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Performance Evaluation and Investment Analysis for Container Port Sustainable Development in China: An Inverse DEA Approach

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Abstract: Container ports play an important role in international maritime trade. However, the rapid growth of the port and terminal industry has caused many environmental pollution problems. This paper intends to develop an inverse data envelopment analysis (IDEA) model for measuring container ports' efficiency and analyzing their resource consumption by considering undesirable outputs. Statistical data from 16 main ports are empirically examined using the proposed method in accordance with the 13th Five-Year Plan in China. The results indicate that the proposed IDEA is a feasible approach for performance evaluation, and provides policymakers with insights into resource optimization of container ports. A comparative study with another DEA model is also discussed.

Keywords: Inverse DEA; container ports; efficiency evaluation; investment analysis; undesirable output

1. Introduction

Nowadays, container ports serve a key role in achieving global logistics and supply chains. With the great opportunity of the Belt and Road Initiative (BRI), a Chinese grand economic plan launched in 2013, many countries invest a great number of resources into developing port terminals [1]. Accordingly, the construction of port facilities, the acceleration of port upgrading, the integration of green energy concepts, and so forth, are crucial for prompting port industry [2] and have been written into the Chinese 13th Five-Year Plan (FYP). China now has 15 ports listed in the top 50 world's ports and harbors in 2016 [3]. However, each port should have features of geographical location, deep-water berth, dispatching system, and pollution controlling, and such differences lead to different port efficiencies (advantages). An overall understanding of each port's competitiveness is not only beneficial for policymakers designing marine transports [1], but also useful in resource prediction or planning. On the other hand, however, the prosperity of the port industry is usually accompanied by much harmful pollution, such as greenhouse gas (CO_2) and toxic emissions (NOx, SOx). In response, many governments have initiated sustainable waterways planning and launched regulations to prevent environmental deterioration. Accordingly, the primary pollutants should be taken into consideration in the process of port efficiency evaluation and consumption analysis [4].

There have been many quantitative analysis techniques for performance measurement in management theory. Data envelopment analysis (DEA), as a nonparametric programming method, is one of the most popular tools in measuring efficiency for a set of decision-making units (DMUs) [5]. Classical DEA models (e.g., the CCR, BCC, cone ratio, SBM, allocative models) have been extensively applied in a wide range of areas including evaluations of R&D projects [6], universities [7,8], production systems [9], banks [10], environmental regulation [11,12], and so on. For further applications of DEA in decision analysis, Wei et al. [13] introduced a new DEA approach called inverse DEA (IDEA) to deal with a kind of investment optimization problem. Unfortunately, existing literature has rarely discussed the efficiency evaluation or investment analysis of container ports based on IDEA. Additionally, in efficiency analysis, traditional IDEA or DEA models often neglect the undesirable outputs, such as pollution and waste that usually are produced along with the desirable ones during a production process [14]. Therefore, the objective of this study is to suggest a novel IDEA model considering undesirable outputs to manage the performance evaluation and prediction of container ports.

The remainder of this paper is structured as follows. Section 2 presents a literature review and Section 3 introduces preliminaries. The proposed IDEA model with undesirable outputs is introduced in Section 4. Section 5 conducts an empirical study with some comparative analyses. Section 6 concludes this paper.

2. Literature Review

In this section, we firstly survey the DEA technique as well as its application in port evaluation. Then, we review some related studies on the inverse DEA.

DEA, originally proposed by Charnes et al. [5], utilizes multiple inputs to produce multiple outputs without parametric assumptions. The past 40 years have witnessed the appearance of a great number of studies on DEA theory and its application [15]. Tavares [16] listed more than 3000 references about DEA from 1978 to 2001, where 40% of them were published in qualified journals. Using DEA to estimate the performances of container ports has aroused much attention in recent years. The pioneering work in port assessment using DEA was developed by Roll and Hayuth [17], based on the work of Tongzon [18], who proposed an additive CCR model for estimating several Australian ports and international ports. Wu and Liang [2] applied the DEA model under variable returns to rate (VRS) to evaluate the performance of 77 global ports (DMUs), and a benchmark was also established to improve the performance of inefficient DMUs. As for Asia ports, Itoh [19] employed the window BCC model to examine the efficiency variations of eight Japanese ports. The results showed a difference among port terminals with timely development. Hung et al. [20] combined traditional DEA models with the bootstrap method to estimate the operating performance of 31 main ports in Asia, which provided insight for resource allocation as well as procedure optimization. Dong et al. [21] evaluated the environmental performance and compared the operational efficiency of 10 Asian ports along the BRI using slack-based measures. Inspired by supply chain pattern, Bichou [22] applied the DEA technique to model the container-terminal system as a two-stage operational process and assessed the performances of combined port terminals.

With a boom in international maritime trade, however, exhaust gas emissions (i.e., CO_2, NOx, PM2.5) from shipping severely deteriorate the coastal air quality. Accordingly, many studies [11,23–27] have been conducted investigating the port efficiency with undesirable (bad) outputs from an environmental perspective. Seiford and Zhu [23] argued that undesirable outputs (or inputs) could be integrated into traditional DEA models by data transformation. Song et al. [11] reviewed the environmental efficiency evaluation based on DEA technique with undesirable output under small samples. In the context of ecological pollution, most researchers take air emissions into account as undesirable outputs in DEA models. Liu et al. [27] suggested a unified framework of several traditional DEA models considering both undesirable inputs and outputs under disposability assumptions. Sun et al. [28] developed a nonradial DEA preference mode for analyzing the operational efficiency of Chinese ports, where the NOx emission is represented as an undesirable output. Haralambides and Gujar [29] presented a novel eco-DEA model that evaluates both desirable and undesirable outputs (CO_2) of port service production in India. In order to improve the level of pure technical environmental efficiency, Na et al. [30] proposed an inseparable slacks-based measure (SBM) model to estimate the environmental efficiencies of eight harbors in China, which reveals that most ports exhibit too much exhaust emissions. By incorporating undesirable variables, Lee et al. [31] measured the environmental efficiency of several port cities using the SBM model, and concluded that Singapore and Busan are the most environmentally efficient. Based on the assumption of undesirable output weak disposability, Bian et al. [32] developed an interval SBM model to estimate regional energy efficiency, as well as CO_2 emissions efficiencies. As random errors may exist in collected data, Wu et al. [33] defined the efficiency of DMUs within risk factors and offered a stochastic DEA method with undesirable outputs to handle random errors.

It has been known that DEA results depend heavily on the selection of input and output variables. However, little attention has been given to the issue of how changes of output (or input) would affect the data on the other side. Specifically, if a DMU alters its output (input), to what extent should its input (output) be changed to maintain the current efficiency level [34]? This question implicates the concept of inverse DEA (IDEA), a kind of optimization technique in the form of DEA. Wei et al. [13] presented a multiple objective linear programming (MOLP) to calculate the output levels for inefficient DMUs. Jahanshahloo et al. [35] indicated that the IDEA can effectively estimate the optimal level of inputs, or find out the input excesses of a DMU when preserving its efficiency. Similar to returns to scale in DEA, Lertworasirikul et al. [36] applied the IDEA model for resource allocation under variable returns to scale. Then, a Pareto-efficient solution was introduced to solve this problem. Later, Ghiyasi [34] had a comment on the use of MOLP in [36] and rectified the input estimation of the IDEA model. On the other hand, combining DEA with undesirable outputs is rare in the existing literature. Chen et al. [14] put forward an IDEA model with undesirable outputs to analyze the sustainable investment problem in China; some suggestions on investment schemes were then provided corresponding to the results. Based on the philosophy of IDEA, Wegener and Amin [37] developed an optimization model to reduce greenhouse gas emissions; Emrouznejad et al. [38] initialized a three-stage method to allocate CO_2 emission quota.

Based on the literature review above, much research has been done to measure port efficiency by various DEA models. Some scholars have also paid attention to the IDEA approach, the inverse optimization of the DEA technique. Despite its explanatory power, no research has yet utilized IDEA to study the performance of container ports with undesirable outputs. This paper aims to establish an IDEA approach for measuring the ports' efficiency and predicting resource investment in the presence of undesirable outputs.

3. Preliminaries

3.1. CCR Model

Suppose there are n DMUs, and each DMU_j (j = 1, 2, ..., n) utilizes m inputs $x_{i\,j}$ (i = 1, 2, ..., m) to produce s outputs $y_{r\,j}$ (r = 1, 2, ..., s). For the DMU_0 under evaluation, its efficiency score can be measured by the CCR model in envelopment form as follows [5]:

$$\begin{aligned} &\min\ \theta_0 \\ &\text{s.t. } \sum_{j=1}^{n} \lambda_j\, x_{i\,j} \leq\ \theta_0 x_{i0}, \quad i = 1,\ 2,\ \ldots, m \\ &\qquad \sum_{j=1}^{n} \lambda_j y_{rj} \geq\ y_{r0}, \quad r = 1, 2,\ \ldots,\ s \\ &\qquad \lambda_j \geq 0, \quad j = 1,\ 2,\ \ldots,\ n \end{aligned} \tag{1}$$

where θ_0 is a real variable related to DMU_0 and $\lambda = \{\lambda_j \big| j = 1, 2, \ldots, n\big\}$ is a non-negative vector. The above model is an estimation approach of constant returns to scale (CRS). We call DMU_0 CCR-efficient if and only if $\theta_0 = 1$.

3.2. Inverse DEA Model

Let θ_0^* be the optimal value of DMU_0 evaluated by the above CCR model. If we want to increase a certain output amount of DMU_0, say Δy_0, from y_0 to β_0 where $\beta_0 = y_0 + \Delta y_0$, then inputs would have a corresponding change Δx_0 from x_0 to α_0, and the following model can be established to estimate the minimum increment Δx_0 [34]:

$$\begin{aligned} \min \quad & \Delta \boldsymbol{x}_0 = \boldsymbol{w}^T(\Delta x_{10}, \Delta x_{20}, \ldots, \Delta x_{m0}) \\ \text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j x_{ij} + \lambda_{0'}(x_{i0} + \Delta x_{i0}) \leq \theta_0^*(x_{i0} + \Delta x_{i0}), i = 1, 2, \ldots, m \\ & \sum_{i=1}^{n} \lambda_j y_{ij} + \lambda_{0'}(y_{r0} + \Delta y_{r0}) \geq y_{r0} + \Delta y_{r0}, r = 1, 2, \ldots, s \\ & x_{i0} + \Delta x_{i0} \geq 0, i = 1, 2, \ldots, m \\ & \lambda_j, \lambda_{0'} \geq 0, j = 1, 2, \ldots, n \end{aligned} \tag{2}$$

where θ_0^* is the efficiency score solved by model (1) and $\boldsymbol{w}^T = (w_1, w_2, \ldots, w_m)$ is the weight vector of $\Delta \boldsymbol{x}_0$. For any given $\Delta y_0 \neq 0$, the above model can be equivalently solved by converting into model (3) as below,

$$\begin{aligned} \min \quad & \Delta\, \boldsymbol{x}_0 = \boldsymbol{w}^T(\Delta\, x_{10}, \Delta\, x_{20}, \ldots, \Delta\, x_{m0}) \\ \text{s.t.} \quad & \sum_{i=1}^{n} \lambda_j\ x_{ij} \leq\ \theta_0^*(x_{i0} + \Delta\, x_{i0}),\ i = 1,\ 2,\ \ldots, m \\ & \sum_{i=1}^{n} \lambda_j\ y_{i\,j} \geq\ y_{r0} + \Delta\, y_{r0}, \quad r = 1,\ 2, \ldots, s \\ & \lambda_j \geq 0 \quad , \quad j = 1,\ 2,\ \ldots, n \end{aligned} \tag{3}$$

4. Proposed IDEA Model

4.1. CCR Efficiency with Undesirable Outputs

As aforementioned, efficiency assessment and investment analysis of container ports are quite important in promoting BRI. Every ship powered by fuel oil brings merchandise into a harbor characterized by high environmental pollution. An overall evaluation of a container port must take inputs and desirable and undesirable outputs into account. Assume each DMU$_j$ (j = 1, 2,..., n) to be evaluated against m inputs x_{ij} (i = 1, 2,..., m), s desirable outputs y_{rj} (r = 1, 2,..., s) and g undesirable outputs z_{lj} (l = 1, 2,..., g). Firstly, we measure the efficiency scores of n DMUs. When a DMU is allowed to alter its output level, it often assumes the original efficiency remains unchanged [13] especially when it is efficient. Note that model (1) cannot be directly applied to a production process involving undesirable output variables. Inspired by the work in [23], we extend the traditional CCR model involving both desirable and undesirable outputs, which is constructed as follows,

$$\begin{aligned} \min \quad & \theta_0 \\ \text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j\, x_{i\,j} \leq\ \theta_0 x_{i\,0}, \quad i = 1,\ 2,\ \ldots, m \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geq\ \ y_{r\,0}, \qquad r = 1,\ 2, \ldots\ , s \\ & \sum_{j=1}^{n} \lambda_j \bar{z}_{lj} \geq\ \ \bar{z}_{l\,0}, \qquad l = 1,\ 2, \ldots\ , g \\ & \lambda_j \geq 0\,, \quad j = 1,\ 2, \ldots\ , n \end{aligned} \tag{4}$$

In model (4), we turn the negative variable $-z_{l\,j}$ into a positive one $\bar{z}_{l\,j}$,

$$\bar{z}_{l\,j} = -z_{l\,j} + \delta_l,\ j\ = 1,\ 2,\ \ldots,\ n \tag{5}$$

where δ_l is a positive number such that $\delta_l = \max\left\{ z_{l\,j} \right\} + 1$, j = 1, 2, ..., n [23]. Obviously, $\bar{z}_{l\,j} > 0$ and a larger value of $\bar{z}_{l\,j}$ signifies a better output level.

4.2. Consumption Analysis by IDEA

Let θ_0^* be the efficiency of DMU_0 obtained by model (4). The essence of consumption analysis by inverse DEA, just as its name indicates, is assuming DMU_0 has a perturbation in outputs at first, and finding out the required minimum changes in inputs. Notice that we still use $\overline{z}_{l\,j}$ instead of $z_{l\,j}$ in the IDEA model to make sure they are consistent with each other. Otherwise, the undesirable variables would be optimized in decreasing values which are contrary to the desirable ones. According to this idea, the IDEA model with the undesirable outputs (IDEAU) can be formulated as:

$$
\begin{array}{ll}
\min & \sum_{i=1}^{m} \Delta x_{i\,0} \\
\text{s.t.} & \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_0^*(x_{i0} + \Delta x_{i0}), i = 1, 2, \ldots, m \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} + \Delta y_{r0}, r = 1, 2, \ldots, s \\
& \sum_{j=1}^{n} \lambda_j \overline{z}_{lj} \geq \overline{z}_{l0} + \Delta z_{l0}, l = 1, 2, \ldots, g \\
& \lambda_j \geq 0, j = 1, 2, \ldots, n \\
& \Delta x_{i0} \text{unrestrictedinsign}
\end{array}
\tag{6}
$$

where x_{i0} and y_{r0} ($i = 1, 2, \ldots m$, $r = 1, 2, \ldots, s$) are respectively the input and desirable output variables. $\overline{z}_{l\,0}$ is the undesirable output variable converted by z_{l0} ($l = 1, 2, \ldots, g$), while Δy_{r0} and Δz_{l0} are the given changed amount. All Δx_i ($i = 1, 2, \ldots, m$) are treated as equally important in the objective function, as they have the same weights. Note that Δx_i ($i = 1, 2, \ldots, m$) are allowed to be negative as long as their combination satisfies the constraints in model (6).

Theorem 1. *For given changes $\Delta y_{r0} \neq 0$ and $\Delta z_{l0} \neq 0$ in desirable and undesirable outputs of DMU_0, respectively. The minimum input alternation Δx_{i0}* can be derived by model (6) while the efficiency θ_0^* *remains unchanged.*

The proof of Theorem 1 is similar to the proof of the theorem in [34] by using the definition of weak efficient solution.

4.3. Performance Improvement by IDEA

According to model (6), the minimum input changes of efficient DMUs can be estimated under the new given outputs. On the other hand, we can also identify the relative input excesses for inefficient DMUs by resetting the efficiency score as $\theta_0 = 1$, under the current output capacity. This leads to another version of the IDEAU model:

$$
\begin{array}{lll}
\max & \sum_{i=1}^{m} \Delta\, x_{i\,0} & \\
\text{s.t.} & \sum_{j=1}^{n} \lambda_j\, x_{i\,j} \leq x_{i0} - \Delta x_{i0}, & i = 1,\, 2,\, \ldots, m \\
& \sum_{j=1}^{n} \lambda_j\;\, y_{rj} \geq y_{r0}, & r = 1,\, 2, \ldots, s \\
& \sum_{j=1}^{n} \lambda_j\;\, z_{l\,j} \geq \overline{z}_{l\,0}, & l = 1,\, 2, \ldots, g \\
& \lambda_j\; \geq 0\;\;, & j = 1,\, 2,\, \ldots, n \\
& \Delta x_{i0} \text{ unrestricted in sign} &
\end{array}
\tag{7}
$$

It should be pointed out that model (7) may be infeasible to some DMUs in optimizing resource consumption since there seems to be a dilemma that regulates desirable and undesirable outputs at the same time. Intuitively, decreasing gas emissions may be accompanied by an effort of reducing resource inputs, which usually results in lower (desirable) production quantity. However, it is not allowed to reduce the current level of outputs.

According to the aforementioned analyses, the evaluation process of the proposed IDEAU method is graphically depicted in Figure 1.

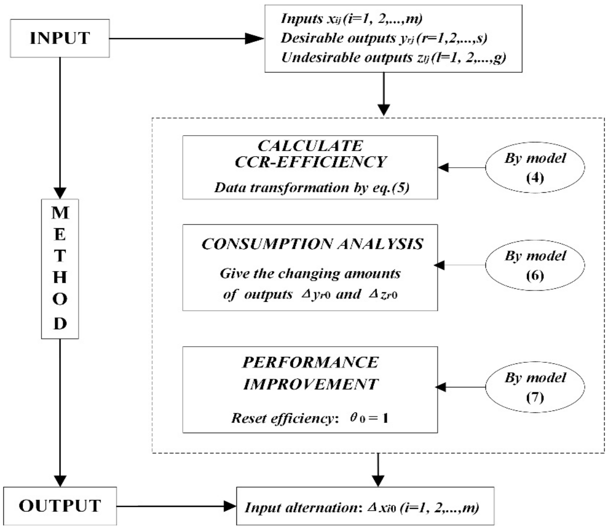

Figure 1. Evaluation process of the proposed method.

5. Empirical Research

In this section, an empirical case about 16 Chinese container ports (Ningbo, Shanghai, Tianjin, Tangshan, Dalian, Rizhao, Yingkou, Nanjing, Xiamen, Lianyungang, Chongqing, Yantian, Shenzhen, Zhuhai, Jinzhou, and Fuzhou) in 2017 is studied. These container ports are ranked in the top 20 in China according to the annual throughputs, which have a significant impact on the strategy of Chinese BRI. Figure 2 shows geographical information about these ports. The Chinese government enacted the 13th FYP (2016–2020) in 2016. The blueprint for economic and social development grabs the general public's attention. As to the Transport sector of the 13th FYP in China, port construction is a hot issue under the big opportunity of BRI; issues like consumption prediction or optimization analysis have aroused people's concern.

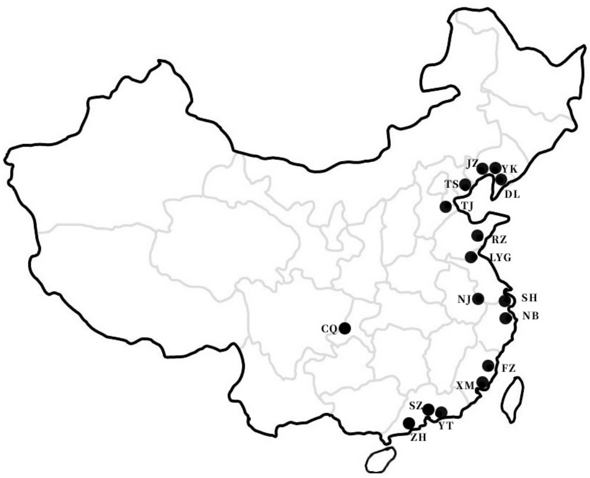

Figure 2. Distribution of sixteen Chinese ports.

5.1. Data Description

In this study, berth length (x_1), equipment asset (x_2), number of employees (x_3), and cost (x_4) are used as four input variables, and throughput (y_1), profit (y_2) are two desirable output variables while emission amount of CO_2 (z_1) and NOx (z_2) are two undesirable output variables. The data of these criteria were taken from Chinese ports yearbook [39] and the published work in Lai et al. [40], which are documented in Table 1. Nevertheless, the statistics about CO_2 and NOx are unavailable to collect directly from the existing reference. Thus, we estimate these emissions using two specific formulas shown in Appendix A.

Table 1. Statistics of the 16 ports in 2017.

Port	Berth	Equipment	Employee	Cost	Throughput	Profit	CO_2	NO_x
	Units	Million *	Units	Million *	Million Tons	Million *	Tons	Tons
NB	615	5390	1170	14,026	91,800	2299	59.05	1.18
SH	608	5560	1830	24,420	70,000	6939	45.03	1.13
TJ	162	2530	760	11,783	55,000	1264	35.38	0.88
TS	77	3340	270	4306	51,600	1320	37.00	1.23
DL	240	1090	680	12283	42,900	531	28.65	0.57
RZ	52	1660	160	5101	53,100	176	24.30	0.61
YK	87	160	490	2208	34,700	353	22.32	0.45
NJ	69	30	70	138	21,700	85	13.96	0.31
XM	173	360	390	8785	20,900	207	8.22	0.10
LYG	62	810	460	869	20,200	7.0	13.99	0.28
CQ	191	670	220	2121	17,200	78	9.37	0.19
YT	20	60	50	141	10,900	352	7.01	0.14
SZ	25	650	170	137.3	10,600	532	6.82	0.14
ZH	153	133	200	169.7	9000	104	4.78	0.08
JZ	23	149	15	249.7	8900	56	5.07	0.10
FZ	120	320	260	705.1	15,800	293	8.39	0.12

Note: * The monetary unit is RMB.

5.2. Performance Evaluation of Container Ports

We firstly use model (4) to measure the efficiencies of the 16 container ports (DMUs), and depict the results in Figure 3. Clearly, there are four container ports (TS, RZ, NJ, YT) evaluated as CCR-efficient with a score of 1.0, while seven ports with the lowest scores are NB (0.234), DL (0.324), XM (0.239), LYG (0.241), CQ (0.266), ZH (0.099), and FZ (0.195), all having a score below 0.4. Besides, other inefficient DMUs are JZ (0.904), YK (0.708), TJ (0.571), SZ (0.448), and SH (0.473), which are ranked in descending order.

We classify and discuss these ports (DMUs) in two categories according to their efficiency scores. As to the four efficient DMUs, we utilize model (5) to optimize the input consumption with a given output level. To do so, we estimate the variation in output level at the target year first. According to the Transport sector of the 13th FYP in China and the Eco-Environmental Protection of the 13th FYP [41], the expected throughput and the expected growth rate of profit for the four ports in 2020 can be approximately derived. Moreover, the estimation of the expected profit growth rate refers to their financial reports for the years between 2015 and 2017. The plan also sets a general target for decreasing pollutant emissions such as CO_2 and NOx. The relevant data are listed in Table 2.

Combined with model (5) and the data stored in Table 2, we can establish the IDEAU model for consumption predictions. The excepted investment optimization corresponding to the given development targets for the four efficient DMUs are listed in Table 3.

On the other hand, as to the twelve inefficient DMUs, we apply model (7) to estimate the potential input excesses of them to improve their productivity. We find the six container ports of NB, DL, LYG, SZ, JZ, and FZ can be improved by disinvesting, as shown in Table 4. As to the other six ports, namely, SH, TJ, YK, XM, CQ, and ZH, there are no feasible solutions for them since the constraints in model (7) are quite strict for the variables y_{r0} and $\bar{z}_{l\,0}$ that are optimized in opposite directions.

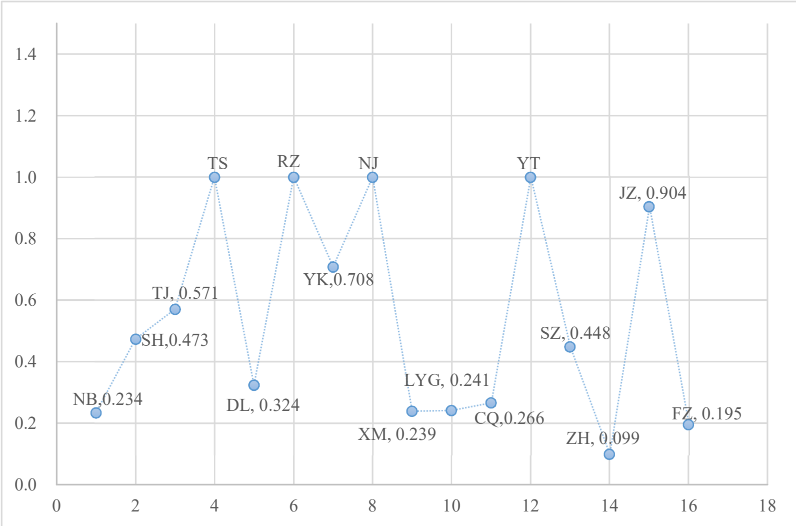

Figure 3. CCR efficiencies of the 16 ports.

Table 2. Expected changes of the four ports in 2020.

Port	Output Variation			
	Δy_1	Δy_2	Δz_1	Δz_2
TS	11.2%	6.84%	−7.0%	−8.7%
RZ	15.0%	2.57%	−7.0%	−8.1%
NJ	6.1%	1.58%	−3.6%	−6.0%
YT	5.8%	5.28%	−3.3%	−2.5%

Table 3. Input predictions of the four ports.

Port	Inputs			
	Berth (Δx_1)	Equipment * (Δx_2)	Employee (Δx_3)	Cost * (Δx_4)
TS	12	−42.2	1	−4.7
RZ	4	−14.6	33	−1.8
NJ	0	4.71	1	7.5
YT	0	12.1	0	3.1

Note: * The monetary unit is million RMB.

Table 4. Potential input excesses of six ports.

Port	Inputs			
	Berth (Δx_1)	Equipment (Δx_2)	Employee (Δx_3)	Cost (Δx_4)
NB	112.6	390.8	58	0.0
DL	77.2	178.9	92	837.8
LYG	0.0	76.3	37	50.4
SZ	0.0	52.6	18	11.5
JZ	0.0	53.8	2	8.1
FZ	24.5	76.6	35	259.2

5.3. Results Analysis

It is found in Table 3 that some values are negative, which indicates a reduction in the amount of input. This is because we do not put a restraint on Δx_i (i = 1, 2, 3, 4), as shown in model (6), to avoid being unsolved for each DMU under evaluation. The results suggest increasing 12 berths and 4 berths for TS and RZ, respectively, whereas the equipment investment and cost can be cut down. This means the carrying capacity of the two ports, especially TS, have not been fully utilized. For the NJ and TY ports, it suggests to invest more capital on equipment (Δx_2) and cost (Δx_4) without increasing the number of berths. For the input element of Δx_3, only the RZ port has a striking number of hiring an additional 33 qualified persons. This advice sounds reasonable because the employees in the RZ port are too few to ensure efficient operation as related to the number of 52 berths.

Table 4 demonstrates the input excesses of six inefficient DMUs. In DEA literature, another popular technique for measuring input excesses of DMUs is the slacks-based model (SBM) [31,42]. To verify the obtained results, we empirically conducted a comparison between the SBM model with undesirable outputs (SBMU) [31] and the proposed IDEAU model. The results are depicted in Table 5, which only lists the same six ports for comparison with Table 4.

Table 5. The input excesses by SBMU model.

Port	Inputs				Score
	Δx_1	Δx_2	Δx_3	Δx_4	
NB	246.6	488.4	74	283.8	0.189
DL	161.3	453.8	283	1172.8	0.154
LYG	24.9	298.8	167	60.7	0.028
SZ	0.0	0.0	0.0	0.0	1.00
JZ	0.0	0.0	0.0	0.0	1.00
FZ	20.52	85.98	32	241.8	0.754

Obviously, the values in Table 5 are generally greater than those in Table 4, except for the FZ port. Moreover, Both SZ and JZ ports are evaluated as efficient DMUs by the SBMU method, but inefficient by the IDEAU model. Nevertheless, we observe the relative changing amounts of the three ports (NB, DL, LYG) are consistent with the two models. Although the two models are all categorized to nonradial measure, they are much different in modeling mechanism and objective target. Firstly, the objective of model (7) is to calculate how the maximum amounts of input excesses can be altered at the current level of outputs, while the latter aims to minimize the ratio of input and output mix inefficiencies [43]. Secondly, the model (7) is input-oriented and pursues the minimum investments in inputs while maintaining the output, yet the SBMU method is nonoriented and applies the input and output slacks in deriving an efficiency measure directly. Thirdly, we allow the variables in model (7) to be negative owing to the fact that the investment of an input factor may be rising or falling according to the future productivity scheme.

As to this case, we employ four input variables and four output variables, which seem too high compared to the number of 16 DMUs. Just as suggested by Boussofiane et al. [44], the number of input and output variables in DEA analysis should have better less than one-third the number of DMUs. Then, we remove the undesirable output variables (z_1 and z_2) to verify the robustness of the results. Solving by model (4), the efficiency scores of nine ports (NB, SH, TS, RZ, YK, NJ, CQ, YT, SZ) are equal to 1, which is different from the previous result that only four ports (TS, RZ, NJ, YT) are efficient as shown in Figure 3. We now focus on the investment analysis of the four ports (TS, RZ, NJ, YT), which are evaluated as CCR-efficient before and after removing the two undesirable variables. Perturbing their output level of desirable variables according to Table 2, the input predictions can be calculated based on the IDEAU model. The comparison is shown in Figure 4, where the left histogram is generated with the constraint of undesirable output variables.

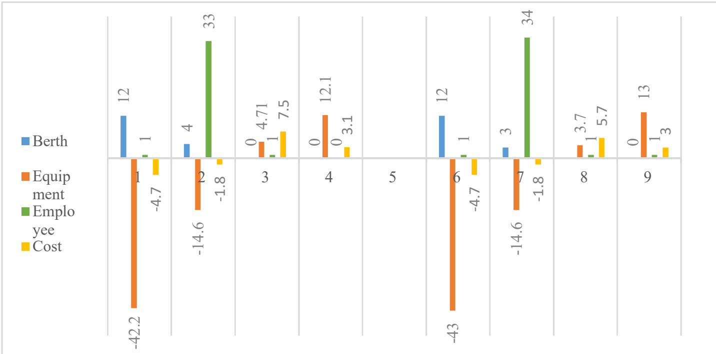

Figure 4. Comparison of input predictions of the four ports.

Generally, the alterations of input levels are quite similar from Figure 4. In other words, despite removing undesirable output variables, the changing amounts of inputs solved by the IDEAU model are consistent with the previous data in Table 3.

As per the empirical results, some policy suggestions are presented for promoting the container ports' sustainable development as follows:

(1) According to Figure 3, the average operational efficiency of the 16 Chinese ports is 0.544, which is generally low and uncompetitive in global trade. Additionally, unbalanced development of main ports is a barrier to the maritime industry, where the ports around Bohai Sea including TS, JZ, YK, and DL ports have a relatively high performance. This region is highly exhaust polluted, and extra efforts should be made to control air emissions.

(2) Resource investments on the ports of NB, DL, LYG, and FZ should be further optimized to enhance their competitiveness. For instance, it is suggested to add 112 berths in the NB port or to invest more than 800 million in the DL port according to Table 4. As China's economy has entered a "new normal" that shows a marked slowdown, local government should upgrade the port industry by switching from resource-dependent mode to resource-friendly mode.

(3) The Yangtze River port system, which includes the NJ, NB, and SH ports, in this case, is an essential container system in China. The total throughput of the SH and NB ports exceeded 1.6 billion tons in 2017. Yet the CCR efficiencies of the two ports are not high when considering undesirable output factors. Taking the NB port as an example, the investments on berth and equipment need to reduce by 112 (units) and 390.8 (million), respectively. Besides, local policymakers should find a balance between ports' development and environmental protection since these ports contribute to a vast amount of exhaust emissions.

(4) As a key area in the BRI, Fujian province has great potential in the international logistics market. However, the XM and FZ ports in Fujian have low efficiency scores (0.239 and 0.195, respectively) compared to the other domestic ports. From Table 4, it is imperative for the FZ port to cut down costs in the future. Other effective policies, such as establishing a green port supply chain or regional linkage system, should be made.

6. Conclusions

Understanding of various main ports is quite crucial for Chinese authorities. The accelerating development of the port industry has caused widespread environmental pollution. Thus, the evaluation of ports efficiency should consider both desirable and undesirable outputs, which contribute to formulating achievable industrial policies. This paper develops a novel IDEA model to assess 16 Chinese ports' efficiency in 2017 by taking undesirable output into consideration. Then, analyses of ports' resource consumption are conducted according to the Chinese 13th FYP. We also discuss the improvement of inefficient ports (DMUs) by measuring their input excesses based on the proposed model. Overall, the IDEA approach for performance assessment and resource investment of ports has the following characteristics: (1) Both desirable and undesirable outputs can be incorporated in the proposed inverse DEA model; (2) the proposed method can be used to predict resource investments of a container port when given an output target; (3) by resetting the current efficiency score, the proposed method can measure the excess amounts of inputs of container ports.

However, this study has some limitations. First, we utilize the CCR model with undesirable outputs in calculating the efficiencies of DMUs. However, this classical model has low discriminating power in ranking efficient DMUs. Also, the data on emissions was not accessible but obtained indirectly. For future studies, other efficiency measures such as super-efficiency or cross-efficiency may be applied and integrated with the IDEA method. Another interesting research is to extend the proposed approach to deal with a more general port system with a multistage structure.

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Appendix A

1. CO_2 emission:

The calculation of CO_2 emissions is based on the relationship between port throughput and energy consumption [30]. The formula of CO_2 emissions is as follows:

$$E_{CO_2} = N_c \times T \times \xi$$

where E_{CO_2} is the amount of CO_2 emissions, N_c is unit consumption of standard coal, T is port throughput, and ξ is the parameter of carbon emissions that equals to 2.458.

2. NO_x emission:

The calculation of NO_x emissions is simplified in our study and mainly refers to the amount of CO_2 emissions and other parameters. The NO_x emissions are calculated as follows:

$$E_{NO_X} = E_{CO_2} \times \psi \times \kappa$$

where E_{NO_X} is the amount of NO_x emissions, ψ is the ratio related to CO_2 emissions, and κ is fuel burning rate.

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