

# Using network centralized data envelopment analysis for shipping line resource allocation

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**Abstract** In liner shipping, the objective of a shipping company is to gain profits with a certain number of dispatched vessels and shipping costs depending on the shipping line conditions and market trends. In view of the current need to address global warming and reduce carbon emissions, the issue of greenhouse gases produced by shipping line operations should be considered in addition to profits. This study applied centralized decision making involving centralized data envelopment analysis for optimal resource allocation for each shipping line in order to achieve optimal output and undesirable output levels with reallocation of resources while using currently available resources. In the empirical analysis, this study sought to verify the resource allocation model for the intra-Asia lines of a Taiwanese shipping company by using the network centralized data envelopment analysis. The results showed that the proposed model provides shipping line operators with information on the amounts by which they should reduce undesirable outputs (carbon emissions), increase line revenue and revenue TEU-nautical mile, and reallocate resources. As such, the model can serve as a guide for resource allocation in shipping lines.

**Keywords** Network data envelopment analysis · Centralized decision making · Shipping liner · Resource allocation

## Introduction

The growth of the international container shipping industry in the past decade is impressive. It now transports more than one-third of the value of global trade and provides more than 4.2 million jobs (World Shipping Council 2017). Like most transportation modes, however, the shipping industry contributes to pressure on the environment at various spatial levels and has a heavy social and environmental footprint. Environmentally motivated regulations are likely to become the most important cost driver in the coming years (BSR 2010). This will put more pressure on international container shipping lines to increase sustainability performance, which may necessitate reallocation of resources. An issue of considerable importance, from both a practical cost reduction standpoint and environmental protection perspective, involves the reallocation of resources or costs of a set of shipping lines in an efficient manner.

Research has been done on resource allocation in different fields. According to the resource-based theory proposed by Barney (1991), enterprise resources include physical capital (factory buildings, equipment, geographic location, and raw materials), human capital (technologies and staff's knowledge), and organizational capital (organizational structure and management systems). In liner shipping, the main resources are shipping costs, human resources, and the number of vessels. Shipping companies aim to gain profits under a certain number of dispatched vessels and shipping costs depending on the shipping line

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operational conditions and market tendencies. However, when shipping costs are adapted to the shipping line operational conditions, the proportions of allocated resources are indeterminate. Therefore, shipping companies face the issue of how to ensure efficient resource utilization and maximize their outputs by allocating limited available resources across shipping lines.

Apart from general inputs and desirable outputs, undesirable outputs are usually jointly produced with desirable outputs. Desirable outputs are general outputs that an operator desires or needs, whereas undesirable outputs refer to outputs that are not favored by an operator, such as pollution and noise produced during the production process (Seiford and Zhu (2002), Guo et al. 2011 and Cherchye et al. 2015). Due to the greenhouse effect, global climate issues have been escalating in recent years. Environmental hazards have been gradually affecting society. Countries have been implementing measures aimed at sustainable development of the environment, as well as regulations restricting the increased greenhouse gas emissions worldwide. Examples of such regulations are the United Nations Framework Convention on Climate Change (UNFCCC) and the Paris Agreement on greenhouse gases including water vapor, carbon dioxide, methane, nitrous oxide, ozone and some artificial chemicals such as chlorofluorocarbons (CFCs). In recent years, CO<sub>2</sub> emission reduction has been taken as an important research issue in the areas of transportation and logistics. Several previous studies have investigated the greenhouse gas issues such as CO<sub>2</sub> emission reduction in transportation, supplier selection with environmental concerns, etc. Ketelaer et al. (2014) identified the subsectors of commercial transport with fewer obstacles to implementing use of electric vehicles, such that the effectiveness of CO<sub>2</sub> reduction can be easily achieved. As a result, Ketelaer et al. investigated the electric vehicle market's potential. Lee et al. (2014) indicated that car sharing can positively contribute to the environment and society, and identified the points where car sharing is most appropriate in a small city, based on estimates of CO<sub>2</sub> emission reduction. Kamruzzaman et al. (2015) estimated the CO<sub>2</sub> emission of residents in rural areas by using their travel behaviors, and identified the reasons for less CO<sub>2</sub> emission by certain groups of residents. Based on green supply chain management, Kuo et al. (2015) developed a multi-criteria decision-making approach for supplier selection from the perspective of carbon management. Celik et al. (2016) also developed an integrated multi-criteria decision-making approach which considered the environment related factors for supplier selection to appraise the logistics service providers.

Pollutants emitted by vessels, such as carbon dioxide (CO<sub>2</sub>), nitrous oxide, and sulfide emissions, are considered undesirable outputs in the maritime industry. In 2009, the

International Maritime Organization (IMO) published a study on greenhouse gas emissions and drafted related indices. The Maritime Environment Protection Committee (MEPC) of the IMO proposed the Energy Efficiency Operational Index (EEOI) to evaluate carbon emissions during shipping, and the use of ship technologies and operation methods to reduce greenhouse gas emissions (Second IMO GHG study 2009). Green shipping is the expected future tendency in container liner shipping, as it allows energy saving and carbon reduction, while complying with regulations and meeting customers and stakeholders' needs.

Selected undesirable outputs have differed depending on the research subject. Most studies have determined undesirable outputs by focusing on industrial manufacturing processes (Borgheipour et al. 2017). Pollutants emitted by vessels, such as CO<sub>2</sub>, nitrous oxide, and sulfide emissions, are considered to be undesirable outputs in the maritime industry. The high complexity of the notion of sustainable development requires new method for operation analysis and measurement of production units. A major concern is how to improve our existing shipping lines' operations to better take into consideration both production performance and ecological issues. The main problem in developing eco-efficiency indicators is the lack of measures like market prices for emissions. Some of these difficulties can be overcome by using data envelopment analysis (DEA) for efficiency measurement (Korhonen and Luptacik 2004). However, liner shipping services cannot be stored, and output consumption may be substantially different from output production. For example, the available capacity of a vessel assigned to a shipping line may not be fully utilized (i.e., not all capacity is used), which means the available capacity is not the same as the service that is actually utilized. Traditional black-box DEA models are unable to examine the efficiency of the production and consumption divisions (or processes) independently or the impact of the production process on consumption and overall shipping line operations. Such an analysis is essential in order to understand the specific processes which contribute to inefficiencies in shipping lines. Network DEA (NDEA) models go beyond the traditional black-box model and allow computation of divisional efficiencies in addition to the overall operational efficiency for shipping line operations (Färe and Grosskopf 2000). A main advantage of DEA is that it does not require any prior assumptions on the underlying functional relationships between inputs and outputs. In primary DEA or NDEA models, the major goal was evaluating the efficiency of the decision-making units (DMUs). Since resource allocation is an important issue in the management of corporations, recently, Golany (1988), Thanassoulis and Dyson (1992) and Athanassopoulos (1995, 1996, 1998) have introduced models for assessing

targets and allocating resources based on the DEA approach. Most of the previous studies applied the black-box centralized data envelopment analysis (CDEA) models to optimize the resource utilization of all DMUs across the total entity, which implies that each DMU produces its services using identical technology. To accommodate non-storable characteristics of liner shipping, and assuming that the role of a shipping company is to possess and provide each shipping line with resources, this paper reviews the involved factors and proposes a two-stage network CDEA (NCDEA) model by integrating the two-stage NDEA and CDEA of resource allocation for internal lines of a shipping company in Taiwan in the period of 2013.

Although DEA has been applied in some studies to analyze operating performance of internal lines of shipping companies, it has rarely been used for resource allocation. The contributions of this study to the literature are, firstly, that it proposes a two-stage NCDEA model which combines network DEA and CDEA to build a model of resource allocation for internal lines of a shipping company. Secondly, in the shipping industry, carbon emissions, which are a kind of undesirable output, are non-separable from energy resource consumptions. Carbon emission reductions are proportional to energy reductions. Thus, emission resistance in a two-stage production system is imposed on the two-stage NCDEA model. Thirdly, lines of a shipping company cannot be investigated in the same manner as general liner shipping performance, in which all inputs are seen as specific inputs leading to the production of shipping line final outputs. In the proposed model, not only were carbon emissions in shipping lines considered to be undesirable outputs, but shared inputs are also shared among lines of a shipping company, since some input items are not able to be specifically attributed to each shipping line. Without separating shared and specific inputs, measuring liner shipping performance is not reasonable. Thus, inputs in this study were divided into three types, namely shared, specific, and energy inputs. Shared inputs refer to resources shared by shipping lines which cannot be identified as being used by one specific line. Specific inputs refer to resources that can be classified as used by a specific line. Energy inputs are ones related to undesirable outputs.

The remaining sections of this study are organized as follows. “[Literature review](#)” section presents the literature discussion. “[Preliminaries](#)” section introduces basic two-stage NDEA and CDEA approaches. “[Two-stage NCDEA resource allocation model](#)” section explains the proposed two-stage NCDEA model of resource allocation in shipping lines. “[An empirical illustration using data from a Taiwanese liner shipping company](#)” section presents an empirical analysis of Asian lines of a Taiwanese shipping

company. Conclusions of this study and suggestions are given in “[Conclusion](#)” section.

## Literature review

Conventionally, managers find it difficult to assess performance when multiple inputs and multiple outputs are involved, especially when the relationships between the inputs and outputs have trade-offs between each other (Sueyoshi et al. 2009). DEA is a mathematical programming approach for evaluating the relative efficiency which uses multiple inputs to produce multiple outputs. The DEA approach is well suited to helping management examine the performance of individual DMUs. In recent years, DEA has been used to evaluate activities as varied as innovation risk management in production systems (Arabshahi and Fazlollahabadi 2017), as well as efficiency and effectiveness in railways (Perelman and Pestieau 1988; Yu and Lin 2008), airports (Oum and Yu 2004; Yu and Hsu 2012), public transportation (Viton 1997; Karlaftis 2004) and sea ports (Cullinane et al. 2006). In the shipping liner industry, Seok’s (1996) study on the financial operating performance of shipping companies analyzed such financial indicators as operating costs, operating revenue, total assets, long-term liabilities, retained earnings, return on sales, return on equity, and return on assets. Panayides et al. (2011) measured the relative market and operating efficiency of companies in the dry bulk, wet bulk and container shipping industries by using both DEA and stochastic frontier analysis models. Bang et al. (2012) investigated the impact of strategic and operational management on efficiency performance by using a two-stage DEA model. The results of the analysis provided container shipping companies with information on the managerial and strategic implications of how managerial options influence operational and financial performance. Gutiérrez et al. (2013) also applied the two-stage DEA model to measure the efficiency of major international container shipping lines (CSLs) and evaluate the effects of the global economic crisis on CSLs. Although the use of DEA to measure the relative efficiency of container shipping lines is increasing rapidly, most DEA studies related to container shipping have been undertaken with firm-level data, which measures the overall performance of the units of observation. Their black-box DEA models only reflect the underlying technology and knowledge of the relationship between the inputs and final outputs.

It is worth noting that, since transportation services cannot be stored, output consumption may be substantially different from output production. Inspired by Fielding (1987), some recent studies have essentially distinguished efficiency from effectiveness under an input–intermediate product–consumption scheme to completely elucidate the

non-storable commodities production process (e.g., Yu 2008). According to Hwang and Kao (2006), in a black-box-based DEA model, all inputs go through the “black-box” production process, resulting in final outputs. Analysis of such “black-box” performance can demonstrate the overall performance of each DMU, while failing to examine performance at each production stage in the overall production process. Due to the fact that the capacity provided by a shipping line will be lost if it is not used by customers, this study employed two-stage network NDEA based on the transportation industry performance evaluation framework (Fielding 1987), which includes production efficiency, service effectiveness and operational efficiency (Yu 2008). Omrani and Keshavarz (2016) illustrated a supply chain network of a shipping company with the input and output variables associated with each member of the supply chain, in which the relational NDEA models are used for measuring the performance of a supply chain and its members. In the traditional DEA or NDEA models, each DMU is projected independently, in either an input-oriented or output-oriented fashion. However, operations in large organizations with a centralized decision-making environment like shipping companies usually involve the participation of more than one individual shipping line, each contributing a part of the total production.

In liner shipping, resources of a shipping company include shipping costs, human resources, and the number of vessels. The modern shipping industry is characterized by a trend toward larger vessels and development of shipping strategic alliances. Despite the increased efficiency of larger vessels and alliances, shipping companies spend a great amount of resources in acquiring them, which can lead to losses due to diseconomies of scale if the market supply is greater than the demand. Moreover, due to resource scarcity and, thus, lack of resources that could be used, it is very important for a shipping company to allocate resource inputs wisely across its lines and ensure their efficient use.

In the traditional DEA model, each operating unit could estimate its own individual targets. However, this decentralized scenario is presumably inappropriate for a centralized organization in which a centralized decision-maker (DM) wishes to optimize the performance of the system of units as a whole. The local managers may accordingly focus on different principles for decision-making such as individual goals and strategies which might not be optimal for a centralized DM. There have been some previous approaches in the literature that handle the DMUs in a joint manner (Golany et al. 1993; Golany and Tamir 1995; Athanassopoulos 1995, 1998; Kumar and Sinha 1999; Beasley 2003). One drawback of their approach, apart from the heuristic or ad hoc character and the fact that they are complex or have additional restrictions, is that no one has developed an appropriate incentives system which is a

simple, intuitive, general centralized resource allocation model and which can encourage the local management of each unit to act in a way which aims at a global objective of minimizing total input consumption (or maximizing total output production) for the organization as a whole.

CDEA suggests that a centralized DM owns or supervises all DMUs and provides them with resources; the DM's goal is to seek the optimization of resource utilization of all DMUs in an organization. After Lozano et al. (2004) first introduced the concept of CDEA, which optimizes the total resource consumption across the total entity, a number of studies about CDEA applications for resource allocation have been published (Lozano and Villa 2004, 2005; Korhonen and Syrjänen 2004; Asmild et al. 2009; Lozano et al. 2011; Fang 2013; Yu et al. 2013; Mar-Molinero et al. 2014; Chang et al. 2015; Fang 2013; Fang and Li 2015). Furthermore, carbon emissions in shipping have attracted increased attention from the IMO and countries all over the world, and regulations have been introduced with regard to greenhouse gas emissions. Lozano et al. (2009) established a CDEA model for resource allocation which treated environmental hazards as undesirable outputs. Li et al. (et al. 2013) examined the input reduction, desirable output reduction and undesirable output reduction in a multiple objective CDEA model. Tohidi et al. (2014) proposed CDEA models to assess the overall efficiency of a system consisting of DMUs when DMUs produce desirable and undesirable outputs. Wu et al. (2013) further considered both the desirable and undesirable outputs in allocating the given resources in the next period. However, the previous studies did not consider impacts of the relationship between carbon emissions and energy inputs on the production process, or production heterogeneity in the presence of two-stage production processes.

## Materials and methods

### Preliminaries

#### *Two-stage NDEA approach*

It is assumed that there are  $N$  DMUs to be evaluated in terms of  $I$  inputs,  $S$  intermediate outputs,  $R$  desirable outputs and  $T$  undesirable outputs. Let  $x_{ij}(i = 1, 2, \dots, I)$ ,  $z_{sj}(s = 1, 2, \dots, S)$ ,  $y_{rj}(r = 1, 2, \dots, R)$  and  $u_{tj}(t = 1, 2, \dots, T)$  represent the input of the production process, intermediate outputs produced by the production process and used as inputs for the service process, and desirable output and undesirable output values produced by the service process of DMU $_{jj}(j = 1, 2, \dots, N)$ , respectively.

The overall efficiency of DMU  $k$  can be estimated by the following slack-based measure (SBM) DEA model:

$$\text{Min}_{\rho, s_i^-, s_r^+, s_t^{b-}, \lambda, \mu} \rho_k(x_k, z_k, y_k, u_k) = \frac{1 - \frac{1}{I} \left( \sum_{i=1}^I \frac{s_{ik}^-}{x_{ik}} \right)}{1 + \frac{1}{(R+T)} \left( \sum_{r=1}^R \frac{s_{rk}^+}{y_{rk}} + \sum_{t=1}^T \frac{s_{tk}^{b-}}{u_{tk}} \right)} \tag{1}$$

s.t.

$$\sum_{j=1}^N \lambda_j x_{ij} = x_{ik} - s_{ik}^-, i = 1, \dots, I, \tag{2}$$

$$\sum_{j=1}^N \lambda_j z_{sj} = \sum_{j=1}^N \mu_j z_{sj}, s = 1, \dots, S, \tag{3}$$

$$\sum_{j=1}^N \lambda_j z_{sj} = z_{sk}, s = 1, \dots, S, \tag{4}$$

$$\sum_{j=1}^N \mu_j z_{sj} = z_{sk}, s = 1, \dots, S, \tag{5}$$

$$\sum_{j=1}^N \mu_j y_{rj} = y_{rk} + s_{rk}^+, r = 1, \dots, R, \tag{6}$$

$$\sum_{j=1}^N \mu_j u_{tj} = u_{tk} - s_{tk}^{b-}, t = 1, \dots, T, \tag{7}$$

$$\lambda_j, \mu_j \geq 0, j = 1, 2, \dots, N. \tag{8}$$

where  $s_{ik}^-$ ,  $s_{rk}^+$ , and  $s_{tk}^{b-}$  are input, desirable output and undesirable output slacks, respectively, while  $\lambda_j$  and  $\mu_j$  are the intensity variables associated with production and service technologies, respectively, for each DMU. A DMU is considered to be efficient overall when  $\rho_k$  is equivalent to 1 and it has zero input, desirable output and undesirable output slacks. Otherwise, the DMU is called inefficient. If the underlying technology is variable returns to scale (VRS) for both production and service technologies, we could impose the constraint  $\sum_{j=1}^N \lambda_j = 1$  and  $\sum_{j=1}^N \mu_j = 1$  on the production and service technology, respectively, in Model (1–8) to obtain the VRS model. Figure 1 illustrates such a scheme for transport service evaluation in which three performance measures are identified.

### Centralized DEA based on a one-stage DEA approach

Let us consider a set of N DMUs, with each DMU consuming I inputs to produce R outputs.  $j, j' = 1, 2, \dots, N$  is the index for the DMUs;  $i = 1, 2, \dots, I$  is the index for inputs that need to be reallocated;  $r = 1, 2, \dots, R$  is the index for outputs that need to be increased; and  $f = 1, 2, \dots, F$  is the index for unadjustable inputs. Furthermore,  $x_{ij}$  is the amount of adjustable input  $i$  consumed by DMU $_j$ ;  $y_{rj}$  is the quantity of output  $r$  produced by DMU $_j$ ; and  $x_{fj}$  is the amount of unadjustable input  $f$  consumed by DMU $_j$ . It is assumed that there are units under control by a centralized decision-maker. The central decision-maker aims to reallocate the adjustable inputs to all of the units operating under the central unit in such a way that the total outputs will be maximized. The centralized resource-allocation model based on a one-stage DEA approach is formulated as the following linear program:

Phase I: Maximum expansion of outputs

$$\max \sum_{r=1}^R \phi_r \tag{9}$$

$$\sum_{r=1}^n \sum_{j=1}^n \lambda_{jj'}^{(I)} x_{ij} \leq \sum_{j=1}^n x_{ij'}, i = 1, \dots, I; \tag{10}$$

$$\sum_{j=1}^n \lambda_{jj'}^{(I)} x_{ij} \leq x_{ij'}, j' = 1, \dots, N, i = 1, \dots, I; \tag{11}$$

$$\sum_{j=1}^n \lambda_{jj'}^{(I)} x_{fj} \leq x_{fj'}, j' = 1, \dots, N, f = 1, \dots, F; \tag{12}$$

$$\sum_{j'=1}^N \sum_{j=1}^N \lambda_{jj'}^{(I)} y_{rj} \geq \phi_r \sum_{j=1}^n y_{rj'}, r = 1, \dots, R; \tag{13}$$

$$\sum_{j=1}^n \lambda_{jj'}^{(I)} y_{rj} \geq y_{rj'}, r = 1, \dots, R; j' = 1, \dots, N \tag{14}$$

$$\sum_{j=1}^n \lambda_{jj'}^{(I)} = 1, j' = 1, \dots, N \tag{15}$$

$$\lambda_{jj'}^{(I)} \geq 0, \forall j = 1, \dots, N; \forall j' = 1, \dots, N, \tag{16}$$

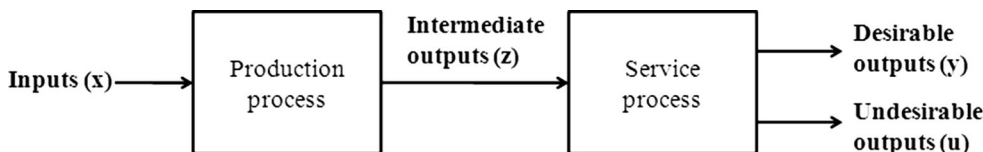


Fig. 1 The structure of a two-stage network production process

$$\phi_r > 0, \forall r = 1, \dots, R; \tag{17}$$

where  $\phi_r$  is the radial expansion rate of the output  $r$ ; and the  $(\lambda_{1j'}^{(I)}, \lambda_{2j'}^{(I)}, \dots, \lambda_{Nj'}^{(I)})$  vector represents the intensity variables that project DMU  $j'$  onto the production frontier in Phase I.

The objective function associated with Eq. (13) seeks to find the maximum expansion of outputs. Equation (10) guarantees that the total projected input consumption is less than the observed ones. Equation (11) and (12) guarantee that each observed adjustable and unadjustable input  $i$  and  $f$  consumed by each DMU  $j'$  fall in the input possibility set. Equation (14) guarantees the observed output quantities of the DMU  $j'$  for each output  $r$  fall in the output possibility set. If VRS over the reference technology is assumed, Eq. (15) can be imposed on this model (Fig. 2).

Phase II: Resource allocation

$$\max = \sum_{j'=1}^N \sum_{i=1}^I (s_{ij'}^- - s_{ij'}^+) \tag{18}$$

$$\sum_{j'=1}^N \sum_{j=1}^N \lambda_{ij'}^{(II)} x_{ij} = \sum_{j'=1}^N (x_{ij'} + s_{ij'}^+ - s_{ij'}^-), i = 1, \dots, I; \tag{19}$$

$$\left( \sum_{j=1}^N \lambda_{ij'}^{(II)} x_{ij} = x_{ij'} + s_{ij'}^+ - s_{ij'}^-, j' = 1, \dots, N, i = 1, \dots, I; \right) \tag{20}$$

$$\sum_{j'=1}^N s_{ij'}^+ \leq \sum_{j''=1}^N s_{ij''}^-, i = 1, \dots, I; \tag{21}$$

$$\sum_{j=1}^n \lambda_{ij'}^{(II)} x_{fj} \leq x_{fj'}, j' = 1, \dots, N, f = 1, \dots, F; \tag{22}$$

$$\sum_{j'=1}^N \sum_{j=1}^N \lambda_{ij'}^{(II)} y_{rj} = \phi_r^* \sum_{j=1}^N y_{rj}, r = 1, \dots, R; \tag{23}$$

$$\sum_{j=1}^n \lambda_{ij'}^{(II)} y_{rj} \geq y_{rj'}, j' = 1, \dots, N, r = 1, \dots, R; \tag{24}$$

$$\sum_{j=1}^n \lambda_{ij'}^{(II)} = 1, j' = 1, \dots, N; \tag{25}$$

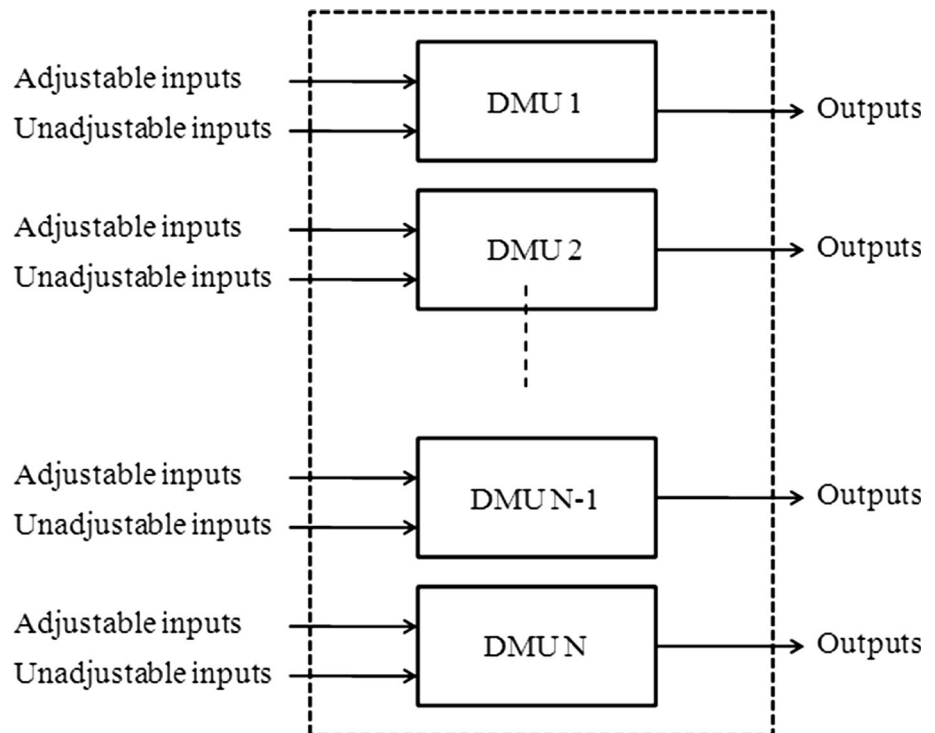
$$\lambda_{ij'}^{(II)} \geq 0, \forall j, j' = 1, \dots, N, \tag{26}$$

$$s_{ij'}^+, s_{ij'}^- \text{ are integers}, \forall j' = 1, \dots, N; \forall i = 1, \dots, I \tag{27}$$

where  $s_{ij'}^+$  is the transfer-in slack with respect to the input  $i$  for DMU $_{j'}$ ;  $s_{ij'}^-$  is the transfer-out slack associated with input  $i$  for DMU $_{j'}$ ; and  $(\lambda_{1j'}^{(II)}, \lambda_{2j'}^{(II)}, \dots, \lambda_{Nj'}^{(II)})$  represents the intensity variables for DMU  $j'$  in Phase II.

The objective function indicates that the maximal total input can be reduced and that the minimal total input can be transferred for all the DMUs, and  $\phi_r^*$  is obtained from the optimal output  $r$  scalar value of Model (10–17). Equations (19) and (20) associated with Eq. (21) seek to reduce the total input consumption of all the DMUs as

**Fig. 2** The structure of resource reallocation based on CDEA approach



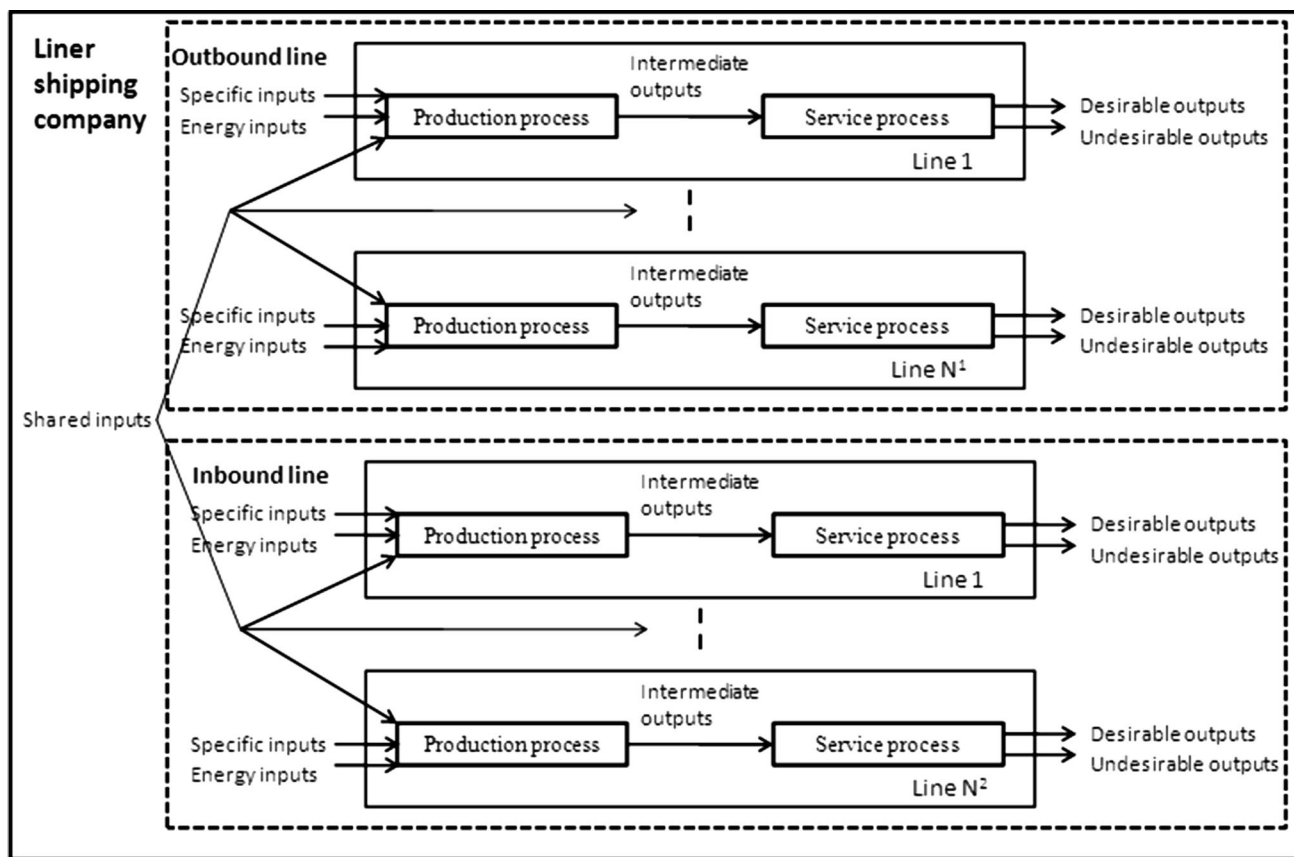


Fig. 3 The structure of resource reallocation based on two-stage NCDEA approach

much as possible, in which Eq. (21) implies that the total amount of each adjustable input will be reduced after resource reallocation. Equation (24) guarantees the observed output quantities of the DMU  $j$  for each output  $r$  fall in the output possibility set.

### Two-stage NCDEA resource allocation model

In order to examine resource allocation in each line of a company based on characteristics of the liner shipping industry, this study integrated CDEA and a two-stage network production model to construct a two-stage network CDEA model. The objective function and constraints of the model were imposed according to characteristics of inputs and outputs in order to reflect the actual operating situation of the company. Unlike traditional two-phase CDEA proposed by Lozano et al. (2004), in which the optimal resource allocation solution is solved in two separate phases, this study not only opens the “black-box” to form a two-stage production process, but also solves the resource allocation solution using a single-phase NCDEA algorithm. Resources were reallocated for each sub-production process in each shipping line based on the multiple objectives

of maximizing desirable outputs and minimizing undesirable outputs. The resource allocation concept of liner shipping services is demonstrated in Fig. 3. The first stage (production process) regards the relationship between resource inputs by a shipping company to provide service capacity. Service capacity in the first stage was set as fixed intermediate outputs in view of the difficulty associated with changing an established short-term liner shipping schedule. These intermediate outputs were used as inputs in the second stage (service process), the outputs of which were divided into two types, desirable and undesirable. Shared inputs are also shared among lines of the target shipping company.

Consider a set of  $N$  lines, with each line  $j$  ( $j = 1, 2, \dots, N$ ) characterized by a production process of consuming  $I_1$  shared inputs  $x_{i_1j}$ , ( $i_1 = 1, 2, \dots, I_1$ ),  $I_2$  specific inputs  $x_{i_2j}$ , ( $i_2 = 1, 2, \dots, I_2$ ) and  $I_3$  energy inputs  $x_{i_3j}$ , ( $i_3 = 1, 2, \dots, I_3$ ) to produce  $S$  intermediate outputs  $z_{st}$ , ( $s = 1, 2, \dots, S$ ), and those intermediate outputs used as inputs to yield  $R$  desirable outputs  $y_{rj}$ , ( $r = 1, 2, \dots, R$ ) and  $T$  undesirable outputs  $u_{tj}$ , ( $t = 1, 2, \dots, T$ ). Some portion  $\alpha_{i_1j}$  of the shared input is allocated to the  $j$ th line. (Note that  $\alpha_{i_1j} \geq 0$ ,  $\sum_{j=1}^N \alpha_{i_1j} = 1$ .) In the proposed model,  $\alpha_{i_1j}$  is a decision variable which must be determined.

Moreover, shipping lines can be inbound and outbound and, thus, have different requirements. Consideration of inbound and outbound shipping lines as homogeneous DMUs would lead to biases in the analysis. Therefore, inbound and outbound shipping lines were considered as different DMUs in the analysis. In this study, shipping lines were divided into inbound and outbound lines. With the emphasis on the two directions, there is a need to provide a performance measurement tool with way-based information as part of the aggregate efficiency score. For notational purposes, let  $j^1(j^1 = 1, 2, \dots, N^1)$  and  $j^2(j^2 = 1, 2, \dots, N^2)$  denote the index of outbound and inbound lines, respectively, where  $N = N^1 + N^2(j = 1, 2, \dots, N)$ .

In the model, the optimal distribution ratio of shared inputs was determined as a decision variable of the model. The  $P_{i_1,lower}$  and  $P_{i_1,upper}$  are lower and upper bounds, respectively, defined by any restrictions imposed on distribution ratios. Specific inputs refer to resources used by a specific shipping line. Their reallocation was determined using the non-radial DEA approach. Energy inputs are ones related to undesirable outputs with a weak disposability assumption. Due to such a relationship, their reduction was considered to be proportional to that of undesirable outputs, based on which the optimal reduction ratio was calculated. Due to the presence of outbound and inbound shipping lines, failure to distinguish between them can lead to biased analytical results. Therefore, outbound and inbound shipping lines were analyzed as different DMUs, and a two-stage NCDEA model was constructed. For resource allocation of lines under control by a central decision-maker, we solve the following linear program.

$$\begin{aligned} \text{Max } & \frac{1}{R} \sum_{r=1}^R \frac{\sum_{k=1}^N y'_{rk}}{\sum_{j=1}^N y_{rj}} - \frac{1}{T} \sum_{t=1}^T \frac{\sum_{k=1}^N e_k u_{tk}}{\sum_{j=1}^N u_{tj}} \\ & - \left( \frac{1}{I_1} \sum_{i_1=1}^{I_1} \frac{\sum_{k=1}^N x'_{i_1k}}{\sum_{j=1}^N x_{i_1k}} + \frac{1}{I_2} \sum_{i_2=1}^{I_2} \frac{\sum_{k=1}^N x'_{i_2k}}{\sum_{j=1}^N x_{i_2k}} \right) \end{aligned} \tag{28}$$

s.t. Stage 1: production process (Shared inputs)

$$\sum_{k^1=1}^{N^1} \left( \sum_{j^1=1}^{N^1} \lambda_{j^1k^1}^1 \alpha_{i_1j^1}^1 x_{i_1} \right) \leq \sum_{k^1=1}^{N^1} x'_{i_1k^1}, \quad i_1 = 1, 2, \dots, I_1 \tag{29}$$

$$\sum_{k^2=1}^{N^2} \left( \sum_{j^2=1}^{N^2} \lambda_{j^2k^2}^2 \alpha_{i_1j^2}^2 x_{i_1} \right) \leq \sum_{k^2=1}^{N^2} x'_{i_1k^2}, \quad i_1 = 1, 2, \dots, I_1 \tag{30}$$

$$\sum_{j^1=1}^{N^1} \alpha_{i_1j^1}^1 = \alpha^1, \quad i_1 = 1, 2, \dots, I_1 \tag{31}$$

$$\sum_{j^2=1}^{N^2} \alpha_{i_1j^2}^2 = \alpha^2, \quad i_1 = 1, 2, \dots, I_1 \tag{32}$$

$$\alpha^1 + \alpha^2 = 1, \tag{33}$$

$$p_{i_1j^1,lower}^1 \leq \alpha_{i_1j^1}^1 \leq p_{i_1j^1,upper}^1, \quad i_1 = 1, 2, \dots, I_1, \quad j^1 = 1, 2, \dots, N^1 \tag{34}$$

$$p_{i_1j^2,lower}^2 \leq \alpha_{i_1j^2}^2 \leq p_{i_1j^2,upper}^2, \quad i_1 = 1, 2, \dots, I_1, \quad j^2 = 1, 2, \dots, N^2 \tag{35}$$

(Specific inputs)

$$\sum_{j^1=1}^{N^1} \lambda_{j^1k^1}^1 x_{i_2j^1} \leq x'_{i_2k^1}, \quad i_2 = 1, 2, \dots, I_2, k^1 = 1, \dots, N^1 \tag{36}$$

$$\sum_{j^2=1}^{N^2} \lambda_{j^2k^2}^2 x_{i_2j^2} \leq x'_{i_2k^2}, \quad i_2 = 1, 2, \dots, I_2, k^2 = 1, \dots, N^2 \tag{37}$$

(Energy inputs)

$$\sum_{j^1=1}^{N^1} \lambda_{j^1k^1}^1 x_{i_3j^1} \leq e_{k^1} x_{i_3k^1}, \quad i_3 = 1, 2, \dots, I_3, k^1 = 1, \dots, N^1 \tag{38}$$

$$\sum_{j^2=1}^{N^2} \lambda_{j^2k^2}^2 x_{i_3j^2} \leq e_{k^2} x_{i_3k^2}, \quad i_3 = 1, 2, \dots, I_3, k^2 = 1, \dots, N^2 \tag{39}$$

(Intermediate products)

$$\sum_{j^1=1}^{N^1} \lambda_{j^1k^1}^1 z_{sj^1} = \sum_{j^1=1}^{N^1} \mu_{j^1k^1}^1 z_{sj^1}, \quad s = 1, 2, \dots, S, k^1 = 1, \dots, N^1 \tag{40}$$

$$\sum_{j^2=1}^{N^2} \lambda_{j^2k^2}^2 z_{sj^2} = \sum_{j^2=1}^{N^2} \mu_{j^2k^2}^2 z_{sj^2}, \quad s = 1, 2, \dots, S, k^2 = 1, \dots, N^2 \tag{41}$$

Stage 2: service process (Desirable outputs)

$$\sum_{j^1=1}^{N^1} \mu_{j^1k^1}^1 y_{rj^1} \geq y'_{rk^1}, \quad r = 1, 2, \dots, R, k^1 = 1, \dots, N^1 \tag{42}$$

$$\sum_{j^2=1}^{N^2} \mu_{j^2k^2}^2 y_{rj^2} \geq y'_{rk^2}, \quad r = 1, 2, \dots, R, k^2 = 1, \dots, N^2 \tag{43}$$



$$y'_{rk} \geq y_{rk}, \quad r = 1, 2, \dots, R, k = 1, \dots, N \tag{44}$$

(Undesirable outputs)

$$\sum_{j^1=1}^{N^1} \mu_{j^1k^1}^1 u_{j^1} \leq e_k u_{rk^1}, \quad t = 1, 2, \dots, T, k^1 = 1, \dots, N^1 \tag{45}$$

$$\sum_{j^2=1}^{N^2} \mu_{j^2k^2}^2 u_{j^2} \leq e_k u_{rk^2}, t = 1, 2, \dots, T, k^2 = 1, \dots, N^2 \tag{46}$$

$$e_k \leq 1, t = 1, 2, \dots, T, k = 1, \dots, N \tag{47}$$

(Available inputs)

$$\sum_{k^1=1}^{N^1} x'_{i_1k^1} \leq g_{i_1}^1, i_1 = 1, 2, \dots, I_1 \tag{48}$$

$$\sum_{k^2=1}^{N^2} x'_{i_1k^2} \leq g_{i_1}^2, i_1 = 1, 2, \dots, I_1 \tag{49}$$

$$\sum_{k=1}^N x'_{i_2k} \leq g_{i_2}, i_2 = 1, 2, \dots, I_2 \tag{50}$$

$$\sum_{k=1}^N e_k x_{i_3k} \leq g_{i_3}, i_3 = 1, 2, \dots, I_3 \tag{51}$$

$$x'_{i_1k}, x'_{i_2k}, x'_{i_3k}, y'_{rk} \alpha_{i_1j}, e_k, \lambda_{jk}, \mu_{jk} \geq 0 \tag{52}$$

where  $x'_{i_1k}, x'_{i_2k}, x'_{i_3k}$  and  $y'_{rk}$  represent shared input, specific input and energy input, and desirable output of the  $k^{\text{th}}$  line after allocation.  $\lambda_{1k}, \dots, \lambda_{Nk}$  and  $\mu_{1k}, \dots, \mu_{Nk}$  denote intensive variables of the  $k^{\text{th}}$  line in stage 1 and stage 2, respectively.  $e_k$  denotes the environmental efficiency value of the  $k^{\text{th}}$  line.

The objective function (28) seeks to maximize the average ratio of desirable outputs (ratio between the assigned and observed values) and minimizes the average ratio of undesirable outputs (ratio between the assigned and observed values) simultaneously. In stage 1, inputs were divided into three types, namely shared inputs, specific inputs, and energy inputs. Shared inputs are factors of production shared by lines, and the specific amount for each line cannot be determined. This study used the model for their allocation, and established upper and lower boundaries to ensure their utilization in each line. Specific inputs are inputs used by a specific line. Based on the approach of Guo et al. (2011) and Maghbouli et al. (2014) for processing energy inputs and undesirable outputs, undesirable outputs are characterized by weak disposability, and are directly correlated with energy inputs. Therefore, resource allocation with regard to energy inputs was conducted based on the environmental efficiency values ( $e_k$ ) and affected distribution of undesirable outputs. Intermediate products of stage 1 served as inputs in

stage 2. Based on liner shipping operating characteristics, service capacities did not change after establishing the shipping schedule. Thus, outputs of Stage 1 were fixed and did not change. Outputs of stage 2 included desirable and undesirable outputs of the model.

Constraint (29) introduces a shared input efficiency frontier for outbound shipping lines, which cannot exceed the total amount of shared input resources in outbound shipping lines after allocation. Constraint (30) introduces a shared input efficiency frontier for inbound shipping lines, which cannot exceed the total amount of shared input resources in inbound shipping lines after allocation. Constraint (31) is the distribution ratio of shared input  $i_1$  in each outbound line; its total  $\alpha$  value is equal to  $\alpha^1$ . Constraint (32) is the distribution ratio of shared input  $i_1$  in each inbound line; its total  $\alpha$  value is equal to  $\alpha^1$ . Constraint (33) guarantees that the total distribution ratio of shared input  $i_1$  in outbound and inbound lines is equal to 1. Constraint (34) introduces restrictions for the distribution ratio of shared input  $i_1$  in each outbound line. Constraint (35) introduces restrictions for the distribution ratio of shared input  $i_1$  in each inbound line. Constraints (36) and (37) guarantee that specific input boundaries cannot be higher than the total amount of specific inputs in all lines after allocation for outbound and inbound lines, respectively. Constraints (38) and (39) involve energy input boundary constraints for outbound and inbound lines, respectively. As there is a direct correlation between energy inputs and undesirable outputs,  $e_k$  is environmental efficiency value. Allocation results were obtained by multiplying  $e_k$  by the observed energy input value. Constraints (40) and (41) involve intermediate outputs for outbound and inbound lines, respectively. The transportation industry is characterized by perishability of its services. Once established, a short-term liner shipping schedule is difficult to change. Therefore, outputs of stage 1 become fixed inputs in stage 2.

With regard to constraints in stage 2, constraints (42) and (43) determine that allocated desirable outputs should at least exceed the original amount of desirable outputs for outbound and inbound lines, respectively. Constraint (44) guarantees that the amount of allocated desirable outputs is larger than the original one.

Constraints (45) and (46) involve undesirable output boundaries for outbound and inbound lines, respectively. The environmental efficiency value of  $e_k$  is less than or equal to one. Constraint (47) introduces restrictions for undesirable outputs; the amount of undesirable outputs after allocation is less than or equal to the one before. Constraint (48) determines that the amount of reallocated shared input resources in outbound lines does not exceed the total amount of a given level of  $g_{i_1}^1$ . Constraint (49) determines that the amount of reallocated shared input

resources in inbound lines does not exceed the total amount of a given level of  $g_{i1}^2$ . Constraint (50) determines that the amount of reallocated specific input resources does not exceed the total amount of a given level of  $g_{i2}$ . Constraint (51) determines that the amount of reallocated energy input resources does not exceed the total amount of a given level of  $g_{i3}$ . Constraint (52) introduces non-negative restrictions on decision variables.

## An empirical illustration using data from a Taiwanese liner shipping company

### Selection of decision-making units

Chang et al. (2011) proposed to follow operating characteristics of the shipping industry and differentiate outbound and inbound shipping lines; data obtained from such analysis would be better able to assist in decision-making at the management level. In the shipping industry, inbound and outbound shipping lines differ greatly in terms of single-direction freight traffic, cargo lifting, transferring capacity, and the number of empty containers, meaning that the two groups of DMUs face different needs. However, DEA assumes homogeneity in its analysis subjects, suggesting that comparison subjects must have similar production characteristics. Estimation of performance in both inbound and outbound shipping lines can provide decision-making information that can be referred to by managers for operation adjustments and that indicates how to improve the operational efficiency of a company. However, due to limitations associated with actual data collection and operating characteristics of shipping lines, for instance frequent changes in shipping line operations, data should be collected over a relatively short period. Therefore, this study analyzed data collected from one season of a shipping company's fixed lines.

DMUs in this study were lines of a Taiwanese liner shipping company. The range of shipping line operations of this company spans the entire world. There are Asian, European, and American lines. Homogeneity between lines should be considered in their comparison. This study analyzed Asian shipping lines due to their high density, as well as high concentration of ports. European and American lines of the investigated company were excluded from the analysis. Among Asian shipping lines, joint venture lines with expired contracts and leases were excluded. As some lines had been operating for less than one year, collection and analysis of data from one year were not possible. After arranging the data provided by the company, its Asian shipping lines operating in the fourth quarter of the year 2013 were chosen for analysis. As requirements may differ for

inbound and outbound shipping lines, analysis was conducted separately for inbound and outbound Asian lines.

## Results and discussion

### Data

A two-stage NCDEA model was developed in this study. Its empirical analysis was conducted using data provided by a shipping company in Taiwan. Appropriate input and output variables were selected to be included in the model after reviewing related literature and interviewing shipping industry operators. The production process regards the relationship between resources input by a shipping company to provide service capacity (intermediate products). A total of six variables were selected as production process inputs. Inputs were divided into shared, specific, and energy inputs. As seen from Table 1, shared inputs included seafarers' remuneration (SR) and empty container repositioning costs (ECRC); specific inputs included vessel capacity (VC),<sup>1</sup> cargo handling costs (CHC), and other costs (OC); and energy input is fuel costs (FC). Outputs in the production process were available twenty-foot equivalent unit (TEU)-nautical miles (ATNM) and the number of destination ports (DP) in each shipping line, where ATNM is the sum of the products obtained by multiplying the number of TEUs carried on each ship by the shipping distance. In the service process, the use of liner shipping services provided by the first stage produces two types of outputs, desirable outputs (Y), which include line revenue (LR) and revenue TEU-nautical miles (RTNM), and undesirable outputs (W), which include carbon emissions (CE).

With regard to carbon emissions, the IMO has established the Energy Efficiency Design Index (EEDI) for new ships to manage pollutants produced by vessels. EEDI introduces measures to improve the energy efficiency of ships and provides design improvements for seven types of ships in terms of environmental costs (CO<sub>2</sub> emissions) per ship. The IMO has also proposed the Ship Energy Efficiency Management plan (SEEMP), which introduces standards for already operating international ships. With regard to operating management, the Energy Efficiency Operational Index (EEOI) was developed to measure actual efficiency of each transportation unit in terms of CO<sub>2</sub> emissions. Currently, EEOI is not a mandatory index but can serve as a reference in SEEMP (Second IMO GHG study 2009).

Apart from EEDI and EEOI formulas, carbon emissions can be measured by other means. Leonardi and Browne

<sup>1</sup> It is more reasonable to take into account vessel size and weight of shipment to represent the capital variable. In this paper, the capital variable is proxied by the number of vessels, due to unavailability of data on vessel size and weight of shipment.

**Table 1** Descriptive statistics of input and output variables

Variable	Mean	SD	Maximum	Minimum
<i>Shared inputs</i>				
SR (thousand USD)	44.65	44.91	132.76	0.00
ECRC (thousand USD)	398.52	156.92	725.43	191.02
<i>Specific inputs</i>				
VC (ten TEUs)	1085.42	438.56	1820.00	520.00
CHC (thousand USD)	1630.60	758.06	2889.58	647.20
OC (thousand USD)	2483.44	1097.05	3966.61	1078.70
<i>Environmental input</i>				
FC (thousand USD)	1715.88	810.03	2729.90	739.73
<i>Intermediate products</i>				
ATNM (thousand TEU-nautical miles)	65317.42	34957.92	122431.40	25351.80
DP (number of ports)	6.00	2.42	10.00	4.00
<i>Desirable outputs</i>				
LR (thousand USD)	5514.80	2815.57	10285.25	2617.07
RTNM (thousand TEU-nautical miles)	64023.04	39454.77	168744.14	20650.86
<i>Undesirable outputs</i>				
CE (thousand kilograms)	5363.37	3676.72	15823.14	1731.06

(2010) estimated carbon emissions of container ships and bulk carriers by measuring the consumed heavy oil volume, and proposed emission and conversion factors to calculate carbon emissions of passenger ships. As this study did not aim to discuss methods to calculate carbon emissions in the shipping industry, it mainly used data provided by the company because the company has its own set of carbon emission calculation methods. The calculation Eq. (4.1) incorporates the number of TEUs and mileage of a shipping line. Each shipping line has a different CO<sub>2</sub> emission factor, which can result in different CO<sub>2</sub> emission values. In this study, the obtained carbon emission values were an undesirable output. Due to the undesirable output feature, it is reasonable to reduce the amount of undesirable output related to the environmental efficiency values obtained in the model.<sup>2</sup> Due to the relation between a shipping line's carbon emissions and fuel costs, fuel allocation was obtained by multiplying environmental efficiency values by the observed carbon emission values; these were the results of distribution of carbon emissions in shipping lines.

$$\text{CO}_2\_ \text{Emission}(A) = \text{CO}_2 \text{ Emission Factor} \times \text{Distance} \\ \times \text{Cargo Weight} \quad (53)$$

The case company studied in this paper generally determines the shipping line design for one year. However, due to the rapid change in shipping line operations, said company may slightly adjust the shipping lines to respond to market changes. As a result, it is difficult

<sup>2</sup> We assume that fuel costs are proportional to the number of TEUs and mileage of a shipping line.

to obtain data from shipping lines operating for one quarter without changes in shipping lines. For the sake of homogeneity of DMUs, this study analyzed data of Asian shipping lines as of the fourth quarter of 2013. The selected shipping lines had their own vessels and operated through the entire fourth quarter without any interruptions. Shipping lines which engaged in joint operations with other shipping companies were excluded from the analysis. As a result, seven shipping lines with complete data and own vessels were the basis for the analysis. After dividing shipping lines into inbound and outbound lines, 14 shipping lines were derived from the original sample of seven lines. A summary of the descriptive statistics related to the shipping line input and output variables for the 14 Asian shipping lines of a Taiwanese shipping company is presented in Table 1.

### Empirical analysis

In this study, data of inbound and outbound shipping line operations in the fourth quarter of 2013 were analyzed separately using the proposed model to allocate the existing resources of shipping lines. In this model, the outbound shipping ratio had its individual upper and lower bounds, with the total distribution  $\alpha_{i,j^1}$  equal to 1. The inbound shipping ratio had its individual upper and lower bounds, with the total distribution  $\alpha_{i,j^2}$  equal to 1. To ensure that shared inputs are allocated to all shipping lines, the ratio of shared inputs per line was calculated by dividing the observed shared input values by the total amount of shared input resources. The smallest ratio value was set as the  $\alpha$  lower bound, and 110% of the largest ratio value was set as the  $\alpha$  upper bound. Lower and upper bounds were different



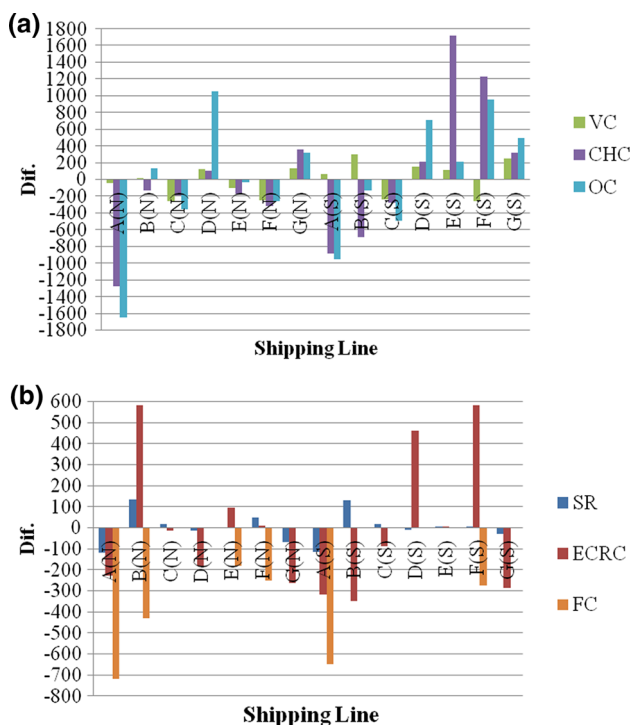
for each case. The only energy input that was consistently distributed across outbound and inbound shipping lines from the very beginning was fuel costs, meaning that fuel expenses in outbound and inbound shipping lines were the same. However, after allocation based on the environmental efficiency values, outbound and inbound lines need not be similar in their fuel costs. ATNM and DP were intermediate outputs in the production process. The transportation industry is characterized by perishability of its services. Once established, a short-term liner shipping schedule is difficult to change. Therefore, intermediate outputs of the production process were set as a fixed link between the production and services processes. Moreover, as shipping line data are non-public information, this study used the pre- and post-allocation difference values to represent reduction or increase in inputs and outputs of shipping lines after their allocation. No change in resources after their allocation was indicated by the value of 0.00, whereas the increase and reduction in resources were indicated by positive and negative values, respectively.

Results of this study showed that the model’s optimal value was 1.016, meaning that in the fourth quarter of 2013, the average rate of the total of line revenues and revenue TEU-nautical miles in outbound and inbound shipping lines was greater than the one of carbon emissions by 1.016 after resource reallocation. Allocation results are provided in Table 2. The results show that there is room to reduce the total VC by 0.91 TEU, fuel oil costs by US\$2,505,000, and carbon emissions by 12,560,000 kilograms, as well as room to increase line revenues by US\$111,730,600 and revenue TEU-nautical miles by 224,180,000 TEU-nautical miles.

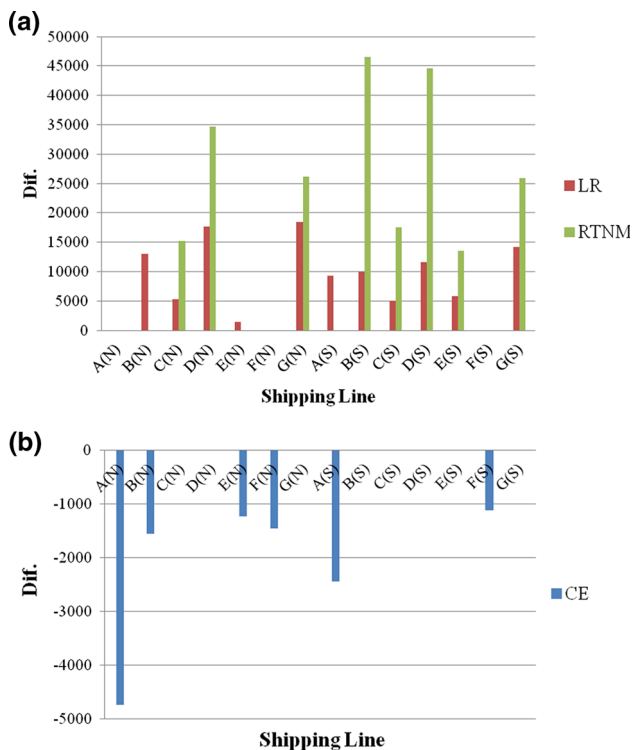
Allocation results of Stage 1 inputs and Stage 2 are demonstrated using bar charts in Figs. 4a, b and 5a, b. Allocation results are explained separately for outbound (N direction) and inbound (S direction) shipping lines. In general, a comparison of the shipping lines was complicated due to their division into outbound and inbound lines. Resource allocation showed how currently operating shipping lines should adjust their inputs to gain more revenues and achieve more RTEU-nautical miles. With regard to deduction of shared inputs, input resources were reduced in outbound lines A and F without affecting their original revenues and RTEU-nautical miles. Inputs were reduced in outbound lines C and E, while their revenues and RTEU-nautical miles were increased. In outbound line B, the vessel capacity and other costs were increased, whereas cargo handling and fuel costs were reduced, resulting in higher line revenues and more RTEU-nautical miles. In outbound lines D and G, the vessel capacity, cargo handling costs, and other costs were increased, whereas fuel costs were reduced, resulting in higher line revenues and more RTEU-nautical miles. With regard to

**Table 2** Allocation results

Shipping line	A(N)	B(N)	C(N)	D(N)	E(N)	F(N)	G(N)	A(S)	B(S)	C(S)	D(S)	E(S)	F(S)	G(S)	Total change
SR (thousand USD)	-117.3	135	15.5	-12.9	-0.2	47.8	-67.9	-113.9	131.6	19	-11.8	1.2	5.1	-31.2	0
ECRC (thousand USD)	-229.6	581.8	-14.9	-180.1	95.4	10.3	-262.9	-319.5	-350.5	-87.9	460	4	581.3	-287.5	0
VC (ten TEUs)	-45.011	17.161	-262.735	119.913	-106.045	-245.906	133.175	66.817	299.72	-237.635	152.479	117.132	-259.12	250.054	-0.091
CHC (thousand USD)	-1279.6	-133.4	-186.7	106.4	-169.6	-316.6	362.4	-881.9	-684.8	-281.5	208.9	1714.4	1226	316.3	0
OC (thousand USD)	-1652.1	133.2	-357.2	1054.9	-35.2	-256	322.6	-958.2	-129.3	-491.9	712.3	214.5	952.4	490.1	0
FC (thousand USD)	-720.6	-429.3	0	0	-180	-249.7	0	-649.8	0	0	0	0	-275.6	0	-2505
ATNM (thousand TEU-nautical miles)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DP (number of ports)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CE (thousand kilograms)	-4740	-1560	0	0	-1230	-1460	0	-2450	0	0	0	0	-1120	0	-12560
LR (thousand USD)	0	13011.6	5336.4	17682.5	1462	0	18447.8	9267.6	9893.9	5042.7	11559.9	5857.6	0	14168.7	111730.6
RTNM (thousand TEU-nautical miles)	0	0	15210	34680	0	0	26130	0	46530	17530	44580	13580	0	25950	224180



**Fig. 4** 2013 Fourth-quarter case: **a** Stage 1 specific input changes, **b** Stage 1 shared and environmental input changes. Note: Dif. represents difference between resources before and after reallocation



**Fig. 5** 2013 Fourth-quarter case: **a** Stage 2 desirable output changes, **b** Stage 2 undesirable output changes. Note: Dif. represents difference between resources before and after reallocation

inbound lines, in inbound lines A and B, the vessel capacity was increased, whereas cargo handling costs and other costs were reduced, resulting in higher line revenues and more RTEU-nautical miles. In inbound line C, the vessel capacity, cargo handling costs, and other costs were reduced, whereas fuel costs were not, resulting in higher line revenues and longer RTEU-nautical miles. In inbound lines D, E, and G, the vessel capacity, cargo handling costs, and other costs were increased without reducing fuel costs, resulting in higher line revenues and more RTEU-nautical miles. In F line, the vessel capacity and fuel costs were reduced and cargo handling costs and other costs were increased without affecting their original revenues and RTEU-nautical miles.

With regard to inputs and outputs in outbound lines, seafarers’ remuneration was most increased (by US\$135,000) in outbound line B and most reduced (by US\$117,300) in outbound line A. Empty container repositioning costs were most increased (by US\$581,800) in outbound line B and most reduced (by US\$262,900) in outbound line G. The vessel capacity was most increased (by 1331.75 TEUs) in outbound line G and most reduced (by 2627.35) in outbound line C. Cargo handling costs were most increased (by US\$362,400) in outbound line G and most reduced (by US\$1,279,600) in outbound line A. Other costs were most increased (by US\$1,054,900) in outbound line D and most reduced (by US\$1,652,100) in outbound line A. Fuel costs and carbon emissions were adjusted based on environmental efficiency  $e_k$  values and were most reduced in outbound lines A, B, E, and F. Line revenues were most increased (by US\$18,447,800) in outbound line G. RTEU-nautical miles was most increased (by 34,680,000 TEU-nautical miles) in outbound line D. A possible reason for the increase in line revenues and revenue TEU-nautical miles was the increased vessel capacity.

With regard to inputs and outputs in inbound lines, seafarers’ remuneration was most increased (by US\$131,600) in inbound line B and most reduced (by US\$113,900) in inbound line A. Empty container repositioning costs were most increased (by US\$581,300) in inbound line F and most reduced (by US\$350,500) in inbound line B. The vessel capacity was most increased (by 2997.20 TEU) in inbound line B and most reduced (by 2591.20 TEU) in F line. Cargo handling costs were most increased (by US\$1,714,400) in inbound line E and most reduced (by US\$881,900) in inbound line A. Other costs were most increased (by US\$952,400) in inbound line F and most reduced (by US\$958,200) in inbound line A. Fuel costs and carbon emissions were adjusted based on environmental efficiency  $e_k$  values and were most reduced in inbound lines A and F. Line revenues were most increased (by US\$14,168,700) in inbound line G. RTEU-nautical miles was most increased (by 46,530,000 TEU-nautical

miles) in inbound line B. A possible reason for the increase in line revenues and revenue TEU-nautical miles was the increased vessel capacity.

Overall, during the fourth quarter of 2013, outbound and inbound shipping lines faced different needs despite being a part of one shipping line. Their resource allocation was also different. In outbound lines, input resources were reduced in A and F lines without affecting line revenues and revenue TEU-nautical miles. In outbound line B, the vessel capacity and other costs were increased, whereas cargo handling and fuel costs were reduced, resulting in higher line revenues and more revenue TEU-nautical miles. Inputs were reduced in outbound lines C and E, while their line revenues and revenue TEU-nautical miles were increased. In outbound lines D and G, the vessel capacity, cargo handling costs, and other costs were increased, whereas fuel costs were reduced, resulting in higher line revenues and more revenue TEU-nautical miles. With regard to deduction of shared inputs in inbound lines, in A and B lines, the vessel capacity was increased, whereas cargo handling costs and other costs were reduced, resulting in higher line revenues and more revenue TEU-nautical miles. In inbound line C, the shipping berth capacity, cargo handling costs, and other costs were reduced, whereas fuel costs were not, resulting in higher line revenues and more revenue TEU-nautical miles. In inbound lines D, E, and G, the vessel capacity, cargo handling costs, and other costs were increased without reducing fuel costs, resulting in higher line revenues and more revenue TEU-nautical miles. In inbound line F, the vessel capacity and fuel oil costs were reduced and cargo handling costs and other costs were increased without affecting their original revenues and revenue TEU-nautical miles. With regard to carbon emissions, they were effectively reduced in outbound lines A, B, E, and F. Among inbound lines, only A and F lines required carbon emissions to be reduced. Thus, it can be seen that shipping lines face different needs. Their resource allocation methods and carbon emission reduction are also different. Therefore, shipping companies can allocate resources across shipping lines according to their needs based on the current shipping operating situation.

### *Discussion and implications*

The empirical results of this analysis that uses the proposed two-stage CNDEA model to allocate the existing resources of the inbound and outbound shipping line operations provide significant implications for theory and practice. In addition, apart from making key contributions to resource allocation among shipping lines of a shipping company, treatment of the inbound and outbound shipping lines as different DMUs in the study provides a strong basis for further research in the area. The results obtained from the

application of both the inbound and outbound shipping lines were different. As intended, this serves as evidence that outbound and inbound shipping lines faced different needs despite being parts of one shipping line. Their resource allocation was also different.

The above-outlined example of a shipping company with multiple lines can properly be modeled in the context of the principal agent framework in general and that of short-run resource allocation in particular. Shipping lines under different external environments are given different shipping line operations in terms of how, e.g., the central management can take actions, make decisions and allocate resources to deliver expected services to customers. This places emphasis on how the proposed two-stage NCDEA resource allocation model as a vehicle allocates resources among shipping lines of a shipping company in one season. It is easy to apply the proposed model to the consecutive period's resource allocation.<sup>3</sup> The proposed resource allocation model is a non-oriented efficiency model, that is, the objective function is concerned with both maximizing average shipping line output efficiency and minimizing input efficiency. Plainly, one could conceive of circumstances in which one can only reallocate resources at a given level of outputs, for example, an input orientation (minimize total input). In addition, if the quantity of some input items is not easy to change, one can also allocate some reallocatable inputs. Moreover, this model can also be modified to a more complex one in which common inputs are shared among not only production processes of routes, but also both their production and service processes.

### **Conclusion**

Very few studies have investigated the use of a shipping company's internal data for resource allocation in the company's shipping lines. The one-stage black-box-based DEA model has been the main analysis tool applied in the evaluation of liner shipping efficiency, but cannot provide an in-depth analysis of performance at each production process stage. This study used a two-stage network CDEA model to allocate resources in lines of a Taiwanese shipping company based on operating data from the fourth quarter of 2013. Apart from investigating the actual utilization of resources by the company and resource allocation aimed at optimal outputs, the model considered undesirable outputs in order to comply with international carbon emission restrictions. Furthermore, various transfers

<sup>3</sup> Due to lack of space, the results obtained by applying the proposed model in the monthly data of Asian shipping lines of 2013 are not reported in this paper, but can be obtained from the authors upon request.



of resources were made. A shipping company can independently allocate resources according to the determined amount of input resources. Resource allocation results obtained in the model in this study can provide a reference for shipping companies in their future operations.

Limitations in this study included resource restrictions. Seafarers' remuneration was used for human resource allocation in shipping lines. However, international ship regulations include minimum safe manning requirements for vessels. Therefore, reduction of seafarers' remuneration through resource allocation may not reflect the actual human resource situation. Therefore, actual human resource data should be collected for future evaluation of human resources in shipping lines. Moreover, as the research subject in this study was shipping lines self-operated by a shipping company and joint shipping lines were not examined, it is suggested that future studies include joint shipping lines in the research. In resource allocation across self- and jointly operated shipping lines, mode DMUs can be incorporated into the model, which better corresponds to the actual operating situation in shipping companies and can provide them with suggestions regarding resource allocation.

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