This paper extends the data envelopment analysis model presented by Ablanedo-Rosas et al. (2010), aimed to assess the efficiency of ports based on financial-ratios information. A variant of cross-efficiency method is adapted. This approach alleviates the weakness of traditional data envelopment analysis models for ranking efficient decision making units, and the multiple optimal solutions when finding weights associated to each decision making unit. The results prove the usefulness and applicability of the model.

KEYWORDS: data envelopment analysis, efficiency, cross-efficiency, financial-ratio, ports

INTRODUCTION

Sea ports are major components of global supply chains and have been extensively studied by researchers worldwide. Most of the studies are based on infrastructure information of the port such as number of cranes, number of tugs, number of berths, terminal area, terminal length, quay length, and yard gantries, among others. A different study of the Chinese sea port system was performed by Ablanedo-Rosas et al. (2010); they used financial ratios to evaluate the performance of 11 major Chinese ports. Their study proved the relevance of financial ratios for assessing ports, but it also confirmed the weak discrimination of the classical Data Envelopment Analysis (DEA) model.

This paper extends the DEA model presented by Ablanedo-Rosas et al. (2010). An innovative cross-efficiency approach, for solving the only outputs DEA model introduced by Ablanedo-Rosas et al. (2010), is presented. The results are compared with previous research and confirm the usefulness of the approach.
LITERATURE REVIEW

The literature about ports’ efficiency is extensive and covers ports all over the world. Hence, this literature review focuses on recent studies which are related to Chinese ports’ performance and using any of the two most common techniques for quantitative benchmarking which are DEA and Stochastic Frontier Analysis (SFA). The former is a non-parametric approach and the latter a classic parametric technique.

The Chinese ports have experienced a tremendous growth and play a major role in current global supply chains (Comtois, 1999). Cullinane et al. (2002) applied a modified SFA to analyze the impact of administrative and ownership structures in Asian ports’ performance. Results showed that port size and transformation of ownership from public to private sector have an impact in ports’ efficiency. Tongzon and Heng (2005) applied a SFA model and found that private sector participation can improve port operation efficiency and competitiveness. Changxin and Hui (2007) measured the technical efficiencies of the Chinese major ports with SFA. The empirical results suggest that ownership reform increases technical efficiencies. Yip et al. (2011) developed a SFA model to make a connection between efficiency and port operations. An interesting study is the cross-efficiency SFA model discussed by Hai-bo and He-zhong (2009).

Cullinane et al. (2005) evaluated the efficiency of the world’s most important ports using the two alternative techniques of DEA and the Free Disposal Hull (FDH) model. A study with five models of DEA for evaluating the operational efficiency of major container ports in the Asia-Pacific region and for identifying trends in port efficiency was developed by Lin and Tseng (2007). DEA models and a Malmquist approach were used by Liu et al. (2008) to measure the efficiency of ports in mainland China. De Koster et al. (2009) studied 38 ports using DEA and found that port size is a determinant of efficiency. Sharma and Yu (2009) fused data mining and DEA to perform a diagnostic of port’s efficiency. Wu and Liang (2009) utilized DEA and assessed 77 world ports; they stated the usefulness of creating comparison groups that result in more homogeneous efficiency evaluations.

The traditional analysis of port efficiency has been largely based on port’s infrastructure without considering financial information. Ablanedo-Rosas et al. (2010) suggested a financial ratio-based DEA to analyze the Chinese ports efficiency. The DEA approach is an output oriented model with only outputs. However, this approach still shows the weak discrimination of classic DEA models. One way to deal with this issue is the so called super efficiency DEA model introduced by Andersen and Petersen (1993). Alternatively, a cross-evaluation DEA approach with secondary goals, proposed by Doyle and Green (1994) and extended by Wu et al. (2009), has been widely used to define appropriate weights for estimating efficiency scores. This paper differs from the aforementioned two approaches and makes a novel contribution adapting a method for determining unique weights for the DEA model presented by Ablanedo-Rosas et al. (2010).

MATHEMATICAL MODEL

DEA was introduced by Charnes et al. (1978) and has been developed into a widely accepted academic field. The output oriented and financial ratio based DEA model with variable returns to scale used by Ablanedo-Rosas et al. (2010) is defined as follows: There are \( n \)
Units (DMUs), where each DMU \( i (i = 1, \ldots, n) \) generates \( q \) outputs \( y_{ij} (j = 1, \ldots, q) \). Let \( \alpha_i \) be the DEA coefficient (decision variable) associated with DMU \( i \). The DEA model is the following linear programming problem:

\[
\begin{align*}
\text{max } & \quad \lambda_p \\
\text{subject to } & \quad \sum_{i=1}^{n} \alpha_i = 1 \\
& \quad \sum_{i=1}^{n} y_{ij} \alpha_i \geq y_{ip} \lambda_p, \quad j = 1, \ldots, q \\
& \quad \lambda_p \geq 0, \quad \alpha_i \geq 0, \quad \forall i
\end{align*}
\]

The efficiency score for the DMU \( p \) in the study is given by \( \phi_p = \frac{1}{\lambda_p} \), and it is positive and less than or equal to one. The efficiency score \( \phi_p \) allows ranking the corresponding DMU \( p \); a port with an efficient score \( \phi_p = 1 \) is considered relatively efficient, and a port with an efficiency score \( \phi_p < 1 \) is considered relatively inefficient.

An extension of DEA is the cross efficiency method which was developed for identifying the best performing DMUs and for ranking DMUs using cross efficiency scores. The advantage of the cross efficiency method is that it alleviates the weak discrimination of the classical DEA model. The cross efficiency method has two steps. In the first step, the classical efficiency scores are determined using the model described by equations (1) to (4). A set of optimal weights \( u_{jp} \) preserving the efficiency values for each DMU is determined in the second step, and these weights are used for calculating the peer evaluation score \( \theta_{pi} \) (5) of DMU \( i (i = 1, \ldots, n) \) using the weights obtained for DMU \( p \).

\[
\phi_{pi} = \sum_{j=1}^{q} u_{jp} y_{ji}, \quad i = 1, \ldots, n
\]

There are multiple solutions when determining the optimal weights for the efficiency scores generated by model described by equations (1) to (4). Recently, Bal et al. (2008) developed a model which minimizes the variation of weights and obtains a unique optimal set of weights; we adapt this model to the presented in Ablanedo-Rosas et al. (2010). The corresponding weights are determined solving the model described by equations (6) to (9).

\[
\min CV_U = \sqrt{\frac{\sum_{j=1}^{q} (u_j - \bar{u})^2}{q - 1}}
\]
subject to

\[ \sum_{j=1}^{q} u_j y_{jp} = \phi_p, \quad (7) \]

\[ \sum_{j=1}^{q} u_j y_{ij} \leq 1, \quad i = 1,2,\ldots,n \quad (8) \]

\[ u_j \geq 0, \quad j = 1,2,\ldots,q \quad (9) \]

After solving this non-linear programming model, a set of optimal unique weights are defined for each DMU\(p\) and peer evaluation scores can be determined using (5). Once all peer evaluations scores are calculated, each DMU\(i\) has \(n\) cross efficiency scores. The overall cross efficiency score \(CE_i\) for each specific DMU\(i\) is determined by calculating its corresponding mean of cross efficiency scores (10).

\[ CE_i = \frac{\sum_{k=1}^{n} \phi_{ki}}{n} \quad i = 1,\ldots,n \quad (10) \]

This approach alleviates both the weakness of traditional DEA model for ranking efficient DMUs and the multiple optimal solutions when finding weights associated to efficient DMUs.

RESULTS

The case of Chinese ports studied by Ablanedo-Rosas et al. (2010) is used to test the model described in the previous section. Table 1 shows the results.

<table>
<thead>
<tr>
<th>Port</th>
<th>Efficiency score</th>
<th>Super efficiency score</th>
<th>Super efficiency rank</th>
<th>Cross-efficiency score</th>
<th>Cross-efficiency rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yantian</td>
<td>1.0000</td>
<td>2.8464</td>
<td>1</td>
<td>0.9984</td>
<td>1</td>
</tr>
<tr>
<td>Tianjin</td>
<td>1.0000</td>
<td>1.2655</td>
<td>5</td>
<td>0.9745</td>
<td>2</td>
</tr>
<tr>
<td>Nanjing</td>
<td>1.0000</td>
<td>1.4746</td>
<td>3</td>
<td>0.9102</td>
<td>3</td>
</tr>
<tr>
<td>Shenchiwian</td>
<td>1.0000</td>
<td>1.5617</td>
<td>2</td>
<td>0.8150</td>
<td>4</td>
</tr>
<tr>
<td>Wuhu</td>
<td>0.8641</td>
<td>0.8641</td>
<td>8</td>
<td>0.7312</td>
<td>5</td>
</tr>
<tr>
<td>Chongqing</td>
<td>0.7950</td>
<td>0.7950</td>
<td>9</td>
<td>0.6873</td>
<td>6</td>
</tr>
<tr>
<td>Jinzhou</td>
<td>1.0000</td>
<td>1.0463</td>
<td>6</td>
<td>0.6619</td>
<td>7</td>
</tr>
<tr>
<td>Xiamen</td>
<td>1.0000</td>
<td>1.3366</td>
<td>4</td>
<td>0.6537</td>
<td>8</td>
</tr>
<tr>
<td>Yingkou</td>
<td>0.8787</td>
<td>0.8787</td>
<td>7</td>
<td>0.6163</td>
<td>9</td>
</tr>
<tr>
<td>Shanghai</td>
<td>0.6960</td>
<td>0.6960</td>
<td>10</td>
<td>0.5145</td>
<td>10</td>
</tr>
<tr>
<td>Rizhao</td>
<td>0.5837</td>
<td>0.5837</td>
<td>11</td>
<td>0.4332</td>
<td>11</td>
</tr>
</tbody>
</table>
The second column in Table 1 shows the output oriented variable returns to scale efficiency scores for 11 major Chinese ports. The model used for estimating the efficiency scores (Ablanedo-Rosas et al. 2010) has only outputs and corresponds to 6 financial ratios. The weak discrimination of the DEA model suggested the use of a super-efficiency output oriented model (Ablanedo-Rosas et al. 2010); the super efficiency scores and the corresponding ranks are listed in the third and fourth columns respectively. The fifth and sixth columns show the cross-efficiency scores and the corresponding ranks respectively. The results show differences; but it has been argued by researchers (Sexton et al. 1986; Doyle and Green, 1994; Wu et al., 2009) that cross-efficiency provides a better assessment and discrimination of DMUs. Hence, this preliminary results must be considered robust and be subject to further examination.

CONCLUSIONS

The DEA model presented by Ablanedo-Rosas et al. (2010) has been enhanced and extended. The weak discrimination of the model has been addressed with a cross-efficiency approach which adapts a novel method for obtaining unique weights required for cross-evaluation assessment. The results are promising and suggest as immediate future research the identification of efficiency factors, the inclusion of infrastructure information in cross-evaluation, and the study of financial-ratio target values for increasing efficiency.

REFERENCES


