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RESEARCH ARTICLE

An application of the DEA-cross efficiency approach in Turkish dry-bulk and general cargo terminals

Volkan Efecan[1*]

[1] *Mersin University, Vocational School of Maritime, Department of Transportation Services, Mersin, Türkiye*

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ABSTRACT

Dry bulk and general cargo terminals are the facilities that should quickly adapt to global supply chain dynamics. Each loading/unloading, conveying, horizontal carriage and temporary storage process involves complex organizational structures and procedures. Planned physical investments may lead to inefficiency under dynamic environmental conditions and may also result in a waste of resources. This study aims to examine the technical efficiency of dry-bulk and general cargo terminals in Türkiye with DEA cross-efficiency and DEA Slacks-based models. The findings imply that the terminals handling iron and steel are more efficient than the others. Besides, on average, the dry bulk and general cargo terminals can achieve higher output levels with fewer infrastructures and handling equipment. Therefore, it may be appropriate for the terminals examined to revise their resource utilization rates and short-term investment strategies. Moreover, since it allows pair-wise comparisons of terminals handling similarly featured cargo, DEA cross-efficiency can play a crucial role in dry-bulk performance measurement. Input slacks of relatively inefficient terminals are also calculated.

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Introduction

Seaports are the critical actors in linking sea and land transportation (Antão et al., 2016). It is quite remarkable that the competition between the actors of the port industry is increasing day by day (Fancello et al., 2019). In addition, new trends in international trade, characterized by the globalization of consumption habits, greatly increase the importance of container transportation with its technical and economic advantages (Corbett & Winebrake, 2008). Ports, located at the interface of maritime and inland transportation, play an important role in the transportation (Notteboom et al., 2000).

Increasing marine traffic intensity, integration of logistics services also impacts the global supply of raw materials

* Corresponding author
E-mail address: volkanefecan@mersin.edu.tr (V. Efecan)

classified as dry bulk and general cargo handling demands (Tovar & Wall, 2015; Balci et al., 2018). Increasing ship sizes, triggered by economies of scale strategies, forced dry bulk and general cargo bulk terminals to review their infrastructure and equipment (Wu & Lin, 2015). On the other hand, quick handling with high-tech equipment, optimizing berth allocation to prevent delays, increased storage and providing multi-modal accessibility to the land and sea hinterland push dry-bulk and general cargo terminals to a competitive market. A market established with competitive elements can prevent monopolization and result in service improvement through innovative initiatives (de Langen & Pallis, 2005). However, fierce competition may cause the decrease of profitability of terminal operators and the quality of service (Figueiredo de Oliveira & Cariou, 2015).

The performance of dry-bulk and general cargo terminals is crucial for regional competition and national development strategies. The positive effects of the high performance go beyond the gradual increase in traffic volume. Due to their critical role in the supply chain, these terminals impact related activities such as marine insurance, finance and logistics. They create added value and employment, which affects regional and urban development prospects. In this sense, dry-bulk and general cargo terminal managers are interested in external benchmarks besides internal key performance indicators (Peckham, 2019). Minimizing costs and risks while doing so are the main goals for port managers. In this context, it is crucial to use performance indicators to achieve these goals (Antão et al., 2016). The scarcity of resources frequently makes infrastructure and equipment investments and efforts to improve operational performance riskier. Other factors can be highlighted as crucial when determining terminal performance related to the more organizational side of production, such as how effectively ports use inputs to produce current output and comply with technologies adopted by terminals. Therefore, efficiency measurement should be carried out upon any infrastructure or equipment investment, and medium or long-term investment decisions should be made with a balanced perspective between technical infrastructure and value-added service quality.

In this study, considering the heterogeneous structure of dry bulk and general cargo terminals, the DEA cross-efficiency model (Lim & Zhu, 2015) was applied under input-oriented (IO), variable returns to scale (VRS) production technology. Averaged appraisal by peers were calculated to rank the terminals in terms of efficiency levels. Moreover, similar terminals for handled cargo characteristics such as steel and iron were subjected to pair-wise comparisons in the cross-efficiency matrix, to reveal more accurate inferences.

Improving technical efficiency is crucial for managers to maximize the profitability of a seaport terminal. In this context, it is argued that this approach can pave the way for dry bulk and general cargo terminals to be examined more frequently, and it can be used as an effective benchmarking method in such heterogeneous environments. To our knowledge, this study is the first in the literature of dry-bulk and general cargo terminal efficiency. From this perspective, it will contribute significantly in both a theoretical and empirical manner.

The following section summarizes relevant literature on the container ports evaluated with DAE approaches. The material and methods section summarizes DEA and DEA cross-efficiency, the data and selected input/output variables. The results and discussion section represents the analysis results and comparison of relevant literature. Finally, the conclusions section summarizes the conclusions and limitations of this study and makes recommendations for further research.

Literature Review

Organizations should continually evaluate operations or processes related to products, services, marketing, and others to increase their performance. Performance evaluation techniques through benchmarking are searching for best practices to improve performance and increase productivity when no goals or engineering standards exist. Defining service standards is more complex than defining production standards. Therefore, benchmarking is mainly used to manage service operations. However, in comparisons to be made regarding a system, it is another challenge to evaluate the decision units in the system with more than one criterion and possible different performance metrics of these criteria. Moreover, this issue gets more problematic when the relationships between performance measures involve unknown interactions. Therefore, Data Envelopment Analysis (DEA) is widely used in many areas. DEA is a flexible approach to evaluating systems or operations that include multiple performance measures. Cooper et al. (2011) stated that the DEA is a data-driven approach evaluating the performance of similar decision units (DMUs) that transform multiple inputs into multiple outputs. The purpose of performance evaluation with the DEA is to examine the efficiency of a DMU and compare it with decision units to determine best practices. It is impossible to include every input and output of the production process and form the performance criteria in DEA into the model in all cases. Therefore, efficiency comparisons can be made with more general inputs and outputs. In performance evaluation, by comparison, inputs and outputs can be physical inputs and outputs of a production process or general performance criteria. In the first case, an efficiency score is obtained, while in the latter, a composite performance index is obtained. DEA is a very convenient technique for evaluating operational processes. Because it is easy to adapt the data to the model and the fact that the mathematical model to be established does not require any distributional assumptions, unlike parametric models. This adaptability and flexibility of DEA have come to the fore in cases where other approaches cannot be used due to the complex structure between multiple inputs and outputs.

DEA is frequently used to evaluate the efficiency of seaports. Several studies in the literature are to examine the performance of seaports with DEA (Wiśnicki et al., 2017; Yüksekyıldız & Tunçel, 2020; Kim et al., 2022; da Costa, 2021; Jeh et al., 2022; Efecan & Temiz, 2023). Martinez-Budria et al. (1999) examined the efficiency of Spanish container ports via DEA-BCC and investigated the relationship between efficiency and managerial complexity. Further, Cullinane et al. (2004) analyzed the change in the efficiency of 25 container terminals using DEA window analysis. Cullinane & Wang (2006) evaluated the European container ports using CCR and BCC models to figure out the scale efficiency levels and existing production technology. Moreover, Schøyen & Odeck (2013) analyzed the efficiency of Northern Europe and the UK container ports with traditional DAE approach. Santiago et al. (2021) examined the financial and operational efficiency of Spanish container ports with a two-stage bootstrap DEA model. Wu et al. (2010) obtained the efficiency ranking of 77 container terminals worldwide using DEA cross-efficiency and presented benchmarks for inefficient terminals using cluster analysis. Similarly, Kim et al. (2022) evaluated Korean terminals with cross efficiency and cluster analysis. As known, two-stage models incorporated with DEA have been proposed commonly for the seaport efficiency measurement. Güner (2015) examined the Turkish seaports with a two-stage DEA model. The author argues two sequential steps that appear in the seaport operating process by assuming the outputs from the first stage are the inputs to the second stage. Port managers aim to maximize the freight handled and the number of served ships by using the existing resources in the first stage. Then, maximize the revenue from handling freights and served ships in the second stage. It is concluded that the two-stage DEA approach provides more proper results than those in single-stage DEA when there are sequential stages. In recent research, Baştuğ (2023) applied the DEA-SCOR model to Turkish container ports in the context of BRI (One Belt and One Road Initiative) and concluded that four large terminals are the most efficient gateways to handle inward and outward container traffic with their input variables. However, there are some challenges in port investment for BRI. BRI is related to some Turkish seaports close to the main Asia-Europe routes. Therefore, it can be inferred that the location of a seaport can be a significant heterogeneity factor. Therefore, benchmarked terminals should be as possible as homogenous. To draw inferences about technological changes of each terminal over the years. Baran & Górecka (2015) adopted Malmquist Total Factor Productivity in addition to the traditional DEA models. Yüksekyıldız & Tunçel (2020) evaluated the efficiency of container ports in Türkiye with Fuzzy Data Envelopment Analysis. The main idea behind working in a fuzzy environment was to get more flexible efficiency scores due to the imprecise data. Apart from technical efficiency, the researchers also assessed related handling issues. For instance, Arslan et al. (2021) evaluated the efficiency of maritime supervision services in dry-bulk terminals. Jeh et al. (2022) assessed the global terminal operators based on the operation characteristics and found that when the terminal infrastructure was expanded, the efficiency was improved. However, the returns to scale and technical change factors in the productivity change trend decreased. This result implies decreasing returns to scale production technology, and the infrastructure or equipment investments should be decided under these circumstances. On the other hand, despite the increasing focus on such new services provided in seaports and efforts to adapt to the supply chain and changing technologies, existing literature focuses predominantly on container terminals, overlooking the critical role of dry bulk and general cargo terminals. Possible reasons for the intense interest in container terminals can be the desire of researchers to reflect on the rapidly ongoing containerization on a global scale in their studies or the standard shape of containers. However, scientific studies on the efficiency of dry bulk and general cargo terminals are limited (Balci et al., 2018). Merk & Dang (2012) evaluated the efficiency of dry-bulk and general cargo terminals by dividing them into coal, iron and grain groups. This categorization related to the type of cargo may be linked to a desire to obtain homogenous benchmarking DMU sets. As conclusion, there was an efficiency potential of up to seventy per cent, especially in grain terminals. Suliman et al. (2019) similarly examined the technical efficiency of dry-bulk cargo terminals in Malaysia with DEA. They drew attention to the high performance of the terminals examined in the study in which they tried to create an appropriate empirical framework for frontier-based relative efficiency measurement. Lee et al. (2014) and Balci et al. (2018) argued that the crucial role of dry bulk and general cargo terminals in the supply chain has been ignored in the literature. In addition, Schott & Lodewijks (2007) investigated what can be done for the handling, conveying and storing of bulk cargoes in the Le Havre-Hamburg region, while Bal & Esmer (2015) investigated the operational processes of liquid bulk cargo terminals in Turkey. Balci et al. (2018) examined the competition between dry cargo terminals. They concluded that even though dry cargo terminal selection criteria are similar to container terminals, their criteria importance weights are different. Denktaş Şakar & Uzun (2021) examined the role of dry bulk and general cargo terminals in the supply chain from the perspective of customer profiles in the Aliağa Region. They state that the characteristics of the service provided are at least as important as operational efficiency. Their findings revealed the service features of Aliağa terminals should be improved in a supply chain-oriented manner and the customers also attach importance to value-added service features.

As can be seen clearly from the relevant literature, relative efficiency measurement applications on dry bulk and general cargo terminals are quite limited. Due to the heterogeneity and the unique organizational structures of dry-bulk and general cargo terminals, there is lack of a proper measurement method. In this context, DEA cross efficiency method can be a proper alternative to the relevant literature as it is also applied to container ports and provide beneficial inferences in Wu et al. (2010) and Kim et al. (2022).

Material and Method

Charnes et al. (1978) (CCR hereafter) first introduced DEA-CCR, which gives a total efficiency estimate to draw inferences about what input and output ratio should be achieved in a production process. The CCR approach enabled efficiency evaluation with multiple inputs and outputs using linear programming instead of Farrell's (1957) linear fractional programming technique to measure productive efficiency, which caused controversy in the literature. Thus, the CCR model has gained substantial popularity in the relevant literature. Banker et al. (1984) (BCC hereafter) introduced the DEA-BCC, which makes up the piecewise linear convex frontier model. This technique can separate the scale efficiency from the total efficiency and determine the pure technical efficiency. Thus, it enables drawing inferences about production technology. The BCC model is the standard DEA model commonly used for technical efficiency estimation.

DEA analyses can be made based on the assumptions of production technologies that bring constant (CRS) or variable returns to scale (VRS), or they can be input or output-oriented. Input-oriented models are used to determine how much the inputs of inefficient DMUs should be reduced to achieve a certain output level, and output-oriented models are used to determine how much the outputs should be increased for inefficient DMUs to become effective. Within the scope of the study, it is assumed that the scales of DMUs change their efficiency values. Therefore, the input-oriented variable return to scale assumption is considered. The established efficiency model assumes that production output is exogenously given and inputs[1] should be minimized. Besides, it was assumed that the handling volume (TEU) must be high enough for the port management to cover fixed investment costs and make a profit. If high enough volumes are handled, the handling fee per container can represent almost the entire port activity. In this sense, DEA is a particularly suitable tool for evaluating the efficiency of service businesses, with this type of data condition (Sherman & Zhu 2006). For a dry-bulk and general cargo terminal, it is impossible to control demand. However, it may be possible to minimize inputs to achieve same output level. Therefore, it is assumed that output is given exogenously and the inputs should be minimized. In this context, an input-oriented (IO) VRS model in multiplier form can be written as following Eq. (1):

$$max$$

$$\sum_{r=1}^{s} u_r y_{r0} - \xi$$

$$s.t.$$

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} + \xi \geq 0, \qquad j = 1, \dots, n$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$$v_i, u_r \geq \varepsilon \; \forall i, r, \xi \text{ free in sign.} \tag{1}$$

[1]Due to the difficulty in accessing confidential input prices, this study focused on technical efficiency.

It is assumed that there are n DMUs consuming m inputs to produce s outputs. DMU $k(k = 1, 2, \dots, n)$ uses a vector of inputs $x_k = (x_{1k}, \dots, x_{mk})^T \in R_+^m$ to produce a vector of outputs $y_k = (y_{1k}, \dots, y_{sk})^T \in R_+^s$ where ε is non-Archimedean infinitesimal.

For DEA, it is known as a commonly known rule to select a DMU set consisting of at least twice the total number of inputs and outputs (Golany & Roll, 1989). Banker et al. (1989) suggests at least three times the total number of inputs and outputs. In fact, these rules do not have a statistical basis and are not mandatory. However, they are frequently applied in the literature because they make it easier to distinguish DMUs from each other in terms of their efficiency scores. In addition, the number of samples should not be too small and should be sufficient to allow a partial border to be obtained.

Although DEA is an effective method for determining the best practice frontier, its flexibility in weighing multiple inputs and outputs and its self-assessment nature have been criticized. The cross-efficiency method was developed as an extension of DEA (Sexton et al., 1986). The idea behind this approach is to use DEA for peer assessment rather than pure self-assessment. The cross-efficiency approach has two crucial advantages over traditional DEA approaches (CCR and BCC). The first is to ensure ranking among DMUs, while the latter is to eliminate unrealistic weighting schemes without the need for weighting constraints obtained by using experts' opinions (Anderson et al., 2002).

Solving the model given in Eq. (1), the efficiency score of DMU_0 and the cross-efficiency scores of other DMUs evaluated by DMU_0 are obtained together. The cross-efficiency score is specific to DMU_j is written as following Eq. (2):

$$e_{0j} = \frac{\sum_{r=1}^{s} u_r^* y_{rj} - \xi^*}{\sum_{i=1}^{m} v_i^* x_{ij}} \tag{2}$$

The "*" in Equation (2) represents the optimal solution of the model. In cases where the free variable $\xi > 0$, the value calculated with Eq. (2) may be negative. This situation poses a problem in terms of determining efficiency scores. Averaging e_{ij} over i, a cross-efficiency score of DMU_j is obtained. To overcome this problem, Lim & Zhu (2015) suggest an alternative formulation given in Eq. (3) to calculate non-negative cross-efficiency scores under the VRS option.

$$e_{0j}^{o} = \frac{\sum_{r=1}^{m} v_r^* x_{rj}}{\sum_{r=1}^{s} u_r^* y_{rj} - \xi^*} \tag{3}$$

Cross-efficiency approach has been used in various fields, such as nursing homes (Sexton et al., 1986), preferential voting (Green et al., 1996), and selection of industrial R&D projects (Oral et al., 1991). However, as highlighted in Doyle & Green (1994), the non-uniqueness of DEA optimal weights/multipliers likely reduces the usefulness of the cross-efficiency scores. Specifically, the cross-efficiency scores obtained from the traditional DEA are generally non-unique and depend on alternative optimal solutions to DEA linear programs. Sexton et al. (1986) and Doyle & Green (1994) propose using a secondary objective to deal with non-unique DEA solutions. In this study arbitrary formulation is considered as formulated in Doyle & Green (1994). For more detail, see Doyle & Green (1994). Proposed cross-efficiency matrix is given in Table 1.

Table 1. Cross-efficiency matrix (Adapted from Doyle & Green, 1994)

Ranking DMU	Ranked DMU						Averaged appraisal of peers
	1	***2***	.	.	.	***22***	
1	$E_{1,1}$	$E_{1,2}$	.	.	.	$E_{1,22}$	A_1
2	$E_{2,1}$	$E_{2,2}$	.	.	.	$E_{2,22}$	A_2
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
22	$E_{22,1}$	$E_{22,2}$	.	.	.	$E_{22,22}$	A_{22}
	e_1	e_2	.	.	.	e_{22}	
	Averaged appraisal by peers (peer appraisal)						

Note: Simple efficiencies are in the leading diagonal. $E_{22,2}$ is the cross-efficiency accorded DMU-2 using DMU-22's weights. A and e are averaged without the leading diagonal, which is self-appraisal.

Table 2. Main characteristics of the terminals (TURKLIM, 2023)

DMU	Sub-region	Mainly Handled Cargo	Terminal Name	Throughput (mt)		
				2020	*2021*	*2022*
1	İskenderun	Iron and steel	İsdemir	12,641,715	13,817,579	12,679,955
2	Zonguldak	Coal	Eren	9,598,411	8,618,846	10,075,942
3	Karadeniz	Iron and steel	Erdemir	10,264,136	11,210,065	9,624,318
4	Mersin	General*	MIP	7,597,805	8,225,217	8,732,800
5	İskenderun	Steel and coal	Atakaş	6,065,210	8,513,717	8,182,862
6	İskenderun	Iron and steel	MMK	6,468,293	7,434,830	6,558,959
7	Marmara	Iron and steel	İçdaş	9,970,728	9,773,590	6,332,000
8	İzmir	Iron and steel	İDC	4,244,999	4,749,629	5,609,073
9	Karadeniz	Iron and steel	Yeşilyurt	5,421,909	5,580,908	5,575,650
10	Kocaeli	Cement	Nuh Çimento	5,245,845	5,297,874	5,529,368
11	Aliağa	General*	Batıliman	5,161,060	5,168,043	5,111,533
12	Çanakkale	General*	Çelebi Bandırma	3,876,200	4,377,533	4,386,561
13	İskenderun	Iron and steel	Ekinciler	2,879,628	3,602,393	4,172,882
14	Mersin	Cement	Yeşilovacık	3,989,976	3,771,348	4,061,556
15	Marmara	Iron and steel	Çolakoğlu	5,367,859	4,609,419	3,848,601
16	Gemlik	General*	Borusan	2,856,862	3,486,395	3,456,744
17	Ceyhan	General*	Torosport	3,719,727	2,465,759	3,400,201
18	Tekirdağ	General*	Ceyport	N/A	2,867,191	3,230,579
19	Samsun	General*	Ceynak Samsun	3,382,910	3,230,604	3,230,579
20	Tekirdağ	General*	Martaş	2,864,928	2,982,995	3,050,135

Note: * "General" labels mean various types of dry-bulk or general cargo instead of a specific one is handled. ** "mt" is defined as metric tons to represent the weight of cargo.

Since inconsistent results will be obtained if incorrectly determined input and output variables are included in the model, inputs and outputs should reflect the main objectives of the dry bulk and general cargo port as accurately as possible (Cullinane & Wang, 2006). Input data of 20 dry-bulk and general cargo terminals in Turkey covering the year of 2022; compiled from the annual reports of the Turkish Port Operators Association (TURKLIM, 2023). Output data of the terminals is also gathered from the same source covering the year of 2022 (TURKLIM, 2023). Data not included in the reports regarding input were accessed from the official websites of the examined terminals. The terminals examined are concentrated in the Eastern Mediterranean, Aegean – Aliağa and Marmara. Main characteristics of the terminals are given in Table 2.

When the literature is examined, it is seen that the annual cargo handled (mt) is the main output of a dry-bulk and general cargo terminal (Merk & Dang, 2012; Suliman et al., 2019). This value can represent almost all port activities, such as conveying, storage and discharge, as the handling service is directly or indirectly related to other services. Seaport terminal managers aim to maximize the annual handling amount. Therefore, in the relative efficiency analysis, the cargo handled in 2022 on a metric ton basis was taken as the only output variable.

The operation of dry-bulk and general cargo terminals at optimum capacity, in other words, the efficient use of existing resources, depends on the maximum use of the facilities for the shortest ship accommodate period (Bugaric & Petrovic, 2007). In this regard, infrastructure adequacy (berth dimensions, depth), efficient use of storage area and handling equipment come to the fore.

DEA has been used as a measurement method in many seaport efficiency models. The unique structures of bulk cargo ports make it difficult to measure performance and carry out evaluations. The lack of clarity on common standards on measures makes relative performance analysis even harder (Esmer, 2008). Therefore, it is assumed that technical equipment and infrastructure inputs that are as similar as possible constitute a proxy for other unobserved inputs. In these frontier-based models, direct inputs and outputs are quietly similar (Cullinane et al., 2006; Cullinane & Wang, 2006; Baran & Górecka, 2015; Serebrisky et al., 2016) and represent technical equipment and infrastructure. Dry-bulk and general cargo handling services, which consist of loading, unloading, conveying, storage and discharge processes, are carried out with basic direct input combinations. These combinations of inputs represent direct investments in the infrastructure and superstructure of a dry-bulk and general cargo terminal. The decision-maker can significantly increase the handling amount by various strategic managerial decisions. Inputs frequently used in dry-bulk and general cargo terminals: total terminal area "area" (hectare), "total berth length" (m) where ships dock and the "length" (m) of the berth where handling operations are carried out, and the "equipment" (pieces) which is the total number of shore cranes used in handling operations. These variables constitute the direct inputs of the efficiency frontier model of the study. Merk & Dang (2012) also stated that these selected inputs are the physical inputs required to handle dry bulk and general cargo. The literature related to the bulk terminal efficiency is limited. However, container transportation is quite similar to determine measurable direct inputs. For instance, Cullinane & Wang (2006) examined the European container ports with a cross-sectional DEA framework using the same inputs such as terminal length (m) and area (m) and handling equipment (pcs). Cullinane et al. (2006) and Kim et al. (2022) considered the similar input combination on container ports and compared data envelopment analysis and stochastic frontier analysis. The different aspect of this study was the inclusion of yard handling equipment. These types of handling equipment are not unique and vary between terminals. Therefore, a problem can be occurred in the case of an input exists with a value of zero. Bulk cargoes generally take longer to be unloaded than loaded, as the operations cannot use the same combination of gravity and conveyor belts. Therefore, modeling efficiency based on the time the ship stays at the berth or the loading rate may lead to incorrect interpretations.

Results and Discussion

R computer software with deaR (Coll-Serrano et al., 2023) community contributed package was utilized to perform efficiency analyzes. The descriptive statistics of inputs and output variables are presented in Table 3. While the average berth length used for handling service is 1477.65 meters, the total number of shore cranes is 9.15, and the storage area is 18.101 hectares.

The storage area and the equipment utilized draw attention with its high standard deviation. The reason for this may be that the bulk cargo terminals examined differ in terms of the cargo handled. In this context, some types of cargo are temporarily stored in open storage areas due to their feature, while others are in silos. Similarly in some dry bulk terminals, the conveyors are in use to load the cargo, while others are using grabs to discharge cargo. This heterogeneous structure requires a pair wise comparison of terminals providing temporary storage services of the same features.

Table 4 represents the cross-efficiency matrix of the efficiency measures of the observed terminals. The column mean represents the efficiency, and the row mean represents the differentiated features of each terminal. Higher column averages of the terminal indicate higher efficiency and lower row averages indicate that the terminal is different from others (Kim et al., 2022). Dry bulk and general cargo terminals in Turkey have relatively large column mean, ranging from 0.502 to 0.972. On the other hand, a relatively small row range, from 0.504 to 0.831.

Table 3. Descriptive statistics of inputs and output variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Output					
Average handling throughput (mt)	20	5842.515	2709.341	3050.135	12679.955
Inputs					
Berth length (m)	20	1477.650	772.386	500.000	3370.000
Storage area (Ha)	20	18.101	18.904	2.262	86.125
Handling equipment (pcs)	20	9.150	3.911	2.000	20.000
Depth (m)	20	19.165	5.898	11.000	32.000

Table 4. Cross efficiency matrix - Arbitrary formulation

DMU	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	A	Rank
1	**1**	0.943	0.615	0.793	1	0.608	0.842	0.588	0.678	0.666	0.575	1	0.573	0.491	1	1	0.692	0.855	0.731	0.687	***0.767***	**8**
2	0.918	**1**	0.493	1	0.740	0.14	0.635	0.665	0.352	0.270	0.441	0.819	0.407	0.516	1	1	0.672	0.697	0.558	0.364	***0.634***	**16**
3	0.977	0.927	**0.618**	0.626	1	0.555	0.979	0.544	0.528	0.541	0.613	1	0.451	0.297	0.922	1	0.595	1	0.643	0.503	***0.71***	**12**
4	0.745	1	0.522	**1**	0.884	0.108	1	0.708	0.339	0.233	0.491	0.988	0.464	0.404	1	0.849	0.604	0.655	0.549	0.377	***0.646***	**15**
5	1	1	0.575	1	**1**	0.344	0.708	0.607	0.641	0.529	0.502	0.898	0.565	0.657	1	0.993	0.714	0.733	0.685	0.676	***0.741***	**9**
6	0.746	0.728	0.544	0.914	0.768	**0.943**	0.743	0.575	0.918	0.934	0.515	0.987	0.744	1	1	0.778	0.765	0.623	0.831	1	***0.803***	**2**
7	0.195	0.397	0.286	0.930	0.325	0.087	**1**	0.635	0.251	0.206	0.335	1	0.713	1	0.779	0.297	0.455	0.255	0.510	0.424	***0.504***	**20**
8	0.571	0.821	0.349	1	0.461	0.035	0.883	**1**	0.141	0.084	0.348	0.896	0.240	0.312	1	0.727	0.529	0.503	0.371	0.127	***0.520***	**19**
9	0.989	0.878	0.576	1	1	0.889	0.683	0.566	**1**	0.900	0.502	0.908	0.678	0.938	0.983	0.916	0.757	0.679	0.776	1	***0.831***	**1**
10	0.737	0.728	0.550	0.898	0.782	0.942	0.760	0.575	0.917	**0.935**	0.522	1	0.746	0.951	1	0.773	0.758	0.629	0.832	1	***0.802***	**3**
11	0.958	0.916	0.616	0.611	1	0.546	1	0.537	0.519	0.533	**0.614**	1	0.445	0.287	0.910	0.983	0.584	1	0.635	0.494	***0.709***	**13**
12	0.737	0.728	0.550	0.898	0.782	0.942	0.760	0.575	0.917	0.935	0.522	**1**	0.746	0.951	1	0.773	0.758	0.629	0.838	1	***0.802***	**4**
13	0.563	0.696	0.522	0.973	0.823	0.442	0.800	0.576	0.822	0.702	0.498	1	**0.781**	1	0.960	0.643	0.698	0.530	0.779	1	***0.740***	**10**
14	0.563	0.696	0.522	0.973	0.823	0.442	0.800	0.576	0.822	0.702	0.498	1	0.780	**1**	0.960	0.643	0.698	0.530	0.779	1	***0.740***	**11**
15	0.910	0.970	0.471	1	0.674	0.138	0.595	0.670	0.331	0.259	0.424	0.795	0.395	0.557	**1**	1	0.679	0.680	0.551	0.343	***0.622***	**17**
16	0.898	1	0.558	0.76	0.836	0.169	0.974	0.651	0.355	0.292	0.550	1	0.399	0.299	1	**1**	0.616	0.852	0.579	0.354	***0.657***	**14**
17	1	0.844	0.543	0.97	0.799	0.839	0.652	0.578	0.827	0.826	0.487	0.898	0.651	1	1	0.947	**0.781**	0.679	0.776	0.862	***0.798***	**7**
18	0.860	0.836	0.496	0.536	0.595	0.207	1	0.585	0.273	0.275	0.556	1	0.313	0.209	0.925	1	0.554	**1**	0.540	0.260	***0.601***	**18**
19	0.737	0.728	0.550	0.898	0.782	0.942	0.760	0.575	0.917	0.935	0.522	1	0.746	0.951	1	0.773	0.758	0.629	**0.832**	1	***0.802***	**5**
20	0.737	0.728	0.550	0.898	0.782	0.942	0.760	0.575	0.917	0.935	0.522	1	0.746	0.951	1	0.773	0.758	0.629	0.832	**1**	***0.802***	**6**
e	***0.792***	***0.828***	***0.525***	***0.884***	***0.793***	***0.513***	***0.817***	***0.618***	***0.623***	***0.585***	***0.502***	***0.959***	***0.579***	***0.688***	***0.972***	***0.843***	***0.671***	***0.689***	***0.681***	***0.673***		

Table 5. Efficiency ranks and input slacks of the terminals

DMU	Efficiency Rank	Cross-efficiency score[1]	SBM Efficiency	Berth length (m)	Storage area (Ha)	Handling equipment (pcs)	Berth depth (m)
İsdemir	8	0.792	1	0	0	0	0
Eren	5	0.828	1	0	0	0	0
Erdemir	18	0.525	0.546	1386.748	11.652	1.294	11.294
MIP	3	0.884	1	0	0	0	0
Atakaş	7	0.793	1	0	0	0	0
MMK	19	0.513	0.657	241	78.025	2.4	0
İçdaş	6	0.817	1	0	0	0	0
İDC	15	0.618	1	0	0	0	0
Yeşilyurt	14	0.623	1	0	0	0	0
Nuh Çimento	16	0.585	0.703	368	24.75	2	0
Batıliman	20	0.502	0.539	713.643	8.790	1.777	14.476
Çelebi Bandırma	2	0.959	1	0	0	0	0
Ekinciler	17	0.579	0.566	1000	2	5	3
Yeşilovacık	10	0.688	1	0	0	0	0
Çolakoğlu	1	0.972	1	0	0	0	0
Borusan	4	0.843	1	0	0	0	0
Torosport	13	0.671	0.632	352.506	5.647	4.959	3.959
Ceyport	9	0.689	1	0	0	0	0
Ceynak Samsun	11	0.681	0.592	352.795	6.533	3.772	2.076
Martaş	12	0.673	1	0	0	0	0
Average		0.712	0.862				

According to the findings of the cross-efficiency analysis represented in Table 4, it is possible to make pair wise comparisons between terminals handling similar cargoes. For the cross-efficiency scores, based on the set of optimal weights, the performance and rank of terminals may vary. Therefore, the prices without further consideration cannot be used (Jahanshahloo et al., 2011). However, in light of the information given in Table 3, a pair wise comparison can be performed. For instance, İSDEMİR and MMK are two major iron and steel terminals serving in the same sub-region. In terms of cargo tonnage handled, it is seen that İsdemir handles approximately twice as much cargo.

The simple efficiency score of İSDEMİR is 1 and the score of the MMK is 0.94. When İsdemir was evaluated using the coefficients of the MMK terminal, the efficiency score was estimated to be 0.665. On the other hand, when MMK is evaluated using İSDEMİR's coefficients, the estimated efficiency score is 0.608. Similarly, the simple efficiency scores of İÇDAŞ and ÇOLAKOĞLU terminals located in the Marmara sub-region, which handle iron and steel intensively, are both 1. In this case, it can be said that İÇDAŞ and ÇOLAKOĞLU are fully efficient in terms of technical efficiency with their own weights. The efficiency level of ÇOLAKOĞLU is estimated to be 0.59 when evaluated with the input coefficients of the İÇDAŞ terminal. However, the efficiency level of the İÇDAŞ estimated, using the input weights of the ÇOLAKOĞLU is 0.78. Merk & Dunk (2012), in their efficiency evaluation of dry-bulk and general cargo terminals, found that iron-steel and grain terminals are more efficient than terminals that handle other types of cargo. They implied this finding was due to unique cargo features that can quickly adapt to the current developments in port technologies. In alignment with Merk & Dunk (2012), our finding simply that most efficient dry-bulk and general cargo terminals are iron and steel terminals handling heavier cargo in terms of tonnage output.

In addition to the IO-VRS cross efficiency (Lim & Zhu, 2015), the well-known IO-VRS Slacks-Based (SBM) DEA proposed by Tone (2003) is applied to figure out efficiency ranks and input slacks of the terminals and is shown in Table 5. The findings imply that Yeşilyurt, MMK and Nuh Çimento are

[1] Averaged appraisal by peers

the most efficient terminals. Contrarily, İçdaş, İDÇ and Ceyport are the least in terms of efficiency. These terminals can use the resources more efficiently, considering the technical infrastructure and equipment required to perform the handling processes. On average, the current output can be achieved with %16.8 less input. IO-VRS SBM model also provide beneficial information to draw inference regarding input slacks of relatively inefficient terminals. As shown in Table 5, Erdemir, MMK, Nuh Çimento, Batıliman, Ekinciler, Torosport and Ceynak Samsun can perform handling processes with less inputs. For instance, ERDEMİR can handle the same amount of output with 1386,8 meters less pier length, 11.65 Ha less storage area and 1.29 pcs less handling equipment.

Conclusion

Dry bulk and general cargo terminals are the facilities that should quickly adapt to global supply chain dynamics. Each loading/unloading, conveying, horizontal carriage and temporary storage process involves complex organizational structures and procedures. In addition, they are likely to face many risks in terms of safety depending on the physical and chemical structure of the cargo handled. Therefore, technical and operational efficiency should be given importance, and infrastructure and equipment should be evaluated together with the right strategies. For this, decision-makers need to determine dynamic strategies that take environmental conditions into account. Planned physical investments may lead to inefficiency under dynamic environmental conditions and may also result in a waste of resources. In this study, the efficiency of major dry-bulk and general cargo terminals in Türkiye was evaluated using DEA cross-efficiency. It is concluded that relatively most efficient terminals are iron and steel cargo handlers. It can be said that the intensity of the iron and steel can play a crucial role in this result. In pair wise comparisons, it can be argued that Yeşilyurt and MMK are the most efficient two iron and steel terminal. Nuh Çimento terminal draw attention as being other than a iron or steel terminal. According to the results, on average, it can be implied that higher output levels can be achieved in dry-bulk and general cargo terminals in Türkiye with less infrastructure and shore handling equipment. Therefore, it may be appropriate for the terminals examined to review their current resource utilization and investment strategies. Instead of increasing physical infrastructure and equipment investments, effectively implementing digitalization shaped by an environmentally friendly and sustainable perspective can make a significant contribution to the output level and increase the efficiency of other value-added services of the terminals. Although shore handling equipment seems unproblematic during the operation process, it may not be efficient due to environmental factors. By using artificial intelligence in berth planning, the berth occupancy rate, and thus, the crane utilization rate in handling operations can increase. In addition, reducing the horizontal transport distance by using less space will reduce the cargo on the transport equipment and carbon emissions, and will have a positive impact on the performance of the shore cranes. In this way, while the traffic flow within the terminal will be eased, it can be possible to develop an environmentally friendly strategy. As a result, technical efficiency can be increased by reaching higher handling levels with fewer inputs. In conclusion, improving technical efficiency can lead to higher productivity, lower costs, and improved competitiveness for the dry-bulk and general cargo terminals in the port sector. This application of the DEA-cross efficiency approach on dry-bulk and general cargo terminals is the first in the literature. It allows pair wise comparisons of terminals handling similar featured cargo. In this respect, the study will make significant contributions to the literature. The easy applicability of the method used shows that it is suitable for efficiency measurement in similar sectors and business lines.

The study is based on cross-sectional data that can be considered as a limitation. Because it could not be possible to draw inferences about technological changes of each terminal over years, which can be possible by a Malmquist Total Factor Productivity evaluation. By increasing the number of DMUs in future studies, it may be possible to integrate current clustering approaches into cross-efficiency analysis and make more accurate efficiency evaluations. Moreover, it paves the way to figure out technological improvements for each DMUs. To generalize the results, more comprehensive works must be carried out. As pointed out by Cullinane et al. (2004), to get a deeper insight about the inefficiency determinant, a two-stage analysis may be performed to consider observable heterogeneity factors such as location. Moreover, due to the difficulty in accessing confidential input prices, this study could not draw inferences about cost efficiency and lies around the technical efficiency. Lastly, for cross efficiency method, the weights used to calculate scores are not unique, and therefore much of the discussion in the literature is a about how appropriate weights can be selected (Balk et al., 2021).

Compliance With Ethical Standards

Conflict of Interest

The author declares that there is no conflict of interest.

Ethical Approval

For this type of study, formal consent is not required.

Data Availability Statement

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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