (M&As) among shipping companies also increased for service differentiation and cost reduction. These strategic alliances and M&As among shipping companies led to greater bargaining power against terminal operating companies. Moreover, the focus has shifted to a few large shipping companies based on strategic alliances and M&As, which served as a key trigger for competition among hub ports worldwide (Ryoo et al., 2012).

In sum, with various environmental changes from the past to present combined with industrial characteristics of ports and terminals, the competition among container terminals in Korea has taken the form of the winner-takes-all model, with a huge volume concentrated in specific terminals with other terminals inevitably falling behind (Kim, 2020). Thus, there is an urgent need to establish terminal rationalization plans to address the excessive competition among container terminals at the national level.

This study aims to set the direction for terminal rationalization at the national level to alleviate excessive competition among container terminals based on the theory of supply base rationalization. To this end, we measured the efficiency of container terminals in Korea using data envelopment analysis (DEA) cross-efficiency and classified them into four types: superior, good overall, niche, and inferior. In addition, we examined the structural similarity of each terminal through cluster analysis and provided rationalization plans such as a functional shift of inferior terminals and integration of good overall terminals.

This study has made a substantial contribution by presenting a strategic analytical tool to establish terminal rationalization plans at the national level and proving its applicability. Beyond just efficiency analysis and benchmark selection, this study conducted an analysis based on the theory of supply base rationalization. It analyzed container terminal rationalization plans from multiple perspectives while also providing insight for terminal development and rationalization through cluster analysis. Further, the study examined ports in Korea, but the results can also be applied to other countries facing the issue of excessive competition among terminals.

This study has the following structure. Chapter 2 presents a literature review, and Chapter 3 explains DEA cross-efficiency and cluster analysis. Further, Chapter 4 describes data collection methods and data characteristics, and Chapter 5 provides the analysis results and rationalization plans for container terminals in Korea. Finally, Chapter 6 provides the conclusions and limitations of this study and sets the direction for further research.

2. Literature review

This chapter reviews previous studies with a focus on research methodologies using (1) the theory of supply base rationalization and (2) terminal efficiency studies using DEA.

2.1. Supply base rationalization

Supply base rationalization is a major research topic in the supply chain. However, it is not a generalized term and is used in association with terms such as supplier evaluation, supply base reduction, and sourcing decision (Cousins, 1999; Sarkar & Mohapatra, 2006; Talluri, Decampos, & Hult, 2013). Sarkar and Mohapatra

(2006) compared supply base rationalization with reduction. They stated that rationalization is not only about reducing the supply base but also embraces the process of determining the adequate size of the supply base as well as suppliers that form the base. In other words, they defined rationalization as a superordinate concept that includes reduction. Talluri et al. (2013) argued that supplier evaluation is necessary for sourcing decisions and regarded supplier evaluation as a part of the supplier rationalization process. In this study, we also assumed that supply base rationalization includes evaluation and reduction, determined whether the current supply base size is adequate, and evaluated the suppliers. We defined supply base rationalization as a set of procedures to choose suitable suppliers or enhance supplier competency.

Studies on the necessity and effect of supply base rationalization are as follows. Deming (1981) argued that firms with a large supply base might have a negative effect on product quality and production costs; thus, it is important to maintain an adequate supply base size. Agrawal and Nahmias (1997) claimed that forming an optimal supply base is one of the key aspects of supply chain management. They provided a model to determine the optimal number of suppliers when the product output of suppliers is random. Cousins (1999) conducted a study on supply base rationalization implemented by companies in the UK and examined its effects. The results showed that not many companies actually saved costs through rationalization and that it is necessary to establish a strategic framework for successful rationalization. Sarkar and Mohapatra (2006) argued that it is necessary to maintain a manageable level of the supply base first to develop partnerships with suppliers and presented a process to reduce the supply base. Song, Dong, and Xu (2014) claimed that manufacturers must have supply base reduction and supplier differentiation strategies for the balanced operation of purchase and production and provided a dynamic programming method. Cavalcante, Frazzon, Forcellini, and Ivanov (2019) argued that flexible supply chain formation is more important than anything else to manage modern supply chains with high uncertainty. They added that it is necessary to manage the supply base and choose adequate suppliers.

The need for supply base rationalization has been proven in many studies, but it is difficult to actually implement it. As a precise methodology is required for rationalization, developing a suitable methodology has also become a major research topic. There are various methods such as mathematical programming, cost-based method, multicriteria decision methods, and simulation-based methods. However, DEA is one of the most suitable methodologies for rationalization. This is because the supply base can be rationalized more comprehensively as DEA evaluates suppliers with a focus on efficiency rather than absolute output (Talluri et al., 2013). Studies using DEA are as follows. Narasimhan, Talluri, and Mendez (2001) evaluated the efficiency of suppliers that form the supply base through DEA and aligned this with managerial performance, classifying all suppliers into four clusters: high performers and efficient, high performers and inefficient, low performers and efficient, and low performers and inefficient. Wu and Blackhurst (2009) presented an augmented DEA model adopting weight constraints for supplier evaluation and selection and proved the effect through a case study. Azadi and Saen (2011) studied supplier selection in a case with undesirable output using a slacks-based measure model based on DEA. More and Mateen (2012) presented a method to set the ideal goal for supplier selection and select the most suitable supplier through DEA and proved the effect through a case study of an Indian company. Talluri et al. (2013) calculated the efficiency and performance diversity of each supplier using the DEA cross-efficiency model. They classified all suppliers into four groups such as superior, good overall, niche, and inferior using these two scores. Karami, Ghasemy Yaghin, and Mousazadegan (2021) presented a three-stage integrated DEA-PCA (principal component analysis)-VIKOR (Vlse

Kriterijumska Optimizacija Kompromisno Resenje) approach. In this model, the supplier selection criteria are first reduced through PCA, and supplier efficiency is evaluated through DEA, after which suppliers are ranked through VIKOR.

This study considered Korean container terminals as suppliers providing cargo handling services based on supply base rationalization by Talluri et al. (2013) and examined supply rationalization plans at the national level. The method by Talluri et al. (2013) is explained in more detail in Chapter 3.

2.2. Terminal efficiency evaluation

Terminal efficiency measurement using DEA is an important research topic in port operation. Martínez-Budria, Díaz-Armas, Navarro-Ibanez, and Ravelo-Mesa (1999) measured the efficiency of 26 container terminals in Spain using the DEA-BCC model and studied the relationship between efficiency and managerial complexity. Cullinane, Song, Ji, and Wang (2004) analyzed the change in the efficiency of 25 container terminals using DEA window analysis. Further, Cullinane and Wang (2006) measured the efficiency of 69 container terminals in Europe using the DEA-CCR and BCC models and analyzed the relationship between efficiency and production scale. Wu, Yan and Liu (2010) measured the efficiency of 77 container terminals using the DEA-CCR model and analyzed the input and output adjustment plan to improve the efficiency of inefficient ports. Wu, Liang et al. (2010) obtained the efficiency ranking of 77 container terminals worldwide using DEA cross-efficiency and presented benchmarks for inefficient terminals using cluster analysis. Additionally, Schøyen and Odeck (2013) analyzed the efficiency of 24 container terminals in Northern Europe and the UK through the DEA-BCC model. They presented ways to improve efficiency of terminals in Norway. Nguyen et al. (2016) measured the efficiency of 43 ports in Vietnam using the bootstrapped DEA model to make up for the deficiencies of general DEA and compared the results with those of general DEA and SFA (stochastic frontier analysis). Lin, Yan, and Wang (2019) studied the environmental pollution issues of 16 major container terminals in China. They conducted an analysis using the inverse DEA model to measure terminal efficiency considering unexpected output like exhaust gas. Zarbi, Shin, and Shin (2019) collected the 10-year data of five ports in Iran and comparatively analyzed the efficiency before and after the sanctions on port operators in Iran. Santiago, Orive, and Cancelas (2021) measured the operating and financial efficiency of ports in Spain using the bootstrapped DEA model. They first measured the individual efficiency of 28 ports, after which they formed clusters based on proximity and seafront and compared the efficiency.

There are many other studies on port and terminal efficiency analysis applying DEA, but most derive and compare the efficiency of individual ports or terminals and provide improvement plans. Some present benchmarks and efficiency improvement plans in combination with other methods such as cluster analysis and aim to set the direction for efficiency improvement of individual terminals. However, only a few studies explored methods to alleviate excessive competition or rationalize terminals at the national level based on terminal efficiency.

2.3. Contribution to the literature

This study focuses on establishing rationalization plans to alleviate excessive competition among terminals at the national level based on the theory of supply base rationalization beyond terminal efficiency measurement and improvement plans using DEA. Its biggest contribution is that it suggests a method of combining DEA cross-efficiency with cluster analysis and proves the method's effectiveness by applying it to container terminals in Korea.

3. Methodology

3.1. DEA cross-efficiency

The concept of efficiency originates from that of productivity in economics and is defined in various ways. The key definitions of relative efficiency covered in this study are as follows. First established by Vilfredo Pareto, Pareto efficiency is defined as resource allocation where no independent individual can be better off without making at least one individual worse off. In other words, 100% efficiency can be possible when input and output cannot be better off without making other input and output factors worse off. However, when applied mostly to social sciences, it is impossible to identify the level of efficiency that can be theoretically achievable. In other words, the achievable level of efficiency cannot be identified due to the limitation in estimating the theoretically possible output in the input-output ratio. The concept of relative efficiency was suggested to solve this problem. In relative efficiency, when the performance of decision-making units (DMUs) is not showing improvement in certain input or output factors without deteriorating other input or output factors, certain DMUs have 100% efficiency. This definition avoids the assumption of weights in which various inputs and outputs reflect relative importance and does not require a clear specification of the relationship that exists between input and output. DEA is a non-parametric analytical technique that uses this concept of relative efficiency to estimate the production frontier of DMUs comprising multiple input and output factors and assume the relative efficiency among the subjects of analysis (Kim & Shin, 2019).

DEA was introduced by Charnes, Cooper, and Rhodes (1978) and has many input and output factors, unlike conventional research methods for efficiency evaluation. Moreover, efficiency can be evaluated even without the weight information. The BCC model, one of the most basic models of DEA, can be expressed as follows.

Min θ_k

$$\text{s. t. } \theta_k x_{ik} - \sum_{j=1}^n x_{ij} \lambda_j \geq 0 \quad i = 1, 2, \dots, m$$

$$\sum_{j=1}^n y_{\tau j} \lambda_j \geq y_{\tau k} \quad \tau = 1, 2, \dots, s$$

$$\sum_{j=1}^n \lambda_j = 1, \quad \lambda_j \geq 0 \quad j = 1, 2, \dots, n \quad (1)$$

Here, y_j is the value of the τ th output factor of DMU_j , and x_{ij} is the value of the i th input factor of DMU_j . λ_j represents the effect of DMU_j for comparison, and θ_k represents the efficiency of DMU_k , which is efficient when the value is 1 and inefficient when not.

The CCR model is also one of the basic DEA models for efficiency that can be expressed by the ratio of actual quantity and maximum possible quantity. It first started as fractional programming and was transformed into a typical form of linear programming. Each DMU determines the weight of input and output with maximum θ . Like the BCC model, the DMU is generally efficient when θ is 1 and inefficient when not. The CCR model can be expressed as follows.

$$\text{Max } \theta_k = \frac{\sum_{r=1}^s u_r y_{rk}}{\sum_{i=1}^m v_i x_{ik}}$$

$$\text{s. t. } \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1 \quad j = 1, 2, \dots, n$$

$$v_i, u_r \geq 0, \quad r = 1, 2, \dots, s; i = 1, 2, \dots, m \quad (2)$$

Here u_r is the weight of the r th output factor, v_i is the weight of the i th input factor, n is the number of DMUs, s is the number of

output factors, m is the number of input factors, k is the specific DMU to evaluate, y_{rj} is the quantity of r th output of DMU_j , and x_{ij} is the i th input of DMU_j .

DEA has several advantages, such as estimation with multiple input and output factors, comparison of units with similar inputs and outputs in a complicated production structure, measurement of relative efficiency, and usability of existing units without having to set random weights. However, absolute efficiency cannot be measured with DEA. Moreover, as the most beneficial weight for each DMU is applied for calculation, multiple DMUs can be identified as “efficient.” In particular, there is the problem of maverick DMU in which the DMU is identified as “efficient” when low and the most beneficial weight is applied to the DMU (Doyle & Green, 1994).

Unlike general DEA, this study used cross-efficiency analysis that can measure efficiency from a conservative view and prevent the derivation of extreme values by certain weights. Multiple DMUs are identified as efficient in DEA because each DMU applies the most beneficial weight. Cross-efficiency analysis is the method to solve this problem, and it is based on θ_{kj} defined in Eq. (3). Here, u_{rk} and v_{ik} are constants obtained when estimating the model to obtain efficiency values of DMU_k and the optimal weights of r th output factor and i th input factor. Therefore, θ_{kj} indicates the efficiency of DMU_j when the optimal weight beneficial for DMU_k is applied.

$$\theta_{kj} = \frac{\sum_{r=1}^s u_{rk} y_{rj}}{\sum_{i=1}^m v_{ik} x_{ij}}, \quad k = 1, \dots, n; j = 1, \dots, n \quad (3)$$

Meanwhile, goal programming can be applied to select one of the multiple solutions when the optimal solution of the linear programming model to obtain efficiency does not exist as a unique solution. This can be solved by applying the aggressive method that maximizes the efficiency of DMU_k and minimizes the cross-efficiency of other DMUs and the benevolent method that maximizes the cross-efficiency of both DMU_k and other DMUs simultaneously (Adler, Friedman, & Sinuany-Stern, 2002; Doyle & Green, 1994; Sexton, Silkman, & Hogan, 1986).

Here, the aggressive method maximizes the efficiency of DMU k , and the benevolent method maximizes the efficiency of DMU k while minimizing the cross-efficiency of other $k-1$ DMUs. The researchers discovered that there is no difference in the results obtained by using these two methods. The benevolent method may abnormally increase the efficiency of maverick DMU as other DMUs aside from the one being evaluated are also evaluated with certain benefits, considering which this study used the aggressive method of Eq. (4).

$$\begin{aligned} & \text{Min } \sum_{r=1}^s (u_{rk} \sum_{j \neq k} y_{rj}) \\ & \text{s. t. } \sum_{i=1}^m v_{ik} \sum_{j \neq k} x_{ij} = 1 \\ & \sum_{r=1}^s u_{rk} y_{kj} - \sum_{i=1}^m v_{ik} x_{ij} \leq 0 \quad \forall i \neq k \\ & \sum_{r=1}^s u_{rk} y_{rk} - \theta_{kk} \sum_{i=1}^m v_{ik} x_{ij} = 0 \\ & v_{ik} y_{ik} \geq 0 \quad \forall r \in (1, s), i \in (1, m) \end{aligned} \quad (4)$$

Next, the matrix of cross-efficiency can be formed using the efficiency value. CE_j can be calculated with the mean of efficiency θ_{*j} of DMU_j —the efficiency of DMU_j —to obtain in the cross-efficiency analysis. The significance of cross-efficiency analysis is that DMUs with efficiency can be differentiated and prioritized, and that objective efficiency can be calculated rather than reflecting the relative weight and eliminating unrealistic weights of input and output. In

Table 1
Cross-Efficiency Matrix.

Classification	Evaluated DMUs					
DMUs for application of optimal weight	DMU	1	2	j	n	Mean
	1	θ_{11}	θ_{12}	\cdot	θ_{1n}	RE_1
	2	θ_{21}	θ_{22}	\cdot	θ_{2n}	RE_2
	k	\cdot	\cdot	θ_{kj}	\cdot	\cdot
	n	θ_{n1}	θ_{n2}	\cdot	θ_{nn}	RE_n
	Mean	CE_1	CE_2	\cdot	CE_n	—

other words, prioritization using cross-efficiency provides more objectivity than general DEA by adding the process of evaluation with the optimal weights of other DMUs as shown in Table 1.

The DEA cross-efficiency method is obtaining efficiency through column means (CE) in Table 8 and comparing them to diagnose the efficiency level of each DMU. Talluri et al. (2013) added the concept of row means (RE) and used it in supply base rationalization. Row means to explain the characteristics of each DMU, and when the value is relatively lower than other DMUs, the DMU is differentiated from others; thus, performance diversity is high. In other words, when the means of rows and columns calculated through cross-efficiency analysis are presented in quadrants, DMUs in Quadrant II have higher efficiency compared to other DMUs and are differentiated from others. DMUs in Quadrants I and II must be drawn into Quadrant II. However, DMUs in Quadrant IV have low efficiency and are not differentiated from other DMUs. Fig. 1 shows the supplier classification method by Talluri et al. (2013) using DEA cross-efficiency.

3.2. Benchmarking - cluster analysis

Cluster analysis is a statistical method that classifies the objects of observation into a few clusters based on data similarity (Punj & Stewart, 1983). The most traditional method to improve the efficiency of inefficient DMUs is to use efficient DMUs as a reference set and set up the target of improvement through linear combination. However, this method cannot be applied when there is a structural difference between DMUs that are a reference set and DMUs that must be improved. Thus, benchmarks must be selected using different methods such as cluster analysis and multidimensional scaling (Doyle & Green, 1994). Cluster analysis can be used to set the benchmarks because DMUs with high similarity can be classified, and relevant cases have been also found in many studies (Flokou, Kontodimopoulos, & Niakas, 2011; Wu, Liang et al., 2010; Yuan & Shan, 2016).

This study conducted a cluster analysis using input and output data (as they are) used in DEA cross-efficiency. This method can set more accurate benchmarks by deriving the structural similarity among terminals (Wu, Liang et al., 2010). We combined the results of container terminal classification based on the theory of supply base rationalization with terminal classification derived through cluster analysis to provide terminal rationalization plans.

4. Data

4.1. Container Terminals in Korea

Ports in Korea with exclusive container terminals include Busan Port, Gwangyang Port, Incheon Port, Pyeongtaek-Dangjin Port, Ulsan Port, Masan Port, and Pohang Port. By container cargo volume, Busan Port, Incheon Port, and Gwangyang Port account for approximately 98% of all container cargo volume in Korea. Total 8 terminals are operated in Busan Port, and the annual cargo handling capacity is 17.58 million TEU. When the New Port Phase 2 and Phase 3 piers currently in development are completed, the annual cargo handling

Table 2
Status of Korean Container Terminals.

Classification	Terminal name	Berth composition	Quay wall length (m)	Berthing capacity (DWT)	Cargo handling capacity (1000 TEU)
Busan Port	PNIT	(400 × 3)	1200	50,000	2,091
	PNC	(333 × 6)	2000	50,000	3677
	HJNC	(350 × 2200 × 2)	1100	50,000	2310
				20,000	
	HPNT	(350 × 2225 × 2)	1150	50,000	1936
				20,000	
	BNCT	(350 × 4)	1400	50,000	2440
	Shingamman (SHGA)	(126 × 1350 × 2)	741	50,000	819
	Shinseondae (SHIN)	(300 × 4)	1200	5000	1789
	Gamman (GAMM)	(350 × 2)	7,00	50,000	800
Gwangyang Port	Jaseongdae (JASU)		1447	50,000	1722
				10,000	
	GWCT	(350 × 4)	1400	50,000	1600
	ICT	(300 × 2)	600	40,000	552
	SNCT	(300 × 1, 500 × 2)	800	20,000	1050
Incheon Port				40,000	
	HJIT	(300 × 1, 500 × 2)	800	20,000	1050
				40,000	
	PCTC	(280 × 2, 240 × 2)	1040	50,000 * 2	720
				30,000 * 2	
Ulsan Port	PNTC	(240 × 2)	480	30,000 * 2	400
	UNCT	(250 × 2210 × 2)	920	2000 * 4	962
	PICT	(250 × 4)	1000	20,000 * 4	260

Table 3
Basic statistics on loading capacity per hour.

Classification		N	Min	Max	Mean	Median	S.D
Busan North Port	1	JASU	167	15.0	86.0	37.7	38.5
	2	SHIN	62	16.4	93.5	53.7	53.8
	3	GAMM	53	19.7	57.7	42.4	43.9
	4	SHGA	70	24.2	92.5	74.1	62.1
Busan New Port	5	PNIT	1030	15.8	299.1	105.6	108.4
	6	PNC	778	15.1	165.1	84.4	83.2
	7	HJNC	1316	16.5	208.4	102.5	101.9
	8	HPNT	594	17.3	221.8	90.5	84.1
	9	BNCT	90	44.2	91.0	73.9	62.6
Incheon Port	10	ICT	73	20.2	77.1	47.2	51.7
	11	SNCT	83	19.7	86.8	57.3	55.8
	12	HJIT	85	21.2	101.2	65.9	69.3
Gwangyang Port	13	GWCT	437	16.4	176.2	77.6	75.5
Pohang Port	14	PICT	16	17.3	52.0	38.0	44.6
Pyeongtaek-Dangjin Port	15	PNCT	17	18.3	34.9	28.4	28.9
	16	PCTC	49	17.8	58.5	41.0	42.6
Ulsan Port	17	UNCT	63	15.2	60.5	36.6	36.8

capacity of all containers in Busan Port will increase up to 30 million TEU. Table 2 is a summary of major container terminals in Korea. Total 17 container terminals are selected as DMUs for analysis.

4.2. Data

This study analyzed the cross-efficiency of container terminals, and the input and output variables used in cross-efficiency analysis were selected with reference to previous studies. Quay length, twenty-foot ground slot (TGS), depth of water, and the number of cranes were used as input variables, and container cargo volume and loading capacity per hour were used as output variables. Among input variables, TGS indicates the ground space for one 20-foot container. TGS is used to calculate the required shed space, which indicates the horizontal shed area. Input variables were collected from the annual reports and websites of each Port Authority or terminal operating company.

Among output variables, cargo volume was collected from PORT-MIS, new port general plans by the Ministry of Oceans and Fisheries, and annual reports of each Port Authority. Loading capacity per hour was calculated by processing berthing data of each vessel of IHS Markit. Loading capacity per hour is the number of moves per hour by loading and unloading the containers on or from the vessel. High values indicate the shorter time required for container handling; thus, it is a key factor for shipping companies in selecting the port of call. Loading capacity per hour is becoming more important because cargo volume handled per port entry has increased due to the enlargement of vessel size, which caused vessels to stay longer at the port. Accordingly, shipping companies require ports to have higher productivity for punctuality; thus, ports are adopting high-efficiency equipment and increasing the number of cranes per vessel. Consequently, shipping companies and ports are showing continued interest in loading capacity per hour (JOC Port Productivity, 2014).

To calculate loading capacity per hour, arrival and departure performance data of container ships at the port of call are needed.

Table 4
Input and Output Data.

Classification			Input variables				Output variables	
			Quay length (m)	TGS (slot)	Depth of water (m)	Crane (crane)	Cargo volume (10,000 TEU)	Loading capacity per hour (move/hour)
Busan North Port	1	JASU	1447	10,484	15	14	193	37.7
	2	SHIN	1200	14,967	16	15	249	53.7
	3	GAMM	700	5797	15	11	129	42.4
	4	SHGA	826	6083	15	7	97	74.1
Busan New Port	5	PNIT	1200	12,354	16	12	248	105.6
	6	PNC	2000	21,112	17	22	494	84.4
	7	HJNC	1100	11,940	17	12	277	102.5
	8	HPNT	1150	10,031	17	12	206	90.5
	9	BNCT	1400	14,382	17	11	227	73.9
Incheon Port	10	ICT	600	4956	14	5	88	47.2
	11	SNCT	800	8750	16	7	125	57.3
	12	HJIT	800	8750	16	7	99	65.9
Gwangyang Port	13	GWCT	1400	14,982	16	9	94	77.6
Pohang Port	14	PICT	1000	7495	12	2	1	38.0
Pyeongtaek-Dangjin Port	15	PNCT	720	5778	13	3	25	28.4
Ulsan Port	16	PCTC	1040	6998	14	4	36	41.0
	17	UNCT	920	6464	14	3	30	36.6

Table 5
Cross-Efficiency Matrix of Korean Container Terminals.

	JASU	SHIN	GAMM	SHGA	PNIT	PNC	HJNC	HPNT	BNCT	ICT	SNCT	HJIT	GWCT	PICT	PNCT	PCTC	UNCT	row mean
JASU	0.788	0.713	0.958	0.698	0.867	1.000	1.000	0.886	0.678	0.776	0.617	0.492	0.276	0.015	0.191	0.226	0.207	0.611
SHIN	0.537	0.829	0.720	0.463	0.826	1.000	1.000	0.713	0.650	0.573	0.612	0.484	0.270	0.005	0.137	0.137	0.130	0.534
GAMM	0.788	0.713	0.958	0.698	0.867	1.000	1.000	0.886	0.678	0.776	0.617	0.492	0.276	0.015	0.191	0.226	0.207	0.611
SHGA	0.426	0.528	0.492	1.000	0.987	0.619	1.000	0.795	0.748	1.000	0.838	0.878	0.765	1.000	0.698	0.787	0.858	0.789
PNIT	0.418	0.533	0.472	0.961	1.000	0.628	1.000	0.785	0.758	0.931	0.815	0.863	0.806	1.000	0.660	0.760	0.807	0.776
PNC	0.606	0.730	0.509	0.582	0.898	1.000	1.000	0.744	0.889	0.724	0.746	0.590	0.447	0.022	0.322	0.354	0.381	0.620
HJNC	0.597	0.719	0.508	0.600	0.895	0.973	1.000	0.744	0.894	0.766	0.773	0.611	0.453	0.026	0.360	0.386	0.433	0.632
HPNT	0.634	0.589	0.913	1.000	0.921	0.759	1.000	0.915	0.622	0.967	0.678	0.654	0.413	0.256	0.351	0.417	0.396	0.676
BNCT	0.597	0.719	0.508	0.600	0.895	0.973	1.000	0.744	0.894	0.766	0.773	0.611	0.453	0.026	0.360	0.386	0.433	0.632
ICT	0.426	0.528	0.492	1.000	0.987	0.619	1.000	0.795	0.748	1.000	0.838	0.878	0.765	1.000	0.698	0.787	0.858	0.789
SNCT	0.443	0.561	0.484	0.932	0.964	0.669	1.000	0.774	0.784	1.000	0.863	0.866	0.729	1.000	0.709	0.758	0.873	0.789
HJIT	0.330	0.493	0.549	1.000	0.965	0.486	1.000	0.776	0.612	1.000	0.824	0.916	0.681	0.569	0.540	0.549	0.574	0.698
GWCT	0.327	0.436	0.435	1.000	1.000	0.461	0.950	0.763	0.659	0.871	0.750	0.864	0.882	0.995	0.629	0.754	0.756	0.737
PICT	0.262	0.367	0.411	1.000	0.864	0.349	0.853	0.679	0.566	0.986	0.779	0.896	0.756	1.000	0.713	0.747	0.828	0.709
PNCT	0.297	0.408	0.430	1.000	0.892	0.411	0.891	0.705	0.610	1.000	0.803	0.902	0.759	1.000	0.717	0.753	0.838	0.730
PCTC	0.352	0.431	0.454	1.000	0.882	0.477	0.888	0.724	0.631	1.000	0.775	0.840	0.695	1.000	0.707	0.788	0.873	0.736
UNCT	0.460	0.567	0.491	0.930	0.962	0.688	1.000	0.780	0.791	1.000	0.856	0.849	0.711	1.000	0.706	0.768	0.886	0.791
Column mean	0.488	0.580	0.576	0.851	0.922	0.712	0.975	0.777	0.718	0.890	0.762	0.746	0.596	0.584	0.511	0.564	0.608	0.698

Table 6
Comparison of efficiency analysis results.

Classification			CCR Efficiency	CCR Ranking	Cross-efficiency	Cross-efficiency Ranking
Busan North Port	1	JASU	0.788	15	0.488	17
	2	SHIN	0.829	14	0.580	13
	3	GAMM	0.958	7	0.576	14
	4	SHGA	1.000	1	0.851	4
Busan New Port	5	PNIT	1.000	1	0.922	2
	6	PNC	1.000	1	0.712	9
	7	HJNC	1.000	1	0.975	1
	8	HPNT	0.915	9	0.777	5
	9	BNCT	0.894	10	0.718	8
Incheon Port	10	ICT	1.000	1	0.890	3
	11	SNCT	0.863	13	0.762	6
	12	HJIT	0.916	8	0.746	7
Gwangyang Port	13	GWCT	0.882	12	0.596	11
Pohang Port	14	PICT	1.000	1	0.584	12
Pyeongtaek-Dangjin Port	15	PNCT	0.717	17	0.511	16
	16	PCTC	0.788	16	0.564	15
Ulsan Port	17	UNCT	0.886	11	0.608	10

Table 7
Terminal group classification results.

	Group 1	Group 2	Group 3
Terminal	PNC	JASU SHIN PNIT HJNC HPNT BNCT GWCT	GAMM SHGA ICT SNCT HJIT PICT PNCT PCTC UNCT

Table 8
Comparison of the number of berths per operating company in overseas ports and Busan Port (2018).

Classification	Shanghai	Singapore	Dubai	Busan
No. of berths	48	62	28	46
No. of operating companies	7	8	3	11
No. of berths per operating company	6.8	7.7	9.3	4.1

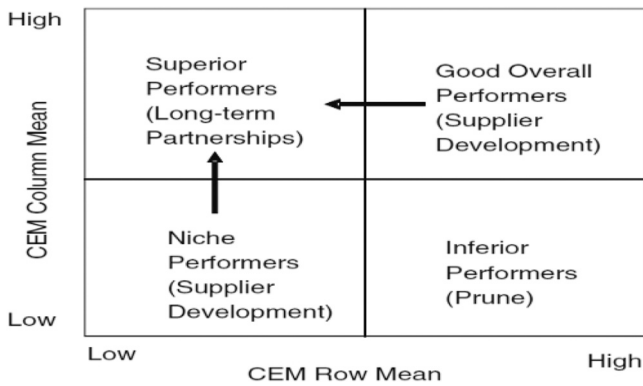


Fig. 1. Supply base rationalization framework.

Source: Talluri et al. (2013), p.70.

Thus, we analyzed the loading capacity per hour of major ports worldwide using raw data collected by IHS Markit. We collected 4983 samples from the year 2018 among container terminals in Korea, calculated the average loading capacity per hour with Eq. (9), and used the results in efficiency analysis.

$$MU_i = \frac{\sum_{j=1}^n \sum_{l=1}^n \left(\frac{TEU_{ij}}{t_e - t_s} \right)}{n_i} \quad (9)$$

Here, MU_i is the loading capacity per hour of terminal i , TEU_{ij} is the volume of cargo handled by vessel j after arriving at terminal i , t_e is the end time, t_s is the start time, and n_i is the number of data counted in terminal i , using the mean as output variable. The basic statistics of data collected to calculate the loading capacity per hour are as shown in Table 3. Over 1000 samples were collected from HJNC and PNIT of Busan New Port, and 16 samples were collected from PICT of Pohang Port, which is the smallest number. Despite the small number of samples, PICT was included in the analysis as the samples represent statistically significant data in terms of freedom.

The final input and output data, including the calculation results of loading capacity per hour, are as shown in Table 4.

5. Result and discussion

5.1. Efficiency analysis

For efficiency analysis, we used MultiplierDEA of statistical package R 4.0.0. Table 5 shows the matrices of cross-efficiency analysis of container terminals in Korea. The column mean represents the efficiency of each DMU, and the row mean represents the distinction of each DMU. Higher column means of DMUs indicate higher efficiency, and lower row means show that the DMU is differentiated from others. Container terminals in Korea have a relatively wide range of column means from 0.488 to 0.975 but a relatively small range of row means from 0.534 to 0.791. This indicates that each terminal is not considerably different compared to other terminals, which proves the homogeneity of services among container terminals.

Table 6 is a summary of the general DEA-CCR efficiency analysis results and cross-efficiency analysis results. In CCR efficiency analysis, Busan North Port SHGA, Busan New Port PNIT, PNC, HJNC, Incheon Port ICT, and Pohang Port PICT showed the highest efficiency; Pyeongtaek-Dangjin Port PNCT and PCTC showed the lowest efficiency. In the cross-efficiency analysis, Busan New Port HJNC showed the highest efficiency, and Busan North Port JASU showed the lowest efficiency. Among terminals showing the highest efficiency in CCR analysis, HJNC, PNIT, ICT, and SHGA were also ranked relatively high in cross-efficiency analysis. However, PNC was ranked 9th, showing a

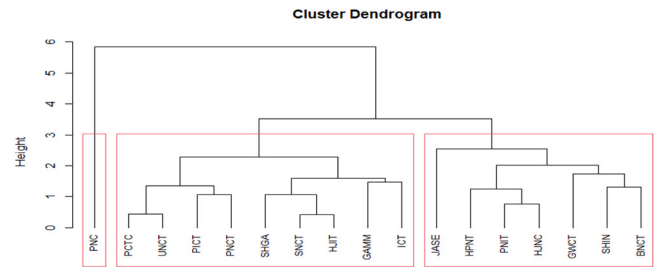


Fig. 2. Hierarchical clustering results.

medium level of efficiency among all terminals, and PICT was ranked 12th, showing low efficiency. PNC is the DMU with the highest values of four inputs out of all terminals that also handled the biggest cargo volume, but its loading capacity per hour was lower than other terminals of Busan New Port. PICT had only two cranes, which is the smallest number, and the cargo handling volume was also 10,000 TEU, which is the lowest. Its loading capacity per hour was also low, indicating that it has both low input and output. Therefore, by applying the beneficial weight for each of the two terminals, the efficiency is 1, but the rank becomes lower when evaluated with cross-efficiency. This indicates that it is necessary to perform more objective evaluation through cross-efficiency analysis rather than ranking the efficiency of terminals using CCR analysis while analyzing efficiency and establishing rationalization plans.

5.2. Cluster analysis

We additionally conducted a cluster analysis to determine benchmarks for port rationalization strategies and terminal efficiency improvement. As previously mentioned, the analysis was conducted using the input and output data of DEA as they are, and the stats package of R 4.0.0 was used for hierarchical clustering. Fig. 2 shows the results of hierarchical clustering, and Table 7 shows the group classification results.

Only Busan New Port PNC belongs to Group 1. PNC is the biggest terminal in Korea with higher inputs, such as quay length, TGS, and number of cranes, than other terminals. Its cargo volume is also approximately 1.8 times greater than HJNC, which is ranked 2nd. Thus, it was classified as a single group that does not belong to any other group. Group 2 includes Busan North Port JASU and SHIN, Busan New Port PNIT, HJNC, HPNT, and BNCT, and Gwangyang Port GWCT. These are large terminals with at least 1000 m quay length, 10,000 TGS, and 9–15 cranes. Group 3 includes Busan North Port GAMM and SHGA, Incheon Port ICT, SNCT, and HJIT, Pohang Port PICT, Pyeongtaek-Dangjin Port PNCT and PCTC, and Ulsan Port UNCT. These terminals have less than 10,000 TGS, 600–1040 m quay length, and 2–11 cranes, which are less than Group 2, and the cargo volume and loading and unloading productivity are also lower than Group 2. In other words, Group 1 is classified as a mega-terminal, Group 2 as large terminals, and Group 3 as small and medium-sized terminals.

5.3. Terminal rationalization framework

Fig. 3 provides the cross-efficiency calculation results of all DMUs in Quadrant IV for rationalization. The average matrix was 0.678. The results showed that there were four superior DMUs (Quadrant II) with high efficiency and distinction, such as Busan New Port PNC, HJNC, HPNT, and BNCT. There were five good DMUs (Quadrant I) with high efficiency but lack of distinction as a terminal, such as Busan New Port PNIT, Busan North Port SHGA, Incheon Port ICT, SNCT, and HJIT. There were three niche DMUs (Quadrant III) with distinction but lack of efficiencies, such as Busan North Port JASU, SHIN, and GAMM. There were five inferior DMUs (Quadrant IV) with

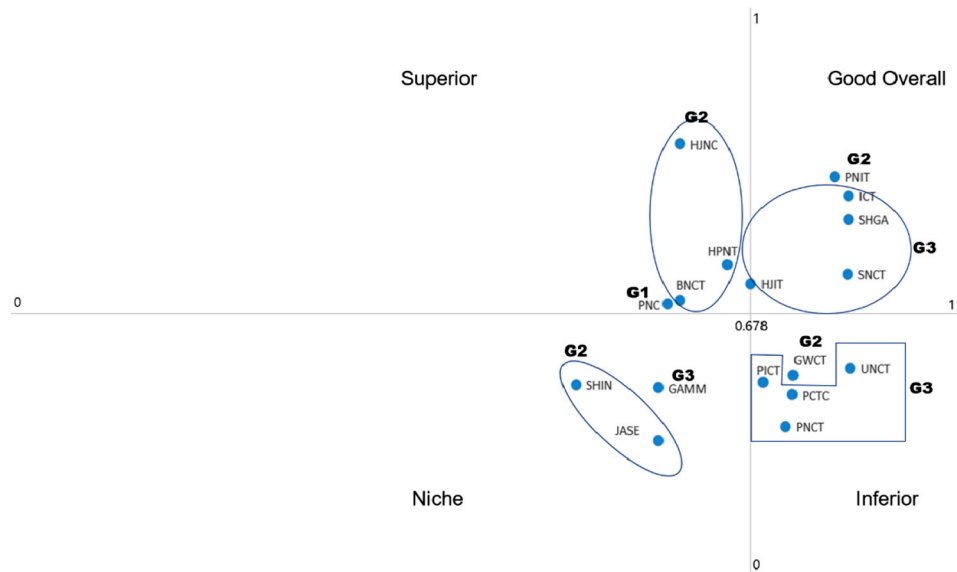


Fig. 3. Terminal Rationalization framework for Korean Container Terminal.

a lack of efficiency and no distinction, such as Gwangyang Port GWCT, Pohang Port PICT, Pyeongtaek Port PNCT and PCTC, and Ulsan Port UNCT. The group classification results are also provided in the figure. Groups 1 and 2 are located in the superior group and Group 3 mostly in the good and inferior groups. This indicates that large terminals have higher efficiency than small and medium-sized terminals, and their size differentiates them from other terminals.

5.4. Discussion

We will provide port-terminal rationalization plans by combining the results of cross-efficiency and cluster analyses.

5.4.1. Inferior terminal

We first examined the case of inferior terminals that lack efficiency and distinction the most. All inferior terminals except GWCT are small and medium-sized terminals in Group 3, and they are close to the hub ports in Korea. PICT and UNCT are located near Busan Port, and PNCT and PCTC are located near Incheon Port, thus sharing the same hinterland. In this case, shippers prefer the more efficient terminals of Busan Port or Incheon Port, which makes it difficult for other terminals to attract cargo volume. In fact, the annual cargo volume of PICT is merely 12 thousand tons, and other terminals are also showing lower cargo volume and loading and unloading productivity than competing terminals. Therefore, for PICT, UNCT, PNCT, and PCTC, it is more rational to seek a functional shift to a multi-purpose terminal than to improve terminal efficiency through benchmarking.

GWCT is structurally a large port but severely lacks efficiency. This is because while the input size is similar to Busan New Port terminals, the cargo volume is less than half. Three plans can be considered for the rationalization of GWCT. First, the functional shift can be applied like other inferior terminals. Next, efficiency can be improved by benchmarking superior terminals in Group 3, especially HJNC with the highest efficiency. Finally, good terminals in Group 2 can be benchmarked to reduce the port size. Gwangyang Port is a large port in terms of input size; therefore, a functional shift is not a reasonable plan considering the investment costs. Moreover, to improve efficiency by benchmarking Group 3, it is necessary to additionally obtain cargo volume and improve loading and unloading productivity by streamlining the operations. However, as Gwangyang Port is located relatively close to Busan Port, it is difficult

to obtain additional cargo volume. The loading and unloading productivity of GWCT is the fourth highest out of all terminals and thus cannot be improved significantly. Thus, it is more rational for GWCT to benchmark Group 2 and maintain cargo volume while improving efficiency by adjusting input size such as TGS and aiming for a good terminal.

5.4.2. Niche terminal

JASU and SHIN, among niche terminals, belong to large terminals in terms of size and also have a big cargo volume and thus are differentiated from other terminals. However, their loading and unloading productivity is lower than other terminals in Group 2 and thus lacks efficiency. Therefore, the two terminals must strive to improve loading and unloading productivity through streamlining of operations by benchmarking the terminals in Group 2, especially HJNC with high loading and unloading productivity. GAMM has the lowest quay length and TGS out of all terminals located in Busan Port. As Busan North Port has limitations in expanding the terminal input size, it is more rational to aim for a good terminal by benchmarking ICT with the highest efficiency among terminals in Group 3 rather than moving up to a superior terminal by benchmarking Group 2.

5.4.3. Good overall terminal

ICT, SNCT, and HJIT, among good overall terminals, are all located in Incheon Port and belong to Group 2. Their cross-efficiency is ranked 3rd to 7th, which is higher than the medium level. To aim for superior terminals, it is more rational to expand the size of these three terminals through integration rather than improving efficiency individually. By turning them into a large terminal through integration while maintaining cargo volume but increasing quay length, TGS, and the number of cranes to an adequate size, they can develop into a superior terminal. However, many other factors aside from efficiency must be considered in terminal integration—it requires a long-term view and institutional support measures from the government. If integration is not an option, an alternative for SNCT and HJIT could be to improve efficiency by benchmarking ICT, which shows the highest efficiency within the same group.

PNIT is ranked second in terms of cross-efficiency, which is extremely high, but it is not included among superior terminals, unlike other Group 3 terminals (HJNC, HPNT, BNCT) of Busan New Port. The quay length, TGS, cranes, and cargo volume of PNIT are similar to

other terminals in Group 3, and the productivity for loading and unloading is the highest among all terminals, but the depth of water is lower than other Busan New Port terminals. As the depth of water is the input data most difficult to adjust, it is rational for PNIT to benchmark HJNC with the highest efficiency or consider improving efficiency by integrating with other Busan New Port terminals rather than striving for specialization. SHGA is the only Busan North Port terminal that is good, ranked fourth in cross-efficiency, which is due to the high loading and unloading productivity compared to the input. Considering the circumstances of Busan North Port, the rational plan for SHGA is to seek efficiency improvement by benchmarking ICT with high efficiency within the same group rather than trying to move up to a superior terminal through expansion.

5.4.4. Superior terminal

Superior terminals have high efficiency among container terminals in Korea and are large terminals. However, HPNT and BNCT are ranked 5th and 8th in cross-efficiency, which is not high. Thus, it is necessary to seek efficiency improvement by benchmarking HJNC that belongs to the same Group 2 with the highest efficiency. As PNC does not have other terminals that belong to the same group in Korea, it is necessary to find benchmarks by examining mega terminals overseas.

Another plan to consider in the rationalization of superior terminals in Korea is to integrate the terminals. Table 8 shows the number of berths per terminal in Busan Port and other major container terminals in the world. Port of Shanghai, Port of Singapore, and Dubai Ports have at least six berths per terminal, but Busan Port only has 4.1 berths. The fact that there are relatively few berths per terminal indicates that many of the terminal operating companies are competing within the same port, and the available berth extension is relatively short, making it difficult to deal with the recent trend of vessel enlargement. Moreover, Busan Port has small terminals compared to the alliances, causing dispersion of alliance volume and transshipment cargo of other piers, which incur additional time and costs. In these circumstances, integration of container terminals may bring positive effects such as increased operating efficiency, reduced logistics costs, improved port competitiveness, and stronger bargaining power over large shipping company alliances. Considering that the Korean government is also discussing terminal integration of Busan New Port, integration of superior terminals may be a good plan for terminal rationalization. However, as previously mentioned, there are many matters to consider in terminal integration such as legal review, agreement among terminal operating companies, and monopoly and oligopoly issues, which is why it must be pursued as a long-term goal at the national level.

6. Conclusion

This study measured the efficiency of container terminals by combining DEA cross-efficiency and cluster analysis and presented terminal rationalization plans at the national level. Moreover, we proved the usefulness of the plans provided through the cases of container terminals in Korea and set the future direction for the rationalization of 17 container terminals.

This study was conducted in terms of improving individual terminal efficiency and examined terminal rationalization plans at the national level based on the theory of supply base rationalization. Container terminals are acting as suppliers that provide international logistics services at the national level. For efficient operations, it is necessary to improve investment and operating systems to establish an efficient logistics system at the level of individual terminals. However, it is also absolutely necessary to establish terminal rationalization plans to establish a smooth logistics system at the national level. Considering that most studies on terminal efficiency

improvement thus far are focused on individual terminals, this study has significance as it studied rationalization plans at the national level.

The limitations and future tasks of this study are as follows. First, this study was conducted only on container terminals in Korea. As the goal is to establish rationalization plans at the national level, the main subjects of research must be Korean container terminals. However, it will be more meaningful to include major terminals overseas when comparing the efficiency and selecting benchmarks. Furthermore, this study used only cluster analysis for the selection of benchmarks. Using other methods presented by previous studies, such as multidimensional scaling and principal component analysis (PCA), and choosing a more suitable method will broaden the scope of interpretation. Finally, this study can also establish terminal rationalization plans in terms of sustainability by adding data that can measure sustainability, such as data on exhaust gas, to the input and output data used in DEA cross-efficiency.

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Conflicts of Interest

The authors declare no conflict of interest.

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