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Optimizing the Allocation of Quay Cranes and Prime Movers for Container Handling Operations: A Data Envelopment Analysis Approach

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ABSTRACT

Congestion arises due to the significant influx of containers and ships from various global locations, primarily resulting from inadequate resource allocation or inaccurate resource configuration. This paper examines the optimal configuration of quay cranes and prime movers required for a vessel to complete unloading and loading operations efficiently. Through simulation, the model generates performance metrics such as the average container waiting time, the average utilization of quay cranes and prime movers separately, and the number of containers handled within an observed time interval. The efficiency of handling equipment configurations is evaluated using the Charnes-Cooper-Rhodes Data Envelopment Analysis (CCR DEA) model and the Bi-Objective Multi-Criteria Data Envelopment Analysis (BiO-MCDEA). The optimal handling equipment configuration is then determined using the super-efficiency of both models. The model includes quay crane number, prime mover number and average container waiting time as inputs and the other three simulation performance measures and Gross Moves Per Hour (GMPH) for quay cranes and prime movers as outputs. Three quay cranes with fifteen prime movers are the best unloading and loading configuration for super-efficiency CCR DEA. Alternatively, super-efficiency BiO-MCDEA recommends two quay cranes with eighteen prime movers. The obtained results provide valuable insights for decision-makers to enhance terminal productivity and optimize handling equipment efficiency.

1. Introduction

Functioning as integrated hubs, ports orchestrate vital linkages between land and sea transportation, facilitating the symbiotic interplay between the global supply chain and localized spheres of production and consumption. Specifically, container terminals, the demarcated areas within the port precinct emerge as pivotal arenas designed to streamline and optimize the seamless

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transfer of shipping containers and merchandise across diverse modes of transportation, be it maritime vessels, trucks, or trains. Remarkably, the extant literature, as explained by Hsu *et al.*, [1] illuminated the apparent void in scholarly investigations related to assessing of relative efficiency among container terminals, in contrast to the prevailing focus on port-level relative efficiency. Moreover, the scope of previous research is still limited in its investigation of operational efficiency in the container terminal environment. Since terminals need to handle and store containerized goods and materials in a timely manner, the need for efficient container management and the provision of corresponding equipment and facilities emerges as important dimensions that require deeper scrutiny to improve operational smoothness.

In light of the considerable expenses associated with port equipment and facilities, it is more economically advantageous to optimize the utilization of existing resources rather than investing in new equipment. Mokhtar [2] discovered that the efficiency of a container terminal resulted from efficient resource allocation regardless of terminal size. Moreover, efficient resource allocation contributes to environmental sustainability by reducing energy consumption and emissions associated with terminal operations. Thus, prioritizing the optimization of quay crane and prime mover allocation is essential for ensuring that specific resources are not over- or underutilized, maximizing operational efficiency, improving overall performance, and meeting the evolving demands of global supply chains. One strategy to increase resource engagement and efficiency is to regularly examine resource usage as well as develop opportunities to optimize the equipment utilized for operations. Port operations are inherently complex, involving a multitude of resources such as cranes, internal trucks, storage facilities, and personnel. Given this complexity, achieving an optimal configuration becomes imperative to ensure operational efficiency and avoid undue burdens. The ideal configuration includes the strategic allocation and utilization of resources in a way that minimizes bottlenecks, maximizes throughput, and lowers operational costs. By achieving the ideal configuration, port operators can mitigate potential challenges such as congestion, delays, and inefficient resource allocation. To determine the ideal configuration, the efficiency of all possible configurations must be assessed. Such efficiency evaluation can be accomplished using Data Envelopment Analysis (DEA).

Existing literature on the application of DEA to evaluate the efficiency of quay crane and prime mover allocation in container terminals typically concentrate on assessing overall port performance rather than specific resource allocation strategies [3]. While some studies apply DEA to analyse port performance, they primarily concentrate on broader operational aspects, such as productivity and effectiveness, without delving into the intricacies of quay crane and prime mover allocation [4]. Additionally, while DEA has been employed in port efficiency evaluation, there's a lack of research specifically targeting the allocation of quay cranes and prime movers, which are pivotal for terminal operations [5]. Therefore, a significant gap exists in the literature regarding the application of DEA to assess the efficiency of quay crane and prime mover allocation in container terminals. Addressing this gap could provide valuable insights into optimizing resource allocation strategies, enhancing operational efficiency, and ultimately improving the performance of container terminals.

In term of DEA models used in container terminal efficiency, most research used conventional DEA which include Charnes-Cooper-Rhodes DEA (CCR DEA) and Banker, Charnes and Cooper DEA (BCC DEA). Cullinane and Wang [6] are credited with being among the initial researcher to use DEA in container terminal studies. The findings indicated that BCC DEA yielded higher average efficiency estimates than CCR DEA. This difference can be attributed to the fact that the BCC DEA model assuming variable returns to scale assesses technical efficiency separately, while the CCR DEA model assuming Constant Returns to Scale (CRS) evaluates both technical and scale efficiency together. It suggests that the CCR DEA model typically has fewer efficient DMUs, and the DMUs that are efficient in CCR DEA are also efficient in BCC DEA. Rios and Maçada [7] argued that container terminals experienced variable returns to scale; the BCC DEA model was chosen to evaluate twenty-three container terminals in Brazil. Mokhtar [2] employed the CCR DEA and BCC DEA models to analyze six container terminals in Peninsular Malaysia and discovered that the resources were not being used to their full potential, resulting in inefficiency. As China is trying to catch up with the rapid growth in the shipping industry, CCR DEA and BCC DEA models were employed by Sheng and Kim [8] to construct an analysis from the input-oriented and output-oriented viewpoints.

Advanced methods are always used to overcome the shortcomings of conventional models. The lack of discriminating power among efficient DMUs is one of the weaknesses of the conventional models. Hence, super-efficiency has been established to rank efficient DMUs and identify the most efficient DMUs. By eliminating the assessed DMUs from the production possibility set, the super efficiency method increased the efficiency score of the efficient DMUs to greater than one [9]. Ghasemi *et al.*, [10] proposed a Bi-Objective Multi-Criteria DEA (BiO-MCDEA) model with two objectives in mind; to minimize the maximum deviation and sum of deviations. Essentially, the concept stems from analysing three objectives individually in the MCDEA model, which is then conducted concurrently in the Goal Programming DEA (GPDEA) model. Ghasemi *et al.*, [10] on the other hand, argued that the first objective can be ignored as it is equivalent to the standard CCR DEA model. The discovered model is superior in terms of discrimination power and weight dispersion. Furthermore, the fact that BiO-MCDEA requires less computational code makes this model easier to use for the analysis.

The port under investigation in this study is a port in Penang, Malaysia where the primary focus lies on container operations, and the central hub for these activities is the North Butterworth Container Terminal (NBCT). NBCT plays a vital role as a gateway port, enabling trade connections to the neighbouring hinterland, particularly in North Malaysia and Southern Thailand. As container trade continues to expand, the NBCT serves as a vital nexus, orchestrating the flow of goods and fostering economic connectivity across the region. Its architecture includes several berths on a wharf, with quay cranes for container loading and unloading and yard cranes for container stacking and unstacking in the storage yard. Instead of the previously mentioned cranes, the terminal also uses internal trucks for intra-terminal transport. There are two main classifications for internal trucks. One type, called a prime mover, is used to move containers between the yard and the berth. Another type, known as a terminal tractor, is used to move containers between the yard and transportation on the road or railway. Internal trucks facilitate smooth movement within the terminal, while quay and yard cranes ensure timely loading and unloading operations. In some modern ports, Automated Guided Vehicles (AGVs) are self-driving vehicles outfitted with navigation technology, allowing them to autonomously move containers within the terminal without human involvement. However, this capability is not present in the terminal under investigation.

Considering that the terminal analysed in this study relies on prime movers and currently lacks intentions to adopt more advanced transport technology in the foreseeable future, such as Automated Guided Vehicles (AGVs), it is imperative to conduct a configuration analysis to uphold productivity levels at a minimum. Most studies typically examine a single operation within a container terminal. However, this study specifically concentrates on the unloading and loading operations that impact the equipment needs of a vessel. Based on our current understanding, there is a lack of prior research utilizing DEA to assess the efficiency of quay cranes and prime mover configurations in both unloading and loading operations. This research demonstrates a notable enhancement in the efficiency of utilizing quay cranes and prime movers during container terminal loading and unloading operations, consequently offering port management additional options for resource management strategies. This study aims to determine the optimal number of quay cranes and prime movers required for efficiently unloading and loading a vessel carrying approximately one thousand containers. The proposed configurations include the allocation of quay cranes to unload and load the containers and prime movers to transport the containers between the quay and the yard. As this study intends to find the ideal equipment configurations, the CCR DEA model is sufficient to get several efficient DMUs for further ranking by super-efficiency DEA. Furthermore, BiO-MCDEA was suggested as the second method in comparison to the conventional approach since it is commonly used in power discrimination methods to limit the number of efficient DMUs for the second opinion of quay cranes and prime movers' configuration. A CCR DEA and BiO-MCDEA are utilized to evaluate the handling equipment configurations and discriminate between inefficient and efficient configurations. In order to rank the efficient configurations of the previous results, the super-efficiency of both CCR DEA and BiO-MCDEA are applied.

The rest of the paper is organized as follows. Simulation results, operations flow as well as data selection and its description are explained in Section 2. A theoretical framework for the CCR DEA and BiO-MCDEA models is described in Section 3, and super efficiency for both models is also discussed for the purpose of ranking. The empirical findings for both models and interpretations are presented in Section 4, and the summary and recommendations for further study are provided in Section 5.

2. Operations Description, Simulation, and Input and Output Measures

2.1 Operations at the Seaside Subsystem

Both unloading and loading operations happened in the seaside subsystem area using quay cranes. Container unloading from a vessel commences if at least one empty prime mover is waiting at the berth where the vessel is anchored. The containers also form a queue at the berth, waiting to be transferred from the berth to storage yard. Since the unloading operation is prioritized in this study, a prime mover's complete trip is the time it takes to transport the container from the berth to the storage yard and return to the berth. Following complete container unloading from the vessel, loading begins. The prime mover returns to the yard once the last container has been unloaded from the vessel. The time taken by a prime mover from the yard to the berth and back to the yard is considered the complete trip for the loading operation.

The vessel's operation was originally separated into three sections, each with its own quay crane, named Q1, Q2, and Q3 with eight prime movers allocated to support each quay crane. Depending on the workload that has been assigned, each quay crane behaves differently. This study investigates variations in the number of quay cranes deployed in container terminal operations, focusing on configurations featuring either two or three quay cranes. For the alternatives of two quay cranes used, the selection is between these three operated quay cranes. The behavior of each quay crane is closely observed, considering the overall workload assigned to each crane. Table 1 provides a breakdown of the workload distribution, delineating the number of containers handled in different terminal sections. While it's evident that the joint operation of quay cranes Q1 and Q2 lacks the logical capacity to lift 1,000 containers, this analysis solely focuses on the performance of the quay crane operation. On the other hand, Table 2 outlines the specific quay cranes selected for our in-depth analysis. These tables serve as essential reference points for the comprehensive assessment of quay crane configurations, offering valuable insights to understand how changes in the number of quay cranes and their workloads can impact operational efficiency and performance in container terminal settings.

Table 1
Workload on vessel based on quay crane

Quay crane	Number of handled containers	Percent
Q1	289	28.22
Q2	350	34.18
Q3	385	37.60

Table 2
Selection of QC

Reference	Q1	Q2	Q3
1	/	/	
2	/		/
3		/	/
4	/	/	/

2.2 Simulation Results

In the development of simulation model, Figure 1 illustrates the first step which involves setting the parameters that define the configuration of quay cranes and prime movers. The higher number of replications produce more accurate results. Since the simulation results produced by using the student version of Arena Simulation Software, the highest possible number of replications is 30. Following this setup, the model is subjected to thorough evaluation through 30 replications spanning a 22-hour period. This timeframe is determined by the period between the arrival and departure times of the vessel, taking into account potential delays during container loading and unloading operations, ensuring a comprehensive assessment of operational scenarios. Throughout the simulation runs, various performance metrics are analysed to gauge the effectiveness of the model. These metrics include the average waiting time experienced by containers, the utilization rates of quay cranes and prime movers, and the overall volume of containers handled within the specified timeframe. By analysing these metrics, researchers can derive valuable insights into the efficiency and efficacy of simulated terminal operations, thus aiding informed decision-making and optimization strategies in port management and logistics planning.

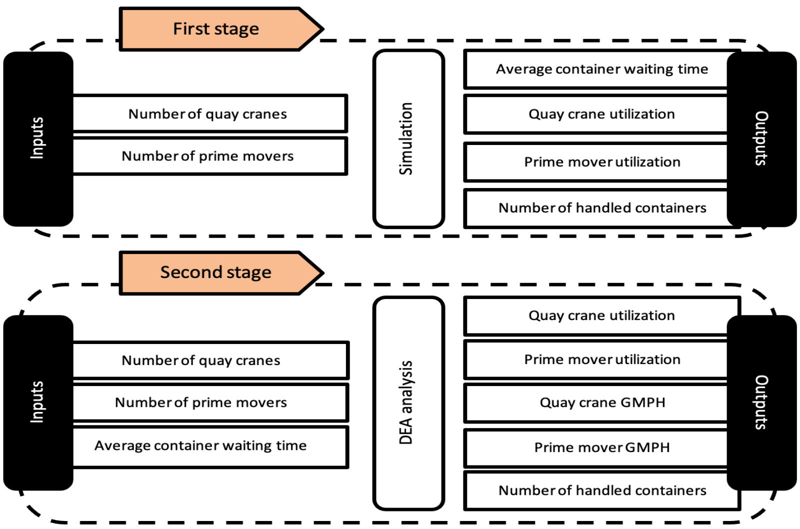

Fig. 1. Inputs and outputs for simulation and DEA analysis

In order to validate the simulation findings, the results obtained from the simulation are carefully compared with empirical data, and conformity is assured within a 10% predetermined margin of error. Following that, a port operations expert performs a comprehensive validation of the outcomes. This careful examination seeks to determine the accuracy and reliability of the simulated results by leveraging the expert's subject expertise and judgment in port operations. Any differences between the simulated and real data can be found and fixed using this repeated validation process, which improves the simulation model's realistic and robustness. This method emphasizes how important expert validation is for supporting the validity and relevance of simulation results in the field of port operations research. Following the simulation findings, an efficiency analysis utilizing the DEA method was conducted.

2.3 Specification of Input and Output Variables

In the initial stage depicted in Figure 1, only two inputs are utilized, resulting in the generation of four outputs. Then, in the second stage, eight variables are included in this study, consisting of three inputs and five outputs. The equipment configurations, which include the number of quay cranes and prime movers, are employed as independent inputs, while the average container waiting time generated by the simulation run is the third input. The outputs are the quay crane utilization, the prime mover utilization, the Gross Moves Per Hour (GMPH) for the quay crane, the GMPH for the prime mover and the number of handled containers. The GMPH is computed based on the analysis from the first stage for both the quay crane and prime mover, contributing to a total of five outputs in the second stage. The formula of GMPH for quay crane and prime mover are as Eq. (1) and Eq. (2).

$$GMPH\ (Quay\ Crane) = \frac{Number\ of\ handled\ containers}{Number\ of\ quay\ cranes \times Total\ working\ hours} \tag{1}$$

$$GMPH\ (Prime\ Mover) = \frac{Number\ of\ handled\ containers}{Number\ of\ prime\ movers \times Total\ working\ hours} \tag{2}$$

Container handling equipment such as cranes is commonly used to evaluate port and container terminal efficiency. The efficient operations in a port or terminal are driven by the efficiency of handling equipment, and the quantity of equipment engaged is regarded as a very reliable measure of the efficiency of the container terminal. Since stacking and unstacking operations at the yard were not included in this study’s scope of operations, only the number of quay cranes and prime movers is taken into consideration. The number of quay cranes is typically considered to evaluate both the port and the terminal by previous studies [8,11-16]. Pjevčević *et al.*, [17] stressed that the number of cranes directly increases the efficiency and flexibility, allowing the port to work with more vessels simultaneously. Meanwhile, the number of prime movers or trucks is mostly discovered in determining the efficiency of a container terminal [18-20]. Some studies include time or duration as input, such as duration of cargo handling operations [21], service time [19], working time [13,22], and delay time for loading and unloading [23]. This study, however, intends to employ average container waiting time as the third input.

The first and second outputs are related to equipment utilization, the process of strategically determining how effective equipment is, and the utilization is measured as a percentage of the amount of time productively used out of all available time. Regarding performance, it suggests how efficiently equipment is used. When discussing the efficiency of container terminals and port operations, GMPH is often cited as a key performance statistic. It evaluates how quickly and easily containers can be moved using quay cranes and prime movers. A higher GMPH indicates that containers are being loaded and unloaded efficiently from ships. Prime movers with high GMPH are moving containers quickly and efficiently, which benefits both the terminal's operations and the customers' experience. Instead of the usual output of container throughput, this study focuses on number of handled containers as one of the outputs. Due to its relationship to the quay cranes and prime movers that count the number of containers transported, the number of containers is observed throughout a selected period of time. In Table 3, the study's inputs and outputs were collected from the simulation results, as well as the quay crane selection when only two quay cranes were included in the analysis. The sample size used complies with the DEA's minimum sample size requirement of three times the number of inputs and outputs. The current practice is referred to as DMU 22.

Table 3
Inputs and outputs from simulated scenarios

DMU	(Number of quay cranes, Reference of selected quay cranes, Number of prime movers per quay crane)	Average container waiting time (min)	Average utilization of quay crane (%)	Average utilization of prime mover (%)	GMPH of quay crane	GMPH of prime mover	Number of handled containers
1	(2, 1, 7)	5.1168	89.58	82.4	20.61	2.94	907
2	(2, 1, 8)	4.7349	90.86	74.9	20.84	2.61	917
3	(2, 1, 9)	4.7416	90.47	66.48	20.80	2.31	915
4	(2, 1, 10)	4.6933	91.85	60.71	21.05	2.10	926
5	(2, 1, 11)	4.6758	91.46	54.81	20.89	1.90	919
6	(2, 1, 12)	4.4229	90.79	50.02	20.91	1.74	920
7	(2, 2, 7)	5.1496	83.84	79.4	20.16	2.88	887
8	(2, 2, 8)	4.5073	85.8	73.19	20.50	2.56	902
9	(2, 2, 9)	4.4001	85.15	64.77	20.41	2.27	898
10	(2, 2, 10)	4.4119	85.52	58.76	20.43	2.04	899
11	(2, 2, 11)	4.0434	85.89	54.02	20.68	1.88	910
12	(2, 2, 12)	4.2052	85.81	49.15	20.55	1.71	904
13	(2, 3, 7)	3.587	84.96	87.3	21.86	3.12	962
14	(2, 3, 8)	2.9234	86.95	78.77	22.27	2.78	980
15	(2, 3, 9)	2.57	86.89	70.59	22.25	2.47	979
16	(2, 3, 10)	2.8411	86.69	63.53	22.20	2.22	977
17	(2, 3, 11)	2.6925	87.41	57.67	22.39	2.04	985
18	(2, 3, 12)	2.472	87.53	53.05	22.48	1.87	989
19	(3, 4, 5)	3.6259	61.65	83.49	14.97	2.99	988
20	(3, 4, 6)	1.6077	64.04	72.15	15.41	2.57	1017
21	(3, 4, 7)	1.0345	63.75	62.06	15.42	2.20	1018
22	(3, 4, 8)	0.9934	64.34	55.16	15.47	1.93	1021
23	(3, 4, 9)	0.94	64.49	48.5	15.47	1.72	1021
24	(3, 4, 10)	0.8791	64.05	43.69	15.41	1.54	1017
25	(3, 4, 11)	0.9368	64.1	39.77	15.42	1.40	1018
26	(3, 4, 12)	0.9471	64.39	36.47	15.45	1.29	1020

3. DEA Models

According to the data presented in Table 3, there was no significant difference in the average waiting time for containers among the different alternatives. The time is measured in minutes, which is a small unit for the entirety of the operations. The most suitable scenario for unloading and loading operations also could not be determined due to the underutilization of quay cranes and prime movers demonstrated for a higher number of containers handled. For that reason, this study used DEA methodology to evaluate the efficiency of proposed alternatives and to suggest their rank taking the measurements from the simulation results. Twenty-six scenarios for containers unloading and loading operations, mentioned as DMUs, were evaluated in this study. The objective is to transfer all the containers within a provided time interval while minimizing the containers' waiting time. Hence, an efficient scenario of the configuration of quay cranes and prime movers is required to maximize the number of handled containers and utilization of equipment and to minimize the number of containers in a queue during the observed time interval. Subsequently, Figure 2 displays the steps of this study.

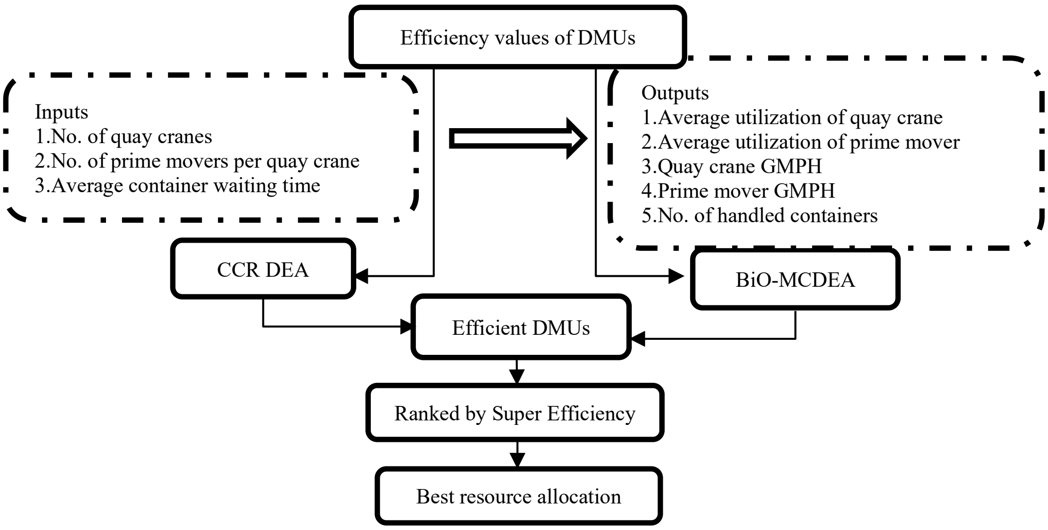

Fig. 2. Flowchart of Methodology

The assessment of handling equipment configurations within this study relies on two prominent analytical models: CCR DEA and BiO-MCDEA. By employing these models, the research aims to comprehensively evaluate the configurations, emphasizing efficiency as the central criterion. The selected handling equipment configurations encompass various inputs, including the number of quay cranes, the number of prime movers, and the average container waiting time, which are crucial in port operations. Additionally, the study incorporates multiple performance measures from simulations, along with GMPH for both quay cranes and prime movers as key output indicators. The super efficiency of CCR DEA and BiO-MCDEA models facilitates a robust analysis, culminating in identifying the most efficient handling equipment configuration. This approach not only ensures an objective and data-driven decision-making process but also holds the potential to enhance the operational efficiency and competitiveness of the container terminal.

3.1 CCR DEA Model

CCR DEA model is the most basic DEA model and is significantly used in evaluating operations in the port industry. Charnes *et al.*, [24] developed DEA to quantify the efficiency of Decision-Making Units (DMUs) based on input and output variables. To be efficient in DEA analysis, a DMU must combine available inputs to attain a higher output level or minimize inputs for a specified output level. Among other DEA models, the two most extensively used DEA models, CCR DEA as well as BCC DEA, deserve special attention, especially as one of the models is used later in this study. CCR DEA is mostly utilized in the evaluation of the efficiency of container terminals, either as the main method of the study or to be compared with another conventional method or cutting-edge DEA approach. Its simplicity, ease of implementation, and interpretability are the reasons for its adoption over the other approaches of container terminals efficiency evaluation. It provides efficiency scores for individual container terminals, identifies efficient benchmarks, and highlights areas for potential improvement. The CCR DEA model assumes CRS, meaning that the input-output relationships are linear and do not exhibit economies of scale or diseconomies of scale. Alternatively, it enables any observed production combinations to be proportionally scaled up or down [6].

In this study, DMUs are the scenarios generated from the simulation results. Due to the objective of this study to find the efficient configuration of quay cranes and prime movers for a vessel, this study uses the input-oriented CCR DEA. It determines the efficiency scores by constructing an efficiency frontier that envelops the efficient container terminals. The Eqs. (3) –(6) provide the input-oriented CCR DEA model of the assessed DMU, k.

$$Max\ \theta_k = \sum_{r=1}^{s} u_r y_{rk} \tag{3}$$

subject to

$$\sum_{i=1}^{m} v_i x_{ik} = 1 \tag{4}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0\ ,\ j = 1,\ldots,n \tag{5}$$

$$u_r, v_i \geq 0 \tag{6}$$

Here, θ_k is the efficiency score of the assessed DMU, s is the number of outputs, u_r is the weight of output r, y_{rk} is the value of output r that belongs to the assessed DMU, which is DMU_k, m is the number of inputs, v_i is the weight of input i, x_{ik} is the value of input i that belongs to the assessed DMU, y_{rj} and x_{ij} are the respective amounts of *r*th output produced and *i*th input consumed by the decision making unit DMU_j, while j represents each DMU with up to n number of DMUs involved.

Notably, the values of u_r and v_i stand for unknowns, and the weights are determined through a linear programming optimization process. These weights represent the relative importance or efficiency of each input and output variable for each DMU. The goal is to find the optimal set of weights that maximizes the efficiency of each DMU while satisfying certain constraints. Various methods, such as weight restriction approaches or solving linear programming models, are utilized to determine a common set of weights for all DMUs or individual sets of weights for each DMU. Ultimately, the weights are adjusted iteratively until the efficiency scores of all DMUs are maximized. [25-26].

3.2 BiO-MCDEA Model

This model was introduced by Ghasemi *et al.*, [10] and has been used in this study to find the efficient configurations of quay cranes and prime movers to be compared with the results of the CCR DEA model. The model of BiO-MCDEA is indicated by the equations as follows:

$$Min\ h\ =\ w_2 M + w_3 \sum_j d_j \tag{7}$$

subject to (4), followed by

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \quad j = 1,\ldots,n \tag{8}$$

$$M\ -\ d_j \geq 0, \quad j = 1,\ldots,n \tag{9}$$

$$u_r \geq \varepsilon,\ r = 1,\ldots,s \tag{10}$$

$$v_i \geq \varepsilon, \qquad i = 1,\ldots,m \tag{11}$$

$$d_j \geq 0,\ j = 1,\ldots,n \tag{12}$$

Here, h is the efficiency score of the inefficient DMUs. Thus, in finding the efficiency score for a DMU, a method of $1 - d_j$ is used. Note that M is the maximum quantity for all variable d_j, where d_j is the deviation variable of DMU_j. The analysis used has equal priority for both objectives, so $w_2 = w_3 = 0.5$ and ε is set to be 0.0001.

3.3 Super Efficiency Model

In extension, to determine the ranking among efficient configurations, the super-efficiency model is then applied. Super-efficiency of CCR DEA and BiO-MCDEA can be achieved by simply redoing the analysis for the efficient DMUs. However, only the assessed efficient DMU of the constraints (5) and (8) must be eliminated for the run; others should be retained. Additionally, the objective function of BiO-MCDEA is changed to CCR's objective function. The following suggests the change in CCR and BiO-MCDEA formulas for the super-efficiency approach given in Eq. (13) and Eq. (14).

3.3.1 Super efficiency CCR DEA model

$$Max\ \theta_k = \sum_{r=1}^{s} u_r y_{rk} \tag{3}$$

subject to (4), followed by

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0\ ,\ j = 1, \ldots, n, j \neq k \tag{13}$$

and bounded by (6).

3.3.2 Super efficiency BiO-MCDEA model

$$Max\ \theta_k = \sum_{r=1}^{s} u_r y_{rk} \tag{3}$$

subject to (4), followed by

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \qquad j = 1,\ldots,n, j \neq k \tag{14}$$

and bounded by (9), (10), (11) and (12).

4. Results and Discussion

This section presents and analyses the results of the relative efficiency of all proposed configurations. Efficiency analysis is able to reflect the level of service operations' efficiency and the productivity of a container terminal. The efficiency score measurements for each of the twenty-six DMUs were evaluated using input-oriented CCR DEA and BiO-MCDEA models. Analysis of proposed configurations was evaluated using LINGO software version 14 for both models. Subsequently, the super efficiency model was used to improve the results of the efficiency decisions to determine the better resource configuration by ranking the efficient DMUs for both models. The current practice in the studied container terminal utilized three quay cranes and twenty-four prime movers to handle approximately one thousand containers, with each quay crane requiring eight prime movers.

Quay crane productivity is a significant indicator of overall terminal productivity and is quantified by the hourly number of moves. A single move refers to the transfer of containers between a vessel and a transport vehicle. According to Bartošek and Marek [27], practically all terminals can reach maximum productivity of 70% to 80% of the estimated number. They revealed that the failure of quay cranes to attain technically possible productivity is related to operational disturbances, resulting in reduced productivity. In this study, the number of quay cranes used for a vessel is either two or three. As provided in Table 3, the average utilization of two quay cranes reaches 80% and higher, whereas the average utilization of three quay cranes falls around 60%. Table 3 indicates that the lifting capacity of two quay cranes is below 1,000 containers. Q2 and Q3 handle approximately 1,000 containers on average, making them the optimal choice for situations with limited availability of quay cranes. Except for the use of five prime movers per quay crane, three quay cranes are capable of lifting over 1,000 containers. The total number of prime movers involved in the operations is multiplied by two or three, depending on the number of quay cranes, as the prime movers are evenly distributed among them. Hence, increasing the number of prime movers by one results in a substantial percentage variation in average prime mover utilization. Clearly, the lower the percentage of utilization, the greater the number of prime movers used. In terms of average container waiting time, DMU 7 experiences the longest waiting time, while the configuration of 3 quay cranes with 10 prime movers for each quay crane results in the shortest waiting time. The difference among average container waiting times for the same cluster of quay cranes number was significant, specifically the involvement of Q3. Average waiting time differed among the cluster of two quay cranes in the range from 2.472 minutes to 5.1496 minutes. Meanwhile, for the cluster of three quay cranes ranged from 0.8791 minutes to 3.6259 minutes. Based on Table 3, DMU 22, which is the current practice and DMU 23 were the options for handling the highest number of containers. The lack of a clearly dominant configuration in terms of equipment utilization, average container waiting time, and number of containers handled necessitates the application of DEA to determine the most efficient DMU.

Table 4 illustrates the efficiency scores obtained using the input-oriented CCR DEA, BiO-MCDEA, and super-efficiency models for twenty-six DMUs. DMU 22 is the current practice in a studied container terminal, while the rest are proposed equipment configurations for the improvement. As displayed in Table 4, there are fourteen efficient DMUs using CCR DEA, which accounts for 54% of the total configurations. When half of the DMUs have a perfect score, performing an in-depth analysis of port efficiency becomes more challenging. The super-efficiency approach helps ranking the efficient DMUs and find the most optimal configuration. Among the fourteen configurations, the DMU with the highest super-efficiency value is DMU 19. Although DMU 19 has a limited capacity of handling only 988 containers, it is considered the most efficient equipment configuration. This alternative proposes the reduction of three prime movers per quay crane, which equals the reduction of nine prime movers for a vessel, while maintaining the current practice of three quay cranes for a vessel. It summarizes that for around 1,000 containers of loading and unloading operations, only three quay cranes and fifteen prime movers are needed within the observed working time. The number of prime movers required for the operations is lower compared to the current practice.

Table 4
Efficiency scores of CCR and BiO-MCDEA models

DMU	(Number of quay cranes, Reference of selected quay cranes, Number of prime movers per quay crane)	CCR DEA	Super efficiency CCR DEA	Super efficiency CCR DEA rank	BiO-MCDEA	Super efficiency BiO-MCDEA	Super efficiency BiO-MCDEA rank
1	(2, 1, 7)	1	1.054379	6	0.7903562		-
2	(2, 1, 8)	1	1.010236	10	0.8014263		-
3	(2, 1, 9)	0.9926298		-	0.7777087		-
4	(2, 1, 10)	1	1.007171	11	0.7693618		-
5	(2, 1, 11)	1	1.001014	14	0.7451716		-
6	(2, 1, 12)	0.9941513		-	0.7410512		-
7	(2, 2, 7)	0.9687114		-	0.7705205		-
8	(2, 2, 8)	0.9686847		-	0.802602		-
9	(2, 2, 9)	0.9603324		-	0.7838104		-
10	(2, 2, 10)	0.9653497		-	0.7630842		-
11	(2, 2, 11)	0.9634334		-	0.7739656		-
12	(2, 2, 12)	0.9623177		-	0.7398661		-
13	(2, 3, 7)	1	1.149279	3	0.9533422		-
14	(2, 3, 8)	1	1.030046	9	1	1.029099	2
15	(2, 3, 9)	1	1.050068	7	1	1.047768	1
16	(2, 3, 10)	0.9931221		-	0.92172799		-
17	(2, 3, 11)	0.9995455		-	0.8745004		-
18	(2, 3, 12)	1	1.037935	8	0.8470896		-
19	(3, 4, 5)	1	1.355436	1	0.6837135		-
20	(3, 4, 6)	1	1.147329	4	0.6912203		-
21	(3, 4, 7)	1	1.155578	2	0.6902503		-
22	(3, 4, 8)	1	1.001460	13	0.6909916		-
23	(3, 4, 9)	1	1.003363	12	0.6897248		-
24	(3, 4, 10)	1	1.065029	5	0.6881068		-
25	(3, 4, 11)	0.9917049		-	0.6866824		-
26	(3, 4, 12)	0.9920118		-	0.6860205		-

In contrast to the CCR DEA approach, the BiO-MCDEA exhibited large value changes for comparisons between identical configurations. It was more challenging for a DMU to be regarded as efficient in the BiO-MCDEA than in the conventional DEA due to the discrimination power of the former method. Consequently, the relative efficiency scores of all DMUs except for DMUs 14 and 15 were all lower than in the results of the CCR DEA model, as summarized in Table 4. Both DMU 14 and DMU 15 utilized two quay cranes, with DMU 14 employing 16 prime movers and DMU 15 utilizing 18 prime movers. Despite the fact that this model revealed that just two DMUs are efficient, it was essential to establish which of these efficient DMUs was the most efficient. The method of super-efficiency was employed once more in order to rank these efficient DMUs. With the highest super-efficiency value of 1.047768, DMU 15 was identified as the most efficient. DMU 15 recommends that merely two quay cranes be employed, with an additional prime mover required for each quay crane compared to the current practice. The limited use of only two quay cranes continues to result in a reduced number of prime movers for the operations. Instead of twenty-four prime movers, nine are required for each quay crane, resulting in 18 prime movers. Interestingly, all proposed configurations involving three quay cranes exhibit inefficient values of below 0.7, which is contributed by the underutilization of quay cranes and prime movers.

The higher the rate, the more a terminal is using its available equipment, which is beneficial to productivity. A capacity utilization rate ranging from 85% to 100% is generally deemed suitable for economic and business operations [28]. To ensure efficient resource utilization and prevent excessive equipment usage, it is recommended to maintain a rate of approximately 80%. It can be observed in Table 3 that DMU 15 averagely used the quay cranes up to 86.89%. Meanwhile, each prime mover has been used up to 70.59% on average. The utilization rate of the three quay cranes for DMU 19 was approximately 61.65%, indicating that the terminal operated below its maximum capacity due to underutilization of this equipment. However, the fifteen prime movers were utilized efficiently, with an average utilization rate of 83.49%. Insufficient resource utilization can be attributed to excessive allocation of resources to loading and unloading operations or the presence of pending operations, both of which hinder the berthing of incoming ships. Extended waiting periods adversely affect the efficiency of port terminals [29]. Suppose any of these situations occur during peak hours. In that case, it will lead to delays in unloading and loading operations, inadequate resources for simultaneous operations of multiple vessels, missed vessel processing schedules, and increased costs.

A smaller quantity of equipment indicates more efficient utilization. The BiO-MCDEA model proposes a reduction of six prime movers, whereas the CCR DEA model necessitates a reduction of nine prime movers. The prime mover utilization rate for the efficient DMU in CCR DEA was 83.49%, whereas the efficient DMU in BiO-MCDEA was approximately 70.59%. Moreover, the BiO-MCDEA model suggests the utilization of two quay cranes, while the CCR DEA model necessitates the use of three quay cranes. Using two quay cranes is more advantageous in terms of utilization, as it results in a higher utilization rate of 86.89% compared to the utilization rate of three quay cranes, which is 61.65%. The CCR DEA results indicate that DMU of prime movers with lower number and resource consumption are the most efficient. BiO-MCDEA suggests the optimal choice for quay cranes. The employment of 18 prime movers was more efficient than the fleet of 16 prime movers, with efficiencies of 104.67% and 102.91% respectively. However, the difference in efficiencies between the two was minimal. The data suggests that the system's performance is not significantly affected by having either 18 or 16 prime movers in the fleet. However, improving the fleet to include 15 prime movers will greatly enhance the system's efficiency. If port management intends to retain the restriction of allowing only eight prime movers per operating quay crane at the container terminal, the optimal choice would be to employ three quay cranes, each equipped with five prime movers. Despite the same number of quay cranes used, the number of prime movers per quay crane is reduced, with a total usage of fifteen prime movers. Port management must exercise caution when dealing with a reduced number of equipment, as this can lead to operational delays and the potential for missed timeframes. Such delays can result in congestion for incoming vessels in the quay area.

Both models propose reducing the number of prime movers, as depicted in Table 5. CCR DEA proposes fifteen prime movers, while BiO-MCDEA suggests eighteen. BiO-MCDEA model suggests reducing the number of quay cranes from three to two, in contrast to CCR, which maintains the current practice of using three quay cranes. CCR DEA achieved a 37.5% improvement in the utilization of prime movers compared to the existing practice. Alternative by BiO-MCDEA demonstrated a 33.3% improvement in the number of quay cranes used and a 25% improvement in the number of prime movers used compared to the current practice. Although the current practice effectively handles a larger volume of containers and reduces wait times compared to other alternatives, there is still a noticeable waste of resources in using quay cranes and prime movers.

Table 5
Improvement in the number of quay cranes and prime movers

	Number of quay cranes	Number of prime movers	Average container waiting time	Quay cranes' utilization	Prime movers' utilization	Number of handled containers	Percent improved (%)	
							Quay cranes	Prime movers
Current practice	3	24	0.9934	64.34	55.16	1021	-	-
SE CCR results	3	15	3.6259	61.65	83.49	988	-	37.5
SE BiO-MCDEA results	2	18	2.57	86.89	70.59	979	33.3%	25%

Since prime movers or trucks are usually rented from a third party [30], there are concerns about maintenance. Ensuring proper upkeep becomes challenging since the responsibility lies with the rental provider. Additionally, the reliability of these rented vehicles can vary, leading to potential breakdowns that disrupt port operations. Coordinating their movements with other port activities is also a challenge when there is poor communication between the rental provider and the port. Ports may have limited control over the scheduling and availability of rented prime movers, causing delays in cargo handling. Lastly, relying on third-party rentals may bring unpredictable costs due to unexpected fees, rate fluctuations, or additional maintenance charges, creating financial challenges for the port. Hence, the reorganization of equipment allocation at the port greatly helped to reduce potential issues related to the operation of leased prime movers in a port setting.

Both the port operator and shipping companies derive advantages from an upsurge in container handling. However, it is incumbent upon the port operator to oversee the efficiency of their equipment. Excessive equipment and suboptimal utilization result in financial waste. For better utilization of equipment, it is necessary to have a minimum of two quay cranes and nine prime movers per quay crane. Since this option has a shorter average container wait time, it may accommodate a larger volume of containers. However, to efficiently handle approximately one thousand containers within an observed period, three quay cranes and five prime movers per quay crane are required. The achievement of this goal is contingent upon the presence of pre-existing quay cranes. Otherwise, the procurement of new equipment will lead to increased operational expenses. These two options might be considered by the port operator when allocating the appropriate number of prime movers and cranes to maximize a vessel's operational efficiency.

5. Conclusion

The container terminal is recognized as a highly active and congested facility within a port. Efficient and sufficient container handling equipment, such as quay cranes and prime movers, is necessary for the proper functioning of the seaside subsystem in a port. Insufficient or excessive resource allocation can result in common problems such as slower operations, resource waste, delays, longer waiting times, and increased operational costs. These potential problems may lead shipping companies to choose more efficient nearby ports, resulting in financial losses for the affected port. Port operators should aim to optimize resource utilization, monitor resource availability, and evaluate resource utilization to improve efficiency and maintain or enhance terminal performance. Optimizing the operational performance of container terminals is a practical approach to enhancing the overall efficiency of ports.

After analysing the simulation results of twenty-six configurations of quay cranes and prime movers, several noteworthy observations emerge from comparing the highest number of handled containers of current practices of DMU 22 and DMU 23 in container terminal operations. Despite DMU 22 handling a similar volume of containers as DMU 23, it experiences a slightly longer average waiting time. However, DMU 22 demonstrates better performance in terms of prime mover quantity and utilization. Notably, an assessment of quay crane and prime mover utilization reveals inefficiencies and potential resource wastage in both options. Determining the optimal choice for operations management solely based on simulation results is challenging, highlighting the necessity for further investigation into resource optimization. Conducting efficiency analysis through DEA is essential to ascertain the most effective option.

In the DEA approach, inputs used were the number of quay cranes, the number of prime movers that established the configuration of each DMU, and the average container waiting time from the simulation. Meanwhile, the outputs used were the average utilization of quay cranes, the average utilization of prime movers and the number of handled containers. To identify the efficient configuration using efficiency scores, a comparison between conventional DEA model such as CCR and advanced DEA model such as BiO-MCDEA was proposed. The initial results suggest that thirteen DMUs were efficient for the CCR model, making it difficult to determine which configuration can be adopted for the operation. The super-efficiency DEA model then ranked the configuration of quay cranes and prime movers. The super-efficiency model enhances the results and reveals that the configuration of three quay cranes with fifteen prime movers is the most efficient. Although the super-efficiency of CCR succeeds in ranking all the efficient configurations, the BiO-MCDEA model has better power of discrimination and is able to reduce a large number of efficient configurations to just two; the final rank is totally different from the super efficiency of CCR results. Instead of three quay cranes, this model suggested two quay cranes with only eighteen prime movers.

Customized handling equipment allocation approaches developed to optimize equipment utilization, enhance productivity, and improve overall operational efficiency. Handling equipment allocation strategies may vary based on the specific characteristics and requirements of each container terminal. Efficient allocation of handling equipment, such as cranes and prime movers, is essential for maximizing equipment utilization and productivity. Studies emphasize the importance of matching equipment capacity with operational demands and optimizing equipment allocation to minimize idle time and maximize throughput. Since this study compared two DEA models results which in terms of quay crane utilization, BiO-MCDEA suggests a lower number. Meanwhile in terms of prime mover utilization, CCR DEA suggests a lower number. Both alternatives propose reducing the use of prime movers, which is worth noting. Reflectively, the findings will be able to assist the management in choosing the best configuration of unloading and loading operations subjected to the availability of the equipment. Future research can explore extensions to the proposed approach. (i) The operations encompass container stacking and unstacking at yard storage. (ii) A larger illustration involving concurrent unloading and loading activities for multiple vessels would yield more precise equipment counts. (iii) Expanding the analysis to include cost would offer additional insights into the observed process.

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