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Yu Yu
School of Business, Nanjing Audit University, Nanjing 211815, Nanjing, P.R. China

Dai-Peng Ma
School of Business, Nanjing Audit University, Nanjing 211815, Nanjing, P.R. China

Guo-ya Gan
School of Business, Nanjing Audit University, Nanjing 211815, Nanjing, P.R. China, ganguoya@foxmail.com

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RESEARCH ARTICLE

Context-dependent Data-envelopment-analysis-based Efficiency Evaluation of Coastal Ports in China Based on Social Network Analysis

Yu Yu, Dai-Peng Ma, Guo-Ya Gan*

School of Business, Nanjing Audit University, Nanjing, 211815, Nanjing, PR China

Abstract

An emerging trend in performance evaluation is combining social network analysis methods with data envelopment analysis (DEA) models and using network centrality methods to distinguish DEA results. One study employed an input-oriented variable-returns-to-scale DEA model to address referent decision-making units and the corresponding lambda values to construct a network. This study referenced the literature and improved on the use of DEA weight sets to construct a network. We employed a context-dependent DEA model to delineate multiple effective frontier planes, aggregate the reference set relationships on each frontier plane to construct a network relationship matrix, and assess the influences of the interaction layers between the networks transformed by multiple frontier planes. Finally, our method was employed to evaluate the efficiency of coastal ports in China and rank ports by their efficiency. The results indicated that Qingdao Port was the most efficient, followed by Shenzhen Port; this finding verified the feasibility and rationality of the improved method. The present study contributes considerably to the theories on evaluation methods and identifying highly efficient ports.

Keywords: Data envelopment analysis, Social network analysis, Port efficiency, Context dependence

1. Introduction

A port is a meeting point, a hub for land and water transportation, and a platform for transportation and external communication. From the global perspective, the world's most important shipping centers are increasingly becoming those in the Asia−Pacific region [1]. Asia has a population of 4 billion, accounting for two-thirds of the global population. The rapid economic growth of the Asia−Pacific region in the last 30 years has transformed it into the most dynamic region in the world, and the region's maritime transport landscape is changing as a result. With the eastward shift of the world's maritime commercial centers, China's ports are presented with opportunities for development and with challenges. Although China's ports have developed rapidly in recent years, they still require more investment to improve their general layout and infrastructure. Furthermore, maritime access network operations are changing, with the trend for port development shifting toward integrated development in which the focuses are areas such as interactions between ports and between ports and related logistics. Ports that undergo integrated development are characterized by network characteristics, supply chain characteristics, lean port operations, and flexible port services, and they are integrated with the cities in which they are located [2]. Ports compete with each other to become a hub for resource allocation and must have all the technical and service characteristics of a modern port. At present, China's high-energy-consuming, high-emission manufacturing industry is nearing

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* Corresponding author.
E-mail address: ganguoya@foxmail.com (G.-Y. Gan).

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overcapacity [3]. China's overcapacity in steel, cement, and other industries can be addressed by expanding its international market to other countries with a high demand for such products. The higher the demand for transport is, the greater is the likelihood that more high-level ports will be constructed. In addition, China's Belt and Road Initiative is creating investment opportunities for the country [4]. Because China's economy is shifting from a focus on quantity to a focus on quality, its economic structure is constantly being optimized and upgraded. Given that China is the world's most prolific trading nation, the basis for promoting economic and trade integration between Asia and Europe is connectivity. The key to achieving connectivity is infrastructure; thus, accelerating the construction of high-level ports is the focus for building the 21st Century Maritime Silk Road.

Five major port clusters have formed along China's coast, namely the Bohai Bay, Yangtze River Delta, Southeast Coast, Pearl River Delta, and Southwest Coast clusters [5]. Since 2021, China has accelerated the construction of an integrated transport system. China's major ports continue to implement technologies such as big data, the Internet of Things, cloud computing, and blockchain to enhance their intelligent development, and China has introduced various policies to promote the development of intelligent ports. For example, under the framework for developing intelligent shipping, several key technological barriers that limit the development of intelligent shipping will be overcome by 2025, thereby helping China to become a global innovation center for the development of intelligent shipping [6]. In 2021, China's port throughput and container throughput reached 15,545 million and 283 million tons, respectively; therefore, China's ports are among the world's top ports because of their high throughput, intensive and efficient shoreline utilization, and connection to a worldwide network of shipping routes.

Under challenging international circumstances, the timely adjustment of operational strategies and the rational deployment of resources are the key factors that improve port efficiency. China's ports have always operated efficiently and demonstrated high service resilience, and these factors are essential to efficient and stable flow within the international logistics supply chain. The aim of the present study was to assess the efficiency of China's coastal ports in a new era characterized by complexity and change and to select the optimal set of benchmarks for identifying inefficient ports and helping them to improve. In addition, the present study explored a new method for differentiating high-level benchmarks. The present study has key theoretical and practical implications. It enriches the literature on performance evaluation and enhances China's influence in port evaluation. Additionally, it contributes to a deeper understanding of the levels of port development, provides a basis for the construction of high-level ports, and further enhances the international competitive advantages of China's ports.

The subsequent sections of the present article are organized as follows. Section 2 reviews the literature on the recent application of data envelopment analysis (DEA) in China's ports and international ports and the application of an improved DEA model, namely the social network analysis (SNA)-DEA model, for identifying high-level benchmarks. Section 3 describes the relevant modelling methods applied in the present study. Section 4 reports application of the proposed SNA-context-dependent DEA model to a set of coastal ports in China to evaluate and rank their efficiency. Section 5 provides the conclusions of the present study.

2. Literature review

2.1. Use of DEA in port efficiency evaluation

Port efficiency pertains not only to a port's ability to use resources to generate output but also its competitiveness and management competence. Because port development involves multiple inputs and multiple outputs, the operation process of a port is complex, and no universally accepted production function has been established. Thus, DEA is typically used to evaluate port efficiency [7].

Various scholars have applied DEA to evaluate the efficiency of ports. Van Dyck et al. [8] assessed the efficiency of African ports for the period from 2004 to 2010 and recommended that African governments upgrade their seaport management in terms of their terminal procedures and practices, logistics, and equipment. Wanke et al. [9] studied the efficiency of Brazilian ports, and they discovered that public–private partnerships had a significant positive effect on a port's scale efficiency. Park et al. [10] used a four-stage DEA model to investigate the efficiency of ports in South Korea; their results indicated that the Port of Busan was the most efficient of the ports that they evaluated. Wanke et al. [11] conducted fuzzy two-stage DEA to evaluate the efficiency of Nigerian ports for the period from 2007 to 2013, and they revealed that operator type and cargo type influenced the ports' efficiency. Nguyen et al. [12] used bootstrap DEA to study the efficiency of ports in Vietnam and reported that standard DEA and SFA led to higher efficiency scores than bootstrap DEA did. Mustafa et al. [13] and Seth et al. [14] compared the technical efficiency improvements and management optimization paths of South Asian, Middle Eastern, East Asian, and US ports; they reported that the high efficiency of East Asian ports was attributable to their operational processing being based on modern technology, resource availability, and effective management. Nguyen et al. [15] used a DEA–Malmquist model to investigate the efficiency of container ports in Southern Vietnam, and they indicated that most container terminals exhibited productivity growth between 2017 and 2019; in particular, Cai Mep, Tan Cang Cat Lai, and Tan Cang-Cai Mep were the three most efficient international terminals among those that they evaluated. Chang et al. [16] employed a relaxation-based DEA model to determine the efficiency of China's major container ports for the period from 2002 to 2012 and reported that port efficiency had a significant and positive effect on international trade. Ding et al. [17] assessed the efficiency of small and medium-sized coastal ports in China and found that Lianyungang Port and Rizhao Port were the most efficient of the ports that they evaluated. Sun et al. [18] studied the efficiency of China's ports by applying a non-radial DEA preference model; they reported that the ports' efficiency was low and that factors such as the number of berths available and location significantly influenced port performance. Lin et al. [19] conducted inverse DEA to measure the resource consumption of China's container ports and formulated policy recommendations for solutions and optimization. Huang et al. [20] studied the efficiency of key ports along the 21st Century Maritime Silk Road and reported that several ports, such as Qingdao Port and Ningbo-Zhoushan Port, were efficient. Wang et al. [21] used an improved DEA model to study the efficiency of ports in Eastern China and highlighted the high efficiency of Shanghai, Ningbo, and Nanjing Ports. Li et al. [22] applied a four-stage DEA model to study the logistical efficiency of China's coastal ports for the period from 2014 to 2018, and they revealed that these ports emphasized scale and required more planning. Liu et al. [23] used a slack-based measure DEA model and a DEA model with undesirable output to assess the efficiency of the container terminals of major cities along the Pearl River Delta for the period between 2018 and 2019; they indicated that Guangzhou Port was less efficient than Shenzhen Port and Hong Kong Port.

In summary, most port efficiency studies have applied traditional DEA models or two-, three-, or four-stage models to measure differences over time, within specific regions, and between different port clusters, after which they have provided recommendations as to how a port's efficiency could be improved. However, few studies have used DEA–SNA to evaluate and rank the efficiency of ports.

2.2. Combination of DEA and SNA

In a traditional DEA model, all effective decision-making units (DMUs) are treated as being of equal importance; however, the optimal benchmark must be identified for specific ranking problems. Therefore, numerous scholars have proposed methods for differentiating DEA results. Angulo-Meza et al. [24] divided DEA-based methods for ranking efficient units into two categories, namely those that consider additional information or add preferences to a model and those that do not use additional information; such methods include the cross-efficiency [25], super-efficiency [26], inverted fronts [27], adjustable range RAM [28], and fuzzy DEA [29] methods. Liu et al. [30] explored the second category of ranking methods by combining SNA and DEA to improve the efficiency ranking bias of DMUs. In their model, SNA was performed to obtain the reference set lambda value in a DEA model, enabling the strength of the efficient units referenced by invalid units to be determined; these efficient units were then employed in the reference set as network nodes, and the reference relationship served as the link between two nodes, thereby enabling the construction of a social network and the identification of efficient DMUs through centrality measures.

Scholars have since expanded and improved the DEA–SNA model. For example, Liu and Lu [31] enhanced this model by modifying the convergence of its algorithm and constructing a matrix after normalizing the results for multiple input–output combinations. Leem and Chun [32] applied a PageRank centrality method to SNA to generate information for ranking efficient DMUs. Ghahraman and Prior [33] proposed a network-based method for identifying the optimal stepwise benchmarking path toward efficiency. Kao et al. [34] identified the SNA measures that are most closely related to supply chain efficiency. Blas et al. [35] proposed a method for ranking efficient and inefficient DMUs on the basis of the dominance measure of the SNA method. Aydõn et al. [36] constructed network-aggregated, normalized lambda values [31] and used eigenvector centrality as a multiplier for calculating super-efficiency scores. Ang et al. [37] advanced the DEA–SNA method by using the method of de Blas, Martin [35] to calculate the authority values of inefficient DMUs. An et al. [38] identified the interests between two DMUs cooperating under a VRS model and constructed a weighted interest network. Ang et al. [39] constructed a two-way network to develop a scheme for cross efficiency.

Liu et al. [30] noted that the key to ranking network methods is leveraging the relationships in a reference set to construct a network matrix. In their study, the reference set lambda values from the results of multiple input–output combinations were consolidated; however, the use of multiple input–output combinations may lead to fragmentation of reference set relationships, resulting in large differences in results. By contrast, Blas et al. [35] and Ang et al. [37] applied multiple network centrality measures to rank units. Ang et al. [39] considered only CRS cross-efficiency scores, and An et al. [38] considered the game gain relationship of cooperation between DMUs to construct a weighted network. However, none of these scholars fully used a DEA model to obtain their results.

Few studies have combined SNA and DEA, and a DEA-based SNA model can competently reflect the clustering effect, clarify the potential relationship between DMUs, and identify numerous prominent benchmarking points. Therefore, the present study considered the dependency between indicators and fully used the results from a context-dependent DEA model to construct multiple production frontier surfaces. In the present study, the DMUs are stratified, a corresponding network matrix is constructed for drawing a network on the basis of the reference sets on multiple production frontier surfaces, and the relationship between the aforementioned reference sets is considered to further improve the level of differentiation of a model for efficient DMUs. Context-dependent DEA–SNA was applied to evaluate and rank the efficiency of China's coastal ports. The analysis results provide a unique and novel perspective for improving port efficiency and an objective basis for building world-class ports.

The present study makes three key contributions to the literature. First, it converted a reference set of DEA results into a linkage between SNA nodes, thereby advancing the research on DEA–SNA combinations. Second, it applied context-dependent DEA to delineate multiple effective frontier surfaces, thereby transforming them into a directed weighted network; considered the influence of the interlayer effects of multiple frontier surface networks; and mined a large amount of information on the ranking of distinguished, efficient DMUs. Third, the proposed SNA centrality–based context-dependent DEA model was applied to evaluate and rank the efficiency of coastal ports above designated size in China. We verified that the proposed method is feasible for identifying and ranking efficient DMUs.

3. Methods

3.1. Basic DEA

A DEA model is a linear programming model for evaluating the relative efficiency of homogeneous DMUs. It is nonparametric, and it does not require a priori assumptions to be made about the form of a production function or the individual weights of inputs and outputs to be subjectively determined. In the DEA method, an optimal practice frontier is defined as a reference for efficiency. If a ratio of 1 is achieved for a given DMU, the DMU is classified as being on the frontier and regarded as efficient, whereas other inefficient DMUs can refer to the frontier. Because a port is likely to use its input resources and facilities to expand its output in practice, the present study used the input-oriented CCR model [40] and the BCC model [41] as follows:

$$
\begin{aligned}
& Max \sum_{r=1}^{s} u_r y_{ro} \\
& s.t. \\
& \sum_{j=1}^{n} u_r y_{rj} \le \sum_{j=1}^{n} v_i x_{ij} \,\forall r, i = 1, 2, \ldots, s, m \\
& \sum_{i=1}^{m} v_i x_{io} = 1 \\
& u_r, v_i \ge 0 \,\forall i, r = 1, 2, \ldots, m, s
\end{aligned}
\tag{1}
$$

where n represents the number of DMUs; m and s are the number of inputs and number of outputs, respectively; and x_{ij} and y_{rj} are the i^{th} input and r^{th} output of the j^{th} DMU, respectively.

Model (1) solves for the technical efficiency of the evaluated DMUs, thereby enabling the efficiency values and weights of all evaluated DMUs to be obtained. If the efficiency value of an evaluated DMU is 1, the DMU is efficient; otherwise, it is inefficient.

$$
\begin{aligned}
& Min\ \theta_o \\
& s.t. \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{ro}, r = 1, 2, \ldots, s \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_o x_{io}, i = 1, 2, \ldots, m \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& \theta_o, \lambda_j \ge 0; \forall j = 1, 2, \ldots, \mathrm{n}
\end{aligned}
\tag{2}
$$

Model (2) is used to obtain the pure technical efficiency θ_o and weight λ_j of an evaluated DMU. It is solved by adding a constraint to λ that is equal to 1 on the basis of the pairwise model of model (1). The sum of the total identity strengths of the evaluated DMU o is further constrained by $\sum_{j=1}^{n} \lambda_j = 1$ to be 1. For a given DMU, the weight λ_j indicates whether DMU j plays the role of a referee for the evaluated DMU o. If λ_j is equal to zero, j is not a reference for the evaluated DMU; if it is greater than zero, the value of λ_j represents the weight of referenced unit j of evaluated DMU o.

3.2. Context-dependent DEA

Seiford and Zhu [42] proposed a context-dependent DEA model that divides the frontier surface and employed this model to study DMU efficiency. Let $J^1 = \{DMU_j, j = 1, 2, \ldots, n\}$ (the set of all DMUs) be defined and let $J^{l+1} = J^l - E^l$ (the hierarchical iterative definition), where $E^l = \{DMU_o \epsilon J^l \,|\, \theta^*(l, o) = 1\}$ and $\theta^*(l, o)$ is the optimal value of the evaluated DMU, which is calculated using the inverse of the optimal value model (2). The specific model is as follows:

$$
\begin{aligned}
&\theta^*(l,o) = Max\,\theta(l,o)\\
&s.t.\\
&\sum_{j\epsilon F(J^l)}^{n} \lambda_j y_{rj} \geq \theta(l,o) y_{ro}, r = 1, 2, \ldots, s\\
&\sum_{j\epsilon F(J^l)}^{n} \lambda_j x_{ij} \leq x_{io}, i = 1, 2, \ldots, m\\
&\sum_{j \in F(J^l)} \lambda_j = 1\\
&\theta(l,k), \lambda_j \geq 0; \quad j \in F(J^l)
\end{aligned}
\tag{3}
$$

where $j \in F(J^l)$ denotes $DMU_j \in J^l$ and represents the correspondence between the hierarchical transfer sets. When $l = 1$, model (3) becomes the initial model (1) and E^1 forms the efficient frontier surface of the DMU, which is defined as the first-level best-practice frontier. When $l = 2$, the efficient DMUs on the first-level frontier are excluded, and model (3) is solved to obtain the second-level best-practice frontier. This process is repeated to identify multiple levels of best-practice frontiers, with E^l denoting the lth level best-practice frontier.

3.3. SNA centrality context-dependent DEA

SNA was first proposed by Barnes [43] from the University of Manchester primarily as a systematic method for presenting relationship patterns, and it has since been improved by several scholars. SNA is generally used to analyze structural relationships, such as the relative importance of nodes. The centrality measures commonly used to study social networks include degree centrality, indirect centrality, intimacy centrality, and eigenvector centrality.

Table 1. DEA reference set-based network construction methods in the existing literature.

SNA-DEA network construction	Reference
A two-way network is constructed to use the scheme under cross-efficiency	[39]
Identify the benefits of cooperation between DMUs under BCC and construct a weighted interest network	[38]
BCC-λ values, two-part directed weighted graph.	[37]
Aggregate results of all λ values specifications onto one directed weighted network.	[36]
BCC-λ values, two-part directed weighted graph.	[35]
BCC-λ values, directed weighted graph.	[32]
Standardized aggregation of multiple BCC-λ values, with directed weighted plots.	[31]
Combination of indicators, aggregation of multiple BCC-λ values, directionally-weighted graphs.	[30]

The main concept of this network-based differentiation method can be divided into three components. First, DEA results are converted into a directed weighted network, where each network node represents a DMU and the directed connections between node pairs represent the reference relationships between the DMUs. The second component is the ability to tap into hidden information unused in DEA and to obtain additional information for further identification by performing multilevel DEA frontier-run calculations. Third, the contradictory results obtained from additional information are resolved through an eigenvector centrality metric that is commonly used in social networks; first proposed by Bonacich [44], this metric is used to indicate the power of a single node in a social network. Eigenvector centrality is based on the concept of weights, and it was selected for the present study because it considers both the number of links and the link weights of nodes to highlight the most popular nodes, making it suitable for directionally weighted networks. Specifically, it is superior to the other three centrality metrics (i.e., degree centrality, indirect centrality, and intimacy centrality).

Table 1 lists the DEA-based network construction methods that have been proposed by scholars. Liu et al. [30] constructed a network relationship matrix by combining multiple input and output indicators, calculating $(2^m - 1)(2^s - 1)$ results using DEA, and aggregating the reference set values of each result by summing them. Given the correlation and dependency between indicators, the multiple combinations used in the present study could have caused

Table 2. Existing research on port efficiency evaluation input–output indicators.

Input	Literature No.	Output	Literature No.
Berth length	[8–12,14–19,21,22,24,25]	Cargo throughput	[9,11–13,16,19,20,24]
Number of berths	[8–11,14–16,19,22,24]	Container throughput	[8–10,14,15,18,19,22,24]
Number of cranes	[8,14,15,17,18,22,25]	Operating profit	[10,15,20]
Number of employees	[11,18,20,21]	Total throughput	[17,21,22]
Yard area	[9,11,12,17]	Delayed cargo	[11,25]
Berth depth	[9,14,15,25]	Passenger throughput	[10]
Total investment	[15,21]	Customer satisfaction	[10]
Operating costs	[9,20,21]		

the fragmentation of reference set relationships, resulting in large differences in results. Therefore, multiple valid boundaries were delineated using hierarchical DEA, and a matrix was constructed using the reference sets under each boundary. The present study emphasized the use of two key DEA features, namely the use of DEA calculations to yield multiple DMUs and use of λ_j to represent the strength of the reference efficient DMU from the inefficient unit being evaluated. The network matrix is constructed using Equation (4) as follows:

A relationship matrix A_{jo} is constructed in a weighted network of n nodes, where each value in this matrix represents the link weight of node o to node j. The main diagonal element of the matrix has a value of zero. The ranking score of each node is assumed to be represented by the column vector $\boldsymbol{I}$. Each element in this column vector represents the ranking score of node j. The basic concept is that the ranking score of each node is proportional to the number and importance of all the nodes that refer to it, and this score is weighted by the weights of the links as follows:

$$\begin{aligned} A_{jo} &= [\lambda_{jo}]_t \quad t=1,\dots l \\ A_{jo} &= \left[\lambda_{jo}^t\right] \quad t=1,\dots l \end{aligned} \tag{4}$$

where A is an n^{th} order matrix, $[\lambda_{jo}]_t$ represents the weight of the o^{th} evaluated DMU referencing the j^{th} DMU at the t^{th} most effective frontier surface level, and $[\lambda_{jo}^t]$ represents the aggregation of all reference sets under l fronts in a relationship matrix while accounting for the interlayer forces of the multiple boundary fronts in the network relationships.

$$A_{jo} \times \boldsymbol{I} = c \times \boldsymbol{I} \tag{5}$$

In the aforementioned equation, c is a scale factor in the matrix and is the eigenvalue of matrix A, whereas $\boldsymbol{I}$ is the eigenvector corresponding to the eigenvalue c of matrix A, where each element is the corresponding importance score of each node. The eigenvector centrality judgement of the winning node is established on the basis of the combined result of the number of links (popularity) and the link weights (strength of support).

The reference set between DMUs in the DEA results is taken as a link between the network nodes, and the weights are used to mine differential information from the network perspective. The link between multiplier weights is not considered; by contrast, for super-efficiency results, units are further differentiated by the efficiency value scores of DEA results. Instead, because the network approach is incorporated, the DMUs that are inefficient overall can be fully considered as a reference relationship for the efficient DMUs; this approach has the advantage of integration and enables potential ranking information to be obtained.

4. Empirical analysis

4.1. Data

The data for the present study were collected from the statistical records of the cities where the studied ports are located (i.e., China Statistical Yearbook [2021, http://www.stats.gov.cn/], China Port Yearbook [2021], and Statistical Yearbook [2021]) and the official websites of the studied ports. On the basis of data up to 2020, the present study selected 26 coastal ports in China that met specific scale thresholds and evaluated them as DMUs; these ports included large ports (i.e., ports with a berth length of >30,000 m and >100 berths), such as Dalian, Tangshan, Tianjin, Shanghai, Ningbo-Zhoushan, Shenzhen, Guangzhou, Yantai, and Qingdao Ports, and medium-scale ports (i.e., ports with a berth length of 10,000–30,000 m and 50–100 berths), such as Yingkou, Qinhuangdao, Weihai, Rizhao, Lianyungang, Quanzhou, Haikou, and Qinzhou Ports.

4.2. Indicator selection and relevance

The specific input and output indicators that studies have used to evaluate port efficiency are listed in Table 2. At least four studies have used berth length, number of berths, number of cranes,

Table 3. Descriptive statistics and correlation of input–output indicators.

Indicator	Mean	S.D.	Berth length	Number of berths	Cargo throughput	Container throughput
Berth length	28495.08	19913.949	1			
Number of berths	178.77	153.131	0.935**	1		
Cargo throughput	32287.92	26026.800	0.840**	0.727**	1	
Container throughput	859.31	1126.633	0.798**	0.742**	0.679**	1

Note: ***p < 0.001,**p < 0.01, and *p < 0.05.

yard area, and number of employees as input indicators. One study used total investment, cargo stability, time spent waiting for a berth, time spent waiting for loading and unloading, import and export volume, and gross domestic product as input indicators. At least eight studies have utilized container throughput and cargo throughput as output indicators. Some studies have employed passenger throughput, total throughput, service level, customer satisfaction, vessel efficiency, and cargo delay handling as output indicators. The present study used berth length (meters) and the number of berths available as input indicators and cargo throughput (million tons) and container throughput (million 20-ft equivalent units [TEUs]) as output indicators. The indicators that have been most frequently used in studies related to data that can be easily obtained from official government and port websites. However, several types of data, such as yard area and number of cranes, are difficult to obtain. Container throughput is measured in terms of the number of container units (i.e., TEUs), whereas cargo throughput relates to cargo only and is measured in terms of tonnage or cargo volume. These two indicators directly reflect the role played by ports in the domestic materials trade and foreign trade transport, and they also serve as the basis for port planning and capital construction. Berth length generally includes ship length and the required safe separation distance between ships. The number of berths represents the number of units available for port handling work. Berth length and number of berths are key indicators of the size of a port.

Table 3 lists the means, standard deviations, and correlation coefficients of each input and output indicator for the 26 ports. The results indicated that the correlation coefficients r of the correlations between the input and output indicators was mostly >0.7; the coefficient of correlation between cargo throughput and container throughput was 0.679 ($p < 0.01$). Thus, all the indicators were positively and significantly correlated. These findings reveal that the correlations between the selected indicators were favorable and that these indicators were suitable for evaluating the efficiency of ports.

4.3. DEA efficiency results

The collected data were solved using models (1) and (2) to obtain the efficiency results for all ports (Table 4).

As indicated in the CCR model presented in Table 4, Qingdao Port, Shenzhen Port, and Huanghua Port exhibited high overall levels of technical efficiency, whereas Taizhou Port exhibited the lowest level of efficiency. When the BCC model was applied, the number of efficient ports increased to include four additional ports, namely Tangshan Port, Rizhao Port, Shanghai Port, and Ningbo-Zhoushan Port; Taizhou Port remained the least efficient port. The BCC model has the characteristic of having a greater number of efficient DMUs relative to other models, which was a justification for applying the centrality method to the ranking analysis performed in the present study. Another reason for using the BCC

Table 4. Port efficiency results.

Port	TE	PTE	SE	Efficiency status
Dalian	0.26	0.44	0.59	TE inefficient
Yingkou	0.50	0.52	0.96	TE inefficient
Qinhuangdao	0.32	0.45	0.71	TE inefficient
Tangshan	0.58	1	0.58	TE and SE inefficient
Weihai	0.14	0.19	0.74	TE inefficient
Huanghua	1	1	1	Efficient
Tianjin	0.65	0.77	0.84	TE inefficient
Yantai	0.30	0.53	0.57	TE inefficient
Qingdao	1	1	1	Efficient
Rizhao	0.75	1	0.75	TE and SE inefficient
Lianyungang	0.52	0.55	0.95	TE inefficient
Shanghai	0.72	1	0.72	TE and SE inefficient
Ningbo-Zhoushan	0.49	1	0.49	TE and SE inefficient
Wenzhou	0.14	0.17	0.82	TE inefficient
Taizhou	0.10	0.12	0.83	TE inefficient
Quanzhou	0.35	0.43	0.81	TE inefficient
Fuzhou	0.32	0.42	0.76	TE inefficient
Xiamen	0.48	0.48	1	SE efficient
Shenzhen	1	1	1	Efficient
Guangzhou	0.67	0.88	0.76	TE inefficient
Dongguan	0.34	0.39	0.87	TE inefficient
Zhuhai	0.21	0.26	0.81	TE inefficient
Zhanjiang	0.29	0.44	0.66	TE inefficient
Qinzhou	0.47	0.65	0.72	TE inefficient

Note: TE (technical efficiency), PTE (pure technical efficiency), and SE (scale efficiency).

model was that it could be solved to obtain the reference weights of the evaluated DMUs; by contrast, the CRR model had to obtain the weights of the input–output indicators. Thus, the results of the BCC model could be combined with the network method to improve the differentiation of efficient DMUs.

Column 4 of Table 4 presents the scale efficiency results based on the efficiency correlations obtained through DEA, which were valid for Qingdao Port, Huanghua Port, Xiamen Port, and Shenzhen Port. The results shown in Table 4 revealed that large ports such as Dalian Port, Lianyungang Port, and Guangzhou Port were inefficient, indicating that they were affected by resource redundancy, inefficient resource use, and insufficient output. Qingdao Port, Shenzhen Port, and Huanghua Port exhibited favorable results in terms of overall efficiency, pure technical efficiency, and scale efficiency; these ports exhibited more stable and prominent development than other ports did, and they should continue to innovate to strengthen their advantages.

4.4. Construction of directed weighted networks with reference sets

4.4.1. Stratified frontier surfaces

The relativity of DEA is demonstrated by context-dependent DEA; whether cell X is valid relative to cell Y is dependent on the presence or absence of a third alternative such as cell Z or a set of cells. For example, cell X is invalid relative to cell Y on frontier face 1, but if one or more cells are reduced to construct a new frontier face, cell X is valid on the new frontier face. Therefore, in the present study, multiple valid frontiers were divided, and matrices were constructed using the reference set relationships on each frontier. Table 5 lists the valid frontier surfaces obtained using model (3).

4.4.2. Directed weighted network mapping

The reference set λ values under the two horizontal frontier surfaces were used to construct a matrix, and social relationship network diagrams were drawn using the Gephi software (Figs. 1 and 2). In the diagrams, the thickness of a line indicates the weight of the link, and the size of a circle represents the size of a node entry. All the nodes in the two-level network rotate around the central nodes of the ports that correspond to their respective effective frontier surfaces, indicating that the network has a core–periphery structure and that there is a considerable network hierarchy effect and a highly three-dimensional distribution. A centrality score facilitates differentiation during the ranking of efficient DMUs. In the present study, a link was established between two DMUs; therefore, if a node referred to another node, the link pointed toward the efficient unit. The link weights were obtained from the λ values calculated through hierarchical DEA. To calculate an evaluated unit, an inefficient unit established several outward links to its reference unit, and n sets of such outward links were established when an efficiency bound was completed. When these links were aggregated into a network, the network was based on an efficiency boundary. Through a combination of such structures, efficient cells could have numerous inward links, and inefficient cells could have several outward links; however, no cells could have both inward and outward links.

In Fig. 1, ports such as Qingdao Port, Huanghua Port, Tangshan Port, Ningbo-Zhoushan Port, Shanghai Port, and Shenzhen Port are situated at the center of the network. These ports are located along the Bohai Bay, Yangtze River Delta, and Pearl River Delta, and they are in close proximity to China's first-tier cities (i.e., Beijing, Shanghai, Guangzhou, and Shenzhen), which have advantageous geographical positions. Xiamen Port, which belongs to the southeast coastal port group, was scale-effective but had marginal network results because of its technical inefficiencies. Xiamen Port lies at the heart of the 21st Century Maritime Silk Road and plays a role in further expanding cooperation with the countries located along this route. Therefore, Xiamen Port holds great potential for development. Zhanjiang Port and Qinzhou Port are classified under the southwest coastal port group, and because of their special geographical locations, their levels of development were lower than those of the ports in the other four major port groups of China. With the support of the Western Development Policy and the Belt and Road Initiative, the southwest coastal port group has ample room for development, and the efficiency levels of Zhanjiang Port and Qinzhou Port could be greatly enhanced.

The reference set information from the two frontier surfaces were aggregated into a single network

Table 5. Effective frontier surfaces for context-dependent DEA.

E^1- Efficient ports	E^2- Efficient ports
Tangshan	Tianjin
Huanghua	Lianyungang
Qingdao	Guangzhou
Rizhao	
Shanghai	
Ningbo - Zhoushan	
Shenzhen	

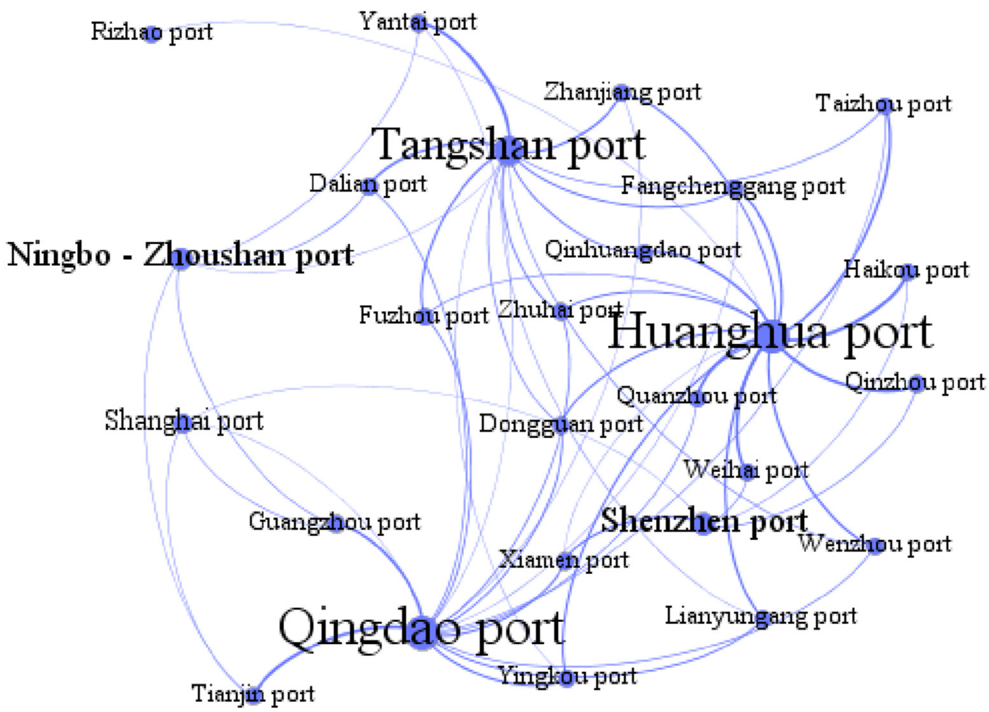

Fig. 1. Social network relationships under effective frontier surface at level 1.

(Fig. 3). In Fig. 3, the blue nodes represent the efficient ports on the first horizontal frontier plane, the red nodes represent the efficient ports on the second horizontal frontier plane, the green nodes represent the inefficient ports, and the purple lines represent the links between the E2 efficient ports and the reference efficient ports under E1. Under network theory, the relationships between the efficient ports (Figs. 1 and 2) could be regarded as an interlayer force in a multilayer network, that is, the efficient ports influenced each other when they were aggregated. Correspondingly, both the nodes inside the network and those between the layers outside the network were influenced. In addition, the inefficient ports (green nodes) shared reference relationships with the efficient ports at the E1 and E2 levels. When the aforementioned ports were aggregated into a single network, all the links that could refer to and influence the efficient ports were accounted for; consequently, more information could be obtained from the network in Fig. 3 than from the networks in Figs. 1 and 2, and the ranking of the efficient ports was more realistic and reliable.

4.5. Ranking results

The eigenvector centrality values of the valid nodes in Figs. 1–3 were calculated, and the relevant results were used as a basis for ranking (Tables 6 and 7). In the port efficiency results presented in Figs. 1 and 2, Huanghua Port (0.684) is ranked first on frontier plane 1, followed by Tangshan Port (0.255), and Qingdao Port (0.248); by contrast, Rizhao Port has a score of 0.001 on frontier plane 1.

As shown in Fig. 1, Rizhao Port was not in a citation relationship with any other port, leading to its low importance and bottom-most ranking. On frontier plane 2, Lianyungang Port (0.763) was ranked first, followed by Tianjin Port (0.050) and Guangzhou Port (0.046). As shown in Fig. 2, Lianyungang Port was referenced much more frequently than was Tianjin Port or Guangzhou Port and had more links, which granted it considerable authority.

The final ranking results are presented in Table 7. The second and third columns show the rankings of the efficient ports as determined using our method; Qingdao Port (0.6862) was ranked first, followed by Shenzhen Port (0.6861) and Ningbo-Zhoushan Port (0.2417). Unlike in the rankings listed in Table 6, which were obtained using a separate frontier surface, Huanghua Port (1.1279E-05) was ranked fifth in the final rankings. Rizhao Port was still the lowest-ranked port because it remained in an isolated state with few reference relations even after the two-layer network had been aggregated.

Columns 4 and 5 report the ranking scores as calculated under super-efficiency; Huanghua Port

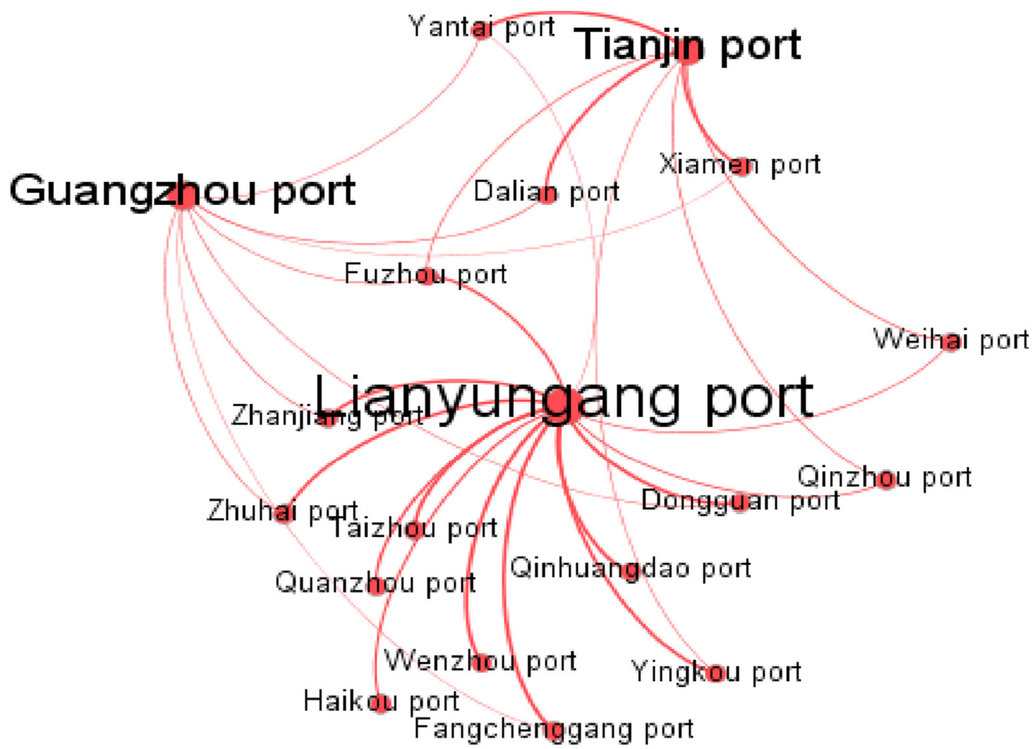

Fig. 2. Social network relationships under effective frontier surface at level 2.

(2.2104) was ranked first, followed by Qingdao Port (1.4917) and Ningbo-Zhoushan Port (1.2727). A comparison of the ranking results obtained in the present study revealed a considerable difference for the first-place rank; specifically, the ranking result for Huanghua Port under super-efficiency was identical to that obtained using the single-layer network E1 (Table 6). This finding can be attributed to the division of the multiple frontier surfaces and aggregation of multiple layers of reference set relationships, which allowed for potential ranking information to be obtained. The super-efficiency results corresponded to the results obtained using the E1 frontier surface.

Columns 6 and 7 present the ranking results as obtained using the method proposed by Liu et al., which involved combining input–output indicators. Compared with the method applied and the super-efficiency results obtained in the present study, the method proposed by Liu et al. resulted in Tangshan Port (0.5403) being ranked first, followed by Qingdao Port (0.4630) and Shenzhen Port (0.4629). The smaller score differences between ports for this method were attributable to the stable ranking of Qingdao Port; Qingdao Port was ranked first in our results, which were more objective and reasonable in terms of stability. Regarding Shenzhen Port, Ningbo-Zhoushan Port, and Shanghai Port, the differences in rankings were minor. These findings indicate that the SNA context-dependent DEA ranking method is a feasible method and produces reliable results.

Our efficiency ranking results are highly similar to those reported by Sun et al. [18] and Lee et al. [32]; the only difference is that they identified Lianyungang Port as the most efficient port, followed by Shenzhen Port and Shanghai Port. Our results also align closely with those of Huang et al. [20], who identified Qingdao Port, Ningbo-Zhoushan Port, Shanghai Port, and Shenzhen Port as the most efficient ports. However, our findings differ considerably from those of Ang et al. [39], who identified Qinhuangdao Port, Weihai Port, and Wenzhou Port as efficient ports but reported that Shanghai Port and Ningbo-Zhoushan Port were inefficient. This difference could be due to their decision to combine cross-efficiency and SNA (i.e., each DMU in a cross-efficiency model receives the same number of ratings, including ratings from others and self-ratings). If the contribution of ratings from others is high, an evaluated unit tends to receive a higher score, which is detrimental to the ranking of large ports. This phenomenon explains the considerable discrepancy between the results of Ang et al. and those of the present study. In the present study, Rizhao Port was identified as a small but efficient port, indicating that our method produced reasonable results for both

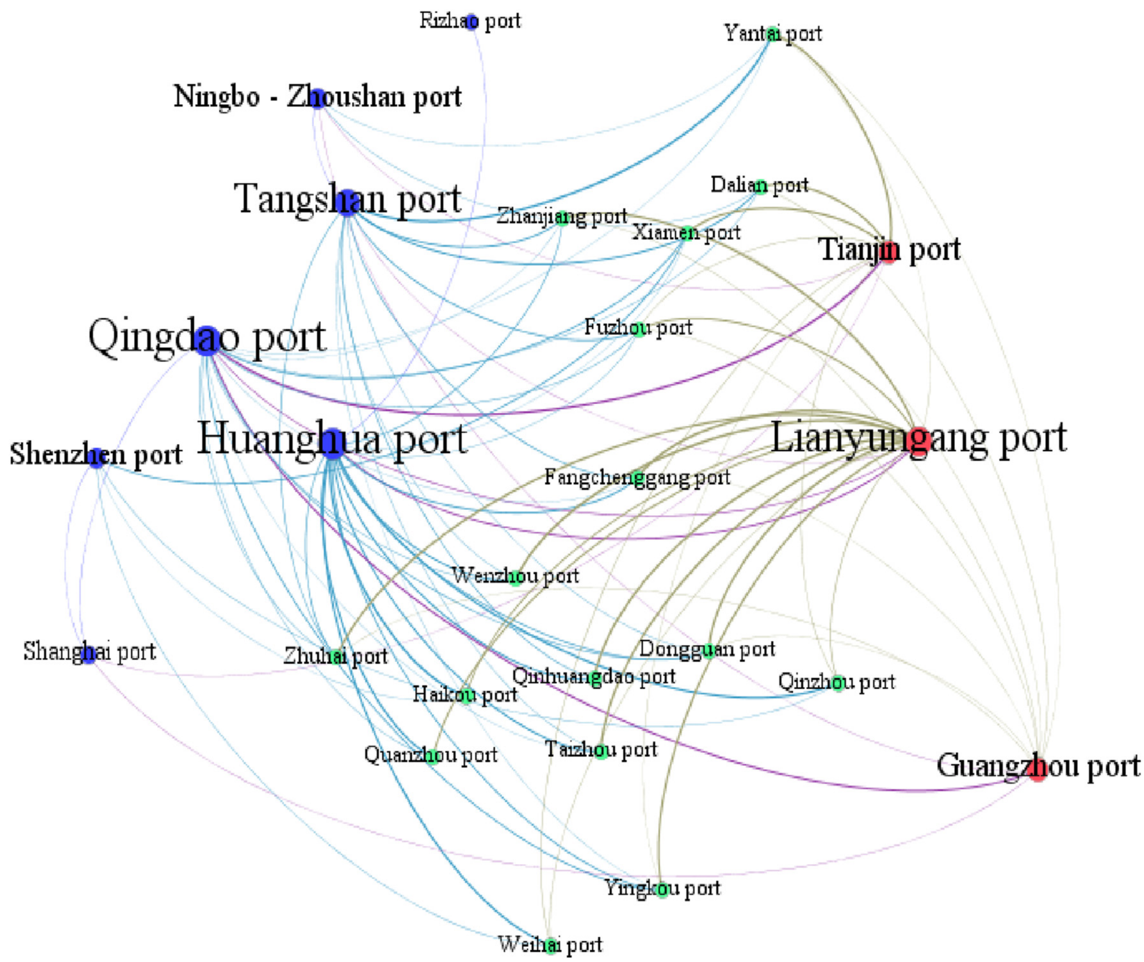

Fig. 3. Map of the integrated social network relationship, showing interlayer forces.

large and small ports and that our results correspond to those of most other studies. This finding supports the favorable objectivity and feasibility of our proposed method, which combines SNA with context-dependent DEA.

4.6. Theoretical and practical implications

Theoretically, our improved method produces a greater clustering effect that is obtained with other methods such as the indicator combination method proposed by Liu et al. and the super-efficiency method. DMUs with higher efficiency levels receive higher scores. Furthermore, the results of the present study exhibit similarities to the results of other port efficiency studies. Therefore, our method was feasible and produced objective results, and it can be applied to other types of performance evaluation. Practically, the proportion of ports in China that are efficient is low. For the studied ports, low pure technical efficiency was the main cause of low port efficiency. Efficient ports such as Qingdao Port,

Table 6. Frontier surface separation ranking results.

E^1	Eigenvector centrality	Rank (Fig. 1)	E^2	Eigenvector centrality	Rank (Fig. 2)
Huanghua Port	0.684	1	Lianyungang Port	0.763	1
Tangshan Port	0.255	2	Tianjin Port	0.050	2
Qingdao Port	0.248	3	Guangzhou Port	0.046	3
Shenzhen Port	0.058	4			
Ningbo-Zhoushan Port	0.016	5			
Shanghai Port	0.006	6			
Rizhao Port	0.001	7			

Table 7. Aggregate frontier network ranking results.

Efficient port	Eigenvector centrality	Rank (Fig. 3)	Super- efficiency	Rank	Liu et al. (2009) methods	Rank
Qingdao Port	0.6862	1	1.4917	2	0.4630	2
Shenzhen Port	0.6861	2	1.0631	5	0.4629	3
Ningbo-Zhoushan Port	0.2417	3	1.2727	3	0.3502	4
Shanghai Port	3.2014E-05	4	1.2165	4	0.2307	6
Huanghua Port	1.1279E-05	5	2.2104	1	0.3096	5
Tangshan Port	1.1278E-05	6	1.0598	6	0.5403	1
Lianyungang Port	4.3830E-13	7	0.4927	10	5.7536e-17	8
Guangzhou Port	2.3305E-13	8	0.5232	9	−2.8154e-17	10
Tianjin Port	8.9945E-14	9	0.5725	8	−2.0709e-18	9
Rizhao Port	−5.2389E-14	10	1.0015	7	0.0879	7

Shenzhen Port, and Ningbo-Zhoushan Port must retain their development advantages and apply emerging technologies to modernize further. Ports with low efficiency must further expand the scope of their productivity gains and adjust their port development plans in a timely manner. Efforts should be made to improve the management standards of enterprises, increase investment in science and technology, and learn from the management experiences of high-level ports in China and abroad, thereby substantially improving the ability of China's ports to appropriately allocate resources and reduce a waste of capacity.

5. Conclusions

The present study constructed an SNA context-dependent DEA model by improving the network ranking method proposed by Liu et al. and applying it to evaluate and rank the efficiency of 26 coastal ports in China. Efficient ports were ranked by dividing multiple effective frontier surfaces. When multiple layers of frontier surface reference set relationships were aggregated and the influences of interlayer forces in the network were considered, Qingdao Port was ranked first, followed by Shenzhen Port and Ningbo-Zhoushan Port. Compared with the method proposed by Liu et al. and the super-efficiency method, the proposed method produced more objective and stable results for the top-ranked ports, especially the first-ranked Qingdao Port. That is, the proposed network-based ranking method was able to obtain additional information that was not used in DEA, and the reference set of layer fronts yielded more ranking information when the set was aggregated into the same network than when it was aggregated into only a single layer. By contrast, when the method proposed by Liu et al. and the super-efficiency method were applied, a given DMU was cited less often in the reference set, but a higher score was obtained (e.g., Rizhao Port). Thus, if a DMU is cited more often by other DMUs, it is more likely to be regarded as being highly recognized by other DMUs; this phenomenon validates the feasibility and rationality of our proposed method for ranking the efficiency of China's coastal ports.

Nevertheless, the present study has several limitations. Numerous methods can be employed to measure centrality in SNA, but only one was considered in the present study. Therefore, the findings of the present study can be expanded in two directions. First, the combination of SNA and DEA can explored at a greater depth, and unique methods for constructing networks can be examined. Second, the proposed method can be applied to evaluate other types of performance. Furthermore, although the proposed method demonstrated its usefulness and robustness for assessing the efficiency of China's ports, it could not identify the underlying factors that contributed to port inefficiency. These key limitations should be addressed in future studies.

Conflict of interest

There is no conflict of interest.

Acknowledgements

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