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Environmental efficiency assessment of Dublin Port using two-stage non-radial DEA model

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A B S T R A C T

The operation of a port is of critical economic importance because of its role in international trade. However, increased operations increase the port's environmental impact and contribute to climate change and global warming. Dublin Port is one of the busiest ports in Ireland, and throughput is expected to increase as the economy continues to grow. Achieving a balance between growing economic activity and reducing environmental impacts is critical to a sustainable future. The efficiency of the port considering operation, economic, and environmental factors can be evaluated using the well-known nonparametric model of Data Envelopment Analysis (DEA). In this study, a novel two-stage non-radial DEA model is used to evaluate the environmental efficiency of Dublin Port considering landward and seaward operations. The proposed two-stage model DEA isolates the efficiency of the two port sides and calculates the overall efficiency. The model minimizes Dublin Port's annual CO_2 emissions by reducing a combination of variables that can be realistically controlled by engineering and policy measures. The analysis was extended to account for possible variations in a number of key environmental output factors to compensate for the lack of real-world data availability. The study found that the number of terminals and capital expenditures have significant impacts on the port's environmental efficiency. Small adjustments or reductions in key indicators can improve Dublin Port's efficiency. This methodology can be applied to other ports in growing economies that use similar indicators to assess their environmental efficiency.

1. Introduction

Global maritime trade has reached 11 billion tons and accounts for more than 80% of global merchandise trade (United Nations Conference on Trade & Development (UNCTAD), 2019). As a result, there is a wide range of vessels, from very large bulk carriers (coal, ores, grains, etc., and crude oil/refinery carriers) to container ships to various cruise ships and naval vessels. To efficiently accommodate these various vessels, ports have had to evolve from wharves to efficient logistical hubs within the larger supply chain that move vessels deeper into the hinterland. Port development is critical to managing the growing volume of cargo (European Commission (EC), 2011).

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The flip side of increased shipping and associated port throughput is increased transportation-related greenhouse gas (GHG) pollution. Shipping is responsible for approximately 940 million metric tons or about 2.5% of global GHG emissions (International Maritime Organization (IMO), 2014). A significant portion of CO_2 emissions are caused by ships, up to ten times more than emissions caused by ports (Habibi and Rehmatulla, 2009). Maritime transport is the main source of air pollution in most ports (International Transport Forum, 2018). In addition to shipping traffic, emissions from loading and unloading activities and truck/vehicle traffic on the landside of ports are also significant sources of air pollution (Na et al., 2017). Therefore, air quality at the ship/port interface is a critical environmental issue with respect to climate change and global warming.

As global trade, supply chains, production processes, and countries' economies are linked by well-functioning port systems, it is increasingly important to monitor and measure ports' environmental performance in addition to their operation, financial, economic, and social performance (UNCTAD, 2019). The European Union (EU) has recognized the environmental problem and has focused on the recording and reporting of GHG emissions from international maritime transport to the International Maritime Organization (IMO) and also adopted legislation in 2018 (European Commission 2016). In addition, EC supports further consideration of measures and best practices to reduce GHG emissions and improve overall efficiency in the port sector (International Maritime Organization, 2015; European Commission 2016).

The largest port in the EU member state of Ireland is Dublin Port. The port is located on both sides of the River Liffey and occupies 260 hectares of land in the Dublin city area. Dublin Port has ship docks on the north side, while the main infrastructure is located on the south side (Brooks et al., 2016). In Ireland, 99.5% of foreign trade is handled by the ports, and in 2016, 43% of GDP was handled by Dublin Port (DPC, 2015). In 2018, containers and cargo trailers accounted for 82% of cargo volumes, while ro-ro (roll-on/roll-off) and lo-lo (lift-on/lift-off) saw record growth. Dublin Port is the busiest port in Ireland (Brooks et al., 2016), with cargo volume growth of 35.7% since 2013 and a new record of 38 million gross tons in 2018 (Dublin Port Company 2019). This has led to economic growth, but also increased energy consumption and environmental impact.

Sustainable growth of Dublin Port is of national importance to Ireland. There is a need to analyze the efficiency of Dublin Port, taking into account economic and environmental objectives. Data Envelopment Analysis (DEA) models have received considerable attention in this regard when evaluating port terminal efficiency (Cullinane et al., 2006; Muñuzuri and Muñoz-Díaz 2019). In this study, DEA analysis has been used to investigate the environmental efficiency of Dublin port.

For a detailed literature review on the application of different DEA models in port environmental efficiency assessment, we refer to Quintano et al. (2020), who used a non-radial DEA (NRDEA) model for eco-efficiency assessment. NRDEA models avoid all the drawbacks of traditional and radial DEA models in terms of remaining gaps, overestimated efficiency values, discriminatory power, and missing preference weights and were used in this study.

All variants of the DEA models used to evaluate the environmental efficiency of ports are basically one-stage models. However, one-stage models treat DMUs as black boxes where the sources of inefficiency and the linkage of variables within such systems are not explicitly explored. In contrast, two-stage models provide the ability to split a production process into two parts and link the variables between these parts. In addition, the performance of production processes composed of two sub processes can best be evaluated when they are analyzed separately to identify the sources of inefficiency (Kao, 2014). Two-stage models DEA have been used to evaluate efficiency, using the results of the first stage as input to the second stage (Cook et al., 2010; Mahdiloo et al., 2016). This, in turn, supports the decision-making needs of policy makers by isolating the impact of specific variables on overall efficiency.

The operation processes in a port terminal can be divided into two main components: Berth and quay form the seaside, while the (storage) yard and (terminal) gate form the landside (Carlo et al., 2014). The overall efficiency of a port depends on both seaward and landside services and is influenced by equipment and operations (Lee et al., 2014). Since port operations can be represented as two separate and distinct processes, a two-stage DEA model should be most appropriate (Mahdiloo et al., 2016). Consequently, this two-stage DEA model was used to evaluate the environmental efficiency of the Dublin port.

Characterizing harmful environmental impacts as undesirable and economic growth as desirable indicators is critical for a comprehensive efficiency assessment of ports (Tovar and Wall 2019). Therefore, in this study, the assessment of environmental efficiency of port services considering environmental and operation factors treated as desirable and undesirable inputs, intermediate measures, and outputs was conducted using a new two-stage NRDEA model with the added flexibility of incorporating decision-maker requirements (weights) and strong discriminatory power. The proposed two-stage NRDEA model is an extension of the NRDEA model presented by Djordjević et al. (2018).

The main contribution of this paper are assessing the environmental efficiency of Dublin port for the first time using two-stage non-radial DEA model which alludes to find a balance between a port's contribution to economic development and minimization of negative environmental impacts; Consideration of new environmental and operation factors in the efficiency assessment while exploration the impact of each variable on environmental efficiency. This study also brings attention to lack of availability of relevant data to extensively investigate the environmental efficiency of port operations in Ireland.

2. Literature review

To identify the differences from previous work and to confirm the novelty of this paper literature review was conducted. In the literature, the environmental efficiency of port has been analysed in numerous studies (Lee et al., 2014; Liu and Lim 2017; Sun et al., 2017; Rødseth et al., 2020; Wang et al., 2020; Paraskevas and Dimitriou, 2021; Quintano et al., 2021). In the literature, mainly Slack-Based DEA (SMB-DEA) models have been used to evaluate environmental efficiency of ports. Evaluation of environmental efficiency of ports using SBM-DEA was conducted in (Chin and Low 2010; Chang 2013; Lee et al., 2014; Na et al., 2017; Chang et al.,

2018, Chang et al., 2018; Gong et al., 2019; Quintano et al., 2020; Liu et al., 2021). A detailed study of 23 Korean ports used single one-stage, Slack-Based DEA (SBM-DEA) models that considered environmental and economic indicators (Chang 2013). The environmental efficiency of 11 major port cities in the world was evaluated using SBM-DEA models (Lee et al., 2014), and Chin and Low (2010) analyzed negative externalities for port efficiency evaluation. SBM-DEA models were used due to their advantages over radial and input-output oriented models (Chang et al., 2018). By estimating the environmental efficiency of ports using the SBM-DEA model with undesirable variables Chang (2013) concluded that a more comprehensive efficiency can be modelled and estimated by combining economic performance and environmental performance. Through analysis, Tovar & Wall (2019) concluded that an increase in environmental efficiency is possible in the form of a reduction in Carbon Dioxide (CO_2) emissions. Gobbi et al. (2019) considered different port areas in terms of plastic segregation and how much of that plastic is recycled. Environmental regulations known as emission control areas (ECAs) were applied to reduce emissions. However, Chang et al. (2018) concluded that ECA decreased port productivity. Chin and Low (2010) also highlighted that technically efficient shipping is more likely to achieve environmental efficiency, while the optimum amount of shipping capacity dramatically falls when undesirable outputs are considered. Sun et al. (2017) have concluded that fixed assets, berth quantity, and the geographical location significantly affected the efficiency of a port. Based on purely technical environmental efficiency, Na et al. (2017) indicated that different container port present dissimilar CO_2 emission reduction potentials. In previous studies, port environmental efficiency was estimated using the inputs listed in Table 1.

The operation processes in the port terminal can be divided into areas of the port: the berth, quay, transport area, (storage) yard, and (terminal) gate. Then, berth and quay parts can be grouped and represented as *sea-side* area, while the yard and gate can be presented as a *land-side* area (Carlo et al., 2014). The overall efficiency of a port depends on both sea-side and land-side areas and basically influenced by equipment and operation flows (Lee et al., 2014). Previous studies related to the evaluation of port efficiency have employed one-stage DEA models. The environmental efficiency of a number of Spanish ports has been assessed using one-stage non-radial models (Tovar and Wall, 2019). The main reason for using different one-stage models DEA is their ability to combine multiple inputs and outputs in an optimization framework (Gobbi et al., 2019). These models treat DMUs as black-boxes where sources of inefficiency and interconnection of variables within such systems are ignored. Nevertheless, in measuring the performance of DMUs their component processes should be evaluated separately with the aim to identify the source of inefficiency (Kao 2014). Due to this limitation of one-stage models, two-stage DEA models have been applied in evaluation of efficiency where outputs of the first stage have been used as inputs to the second stage (Cook et al., 2010; Mahdiloo et al., 2016). For processes that can be made up of two separate and distinct stages like processes in ports (sea-side and land-side), a two-stage DEA model should be used (Mahdiloo et al., 2016).

In the literature, the two-stage DEA model was applied in evaluating different aspects in different modes of transport. Two-stage DEA models have been mainly used in evaluating efficiency and performance of airports and airlines (Chu et al., 2010), (Merkert and Luca, 2013) and national civil aviation strategies (Itani et al., 2015). Then, two-stage DEA models were applied in analysing the efficiency of rail freight (Marchetti and Wanke, 2017) and for evaluating efficiency of urban transportation terminals (Sun, 2007). Measuring port efficiency using a two-stage network DEA model has only been presented by Wanke et al., 2011. However, there are no studies that evaluate environmental efficiency of ports using two-stage DEA model.

3. Methodology

A two-stage NRDEA model was applied here to evaluate the environmental efficiency of Dublin Port. No specific definition of environmental efficiency can be found in the literature; rather, this variable is described in coordination with the purpose of the study and the available data (Sorvari et al., 2011; Graham, 2008). For this study, the environmental efficiency of a port is the optimization of energy consumption and reduction of emissions from services while maintaining the ability of the port to operate as effectively as possible. The novel model used in the study is an extension of the non-radial model (Djordjević et al., 2018), which takes into account the introduction of desirable and undesirable intermediate measures. The new two-stage model is used to evaluate environmental efficiency, considering environmental and operation factors as desirable and undesirable inputs, intermediate measures, and outputs. All variables with significant negative environmental impacts are grouped as undesirable variables, while the other variables are grouped as desirable variables. A brief theoretical description of the model is given here.

3.1. Theory of DEA models

DEA is a nonparametric linear programming method used for relative efficiency evaluation of a set of similar entities or decision-making units (DMUs) (Markovits-Somogyi, 2011). The efficiency score is determined by the method DEA using multiple inputs and outputs. Based on the efficiency index, an efficiency frontier is established with a set of efficient DMUs that represent best practices. For inefficient DMUs, the efficiency level is determined based on their distance from the efficiency frontier. The DEA method can be effectively represented by a production process. Suppose there are K DMUs, each of which produces $y_m(m = 1, ..., M)$ outputs and consumes $x_n(n = 1, ..., N)$ inputs. In real applications, production processes may include some undesirable factors (Sun et al., 2017), such as waste materials, pollutants, etc., which are an inseparable part of the production process and constitute undesirable products. In such cases, each DMU can be considered to produce M desired outputs $y_m(m = 1, ..., M)$ and J undesirable outputs $u_j(j = 1, ..., J)$ using N desirable inputs $x_n(n = 1, ..., N)$ and L undesirable inputs $e_l(l = 1, ..., L)$. Consequently, the production process can be described as:

$$P = \{(x, e, y, u) : ((x, e) \, can \, produce(y, u))\} \tag{1}$$

Two main types of DEA models are radial and non-radial DEA models. A radial DEA model assumes a proportional change in input and output indicators and does not consider slacks for DMU inefficiency. The non-radial models consider slacks individually and independently for each input and output and incorporate them into an efficiency measure. This improves the discriminatory power of the model and causes less bias. NRDEA models are better suited for evaluating environmental performance through a comprehensive comparison of DMUs (Djordjević and Krmac, 2019).

3.2. Two-stage DEA model

Traditional one-stage DEA models have been extended to two-stage DEA models to account for production processes where the process should be studied as two independent single-stage units (Chen et al., 2010). In two-stage DEA models, the component processes of the DMU are evaluated separately to identify the source of inefficiency (Kao, 2014). In these models, an overall efficiency score for the production process and an efficiency score for each of the individual stages can be determined (Chen et al., 2010). In a two-stage DEA model, each DMU_k $(k = 1, ..., K)$ is modeled as two sub-DMUs connected in series. In the first stage, $DMU_{k,1}$ has N inputs $x_n(n = 1, ..., N)$ to produce M outputs $y_m(m = 1, ..., M)$. These M outputs are treated as inputs to the second stage to generate the final outputs $y_i(i = 1, ..., I)$ of $DMU_{k,2}$. These M outputs effectively represent the intermediate measures. Cook et al. (2010) reviewed various two-stage DEA models and classified them into four groups, such as the standard DEA approach, the efficiency decomposition approach, the network DEA approach, and the game-theoretic approach. In the literature on two-stage DEA modeling, undesirable indicators have been considered only few times (Maghbouli et al., 2014). In the eco-efficiency assessment, undesirable inputs, intermediates, and outputs were modeled only by Mavi et al. (2019).

3.3. Two-stage NRDEA model

A novel two-stage NRDEA model was proposed here to evaluate the environmental efficiency of Dublin Port. This model is an extension of the improved NRDEA model presented by Djordjević and Krmac (2019). This novel two-stage NRDEA model is based on the efficiency decomposition methodology, and the extension consists of introducing intermediate measures into the optimization framework.

According to the traditional CCR model formulation (Charnes, Cooper, and Rhodes), the individual efficiencies θ_k^1 for the first stage and θ_k^2 for the second stage of the two stages of DMU_k can be defined as follows:

$$\theta_k^1 = max \sum_{m=1}^{M} u_m y_{mk} \Big/ \sum_{n=1}^{N} v_n x_{nk} \qquad (2)$$

subject to: $\sum_{m=1}^{M} u_m y_{mk} / \sum_{n=1}^{N} v_n x_{nk} \leq 1,$

$$u, v \geq 0, \ m = 1, ..., M, \ n = 1, ..., N \qquad (3)$$

and,

$$\theta_k^2 = max \sum_{i=1}^{I} w_k z_{ik} \Big/ \sum_{m=1}^{M} u_m y_{mk} \qquad (4)$$

subject to: $\sum_{i=1}^{I} w_k z_{ik} / \sum_{m=1}^{M} u_m y_{mk} \leq 1$

$$w, u \geq 0; \ i = 1, ..., I; \ m = 1, ..., M, \qquad (5)$$

where v_n and u_m are the estimated parameters associated with the input and output variables in the first stage, and u_m and z_i are the estimated parameters associated with the input and output variables in the second stage. This non-linear output-oriented model, shown in Eqs. ((2)–(5)), does not consider undesirable factors. To include undesirable inputs and outputs, the model DEA should be extended. In the first stage, each DMU uses N desirable inputs and L undesirable inputs, and M desirable outputs and J undesirable outputs, denoted respectively as $x = (x_1, ..., x_{NK})$, $e = (e_1, ..., e_{LK})$, $y = (y_1, ..., y_{MK})$ and $u = (u_1, ..., u_{JK})$. The variable x_1 denotes the desirable inputs of the first DMU, while x_{nK} denotes the nth desirable inputs of the kth DMU, and similar holds for all other variables. Following Song et al. (2013, 2014), the equations are formulated as follows:

$$\theta_k^1 = max \frac{\sum_{m=1}^{M} u_m y_{mk}}{\sum_{n=1}^{N} v_n x_{nk} + \sum_{l=1}^{L} \delta_l e_{lk} - \sum_{j=1}^{J} \mu_j u_{jk}} \qquad (6)$$

subject to:

$$\sum_{m=1}^{M} u_m y_{mk} \Big/ \sum_{n=1}^{N} v_n x_{nk} + \sum_{l=1}^{L} \delta_l e_{lk} - \sum_{j=1}^{J} \mu_j u_{jk} \leq 1 \qquad (7)$$

$$u, v, \delta, \mu \geq 0, \ m = 1, ..., M, \ n = 1, ..., N, \ l = 1, ..., L, \ j = 1, ..., J, \qquad (8)$$

where v_n and u_m are the estimated parameters related to desirable input and output variables in the first stage, while δ_l and μ_j are estimated parameters related to undesirable input and undesirable outputs or intermediate measures in the second stage, and

$$\theta_k^2 = max \frac{max \sum_{i=1}^{I} w_k z_{ik}}{\sum_{m=1}^{M} u_m y_{mk} + \sum_{l=1}^{L} \mu_l u_{lk} - \sum_{t=1}^{T} \partial_t v_{tk}} \tag{9}$$

subject to:

$$\sum_{i=1}^{I} w_k z_{ik} \Big/ \sum_{m=1}^{M} u_m y_{mk} + \sum_{l=1}^{L} \mu_l u_{lk} - \sum_{t=1}^{T} \partial_t v_{tk} \leq 1 \tag{10}$$

$$w, u, \mu, \partial \geq 0, \ i = 1, \dots, I, \ m = 1, \dots, M, \ l = 1, \dots, L, \ t = 1, \dots, T. \tag{11}$$

where w_i, u_m, μ_j and δ_l are similar estimated parameters as described for Eq. (8).

A linear programming formulation was considered for the solution of Eqs. ((6)–(11)) with the aim of maximizing desirable outputs.

$$\theta_k^1 = max \sum_{m=1}^{M} u_m y_{mk} \tag{12}$$

subject to:

$$\sum_{n=1}^{N} v_n x_{nk} + \sum_{l=1}^{L} \delta_l e_{lk} - \sum_{j=1}^{J} \mu_j u_{jk} = 1, \tag{13}$$

$$\sum_{n=1}^{N} v_n x_{nk} + \sum_{l=1}^{L} \delta_l e_{lk} - \sum_{j=1}^{J} \mu_j u_{jk} \geq \sum_{m=1}^{M} u_m y_{mk} \tag{14}$$

$$u, v, \delta, \mu \geq 0, \ m = 1, \dots, M, \ n = 1, \dots, N, \ l = 1, \dots, L, \ j = 1, \dots, J, \tag{15}$$

and

$$\theta_k^2 = max \sum_{i=1}^{I} w_k z_{ik} \tag{16}$$

subject to:

$$\sum_{m=1}^{M} u_m y_{mk} + \sum_{l=1}^{L} \mu_j u_{jk} - \sum_{t=1}^{T} \partial_t v_{tk} = 1, \tag{17}$$

$$\sum_{t=1}^{T} \partial_t v_{tk} - \sum_{m=1}^{M} u_m y_{mk} + \sum_{l=1}^{L} \mu_j u_{jk} - \sum_{t=1}^{T} \partial_t v_{tk} \geq \sum_{i=1}^{I} w_k z_{ik}, \tag{18}$$

$$w, u, \mu, \partial \geq 0, \ m = 1, \dots, M, \ i = 1, \dots, I, \ j = 1, \dots, J. \tag{19}$$

The overall efficiency of these two-stages can be calculated as the average $\{\frac{1}{2}(\theta_k^1 + \theta_k^1)\}$ or product $\theta_k^1 * \theta_k^2$ of the efficiencies of each stage, while for the input-oriented models the constraints $\theta_k^1 \leq 1$ and $\theta_k^2 \leq 1$ should be satisfied. The product formulation in this study is adopted following the formulation of Cook et al. (2010) and (Kao and Hwang 2008). The two-stage process is considered efficient only when $\theta_k^1 = \theta_k^2 = 1$.

The formulation presented in Eqs. ((12)–(19)) was extended in the proposed two-stage NRDEA model by including weights, and intermediate measures, and presented using the dual programming formula in Eqs. ((20)–31)) after Song et al. (2013) and Wu et al. (2015). In this formulation, undesirable inputs and intermediate measures of the first stage are represented as θ_l and θ_j, respectively, and undesirable inputs and outputs of the second stage are represented as θ_j and θ_t, respectively, along with weights W_n, W_l, W_t, W_m and W_j of the decision maker. The first stage (**STAGE 1**) of 2-stage NRDEA is presented in Eqs. ((20)–(25)) as following:

STAGE 1 (20)

$$\theta_k^1 = min\ W_n\frac{1}{N}\sum_{n=1}^{N}\theta_n + W_l\frac{1}{L}\sum_{l=1}^{L}\theta_l + W_j\frac{1}{J}\sum_{j=1}^{J}\theta_j$$

subject to:

$\sum_{k=1}^{K}\lambda_k x_{nk} \le \theta_n x_{n1}$	$n = 1,..,N.$	(21)
$\sum_{k=1}^{K}\lambda_k e_{lk} \le \theta_l e_{l1}$	$l = 1,..,L.$	(22)
$\sum_{k=1}^{K}\lambda_k y_{mk} \ge y_{m1}$	$m = 1,..,M.$	(23)
$\sum_{k=1}^{K}\lambda_k u_{jk} = \theta_j u_{j1}$	$j = 1,..,J.$	(24)
$\lambda_k \ge 0,\ \theta_k^1 \le 1$	$k = 1,..,K.$	
$\sum W_n + W_l + W_j = 1$		(25)

In the second stage (**STAGE 2**), the NRDEA model includes M desirable outputs $y = (y_1, ..., y_{MK})$ and J undesirable outputs $u = (u_1, ..., u_{JK})$ of the first stage. These variables represent the desirable and undesirable inputs of the second stage, which are the intermediate measures and z desirable outputs $z = (z_1, ..., z_{IK})$ and t undesirable outputs $v = (v_1, ..., v_{TK})$ of the second stage. This observation for n desirable inputs, l undesirable inputs and m desirable outputs and j undesirable outputs of the first stage and z desirable outputs and t undesirable outputs of the second stage is satisfied and confirmed by Eqs. ((21)–(24) and (27)–(30)).

STAGE 2

$$\theta_k^2 = min\ W_m\frac{1}{M}\sum_{m=1}^{M}\theta_n + W_j\frac{1}{J}\sum_{j=1}^{J}\theta_j + W_t\frac{1}{T}\sum_{t=1}^{T}\theta_t \quad (26)$$

subject to:

$\sum_{k=1}^{K}\lambda_k y_{mk} \le \theta_n y_{m1}$	$m = 1,..,M.$	(27)
$\sum_{k=1}^{K}\lambda_k u_{lk} \le \theta_l u_{l1}$	$j = 1,..,J.$	(28)
$\sum_{k=1}^{K}\lambda_k z_{ik} \ge z_{i1}$	$i = 1,..,I.$	(29)
$\sum_{k=1}^{K}\lambda_k v_{tk} = \theta_j v_{t1}$	$t = 1,..,T.$	(30)
$\lambda_k \ge 0,\ \theta_k^2 \le 1$	$k = 1,..,K.$	(31)
$\sum W_m + W_t + W_j = 1$		

Based on this formulation, the inefficiency of each DMU at each stage can be identified and an evaluation of the *efficiency decomposition* of the whole process is possible. The formulation preserves the inseparable characteristics of all input and output indicators. Moreover, the efficiency scores (θ_n, θ_l, θ_j, θ_m, θ_t) can be regulated by considering specific decision maker weights (W_n, W_l, W_j, W_m, W_t) assigned to each of the efficiency scores. The sum of the weights should be equal to 1 (i.e., $\sum W = 1$). This leads to a stronger discriminatory power. The ranking of DMUs is better recognized, and no additional ranking methods are required because the weighting of decision maker, priority, and degree of desirability of the inputs, intermediate measures, and output indicators are taken into account. This formulation is effective in discriminating outputs, i.e., reducing undesirable outputs without compromising desirable outputs, and should be adopted for port environmental efficiency assessment.

4. Dublin Port: indicator data

Dublin Port in Fig. 1. is the largest cargo and passenger port in Ireland, handling nearly 50% of all trade in Ireland and is classified as a core port of the Trans-European Transport Network (TEN-T). Dublin Port Company (DPC) is a parastatal company responsible for the operation and development of the port. The sustainability, efficiency and growth of this port are of grate national and European interest.

Cargo and passenger volumes at Dublin port are expected to increase significantly due to the country's projected economic and population growth. A Port Masterplan 2011–2040 has been developed to support future growth (Dublin Port Company (DPC) 2012). This master plan considers investments in new infrastructure with environmental concerns in mind (Dublin Port Company 2019). Environmental objectives have been incorporated into future port development plans and presented in the Strategic Environmental Assessment Report (Dublin Port Company (DPC), 2012), as required by the European Directive (2001/42/EC) that requires the environmental assessment of all plans and programs (European Communities, 2004). This analysis of the environmental efficiency of Dublin Port, taking into account economic growth, supports this objective.

In this study, the efficiency of the port was evaluated for a 10-year period (2009 to 2018), since detailed data were available within this period. The data and factors used for the modeling are shown in Table 2. Information on the number of vessels arriving, goods received and forwarded, and total number of vehicles/trucks during 2009–2018 was collected from the Central Statistics Office (CSO) of Ireland (Central Statistics Office 2019). Dublin Port's sustainability reports (Dublin Port Company, 2016; Dublin Port Company, 2017b) provided the information on annual values of energy consumption per ton of throughput volume, while the data on total CO_2 emissions were provided by Dublin Port Company (2019).

Detailed financial information on Dublin Port operations was provided in annual reports prepared by the DPC, and data for capital expenditures and operating profits were taken from these (Dublin Port Company 2015a; Dublin Port Company 2018a). Information on terminals was very limited. The number of terminals was recorded for 2017 and 2018 in the Dublin Port Yearbooks (Dublin Port Company 2017a; Dublin Port Company 2018). The same value for this input was assumed for the other years. The next section

discusses in detail the distribution of these variables as desirable and/or undesirable and the analyses performed.

5. DEA analysis and results

The proposed two-stage NRDEA model described in Section 3.3 was applied to estimate the environmental efficiency of Dublin Port by simultaneously reducing the desirable and undesirable inputs and intermediate measures, as well as the undesirable outputs for a given level of desirable output indicators. These variables were selected considering the existing literature in the field and the

Table 1
Variables used in previous studies.

| Ref.	Inputs	Outputs
Chang (2013)	- labor, - capital, - energy	- *Desirable outputs:* cargo tonnage and vessel tonnage handled - *Undesirable output:* CO2 emissions
Gobbi et al. (2019)	- total amount of solid waste (metric tons), - amount of plastic waste segregated (metric tons)	- *Desirable outputs:* percentage of segregated plastics in relation to total solid waste (%), - *Undesirable output:* percentage of plastics recycled in relation to segregated plastics (%)
Lee et al. (2014b)	- labor population	- *Desirable outputs:* GDP and container throughput, - *Undesirable output:* NOx, SO2 and CO2 emissions
Sun et al., (2017)	- staff number, - operational costs, - fixed assets	- *Desirable outputs:* net profit and cargo throughput, - *Undesirable output:* NOx emissions
Chin and Low (2010)	- the frequency of shipping services - the bilateral trade flows	- *Desirable outputs:* container capacity flows, - *Undesirable output:* NOx, SO2, CO2 and PM emissions
Na et al. (2017)	- berth length (m), - port area (m2), - number of quay cranes, yard cranes	- *Desirable outputs:* container throughput - *Undesirable output:* CO2 emission
Liu and Lim (2017)	- crane, - berth	- *Desirable output:* throughput - *Undesirable output:* emissions
Tovar And Wall (2019)	- labor, - capital, - intermediate	- *Desirable outputs:* ships, cargo and passenger traffic - *Undesirable output:* CO2 emission
Chang et al. (2018)	- berth length, - number of container crane, - terminal total area	- *Desirable output:* cargo throughput
Gong et al. (2019)	- total assets, - capital expenditure, - capacity, - number of ships, Employees, - fuel cost	- *Desirable outputs:* revenue and cargo carried - *Undesirable output:* emissions
Quintano et al. (2020)	- -labor, - -energy	- *Desirable output:* total gross weight of goods handled in each port - *Undesirable output:* emissions
Rødseth et al. (2020)	- port area, - berth length, - quay cranes, yard cranes, - straddle carriers, - container handling trucks	- *Desirable outputs:* containers, SOx emissions
wang et al. (2020)	- labor, - total assets, - terminal length, - berth quantity	- *Desirable output:* standard container throughput, water freight turnover volume, freight throughput - *Undesirable output:* emissions
Liu et al. (2021)	- number of berths, - length of berths, - capital, - labor	- *Desirable outputs:* cargo throughput, container throughput, sales revenue - *Undesirable outputs:* pollutant, emissions
Paraskevas and Dimitriou, (2021)	- quay length, quay cranes, - stacking area	- *Desirable output:* throughputs
Quintano et al. (2021)	- number of employees, - energy	- *Desirable output:* total gross weight of goods - *Undesirable output:* emissions
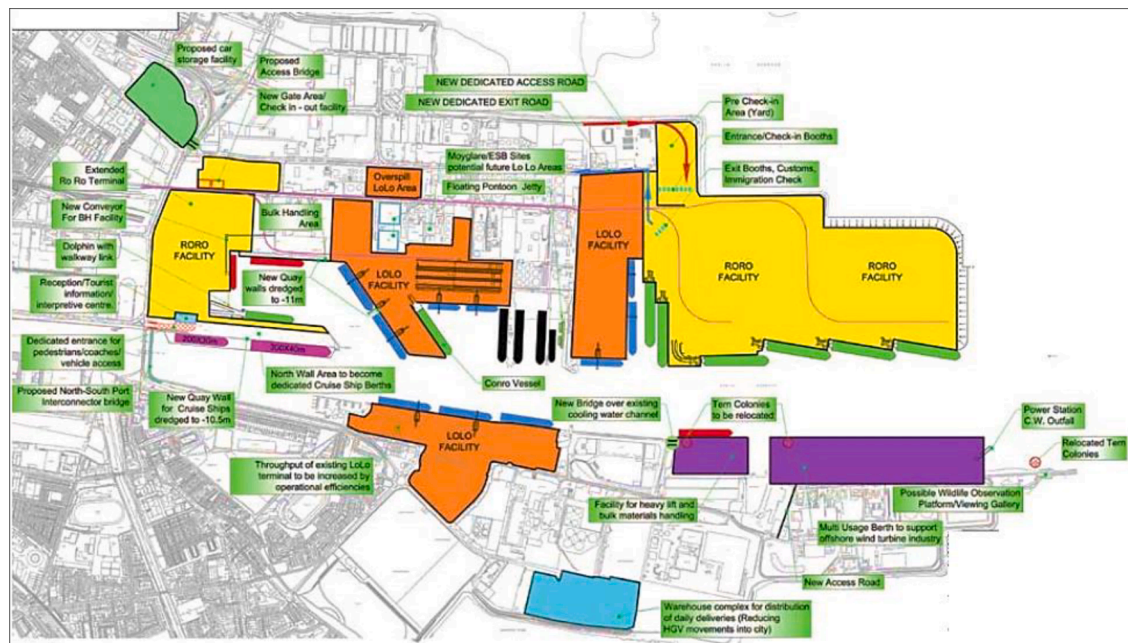
Fig. 1. Map of Dublin port (Source: Dublin port Masterplan (DPC, 2012)).

availability of data for Dublin Port. In this study, the variables listed in Table 2 were used. Ten years of available data were analyzed (see Table 2), with each year representing a DMU in the model. These variables were selected and categorized as desirable and undesirable based on the studies examined, Dublin Port operations, and environmental impacts (see Table 3).

Variables were categorised on inputs and outputs based on the assumption that port is divided on sea-side and yard-side of port. Stage 1 of the NRDEA model was designed to be representative of seaport operations. In this stage, the number of terminals was classified as a desirable input because their number and efficiency contribute positively to the overall efficiency of port operations. To estimate the environmental efficiency of a port, Tovar and Wall (2019) used the number of vessels as a desirable input, while Chin and Low (2010) used shipping services as an input for their assessment. In our study, we similarly used the number of arriving ships as an input. Vessels are considered pollution for the seaward operations of the port.

Due to their role in the production process and in relation to environmental issues, arriving ships were classified as an undesirable input because the number of ships directly indicates one of the main sources of emissions on the seaward side of the ports (Na et al., 2017). Although capital expenditures are not directly related to emissions, this input was selected as an undesirable input because it is related to port capital and maintenance costs and its overall impact on the port economy. The variables, goods received and forwarded, were selected as outputs because the throughput of goods or volume causes a corresponding energy consumption and generates emissions on the seaward and landward sides of the port. These outputs are presented as desirable variables because the volume of goods handled indicates the activity of the port and should be maximized for sustainability. The outputs of the first stage of the NRDEA model represent intermediate variables that serves as inputs to the second stage, which is representative of landside port operations.

Energy consumption per ton of volume throughput was selected as an undesirable output of port operations. Trucks represent the production output of the port operations process and are a source of emissions on the land side of the port. Since truck operations within the port are closely associated with cargo handling, they were identified as DO. It is important to note that all trucks in Dublin

Table 2
Indicator Data of Dublin Port.

Variables	Unit	Year 2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Goods received	kt	12,667	12,750	12,275	12,160	12,713	13,440	14,205	15,177	15,889	16,922
Goods forwarded*	kt	5939	6797	7192	7178	7153	7639	8000	8672	9107	9410
Vessels arrived	Number	7247	7434	6767	6624	6651	7040	7106	7665	7713	7860
Vehicles/trucks	thousand	642	726.3	724.1	810.9	861.3	921.1	973.6	1064	1113.9	1158.6
Terminals	Number	17	17	17	17	17	17	17	17	17	17
Energy consumed per ton of volume throughput	kWh/t	600	650	580	600	600	550	570	550	540	535
CO2 Emissions/year	kg	3962	4754	4016	4213	4222	4022	4571	4255	4189	3886
Capital expenditure	Mil €	22.3	7.8	4.4	16.3	13.5	9.4	17	44.2	96.2	87.4
Operating profit	Mil €	25.6	27	27.8	29.1	32.8	36.1	42.9	45.6	46.5	47.4

Table 3

Inputs, intermediate measures, and outputs.

	Indicators	Basic model	Cap_Exp Model A	Cap_Exp Model B	Cap_Exp Model C	Classification
Stage 1	**Inputs**					
	Total number of terminals	√	√		√	DI
	Capital expenditure		√	√	√	UDI*
	Vessels arrived	√	√	√	√	UDI*
	Outputs					
	Goods received	√	√	√	√	DO*
	Goods forwarded	√	√	√	√	DO
	Energy consumed per ton of volume throughput	√	√	√	√	UDO*
Stage 2	**Intermediate measures**					
	Goods received	√	√	√	√	DIM*
	Goods forwarded	√	√	√	√	DIM
	Energy consumed per ton of volume throughput	√	√	√	√	UDIM*
	Outputs					
	Total number of vehicles/trucks	√	√	√		DO*
	Operating profit				√	DO
	Total emissions produced per yr	√	√	√	√	UDO*

*DI-Desirable Input; *UDI-Undesirable Input; *DIM-Desirable Intermediate Measure; *UDIM-Undesirable Intermediate Measure; *DO-Desirable Output; *UDO-Undesirable Output.
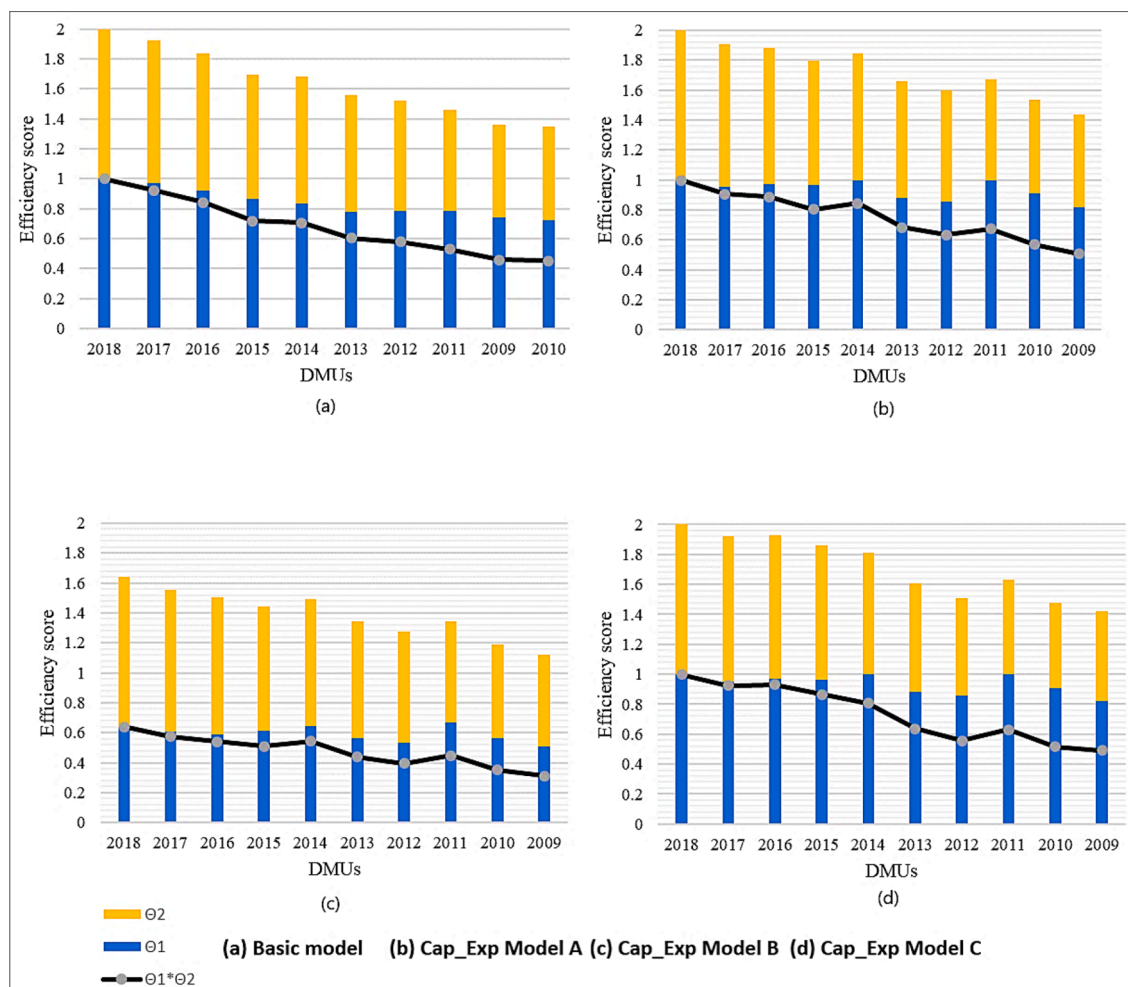
Fig. 2. Port environmental efficiency calculated using two-stage NRDEA models.

Table 4
Environmental Efficiency from Modelling Analysis.

DMUs	Basic model				Cap_Exp Model A				Cap_Exp Model B				Cap_Exp Model C			
	Θ1	Θ2	Θ1*Θ2	Ranking	Θ1	Θ2	Θ1*Θ2	Ranking	Θ1	Θ2	Θ1*Θ2	Ranking	Θ1	Θ2	Θ1*Θ2	Ranking
2018	1	1	1	*1*	1	1	1	*1*	0.641	1	0.641	*1*	1	1	1	*1*
2017	0.971	0.951	0.923	*2*	0.953	0.951	0.906	*2*	0.606	0.951	0.576	*2*	0.953	0.970	0.924	*2*
2016	0.921	0.914	0.842	*3*	0.971	0.914	0.887	*3*	0.592	0.914	0.541	*4*	0.971	0.958	0.930	*3*
2015	0.863	0.833	0.719	*4*	0.964	0.833	0.803	*5*	0.612	0.833	0.510	*5*	0.964	0.897	0.865	*4*
2014	0.836	0.844	0.706	*5*	1.000	0.844	0.844	*4*	0.646	0.844	0.545	*3*	1.000	0.808	0.808	*5*
2013	0.779	0.777	0.605	*6*	0.881	0.777	0.685	*6*	0.566	0.777	0.440	*7*	0.881	0.723	0.637	*6*
2012	0.783	0.738	0.578	*7*	0.857	0.738	0.632	*8*	0.536	0.738	0.396	*8*	0.857	0.648	0.555	*8*
2011	0.786	0.674	0.530	*8*	1.000	0.674	0.674	*7*	0.667	0.674	0.450	*6*	1.000	0.632	0.632	*7*
2010	0.743	0.616	0.458	*9*	0.910	0.626	0.570	*9*	0.564	0.626	0.353	*9*	0.910	0.569	0.518	*9*
2009	0.723	0.626	0.453	*10*	0.821	0.616	0.506	*10*	0.506	0.616	0.312	*10*	0.821	0.600	0.493	*10*

Port are diesel powered. Therefore, the higher the number of trucks, the higher the environmental impacts and operation benefits. The port's total emissions per year were classified as UDO of the second stage of the overall environmental efficiency assessment of Dublin Port. All inputs and outputs considered in Stage 1 and Stage 2 of the two-stage NRDEA model are summarized in Table 3.

The port's efficiency over the 2009–2018 period was examined using a number of methods, the first of which is the use of multiple combinations of variables. In addition, weight variations and sensitivity analyzes were performed to compensate for limited data availability. The most appropriate model and the results of the analysis are presented in the following subsections.

5.1. Model variations

The two-stage NRDEA method was used to evaluate the environmental efficiency of Dublin port using four models that consider four combinations of indicators shown (see Table 3). These models were solved using Excel Solver. To avoid bias, the same weighting of 1/3 (i.e., $W_n = \frac{1}{3}, W_l = \frac{1}{3}, W_j = \frac{1}{3}, W_m = \frac{1}{3}, W_t = \frac{1}{3}$) was chosen for each efficiency score for all variables. These four models are reffered to *Basic model, Cap_Exp Model A, Cap_Exp Model B, and Cap_Exp Model C,* indicating the different combinations of variables considered. The overall efficiency as well as the efficiency levels of each stage are shown in Fig. 2 and Table 4 for all four models.

The *Basic model* was calculated using all the variables listed in the indicator column in Table 3, except that capital expenditure was excluded from stage 1 and operation profit was excluded from stage 2. The results in Fig. 2(a) show that 2018 was the most efficient year, while the lowest efficiency was calculated for 2010. The high efficiency in 2018 can be attributed to the low values of the undesirable variables such as energy consumed and emissions in 2018. The main reason for the lower values of the undesirable variables and the overall improved environmental efficiency of Dublin Port is particularly related to the use of advanced technologies in recent years. Regarding inefficiency, both stages of the NRDEA model have shown the lowest values of θ_k^1 and θ_k^2 for 2010. Efficiencies at both stages of the model are equivalent, indicating that both landward and seaward operations have equivalent efficiencies.

In the remaining three models, *Cap_Exp ModelA, Cap_Exp ModelB, and Cap_Exp ModelC,* the capital expenditure variable was included in Stage 1 because it is an important economic input for Dublin Port. Stage 1 efficiency improved in all models compared to the *Basic model* and is therefore considered an important indicator. *Cap_Exp ModelA* considered the additional indicator capital expenditure and it can be observed that the efficiency level improved for all DMUs (see Fig. 2(b)) except for year 2017. The improvement in efficiency was due to the additional undesirable input indicating the reduction in the value of $\frac{1}{L}$ and the weight of decision maker. The improved efficiency can be attributed to the production of desirable outputs compared to undesirable variables. It can be observed that efficiency improved for all DMUs (see Fig. 2(b)). The improvement in efficiency can be attributed to the addition of additional undesirable variable, indicating the reduction in the value of $\frac{1}{L}$ and the decision maker weight. Moreover, the improved efficiency of all DMUs can be associated with the production of desirable outputs at included levels of capital expenditure. In the next model, the significance of the indicator terminal was tested by omitting it.

For *Cap_Exp Model B,* Fig. 2(c) shows a decrease in the environmental efficiency level for all DMUs and especially for the first stage.
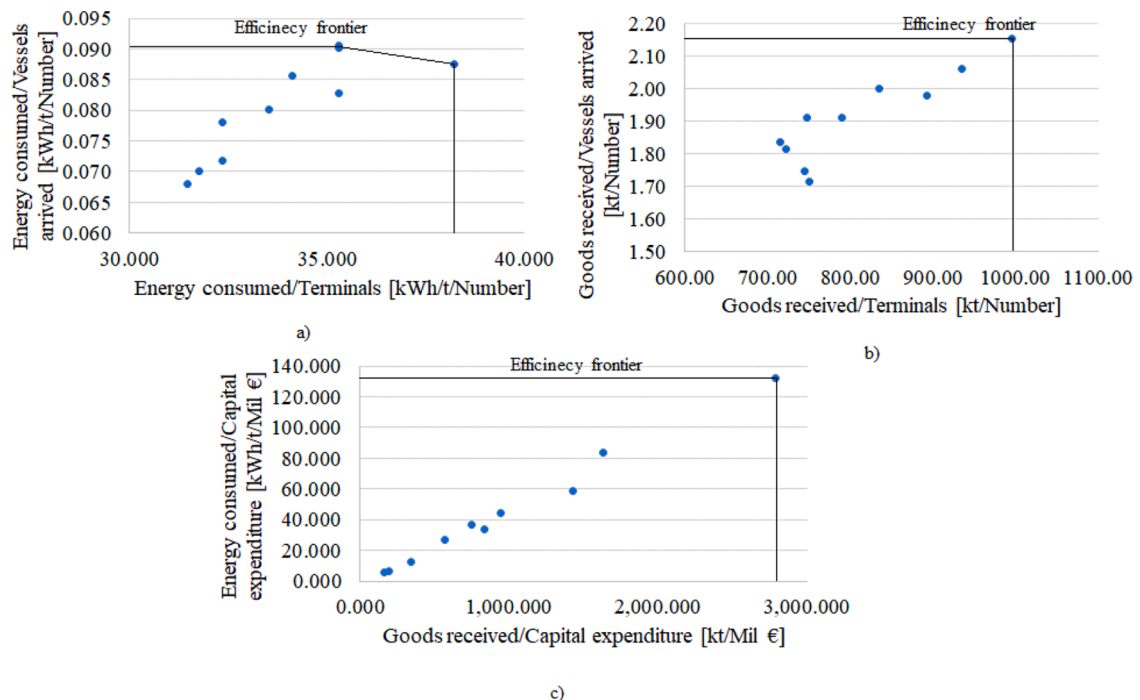

a)

b)

c)

Fig. 3. Efficiency Frontiers of Stage 1.

It can be concluded that the number of terminals has a significant impact on the environmental efficiency of ports. In this model, the level of desirable input and undesirable input and outputs outweighs the desirable outputs. The results show that this model is not suitable for modeling the environmental efficiency of Dublin Port. *Cap_Exp Model C* includes another economic indicator, operation profit, which replaces the number of trucks as the desirable output in Stage 2. The results in Table 4 show that the efficiency has decreased slightly for all DMUs. In 2018, Dublin Port achieved the highest operation profit, so the comparability of efficiency is compromised when considered as desirable output. As a result, this model may not be most suited to assess the environmental efficiency of Dublin Port. Based on this analysis using four different combinations of indicators, *Cap_Exp Model A* was selected as the most appropriate model for further analysis in the following sections.

5.2. Efficiency frontiers of Dublin Port

To further examine the impact of variables on the efficiency level of DMUs, the efficiency frontiers for Stage 1 and Stage 2 were shown in Figs. 3 and 4, respectively. DMUs that are on the efficiency frontier are considered DEA efficient, while inefficient DMUs are away from this frontier. The distance from the efficiency frontier represents the level of inefficiency of the DMUs. In Fig. 3(b,c), there is only one efficient DMU, while in Fig. 3(a), there are two efficient DMUs.

In Fig. 4(a), one DMU was efficient while other DMUs are far from the efficient frontier. In Fig. 4(b,c), three DMUs are on the efficiency frontier. The detailed analysis of the influence of variables on efficiency within the efficiency frontiers is presented in the Discussion section.

5.3. Decision-makers' weight variation

Decision maker weights indicate policy maker preferences, where a particular stage or set of variables may be preferred over others. The results presented in Table 4 were calculated assuming that the weights are equal or that there is no bias, as indicated in Eqs. (13) and (19). In this section, the overall DMU efficiencies were calculated using three cases with different decision maker weights. The aim of these 3 cases was to show the influence of different weights on results, as well as the influence of incorrect sum of weights on final results in case 1 and 2. Therefore, different preferences of policy makers could be assumed in each case.

$$\text{Case 1}: W_n = 1/3, \ W_l = 1/4, \ W_j = 1/3 \tag{20}$$

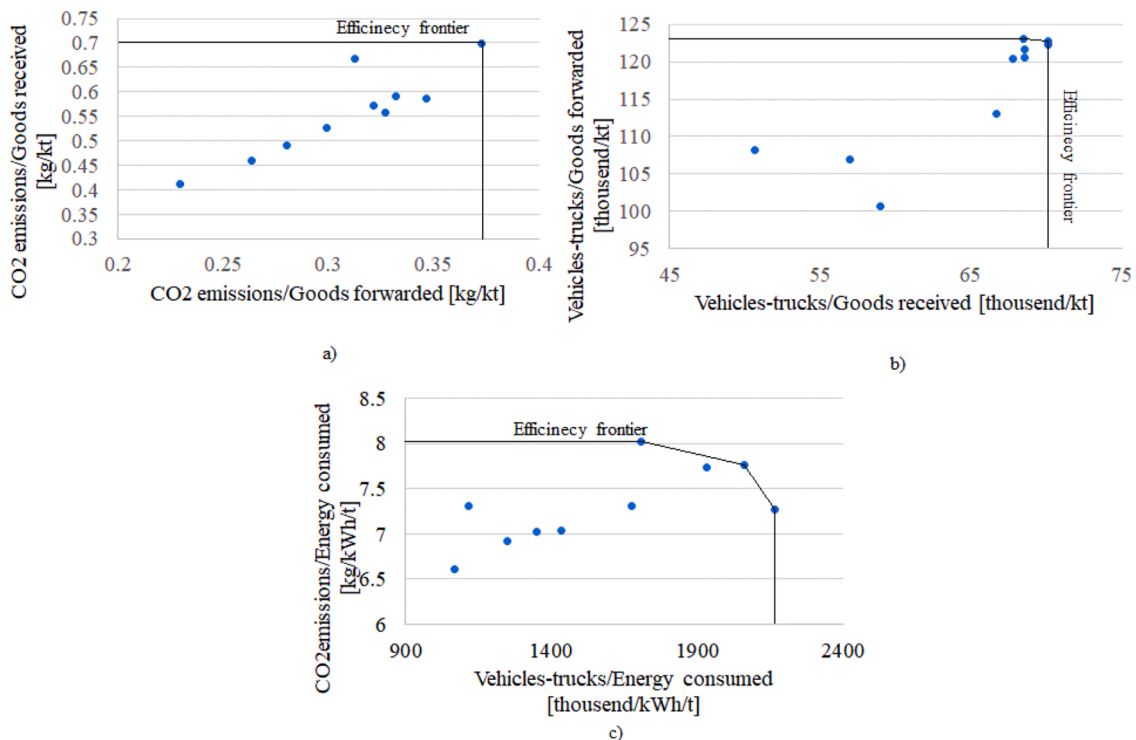$$\text{Case 2}: W_n = 1/4, \ W_l = 1/4, \ W_j = 1/3 \tag{21}$$

Fig. 4. Efficiency Frontiers of Stage 2.

$$\text{Case 3}: W_n = \frac{1}{4}, \ W_l = \frac{1}{4}, \ W_j = 1 \Big/ 2 \tag{22}$$

The results of these variations (see Table 5) show that the efficiency in Stage 1 and Stage 2, as well as overall environmental efficiency, were lowest in Case 2. Consequently, undesirable outputs, which have a higher weight among decision makers compared to desirable inputs and undesirable inputs, play an important role in the environmental efficiency of Dublin Port. In addition, the introduction of a bias in decision maker weights leads to a significant reduction in overall efficiency compared to the models without bias shown in Table 4. However, at Stage 1, the efficiency of the decision maker weights in Case 3 is better than for the models in Table 5. In all other cases, the bias caused by the decision maker weights has a negative effect on the overall efficiencies.

5.4. Sensitivity analysis: one-factor-at-a-time

The Masterplan for the development of Dublin Port envisages an increase in throughput to 60 million tons by 2040. Therefore, expansion on the landside is required and reintegrating of port into the city is a challenge (DPC, 2012). This expansion requires the provision of additional terminals. The impact of terminal changes on environmental efficiency should be evaluated. This also compensates for the assumptions regarding the number of terminals. The number of terminals was varied between 15 and 19. For illustration, Table 6 shows the impact of changes in the number of terminals for the year 2011 and the resulting environmental efficiencies of the port. This change has a significant impact on the efficiency levels of some DMUs.

A key economic indicator, capital expenditure, was varied to test the sensitivity of the model and to identify variations in Dublin Port's efficiency. For illustration purposes, the efficiency results as the values of capital expenditures changed for 2011 are shown in Table 7. As capital expenditure increased, the efficiency level for 2011 was decreased, while it improved for 2010. The results of increasing energy consumed for 2011 in Stage 1 and Stage 2 are shown in Table 8. Stage 1 showed an improvement in efficiency for 2010, while Stage 2 showed a decrease in efficiency for 2011. The reason for the unchanged efficiency for 2011 in Stage 1 is related to the larger number of inputs and outputs in Stage 1.

A key factor to notice here that the efficiencies improved drastically from 2014 onwards for Dublin Port except in case of variations in energy consumption. This is in line with the new energy efficiency measures introduced in Dublin Port in 2014.

5.5. Sensitivity analysis: factor interaction

In this section, the sensitivity of the model DEA is presented with particular reference to factor interactions. The study was conducted using two hypothetical scenarios by changing the indicator values of the *Cap_Exp ModelA*, as follows:

Scenario 1: Desirable Input (DI) and Undesirable Input (UDI), Desirable Input Measure (DIM) and Undesirable Input Measure (UDIM), and the Undesirable Output (UDO) were reduced by 10% for all inefficient DMUs, while for efficient DMUs the values of these indicators were increased by 10%. However, the values of desirable outputs were kept unchanged.

Scenario 2: This scenario is the same as the previous one, except that the changes are made in the amount of 20% instead of 10% of the original values given in Table 9.

In Table 9, the critical observation is that a 10% change produces a huge improvement in all efficiency values compared to a 20% change. This is critical to understanding that small changes to key indicators can significantly improve port environmental efficiency. A detailed discussion of the implications of the results presented in this section is provided in the next section.

6. Discussion and policy implications

The analysis included several combinations of indicators and four NRDEA models to examine the contribution of each indicator in assessing the environmental efficiency of Dublin Port and to identify potential policy implications and improvements. The methodology helped identify an appropriate DEA model using a limited number of variables due to the limited availability of DMU time series data. In addition, the analysis explored a range of variations in weights, indicator variables, and sensitivities to understand the

Table 5
Efficiencies of Dublin Port under Variation of Decision-Maker Weights.

| DMUs | Changes in weights | | | | | | | | |
| | Θ1 | | | Θ2 | | | Θ1*Θ2 | | |
	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
2018	0.917	0.833	1	0.917	0.833	1	0.841	0.694	1
2017	0.875	0.795	0.955	0.872	0.788	0.936	0.763	0.626	0.894
2016	0.914	0.823	1	0.84	0.755	0.895	0.768	0.621	0.895
2015	0.896	0.808	0.978	0.767	0.684	0.803	0.687	0.553	0.785
2014	0.917	0.833	1	0.779	0.697	0.825	0.714	0.581	0.825
2013	0.812	0.733	0.878	0.722	0.64	0.754	0.586	0.469	0.662
2012	0.793	0.715	0.858	0.686	0.608	0.715	0.544	0.435	0.613
2011	0.917	0.833	1	0.626	0.556	0.656	0.574	0.463	0.656
2010	0.839	0.76	0.894	0.583	0.512	0.598	0.489	0.389	0.535
2009	0.766	0.688	0.832	0.574	0.507	0.598	0.44	0.349	0.498

Table 6
Efficiencies of the Dublin Port varying with the number of terminals in 2011.

DMUs	Number of terminals in 2011										
	Θ1					Θ2	Θ1*Θ2				
	15	16	17	18	19		15	16	17	18	19
2018	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2017	0.953	0.953	0.953	0.953	0.953	0.951	0.906	0.906	0.906	0.906	0.906
2016	0.971	0.971	0.971	0.971	0.971	0.914	0.887	0.887	0.887	0.887	0.887
2015	0.964	0.964	0.964	0.964	0.964	0.833	0.803	0.803	0.803	0.803	0.803
2014	0.968	0.989	1.000	1.000	1.000	0.844	0.817	0.835	0.844	0.844	0.844
2013	0.870	0.881	0.881	0.881	0.881	0.777	0.676	0.685	0.685	0.685	0.685
2012	0.830	0.850	0.857	0.857	0.857	0.738	0.613	0.627	0.632	0.632	0.632
2011	1.000	1.000	1.000	1.000	1.000	0.674	0.674	0.674	0.674	0.674	0.674
2010	0.869	0.890	0.910	0.924	0.924	0.626	0.544	0.557	0.570	0.578	0.578
2009	0.821	0.821	0.821	0.821	0.821	0.616	0.506	0.506	0.506	0.506	0.506

Table 7
Efficiencies of the Dublin Port varying with capital expenditure in 2011.

DMUs	Capital expenditure in 2011										
	Θ1					Θ2	Θ1*Θ2				
	4.4	14.4	24.4	34.4	44.4		4.4	14.4	24.4	34.4	44.4
2018	1.000	1.000	1.000	1.000	1.000	1	1.000	1.000	1.000	1.000	1.000
2017	0.953	0.953	0.953	0.953	0.953	0.951	0.906	0.906	0.906	0.906	0.906
2016	0.971	0.971	0.971	0.971	0.971	0.914	0.887	0.887	0.887	0.887	0.887
2015	0.964	0.964	0.964	0.964	0.964	0.833	0.803	0.803	0.803	0.803	0.803
2014	1.000	1.000	1.000	1.000	1.000	0.844	0.844	0.844	0.844	0.844	0.844
2013	0.881	0.881	0.881	0.881	0.881	0.777	0.685	0.685	0.685	0.685	0.685
2012	0.857	0.857	0.857	0.857	0.857	0.738	0.632	0.632	0.632	0.632	0.632
2011	1.000	0.877	0.835	0.818	0.808	0.674	0.674	0.591	0.563	0.551	0.545
2010	0.910	0.924	0.924	0.924	0.924	0.626	0.570	0.578	0.578	0.578	0.578
2009	0.821	0.821	0.821	0.821	0.821	0.616	0.506	0.506	0.506	0.506	0.506

Table 8
Efficiencies of the Dublin Port varying with energy consumed in 2011.

DMUs	Energy consumed in 2011								
	Θ1			Θ2			Θ1*Θ2		
	580.0	610.0	640.0	580.0	610.0	640.0	580.0	610.0	640.0
2018	1.000	1	1	1.000	1	1	1.000	1.000	1.000
2017	0.953	0.953	0.953	0.936	0.936	0.936	0.892	0.892	0.892
2016	0.971	0.971	0.971	0.895	0.895	0.895	0.869	0.869	0.869
2015	0.964	0.964	0.964	0.803	0.803	0.803	0.774	0.774	0.774
2014	1.000	1	1	0.825	0.825	0.825	0.825	0.825	0.825
2013	0.881	0.881	0.881	0.754	0.754	0.754	0.664	0.664	0.664
2012	0.857	0.857	0.857	0.715	0.715	0.715	0.613	0.613	0.613
2011	1.000	1	1	0.656	0.649	0.643	0.656	0.649	0.643
2010	0.910	0.924	0.924	0.598	0.598	0.598	0.544	0.553	0.553
2009	0.821	0.821	0.821	0.598	0.598	0.598	0.491	0.491	0.491

Table 9
Sensitivity Analysis with Multiple Factor Variations.

DMUs	Θ1		Θ2		Θ1 *Θ2	
	10%	20%	10%	20%	10%	20%
2018	0.842	0.561	0.876	0.714	0.738	0.401
2017	0.961	0.961	1.000	1.000	0.961	0.961
2016	0.973	0.973	0.955	0.955	0.929	0.929
2015	1.000	1.000	0.854	0.854	0.854	0.854
2014	0.897	0.598	0.879	0.879	0.788	0.526
2013	0.929	0.929	0.801	0.801	0.744	0.744
2012	0.899	0.899	0.760	0.760	0.683	0.683
2011	1.000	0.684	0.698	0.698	0.698	0.477
2010	1.000	1.000	0.634	0.634	0.634	0.634
2009	0.839	0.839	0.635	0.635	0.533	0.533

potential pathways for improving Dublin Port's efficiency given data limitations and expected economic growth.

The four models studied have consistently shown that the port's environmental efficiency has improved over the 10-year period studied. This can be attributed to modernization of the port, improved technologies and practices, and adaptation of stringent environmental standards (DPC, 2011, Dublin Port Company DPC2012, Dublin Port Company 2015a, Dublin Port Company 2017a, Dublin Port Company 2018a, and Dublin Port Company, 2019). The final two-stage NRDEA model selected for further analysis was the *Cap_Exp ModelA*, which was deemed most appropriate because it included a combination of economic and environmental variables, as required for a comprehensive study of port environmental efficiency (Tovar and Wall, 2019). Following this model selection, the influence of a number of key indicator variables was examined in sensitivity analyses in Sections 5.4 and 5.5.

The anticipated economic growth and associated increase in trade projected for Ireland would require an expansion of port operations. As Dublin Port is located in the heart of the City of Dublin, an increase in capacity through a greater number of terminals will require the acquisition of additional land and will result in increased noise and air pollution in the neighborhood. This will have a detrimental effect on the sustainability of Dublin Port. The importance of the indicator (number of terminals) was confirmed in this study. The efficiency frontier shown in Fig. 3(a) further illustrates this. The decrease in the number of terminals in 2011 shows that the environmental efficiency of DMUs decreased between 2010 and 2014, with the exception of 2011. The changes in 2011 do not affect the efficiency values thereafter. This can be related to the values of capital expenditures in 2011, which were significantly lower than in all other years. The increase in the number of terminals is expected to be associated with negative environmental impacts that may be offset by improved operational efficiency in Stage 1, possibly through the use of shore power for vessels. Better planning will also improve efficiency and may further offset the impacts of capacity expansion. Additionally, environmental impacts can be further limited by introducing environmental clauses with stringent measures in terminal contracts (Bjerkan and Setera, 2019).

Two critical financial performance indicators, capital expenditure and operational profit, were considered in modeling port efficiency. The inclusion of capital expenditure resulted in a significant improvement in environmental efficiency (see Fig. 3). Increased capital expenditure in 2011 significantly decreased environmental efficiency for the year, but had no impact on efficiency in other DMUs except 2010. The indicator has a direct impact and should be controlled accordingly. The other financial indicator, operational profit, showed some impact. However, replacing the number of trucks with operating profit as a desirable outcome of port operations did not significantly improve environmental efficiency and was not included in the final model. It should be noted, however, that in years when the ratio of operational profit to capital expenditure is extremely high, an improvement in overall efficiency can be observed by including this indicator (Table 7). Moreover, this indicator is not strictly related to seaward or landside port operations.

Energy consumption is an important undesirable factor that has been considered in the proposed models. This variable has improved over time, as has the port's environmental efficiency. However, in a sensitivity analysis, the indicators showed significant changes in the values of environmental efficiency (see Table 8). Reduction in energy consumption can be achieved by implementing measures such as renewable or alternative energy sources, improved mobility through eco-driving and eco-routing within the catchment area, modal shift, and pollution reduction. A promising technique for improving Stage 2 efficiency may be to shift to rail as a more environmentally friendly mode of transportation (Bjerkan and Setera, 2019).

The analysis of the variability of the weights showed their influence on the final efficiency (Table 5). In case 3, when the weights were reduced with respect to the desirable and undesirable inputs, the model actually became more output-oriented and the overall efficiency was improved. However, for optimal and unbiased analysis, all weights should be set at the same values. However, considering the weights may result in prioritizing the preferences of certain groups of decision makers in the final results. For example, financial policy makers and port authorities are interested in the financial variables that can improve the economic efficiency (profit) of the port (PWC, 2013). On the other hand, the public, the EU, and environmentalists will pay attention to the energy and environmental objectives. Separate modeling should be done to understand the impact of such preferences.

Finally, the multifactor sensitivity analysis presented in Section 5 showed that the proposed two-stage NRDEA model offers variations with minimization of inputs and undesirable outputs by improving efficiency. Consequently, it is critical that the evaluation of Dublin Port's environmental efficiency requires accurate data. In addition, port authorities and policy makers can use this analysis to identify what and how many improvements should be made to improve the efficiency of a particular DMU. For example, it can be seen that the 2010 efficiency level was improved in Stage 1 with a 10% reduction in DI and UDI, DIM and UDIM, as well as the UDO, while higher changes in these variables are required to become efficient in Stage 2. In addition, the efficiency level for 2017 was not significantly improved with a 10% reduction, while this DMU becomes efficient in Stage 2. In addition, this analysis allows improvements to be focused on specific areas of port operations without impacting economic growth.

7. Conclusion

A two-stage NRDEA model was implemented to assess the environmental efficiency of Dublin Port in Ireland. The use of a two-stage model to capture the two separate processes of port operations - landside and seaside - is a novel idea and was successfully evaluated in this study. The strength of the modeling methodology lies in the more efficient discrimination of DMUs compared to other DEA models applied in port efficiency analysis (Quintano et al., 2020). The two-stage model clearly distinguishes all variables as desirable or undesirable, uses specified weights for decision makers, and applies efficiency scores to all variables except outputs with desirable characteristics (DO). The objective function representing environmental efficiency is formulated by combining desirable and undesirable environmental and economic inputs, intermediate measures, and undesirable environmental outputs, all of which can be reduced for some level of DO.

In the case of a DEA model, the choice of indicators is crucial because the comprehensive picture of efficiency levels could change in the case of inappropriate selection of inputs, intermediate measures, and outputs and their categorization as desirable and undesirable

variables. Therefore, several variables and their combinations were considered to investigate their influence and significance on the port's environmental efficiency using four variants of NRDEA models. Variables such as number of trucks, number of terminals, and capital expenditure play an important role in determining the environmental efficiency of Dublin Port. Consequently, measures related to these factors are essential to consider in future sustainability master plans of the port (Sustainability Master Plan 2040). The proposed model has proven to be an appropriate optimization method to successfully assess the environmental efficiency of a port without compromising economic growth. The model can be used as a sustainability optimization tool to achieve a balance between the economy and the environment while ensuring safe and undisturbed throughput of a port.

Using the proposed two-stage NRDEA model, the overall efficiency, the efficiencies of each stage, and possible variations in efficiency were calculated and compared through a sensitivity analysis of Dublin Port over a 10-year period (2010–2018). The results show that environmental efficiency has improved recently without affecting economic growth, due to improved cargo handling technologies and the implementation of energy expenditure and environmental management standards. This gradual improvement demonstrates the success of the energy efficiency agreement signed in 2014 by Dublin Port Company (DPC) and the Sustainable Energy Authority of Ireland (SEAI), which achieved 33% savings and energy efficiency improvements by 2020. As of December 2017, a 24.3% improvement in energy performance has already been achieved. The efficiency analysis carried out using two-stage NRDEA model is in agreement with these undertakings. The effect of recession (2008–2012) and reduced economic activities and subsequent increase of such activities (beyond yr.2014) did not affect the environmental efficiency of Dublin Port which would have been the case in the absence of the energy efficiency agreement.

To fully explore the changes in environmental efficiency of Dublin Port, further extension of this study is necessary. However, no environmental data is available from the Dublin Port outside the studied period which is also the main limitation of this study. O'Connor (2019) has compared the efficiency of Irish ports and Tsakiridis et al. (2021) have compared Irish and Spanish ports. However, in the absence of compatible environmental data-i.e., energy expenditure and emissions, as well as data on the number of trucks and vessels operated-the environmental efficiency estimate could not be extended to other Irish ports. Based on the limitations identified, it is critical to develop policy to collect and report energy expenditure and emission related information for all Irish ports. As future work, an evaluation of environmental efficiency for a longer period of time as well as for multiple ports can be conducted using the two-stage DEA.

Declaration of Competing Interest

No conflict of interest to disclose.

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