Selecting Suitable, Green Port Crane Equipment for International Commercial Ports

Guo-Ya Gan [1], Hsuan-Shih Lee [2, 3*] ,Tao Yu-Jwo [2] , Tu Chang-Shu [4, *]

1. College of Auditing and Evaluation, Nanjing Audit University, Nanjing, Jiangsu 211815, China. ganguoya@foxmail.com
2. Department of Shipping and Transportation Management, National Taiwan Ocean University, Keelung 20224, Taiwan. hslee@email.ntou.edu.tw; ta794260@gmail.com
3. Department of Information Management, Ming Chuan University, Taipei 11103, Taiwan.
4. Department of Information Management, Chang Gung University, Taiwan, ROC
   259 Wen-Hwa 1st Road, Kwei-Shan Tao-Yuan, Taiwan, 33333, R.O.C.

*Correspondence: long.tree@msa.hinet.net; Tel: +886927351833

Abstract: Proposed as a response to the increasing global need for environmental protection, a green port balances economic vibrancy and environmental protection. However, because exhaust emissions (e.g., CO_2 or sulfide) are difficult to monitor in and around ports, data on such emissions are often incomplete, which hinders research on this topic. To remedy this problem, this study aimed to formulate a method for collecting CO_2 emissions data at their source; this method was applied to collect real-world operating data from a large container-handling company in Taiwan. Specifically, to account for undesirable outputs, we formulated a method that combines (1) data envelopment analysis based on a modified slack-based measure and (2) a multichoice goal programming approach. We found that rubber-tired gantry cranes are the greenest and should be used. Our findings aid port managers in selecting port equipment that best balances between environmental protection and profitability.

Keywords: green performance; sustainable development; port equipment; CO_2 emission; data envelopment analysis (DEA); multichoice goal programming.

1. Introduction

Environmental degradation and resource overconsumption are serious global problems, and sustainable development benefits a country (and its economy). Human activity is responsible for both environmental protection and environmentally damaging economic growth. Correspondingly, although a country's natural resources (e.g., air, water, soil, and mineral resources) enable its development; their overexploitation is bound to backfire eventually, leaving future generations to pick up the pieces of environmental problems, such as wildlife extinction and natural resource depletion.

Human overreliance on fossil fuels has resulted in climate change, which is disruptive at best and destructive at worst. Climate change has and will destroy marine ecosystems, melt glaciers, decimate the Amazon rainforest, and trigger large-scale human migration and conflict [1]. Sea levels will also rise due to climate change, and eroded coastal conditions, the release of inundated land, and the threat of submersion will be disastrous for island nations and low-lying coastal areas. This threat is especially serious given that half of the global population lives within 100 km of a coast [2] and that coastal region tend to be wealthy.

In response, many coastal governments have begun formulating strategies for sustainable development. Ports are a crucial driver of economic growth, but they are also energy intensive and a source of

pollution. To remedy this problem and to ensure sustainable development, the concept of a green port has been formulated. The move toward green ports has made much progress in many developed countries, as reflected in the “San Pedro Bay Clean Air Action Plan” (jointly implemented by the Port of Los Angeles, California, and the Port of Long Beach, New York and New Jersey), the “Clean Air Initiatives and Harbor Air Management Plan” (jointly implemented by port authorities in New York and New Jersey), the “Rijnmond Regional Air Quality Action Program” (implemented by the Port of Rotterdam, the Netherlands), and the “Green Port Guidelines” (implemented by the Port of Sydney, Australia).

In the context of these developments, more scholarly attention has been paid to the rational utilization of port resources [3–8]. Studies have aimed to assist port managers in formulating feasible policies from a macroscopic perspective that accounts for scaling effects and the balance between economic vibrancy and environmental protection. However, these studies have not considered the sources of environmental damage in and around ports (e.g., sources of CO_2 emissions). In response to this gap in the literature, this study focused on the container-handling system, which is closely related to daily port operations. Specifically, this study combined data envelopment analysis (DEA) and multichoice goal programming (MCGP) to evaluate the green performance of four types of cranes that are commonly used in ports. The findings aid port managers

in making their port greener.

The remaining parts of the paper are organized as follows: Section 2 reviews the literature on green ports. Section 3 introduces this study's combination of DEA, based on the super slack-based measure (SBM), and the MCGP method that accounts for undesirable outputs. A real-world numerical example in Taiwan is presented in Section 4. Finally, Section 5 concludes the paper and discusses the managerial implications.

2. Literature Review

2.1 Green Ports

In general, green port construction involves aspects such as improving water quality, supervising air quality, ensuring noise control, managing waste, managing hazardous cargo, conducting environmental education and training, and maintaining biodiversity in the port area. Scholars have researched these aspects.

In analyzing the water circulation patterns in the port of Ensenada (one of Mexico's most important ports), Espino et al. [9] suggested the use of a wave energy pumping system to gradually dilute the concentration of pollutants in the port area. Otene and Nnadi [10] focused on water quality indices and water quality conditions in the Port of Harcourt (Nigeria). Their study collected water samples from four key locations in the port and analyzed the water quality parameters using standard methods. Their findings indicated the poor state of

environmental monitoring, thus aiding the port's managers. Lee et al. [11] analyzed a comprehensive 2010–2011 data set on marine environmental trends, including those of water quality, along the coast of Busan New Port. Their findings aided port managers in monitoring the impact of projects on the offshore marine environment around the port. Bolognese et al. [12] noted that in contrast to the many studies that have investigated the management of noise from transportation, few studies have investigated the management of noise from port operations. Those authors investigated the North Tyrrhenian Sea Port by collecting data from monitoring systems, noise measurements, and citizen complaints. Their findings indicated a neglect of noise levels by port managers. Reviewing the regulations and literature on environmental issues in port management systems, Vaio et al. [13] conducted semistructured interviews with users of an Italian port to explore how port management control systems assist port authorities in the decision-making process. To help port managers improve management efficiency during ship mooring, their study also assessed efficiency in port waste management.

Focusing on official regulations, Prati et al. [14] investigated the air quality in the Port of Naples through two experiments. Measurements were made at 15 points within the port. In addition, a laboratory was established within the port area to take continuous measurements of pollutant concentrations, ambient parameters, particulate matter (PM)

levels, and wind direction and intensity. Their findings indicated that ship emissions contributed the most to SO_2 concentrations compared with the concentrations of other pollutants. Kontos et al. [15] focused on the impact of gas emissions from cruise ships and passenger vessels on air quality and human health risks in the area around the Port of Thessaloniki. They estimated the surface concentration of pollutants caused by passenger ship traffic through the CALPUFF dispersion models for 2013, and their study also forecasted trends for future environmental conditions within the port area. Casazza et al. [16] used 3D modeling to achieve the effective regulation of air quality within a port area. Their study not only enabled air pollution monitoring in ports but also provided a new methodology in support of local environmental management systems. Progiou et al. [17] demonstrated that navigation emissions from ships are an important component of the total emissions, whether of a port, port city, or country. Their study used atmospheric models to simulate the dispersion of air pollutants, and their findings indicated a significant increase in activity in the Port of Piraeus over the last decade, especially from merchant ships.

As evident in the preceding literature review, studies have typically monitored the environment in and around port areas through monitoring stations, thus gaining a macro-level understanding [18–21]. Few studies have monitored greenhouse gas emissions at their source. The cranes in a

port are one such source; they emit greenhouse gases when continually loading and unloading cargo. Therefore, the construction of an effective evaluation approach for selecting environmentally friendly cranes is a research problem of practical importance, and it is this problem (and gap in the literature) that this study aimed to address.

2.2 DEA Applied in Green Ports

Among the many existing methods for evaluating performance, DEA is well known by many managers or researchers because of its unique advantages in processing multiple inputs and outputs. The conventional DEA model was first proposed by Charnes et al. [22] in 1978. It was based on linear programming, which is a quantitative method of evaluating the relative effectiveness of comparable units of the same type. As DEA became methodologically more sophisticated with time, it has developed into a new field that integrates operations research, management science, and mathematical economics. Subsequently, Banker et al. [23] extended the DEA model to cover variable returns to scale (VRS). Since then, DEA models have been extended to other practical domains in the form of super-efficiency models [24–26], cross-efficiency models [27, 28], SBM models [29, 30], super-SBM models [31, 32], and network DEA models [33–35].

Although DEA methods have often been used to evaluate performance with respect to CO_2 emissions [36–39], few have applied

DEA to green ports specifically. Using an inseparable input–output SBM-DEA model, Na et al. [30] analyzed how environmentally friendly eight major container ports in China were by using 2005–2014 environmental monitoring data. Their results indicated that the eight ports significantly differed in their CO_2 emission levels and that their pure technical environmental efficiency was low. Li et al. [40] noted that the rapid development of China's port industry has led to serious problems with CO_2 emissions. Specifically, those authors analyzed 2013–2018 data on 16 Chinese port companies; the ports were segmented by size and complexity criteria in the analysis. Using an improved nonradial directional distance function, the authors determined the performance of these ports with respect to CO_2 emissions. Wang et al. [41] constructed three DEA models to evaluate the environmental efficiency gained by cooperation between ports under the conditions of environmental control, non-environmental control, and PM emissions. They collected and analyzed data from 11 major Chinese ports and found that ports in the eastern region of China performed the best with respect to environmental friendliness.

In general, few studies have focused on evaluating the environmental performance of green ports probably because port emissions data (pertaining to, for example, CO_2 or sulfide) are difficult to collect; the present study aimed to fill this gap in the literature.

3. Methodology

3.1 SBM-DEA Model

Suppose that n decision-making units (DMUs) have m inputs and s outputs to be evaluated. Let $x_{ij}(i=1,...,m)$, and $y_{rj}(r=1,...,s)$ denote the ith input and rth output, respectively, of the jth DMU $(j=1,...,n)$. The production possible set (PPS) given by the DMUs is as follows:

$$T=\left\{(x_1,...,x_i,...,x_m,y_1,...,y_r,...,y_s)\middle|\sum_{i=1}^{m}v_i x_{ij}\le x_{ik},i=1,...,m;\sum_{i=1}^{m}u_r y_{rj}\ge y_{rk},r=1,...,s\right\},$$

Where v_i and u_r are nonnegative intensity vectors, indicating that the preceding definition corresponds to a situation of constant returns to scale (CRS). The original DEA-CCR model proposed by Charnes et al. [23] is a nonlinear programming model, which traditionally analyzes all positive data. Through the Charnes–Cooper transformation [42], the efficiency of DMU-k can be formulated as follows:

$$\begin{aligned}
&\max \sum_{r=1}^{s}u_r y_{rk}\\
&s.t. \quad \sum_{i=1}^{m}v_i x_{ik}=1;\\
&\frac{\sum_{r=1}^{s}u_r y_{rj}}{\sum_{i=1}^{m}v_i x_{ij}}\le 1;\ j=1,...,n;\\
&v_i\ge 0,i=1,...,m;\\
&u_r\ge 0,r=1,...,s.
\end{aligned}\tag{1}$$

Model (1) is the basic DEA-CCR model in multiplier form. The dual model presented in the envelopment form is as follows:

$$\begin{aligned} &\max\ \theta \\ &s.t.\quad \sum_{j=1}^{n}\lambda_j x_{ij} \le \theta \cdot x_{ik}; \\ &\qquad \sum_{j=1}^{n}\lambda_j y_{rj} \ge y_{rk}; \\ &\qquad \lambda_j \ge 0,\ j=1,\ldots,n. \end{aligned} \tag{2}$$

Subsequently, Banker et al. [24] extended model (2) to cover VRS. However, the two radial approaches may be limited by some of the inefficient components not being reflected in the measurement results (such as the mix inefficiencies). To address this problem, Tone [29] proposed the following SBM model:

$$\begin{aligned} &\min\ \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1+\frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{rk}} \\ &s.t.\quad x_{ik} = \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^-, i=1,\ldots,m \\ &\qquad y_{rk} = \sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+, r=1,\ldots,s \\ &\qquad \lambda_j \ge 0,\ j=1,\ldots,n \\ &\qquad s_i^- \ge 0, i=1,\ldots,m \\ &\qquad s_r^+ \ge 0, r=1,\ldots,s \end{aligned} \tag{3}$$

where s_i^-, s_r^+ denote the inefficient components. In model (3), Tone [29] defined the evaluated DMU to be efficient if and only if the optimal solution of $s_i^{-*} = s_r^{+*} = 0$ for all i and r (or equivalently, the efficiency $\rho^* = 1$). To further enhance the discrimination of all efficient units, Tone

[43] constructed a new super-SBM model to identify the super-efficiency as follows:

$$\begin{aligned}
\min\ \delta &= \frac{\frac{1}{m}\sum_{i=1}^{m}\tilde{x}_i / x_{ik}}{\frac{1}{s}\sum_{r=1}^{s}\tilde{y}_r / y_{rk}} \\
s.t.\quad \tilde{x}_i &\geq \sum_{j=1, j\neq k}^{n}\lambda_j x_{ij}, i = 1,...,m \\
\tilde{y}_r &\leq \sum_{j=1, j\neq k}^{n}\lambda_j y_{rj}, r = 1,...,s \\
\lambda_j &\geq 0,\ j = 1,...,n,\ j \neq k \\
\tilde{x}_i &\geq x_{ik},\ i = 1,...,m \\
\tilde{y}_r &\geq k, \tilde{y}_r \leq y_{rk}, r = 1,...,s
\end{aligned} \tag{4}$$

In model (4), the new PPS can be defined as $PPS = \left\{(\tilde{x},\tilde{y}) \middle| \tilde{x} \geq \sum_{j=1}^{n}\lambda_j x_j, \tilde{y} \leq \sum_{j=1}^{n}\lambda_j y_j, \tilde{y} \geq 0, \lambda_j \geq 0,\ j = 1,...,n\right\}$. Note that for the inefficient DMUs, the efficiency evaluated by model (4) is necessarily 1. That is, model (4) is only effective for distinguishing between efficient DMUs. Thus, applications typically use model (3) and model (4) in combination.

Fang et al. [44] noted that model (4) does not incorporate slacks explicitly, and they suggested adding two slack variables (w_i^-, w_r^+) to account for the incorporated slacks of the first two constraints of model (4). Furthermore, because our variable of CO_2 emissions was considered an undesirable output in this study, referencing Fang et al. [44], we supposed that *n* DMUs obtain *m* inputs, *s* outputs, and *g* undesirable

outputs. Let three vectors $x_i \in R^m, y_r \in R^s$ and $u_h \in R^g (h = 1,..., g)$ denote *m*, *s*, and *g*, respectively. Correspondingly, we can obtain the matrices X, Y and U as follows: $X = [x_1,...,x_m] \in R^{m \times n}$, $Y = [y_1,...,y_s] \in R^{s \times n}$, and $U = [u_1,...,u_g] \in R^{g \times n}$. Note that because all the research data are nonnegative, we obtain $X > 0, Y > 0$ and $U > 0$. The new PPS can be defined as follows:

$$PPS = \left\{(x_i, y_r, u_h) \middle| x_i \geq X\lambda, y_r \leq Y\lambda, u_h \geq U\lambda, \lambda \geq 0\right\}, \quad (5)$$

where the intensity vector $\lambda \in R^n$, and the preceding definition of *PPS* corresponds to the CRS in envelopment form.

In fact, the original SBM-DEA model involved calculating the ratio of the average input reduction to the average output growth when evaluating the efficiency. In other words, the purpose of the objective function of the SBM-DEA model is to determine the most appropriate extent of improvement between inputs and outputs. Thus, the SBM-DEA model can be referred to as a non−radial model or non−oriented model. One advantage of this model is that it allows the analyst to evaluate the efficiency by analyzing the maximum adjustable quantity of each vector instead of only analyzing the improvement of one dimension (inputs or outputs) alone. In this study, we aimed to minimize both the inputs and undesired outputs. Therefore, we propose the following model to evaluate the super-efficiency:

$$\min \ \rho = \frac{1+\frac{1}{m+g}\left(\sum_{i=1}^{m} w_i^- \Big/ x_{ik} + \sum_{i=1}^{m} w_h^- / u_{hk}\right)}{1-\frac{1}{s}\left(\sum_{r=1}^{s} w_r^+ / y_{rk}\right)}$$

$$\begin{aligned} s.t. \quad & x_{ik} \geq \sum_{j=1,}^{n} \lambda_j x_{ij} - w_i^-; \\ & y_{rk} \leq \sum_{j\neq k}^{n} \lambda_j y_{rj} + w_r^+; \\ & u_{hk} \geq \sum_{j=1, j\neq k}^{n} \lambda_j u_{hj} - w_h^-; \\ & \lambda_j \geq 0, j = 1,...,n; \\ & w_i^- \geq 0, i = 1,...,m; \\ & w_r^+ \geq 0, w_r^+ \leq y_{rk}, r = 1,...,s; \\ & w_h^- \geq 0, w_h^- \leq u_{hk}, h = 1,...,g. \end{aligned} \tag{6}$$

where $w_i^-, w_r^+, and\ w_h^-$ denote the incorporate slacks (or super-efficient components) of inputs, good outputs, and undesirable outputs, respectively. In model (6), the constraints $w_r^+ \leq y_{rk} (r = 1,...,s)$ and $w_h^- \leq u_{hk} (h = 1,...,g)$ ensure that the computed super-efficiency value is always nonnegative.

Similar to model (4), model (6) is such that when DMU-*k* is located outside the new *PPS* (5), the efficiency value of DMU-*k* is greater than 1; this DMU is then evaluated as an efficient unit. In other words, model (6) can determine the minimum distance ($w_i^-, w_r^+, and\ w_h^-$) between the efficient frontier and the evaluated DMU. However, for any evaluated DMU-*k* that falls within the region of the new *PPS* (5), the minimum distance ($w_i^-, w_r^+, and\ w_h^-$) is necessarily zero; that is, model (6) cannot determine the gap between the evaluated DMU and its target. Thus, in

this study, we propose the following model to calculate the efficiency of inefficient DMUs:

$$\begin{aligned}
\min\ \rho &= \frac{1-\frac{1}{m}\left(\sum_{i=1}^{m} s_i^+ \Big/ x_{ik} + \sum_{i=1}^{m} s_h^+ / u_{hk}\right)}{1+\frac{1}{s}\left(\sum_{r=1}^{s} s_r^- / y_{rk}\right)} \\
s.t.\quad x_{ik} &= \sum_{j=1,}^{n} \lambda_j x_{ij} - w_i^{-*} + s_i^+; \\
y_{rk} &= \sum_{j\neq k}^{n} \lambda_j y_{rj} + w_r^{+*} - s_r^-; \\
u_{hk} &= \sum_{j=1, j\neq k}^{n} \lambda_j u_{hj} - w_h^{-*} + s_h^+; \\
&\lambda_j \geq 0,\ j = 1,\ldots,n; \\
&s_i^+ \geq 0, i = 1,\ldots,m; \\
&s_r^- \geq 0, r = 1,\ldots,s; \\
&s_h^+ \geq 0, h = 1,\ldots,g.
\end{aligned} \tag{7}$$

where $w_i^{-*}, w_r^{+*}, and\ w_h^{-*}$ are the optimal solutions that are calculated using model (6), and the optimal solution of the new variables $s_i^{+*}, s_r^{-*}, and\ s_h^{+*}$ denote the inefficient components of the evaluated DMU. Therefore, we formulate efficiency as follows:

$$\varphi^* = \begin{cases} \dfrac{1+\frac{1}{m+g}\left(\sum_{i=1}^{m} w_i^{-*} \Big/ x_{ik} + \sum_{i=1}^{m} w_h^{-*} / u_{hk}\right)}{1-\frac{1}{s}\left(\sum_{r=1}^{s} w_r^{+*} / y_{rk}\right)}, & \text{if } \dfrac{1+\frac{1}{m+g}\left(\sum_{i=1}^{m} w_i^{-*} \Big/ x_{ik} + \sum_{i=1}^{m} w_h^{-*} / u_{hk}\right)}{1-\frac{1}{s}\left(\sum_{r=1}^{s} w_r^{+*} / y_{rk}\right)} > 1 \\ \dfrac{1-\frac{1}{m+g}\left(\sum_{i=1}^{m} s_i^{+*} \Big/ x_{ik} + \sum_{i=1}^{m} s_h^{+*} / u_{hk}\right)}{1+\frac{1}{s}\left(\sum_{r=1}^{s} s_r^{-*} / y_{rk}\right)}, & \text{otherwise} \end{cases} \tag{8}$$

In this study, to determine the optimal loading tool that has satisfactory green performance, we further define a new green energy

index (GI_j), which is obtained by first calculating the super-efficiency value DMU-j ($j = 1,...,n$) before calculating the maximum value $E_{\max} = \max_{j=1}^{n}\{\varphi_j^*\}$. Finally, the green energy index GI_j can be calculated as follows:

$$GI_j = \frac{\varphi_j^*}{E_{\max}} (j = 1,...,n) \tag{9}$$

3.2 MCGP Model for Evaluating Crane Equipment

The MCGP approach encompasses the many modified GP methods in the literature. Chang (2008) developed a multichoice aspiration level model for solving multiobjectives decision-making problems [45]. A typical MCGP problem has the following structure.

In a real-world decision-making problem for choosing crane equipment, the goals are often related. This problem is represented in the following MCGP equations:

Minimize $$\sum_{i=1}^{n}\left[(d_i^+ + d_i^-) + (e_i^+ + e_i^-)\right] \tag{10}$$

Subject to

$$f_i(X)b_i - d_i^+ + d_i^- = b_i y_i \qquad i = 1, 2,\ldots, n, \tag{11}$$

$$y_i - e_i^+ + e_i^- = g_{i,\min} \qquad i = 1, 2,\ldots, n, \tag{12}$$

$$g_{i,\min} \le y_i \le g_{i,\max} \qquad i = 1, 2,\ldots, n, \tag{13}$$

$$d_i^+, d_i^-, e_i^+, e_i^- \ge 0, \qquad i = 1, 2,\ldots, n. \tag{14}$$

As illustrated in Equations (11), (12), and (13), selection restrictions are absent for any single goal, but some goals are dependent on another. For example, we can add the auxiliary constraint $b_i \le b_{i+1} + b_{i+2}$ to the MCGP

model, where b_i, b_{i+1} and b_{i+2} are binary variables. Thus, b_{i+1} or b_{i+2} must equal to 1 if bi = 1. This means that if goal 1 has been achieved, then either goal 2 or goal 3 has been achieved.

4. Empirical Research

4.1 SBM-DEA Model Variables

In general, the selection of input and output variables is critical in the application of DEA. This is because the evaluation results become highly variable when the set of research variables changes. Thus, through considerations of the characteristics of port operations and through consultations with experts, we selected five variables: three inputs (X1, X2, and X3), one good output (Y1), and one undesirable output (U1), which are described as follows:

- X1: operational duration (hours), defined as how long each crane spends loading and unloading in a given year.
- X2: power consumption (kwh), defined as how much power each crane consumes. This constitutes a type of investment resource.
- X3: total energy cost (TWD), defined as the cost incurred by the port operator to operate this crane in a given year.
- Y1: working capacity (number of moves), defined as how many containers the crane can load and unload in 1 year. A higher Y1 value indicates a more productive crane.
- U1: CO_2 emission volume (kg). This study learned from experts

that the total CO_2 emissions of each port crane in a given year can be calculated using the CO_2 emission coefficients provided by China National Petroleum Corporation and Taiwan Electric Power Corporation.

4.2 Evaluation Results

This study aimed to evaluate the green performance of various cranes used to load and unload cargo in port operations. The four most common types of cranes used in international commercial ports in general and by a prominent container-handling company in Taiwan in particular are as follows: gantry cranes (GC), rail-mounted gantry (RMG) cranes, rubber-tired gantry (RTG) cranes, and empty container handlers (ECHs). This study collected and analyzed 2018–2020 data on these cranes (Tables 1–3).

Table 1. Collected data and evaluation results for 2018

DMU	*Input*			*Output*		*Evaluation results*		
	Working time (hours)	Energy consumption (kwh)	Total energy cost (TWD)	Working capacity (moves)	CO_2 emission volume (kg)	Efficiency	GI_j^*	Rank
GC	4,487	534,344	1,528,224	134,595	278,928	1.07794	0.99983	2
RMG	3,556	174,728	499,706	74,670	91,205	0.92779	0.86056	4
RTG	4,983	235,677	674,063	109,617	123,029	1.07813	1.00000	1
ECH	4,464	418,122	1,241,924	102,671	112,548	1.01733	0.94361	3

Table 2. Collected data and evaluation results for 2019

DMU	*Input*			*Output*		*Evaluation results*		
	Working time (hours)	Energy consumption (kwh)	Total energy cost (TWD)	Working capacity (moves)	CO_2 emission volume (kg)	Efficiency	GI_j^*	Rank
GC	3,323	445,287	1,280,598	106,811	223,893	1.09938	0.95843	2
RMG	3,726	168,256	552,876	78,236	96,662	0.88134	0.76834	4
RTG	3,397	117,838	485,277	74,737	84,842	1.14707	1.00000	1
ECH	3,478	312,197	629,643	79,997	87,692	1.02027	0.88946	3

Table 3. Collected data and evaluation results for 2020

DMU	*Input*			*Output*		*Evaluation results*		
	Working time (hours)	Energy consumption (kwh)	Total energy cost (TWD)	Working capacity (moves)	CO_2 emission volume (kg)	Efficiency	GI_j^*	Rank
GC	3,712	442,106	1,388,211	63,635	123,968	1.01786	0.94071	2
RMG	3,235	158,952	499,118	49,402	54,047	1.01518	0.93824	3
RTG	3,313	149,582	469,690	53,008	61,514	1.08201	1.00000	1
ECH	3,047	259,434	812,980	48,752	60,026	0.75103	0.69410	4

The Taiwanese company investigated in this study was large and operated many cranes (including 9 RMG cranes). The data for all cranes of each type also differed little. Thus, the data used in this study were the average values for each crane type.

In Tables 1–3, the basic information on each crane is presented from the second to sixth columns from the left, and the performance values as computed using models (6) and (7) jointly are presented in the seventh column from the left. The penultimate and final columns present the value of the green energy index (GI_j) and the ranking for all four crane types, respectively.

The results indicated that the green performance ranking among the crane differed little from 2018 to 2019 and that the efficiency value of three crane types (RTG, GC, and ECH) exceeded 1. Thus, these three crane types operated efficiently throughout the years, with RTG having the best green performance and being the most efficient. In 2020 (Table 2), in contrast to previous years, RMG and ECH swapped rankings and the green performance of ECH was inefficient; RTG still had the best (and thus most stable) green performance and is thus optimal for use in global commercial ports.

4.3 Tradeoff Analysis

The aforementioned analysis informs port managers only of the green performance of each crane type; it does not provide a quantitative analysis of the advantages and disadvantages of each crane type. Thus, this study determined the most suitable tradeoff among X1, X2, X3, Y1, and U1 for the four crane types. The results are presented in Table 4.

Table 4. Suitable adjustment for each variable

DMU		*X1:Working Time (hours)*		*X2:Energy Consumption (kwh)*		*X3:Total Energy Cost (TWD)*		*Y1:Working Capacity (moves)*		*U1:CO_2 Emission Volume (kg)*	
		Benchmark	Change Rate*	Benchmark	Change Rate*	Benchmark	Change Rate*	Benchmark	Change Rate*	Benchmark	Change Rate*
GC	2018	5,885	31.18%	85,583	-83.98%	1,528,224	0.00%	134,595	0.00%	147,983	-46.95%
	2019	3,977	7.14%	179,571	-59.38%	563,853	-59.38%	63,635	0.00%	73,847	-40.43%
	2020	4,644	39.75%	416,843	-6.39%	840,692	-34.35%	106,811	0.00%	117,085	-47.70%
	Ave	**4,835**	**26.02%**	**227,332**	**-49.92%**	**977,590**	**-31.24%**	**101,681**	**0.00%**	**112,972**	**-45.03%**
RMG	2018	3,556	0.00%	168,173	-3.75%	480,994	-3.74%	78,220	-4.75%	87,790	-3.74%
	2019	3,088	-4.55%	139,407	-12.30%	437,739	-12.30%	49,402	0.00%	57,330	6.07%
	2020	3,726	0.00%	129,227	-23.20%	532,175	-3.74%	81,959	-4.76%	93,042	-3.74%
	Ave	**3,456**	**-1.52%**	**145,602**	**-13.08%**	**483,636**	**-6.60%**	**69,861**	**-3.17%**	**79,387**	**-0.47%**
RTG	2018	5,175	3.85%	235,677	0.00%	792,201	17.53%	109,617	0.00%	132,532	7.72%
	2019	3,471	4.76%	170,554	14.02%	535,548	14.02%	53,008	0.00%	57,992	-5.73%
	2020	3,397	0.00%	153,429	30.20%	504,154	3.89%	71,341	4.54%	88,143	3.89%
	Ave	**4,014**	**2.87%**	**186,553**	**14.74%**	**610,634**	**11.81%**	**77,989**	**1.51%**	**92,889**	**1.96%**
ECH	2018	4,667	4.55%	220,741	-47.21%	631,346	-49.16%	102,671	0.00%	115,232	2.38%
	2019	3,047	0.00%	137,571	-46.97%	431,974	-46.87%	48,752	0.00%	56,575	-5.75%
	2020	3,636	4.55%	126,132	-59.60%	519,432	-17.50%	79,997	0.00%	90,814	3.56%
	Ave	**3,783**	**3.03%**	**161,482**	**-51.26%**	**527,584**	**-37.84%**	**77,140**	**0.00%**	**87,540**	**0.07%**
Total AVE		**4,022**	**7.60%**	**180,242**	**-24.88%**	**649,861**	**-15.97%**	**81,667**	**-0.41%**	**93,197**	**-10.87%**

* = positive values denote the advantage of each input and undesirable output, and negative values denote the disadvantage

Table 4 presents the quantitative results for the tradeoff among the variables for each crane type. The results indicated the target that should be learned for each variable in a given year and the extent of adjustment (expressed in terms of an adjustment ratio) for each variable in the optimal tradeoff. For the input and undesired outputs, the adjustment ratio was calculated by subtracting the original resource value from the target value and then dividing this difference by the original values. A positive adjustment ratio represents the performance of the learning benchmark in that direction being not yet as good as that of the evaluated unit. In other words, a positive adjustment ratio can be interpreted as representing the advantage for a given crane type.

Conversely, if the value of the adjustment ratio for an item is negative, it represents a disadvantage for a given crane type. For good-output variables, this study used reverse processing, in which the original data value was subtracted from the target value and this difference was divided by the target value. This was done to allow positive numbers to also represent advantages.

Table 4 presents the adjustment ratios for all crane types. RTG was the best crane type with respect to all variables, especially in energy consumption and total energy cost, with average three-year advantages of 14.74% and 11.81%, respectively. GC was the second-best crane type, and it was superior primarily in operational duration. Thus, GC is

especially advantageous when used to load and unload the same type of containers. Finally, RMG and ECH were disadvantaged by their high energy consumption and high total energy cost; among the two, ECH emitted less CO_2 and had a better operational duration. These results are visualized in Figs. 1–4.

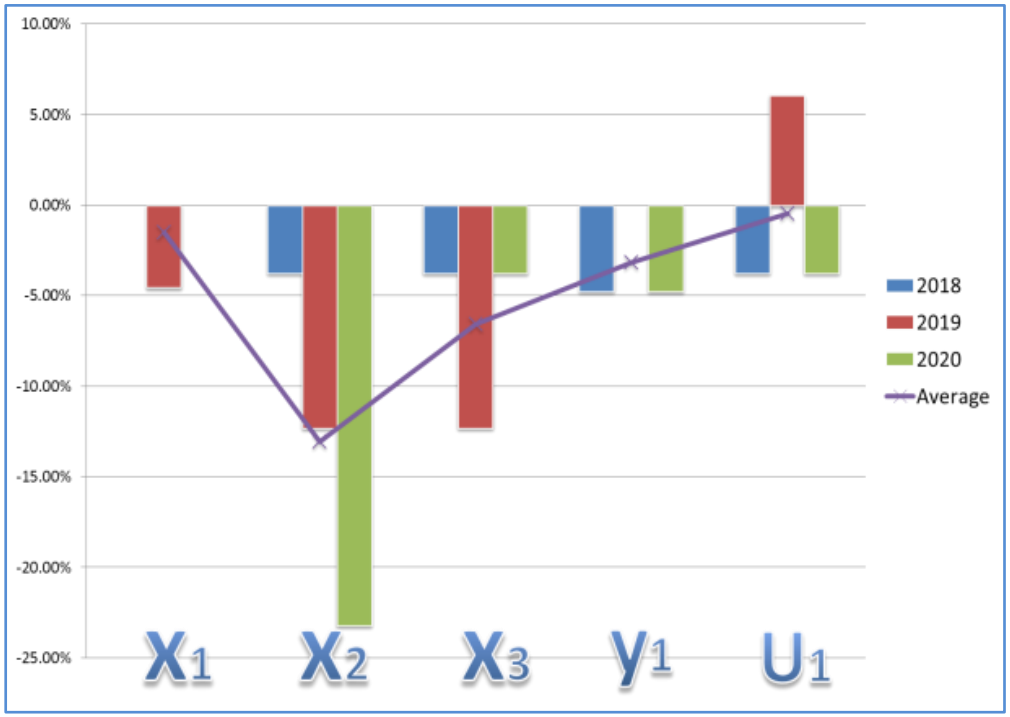

Fig 1. Adjustment ratios for GC cranes

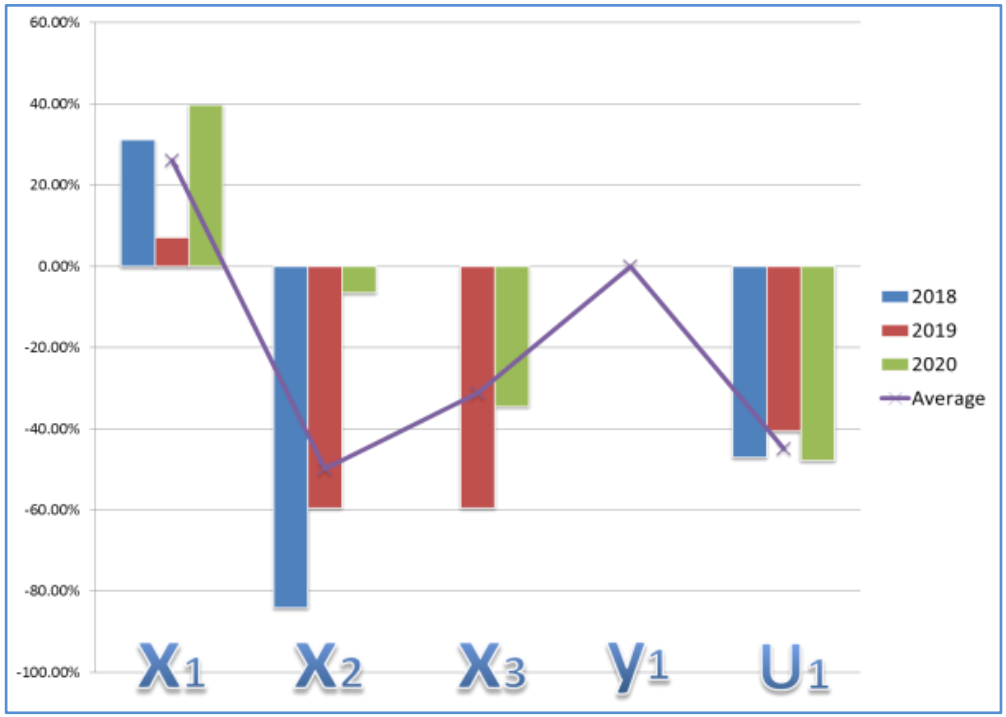

Fig 2. Adjustment ratios for RMG cranes

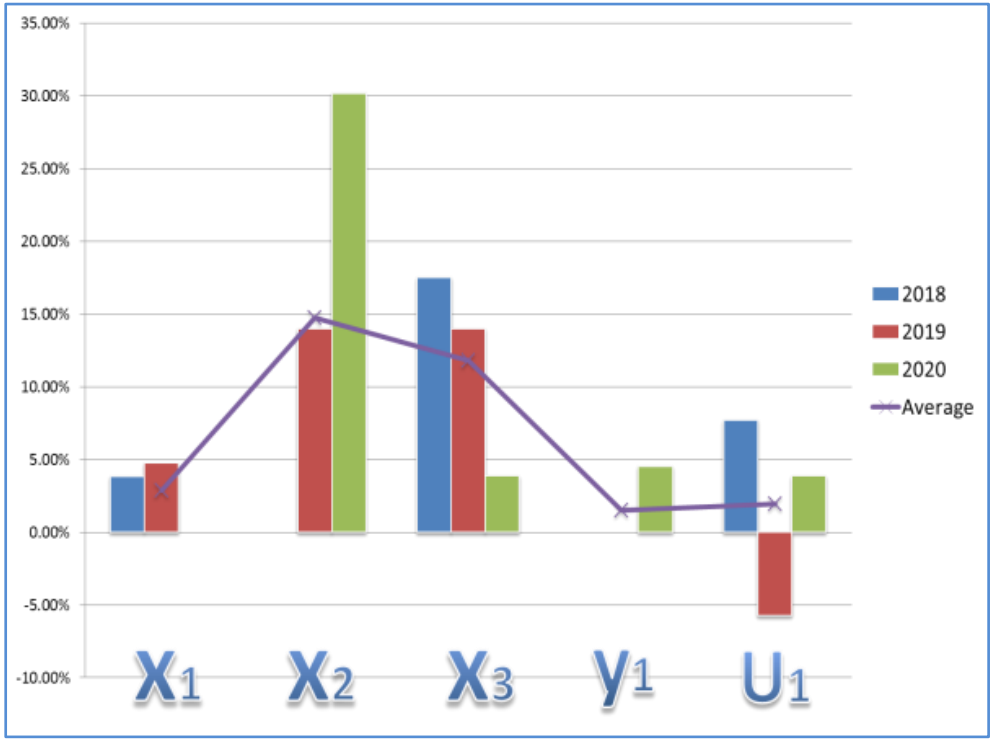

Fig 3. Adjustment ratios for RTG cranes

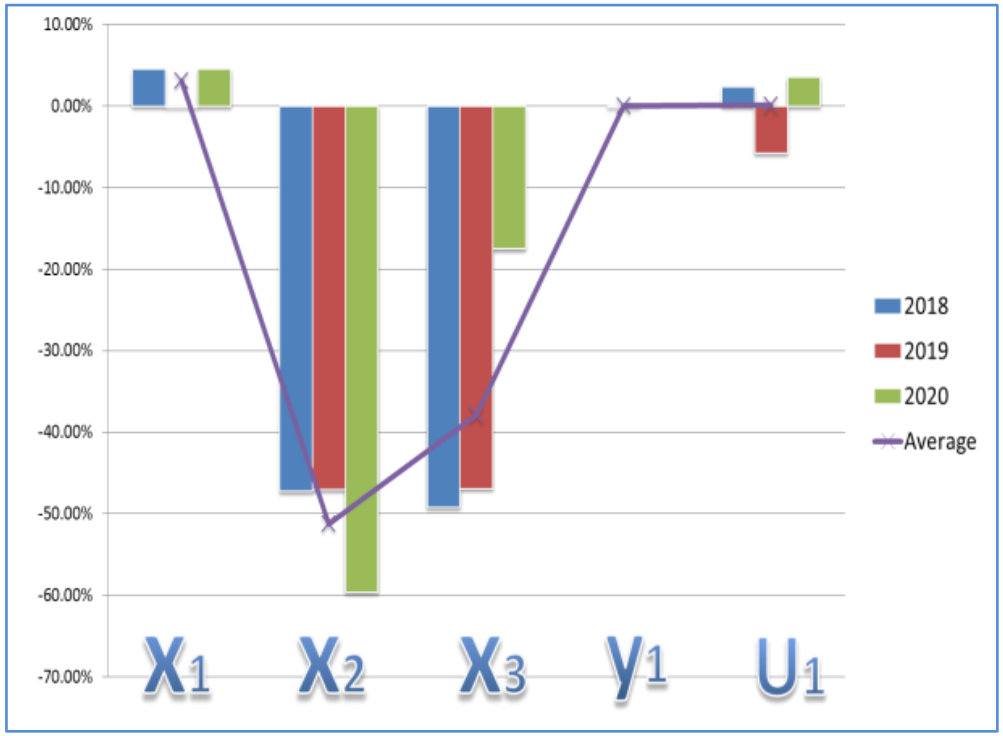

Fig 4. Adjustment rate for ECHs

In the histograms in Figs. 1–4, which each present the adjustment ratios for a given crane type for all variables, the solid line segment indicates the average value of the adjustment ratio for each year. As mentioned, positive and negative values indicate advantages and disadvantages, respectively. The characteristic patterns presented in these four figures remain largely consistent with those highlighted by the average evaluation results.

4.4 Using MCGP to Solve the Problem of Choosing Between Crane Equipment

To solve the problem of choosing between types of cranes, the analyst must define the MCGP model according to the following goals. According to this case, suppose that the decision maker has the following set of priority goals derived from the DMU results for RTG cranes in Table 4:

1. The first goal is *Y1*: working capacity is the RTG benchmark; the DMU of RTG was (71341, 77989) in the results.

2. The second goal is *U1*: emission volume is the RTG benchmark; the DMU of RTG was (88143, 92889) in the results.

3. The third goal is *X1*: operational duration is the DMU of RTG's input; the DMU of RTG was (3397, 4014) in the results.

4. The fourth goal is *X2*: energy consumption is the DMU of RTG's input;

the DMU of RTG was (153,429, 186,553) in the results.

5. The fifth goal is *X3*: total energy cost is the DMU of RTG's input; the DMU of RTG was (504,154, 610,634) in the results.

We then solve the following MCGP model:

$$\text{Min} \quad d_1^+ + d_1^- + d_2^+ + d_2^- + d_3^+ + d_3^- + d_4^- + d_5^- + e_1^+ + e_1^- + e_2^+ + e_2^- + e_3^+ + e_3^- + e_4^+ + e_4^- + e_5^+ + e_5^-$$

$$y1 - e_1^+ + e_1^- = 71341;\ y1 \geq 71341;\ y1 \leq 77{,}989$$

$$123{,}968 \times s1 + 54{,}047 \times s2 + 61514 \times s3 + 60026 \times s4 + d_1^- - d_1^+ = y2 \times b2$$

$$y2 - e_2^+ + e_2^- = 88{,}143;\ y2 >= 88{,}143;\ y2 <= 92{,}889$$

$$3{,}712 \times s1 + 3235 \times s2 + 3313 \times s3 + 3{,}047 \times s4 <= y3 \times b3$$

$$y3 - e_3^+ + e_3^- = 3397;\ y3 \geq 3397;\ y3 \leq 4{,}014;$$

$$442{,}106 \times s1 + 158{,}952 \times s2 + 149{,}582 \times s3 + 259{,}434 \times s4 = y4 \times b4$$

$$y4 - e_4^+ + e_4^- = 153{,}429;\ y4 \geq 153{,}429;\ y4 \leq 186{,}553;$$

$$1{,}388{,}211 \times s1 + 499{,}118 \times s2 + 469{,}690 \times s3 + 12{,}980 \times s4 = y5 \times b5;$$

$$y5 - e_5^+ + e_5^- = 504{,}154;\ y5 \geq 504{,}154;\ y5 \leq 610{,}634;$$

$$s1 + s2 + s3 + s4 = 1;$$

$$b1 = b2 + b3 + b4;$$

$$b2 + b3 + b4 = 1;$$

$$d_1^+ \geq 0;\ d_1^- \geq 0;\ d_2^+ \geq 0;\ d_2^- \geq 0;\ d_3^+ \geq 0;\ d_3^- \geq 0;\ d_4^+ \geq 0;\ d_4^- \geq 0;\ d_5^+ \geq 0;\ d_5^- \geq 0;$$

$$e_1^+ \geq 0;\ e_1^- \geq 0;\ e_2^+ \geq 0;\ e_2^- \geq 0.\ e_3^+ \geq 0;\ e_3^- \geq 0; e_4^+ \geq 0;\ e_4^- \geq 0.\ e_5^+ \geq 0;\ e_5^- \geq 0.$$

Using Lingo software (2002), we obtained the following solution: s1 = 0, s2 = 0, s3 = 1, and s4 = 0; y1 = 71,341, y2 = 88,143, y3 = 4,014, y4 = 186,553, and y5 = 504,154. This means that RTG is a suitable crane.

5. Conclusions and Implications

5.1 Conclusion

Green ports are becoming increasingly prominent with the increased need for environmental protection globally. However, few studies have monitored exhaust gas or PM emissions (such as CO_2 or sulfide) in and around ports due to the difficulty of doing so, and the data obtained are incomplete.

To fill this gap in the literature, this study measured CO_2 emissions at their source, specifically container-handling cranes (which are indispensable to port operations). Five key variables, including CO_2 emissions, were identified based on consultations with experts. Subsequently, we (1) applied a method that combined a super-SBM-DEA model with the MCGP method to account for undesirable outputs and (2) defined a novel green energy index to evaluate green performance. Our findings determined (1) the crane type with the best green performance

and (2) how advantages and disadvantages are balanced in the use of each crane type. These findings can help port managers select the best machinery that makes their port greener, smarter, and more profitable.

5.2 Managerial Implications

We present the following managerial prescriptions based on our findings. First, we recommend RTG cranes because they are the most environmentally friendly when used in international commercial ports and they strike the best tradeoff between environmental protection and profitability. Second, RMG cranes and ECH consume much energy, which constitutes a point of concern that port managers must pay attention to. Third, to mitigate environmental harm and commercial loss, port managers should replace outdated equipment or, if they are unable to do so, supervise outdated equipment more intensely. Fourth, port managers can invest more in researching and developing smarter port equipment, which incorporates, for example, big data or Internet of Things technology. Smart port equipment minimizes operational waste to mitigate their environmental impact and enhance profitability.

5.3 Limitations

To mitigate the disadvantages of the DEA method, we used the MCGP method to verify the DEA results. To better cope with uncertainty, decision makers can use the novel fuzzy MCGP method in conjunction

with the multicriteria decision-making approach.

5.4 Future Directions

Future studies can use other new DEA methods to solve crane equipment selection problems. Additionally, other mathematical models, such as new MCGP models, can be combined with our study's model which is the light of future direction.

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Reference

1. Carey, M. *In the shadow of melting glaciers: Climate change and Andean society*; Oxford University Press: New York, NY, USA, 2010.

2. Barragán, J. M.; de Andrés, M. Analysis and trends of the world's coastal cities and agglomerations. *Ocean Coast. Manag.* **2015**, *114*, 11–20.

3. Chang, C. C.; Wang, C. M. Evaluating the effects of green port

policy: Case study of Kaohsiung harbor in Taiwan. *Transp. Res. D Transp. Environ.* **2012**, *17(3)*, 185–189.

4. Wan, C.; Zhang, D.; Yan, X.; Yang, Z. A novel model for the quantitative evaluation of green port development – a case study of major ports in China. *Transp. Res. D Transp. Environ.* **2017**, *61*, 431–443. https://doi.org/10.1016/j.trd.2017.06.021

5. Barnes-Dabban, H.; Van Tatenhove, J. P. M.; Van Koppen, K. C. S. A., Termeer, K.J.A.M. Institutionalizing environmental reform with sense-making: west and central Africa ports and the 'green port' phenomenon. *Mar. Policy* **2017**, *86*, 111–120. https://doi.org/10.1016/j.marpol.2017.09.005

6. Meng, B.; Kuang, H.; Niu, E.; Li, J.; Li, Z. Research on the transformation path of the green intelligent port: outlining the perspective of the evolutionary game "government–port–third-party organization". *Sustainability* **2020**, *12(19)*, 8072. https://doi.org/10.3390/su12198072

7. Twrdy, E.; Zanne, M. Improvement of the sustainability of ports logistics by the development of innovative green infrastructure solutions. *Transp. Res. Procedia* **2020**, *45*, 539–546. https://doi.org/10.1016/j.trpro.2020.03.059

8. Liu, P.; Wang, C.; Xie, J.; Mu, D.; Lim, M. K. Towards green

port-hinterland transportation: Coordinating railway and road infrastructure in Shandong Province, China. *Transp. Res. D Transp. Environ.* **2021**, *94*, 102806. https://doi.org/10.1016/j.trd.2021.102806

9. Espino, G.; Rodríguez, I. P.; Czitrom, S. Water quality of a port in NW Mexico and its rehabilitation with swell energy. *Mar. Pollut. Bull.* **2010**, *60(1)*, 123–130. https://doi.org/10.1016/j.marpolbul.2009.08.022

10. Otene, B. B.; Nnadi, P. Water Quality Index and Status of Minichinda Stream, Port Harcourt, Nigeria. *IIARD Int. J. Geogr. Environ. Manag.* **2019**, *5(1)*, 1–9. https://ssrn.com/abstract=3353882

11. Lee, S.; Lee, E.; Yoo, H. S.; Lee, M. J. Analysis of trends in marine water quality using environmental impact assessment monitoring data: A case study of Busan new port. *J. Coast. Res*. **2020**, *102*, 39–6. https://doi.org/10.2112/SI102-005.1

12. Bolognese, M.; Fidecaro, F.; Palazzuoli, D.; Licitra, G. Port Noise and Complaints in the North Tyrrhenian Sea and Framework for Remediation. *Environments* **2020**, *7(2)*, 17. https://doi.org/10.3390/environments7020017

13. Vaio, A. D.; Varriale, L.; Trujillo, L. Management control systems in

port waste management: evidence from Italy. *Util. Policy* **2019**, *56*, 127–135. https://doi.org/10.1016/j.jup.2018.12.001

14. Prati, M. V.; Costagliola, M. A.; Quaranta, F.; Murena, F. Assessment of ambient air quality in the port of Naples. *J. Air Waste Manag. Assoc.* **2015**, *65(8)*, 970. https://doi.org/10.1080/10962247.2015.1050129

15. Kontos, S.; Liora, N.; Poupkou, A.; Giannaros, C.; Melas, D. Air-quality impact of cruise and passenger ship emissions in the port of Thessaloniki. *Perspect. Atmos. Sci.* **2017**, 1129–1134. https://doi.org/10.1007/978-3-319-35095-0_162

16. Casazza, M.; Lega, M.; Jannelli, E.; Minutillo, M.; Jaffe, D.; Severino, V.; Ulgiati, S. 3D monitoring and modelling of air quality for sustainable urban port planning: review and perspectives. *J. Clean. Prod.* **2019**, *231(10)*, 1342–1352. https://doi.org/10.1016/j.jclepro.2019.05.257

17. Progiou, A.G.; Bakeas, E., Evangelidou, E.; Kontogiorgi, C.; Lagkadinou, D.; Sebos, I. Air pollutant emissions from Piraeus port: external costs and air quality levels. *Transp. Res. D Transp. Environ.* **2021**, *91*, 102586. https://doi.org/10.1016/j.trd.2020.102586

18. Gobbi, G. P.; Di Liberto, L.; Barnaba, F. Impact of port emissions on EU-regulated and non-regulated air quality indicators: The case of

Civitavecchia (Italy). *Sci. Total Environ.* **2020**, *719*, 134984. https://doi.org/10.1016/j.scitotenv.2019.134984

19. Ee, J. Y. C.; Chan, J. Y.; Kang, G. L. Carbon reduction analysis of Malaysian green port operation. *Prog. Energy Environ.* **2021**, *15*, 1–7. https://orcid.org/0000-0002-4262-1628

20. Fabregat, A.; Vázquez, L.; Vernet, A. Using Machine Learning to estimate the impact of ports and cruise ship traffic on urban air quality: The case of Barcelona. *Environ. Model. Softw.* **2021**, *139*, 104995. https://doi.org/10.1016/j.envsoft.2021.104995

21. Yang, L.; Zhang, Q.; Zhang, Y.; Lv, Z.; Wang, Y.; Wu, L.; Feng, X.; Mao, H. An AIS-based emission inventory and the impact on air quality in Tianjin port based on localized emission factors. *Sci. Total Environ.* **2021**, 146869. https://doi.org/10.1016/j.scitotenv.2021.146869

22. Charnes, A.; Cooper, W.W., Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–44. https://doi.org/10.1016/0377-2217(78)90138-8

23. Banker, R. D.; Charnes, A.; Cooper, W. W. Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

24. Andersen, P.; Petersen, N. C. A procedure for ranking efficient units in data envelopment analysis. *Manag. Sci.* **1993**, *39(10)*, 1261–1264. https://doi.org/10.1287/mnsc.39.10.1261

25. Zhu, J. Super-efficiency and DEA sensitivity analysis. *Eur. J. Oper. Res.* **2001**, *129(2)*, 443–445. https://doi.org/10.1016/S0377-2217(99)00433-6

26. Lee, H. S.; Chou, M. T.; Kuo, S. G. Evaluating port efficiency in Asia Pacific region with recursive data envelopment analysis. *J. East. Asia Soc. Transp. Stud.* **2005**, *6*, 544-559. https://doi.org/10.11175/easts.6.544

27. Tovar, B.; Wall, A. Environmental efficiency for a cross-section of Spanish port authorities. *Transp. Res. D Transp. Environ.* **2019**, *75*, 170–178. https://doi.org/10.1016/j.trd.2019.08.024

28. Wang, L.; Zhou, Z.; Yang, Y.; Wu, J. Green efficiency evaluation and improvement of Chinese ports: a cross-efficiency model. *Transp. Res. D Transp. Environ.* **2020**, *88(6)*, 102590. https://doi.org/10.1016/j.trd.2020.102590

29. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498-509. https://doi.org/10.1016/S0377-2217(99)00407-5

30. Na, J. H.; Choi, A. Y.; Ji, J.; Zhang, D. Environmental efficiency analysis of chinese container ports with CO_2 emissions: an inseparable input-output SBM model. *J. Transp. Geogr.* **2017**, *65*, 13 – 24. https://doi.org/10.1016/j.jtrangeo.2017.10.001

31. Wang, C. N.; Day, J. D.; Lien, N. T. K.; Chien, L. Q. Integrating the Additive Seasonal Model and Super-SBM Model to Compute the Efficiency of Port Logistics Companies in Vietnam. *Sustainability* **2018**, *10(8)*, 2782. https://doi.org/10.3390/su10082782

32. Xiao, Y.; Qi, G.; Jin, M.; Yuen, K. F.; Chen, Z.; and Li, K. X. Efficiency of Port State Control Inspection Regimes: A Comparative Study. *Transp. Policy* **2021**. *106*, 165 – 172. https://doi.org/10.1016/j.tranpol.2021.04.003

33. Wanke, P. F. Physical infrastructure and shipment consolidation efficiency drivers in Brazilian ports: A two-stage network-DEA approach. *Transp. Policy* **2013**, *29*, 145 – 153. https://doi.org/10.1016/j.tranpol.2013.05.004

34. Chao, S. L.; Yu, M. M.; Wei-Fan, H. Evaluating the efficiency of major container shipping companies: a framework of dynamic network DEA with shared inputs. *Transp. Res. A Policy Prac.* **2018**, *117*, 44 – 57. https://doi.org/10.1016/j.tra.2018.08.002

35. Saeedi, H.; Behdani, B.; Wiegmans, B.; Zuidwijk, R. Assessing the technical efficiency of intermodal freight transport chains using a modified network DEA approach. *Transp. Res. E Logist. Transp. Rev.* **2019**, *126*, 66–86. https://doi.org/10.1016/j.tre.2019.04.003

36. Kwon, D. S.; Cho, J. H.; Sohn, S. Y. Comparison of technology efficiency for CO_2 emissions reduction among European countries based on DEA with decomposed factors. *J. Clean. Prod.* **2017**, *151*, 109–120. https://doi.org/10.1016/j.jclepro.2017.03.065

37. Cui, Q. Investigating the airlines emission reduction through carbon trading under CNG2020 strategy via a network weak disposability DEA. *Energy* **2019**, *180*, 763–771. https://doi.org/10.1016/j.energy.2019.05.159

38. Yang, M.; Hou, Y.; Ji, Q.; Zhang, D. Assessment and optimization of provincial CO_2 emission reduction scheme in china: an improved ZSG-DEA approach. *Energy Econ.* **2020**, 104931. https://doi.org/10.1016/j.eneco.2020.104931

39. Ren, F. R.; Tian, Z.; Liu, J.; Shen, Y. T. Analysis of CO_2 emission reduction contribution and efficiency of China's solar photovoltaic industry: based on input-output perspective. *Energy* **2020**, *199*, 117493. https://doi.org/10.1016/j.energy.2020.117493

40. Li, Y.; Li, J.;Gong, Y.; Wei, F.; Huang, Q. CO_2 emission performance evaluation of Chinese port enterprises: a modified meta-frontier non-radial directional distance function approach. *Transp. Res. D Transp. Environ.* **2020**, *89*, 102605. https://doi.org/10.1016/j.trd.2020.102605

41. Wang, Z.; Wu, X.;Guo, J.; Wei, G.; Dooling, T. A. Efficiency evaluation and pm emission reallocation of china ports based on improved DEA models. *Transp. Res. D Transp. Environ.* **2020**, *82*, 102317. https://doi.org/10.1016/j.trd.2020.102317

42. Charnes, A.; Cooper, W. W. Programming with linear fractional functionals. *Naval Res. Logist. Q.* **1963**, *10(1)*, 273–274. https://doi.org/10.1002/nav.3800100123

43. Tone, K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. https://doi.org/10.1016/S0377-2217(01)00324-1

44. Fang, H. H.; Lee, H. S.; Hwang, S. N.; Chung, C. C. A slacks-based measure of super-efficiency in data envelopment analysis: an alternative approach. *Omega* **2013**, *41*, 731-734.

45. Chang, C.T. Revised multi-choice goal programming. *Appl. Math. Model.* **2008**, *32*, 2587–2595.

46. Schrage, L. *LINGO Release 8.0*; LINGO System Inc.: Chicago, IL. 60622, USA, 2002.