Efficiency Evaluation of Major Coastal Ports in China: Application of the Three-stage DEA Model

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Abstract. With the increasing competition between ports, how to improve port efficiency and promote the sustainable development of ports becomes the focus of attention. The paper applies the three-stage data envelopment analysis (T-S DEA) model to measure the efficiency of top 10 Chinese coastal ports, including the scale efficiency (SE) and technical efficiency (TE). Besides, the principle component analysis approach is adopted to reduce the influence of redundant information of evaluation indicators on results. The stochastic frontier analysis regression model is applied to eliminate the effects of environmental factors and stochastic errors under similar exterior conditions. The results show: (1) The ports efficiency (SE and TE) in different regions is quite different; the efficiency of Chinese coastal ports is generally low, which is mainly caused by scale inefficiency; (2) The SE and TE are improved and the input and output redundancy ratio are decreased significantly by comparing the results of traditional DEA model. (3) Shanghai, Ningbo-Zhoushan, Shenzhen, Hong Kong and Kaohsiung have relatively high comprehensive efficiency. This study provides valuable information for estimating port efficiency and establishing competitive strategies in the future.

1. Introduction

As an important transportation infrastructure, port is the window to realize export-oriented economy, and provides basic support for national economic and foreign trade development. In the current global economic growth slowdown and the aggravation of homogenization competition among ports, as important nodes of the global supply chain, ports are facing great pressure to improve services and reduce costs, and the efficiency is of great importance to ports development. Chinese coastal ports are the main starting point of the 21st-Century Maritime Silk Road and the necessary gateway to Asia, Europe and America. Therefore, it is vital to evaluate the efficiency of these ports and enhance competitiveness. Ports efficiency evaluation has always been a hot issue in the field of transportation and shipping economy.

Port development is affected by many factors and the efficiency evaluation is complex, so the selection of evaluation index and evaluation method is very important. Many scholars dedicate to analyse port efficiency, and the Data Envelopment Analysis (DEA) model that has been applied dominates among the methods of efficiency analysis. Chang and Tovar [1] measured ports productivity, evaluated the influence of the certain specific explanatory variables based on DEA. Kunit et al. [2] evaluated the relative efficiency and competitiveness of ASEAN ports based on traditional output-oriented DEA, and measured the super-efficiency constant. Considering the efficiency of port enterprises and authorities, a non-radial DEA preference model was proposed to analyse the efficient and non-efficient ports and the impact of environmental performance [3], [4]. Because DEA model does not consider environment factors and stochastic errors, the three-stage DEA (T-S DEA) model combining with stochastic frontier analysis (SFA) regression model was proposed.
by Fried et al. [5]. This method allows the examination of the impact of environment variables on DEA efficiency scores by filtering out the environment factors. Li et al. [6] applied the T-S DEA to evaluate pure technology efficiency (PTE), technology efficiency (TE) and scale efficiency (SE) based on the basis of input/output cross-sectional data of ports. Liu [7] adopted the DEA and T-S DEA model to estimate the efficiency changes of ports using cross-period data and results show that the efficiency estimated by T-S DEA is the highest. However, due to the strong correlation between input and output indicators, and the SFA model has a great impact on the evaluation results, principal component analysis (PCA) can transform multiple evaluation indicators into a few typical principal components (PC) with the aid of dimension reduction theory to solve these problems. Therefore, this paper uses T-S DEA combined with PCA and SFA model to evaluate the port efficiency, so as to improve the accuracy of the evaluation results and objectively and truly reflect the actual efficiency of the port.

2. Methodology

2.1. Three-stage DEA model

The T-S DEA model was proposed to eliminate the effects of environment variables and stochastic errors. The flowchart of the T-S DEA model is shown in Figure 1.

Stage 1: using traditional DEA model (CCR and BCC) to evaluate port efficiency. The SFA method will be adopted in stage 2 to eliminate errors and obtain substantially accurate efficiencies.

Stage 2: building the SFA model and regression relationships between input indicators and environment variables and stochastic errors. To build a similar SFA model, environmental factors and input redundancies are the independent and dependent variables, respectively:

\[ S_{ij} = f(z_j, \beta_i) + v_{ij} + u_{ij} \]  

(1)

where \( S_{ij} \) is the slack variables of \( i \)-th input indicator from \( j \)-th DMU; \( f(z_j, \beta_i) \) is the influence of environment factors on the slack variables; \( z_j = [z_{j1}, z_{j2}, \ldots, z_{js}] \) is the value of environment variables; \( s \) is the number of environment variables; \( \beta_i \) is the parameters from the environment variables; \( v_{ij} \) is stochastic error, subject to normal distribution \( N(0, \sigma^2_v) \); \( u_{ij} \) is residual, subject to truncated normal distribution \( N(0, \sigma^2_u) \).

Let \( \gamma = \sigma^2_v / (\sigma^2_v + \sigma^2_u) \in [0, 1] \), if \( \lim \gamma \to 0 \), random errors are main reason that influences the efficiencies, if \( \lim \gamma \to 1 \), environment factors are main reason. The coefficients \( \beta_i, \sigma^2_v, \sigma^2_u, \gamma \) could be

![Figure 1. Empirical process of the T-S DEA model.](image-url)
obtained based on the principle of maximum likelihood estimate in FRONTIER software; \( u_i \) can be obtained through mean formula:

\[
E(u_i | v_i + u_i) = \frac{\lambda \sigma}{1 + \sigma^2} \left[ \frac{\phi(\lambda(v_i + u_i)/\sigma)}{\Phi(\lambda(v_i + u_i)/\sigma)} + \frac{\lambda(v_i + u_i)}{\sigma} \right] 
\]

where \( \lambda = \sigma_v / \sigma_u \), \( \sigma = \sigma_v^2 + \sigma_u^2 \), \( \phi(), \Phi() \) are probability density function and distribution function of standard normal distribution. \( v_i \) can be obtained:

\[
E(v_i | v_i + u_i) = S_i - z_i \cdot \beta_i - E(u_i | v_i + u_i) 
\]

The adjusted input data will be obtained, the uncontrollable factors (environment variables and stochastic errors) will be eliminated, the DMUs will be under the similar exterior conditions.

\[
x'_i = x_i + [\max(z_i \cdot \beta_i) - z_i \cdot \beta_i] + [\max v_i - v_i] 
\]

The adjusted input values from stage 2 and original output values to evaluate port efficiencies in the traditional DEA model.

### 2.2. Index system

To analyse the port efficiency based on the reliability and availability principle of indicators, this study evaluates the main factors influencing port competitiveness. These indicators should reflect the evaluation purpose comprehensively, and the correlations between the input and output indicators and diversity of indicators system should be considered.

Input/output indicators: Port facilities, location conditions, operation level and finance and capital are considered first level indicators. The details of the evaluation indicator system are shown in Table 1.

| Level 1 | Level 2 |
|---------|---------|
| Port facilities/A1 | Number of bridges/A11, Number of berths/A12, Number of KT berths/A13, Number of facilities/A14 |
| Location conditions/A2 | Length of berths/A21, Yard area/A22, Pilot times/A23, Number of workers/A24 |
| Operation level/A3 | Cargo throughput/A31, Growth rate of cargo throughput/A32, Container throughput/A33, Growth rate of container throughput/A34, Cargo handling capacity/A35, Container handling capacity/A36 |
| Finance & capital/A4 | Port investment/A41, Gross annual value/A42, Growth rate of gross annual value/A43, Market value/A44, Earnings per share/A45 |

The input indicators are A11, A12, A13, A14, A21, A22, A23, A24, A41, A44 and A45; output indicators are A31, A32, A33, A34, A35, A36, A42 and A43. This study selects the 10 largest coastal ports in China, in which the cargo and container throughputs also topped the list of the world largest ports. These ports are Shanghai, Ningbo-Zhoushan, Guangzhou, Tianjin, Qingdao, Dalian, Xiamen, Shenzhen, Hong Kong and Kaohsiung. Data were collected from China port Yearbook, Statistics Bulletin of the National Economic and Social Development of the port cities in 2019.

Environment variables: Given that the traditional DEA model does not consider the effects of environment variables and stochastic errors, the results between the DEA efficiency evaluation and realities are inconsistent. Moreover, port efficiency is affected by complicating factors, which include operating management, subjective regulation and exterior environments. As environment variables are unpredictable and uncontrollable, this study chooses the significant influencing factors: number of routes/Z1, mean depth of berth/Z2, hinterland GDP/Z3, and hinterland traffic mileage/Z4.
2.3. **Determination of final indicators**

This study selects 11 input and 8 output indicators that comprehensively influence port efficiency. However, two issues must be considered. The total amounts of input and output are more than the number of DMUs, but the correlations between input and output indicators are close. In both conditions, the accuracy of the evaluation results will be reduced.

This study processes the input and output indicators data based on PCA utilizing the SPSS software. The procedures include the import data, PCA, results analysis, PC loading and scores. This study uses the analysis conducted as basic to determine the final three input indicators (X1, X2 and X3) and two output indicators (Y1 and Y2).

However, environment conditions of ports may influence the evaluation efficiencies. Therefore, the environment variables and stochastic errors should be eliminated. This research adopts the T-S DEA and SFA methods to analyse the efficiencies objectively.

### 3. Empirical results

#### 3.1. Stage 1

According to DEA model (CCR and BCC), the calculation results of CCR model, BCC model and comprehensive evaluation are shown in Table 2, Table 3 and Table 4 respectively.

**Table 2. Evaluating result in stage 1 (CCR model).**

| CCR | Shanghai | Ningbo | Guangzhou | Tianjin | Qingdao | Dalian | Xiamen | Shenzhen | Hong Kong | Kaohsiung |
|-----|----------|--------|-----------|---------|---------|--------|--------|----------|-----------|-----------|
| θ   | 1        | 1      | 0.775     | 0.832   | 0.774   | 0.754  | 0.712  | 1        | 1         | 1         |
| S1- | 0        | 0      | 0         | 0       | 0.018   | 0      | 0      | 0        | 0         | 0         |
| S2- | 0        | 0      | 0.245     | 0.550   | 0.611   | 0.023  | 0.086  | 0        | 0         | 0         |
| S3- | 0        | 0      | 4.526     | 6.692   | 0       | 8.749  | 5.657  | 0        | 0         | 0         |
| S1+ | 0        | 0      | 0         | 0       | 0       | 0      | 0      | 0        | 0         | 0         |
| S2+ | 0        | 0      | 0         | 0       | 0       | 50.52  | 0      | 0        | 0         | 0         |
| Σλι | 1        | 1      | 0.658     | 0.932   | 0.685   | 0.865  | 0.448  | 1        | 1         | 1         |

*Notes: θ is efficiency; S = (S1, S2, S3) is input slack variable; S* = (S1*, S2*) is output slack variable.*

For Shanghai, Ningbo, Shenzhen, Hong Kong and Kaohsiung, the efficiencies θ = 1 and slack variables S = 0. These ports are efficiency, comes to TE and SE simultaneously, the optimal combination of inputs and outputs. The other ports θ < 1, this means they are non-DEA efficient.

**Table 3. Evaluating result in stage 1 (BCC model).**

| BCC | Shanghai | Ningbo | Guangzhou | Tianjin | Qingdao | Dalian | Xiamen | Shenzhen | Hong Kong | Kaohsiung |
|-----|----------|--------|-----------|---------|---------|--------|--------|----------|-----------|-----------|
| θ   | 1        | 1      | 0.815     | 0.912   | 0.810   | 0.900  | 1      | 1        | 1         | 1         |
| S1- | 0        | 0      | 0         | 0       | 0       | 0      | 0      | 0        | 0         | 0         |
| S2- | 0        | 0      | 0.280     | 0.562   | 0.651   | 0      | 0      | 0        | 0         | 0         |
| S3- | 0        | 0      | 5.243     | 6.906   | 0.115   | 9.700  | 0      | 0        | 0         | 0         |
| S1+ | 0        | 0      | 0         | 0       | 0       | 0.056  | 0      | 0        | 0         | 0         |
| S2+ | 0        | 0      | 0         | 0       | 0       | 237.4  | 0      | 0        | 0         | 0         |
| Σλι | 1        | 1      | 1         | 1       | 1       | 1      | 1      | 1        | 1         | 1         |

For Shanghai, Ningbo, Xiamen, Shenzhen, Hong Kong and Kaohsiung, the efficiencies θ = 1 and slack variables S = 0. This result means that these ports are DEA efficient, comes to PTE, the optimal combination of inputs and outputs. For the other ports, θ < 1 means they are non-DEA efficient.
Table 4. Comprehensive valuating result in stage 1.

| Indicator | Shan ghai | Ning bo | Guan gzhou | Tianjin | Qing dao | Xiame n | Shen zhen | Hong Kong | Kaohsiung |
|-----------|-----------|---------|------------|---------|---------|---------|-----------|-----------|-----------|
| RTS       | 1         | 1       | 0.849      | 1.121   | 0.885   | 1.146   | 0.629     | 1         | 1         |
| TE        | 1         | 1       | 0.815      | 0.914   | 0.810   | 0.900   | 1         | 1         | 1         |
| Input redund. ratio | X1 | 0       | 0         | 0       | 0       | 0       | 0         | 0         | 0         |
|            | X2 | 0       | 0         | 0.183   | 0.352   | 0.326   | 0         | 0         | 0         |
| Output deficiencv ratio | X3 | 0       | 0         | 0.125   | 0.179   | 0.003   | 0.255     | 0         | 0         |
|            | Y1 | 0       | 0         | 0       | 0       | 0.136   | 0         | 0         | 0         |
|            | Y2 | 0       | 0         | 0       | 0       | 0.251   | 0         | 0         | 0         |

For Shanghai, Ningbo, Shenzhen, Hong Kong and Kaohsiung, RTS is stable and TE is optimal. For Guangzhou, Qingdao and Xiamen, RTS increases and TE is suboptimal. For Tianjin and Dalian, RTS decreases and TE is suboptimal. The input and output deficiency ratios are 0, thereby showing that the input and output data are optimal. For Guangzhou, the output deficiency ratio is 0, but the input redundancy ratio of X2 and X3 are 0.183 and 0.125, respectively. That is, the input redundancy ratios of the number of facilities and port investment are 18.27% and 12.50%, respectively. For Dalian, the input deficiency ratio of X1 and X2 are zero, but the input redundancy ratio of X3 is 0.255. This result indicates that the input redundancy ratio of port investment is 25.53%. The output deficiency ratio of Y1 and Y2 are 0.136 and 0.251, respectively. This result indicates that the output deficiency ratio of the cargo and container throughputs are 13.55% and 25.12%, respectively.

The preceding results indicate that Shanghai, Ningbo, Shenzhen, Hong Kong and Kaohsiung are efficient; and the other ports are suboptimal in terms of the input and output values. In this stage, the environment factors are not exclusive. Therefore, stage 2 is necessary to analyse practical efficiency.

3.2. Stage 2
The port efficiencies and slack variables of input indicators in stage 1 could be obtained. In this stage, the SFA is adopted to adjust the initial input and evaluate the efficiencies under the similar exterior conditions. The environment factors and input redundancies are the independent and dependent variables, respectively. The principle of maximum likelihood estimate is used to estimate the regression coefficients of the independent variables. The regression results are shown in Table 5.

Table 5. SFA regression results.

| Independent variables | X2            | X3            |
|-----------------------|---------------|---------------|
| Coefficient           | Standard-error| T-ratio       | Coefficient | Standard-error| T-ratio       |
| Constant              | 130.089***    | 1.000         | 130.089     | 18.393***    | 1.779         | 10.339       |
| Z1                    | -0.523***     | 0.043         | -12.182     | -0.126***    | 0.011         | -11.178      |
| Z2                    | 12.975***     | 0.998         | 13.001      | -0.697***    | 0.067         | -10.416      |
| Z3                    | -0.020*       | 0.007         | 2.728       | -0.022***    | 0.005         | -4.887       |
| Z4                    | -0.190***     | 0.009         | -13.021     | -0.006***    | 0.001         | -9.282       |
| σ2                    | 137.232       | 1.000         | 137.232     | 20.370       | 1.395         | 14.597       |
| γ                     | 0.999         | 0.00001085    | 92182.6     | 0.999        | -             | 34937.6      |
| log likelihood function | -8.053        | -             | -8.526      | -             | -             |              |
| LR test of one-sided error | 7.080        | -             | 2.467       | -             | -             |              |

Notes: ***, **, * indicate coefficient pass 1%, 5% and 10% significance test respectively.
From Table 5, all coefficients pass the significance test, and the selected environment indicators have significant influence to input balances. The $\gamma$ tends to 1, and the regression model is effective. The negative coefficient means that the increase of the environment data is good for decreasing input redundancy. The positive coefficient means that the increase of environment data is bad for decreasing input redundancy, and will lead to the waste of port investment and reduce efficiency. The value of log likelihood function is negative, which means that the fitting model is appropriate.

X2: Z1, Z3 and Z4 are negatively correlated to yard area. This result indicates that the input increase of Z1, Z3 and Z4 will decrease the redundancy of X2. Hence, the large yard area is supposed to build in these ports. Z2 is positively correlated to X2. This result indicates that port builds the larger area of warehouse and yard based on the deeper berths, and the results lead to waste of yard.

X3: Z1, Z2, Z3 and Z4 are positively correlated to port investment. This result indicates that the input increase of Z1, Z2, Z3 and Z4 will decrease the redundancy of X3. Therefore, port investment should be increased and production efficiency and international competitiveness must be improved.

The preceding results indicate that the regression results of the SFA are reasonable, and different exterior variables have varying influences. Therefore, the environment factors should be eliminated.

3.3. Stage 3

According to the SFA analysis, the adjusted input data can be obtained. This study calculates the efficiency based on the adjusted input and initial output data again. Table 6, Table 7 and Table 8 show the results of CCR model, BCC model and comprehensive evaluation respectively.

### Table 6. Evaluating results in stage 3 (CCR model).

| CCR | Shanghai | Ningbo | Guangzhou | Tianjin | Qingdao | Dalian | Xiamen | Shenzhen | Hong Kong | Kaohsiung |
|-----|----------|--------|-----------|---------|---------|--------|--------|----------|-----------|-----------|
| $\theta$ | 1 | 1 | 0.775 | 0.901 | 0.776 | 0.754 | 0.712 | 1 | 1 | 1 |
| S1 | 0 | 0 | 0 | 0 | 0.012 | 0 | 0 | 0 | 0 | 0 |
| S2 | 0 | 0 | 0.028 | 0.045 | 0.111 | 0.023 | 0.086 | 0 | 0 | 0 |
| S3 | 0 | 0 | 0.467 | 0.472 | 0 | 1.433 | 5.657 | 0 | 0 | 0 |
| S1+ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| S2+ | 0 | 0 | 0 | 0 | 50.52 | 0 | 0 | 0 | 0 | 0 |
| $\Sigma \lambda_i$ | 1 | 1 | 0.738 | 0.949 | 0.724 | 0.831 | 0.532 | 1 | 1 | 1 |

### Table 7. Evaluating results in stage 3 (BCC model).

| BCC | Shanghai | Ningbo | Guangzhou | Tianjin | Qingdao | Dalian | Xiamen | Shenzhen | Hong Kong | Kaohsiung |
|-----|----------|--------|-----------|---------|---------|--------|--------|----------|-----------|-----------|
| $\theta$ | 1 | 1 | 0.864 | 0.940 | 0.874 | 0.923 | 1 | 1 | 1 | 1 |
| S1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| S2 | 0 | 0 | 0.051 | 0.051 | 0.125 | 0 | 0 | 0 | 0 | 0 |
| S3 | 0 | 0 | 0.973 | 0.603 | 0.018 | 0.970 | 0 | 0 | 0 | 0 |
| S1+ | 0 | 0 | 0 | 0 | 0 | 0.013 | 0 | 0 | 0 | 0 |
| S2+ | 0 | 0 | 0 | 0 | 201.17 | 0 | 0 | 0 | 0 | 0 |
| $\Sigma \lambda_i$ | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

### Table 8. Comprehensive evaluating results in stage 3.

| Indicator | Shanghai | Ningbo | Guangzhou | Tianjin | Qingdao | Dalian | Xiamen | Shenzhen | Hong Kong | Kaohsiung |
|-----------|----------|--------|-----------|---------|---------|--------|--------|----------|-----------|-----------|
| RTS | 1 | 1 | 0.952 | 1.052 | 0.933 | 1.100 | 0.747 | 1 | 1 | 1 |
As shown in Table 6 to Table 8, the preceding results indicate that Shanghai, Ningbo, Shenzhen, Hong Kong and Kaohsiung are efficient, RTS is stable, TE is optimal. For Guangzhou, Qingdao, Xiamen, RTS increases and TE is suboptimal. For Tianjin and Dalian, RTS decreases and TE is suboptimal. The values of input redundancy and output deficiency ratios are 0. Thus, the input and output data are optimal. Although the output deficiency ratio for Guangzhou is zero, the input redundancy ratio of indicators X2 and X3 are 0.041 and 0.027, respectively. This result indicates that the input redundancy ratio of the number of facilities and port investment are 4.1% and 2.65%, respectively. For Dalian, the input deficiency ratio of indicators X1 and X2 are zero, but the input redundancy ratio of X3 is 0.034. This result indicates that the input redundancy ratio of port investment is 3.43% and the output deficiency ratio of indicators Y1 and Y2 are 0.032 and 0.213, respectively. That is, the output deficiency ratios of the cargo and container throughputs are 3.18% and 21.28%, respectively.

### 3.4. Comparison of Results

From above discuss and comparing stage 1 & 3, Table 9 and Figure 2 show the comparison results.

**Table 9.** Comparison of stage 1 & 3 results (RTS & TE).

| Port     | RTS Stage 1 | RTS Stage 3 | TE Stage 1 | TE Stage 3 |
|----------|-------------|-------------|-------------|-------------|
| Shanghai | 1           | 1           | 1           | 1           |
| Ningbo   | 1           | 1           | 1           | 1           |
| Guangzhou| 0.849       | 0.952       | 0.815       | 0.864       |
| Tianjin  | 1.121       | 1.052       | 0.914       | 0.940       |
| Qingdao  | 0.885       | 0.933       | 0.810       | 0.874       |
| Dalian   | 1.146       | 1.100       | 0.900       | 0.923       |
| Xiamen   | 0.629       | 0.747       | 1           | 1           |
| Shenzhen | 1           | 1           | 1           | 1           |
| Hong Kong| 1           | 1           | 1           | 1           |
| Kaohsiung| 1           | 1           | 1           | 1           |

**Figure 2.** Comparison of RTS and TE in stage 1 and 3.
From Table 9 and Figure 2, for Shanghai, Ningbo, Shenzhen, Hong Kong and Kaohsiung, the RTS are still equal to 1; it means RTS is always the best. For Guangzhou, Qingdao, Xiamen, the RTS in stage 3 are closer to 1 than them in stage 1 and have better stability. For Tianjin, Dalian, the RTS are closer to 1 and have better stability. For Shanghai, Ningbo, Xiamen, Shenzhen, Hong Kong and Kaohsiung, the TE in stage 3 are still equal to 1; it means TE is always the optimal. For Guangzhou, Tianjin, Qingdao, Dalian, the TE are closer to 1 and have better stability, it means TE has been improved. According to the above analysis, under the condition of eliminating the influence of environment factors, the combination of adjusted inputs and initial outputs improves the evaluate efficiency. The results are closer to reality. From the perspective of management and operation to estimate the port efficiency and analyse the gaps between various ports, it is more objective, targeted and instructive.

4. Conclusions
With the rapid development of the port industry, every port is exerting its best effort to improve productivity and competitiveness. In this study, 10 leading Chinese coastal ports are selected, and T-S DEA model is adopted to analyse their efficiency. The paper collects mass data of 11 input and 8 output indicators from these ports, representing the basic characteristics. PCA is used to converse the multiple comprehensive indicators into the typical minority PC based on dimension-reduction theory. The final indicators are determined with 3 inputs and 2 outputs. To eliminate the effects of environment factors and random errors, the SFA regression model is proposed in stage 2 to adjust the initial input data based on the slack and surplus variables obtained in stage 1. The results show that the port efficiency in different regions is quite different, and the efficiency of Chinese coastal ports is generally low, which is mainly caused by scale inefficiency. The efficiency of RTS and TE is higher in stage 3 than traditional DEA model in stage 1. Moreover, the input redundancy and output deficiency ratios are significantly decreased. Shanghai, Ningbo-Zhoushan, Shenzhen, Hong Kong and Kaohsiung have relatively high comprehensive efficiency. This study demonstrates that T-S DEA model provides a viable and suitable method for evaluating port efficiency. However, this study has several limitations. (1) Data used in this study are based on a single-period, the development trend of ports cannot be shown comprehensively. (2) A few imperceptible indicators from ports may be disregarded. The derived efficiency may not express the complete details of ports.

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