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Evaluating the Technical Efficiency of Dry-Bulk and General Cargo Terminals in Türkiye using Interval DEA

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Abstract

The efficiency of bulk solid and general cargo terminals, where ore, grain, and many raw materials are handled, plays a crucial role in socioeconomic development and lays the groundwork for reasonable trade costs. This study evaluates the relative performance of dry-bulk and general cargo terminals in Türkiye with interval data envelopment analysis (DEA). The dataset consists of 21 terminals operated by private companies for 2018-2021 and has been transformed into an interval form to apply interval DEA to imprecise data. The results imply that the efficiency levels of dry-bulk and general cargo terminals in the Marmara and Mediterranean tend to increase. It can be inferred that the average efficiency level of the Black Sea terminals has remained stable over the years, and the loss of efficiency in the Aegean is remarkable. The application of the Interval DEA in evaluating the efficiency of dry-bulk and general cargo terminals in the case of imprecise data can contribute significantly to the seaport efficiency literature.

Keywords: Dry-bulk, Terminal, Efficiency, Interval DEA, Fuzzy

1. Introduction

International trade is boosted by the efficient transport of raw materials and bulk solids from one end of the world to the other. Thus, general cargo ports become strategic nodes for sustainable and efficient maritime transportation. Among the common cargo types transported by sea, solid bulk and general cargo have the highest share, 45% [1]. In Türkiye, approximately 232 million tons of bulk solids and general cargo were handled at seaports in 2021 [2].

The essential functions of a dry bulk and general cargo terminal are to handle and transfer cargo that is physically separated from the others in terms of mode of transport [3]. Some of the difficulties encountered in preventing the current load potential of the terminals from shifting to rivals are the product handling speed at an appropriate level, adequate and efficient equipment, optimizing berthing times, reducing waiting and delays at anchor, providing sufficient storage capacity, and offering multimodal hinterland connections [4]. In addition, bulk solid and general cargo-oriented foreign trade firms experience fierce global competition [5]. Dry bulk and general cargo terminals tend to invest in infrastructure and equipment and keep up with new trends concerning technological developments to maintain their dynamic market share shaped by increasing ship sizes and shipowner cooperation.

The efficiency of bulk solid and general cargo terminals, where ore, grain, grain, and many raw materials are handled, plays a crucial role in socio-economic development and lays the groundwork for the competitive prices expected by port customers. The level of efficiency of the terminals varies according to the production technology, the economic behavior of the decision-making units, the environmental factors in which the process takes place and the management strategies adopted. In this context, assessing the relative performance of solid bulk and general cargo terminals is critical for the efficient use of existing resources and for planning future investment strategies of decision makers.

The existing literature constitutes several studies on the efficiency of seaports and terminals. Kutin et al. [6] evaluated the relative efficiency of ASEAN container ports. The authors

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categorized the seaports on the basis of their locations and handling systems to benchmark them with standard data envelopment analysis (DEA) and super-efficiency models under constant returns to scale (CRS) and variable returns to scale (VRS) options. Castellano et al. [7] evaluated the economic and environmental efficiency of Italian seaports using DEA considering an undesirable output approach. They concluded that efficiency converges toward the optimal target when ports feature a high pro-environmental attitude by implementing proactive green policies. da Costa et al. [8] evaluated the efficiency of container terminals in the northern region of Brazil using DEA under CRS and VRS production technologies. Their study is at a regional level and deals with the better management of seaports located in the region. Fancello et al. [9] also evaluated the efficiency of Mediterranean container ports using DEA under the CRS and VRS options. Similarly, Hsu et al. [10] assessed the operational efficiency of terminals located in the Kaohsiung Port using DEA. As inferred from the above recent studies, frontier-based efficiency evaluations are intensively based on standard DEA models.

On the other hand, stochastic approaches are also an alternative to DEA approaches such as stochastic frontier analysis. In particular, with small sample, it may be problematic to establish a parametric frontier model based on the maximum likelihood estimation procedure. Wiegmans and Witte [11] analyzed the efficiency of inland waterway container terminals using stochastic frontier and data envelopment to evaluate capacity design and throughput efficiency. Julien et al. [12] compared common frontier approaches to evaluate efficiency, productivity, and returns to scale in ports by applying them to Caribbean Small Island Developing States. These works also evaluate seaports from various perspectives. However, these studies are mainly related to container terminals, and the number of studies on bulk cargo terminals is limited. The OECD [13] has published a comprehensive study of the efficiency analysis of solid bulk terminals using standard DEA approaches. The most attractive aspect of this distinctive study is the benchmarking of dry bulk and general cargo terminals according to the cargo types handled. The authors concluded that technical efficiency, in other words, the efficient use of equipment and infrastructure, is the most critical factor affecting the overall efficiency of terminals. The most attractive aspect of this distinctive study may be benchmarking the dry-bulk terminals according to the cargo types handled, such as coal or wheat, with the aim of consistent findings.

Balci et al. [14] evaluated the competitiveness and selection criteria of solid-bulk cargo terminals using multi-criteria decision-making methods (MCDMM). The authors state that dry bulk shippers differ in their priorities regarding port selection criteria and highlight a heterogeneity of expectations. Although the dry cargo terminal selection criteria are similar to those of container shippers, the content may be different. Another striking result is that shippers in the dry bulk market deal with some of the same problems as container carriers when choosing a port. Suliman et al. [15] discussed the potential of using technical port indicators and DEA application specifically in dry bulk terminals and examined the technical and scale efficiency of Malaysian solid-bulk cargo terminals with standard DEA approaches. Following classical production theory, the authors propose a framework that consists of equipment, infrastructure/facility, and labor as inputs, and the total throughput in tons as output for dry bulk terminals. However, they highlighted that further studies are required to prove the effectiveness and accuracy of this method.

Based on the studies in the literature, there are some reservations due to data imprecision and the difficulties of the application of frontier models such as DEA to solid bulk and general cargo terminals. Considering the limited relevant literature, it is inferred that the most frequent inputs in determining the technical efficiency of solid-bulk and general cargo terminals are the terminal area, equipment, and pier length, and the most frequently used output is the annual total amount of cargo handled [13,15]. However, the different physical characteristics of the cargo handled at the solid-bulk and general cargo terminals obscure the standardization of the handling equipment. Bulk cargo-specific handling equipment varies as conveyors or cranes using grab, depending on the load type. However, comparing daily tonnage handled with both types of handling equipment, similar results can be achieved. Similarly, the handling cost per ton varies depending on the type of cargo. Moreover, load types with different densities and properties may be sensitive to various environmental conditions such as rain, humidity, swell affecting the dock, and strong wind. For these reasons, interval DEA instead of standard DEA was used. The interval efficiency approach is a convenient and practical method for evaluating the efficiency of bulk solid and general cargo terminals with imprecise data. If the lower and upper limit values of the data can be calculated, limited data may be obtained [16]. Therefore, the crisp data were fuzzified using their standard error (SE) in alignment with fuzzy theory. Thus, the upper and lower bounds of efficiency were obtained. Interval efficiency levels of each terminal were ranked using the minimax regret approach (MRA).

There are few studies on bulk solid and general cargo terminals in the literature, as mentioned above, and this can be related to data unavailability or partly imprecatory. This study aims to overcome the constraints caused by the unique features of private general cargo and dry bulk cargo terminals in Türkiye by using fuzzy logic theory to make a more precise comparison. In this context, it is argued that this study could contribute significantly to the literature. Regardless of the type of bulk cargo handled, interval DEA can act as an alternative efficiency analysis tool. Moreover, it can fill the critical gap in the literature by forming an interval efficiency level to draw inferences about how effectively solid bulk and general cargo terminals use their existing resources by practitioners, terminal managers, and other industry stakeholders.

The overall structure of the study is in the following form: Section 2 represents the analysis technique adopted, while Section 3 presents the results and the discussion with relevant literature. The last section summarizes the research conclusions.

2. Methodology

This study evaluates the technical efficiency levels of 21 large solid-bulk and general cargo terminals in Türkiye using the interval DEA approach based on pooled cross-sectional data consisting of 78 different observations from 2018 to 2021 collected from Turkish Port Operators Association (TURKLIM) annual reports [17-20]. This approach is an input-oriented DEA with interval data, assuming CRS production technology. The interval DEA determines a different efficiency range for each DMU, assuming either input minimization or output maximization. The efficiency frontier comprises a set of efficient decision units. The distance of the DMUs below the production frontier is measured as the radial distance, either input- or output-oriented. It aims to minimize the inputs, considering that solid-bulk and general cargo terminal managers cannot increase the output amount unless there is demand for the decisions they will make.

Multi-purpose seaports that intensively handle containerized cargo are not included in the study despite solid-bulk and general cargo handling because they use infrastructure and handling equipment for different cargo types. All assessed terminals are operated by private companies. Terminals P, G, and N are located in the Black Sea. Terminals L, U, V, I, J, F, and A are located in Marmara. Terminals T, M, and K are in the Aegean region, whereas Terminals E, C, and D, are in Iskenderun Bay in the East Mediterranean.

2.1. DEA

Data envelopment analysis is a mathematical programing technique developed by Charnes et al. [21] and based on Farrell's [22] frontier model to evaluate the relative efficiency of a set of homogeneous decision-making units (DMUs). This model is based on the assumption of CRS, is known as the CCR model, and consists of the first letter of the author's name. In 1984, Banker et al. [23] developed the BCC model based on the assumption of VRS. This model, used to derive the pure technical efficiency level, relaxes the constraint on scale efficiency by allowing output to change almost disproportionately with a marginal increase in inputs. The technical efficiency value of each DMU obtained using the VZA-CCR and VZA-BCC models is used to calculate the scale efficiency of each DMU using the equation $SE_k = U_{CCR,\ k}/U_{BCC,k}$. $SE_k = 1$ means the DMU is scale efficient, $SE_k < 1$ means the scale inefficient [24]. Scale inefficiency results from increasing or decreasing returns to scale, which can be determined by examining the sum of the weights under the specification of the CCR model. If this sum is equal to one, it means a constant return to scale (CRS). If the sum of the coefficients is less than or greater than one, it indicates an increasing return and a decreasing return to scale. Although these two standard forms (DEA-CCR and DEA-BCC) are frequently used in the current literature, advanced DEA models also exist.

During an efficiency measurement made with DEA, the data must be precise and reliable. Imprecise or missing data can cause relative efficiency levels to be overestimated or underestimated. The complex nature of the terminals makes it difficult to obtain an accurate dataset. Extreme conditions such as adverse weather conditions, strikes, and pandemics during the handling operation may adversely affect the accuracy of the data obtained. There may also be difficulties in obtaining precise data on private businesses or accurately measuring inputs and outputs for privacy and accessibility reasons [25]. If the sample size and the specification of the data are not appropriate for parametric efficiency analysis approaches that consider the error term, it would be suitable to use fuzzy modeling together with standard DEA to evaluate the relative efficiency of DMUs [26,27]. Thus, the standard DEA approach gains the ability to model real-life problems more appropriately [27].

Several fuzzy DEA techniques deal with efficiency measurement in the current literature. Sengupta [27], who used a combination of fuzzy set theory and the DEA approaches for the first time in the literature, developed an efficiency model based on tolerance levels of the objective function and constraint violations. Triantis and Girod [28] proposed an approach that transforms fuzzy input and output data into precise data compatible with the standard DEA model using membership function values. In this model, different efficiency scores estimated with various membership functions are averaged to compare the efficiency levels of decision-making units. Guo and Tanaka [26] proposed a fuzzy CCR model in which fuzzy constraints are transformed into precise constraints by defining a probability level. Lertworasirikul et al. [25] transformed the fuzzy DEA model into a probability DEA model, in which fuzzy constraints were treated as fuzzy events using probability measures on fuzzy events. Kim et al. [29] applied fuzzy DEA with partial data. On the other hand, Kao and Liu [30,31] and Saati et al. [32] adopted an approach that transforms fuzzy data into interval data by using α sets so that standard DEA models can be used with fuzzy data. However, because the efficiency level calculated at a certain α level with this approach will vary at each different α level, the comparison can only be made for a specific α level. Entani et al. [33] proposed a DEA model with interval efficiency estimated with pessimistic and optimistic perspectives for fuzzy data. However, this model selects only one input and one output data to obtain the lower bound efficiency of each DMU, regardless of the number of inputs and outputs. This leads to a lack of information about other inputs and outputs in the model. The interval efficiency model used in this study eliminates the downsides associated with other fuzzy DEA models. This model uses a fixed and unified production frontier as a benchmark to measure the efficiency levels of all DMUs; therefore, the generated models are more rational and reliable [34].

2.2. Interval DEA

Wang et al.'s [34] interval DEA approach can deal with imprecise data simply, rationally, and effectively using interval input and output data. Using this approach, the efficiency level obtained for each DMU is characterized by an interval efficiency bounded by the best lower bound efficiency and the best upper bound efficiency of each DMU.

Assuming n DMUs, each DMU consumes m inputs in different amounts for s outputs, DMU_j consumes number of inputs $X_j = \left\{x_{ij}\right\}$ $(i = 1,2,\ldots,m)$, and produces $Y_j = \left\{y_{rj}\right\}$ $(r = 1,2,\ldots,s)$ number of outputs. Without loss of generality, it is assumed that all inputs and outputs x_{ij} and y_{rj} $(i = 1,\ldots,m\ ;\ r = 1,\ldots,s\ ;\ j = 1,\ldots,n)$ it is not known precisely due to uncertainty. However, the values of the inputs and outputs are within the lower and upper bounds represented by x_{ij}^L, x_{ij}^U *and* y_{rj}^L, y_{rj}^U $(x_{ij}^L, y_{rj}^L > 0)$ respectively. In the case of uncertainty expressed in this manner, the following linear programing models are used to create the lower and upper bounds of the efficiency intervals of the DMUs.

$$\begin{aligned}
&\text{Max.}\\
&H_{j_0}^U = \sum_{r=1}^{s} u_r y_{rj_0}^U\\
&\text{Constraints;}\\
&\sum_{i=1}^{m} v_i x_{ij_0}^L = 1,\\
&\sum_{r=1}^{s} u_r y_{rj_0}^U - \sum_{i=1}^{m} v_i x_{ij_0}^U \le 0,\\
&\sum_{r=1}^{s} u_r y_{rj}^L - \sum_{i=1}^{m} v_i x_{ij}^L \le 0,\ j = 1,\ldots,n;\ j \ne j_0,\\
&u_r, v_i \ge \varepsilon\ \forall_{r,\,i.}
\end{aligned} \tag{1}$$

$$\begin{aligned}
&\text{Max.}\\
&H_{j_0}^L = \sum_{r=1}^{s} u_r y_{rj_0}^L\\
&\text{Constraints;}\\
&\sum_{i=1}^{m} v_i x_{ij_0}^U = 1,\\
&\sum_{r=1}^{s} u_r y_{rj_0}^L - \sum_{i=1}^{m} v_i x_{ij_0}^U \le 0,\\
&\sum_{r=1}^{s} u_r y_{rj}^U - \sum_{i=1}^{m} v_i x_{ij}^L \le 0,\ j = 1,\ldots,n;\ j \ne j_0,\\
&u_r, v_i \ge \varepsilon\ \forall_{r,\,i.}
\end{aligned} \tag{2}$$

where j_0 is the decision-making unit (DMU_0) under evaluation; u_r and v_i, weights assigned to outputs and inputs; H_{j0}^U and H_{j0}^L represent the best possible relative efficiency values for KVB_0 under the most favorable and unfavorable situations, respectively, and ε is infinitesimal non-Archimedes.

When the upper- and lower-efficiency DEA models specified in Equation 1 and Equation 2 are examined, the constraints used to measure the efficiency of DMUs differ among DMUs, and even the same constraints used to measure the lower- and upper-efficiency bounds of the same DMU are different. The most obvious downside of using different constraints to measure the efficiency of DMUs is the lack of comparison between DMUs due to the adoption of various production frontiers in efficiency measurement. Since each DMU can use minimum inputs to produce maximum outputs, the actual production frontier should be derived on the basis of each DMU's best production activity state. The interval efficiency model avoids obtaining different production frontiers to measure the efficiency of DMUs. This model is based on interval arithmetic. It also uses a single efficiency frontier that is created with the same constraints for all DMUs and lower and upper bound efficiencies. Upper- and lower-efficiency linear programing models created with the same constraints and projected to a single frontier are as follows for the upper- and lower-efficiency bounds, respectively [34].

Max.

$$\theta^U_{j_0} = \sum_{r=1}^{s} u_r y^U_{rj_0}$$

Constraints;

$$\sum_{i=1}^{m} v_i x^L_{ij_0} = 1, \tag{3}$$

$$\sum_{r=1}^{s} u_r y^U_{rj} - \sum_{i=1}^{m} v_i x^L_{ij} \leq 0, \; j = 1, \ldots, n,$$

$$u_r, v_i \geq \varepsilon \; \forall_{r, i.}$$

Max.

$$\theta^L_{j_0} = \sum_{r=1}^{s} u_r y^L_{rj_0}$$

Constraints;

$$\sum_{i=1}^{m} v_i x^U_{ij_0} = 1, \tag{4}$$

$$\sum_{r=1}^{s} u_r y^U_{rj} - \sum_{i=1}^{m} v_i x^L_{ij} \leq 0, \; j = 1, \ldots, n,$$

$$u_r, v_i \geq \varepsilon \; \forall_{r, i.}$$

θ^U_{j0} represents the best possible relative efficiency achieved by DMU_0 when all DMUs are in the state of best production activity, θ^L_{j0} represents the lower bound of the best possible relative efficiency of DMU_0. Thus, they establish the best possible interval of relative efficiency $\left[\theta^L_{j0}, \theta^U_{j0}\right]$.

Because the final efficiency scores for each DMU are characterized by their relative efficiency interval, a simple and practical approach is needed to rank and compare the efficiency of different DMUs. Several methods have been developed in the literature to compare the efficiency intervals of each of the DMUs and to rank the efficiency levels [35]. However, when interval numbers have the same center but different widths, they fail to distinguish one from the other [36,37].

Wang et al. [34] stated that the MRA can be used to rank and compare the efficiency intervals of DMUs, even if they are concentric but of different widths. The MRA for the interval DEA is summarized as follows.

Let the efficiency intervals of n DMUs be $A_i = [a^L_i, a^U_i] = \langle m(A_i), w(A_i)\rangle (i = 1, \ldots, n)$. $m(A_i) = \frac{1}{2}(a^R_i + a^L_i)$ and $w(A_i) = \frac{1}{2}(a^R_i + a^L_i)$ are the centers and widths, respectively. Without loss of generality, $A_i = [a^L_i, a^U_i]$ is assumed to be the best efficiency interval of DMU. When $b = \max_{j\neq i}\{a^U_j\}$, if $a^L_i < b$, DMU may experience inefficiency and regret. The maximum efficiency loss in this case is:

$$\max(r_i) = b - a^L_i = \max_{j\neq i}\{a^U_j\} - a^L_i. \tag{5}$$

If $a^L_i \geq b$, KVB as DMU has no regrets due to the loss of efficiency, $r_i = 0$. Maximum efficiency loss when both conditions are considered together can be written as follows:

$$\max(r_i) = \max[\max_{j\neq i}(a^U_j) - a^L_i, 0] \tag{6}$$

Thus, the minimax regret (MR) criterion determines the efficiency interval that satisfies the following condition as the best efficiency interval.

$$\min_i\left\{\max(r_i)\right\} = \min_i\left\{\max[\max_{j\neq i}(a^U_j) - a^L_i, 0]\right\}. \tag{7}$$

Based on the efficiency interval analysis above, Wang et al. [34] defined the following equation to compare the efficiency intervals and rank the DMUs.

Let $A_i = [a^L_i, a^U_i] = \langle m(A_i), w(A_i)\rangle (i = 1, \ldots, n)$ be the interval efficiency set. The maximum efficiency loss of each efficiency interval is

$$R(A_i) = \max\,[\underset{j\neq i}{\text{maks}}\, a^U_j) - a^L_i, 0] = \max$$
$$[\max_{i\neq i}\{m(A_i) + w(A_i)\} - (m(A_i) - w(A_i)), 0] \tag{8}$$
$$i = 1, \ldots, n.$$

Relative maximum efficiency losses are calculated on the basis of the maximum efficiency level. Therefore, they cannot be used directly for ranking. The following steps are suggested in order to rank the efficiency using the maximum efficiency losses obtained using the estimated efficiency intervals [34].

Step 1: Maximum efficiency loss is calculated for all DMUs. The lowest maximum efficiency loss is determined to be the most attractive option. Assuming A_{i_1} is selected, with $1 \leq i_1 \leq n$.

Step 2: A_{i_1} value is eliminated from the efficiency interval list. Among the remaining n−1 number of efficiency intervals, the efficiency loss with the lowest maximum efficiency loss is determined again. The value of A_{i_2} is determined so that $1 \leq i_1 \leq n$ ve $i_1 \neq i_2$ is.

Step 3: The value A_{i_2} is also eliminated from the efficiency interval list. Among the remaining n-2 number of efficiency intervals, the efficiency loss with the smallest maximum efficiency loss is determined again.

Step 4: A_{i_3} value is also eliminated from the efficiency interval list. This process continues until only one maximum loss of efficiency remains on the list. Ranking is conducted as $(A_{i_1} > A_{i_2} > A_{i_3} > , \ldots, A_{i_4})$ meaning " >" sign is "superior" [34].

2.3. Input and Output Variables

It is critical to specify the inputs and outputs in the efficiency evaluations performed using data envelopment analysis. When the literature is examined, there are few studies on the efficiency of bulk cargo terminals [10,14,38]. Considering that inputs are transformed into outputs in a classical production function, the annual amount of cargo handled on a ton basis can be accepted as a service output at ports that handle solid bulk cargo. The inputs that likely affect the total throughput to reach the desired level are the existing infrastructure and handling equipment. Pier length (m), storage area (Ha), and handling equipment (units) are considered the inputs, whereas the output variable is the annual amount of cargo handled (Mt). Descriptive statistics of the input and output variables that comprise the dataset are shown in Table 1.

Due to possible data errors, the crisp data were transformed into intervals using Equations 3 and 4. For this, the SE of variables was subtracted from the crisp data, the lower

Table 1. *Descriptive statistics of the model variables*

Inputs and outputs	N	Mean	Standard deviation	Min.	Max.
Output					
Cargo throughput (mt)	78	5,449,548.11	3,179,457.7	2,072,089	15,510,380
Inputs					
Pier length (m)	78	1,266.372	610.55	417	2,974
Terminal area (Ha)	78	13.837	10.514	2.260	34.4
Handling equipment (unit)	78	9.205	4.655	2	25

Table 2. *Efficiency ranking of terminals based on the minimax regret approach*

Rank	Code	Year	Region	Lower Bound	Upper Bound	Max. loss.	Rank	Code	Year	Region	Lower Bound	Upper Bound	Max. loss.
1	Terminal A	2018	Marmara	1	1	0	40	Terminal H	2018	Aegean	0.564	0.774	0.436
2	Terminal B	2019	Black Sea	1	1	0	41	Terminal C	2019	Mediterranean	0.557	0.593	0.443
3	Terminal A	2020	Marmara	1	1	0	42	Terminal L	2020	Marmara	0.542	0.762	0.458
4	Terminal C	2021	Mediterranean	1	1	0	43	Terminal M	2021	Aegean	0.492	0.458	0.508
5	Terminal D	2021	Mediterranean	1	0.630	0	44	Terminal M	2020	Aegean	0.491	0.457	0.509
6	Terminal E	2018	Mediterranean	0.979	0.875	0.021	45	Terminal N	2021	Black Sea	0.471	0.488	0.529
7	Terminal F	2021	Marmara	0.977	1	0.023	46	Terminal K	2018	Aegean	0.474	0.456	0.526
8	Terminal F	2020	Marmara	0.966	0.991	0.034	47	Terminal O	2018	Mediterranean	0.461	0.483	0.539
9	Terminal A	2019	Marmara	0.956	0.962	0.044	48	Terminal K	2019	Aegean	0.458	0.443	0.542
10	Terminal D	2018	Mediterranean	0.925	0.587	0.075	49	Terminal N	2020	Black Sea	0.457	0.475	0.543
11	Terminal B	2020	Black Sea	0.928	0.933	0.072	50	Terminal N	2019	Black Sea	0.426	0.447	0.574
12	Terminal D	2019	Mediterranean	0.899	0.572	0.101	51	Terminal O	2019	Mediterranean	0.422	0.449	0.578
13	Terminal B	2018	Black Sea	0.889	0.897	0.111	52	Terminal N	2018	Black Sea	0.419	0.441	0.581
14	Terminal E	2019	Mediterranean	0.877	0.787	0.123	53	Terminal M	2019	Aegean	0.366	0.360	0.634
15	Terminal E	2021	Mediterranean	0.870	0.782	0.130	54	Terminal P	2018	Black Sea	0.356	0.262	0.644
16	Terminal D	2020	Mediterranean	0.863	0.552	0.137	55	Terminal M	2018	Aegean	0.350	0.346	0.650
17	Terminal G	2021	Black Sea	0.861	0.700	0.139	56	Terminal F	2018	Marmara	0.339	0.430	0.661
18	Terminal A	2021	Marmara	0.849	0.868	0.151	57	Terminal O	2020	Mediterranean	0.336	0.374	0.664
19	Terminal B	2021	Black Sea	0.830	0.841	0.170	58	Terminal P	2020	Black Sea	0.324	0.252	0.676
20	Terminal G	2018	Black Sea	0.801	0.677	0.199	59	Terminal R	2020	Marmara	0.317	0.319	0.683
21	Terminal E	2020	Mediterranean	0.794	0.717	0.206	60	Terminal S	2020	Mediterranean	0.311	0.300	0.689
22	Terminal H	2019	Aegean	0.789	1	0.211	61	Terminal P	2021	Black Sea	0.308	0.241	0.692
23	Terminal G	2020	Black Sea	0.786	0.643	0.214	62	Terminal S	2019	Mediterranean	0.308	0.298	0.692

***Table 2.** Efficiency ranking of terminals based on the minimax regret approach (continued)*

Rank	Code	Year	Region	Lower Bound	Upper Bound	Max. loss.	Rank	Code	Year	Region	Lower Bound	Upper Bound	Max. loss.
24	Terminal H	2020	Aegean	0.767	0.978	0.233	63	Terminal R	2018	Marmara	0.307	0.311	0.693
25	Terminal I	2019	Marmara	0.733	0.766	0.267	64	Terminal S	2018	Mediterranean	0.300	0.291	0.700
26	Terminal F	2019	Marmara	0.707	0.759	0.293	65	Terminal P	2019	Black Sea	0.298	0.229	0.702
27	Terminal J	2018	Marmara	0.706	0.579	0.294	66	Terminal T	2021	Aegean	0.269	0.193	0.731
28	Terminal C	2020	Mediterranean	0.700	0.724	0.300	67	Terminal U	2021	Marmara	0.257	0.249	0.743
29	Terminal G	2019	Black Sea	0.689	0.588	0.311	68	Terminal U	2018	Marmara	0.255	0.247	0.745
30	Terminal I	2018	Marmara	0.668	0.709	0.332	69	Terminal C	2018	Mediterranean	0.248	0.309	0.752
31	Terminal K	2021	Aegean	0.654	0.597	0.346	70	Terminal U	2019	Marmara	0.242	0.237	0.758
32	Terminal J	2020	Marmara	0.648	0.534	0.352	71	Terminal U	2020	Marmara	0.245	0.240	0.755
33	Terminal J	2021	Marmara	0.634	0.524	0.366	72	Terminal R	2019	Marmara	0.241	0.259	0.759
34	Terminal I	2020	Marmara	0.631	0.622	0.369	73	Terminal T	2020	Aegean	0.235	0.172	0.765
35	Terminal I	2021	Marmara	0.608	0.602	0.392	74	Terminal V	2018	Marmara	0.230	0.221	0.770
36	Terminal L	2019	Marmara	0.599	0.828	0.401	75	Terminal T	2019	Aegean	0.224	0.189	0.776
37	Terminal J	2019	Marmara	0.594	0.493	0.406	76	Terminal V	2019	Marmara	0.198	0.196	0.802
38	Terminal L	2021	Marmara	0.592	0.814	0.408	77	Terminal S	2021	Mediterranean	0.195	0.208	0.805
39	Terminal K	2020	Aegean	0.578	0.538	0.422	78	Terminal T	2018	Aegean	0.168	0.149	0.832

limit was added, and the upper limit was obtained. While determining the upper efficiency limit, the lower limit of the input values and the upper limit of the output values were used. To determine the lower efficiency limit, the upper limit data of the input values and the lower limit of the output were used. The generated interval data for each DMU are tabulated in Table 2.

3. Results and Discussions

Descriptive statistics of the inputs and outputs in the efficiency model are given in Table 1. The berth length and terminal area draw attention with high standard deviation values. It can be argued that some observed terminals adopt the clustering strategy and use mutual resources with others serving the same or different load types. Table 3 shows that all correlation coefficients between inputs and outputs in the model are statistically significant at the 5% level. In other words, the DEA technique can be used to measure the efficiency of observed DMUs because the significant positive relationship between the input and output variables shows that the data meet the isotonicity criterion [36].

***Table 3.** Spearman rank correlation coefficients*

Input and output variables	(1)	(2)	(3)	(4)
(1) Cargo throughput (m)	1.000			
(2) Pier length (m)	0.249*	1.000		
(3) Storage area (Ha)	0.507**	0.327**	1.000	
(4) Handling equipment (unit)	0.378**	0.564**	0.320**	1.000
Spearman rho= 0.320, p>0.05: “*”, p>0.01: “**”				

The technical efficiency levels of 21 dry-bulk and general cargo terminals operating in Türkiye for 2018-2021 were evaluated using the interval DEA technique. The interval efficiency values were calculated as suggested by Wang et al. [34]. The obtained values were used to rank the terminals via the MRA from the most efficient to the least efficient, as shown in Table 2.

These findings imply that Terminal C is highly efficient for 2021. Terminal C, which attracts attention in the Eastern Mediterranean with its modern infrastructure, is equipped to handle all types of project cargo, besides solid bulk and general cargo. Terminal A, located in the Northern Black Sea, is one of the 18 most efficient terminals. The findings state that it will be highly efficient in 2018 and 2020. Terminal B

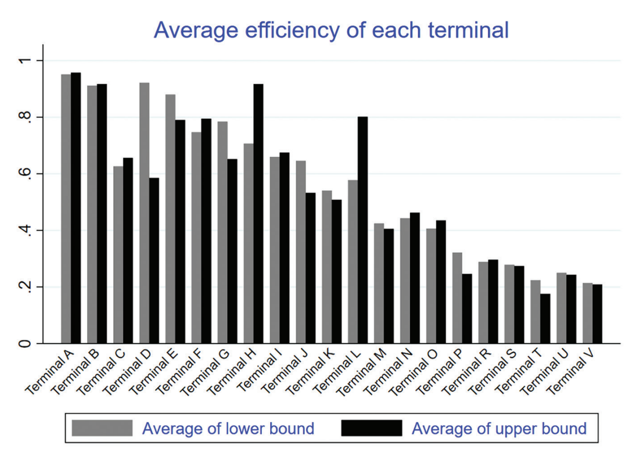

***Figure 1.** The average efficiency levels determined by the average of the upper efficiency scores*

operating in the Black Sea draws attention to its efficiency level in terms of solid-bulk cargo and general cargo for 2019 and low-efficiency losses for other periods. Terminals T, S, and V were evaluated as the terminals with the lowest efficiency interval.

Figure 1 represents the average efficiency of each terminal. This figure illustrates that the average efficiency over the years is mainly related to the terminal rankings. Terminals D, H, and L have the highest range of their lower and upper efficiency bounds. This can be caused by high variation in the data of these terminals.

As seen in Figure 2, apart from the top four, the other terminals in the top ranking achieved a wider interval of efficiency than the other terminals in the lower ranks.

As shown in Figure 3, the efficiency levels of the terminals in the Marmara region have increased monotonically over the years. It has been observed that the increase in the efficiency level, which continued until 2020 in the Aegean region, started to decrease by 2021.

In a regional context, Balci et al. [14] evaluated the competitiveness and selection criteria of dry-bulk terminals in the Aegean region using MCDMM. The authors state that

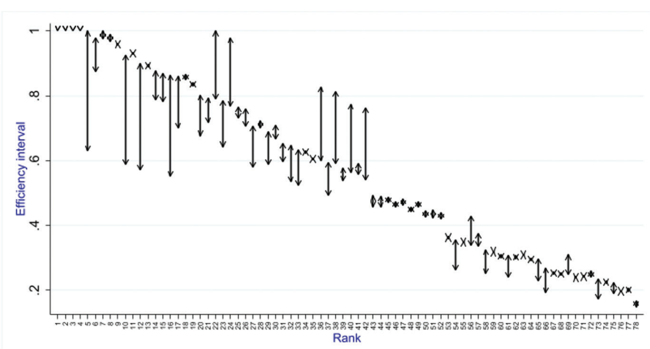

Figure 2. *Efficiency intervals of ranked terminals based on the minimax regret approach*

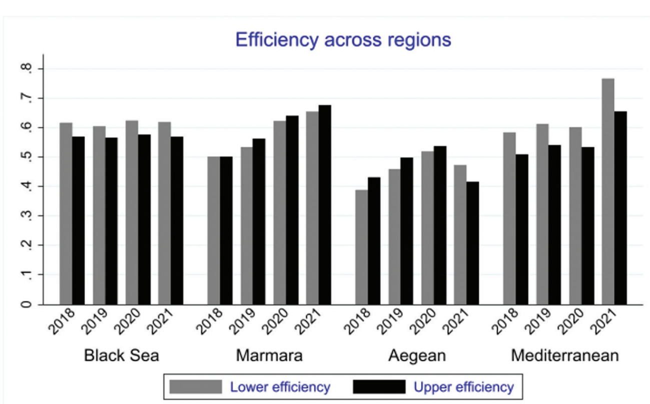

Figure 3. *Average efficiency levels across regions*

the terminals located in the Aegean region are located quite close to each other. Therefore, based on interval efficiency findings, the general cargo and dry bulk terminals in the Aegean region were adversely affected by the clustering strategies. On the other hand, a stable increment of efficiency levels in the Marmara region highlights the possible benefits of clustering triggered by high hinterland activities.

While the average efficiency level of the terminals in the Black Sea region remained stable over the years, it can be inferred that the Mediterranean terminals made a significant improvement in terms of technical efficiency in 2021. Cullinane and Song [38] and Jeh et al. [39] state that regional advantages such as proximity to transit routes positively affect the efficiency of terminals.

Yüksekyıldız and Tunçel [16] also applied the minimax-regret-based ranking approach [34] to rank the fuzzy efficiency intervals and found it beneficial while benchmarking the DMUs. The authors also calculated at five different α levels using Zimmermann's [37] set of α cut approach. Their study was based on container terminals. It can be argued that container terminals are more homogenous in terms of cargo specifications. However, general and dry-bulk cargoes differ substantially, especially in terms of handled cargo specifications.

Therefore, a possible explanation for the stable efficiency level of the general cargo and dry-bulk terminals located in the Black Sea might be the distance to the main routes. Moreover, the Black Sea terminals may suffer from being inland waters only accessible through the İstanbul and Çanakkale straits. Thus, it can be inferred that the findings are in alignment with the relevant literature.

For a dry-bulk terminal, to achieve optimum throughput, it is important that the infrastructure can support the storage capacity of the facility sufficiently [40]. The findings imply that there are significant infrastructure differences between clusters in the same region or geographical features. Moreover, as stated in Arslan et al. [41], an important issue is that the efficiency of supervision service varies depending on many factors, and these factors are connected with each other by a causal link. They stated that education and communication have an important place among the factors affecting the efficiency of cargo survey services.

4. Conclusion

Efficiency measurement using the standard DEA approach is too sensitive to data variations. The fact that the handling speed in dry-bulk and general cargo terminals also depends on many external factors, difficulties, and uncertainties to be experienced in obtaining the data reveals the necessity of blurring the crisp data. Therefore, the interval efficiency model, which is easily applicable, was preferred for efficiency measurement.

The efficiency model minimizes the inputs assuming that the terminal cannot increase the exogenous output. The ranking was made according to the maximum regret values obtained according to the interval efficiency analysis with the assumption of CRS production technology.

Although the interval efficiency model is practical and applicable, one of its limitations is that it can only be calculated according to the CRS assumption. In addition, with this approach, a good comparison cannot be made according to data categories because of specific terminal features and individual cargo types handled intensively in the terminals.

The efficiency levels of dry-bulk and general cargo terminals in the Marmara and Mediterranean tend to increase. It is concluded that the average efficiencies of the Black Sea terminals remain stable over the years, and the loss of efficiency in the Aegean region is noteworthy. While Aegean dry-bulk and general cargo terminals only serve their own hinterlands, fierce competition continues with rivals addressing the same hinterland. In other words, the demand is shared without any increase in potential cargo. Therefore, the transportation infrastructure and road/railway connection opportunities of private terminals, which are handicapped due to topographic reasons, need to be improved. In addition, solving the storage area problem, reducing the financial burdens on the terminals, and providing investment incentives to terminal operators can positively affect technical efficiency along with an increase in handling demand.

The differentiation of bulk solid and general cargo terminals among themselves draws attention as a critical downside of the study. Because of the nature of fuzzy DEA, similar decision units should be compared as much as possible. Although it is bulk, variability in the cargo type will result in more heterogeneity than handling standardized cargo. Therefore, the fuzzy cross-efficiency approach can be used for binary efficiency comparisons of general and bulk solid-liquid cargo terminals. Moreover, larger datasets pave the way for parametric stochastic approaches to evaluate efficiency.

In future studies, to fill the research gap of efficiency evaluations of liquid bulk, ro-ro terminals can be evaluated. The interval DEA model, which is stated to be more suitable for the complex structure of terminal operation processes than standard DEA, can yield new implications for efficiency and can be a guide for dry-bulk and general cargo terminal managers. Using the efficiency interval model, considering the production technology assumption of VRS in addition to CRS, we can draw inferences about scale efficiency. The interval efficiency approach can fill the gap in the relevant literature and contribute significantly to the literature for evaluating the efficiency of bulk solid and general cargo terminals when non-parametric methods are required in the case of imprecise data.

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References

[1] UNCTAD, *United Nations Conference on Trade and Development,* “Review of Maritime Transport”, 2022.

[2] TURKLIM, *Port Operators Association of Türkiye,* “Port Sector Report”, 2022.

[3] J. P. Rodrigue, and B. Slack, “The function of transport terminals”, The geography of Transport Systems, Hofstra University, New York, USA, 2013.

[4] M. Olaf, and T. Dank, “The Effectiveness of Port-City Policies; a comparative approach”, OECD Regional Development Working Papers, vol. 2013/25, 2013.

[5] B. Nicholson, “Supply chain management in the dry bulk shipping industry”, Thesis, Massachusetts Institute of Technology, Dept. of Mechanical Engineering, 2006.

[6] N. Kutin, T. T. Nguyen, and T. Vallée, “Relative efficiencies of ASEAN container ports based on data envelopment analysis”, *The Asian Journal of Shipping and Logistics,* vol. 33, pp. 67-77, 2017.

[7] R. Castellano, M. Ferretti, G. Musella, and M. Risitano. “Evaluating the economic and environmental efficiency of ports: Evidence from Italy”, *Journal of Cleaner Production,* vol. 271, pp. 122560, 2020.

[8] D. S. da Costa, M. V. G. S. de Assis Carvalho, N. M. de Figueiredo, H. B. de Moraes, and R. C. B. Ferreira, “The efficiency of container terminals in the northern region of Brazil,” *Utilities Policy,* vol. 72, pp. 101278, Oct 2021.

[9] G. Fancello, P. Serra, V. Aramu, and D. M. Vitiello, “Evaluating the efficiency of Mediterranean container ports using data envelopment analysis,” *Competition and Regulation in Network Industries,* vol. 22, pp. 163-188, Nov 2021.

[10] W.-K. K. Hsu, S.-H. S. Huang, and N. T. Huynh, “An assessment of operating efficiency for container terminals in a port - an empirical study in Kaohsiung Port using Data Envelopment Analysis,” *Research in Transportation Business & Management,* vol. 46, pp. 100823, Jan 2023.

[11] B. Wiegmans, and P. Witte, “Efficiency of inland waterway container terminals: Stochastic frontier and data envelopment analysis to analyse the capacity design- and throughput efficiency,” *Transportation Research Part A: Policy and Practice,* vol. 106, pp. 12-21, Dec 2017.

[12] S.-A. Julien, J. Cowie, and J. Monios, “Efficiency, productivity and returns to scale in ports: A comparison of data envelopment analysis and econometric estimation with application to Caribbean Small Island Developing States,” *Maritime Economics & Logistics,* vol. 22, pp. 239-264, 2020.

[13] OECD, “Efficiency of World Ports in Container and Bulk Cargo (oil, coal, ores and grain)”, OECD Regional Development Working Papers, 2012.

[14] G. Balci, I. B. Cetin, and S. Esmer, “An evaluation of competition and selection criteria between dry bulk terminals in Izmir,” *Journal of Transport Geography,* vol. 69, pp. 294-304, May 2018.

[15] K. R. Suliman, A. R. Suzari, T. Ramayah, and D. K. Degeras, “Measuring technical efficiency of dry bulk terminal performance using the frontier application of data envelopment analysis: a proposed framework,” *Journal of Physics: Conference Series,* vol. 1366, pp. 012100, 2019.

[16] E. Yüksekyıldız, and A. L. Tunçel, “Determining the relative efficiency of container terminals in Turkey using fuzzy data envelopment analysis.” *Marine Science and Technology Bulletin,* vol. 9, pp. 102-113, 2020.

[17] TURKLIM, Port Operators Association of Türkiye, “Port sector report”, 2018.

[18] TURKLIM, Port Operators Association of Türkiye, “Port sector report”, 2019.

[19] TURKLIM, Port Operators Association of Türkiye, “Port sector report”, 2020.

[20] TURKLIM, Port Operators Association of Türkiye, “Port sector report”, 2021.

[21] A. Charnes, W. W. Cooper, and E. Rhodes, “Measuring the efficiency of decision-making units”, *European Journal of Operational Research,* vol. 2, pp. 429-444, Nov 1978.

[22] M. J. Farrell, “The measurement of productive efficiency”, *Journal of the Royal Statistical Society. Series A (General),* vol. 120, pp. 253-290, 1957.

[23] R. Banker, A. Charnes, and W. W. Cooper, “Some models for estimating technical and scale inefficiencies in data envelopment analysis”, *Management Science,* vol. 30, pp. 1078-1092, Sep 1984.

[24] W. W. Cooper, L. M. Seiford, K. Tone, “Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software”, Second edition, January, pp. 1-490, 2000.

[25] S. Lertworasirikul, S. C. Fang, J. A. Joines, and H. L. W. Nuttle, “Fuzzy Data envelopment analysis (DEA): A possibility approach”, *Fuzzy Sets and Systems,* vol. 139, pp. 379-394, Oct 2003.

[26] P. Guo, and H. Tanaka, “Fuzzy DEA: A perceptual evaluation method”, *Fuzzy Sets and Systems,* vol. 119, pp. 149-160, Apr 2001.

[27] J. K. Sengupta, “A fuzzy systems approach in data envelopment analysis”, *Computers & Mathematics with Applications,* vol. 24, pp. 259-266, Oct-Nov 1992.

[28] K. Triantis, and O. Girod, “A mathematical programming approach for measuring technical efficiency in a fuzzy environment,” *Journal of Productivity Analysis* vol. 10, pp. 85-102, 1998.

[29] S. H. Kim, C. G. Park, and S. K. Park, “An application of data envelopment analysis in telephone offices evaluation with partial data”, *Computers & Operations Research,* vol. 26, pp. 59-72, Jan 1999.

[30] C. Kao, and S. T. Liu, “Fuzzy efficiency measures in data envelopment analysis”, *Fuzzy Sets and Systems,* vol. 113, pp. 427-437, Aug 2000.

[31] C. Kao, and S. T. A. Liu, “Mathematical programming approach to fuzzy efficiency ranking”, *International Journal of Production Economics,* vol. 86, pp. 145-154, Nov 2003.

[32] S. Saati, A. Memariani, and G. R. Jahanshahloo, “Efficiency analysis and ranking of DMUs with fuzzy data”, *Fuzzy Optimization and Decision Making, vol*. 1, pp. 255-267, 2002.

[33] T. Entani, Y. Maeda, and H. Tanaka, “Dual models of interval DEA and its extension to interval data”, *European Journal of Operational Research*, vol. 136, pp. 32-45, Jan 2002.

[34] Y. M. Wang, R. Greatbanks, and J.-B. Yang, “Interval efficiency assessment using data envelopment analysis”. *Fuzzy Sets and Systems,* vol. 153, pp. 347-370, Aug 2005.

[35] Y. M. Wang, J. B. Yang, and D. L. Xu, “A two-stage logarithmic goal programming method for generating weights from interval comparison matrices”, *Fuzzy Sets and Systems,* vol. 152, pp. 475-498, June 2005.

[36] N. Zhu, C. Zhu, and A. Emrouznejad, “A combined machine learning algorithms and DEA method for measuring and predicting the efficiency of Chinese manufacturing listed companies”, *Journal of Management Science and Engineering,* vol. 6, pp. 435-448, Dec 2021.

[37] H. J. Zimmermann, “Fuzzy set theory-and its applications”. *Science & Business Media,* pp. 541. 4th ed. LLC, Springer, New York, USA, 2011.

[38] K. Cullinane, D. W. Song, “Estimating the relative efficiency of European container ports: a stochastic frontier analysis”, *Research in Transportation Economics,* vol. 16, pp. 85-115, 2006.

[39] J. Jeh, J. Nam, M. Sim, Y. Kim, and Y. Shin, “A study on the efficiency analysis of global terminal operators based on the operation characteristics”, *Sustainability*, vol. 14, pp. 536, 2022.

[40] U. Madueke, *“Measuring and Benchmarking Efficiency and Productivity Levels of Liquid Bulk Terminal Operations Using a DEA AND OEE Approach”,* MSc in Maritime Economics and Logistics, Master Thesis, Erasmus University, Rotterdam, 2013.

[41] O. Arslan, O. H. Arıcan, A. U. Ünal, and M. Bamyacı, “Investigation of the effectiveness of maritime supervision services in ship solid bulk cargo handling operations,” *Social Sciences Studies Journal,* vol. 7, pp. 4905-4915, 2021.