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# Analysis of Efficiency and Productivity for Major Korean Seaports using PCA-DEA model

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# PCA-DEA 모델을 이용한 국내 주요항만의 효율성과 생산성 분석에 관한 연구

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## Abstract

Korea has been huge investments in its port system, annually upgrading its infrastructure to turn the ports into Asian hub port. However, while Busan port is ranked fifth globally for container throughput, Other Korean ports are ranked much lower. This article applies Data Envelopment Analysis (DEA) and Malmquist Productivity Index (MPI) to evaluate selected major Korean seaports' operational efficiency and productivity from 2010 to 2018. It further integrates Principal Component Analysis (PCA) into DEA, with the PCA-DEA combined model strengthening the basic DEA results, as the discriminatory power weakens when the variable number exceeds the number of Decision Making Units(DMU). Meanwhile, MPI is applied to measure the seaports' productivity over the years. The analyses generate efficiency and productivity rankings for Korean seaports. The results show that except for Gwangyang and Ulsan port, none of the selected seaports is currently efficient enough in their operations. The study also indicates that technological progress has led to impactful changes in the productivity of Korean seaports.

*Key words: Korean seaports, Efficiency, Productivity, PCA-DEA, MPI*

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# Ⅰ. Introduction

Geographically, Korea has close ties with ocean economies such as Japan and countries in Southeast Asia, as well as continental economies including China, Russia, and America. Korea's national economy has been enjoying prosperous development and growth. According to the World Bank's statistics data, Korea's economy ranks fourth in Asia and the twelveth in the world. Similar to other industrialized countries, Korea suffered significant setbacks from the 2007 recession; however, from 2015, due to the Chinese stock market turbulence that affected world finance - and especially, China's linkage countries - Korea's economy experienced the sharpest annual decline in both exports and imports since the global financial crisis. The decline continued throughout 2016 before briskly rebounding in 2017 (World Bank data, 2019). These developments have significantly increased the chance for seaports' development. Therefore, Korean port authorities have implemented different government-aided programs to improve infrastructure and facilities and upgrade services. In addition, the Korean government has been endeavouring to transform Busan and Gwangyang ports into important regional or global hub-ports by expanding their berths and upgrading infrastructure and superstructure (Yeo et al., 2008). Consequently, Korea has been ranked in the top five in terms of traffic volume and liner shipping connectivity. However, these have also created various difficulties in the seaports' performance. According to 2018 World Bank data, the score for the quality of trade and transport related infrastructure(logistics performance index) of Korean container ports was 3.73. These illustrate that Korea's trade and transport-related infrastructure are not competitive and may create barriers for ports' competitiveness and efficiency. Thus, the study assesses the performance of major Korean seaports using the DEA model and MPI to reveal their efficiency and productivity in recent years. Moreover, the current article could inform port policies to improve efficiency and productivity through different strategies for each port.

The paper is structured as follows: Section 2 reviews the literature on port's efficiency with DEA and MPI, Section 3 mentions some methods used in the study, Section 4 provides the model's results and their implications, and Section 5 presents the findings of the study.

# Ⅱ. Literature Review

The DEA model has been applied in previous studies to examine ports' efficiency. For instance, Tongzon (2001) used the DEA model for container ports in Australia, and Valentine and Gray (2001) used the CCR model of DEA to identify relative efficiencies of 31 global container ports. Bonilla et al. (2002) analyzed the efficiency of the Spanish seaport system using DEA. Turner et al., (2004) used the DEA model to measure infrastructure productivity and Tobit regression to examine the determinants of infrastructure productivity in American container ports. Ryoo (2005) evaluated the efficiency of ports in Busan and Gwangyang. Additionally, by applying the DEA model, Pang (2006) examined the efficiency of 50 major seaports in China. DEA has also been used in many studies: Cullinane and Wang (2006) used DEA for 104 container terminals in Europe, Kwon (2007) used DEA for 22 North-east Asian ports, Park (2011) used DEA for 11 container terminals in Busan, and for the port of Gwangyang, and Kim and Hwang (2012) studied some major container ports in Korea and China by comparing the transportation process results before and after the financial crisis. Also, Wisnicki et al. (2017) analyzed nine European terminals that used different handling technology to measure efficiency by applying the DEA model, while Wanker et al. (2018) assessed the efficiency of six major Nigerian ports from 2003 to 2007 by applying a two-stage fuzzy-based methodology. Thus, previous studies were based on specific physical input variables such as berth length, number of cargo handling equipment, total yard area, and, most commonly, container throughput. While many other variables were considered to affect the port's operational efficiency, such as the port handling capacity, hinterland related factors—such as number of hinterland areas served by the port, number of the industrial complex around the port, and consumer area population—were not considered the parameters for input and output properly in DEA. Moreover, there have been no controlled studies that focused on the efficiency of major Korean seaports, although one study compared a few large Korean seaports to other countries' seaports. (Ryoo, 2005; Park, 2011; Kim and Hwang, 2012)

However, in the above mentioned studies, we could not find the discrimination with the application of DEA because there is a disproportion between inputs, outputs, and the number of Decision Making Units (DMUs). When this occurs, many DMUs will form the frontier and are efficient DMUs; for example, a substantial unit proportion is considered efficient (Adler and Golany, 2007). To overcome this drawback, Adler and Berechman (2001) built a PCA based methodology to change the number of inputs or outputs used in the DEA model into a factor and applied it to measure West-European airport quality from the airlines' perspective. In addition, Adler and Yazhemsky (2010) applied Monte Carlo simulations to analyze two discrimination improving methods. They found that the combination between PCA and DEA provided a more powerful tool than VR (virtual reality) with consistently more accurate results. Therefore, this article will combine the DEA model with PCA to reduce the number of inputs and outputs before using these variables for efficiency and productivity measurement.

Moreover, as the DEA model cannot compare performances across years, the study incorporates the MPI to evaluate the productivity of these seaports during the research period. Some studies utilized MPI to analyze the change in the efficiency of seaports. For instance, Liu, Liu, and Cheng (2006) calculated the productivity of some container terminals in Mainland China between 2003 and 2006 by employing MPI. This study indicated that large ports worked most efficiently, and Sino-foreign joint ventures (in terms of ownership) performed better than domestic companies. Haralambides et al. (2010) employed the Malmquist index and Luenberger indicator (a productivity indicator that can reduce the number of inputs and increase the number of outputs simultaneously) to analyze the productivity of 16 seaports of the Middle East and East Africa. The result indicated that ports in these regions declined in technical efficiency despite adopting new technologies. Wang and Lan (2011) proposed a new approach based on double frontiers input-oriented DEA (DFDEA) based MPI. Gunet and Coskun (2013) combined the DEA model and utilized the MPI to measure the efficiencies of 4 participating passenger ports in Turkey and their efficiency change from 2003 to 2010. Additionally, Nwanosike et al. (2016) employed MPI to benchmark pre-and post-reform productivity growth of 6 major Nigerian seaports from 2000 to 2011, representing six years before and after the reform. This study indicated the source of pre-concession period productivity growth as technological progress, while an increase in scale efficiency generated the productivity change of the post-concession period.

In short, this article combines the DEA model and MPI to measure the efficiency and productivity variation of major Korean seaports during a decade. In addition, this article is the first to merge with the PCA model to account for the shortage of the number of decision-making units.

## Ⅲ. Methodology

### 3.1 Data Envelopment Analysis (DEA) model

The DEA model was developed by Charnes, Cooper, and Rhodes (1978), and the DEA-CCR (Charnes et al. 1978) and DEA-BCC (Banker et al. 1984) are applied commonly to measure the efficiency of DMUs. The primary difference between the CCR and BCC models is that the CCR model supposes a constant return to scale (CRS) while the BCC model supposes a variable return to scale (VRS). CRS implies that a change in the input amount will lead to a similar change in the output number and that all observed production combinations can be increased or decreased proportionally. On the other hand, the BCC model allows for VRS and is graphically represented by a piecewise linear convex frontier.

#### 3.1.1 DEA-CCR model

In the DEA-CCR model, there are n DMUs, and each DMU uses m different inputs to produces different outputs. Specifically, $DMU_j$ consumes amounts $X_j$ = $[x_{ij}]$ of inputs (i=1,⋯,m) and produces amounts $Y_j$ = $[y_{rj}]$ of outputs (r=1,⋯,s). The s × n matrix of output measures is represented by Y, and the m × n matrix of input measures is represented by X. Another assumption is that $x_{ij}$ and $y_{rj}$ are both positive. Let us consider the problem of evaluating the relative efficiency for any one of the n DMUs, which will be identified as $DMU_0$. The relative efficiency for $DMU_0$ is calculated by maximizing the weighted sum of the target output. This weighted sum of the target inputs is equal to unity, and the differences between the weighted sum of the outputs and that of the inputs are smaller than zero and expressed as Equation (1).

$$Max\,\theta = \sum_{r=1}^{s} u_r y_{rj0} \tag{1}$$

$$\left\{\begin{array}{l} s.t. \sum_{i=1}^{m} v_i x_{i0} = 1 \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0 \; (j=1,2,\ldots,n) \\ u_r \geq 0 \, (r=1,2,\ldots s) \\ v_i \geq 0 \, (i=1,2,\ldots m) \end{array}\right\}$$

Where $u_r$ is output r and $v_i$ is input i

A DMU is CCR efficient if $\theta^* = 1$ and there exists at least one optimal where $v_r^* > 0$ and $u_i^* > 0$ are optimal solutions of formula (1). Otherwise, the DMU is inefficient.

### 3.1.2 DEA-BCC model

The BCC model is expressed as Equation (2)

$$Max\,\theta = \sum_{r=1}^{s} u_r y_{rj0} - u_0 \qquad (2)$$

$$\begin{Bmatrix} s.t. \sum_{i=1}^{m} v_i x_{i0} = 1 \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_i - u_0 \le 0 \; (j = 1,2,...,n) \\ u_r \ge 0 \, (r = 1,2,...s) \\ v_i \ge 0 \, (i = 1,2,...m) \end{Bmatrix}$$

If a DMU is CCR efficient, then it is also BCC efficient.

The score of the BBC efficiency will be obtained by running the BBC model for each DMU. These scores are called "pure technical efficiency scores". The CCR-efficiency score of all DMUs will be lower than the BCC-efficiency score. Except for u0, which may be positive, negative, or zero, all the variables of the function in Equation (2) are constrained to be non-negative.

Most studies have divided the efficiency score derived from the DEA-CCR model. One such score is called scale efficiency, and the other is known as pure technical efficiency. This can be achieved by applying both the CRS (DEA-CCR) and VRS (DEA-BCC) models to the same data. If a specific DMU shows a difference between two efficiency scores, it means that DMU has scale inefficiency. The scale inefficiency score can be obtained by calculating the difference between the DEA-CCR and the DEA-BCC efficiency scores, as shown in Equation (3).

*Scale Efficiency Score (SE) = Technical efficiency (TE-CCR)/ Pure Technical Efficiency (PTE-BCC) (3)*

## 3.2 Malmquist Productivity Index (MPI)

The Malmquist Index was introduced by Douglas W. Caves, Laurits R. Christensen, and W. Erwin Diewert (1982). The MPI measures the productivity changes (productivity growth) over time. MPI analyze the change in productivity with regard to the change of time, and it can be divided into changes in efficiency and technology. The non-parametric MPI measures the Total Factor Productivity Changes (TFPCH) of a specific DMU and measures the efficiency change between two adjacent periods based on DEA. The index can be identified as Equation:

$$\begin{aligned} TFPCH &= \left[ \frac{D_t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{1/2} \\ &= \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \left[ \frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} \right]^{1/2} \\ &= EFFCH \times TECHCH = PECH \times SECH \times TECHCH \end{aligned}$$

(4)

Where TFPCH refers to the MPI value, which stands for the whole change that may change over time because of EFFCH (Efficiency Changes) or TECHCH (Technical Changes). EFFCH reflects the change of technology efficiency from this period to the next period and shows the DMU's attempt to improve its efficiency. EFFCH = 1 stands for the steadiness. EFFCH 〉 1 implies that DMU is improving, and EFFCH 〈 1 shows the decline of technical efficiency of DMU. EFFCH can be broken down into two components: PECH (Pure

Efficiency Changes) and SECH (Scale Efficiency Changes). PECH denotes the management degree in employing given resources, while scale efficiency evaluates the ability to exploit scale economies for DMUs. TECHCH reflects the technological change by measuring the production frontier movement between periods.

### 3.3 Principle Component Analysis (PCA)

One of the drawbacks of the DEA model is that the number of DMUs should be large enough to ensure the research result accuracy. In other words, the number of inputs and outputs and the DMUs determine the extent of discrimination between efficient and inefficient units. With a larger population, a greater probability exists of capturing high-performance units that would determine the efficient frontier (Golany and Roll, 1989). Therefore, there are some rules of thumb on input and output number and their relation to the DMU number. Golany and Roll (1989) stated a rule of thumb that the unit number should be at least twice the number of inputs and outputs considered. However, in this paper, only nine seaports have been considered, which is much less than the standard because the seaports system in Korea depends mainly on these major seaports and the remaining seaports account for extremely small proportions.

Therefore, to overcome the limitation of the DEA model, dimensionality reduction schemes were combined, such as PCA. PCA was first used in 1901 by Karl Pearson and is mainly used as an exploratory data analysis tool. A mathematical procedure will transform correlated variables into uncorrelated variables in PCA. In this paper, PCA was employed to embed the inputs and outputs into a reduced subspace for further analyses.

## Ⅳ. Analysis result for efficiency and productivity

This part evaluated the efficiency and productivity of major Korean seaports. These leading seaports significantly influenced cargo trade and maritime transport. The dataset for analysis included 9 Korean seaports selected in terms of cargo handling volume. The analysis period was from 2010 to 2018 (9 years), and the port data were assembled from the relevant websites for port authorities, Korean statistics, etc.The first step was to collect the data related to the performance of these nine seaports and the data were be divided into two types: inputs and outputs. The second step used the PCA model to reduce the dimension in the research. In other words, the number of output variables used in the DEA model were reduced adopting PCA. The reduction here is not factoring elimination but changing factors into the principal components so that the number is always less than the original number of inputs and outputs. Finally, the PCA model results measured efficiency and productivity using the DEA model and the Malmquist index. The details of each step are as follows.

### Step 1. Collecting the data

The dataset for analysis included the 9 Korean seaports in terms of cargo handling volume, and the top three were Busan, Gwangyang, and Ulsan ports. The top three seaports accounted for nearly

60% of total cargo volume in the 2018 Korean seaports system, and the top 9 seaports accounted for about 90% of total cargo volume (see Table 1).

Table 1. Cargo handling performance of major Korean seaports (Mil. R/T)

| | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 |
|---|---|---|---|---|---|---|---|---|---|---|
| Busan | 226.3 | 262.1 | 294.3 | 312.0 | 324.9 | 346.6 | 359.7 | 362.4 | 401.2 | 460.1 |
| Gwangyang | 182.7 | 206.7 | 219.9 | 237.3 | 239.6 | 253.3 | 272.0 | 283.1 | 292.3 | 301.9 |
| Ulsan | 169.4 | 171.7 | 193.8 | 196.9 | 191.0 | 191.7 | 190.9 | 197.6 | 202.4 | 202.8 |
| Incheon | 132.4 | 149.8 | 147.7 | 143.9 | 146.1 | 150.1 | 157.6 | 161.3 | 165.5 | 163.5 |
| Pyeongtaek | 51.3 | 76.7 | 95.6 | 100.7 | 109.3 | 117.0 | 112.2 | 113.0 | 112.5 | 115.1 |
| Daesan | 64.7 | 66.1 | 66.5 | 70.1 | 69.0 | 72.9 | 78.5 | 85.9 | 90.3 | 92.1 |
| Pohang | 58.7 | 63.1 | 66.9 | 62.8 | 61.7 | 65.2 | 61.5 | 62.3 | 58.9 | 60.5 |
| Donghae | 24.6 | 28.0 | 31.3 | 31.2 | 31.7 | 32.5 | 31.3 | 32.3 | 33.3 | 34.2 |
| Mokpo | 15.1 | 16.4 | 17.8 | 16.9 | 20.2 | 23.0 | 22.5 | 23.6 | 23.8 | 22.4 |
| Other | 151.5 | 163.5 | 177.4 | 166.6 | 165.6 | 163.5 | 176.9 | 188.1 | 194.2 | 172.2 |
| Total | 1,076.5 | 1,204.1 | 1,311.2 | 1,338.6 | 1,358.9 | 1,415.9 | 1,463.1 | 1,509.5 | 1,574.3 | 1,624.7 |

Source: Port authorities

Table 2. Result of descriptive statistics of major Korean seaports

| | X1 | X2 (km) | X3 (Mil.R/T) | X4 (㎢) | X5 | X6 | Y1 (Mil. persons) | Y2 | Y3 (1,000 MT) | Y4 (Mil.R/T) |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 70.1 | 14.3 | 231.1 | 100.1 | 1.2 | 8.0 | 12.6 | 34.2 | 349.1 | 135.1 |
| Median | 60.5 | 12.9 | 136.5 | 85.2 | 1.0 | 7.0 | 3.9 | 19.2 | 284.1 | 110.7 |
| S.D. | 41.5 | 8.8 | 275.7 | 92.9 | 1.0 | 5.2 | 15.4 | 27.5 | 337.4 | 104.2 |
| Kurtosis | -1.3 | -0.9 | 10.0 | 1.3 | -0.1 | 0.8 | 1.7 | 0.9 | 1.6 | 0.3 |
| Skew. | 0.3 | 0.3 | 3.1 | 1.4 | 0.6 | 1.1 | 1.7 | 1.4 | 1.5 | 0.94 |
| Min | 15 | 0.6 | 50 | 10.6 | 0 | 2 | 1.5 | 7.3 | 38.0 | 15.1 |
| Max | 162 | 31.1 | 1605 | 355.9 | 4 | 24 | 51.8 | 105.0 | 1342.2 | 460.1 |
| N | 81 | 81 | 81 | 81 | 81 | 81 | 81 | 81 | 81 | 81 |

Six inputs and four outputs belonged to three primary indicators: physical infrastructure, hinterland connection and operating indicators, as indicated in Table 3. The input variables included the necessary physical facilities of seaports, which directly influenced the cargo handling operation, such as berth number ($X_1$), berth length ($X_2$), cargo handling facility ($X_3$), and yard capacity ($X_4$). While berth number, berth length, and handling capacity represented the infrastructure providing an overview of port assets, the handling facility directly influenced the increase in port capacity such that more cargo brings increased efficiency and flexibility, allowing a port to work with more vessels simultaneously. Moreover, hinterland connections such as the number of hinterland zones ($X_5$) and industrial complexes ($X_6$) indicated how well and attractively the seaports worked. The port hinterland can be understood as the market area from where a port attracts its cargo or customers. Therefore, a large hinterland area along with many industrial complexes showed port development ability as well as its network with other areas.On the output side, the port output could be multi-dimensional depending on the objective that the port attained to achieve. The chosen output variables were consumer population ($Y_1$), the number of vessels ($Y_2$), total vessel gross tonnage ($Y_3$), and cargo handling volume ($Y_4$). While cargo handling volume was unquestionably the most important and widely used variable of a seaport and is closely related to the requirement for cargo-related facilities and services, the number of vessels, total vessel gross tonnage, and consumer population represented the attractiveness of the seaport.

Table 3. An evaluation factors for the indicators

| Primary Indicator | Secondary indicator | Properties and Symbols of the Indicators |
|---|---|---|
| Physical infrastructure | Berth number | Input indicator X1 |
| | Berth length | Input indicator X2 |
| | Cargo handling facility | Input indicator X3 |
| | Yard capacity | Input indicator X4 |
| Hinterland connection | Number of hinterlands | Input indicator X5 |
| | Number of industrial complexes | Input indicator X6 |
| | Consumer population | Output indicator Y1 |
| Operating indicators | Number of vessels | Output indicator Y2 |
| | Total vessel gross tonnage | Output indicator Y3 |
| | Cargo handling volume | Output indicator Y4 |

Table 4. Component matrix of the inputs and outputs (a sample for 2018)

| Indicator | Load of the primary components of the input indicators | Indicator | Load of the primary components of the output indicators |
|---|---|---|---|
| $X_5$ | 0.900 | $Y_3$ | 0.962 |
| $X_2$ | 0.895 | $Y_2$ | 0.949 |
| $X_1$ | 0.704 | $Y_4$ | 0.913 |
| $X_4$ | 0.606 | $Y_1$ | 0.873 |
| $X_6$ | -0.027 | | |
| $X_3$ | 0.450 | | |

**Step 2. Reducing the number of related factors**

It has been mentioned that there is some rule of thumb on the input and output number and their relation to the DMU number in the DEA model when the number of chosen seaports is small. Therefore, it was suggested to use the PCA model to reduce the original number of inputs and outputs. The statistical package, SPSS 24, conducts to extract the principal components of all inputs and outputs separately.

Factor loadings serve as a data reduction method designed to explain the correlations between observed variables using fewer factors. The new factors are matched to the original factors based on a linear combination. The number of primary components will always be equal to or less than the number of variables. The rule is to choose the first k eigenvectors that capture at least 85% of the total variance. In Table 4, for example, in 2018, one principal component is obtained from six inputs (PCI), and one principal component is obtained from four outputs (PCO) with an accumulative contribution ratio of about 85% are selected.

Table 5. Input data for efficiency and productivity evaluation (a sample for 2018)

| Port | Principal components of the input indicators (PCI) | Principal components of the Output indicators (PCO) |
|---|---|---|
| Busan | 1799.131 | 1918.520 |
| Gwangyang | 406.694 | 1011.790 |
| Ulsan | 282.213 | 693.677 |
| Incheon | 512.982 | 590.719 |
| Pyeongtaek | 278.058 | 427.684 |
| Daesan | 167.452 | 257.492 |
| Pohang | 231.556 | 191.792 |
| Donghae | 127.459 | 96.307 |
| Mokpo | 141.075 | 117.252 |

Then with that load factors, we recalculate the data used for measuring efficiency and productivity as follows for 2018 data as an example, and the calculated results of the 2018 data are shown in Table 5. The description of the new data is shown in Table 6:

$$PCI = 0.9 \times X_5 + 0.895 \times X_2 + 0.704 \times X_1 + 0.606 \times X_4 - 0.027 \times X_6 + 0.45 \times X_3$$

$$PCO = 0.962 \times Y_3 + 0.949 \times Y_2 + 0.913 \times Y_4 + 0.873 \times Y_1$$

Table 6. Result of descriptive statistics from new data

| Classification | PCI | PCO |
|---|---|---|
| Mean | 377.306 | 532.822 |
| Median | 262.116 | 422.827 |
| S.D. | 347.732 | 478.808 |
| Kurtosis | 5.497 | 1.166 |
| Skewness | 2.353 | 1.353 |
| Range | 1711.567 | 1839.662 |
| Minimum | 87.564 | 78.858 |
| Maximum | 1799.131 | 1918.519 |
| Count | 81 | 81 |

As an example of the 2018 data, in this study, we calculated the coefficient values from 2010 to 2018.

### *Step 3. Evaluation of major Korean seaports' efficiency and productivity*

The following section presents the results of the efficiency and productivity analyses of Korean seaports. In the first stage, the DEA model results used for the efficiency measurement of the studied seaports are analyzed. The MPI model results used for productivity measurement are presented in the second stage. DEA models can be distinguished based on their input or output orientation. The former is closely related to operational and managerial issues, whilst the latter is more related to planning and macroeconomic strategies (Baran and Gorecka, 2015). Both orientations display their usefulness for the seaport industry. The rapid growth of global business and international trade requires seaports to frequently review their operation to ensure that they can provide the best services to customers and maintain their competitiveness. From this viewpoint, the input-oriented model provides a benchmark for the seaport industry. The efficiency results are shown in Table 7.

Table 7. Efficiency results of major Korean seaports (2010-2018)

| Year | 2018 | | | | 2017 | | | | 2016 | | | | 2015 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Seaport | TE | PTE | SE | RTS | TE | PTE | SE | RTS | TE | PTE | SE | RTS | TE | PTE | SE | RTS |
| Busan | 0.43 | 1.00 | 0.43 | DCR | 0.50 | 1.00 | 0.50 | DCR | 0.49 | 1.00 | 0.49 | DCR | 0.55 | 1.00 | 0.55 | DCR |
| Gwangyang | 1.00 | 1.00 | 1.00 | CONT | 0.96 | 1.00 | 0.96 | DCR | 0.95 | 1.00 | 0.95 | DCR | 1.00 | 1.00 | 1.00 | CONT |
| Ulsan | 0.99 | 1.00 | 0.99 | ICR | 1.00 | 1.00 | 1.00 | CONT | 1.00 | 1.00 | 1.00 | CONT | 0.90 | 0.97 | 0.92 | ICR |
| Incheon | 0.46 | 0.50 | 0.92 | ICR | 0.50 | 0.52 | 0.96 | ICR | 0.48 | 0.51 | 0.95 | ICR | 0.53 | 0.60 | 0.89 | ICR |
| Pyeongtaek | 0.62 | 0.78 | 0.79 | ICR | 0.63 | 0.74 | 0.86 | ICR | 0.61 | 0.75 | 0.81 | ICR | 0.72 | 0.90 | 0.81 | ICR |
| Daesan | 0.40 | 0.92 | 0.44 | ICR | 0.68 | 1.00 | 0.68 | ICR | 0.55 | 0.94 | 0.59 | ICR | 0.59 | 0.95 | 0.62 | ICR |
| Pohang | 0.23 | 0.62 | 0.37 | ICR | 0.32 | 0.60 | 0.53 | ICR | 0.31 | 0.62 | 0.50 | ICR | 0.32 | 0.57 | 0.56 | ICR |
| Donghae | 0.20 | 1.00 | 0.20 | ICR | 0.27 | 0.97 | 0.28 | ICR | 0.25 | 0.92 | 0.27 | ICR | 0.26 | 0.82 | 0.32 | ICR |
| Mokpo | 0.27 | 0.96 | 0.28 | ICR | 0.36 | 1.00 | 0.36 | ICR | 0.38 | 1.00 | 0.38 | ICR | 0.45 | 1.00 | 0.45 | ICR |

| Year | 2014 | | | | 2013 | | | | 2012 | | | | 2011 | | | | 2010 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Seaport | TE | PTE | SE | RTS | TE | PTE | SE | RTS | TE | PTE | SE | RTS | TE | PTE | SE | RTS | TE | PTE | SE | RTS |
| Busan | 0.57 | 1.00 | 0.57 | DCR | 0.64 | 1.00 | 0.64 | DCR | 0.71 | 1.00 | 0.71 | DCR | 0.981 | 1.00 | 0.98 | DCR | 0.83 | 1.00 | 0.83 | DCR |
| Gwangyang | 1.00 | 1.00 | 1.00 | CONT | 1.00 | 1.00 | 1.00 | CONT | 1.00 | 1.00 | 1.00 | CONT | 0.877 | 0.88 | 0.99 | DCR | 0.97 | 1.00 | 0.97 | DCR |
| Ulsan | 0.97 | 1.00 | 0.97 | ICR | 0.94 | 1.00 | 0.94 | ICR | 0.87 | 0.91 | 0.96 | ICR | 1.000 | 1.00 | 1.00 | CONT | 1.00 | 1.00 | 1.00 | CONT |
| Incheon | 0.51 | 0.55 | 0.93 | ICR | 0.51 | 0.57 | 0.89 | ICR | 0.52 | 0.57 | 0.91 | ICR | 0.513 | 0.54 | 0.94 | ICR | 0.51 | 0.52 | 0.99 | ICR |
| Pyeongtaek | 0.63 | 0.73 | 0.87 | ICR | 0.79 | 0.95 | 0.83 | ICR | 0.85 | 1.00 | 0.85 | ICR | 0.776 | 0.92 | 0.84 | ICR | 0.89 | 1.00 | 0.89 | ICR |
| Daesan | 0.60 | 0.92 | 0.65 | ICR | 0.58 | 0.97 | 0.60 | ICR | 0.56 | 0.93 | 0.60 | ICR | 0.553 | 0.90 | 0.61 | ICR | 0.68 | 0.90 | 0.75 | ICR |
| Pohang | 0.36 | 0.56 | 0.64 | ICR | 0.31 | 0.54 | 0.58 | ICR | 0.38 | 0.63 | 0.60 | ICR | 0.365 | 0.57 | 0.63 | ICR | 0.47 | 0.61 | 0.76 | ICR |
| Donghae | 0.31 | 0.84 | 0.37 | ICR | 0.37 | 1.00 | 0.37 | ICR | 0.33 | 0.97 | 0.34 | ICR | 0.386 | 1.00 | 0.38 | ICR | 0.51 | 1.00 | 0.51 | ICR |
| Mokpo | 0.51 | 1.00 | 0.51 | ICR | 0.44 | 0.96 | 0.46 | ICR | 0.41 | 1.00 | 0.41 | ICR | 0.399 | 0.88 | 0.45 | ICR | 0.41 | 0.69 | 0.60 | ICR |

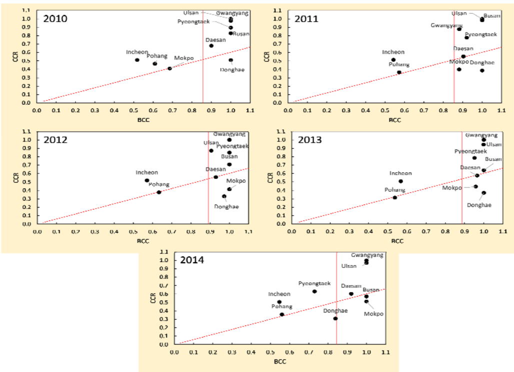
Table 7 indicates the CCR and BCC models that evaluate to nine Korean seaports. A value of one represents ideal efficiency. It was pointed out that during the research period from 2010 to 2018, only Gwangyang and Ulsan ports were considered to have operational efficiency while other seaports attained very low efficiency scores. Some of the inefficient seaports exhibited pure technical efficiencies, such as Busan or Mokpo port.

Meanwhile, most inefficient seaports are increasing returns to scale with the exception of Busan port that displayed decreasing returns to scale. From an economic viewpoint, increasing returns to scale means that the growth rate of output is higher than the growth rate of input. By contrast, when the growth rate of output is lower than the growth rate of input, it is called decreasing returns to scale. When increasing returns to scale occur, it results in economies of scale. The efficiency of an organization will increase when it expands the scale. Even when the product has been expanded, an efficiency loss in the production process results in decreasing returns to scale. Therefore, it is easier for seaports to increase returns to scale. That means they can increase their efficiency by increasing their operational size. While a seaport like Busan cannot reduce its size to increase efficiency, the port needs to change the inbound management or cooperate with neighbouring seaports to increase returns to scale seaports to share equipment.

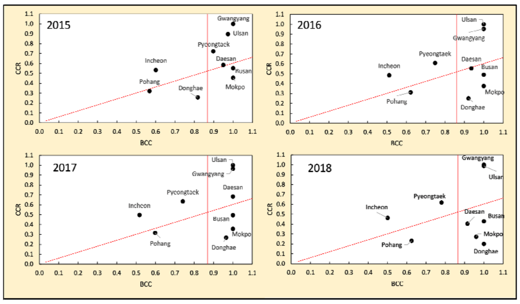
On the other hand, the relative role of pure technical inefficiency and scale effects on the total technical efficiency of major Korean seaports can be more easily explained through the graphical illustration of the corresponding CCR and BCC scores as data pairs in a two-dimensional graph (see Figure 1. (a) and (b))

Figure 1. Graphical illustration of Korean seaport's efficiency

(a) Result from 2010 to 2014



(b) Result from 2015 to 2018



All seaports are divided into four regions by using two lines, one is a vertical line to the x-axis, which is the average pure technical efficiency score (see example in Figure 2, 2018, average BCC=0.865), and the other is a line representing the average scale efficiency (example in 2018, average SE=0.603), that is technical efficiency = scale efficiency*pure technical efficiency or CCR = 0.603*BCC. It is shown in the result of 2018 in Figure 1.(b). that the seaports located in the upper-right region, including Gwangyang and Ulsan ports, have both high pure technical efficiency and scale efficiency, which implies that the seaports effectively manage their facilities and serve a large cargo number. The four seaports located in the lower-right region, Daesan, Busan, Mokpo, and Donghae ports, possessed high pure technical efficiency but relatively low scale efficiency compared to average scale efficiency. Although these seaports effectively managed their facilities, they are subjected to scale effects as they cannot adequately accommodate the cargo's arrival volume. In addition, the seaports located in the upper-left region, including Incheon and Pyeongtaek ports, displayed a relatively large scale but low pure technical efficiency. These seaports accommodated many cargoes with only limited performance as they did not control their resources efficiently. Finally, the lower-left region, which contains only the Pohang port, possessed low pure technical and scale efficiency. This seaport served low cargo traffic with an inefficient use of its facilities. Thus, this port had room to improve its competitive position by attracting more cargoes and better resource management.

The second stage will be the productivity analysis of major Korean seaports from 2010 to 2018. The results will be shown in Table 8.

From Table 8, while the technical efficiency change decreased by 3.1% on average during the research time, except for the slight increase in 2016-2017, the technological change increased by 4.4%. The technical efficiency change can be identified as two changes, including pure technical efficiency and scale efficiency. While pure technical efficiency change slightly increased by 0.3%, the scale efficiency change decreased by 3.3% on average during the research period. The productivity index change rate (1.1% on average) could be due to technological change.

Table 8. Malmquist productive change index and its components

| Year | EFFCH | TECHCH | PECH | SECH | TFPCH |
|---|---|---|---|---|---|
| 2010-2011 | 0.913 | 1.174 | 1.004 | 0.910 | 1.072 |
| 2011-2012 | 0.966 | 1.000 | 1.044 | 0.925 | 0.966 |
| 2012-2013 | 0.990 | 1.073 | 0.989 | 1.001 | 1.063 |
| 2013-2014 | 0.981 | 0.941 | 0.952 | 1.031 | 0.923 |
| 2014-2015 | 0.960 | 1.104 | 1.033 | 0.929 | 1.060 |
| 2015-2016 | 0.933 | 1.104 | 0.987 | 0.945 | 1.030 |
| 2016-2017 | 1.037 | 0.963 | 1.008 | 1.028 | 0.999 |
| 2017-2018 | 0.978 | 1.011 | 1.006 | 0.972 | 0.988 |
| Average | 0.969 | 1.044 | 1.003 | 0.967 | 1.011 |

Table 9. Malmquist productive change index and its components by seaports

| Seaport | EFFCH | TECHCH | PECH | SECH | TFPCH |
|---|---|---|---|---|---|
| Busan | 0.720 | 1.186 | 1.000 | 0.720 | 0.854 |
| Gwangyang | 1.003 | 0.927 | 1.000 | 1.000 | 0.927 |
| Ulsan | 0.974 | 0.960 | 1.000 | 0.974 | 0.935 |
| Incheon | 0.929 | 0.723 | 0.831 | 1.119 | 0.672 |
| Pyeongtaek | 0.882 | 1.127 | 0.940 | 0.939 | 0.995 |
| Daesan | 0.925 | 1.146 | 1.000 | 0.925 | 1.060 |
| Pohang | 0.873 | 1.099 | 0.988 | 0.884 | 0.959 |
| Donghae | 0.848 | 1.146 | 1.000 | 0.848 | 0.972 |
| Mokpo | 0.891 | 1.146 | 0.994 | 0.896 | 1.021 |
| Average | 0.894 | 0.891 | 0.971 | 0.921 | 0.796 |

Table 9 shows the productivity change and its components' change of each seaport during the research period. Regarding technical efficiency change, only Gwangyang port increased by 0.3%; meanwhile, other seaports exhibited a decline, especially with Busan port that indicated a decrease by 7.9%. Three seaports indicated technological regression, especially Incheon port with 27.7%, and six seaports exhibited technological progress, and the top three seaports were Daesan, Mokpo, and Donghae ports. Several seaports maintained their efficiency in pure technical efficiency change and scale efficiency change while some showed a significant reduction, such as Incheon (16.9%) and Busan (28%) ports.

Finally, the efficiency scores, productivity scores, and ranking of major Korean seaports were combined in Table 10. In general, the two big and well-known seaports, Busan and Incheon, failed to maintain their positions. Busan port exhibited a scale inefficiency that indicated that the port required more operational efficiency than a quantitative increase in facilities. For instance, the Busan port had been divided into several operators; therefore, the irrationality of the operating system had become problematic for scale efficiency. Also, Incheon port has to consider the problem regarding not only scale efficiency such as quantitative improvement in port facilities but also operational efficiency about infrastructure and industrial facilities inside the port. Therefore, Incheon port should develop infrastructure such as logistics centers for the e-commerce market and value-added activities to support the port.

Table 10. Overall efficiency score and productivity index of major Korean seaports (2010-2018)

<table>
<tr><th rowspan="3">DMU</th><th colspan="6">Efficiency score</th><th colspan="2">Malmquist productivity index</th></tr>
<tr><th colspan="3">2010</th><th colspan="3">2018</th><th colspan="2"></th></tr>
<tr><th>TE</th><th>PTE</th><th>Rank</th><th>TE</th><th>PTE</th><th>Rank</th><th>2010-2018</th><th>Rank</th></tr>
<tr><td>Busan</td><td>0.83</td><td>1.00</td><td>4</td><td>0.43</td><td>1.00</td><td>5</td><td>0.854</td><td>8</td></tr>
<tr><td>Gwang yang</td><td>0.97</td><td>1.00</td><td>2</td><td>1.00</td><td>1.00</td><td>1</td><td>0.927</td><td>7</td></tr>
<tr><td>Ulsan</td><td>1.00</td><td>1.00</td><td>1</td><td>0.99</td><td>1.00</td><td>2</td><td>0.935</td><td>6</td></tr>
<tr><td>Incheon</td><td>0.51</td><td>0.52</td><td>9</td><td>0.46</td><td>0.50</td><td>4</td><td>0.672</td><td>9</td></tr>
<tr><td>Pyeong taek</td><td>0.89</td><td>1.00</td><td>3</td><td>0.62</td><td>0.78</td><td>3</td><td>0.995</td><td>3</td></tr>
<tr><td>Daesan</td><td>0.68</td><td>0.90</td><td>6</td><td>0.40</td><td>0.92</td><td>6</td><td>1.060</td><td>1</td></tr>
<tr><td>Pohang</td><td>0.47</td><td>0.61</td><td>8</td><td>0.23</td><td>0.62</td><td>8</td><td>0.959</td><td>5</td></tr>
<tr><td>Dong hae</td><td>0.51</td><td>1.00</td><td>5</td><td>0.20</td><td>1.00</td><td>9</td><td>0.972</td><td>4</td></tr>
<tr><td>Mokpo</td><td>0.41</td><td>0.69</td><td>7</td><td>0.27</td><td>0.96</td><td>7</td><td>1.021</td><td>2</td></tr>
</table>

On the other hand, more minor seaports such as Daesan and Mokpo port, which still possessed a lower efficiency score than other ports, have indicated a rapid growth trend in recent years. With a convenient location near China by sea and a convenient transportation system to other areas, Daesan port focusing on oil commodity and Mokpo port focusing on automobiles assert their positions.

## V. Discussion and Conclusion

In this study, we researched major Korean seaports using a combination of the DEA model with PCA and MPI. Previous studies on the DEA model have been based on some rule of thumb on the output number and its relation to the DMU number. However, in this paper, only nine Korean seaports have been considered as the seaports system in Korea depends largely on these major seaports and the remaining seaports account for extremely small proportions. Therefore, to overcome the limitation of applying the DEA model, the DEA model with dimensionality reduction schemes such as PCA was combined. The initial six inputs and four outputs were changed into a single input and output using the PCA model. Subsequently, the new variables were used to measure the efficiency and productivity of major Korean seaports. The efficiency results showed that Gwangyang and Ulsan ports were regarded as efficient seaports, whereas the two well-known seaports (Busan and Incheon) had a low-efficiency score.

The productivity results showed that productivity change improved by 1.7% due to a 4.4% increase in technological change. The technical efficiency change increased only in Gwangyang port while decreasing in the remaining seaports. During the research period, the port with the highest productivity growth was Daesan port, followed by the Mokpo port, while the lowest was the Incheon port. Daesan port focused on oil commodity whereas Mokpo port focused on automobiles resulting in rapid growth in recent years. Meanwhile, well-known seaports like the Incheon and Busan port should employ new strategies to reaffirm their positions.

This study is valuable as it analyzed the efficiency and productivity of Korean major ports using actual ten year's data. The study results provide valuable data while diagnosing the situation of each port, making up for deficiencies, and establishing strategies to improve port competitiveness.

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# PCA-DEA 모델을 이용한 국내 주요항만의 효율성과 생산성 분석에 관한 연구

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## 국문요약

우리나라는 동북아지역에서 아시아 허브항만의 위상을 유지하기 위해 항만시스템의 업그레이드에 막대한 예산을 투입하고 있다. 그 결과로 우리나라 대표항만인 부산항은 세계 5위 수준의 컨테이너 물동량 처리 수준을 보이고 있다. 그러나 부산항을 제외한 다른 항만은 낮은 순위에 자리하고 있다. 이 연구는 자료포락분석(DEA) 모델과 Malmquist 생산성지수(MPI)를 이용하여 국내 주요 항만의 효율성과 생산성을 분석하는데 목적이 있다. 특히 변수의 수가 의사결정단위(DMU) 수를 초과할 경우 판별력이 약해지는 DEA모델을 보완하기 주성분분석(PCA, Principal Component Analysis)을 DEA모델에 결합한 PCA-DEA모델을 이용하였다. 그리고 MPI는 다년간의 항만의 생산성을 측정하기 위하여 적용하였다. 그 결과로 우리나라 주요항만의 효율성과 생산성 순위를 결정할 수 있었으며, 광양항과 울산항 2010년과 2018년 비교시 효율성 측면에서 상위권을 보였으며, 생산성 분석 결과에 있어서 대산항과 목포항이 다른 항만에 비해 상대적으로 높게 나타났다. 이 연구결과는 항만별 경쟁력을 객관적으로 평가하고 전략을 마련하는데 활용될 수 있다.

*주제어: 국내 주요항만, 효율성, 생산성, PCA-DEA,*