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A MANAGERIAL APPROACH IN RESOURCE ALLOCATION MODELS: AN APPLICATION IN US AND CANADIAN OIL AND GAS COMPANIES

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Abstract: In resource allocation and target setting problems, a central decision makers' managerial standpoint has a pivotal role, especially when we encounter undesirable outputs such as the greenhouse gas (GHG) emissions. In such circumstances, firms have to cooperate with each other, to achieve the central planner's aims. Looking into literature reveals that the existing resource allocation models based on data envelopment analysis (DEA) have not aptly considered the influence of managerial efforts and technological innovations in this sense. This study proposes a centralized model incorporating managerial disposability. This model not only reflects the leadership performance of the central planner and the technological novelty perspective in the resource allocation and target setting problem, but also has a positive modification against an environmental adaptation change. In order to illustrate the applicability of our resource allocation and target setting model, a case study of 23 US and Canadian oil and gas companies has been conducted. Analysis of the results reveals the appropriacy and efficiency of our proposed model in dealing with the current perspectives concerning the issue of resource allocation and target setting.

Keywords: Data envelopment analysis, resource allocation, target setting, managerial disposability assumption.

MSC: 90C08, 90C90.

1. INTRODUCTION

Considering the current rapid rate of evolution of the economy and the remarkable growth of living standards around the world, countries have been progressively concentrating on the development of their environmental performances. Regarding this, resource allocation can play a significant role. In the management science, too, resource allocation has always been an issue of great interest and has been studied immensely thereof. The common encountered issues are typically dependent on the existence of a central planner who is responsible for the allocation of decisions for a group of decision makers. In real life situations, however, resources are still limited, so the manner in which they are allocated plays a crucial role in determining the development of societies. This way, resource allocation has always been an interesting subject for company managers and researchers.

A number of researchers (e.g. (Emrouznejad et al. [1], Sueyoshi et al [2]) have done numerous environmental researches for a stable economy, resource allocation, and environmental performance evaluation. These studies aimed at pinpointing how a country could utilize its resources to confront environmental pollution. Evaluating the efficiency of the resource allocation theory is an effective way to develop pollution treatments. On this basis, when addressing environmental pollution, countries need to ponder about how to allocate finite resources more effectively. In addition, countries should note that environmental performance assessment is not only affected by the process of accurate use of resources, but also by the establishment of an appropriate target for environmental pollution. Currently, the usage of data envelopment analysis (DEA) has delivered a new aspect to the above-mentioned problems. DEA is a nonparametric approach to evaluate decision-making units' efficiency (DMUs). A special benefit of the DEA is that it does not require prior assumptions about the fundamental relationships between inputs and outputs. It is a data-based frontier analysis procedure measuring the efficiency of a set of DMUs. Mathematically, DEA employs a linear programming model that defines the relation among various inputs and outputs by the envelopment of the observed data to specify a piecewise linear experimental practice frontier. So, it can provide central decision-makers (CDMs) with recommendations on how to prepare a plan that, based on the experimental piecewise linear function, takes into consideration both their resources (inputs) and expected outputs.

Concerning DEA-based resource allocation, there are two known categories of approaches. The first category supposes that the efficiency of DMUs is constant. Among the studies that have followed this approach (Amirteimoori & Shafiei [3], Jahanshahloo et al. [4] and Madadi et al. [5]) can be named here. The second approach supposes that the efficiency of DMUs is variable concerning which studies by (Zhang et al. [6]) can be listed here. In the current study, we take the second approach as our starting point wherein DMUs' efficiency can alter after the allocation. Moreover, we show how output targets can be arranged simultaneously as decisions about resource allocation are made.

Several researches have been done using DEA in resource allocation and target setting (e.g., Chen et al. [7] and Yang [8]). We review some of these researches: Fang [9] offered a centralized resource allocation model that could support the DMUs with step-by-step improvement pathways to the efficient frontier. Yang et al. [10] have taken into account the potential limits of input-output distortion by establishing a matrix of difficulty coefficients to adjust their production across all prevailing production possibility set. so, managerial feasibilities are guaranteed in that the solution. Mozafari et al. [11] offered a model by designating a common set of weights (CSW). In their model, the minimum resources and targets allocated to each DMU corresponded to the DMU's contribution to input resources and output and to the efficiency of that DMU. Nojoumi et al. [12] applied the centralized resource allocation method to build up a model for constructing new DMUs that are the most productive scale size (MPSS), and all new DMUs set on a strong supporting hyperplane.

The studies pointed out above allocate resources among the DMUs without the assumption of the undesirable factors. Some studies have afforded methods for applying undesirable outputs to resource allocation. A number of them are proposing the allocation of carbon dioxide (CO2) or greenhouse gas (GHG) emissions as undesirable output. For instance, (Lozano et al. [13]) presented a DEA approach to the problem of emission permits reallocation that could apply with conventional command and control along with market permission. It utilizes a centralized approach, which represents the common good. Feng et al. [14] proposed a centralized allocation scheme suffering from implementation difficulty in convincing DMUs into an agreement. They suggested a new method to reduce the probable side effects in a two-step. To elaborate on the main principles of their proposed approach, a data set from the Organization for Economic Co-operation and Development (OECD) was used. Wang et al. [15] offered an improved zero-sum gains model based on DEA, that could treat the fixed total amount of resources. Several schemes of China's economic growth, CO2 emissions, and energy consumption have been offered in this model. Some of these studies viewed the CO2 emission allowance of the production process as a kind of limited resource (input) that required to be allocated among DMUs. In contrast, other studies have considered the carbon emission as undesirable outputs (e.g. Hu & Liu [16]; Madadi et al. [17]). They used weak or strong disposability assumptions when building DEA resource allocation models to deal with these undesirable outputs especially when considering environmental efficiencies of DMUs. Nevertheless, the currently available studies do not consider managerial achievements and technological innovations on the allocation of CO2 or GHG and environmental evaluation. Sueyoshi & Goto [18] have tried to deliver these concepts by proposing the managerial disposability assumption. In the current study, following managerial disposability, the aim is to find a solution to the resource allocation and target-setting problem based on DEA, with an undesirable output reduction orientation. This research supposes the managerial disposability as a constructive modification to a change on environmental adjustment. Our study is conducted in two steps. First, we afford a model to determine each DMU’s efficiency regarding managerial disposability assumption. Our model has an undesirable output reduction orientation that is under the variable returns to scale assumption. In the second step, a centralized model is presented to determine the best resource allocation and target setting results for the DMUs. The results of resource allocation and target setting achieved by the proposed approach not only enhance the overall efficiency compare to the previous production process, but also minimize the weighted sum of adjustments of all DMUs.

The rest of this study is organized as follows. Section 2 briefly defines DEA and some related models supposing undesirable output, especially under the managerial disposability assumption. Section 3 gives the details of the proposed centralized resource reallocation and target setting model of this study. In Section 4, the introduced method is applied for 23 Oil and gas companies in the US and Canada. Finally, Section 5 discusses conclusions.

2. LITERATURE REVIEW

DEA is an impressive procedure in management science. This is a linear programming method that measures the relative efficiency values of DMUs with different inputs and outputs. The first DEA model (i.e., the CCR model), by considering the constant returns to scale assumption, was proposed by Charnes et al. [19] . Banker et al. [20] developed (Charnes et al. [19]) model by introducing the BCC model and supposing the variable returns to scale assumption.

2.1. DEA models with undesirable inputs/outputs

When a DMU generates maximum outputs by utilizing minimum inputs, it is usually considered as efficient. In this case, that DMU is placed on the efficient frontier, and its efficiency value will be equal to one. When the efficient frontier is specified, DMUs seek to reach the efficient frontier by improving performance. So, the current inputs are consumed to produce more outputs.

However, there are often situations where some inputs are allowed to increase and some outputs are allowed to decrease at the same time. A DMU is efficient if the values of some outputs are as small as possible. These types of outputs are called undesirable. This production process can produce both desired and undesirable outputs (waste, pollution, etc.). Undesirable outputs are not desirable for decision-makers, but during the real production process, undesirable outputs come out together with desirable outputs. Various studies have proposed to model undesirable outputs (e.g. Halkos, & Natalia Petrou [21]; Toloo & Hančlová [22]). The first DEA model with unfavorable results was provided by (Färe et al. [23]), after which this approach was applied to extremes to perform environmental assessment problems (e.g. (Wu et al. [24])). Generally, these researches can be categorized into several groups. The first group concentrates primarily on undesirable outputs treatment approaches within the DEA model. (e.g. (Dyckhoff & Allen [25])). The second group uses various efficiency measures in the DEA approach to address efficiencies with undesirable outputs (e.g. (Arabi et al. [26])). The third group considers the disposability of undesirable outputs as the strong and weak disposability assumption. (e.g (Hang et al. [27] ; Zha et al. [28])).

However, the strong and weak disposability assumption of undesirable outputs was not precise and sometimes insufficient.

Sueyoshi and Goto [18] submitted that both definitions presented regarding disposability do not indicate the directional vector of inputs. That is a considerable issue because a directional input vector may provide new concepts on disposability from the environmental evaluation viewpoint. They presented two new concepts on disposability as natural disposability and managerial disposability. In natural disposability, a firm reduces the directional vector inputs to reduce the directional vector of undesirable outputs and increase the directional vector desirable outputs as much as possible. In managerial disposability, a firm augments the directional vector of inputs to reduce the directional vector of undesirable outputs and raise the directional vector of desirable outputs more than conceivable. For case, consider oil and gas refineries, which increase their total assets and capital expenditures so that they can increase their production. The capital assets that will be applied in the production process and new investments may be applied in GHG reduction technologies.

Managerial disposability reflects the impacts of managerial effort and technological innovations on environmental assessment. However, assumptions of different disposability of undesirable outputs may involve different production possible sets, leading to different evaluation results.

Suppose there are n DMUs and each DMU_j $(j = 1,\dots,n)$ consumes $m$inputs $x = (x_1,\dots,x_m) \in R^m$to produce $s$desirable outputs $y = (y_1,\dots,y_s) \in R^s$and Tundesirable outputs $z = (z_1,\dots,z_T) \in R^T$. The production technology is defined by the following output vectors to express the managerial disposability:

$$P(x) = \{(y,z): \sum_{j=1}^{n} \lambda_j y_j \geq y, \sum_{j=1}^{n} \lambda_j z_j \leq z, \sum_{j=1}^{n} \lambda_j x_j \geq x, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \in R_+^n\}. \quad (1)$$

Differences between weak and strong disposability versus managerial disposability is propounded as follows: The undesirable outputs' vector is considered by $\sum_{j=1}^{n} \lambda_j z_j \geq z$ for strong disposability and $\sum_{j=1}^{n} \lambda_j z_j = z$ for weak disposability. The placement of an efficiency frontier on or above the convex combination of all the watched undesirable outputs is shown by the inequality constraint for strong disposability. The placement of an efficiency frontier on the convex combination of all the monitored undesirable outputs is indicated by the equality constraint for weak disposability. In contrary, undesirable output vector under managerial disability is always $\sum_{j=1}^{n} \lambda_j z_j \leq z$. The inequality constraint shows that an efficiency frontier is placed on or below the convex combination of all the monitored undesirable outputs. Moreover, the weak and strong disposability suppose the inequality constraint: $\sum_{j=1}^{n} \lambda_j x_j \leq x$, while the managerial disposability incorporates $\sum_{j=1}^{n} \lambda_j x_j \geq x$. So, the input vector of the weak and strong disposability covers an input region less extensively than that of the managerial disposability. In this study, since the purpose is to present the influence of management decision and technology initiative, the managerial disposability assumption is used.

The right-hand-side technology set (1) is free of variables, and thus, we can readily use the Farrell measure of efficiency. Supposing the managerial disposability property, the efficiency evaluation model is as follows:

$$\begin{aligned}
& Min\ \theta \\
& s.t. \qquad\qquad (2) \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \geq x_{io}, \ \ i = 1,\dots,m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro}, \ \ r = 1,\dots,s,
\end{aligned}$$

$$\sum_{j=1}^{n} \lambda_j z_{tj} \leq \theta z_{to}, \quad t = 1, \dots, T,$$
$$\sum_{j=1}^{n} \lambda_j = 1,$$
$$\lambda_j \geq 0, \quad \theta \text{ Free}$$

From the managerial viewpoint, this model addresses evaluation with an undesirable output minimization orientation. Also, it is under the VRS assumption. The dual formulation of model (2) is:

$$\begin{aligned} & Max \sum_{i=1}^{m} v_i x_{io} + \sum_{r=1}^{s} u_r y_{ro} + u_o \\ & s.t. \\ & \sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} u_r y_{rj} - \sum_{t=1}^{T} w_t z_{tj} + u_o \leq 0, \quad j = 1, \dots, n, \\ & \sum_{t=1}^{T} w_t z_{to} = 1, \\ & v_i, u_r, w_t \geq 0, \quad u_o \text{ free} \end{aligned} \tag{3}$$

where the v_i, u_r and w_t are weights of the *i*-th input, the *r*-th desirable output, and the *t*-th undesirable output, respectively. Note that the variable $u_o$is a variable corresponding to VRS assumption. Model (3) is in fractional form that can be interpreted as the original efficiency evaluation form as follows:

$$\begin{aligned} & Max \quad \rho_j = \frac{\sum_{i=1}^{m} v_i x_{io} + \sum_{r=1}^{s} u_r y_{ro} + u_o}{\sum_{t=1}^{T} w_t z_{to}} \\ & s.t. \\ & \frac{\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} u_r y_{rj} + u_o}{\sum_{t=1}^{T} w_t z_{tj}} \leq 1, \quad j = 1, \dots, n, \\ & v_i, u_r, w_t \geq 0, \quad u_o \text{ free.} \end{aligned} \tag{4}$$

$DMU_j, j = 1, \dots, n,$ is efficient, if and only if $\rho_j^* = 1, j = 1, \dots, n,$ in model (4).

If we suppose $(\rho^*, v^*, u^*, w^*, u_o^*)$ as an optimal solution of model (4), where $v^* = (v_1^*, v_2^*, \dots, v_m^*), u^* = (u_1^*, u_2^*, \dots, u_s^*)$ and $w^* = (w_1^*, w_2^*, \dots, w_T^*)$. Then DMU_k is efficient, if $\rho_k^* = 1$, and there is at least one optimal solution (v^*, u^*, w^*, u_o^*) , with $v^* > 0, u^* > 0, w^* > 0, u_o^* > 0$. Otherwise, it is inefficient.

3. RESOURCE ALLOCATION AND TARGET SETTING MODELS WITH UNDESIRABLE OUTPUTS

Resource allocation and target setting issue is one of the classic applications in environmental assessment and management science. Considering that there is a decision-making environment in which various firms operate under a central firm's decision, the central firm has the potential to govern the resources of these firms and set their targets. Hence, the major aim of the resource allocation and target setting is to allocate resources and set targets, so that the comprehensive aims of the organization are fulfilled as much as possible (e.g., the amount of the total outputs to be maximized or overall efficiency to be increased). Nevertheless, as mentioned in (Korhonen & Syrjänen [29]), there are some restrictions on using the traditional DEA model in resource allocation. For instance, the traditional DEA approach does not address the preferences of decision makers. Moreover, the production process generates various outputs (desirable and undesirable), which may be freely disposable. These models in resource allocation and target setting do not suppose undesirable outputs. This is a significant point in enhancing the efficiency of resource allocation and target setting.

With the improvement of DEA methodology, many studies have explored the resource allocation and target setting issue (e.g. (J.-Sharahi & Khalili-Damghani [30]) and (Madadi et al. [17])).

Different methodologies have been presented to treat undesirable output problems up to now. In this paper, we will combine the GHG emission target as the undesirable output with a resource allocation scheme through DEA models and propose a linear programming model for resource allocation and target setting by considering the managerial disposability assumption that is a new concept to deal with undesirable outputs.

3.1. Resource allocation models under managerial disposability assumption

GHG emission reduction has become one of the most critical threats to the economic growth of countries recently. Constructing innovative structures in the energy industry, especially oil and gas industries, helps to control or reduce the amount of GHG emission. Recently, with the fast growth in oil and gas production, we do not only concern about how to accomplish the target of GHG emission reduction but also how to allocate worthwhile resources efficiently.

So according to the concept introduced by (Sueyoshi & Goto [18]), we present a resource allocation model which deals with the managerial disposability assumption. We primarily concentrate on the following aspects. We propose a method with the same desirable outputs production as well as the reduction in undesirable outputs. On the other hand, we consider some input augmentation along with not deteriorating DMUs' efficiency scores. Accompanying the abatement of undesirable outputs, DMUs also use up more inputs to produce. We assume the desirable outputs variables are unchanged. What we care about is how to minimize the amount of the inputs and undesirable output adjustments.

The following mathematical programming problem is under the VRS constraint and considers the managerial disposability assumption:

$$Min \sum_{i\in I_1}\sum_{j=1}^{n}\delta_i|\Delta x_{ij}| + \sum_{t=1}^{T}\sum_{j=1}^{n}\sigma_t|\Delta z_{tj}|$$

$$s.t. \tag{5}$$

$$\frac{\sum_{i\in I_2} v_i x_{ij} + \sum_{i\in I_1} v_i(x_{ij}+\Delta x_{ij}) + \sum_{r=1}^{s} u_r y_{rj} + u_o}{\sum_{t=1}^{T} w_t(z_{tj}+\Delta z_{tj})} \geq \rho_j{}^*,\ \ j=1,\ldots,n,$$

$$\frac{\sum_{i\in I_2} v_i x_{ij} + \sum_{i\in I_1} v_i(x_{ij}+\Delta x_{ij}) + \sum_{r=1}^{s} u_r y_{rj} + u_o}{\sum_{t=1}^{T} w_t(z_{tj}+\Delta z_{tj})} \leq 1,\ \ j=1,\ldots,n,$$

$$\sum_{j=1}^{n}\Delta x_{ij} = C_i, i \in I_1,$$

$$\sum_{j=1}^{n}\Delta z_{tj} = Q_t,\ \ t=1,\ldots,T,$$

$$L_{ij}^x \leq \Delta x_{ij} \leq U_{ij}^x, i\in I_1,\ \ j=1,\ldots,n,$$

$$L_{tj}^z \leq \Delta z_{rj} \leq U_{tj}^z,\ \ t=1,\ldots,T;\ j=1,\ldots,n,$$

$$v_i, u_r, w_t \geq 0,\ \ u_o \text{ free}$$

The decision variables in (5) consist of the adjustment variables of the *i-th* input Δx_{ij}, the adjustment variables of the *t-th* undesirable output Δz_{tj},v_i as the weight assigned to the *i-th* input, u_r as the weight assigned to *r-th* desirable output, and w_t as the weight assigned to the *t-th* undesirable output. Also $u_o$is considered as VRS variable. Assume that the central planner wants to allocate the resources $i_1, i_2, \ldots, i_l$. Besides, he wants to set targets for the undesirable outputs. Denote $I_1 = \{i_1, i_2, \ldots, i_l\}$,$I_2 = \{1,2,\ldots,m\} - I_1$as a set of resources that has to be allocated and a set of unchanged resources, respectively. In the objective function, selecting δ_i as the weight of the adjustment variables of the *i-th* input and$\sigma_t$as the weight of the adjustment variables of the *t-th* undesirable are based on the central planner idea when prioritizing industrial factors.

In formula (5), $\rho_j{}^*$expresses the VRS efficiency score derived from (4). The model implies the efficiency score of DMU_j after resource allocation and target setting benchmarked against all other DMUs cannot be decreased to less than $\rho_j{}^*$, since the first constraint in (5) is used to show that the efficiency of adjusted DMUs does not get worse than before. The second constraint in (5) is used due to the VRS model (4).

As in common resource allocation and target setting problems, we first propose restraints on the ranges of permissible adjustments for the inputs and undesirable outputs of the DMUs. To form inputs adjustment, the restraints on permissible inputs change ranges may arise from equity and feasibility matters concerning resource allocation. For example, to maintain a balance of total assets allocated to different oil and gas companies, the central planner may only adjust the input for each company within a certain range. For the *i-th* input of DMU_j, we suppose the adjustment must be bounded between $L_{ij}^x$and $U_{ij}^x$where $L_{ij}^x$and U_{ij}^x are assigned by the central planner. Moreover, for the total increment's amount of the *i-th input*,C_i: $i \in I_1$is assumed.

For the *t-th* undesirable output of DMU_j, we suppose the adjustment Δz_{tj} must be bounded between L^z_{tj} and U^z_{tj}. Q_t: $t = 1, \dots, T$ is a predetermined amount by central planner denoted as total reduction of the *t-th* undesirable output.

Besides the range restraints on inputs and undesirable outputs in the last four restraints, it is imperative that the efficiency of an individual DMU after resource allocation and targeting does not degrade compared to the efficiency before resource allocation, will not deteriorate. The objective of the central planner is to determine the optimal combination of inputs and undesirable outputs to minimize the weighted sum of adjustments. Incorporating the preceding considerations in resource allocation and target setting, the optimization program can be extended in this model.

Model (5) is a nonlinear model and it can be transformed to be a linear form in two steps. First, let $\bar{\Delta} x_{ij} = v_i \Delta x_{ij}$ and $\bar{\Delta} z_{tj} = w_t \Delta z_{tj} (for \forall i \in I_1, t, j)$, then model (5) is transformed in the following form:

$$
\begin{aligned}
& Min \sum_{i \in I_1} \sum_{j=1}^{n} \delta_i |\bar{\Delta} x_{ij}| + \sum_{t=1}^{T} \sum_{j=1}^{n} \sigma_t |\bar{\Delta} z_{tj}| \\
& s.t. \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (6) \\
& \sum_{i=1}^{m} v_i x_{ij} + \sum_{i \in I_1} \bar{\Delta} x_{ij} + \sum_{r=1}^{s} u_r y_{rj} + u_o \geq \rho_j^* (\sum_{t=1}^{T} w_t z_{tj} + \sum_{t=1}^{T} \bar{\Delta} z_{tj}), \\
& \sum_{i=1}^{m} v_i x_{ij} + \sum_{i \in I_1} \bar{\Delta} x_{ij} + \sum_{r=1}^{s} u_r y_{rj} - \sum_{t=1}^{T} w_t z_{tj} - \sum_{t=1}^{T} \bar{\Delta} z_{tj} + u_o \leq 0, \;\; j = 1, \dots, n, \\
& \sum_{j=1}^{n} \bar{\Delta} x_{ij} = C_i * v_i, \;\; i \in I_1, \\
& \sum_{j=1}^{n} \bar{\Delta} z_{tj} = Q_t * w_t, \;\; t = 1, \dots, T \\
& L^x_{ij} * v_i \leq \bar{\Delta} x_{ij} \leq U^x_{ij} * v_i, \;\; i \in I_1;\; j = 1, \dots, n, \\
& L^z_{tj} * w_t \leq \bar{\Delta} z_{tj} \leq U^z_{tj} * w_t, \;\; t = 1, \dots, T;\; j = 1, \dots, n, \\
& v_i, u_r, w_t, \geq 0, \;\; \bar{\Delta} z_{tj}, \bar{\Delta} x_{ij}, \;\; u_o \text{ free}
\end{aligned}
$$

Now, set $a_{ij} = \frac{1}{2}[|\bar{\Delta} x_{ij}| + \bar{\Delta} x_{ij}] \geq 0$, $b_{ij} = \frac{1}{2}[|\bar{\Delta} x_{ij}| - \bar{\Delta} x_{ij}] \geq 0$, $c_{tj} = \frac{1}{2}[|\bar{\Delta} z_{tj}| + \bar{\Delta} z_{tj}] \geq 0$, and $d_{tj} = \frac{1}{2}[|\bar{\Delta} z_{tj}| - \bar{\Delta} z_{tj}] \geq 0$. With these changes of variables, model (7) is converted into the following linear form:

$$
\begin{aligned}
& Min \sum_{i \in I_1} \sum_{j=1}^{n} \delta_i (a_{ij} + b_{ij}) + \sum_{t=1}^{T} \sum_{j=1}^{n} \sigma_t (c_{tj} + d_{tj}) \\
& s.t. \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (7) \\
& \sum_{i=1}^{m} v_i x_{ij} + \sum_{i \in I_1} (a_{ij} - b_{ij}) + \sum_{r=1}^{s} u_r y_{rj} + uo \geq \rho_j^* (\sum_{t=1}^{T} w_t z_{tj} + \sum_{t=1}^{T} (c_{tj} - d_{tj})), \\
& \sum_{i=1}^{m} v_i x_{ij} + \sum_{i \in I_1} (a_{ij} - b_{ij}) + \sum_{r=1}^{s} u_r y_{rj} - \sum_{t=1}^{T} w_t z_{tj} - \sum_{t=1}^{T} (c_{tj} - d_{tj}) + uo \leq 0, \;\; j = 1, \dots, n, \\
& \sum_{j=1}^{n} (a_{ij} - b_{ij}) = C_i * v_i, \;\; i \in I_1, \\
& \sum_{j=1}^{n} (c_{tj} - d_{tj}) = Q_t * w_t, \;\; t = 1, \dots, T, \\
& L_{ij}^{x} * v_i \leq (a_{ij} - b_{ij}) \leq U_{ij}^{x} * v_i, \;\; i \in I_1; \; j = 1, \dots, n, \\
& L_{tj}^{z} * w_t \leq (c_{tj} - d_{tj}) \leq U_{tj}^{z} * w_t, \;\; t = 1, \dots, T; \; j = 1, \dots, n, \\
& v_i, u_r, w_t, \geq 0, \;\; a_{ij}, b_{ij}, c_{tj}, d_{tj} \geq 0, \;\; u_o \text{ free.}
\end{aligned}
$$

Ultimately, the test of the objective and restraint points out that model (7) is a linear program and can be solved efficiently. This model ensures that the efficiency score of the adjusted DMUs will not deteriorate in the new production period along with some input inflation. The model also aims to generate the same desirable outputs while reducing undesirable outputs, and maximizing overall efficiency.

4. AN EMPIRICAL EXAMPLE

According to the Paris Agreement on climate change, which is the world's first comprehensive climate agreement, each country must specify, project, and regularly announce the contribution that it pledges to reduce global warming. This strategy entails energy and climate policy involving the so-called 20/20/20 targets, denoted as the mitigation of CO2 emissions by 20%, the augmentation of renewable energy's market share to 20% and a 20% boost in energy efficiency. Countries aim at attaining a global level of GHG emissions reduction as soon as possible.

The agreement calls for reducing greenhouse gas emissions at the national level, but it is worth noting that companies in high-emitting industries bear some of the burden. Some of these products, such as oil and gas, cannot be surpassed because they are so inseparable from our lives. Rather than recommending changes in consumption, we focus on the impact of companies including GHG emissions as additional output production (undesirable outputs) when analyzing efficiency. As well, we are looking at how these undesirable outputs should be distributed among companies so that the industry's total greenhouse gas emissions are minimized. In spite of including GHG emissions as undesirable output, we argue that companies should at least be able to sustain their current performance. Herein, we consider the data set, investigated by(Wegener & Amin [31]). The current study uses a data set of oil and natural gas companies in the US and Canada that announced scope 1 GHG emissions through the Carbon Disclosure Project (CDP) between 2011 and 2015. The CDP operates the global disclosure system that authorizes companies, cities, states, and regions to measure and administrate their environmental influences. They have produced the most comprehensive collection of self-reported environmental data.

Oil and gas companies are now recognized as a high-growth, greenhouse-gas emitting industry and could greatly benefit from improved efficiency. In order to change their eco-efficiency, they need to produce more oil and gas without increasing their GHG emissions. For example, Canada's economy developed 8.4% between 2005 and 2011, but greenhouse gas emissions fell 4.8% over the same period. This indicates that Canada's greenhouse gas emissions are starting to be decoupled from economic growth. The indicators also show that further efforts are needed to meet Canada's GHG reduction target of 17% below 2005 levels by 2020. Our DEA resource allocation model can suggest an idea of how much each company can increase its resources while decreasing GHG emissions, without any change in its production.

Various factors depend on the amount of greenhouse gases emitted by oil and gas companies. Considering the number of new wells drilled each year, employees, total assets and capital expenditures, follow (Wegener & Amin [31]). Employees and total assets represent size. Larger companies may have access to more resources to reduce their greenhouse gas emissions. Capital assets and new investments used in production processes must be invested in technologies to reduce greenhouse gases. Below, we summarize the datasets of this study. The inputs consist of capital expenditures, employees, wells and total assets. Production and greenhouse gas emissions are desired and undesirable outputs respectively.

Capital expenditures: This value is converted to US dollars at the December 31, 2015 exchange rate. It includes a way to express the development of green industries.

Employees: They are representative of size. Larger companies may have access to more resources to reduce their greenhouse gas emissions.

Total assets: This value is converted to US dollars at the December 31, 2015 exchange rate. It also represents the purpose of the investment used in the business process. It is also included as a representative size.

Wells: Values are net wells drilled. This represents the company's ownership of all wells drilled each year.

GHG emissions: CDP reported total self-reported direct/Scope 1 GHG emissions for 2015. Direct/Scope 1 emissions represent all GHG emissions directly generated by each company.

Production: It is measured in end-2015 oil equivalent barrels. Each barrel is equivalent to 6,000 cubic feet of natural gas. Table 1 presents the 23 companies data set based on four inputs and two outputs.

The efficiency scores obtained from model (4) are also given in the column 8 of Table1.

Table1: Data set and original efficiency

DMU	Employees	Capital expenditures	Total Assets	Wells	Production	GHG Emission	Initial Efficiency
DMU01	560	542	4267	61	42	763457.00	1
DMU02	294	376	3948	82	31	1284090	0.535
DMU03	3985	1233	18553	772	490	5564499	1
DMU04	1005	1155	12672	700	60	2024889	1
DMU05	10765	4465	38721	3	367	7412436	1
DMU06	2891	2232	15644	400	248	4474446	0.759
DMU07	588	493	2581	47	39	858929	0.845
DMU08	5552	2162	23779	135	239	11260000	0.382
DMU09	5700	2586	31055	46	274	10711614	0.467
DMU10	449	132	3274	7	26	1020934	0.565
DMU11	12750	6220	77527	362	369	18957327	0.745
DMU12	721	350	3028	36	20	511213	1
DMU13	5800	5888	46414	608	305	11807749	0.717
DMU14	3860	4748	18842	467	195	7100000	0.603
DMU15	58178	29504	266103	1866	1955	55746124	1
DMU16	15900	10050	97484	498	580	26039254	0.712
DMU17	6600	4735	29532	420	248	5925440	1
DMU18	2760	5013	26975	489	209	6723280	0.722
DMU19	73500	336758	26490	1210	3135	121000000	1
DMU20	2770	4049	34195	196	136	5561176	0.826
DMU21	1111	1419	4768	139	55	982304	1
DMU22	2395	2852	24196	219	130	2352253	1
DMU23	11100	5272	43437	671	244	10400000	1
Sum	229234	432234	853485	9434	9397	318481414	18.876

We solve the resource allocation and target setting problem (7) by adjusting the input variable, including employees, capital expenditures, and total assets, and GHG emission as undesirable output for each company. The central planner has the desire to increase the total assets and capital expenditures to help “greener” production. Moreover, an increase in the number of employees is another demand of central planner, since larger companies may have accessibility to more resources. A reasonable objective is to allocate the resources and set targets to minimize the weighted sum of total adjustments of all companies. In allocating the resources, constraints on the range of resources that can allocate to an individual company and the accessibility of total resources are what the central planners face. According to fairness and regional balance considerations, constraints on resource allocation to an individual company can come up. The resource accessibility constraint limits the total quantity allocated to all companies and usually can link to each country's economic policy. We focus on the adjustment of employees, capital expenditures, and total assets. Besides, we concentrate on the adjustment on GHG emission as an undesirable output that we desire to decrease its total amount as our target. Production as a desirable output assumes to be fixed by managerial decisions from a central planner's perspective. In this paper, we suppose that the total amount of our selected inputs has to increase by 2% based on their total amount in the year 2015. For example:

$$\sum_{j=1}^{n} \Delta x_{ij} = 0.02 \sum_{j=1}^{n} x_{ij}$$

where i corresponds to the input's employees, capital expenditures, and total assets, respectively. Further, we allow for the deterioration of the total amount of GHG emission by 15% based on their total amount emission at the year 2015. So, each company's GHG emission can be reduced after resource allocation, i.e.,

$$\sum_{j=1}^{n} \Delta z_{tj} = 0.15 \sum_{j=1}^{n} z_{tj}$$

where t corresponds to the GHG emission as undesirable output. To implement model (7), we suppose a set of adjustment range for Δz_{tj}, where $0.5z_{tj}$ as adjustment range lower bound is allowed for undesirable output of an individual company. For Δx_{ij}, assume a moderate setting upper bound $0.2x_{ij}$.There are several possible settings in the choice of weights assigned to the three inputs and one undesirable output in the objective function of the model (7). The preference of the central planners is shown by the weighting plot. We assume an equal preference assigned to all of the weights. Regarding the total sum of each input (the last row of Table 1), the increment amount of the selected inputs must be 4584.68, 8644.68 and 17069.70. Also, the mitigation amount of GHG emissions has to be 47772212.1.

Table 2 provides details on the adjustment of inputs, undesirable output, and alteration of efficiencies after resource allocation and target setting.

To illustrate the applicability of our resource allocation and target setting model, we start with two companies, DMU11 and DMU20. As Table 1 displays, both of these companies were inefficient in the year 2015, but after the resource allocation model implementation, they had an improvement in their efficiency score such that DMU11 has a 0.177 score extension, its score from 0.745 becomes 0.922. This occurs by spending 1243.999 more capital expenditures, with a 0.072 increase in total assets, and 7709027.990 reductions in its GHG emission. DMU20 by an 809.799 increase in its capital expenditures, a slight amount of total assets, and 1961047.248 decrease in GHG emission becomes efficient. Some efficient DMUs, such as DMU1, DMU5, DMU12, DMU15, and DMU23, through less amount of total assets and capital expenditures enhancement but remarkable amount abatement in their GHG emission is still efficient.

Table 2: Adjustments on data and efficiency score

DMU	Employees adjustment	Capital expenditures adjustment	Total Assets adjustment	Wells adjustments	GHG Emission adjustment	Efficacy adjust
DMU01	0.001	0.001	0.072	0	-236503.300	0.000
DMU02	58.800	75.200	789.490	0	-617960.460	0.181
DMU03	0.001	0.001	0.072	0	-0.020	0.000
DMU04	0.001	227.907	0.072	0	-1012444.500	0.000
DMU05	0.001	0.001	0.072	0	-347648.672	0.000
DMU06	0.001	153.673	0.072	0	-0.020	0.000
DMU07	0.001	18.291	0.072	0	-270991.406	0.008
DMU08	757.331	432.400	0.072	0	-0.020	0.001
DMU09	1139.998	517.200	6210.136	0	-227653.550	0.020
DMU10	89.800	26.400	654.709	0	-497752.518	0.218
DMU11	0.001	1243.999	0.072	0	-7709027.990	0.177
DMU12	0.001	0.001	0.072	0	-179707.352	0.000
DMU13	0.001	1177.599	0.072	0	-3734997.144	0.091
DMU14	771.998	949.599	3767.876	0	-230227.160	0.000
DMU15	0.001	0.001	0.072	0	-15937602.564	0.000
DMU16	1766.732	2009.998	5644.822	0	-8296116.698	0.098
DMU17	0.001	0.001	0.072	0	-984828.048	0.000
DMU18	0.001	1002.599	0.072	0	-1394325.578	0.078
DMU19	0.001	0.001	0.072	0	-0.020	0.000
DMU20	0.001	809.799	0.072	0	-1961047.248	0.174
DMU21	0.001	0.001	0.072	0	-0.020	0.000
DMU22	0.001	0.001	0.072	0	-0.020	0.000
DMU23	0.001	0.001	0.072	0	-4133377.790	0.000
Sum	4584.68	8644.68	17069.70	0.0	-47772212.10	1.045

DMU8 has the worst performance after model (7) implementation, it has to increase all its resources, but it has a less diminution in its GHG emission, although efficiency growth is observed. Among all DMUs, DMU6 and DMU14 have the same inefficiency score as preceding. Yet, the increment is observed in all the resources of DMU6 and DMU14. DMU6's GHG emission is insignificant while DMU14 has a 230227.160 reduction in GHG emission. It is noteworthy that the number of efficient DMUs grows from 11 to 12. Moreover, we have a 1.045 score improvement in total efficiency. The modified data and each company's new efficiency score are presented in Table 3.

Table 3: Modified data and final efficiency scores

DMU	Employees	Capital expenditures	Total Assets	Wells	Production	GHG Emission	Final Efficiency
DMU01	560.001	542.001	4267.072	61	42	526953.7	1
DMU02	352.8	451.2	4737.49	82	31	666129.54	0.716
DMU03	3985.001	1233.001	18553.072	772	490	5564499	1
DMU04	1005.001	1382.907	12672.072	700	60	1012444.5	1
DMU05	10765.001	4465.001	38721.072	3	367	7064787.3	1
DMU06	2891.001	2385.673	15644.072	400	248	4474446	0.759
DMU07	588.001	511.291	2581.072	47	39	587937.59	0.853
DMU08	6309.331	2594.4	23779.072	135	239	11260000	0.383
DMU09	6839.998	3103.2	37265.136	46	274	10483960	0.487
DMU10	538.8	158.4	3928.709	7	26	523181.48	0.783
DMU11	12750.001	7463.999	77527.072	362	369	11248299	0.922
DMU12	721.001	350.001	3028.072	36	20	331505.65	1
DMU13	5800.001	7065.599	46414.072	608	305	8072751.9	0.807
DMU14	4631.998	5697.599	22609.876	467	195	6869772.8	0.603
DMU15	58178.001	29504.001	266103.07	1866	1955	39808521	1
DMU16	17666.732	12059.998	103128.82	498	580	17743137	0.81
DMU17	6600.001	4735.001	29532.072	420	248	4940612	1
DMU18	2760.001	6015.599	26975.072	489	209	5328954.4	0.8
DMU19	73500.001	336758	26490.072	1210	3135	121000000	1
DMU20	2770.001	4858.799	34195.072	196	136	3600128.8	1
DMU21	1111.001	1419.001	4768.072	139	55	982303.98	1
DMU22	2395.001	2852.001	24196.072	219	130	2352253	1
DMU23	11100.001	5272.001	43437.072	671	244	6266622.2	1
Sum	233818.68	440878.68	870553.7	9434	9397	270709202	19.921

Generally, most companies should be able to produce their current level of oil identical with less GHG emissions. This would help to deal with climate change. As a result, they improve their performance with the hope of increasing their inputs and decreasing GHG emissions. Efficient companies, on the other hand, could fix their efficiency score.

In fact, this study is an attempt in the resource allocation and target setting method regarding managerial disposability assumption which minimizes undesirable output as its target.

5. CONCLUSIONS

The significance of resource allocation in management has made it a fascinating topic. When it comes to resource allocation issues, environmental issues are usually linked to economic issues, so they should be addressed by all decision makers in this area. This study proposes a model of target setting and resource allocation to improve the environmental performance of DMUs. To further explore this topic, economic and environmental aspects are considered in this study. Also, it uses a new concept of disposability, that is, “managerial disposability” to adjust a regulation adjustment on undesirable outputs based on the perspective of corporation strategies; moreover, it considers the influence of the managerial effort and technological innovations. We consider an undesirable output reduction approach to obtain each DMU's efficiency score. Then, a centralized resource allocation and target setting model is suggested to allocate resources and establish undesirable output targets for the DMUs.

The suggested approach has some advantages, including the ability to produce resource allocation and target setting results that maximize the overall efficiency and the assurance that the efficiency score of the adjusted DMUs will not experience a reduction in the new production period. In addition, this model reflects the leadership performance of the central planner and the technological novelty perspective in the resource allocation and target setting problem, also it has a positive modification against an environmental adaptation change. Finally, the proposed approach is applied for 23 oil and natural gas companies in the US and Canada that announced scope 1 GHG emissions. The empirical analyses indicate that these companies, by maintaining the current total production level, are capable to reduce their total GHG emission by increasing their resources. GHG emissions allowance trading is an impressive mechanism for emission control that we take advantage of in this study.

Some further research draws from this paper. Firstly, this study has analyzed the performance of the US and Canadian oil and gas companies by the presented approach. We can assume different applications in the other energy sectors such as electricity, hydropower, and so forth. Only one year's worth of data from US and Canadian oil and gas companies was taken into account for the empirical study. Data for at least two years could be gathered, and our models could be developed to achieve dynamic resource allocation and target setting for these oil and gas companies.

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