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Centralized resource allocation based on energy saving and environmental pollution reduction using data envelopment analysis models

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Abstract

Environmental pollution has caused governments to be concerned about energy saving and the reduction of environmental pollution. Some researchers have presented resource allocation models as multi-objective linear programming (MOLP) in order to pay more attention to energy saving and environmental pollution reduction. Energy saving affects both desirable and undesirable outputs. In this paper, we argue for the inapplicability of the existing models for reducing the undesirable outputs through energy saving. The purpose of this paper is to design a model based on data envelopment analysis (DEA) that would result in reduced pollution through energy saving. Moreover, since an undesirable output is

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considered as a function of the total desirable outputs, if necessary, the changes should be applied to the total desirable outputs and there is no need to reduce each desirable output individually. Finally, the model proposed based on goal programming (GP) is used in 20 different regions in China. The results produced by this model indicate that the reduction proportion of total environmental pollution emissions per energy saving was larger than the reduction proportion of total desirable outputs.

Keywords: resource allocation, data envelopment analysis, energy saving, environmental pollution, desirable output, undesirable output

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Introduction

One of the outputs of industrial development is environmental pollution. Carbon dioxide gas accounts for about 60 percent of all greenhouse gases, and about 81 percent of all greenhouse gas emissions come from fossil fuel consumption. Fossil fuels, on the one hand, are the most important sources of energy for cities, while being the main source of pollution. Iran is one of the highest carbon emission-intensive countries in the world. Total CO_2 emissions in 1990 were 201.8 million metric tons (MMT), which has increased rapidly at an average annual rate of 5.7% to 372 MMT by 2003 [1].

The amount of particulate matters in the atmosphere is one of the most important indicators of air pollution. Aerosols have a great impact on the climate and human environment. Tropospheric aerosols, known as particulate matter, have an adverse effect on human health [2]. One of the atmospheric pollutants, sulfur dioxide, causes acid rain and many other adverse environmental effects and health hazards [3].

The main reason for the increasing CO_2 emissions in industries is high levels of energy consumption. Based on reports from the International Energy Agency [4], the global industrial sector is responsible for about 40% of total energy consumption in the world. Due to the raised awareness about environmental issues and technological advancements that help reduce environmental damage, there has been a decline in CO_2 emissions from industries in developed countries; however, such emissions are greatly increasing in developing countries [5].

Data envelopment analysis (DEA) is novel area of study, as well as a necessary mathematical tool for evaluating the relative efficiency of a set of homogenous decision-making units (DMU). This method has attracted a lot of attention in various fields of management sciences [6]. DEA, which is a non-parametric method, has had many applications in solving the problem of resource allocation when all DMUs are under the control of a single centralized decision maker (DM). There is no prior functional form in DEA, and there is no need for the many assumptions that emerge by using statistical methods for function estimation. At the same time, DEA produces good results when used in resource allocation [5, 7]. Many papers have been presented based on DEA for allocating resources to a set of DMUs in which the purpose of the DM has been to minimize the total input consumption or to maximize the total output production of all DMUs instead of considering each one individually and set separate targets for each DMU. Centralized resource allocation was presented by [8] for the first time, which sought radical reduction in the total consumption of every input by all units. In [7], the authors designed a multi-objective model for resource allocation to find the maximum amount of production. They defined a transformation possibility set for each DMU with two assumptions; the first one was to assume that the unit's efficiency stays constant during the planning period, and the other assumption was that each unit could have a proportional scaling of changes in inputs and outputs. Later, [9] considered one of the models presented by [8] and modified it to adjust the inefficient units. The study [10] extended a simplified model of [8]. This model recognized more efficient units and was much simpler to execute than the previous models. The special characteristic of this model was that the centralized DM did not necessarily need to keep the original number of DMUs fixed. For other extensions of the model proposed by [8], one can refer to [11, 12]. Other proposed models for centralized resource allocation can be found in [13–15]. The study [14] proposed two ideas: one idea maximized the total efficiency, while the other one simultaneously maximized the output production and minimized the input consumption. In this method, the new efficiency of all DMUs becomes equal to one after production design; this efficiency improvement is not logical and feasible in practice. On the other hand, there is no guarantee that the inputs (outputs) will decrease (increase) significantly. Also, there is no logical connection between these changes and they may not be fair. In [16], the authors extended a method that implemented the demand and supply changes in a centralized decision-making environment under a predictable assumption. The study [17] presented a DEA model for centralized resource allocation with the assumption of adjustable and non-adjustable inputs and transferable and non-transferable outputs. Then, he analyzed the structural efficiency of the model using the structural efficiency analysis presented by [18]. The study [19] combined energy consumption reduction through resource allocation with DEA models with undesirable outputs, and proposed a multi-objective model for resource allocation under energy saving constraints. Since energy saving decreases both the desirable and undesirable outputs, the aim of their model was to make the reduction proportion of the desirable outputs would be less than the reduction proportion of the harmful outputs. This way, recommendations can be made regarding energy and environmental policies toward saving energy and reducing air pollution. They also studied the classification of natural resources in China and used an input-oriented slacks-based model for measuring the efficiency of provinces [20]; then, they proposed a DEA-based approach for allocating the total natural resources. Unlike conventional DEA models, it seems necessary to consider both desirable and undesirable outputs in environmental performance evaluation [21].

Many of the findings of DEA studies have been used for environmental performance measurement. The study [22] focused on the analysis of optimal energy allocation and environmental performance of China's three major urban agglomerations. In particular, that study first used a fixed-input DEA model to obtain the optimal allocation of energy input. Then, an evaluation model based on the optimal allocation of energy input was proposed to evaluate the environmental performance. In [23], the researchers constructed an evaluation indicator system based on three stages, namely economic production, wastewater treatment, and human health, and used the undesirable three-stage dynamic data envelopment analysis model to empirically evaluate the total efficiency, stage efficiency, and the efficiency of various indicators.

Goal Programming (GP) is a developed form of Linear Programming. GP tries to achieve several goals simultaneously and allows deviation from the goal. Therefore, it has flexibility in decision-making processes. The main approach of GP is to allocate a special target value to each objective function and then look for a solution that would minimize unwanted deviations from the intended goals [24]. GP was used as a method for solving multi-objective problems with the aim of minimizing unwanted deviations from the set goals. There exist two main algorithms for solving a GP problem: the weighted sum model and the lexicographic model. The studies [25, 26] proposed using GP for MCDEA models. The difficulty in solving a multi-objective problem is finding a solution that would optimize all the objectives simultaneously [27]. Since there is no such solution in most cases, a non-dominated solution set is needed. Paper [25] proposed using the lexicographic model to solve GP problems and allocating priority to the objective functions of MCDEA.

In [26] was proposed the weighted goal programming method (GPDEA). The studies [28, 29] addressed the connections between multi-objective problems and DEA. Furthermore, there have been some models that maximized the efficiency of all DMUs simultaneously (e.g., [30–33]). Industrial production is always associated with energy consumption and greenhouse gas emission (the most important is CO_2 emission). As energy consumption decreases, the desirable output will also decrease, but when industrial estates are required by governments to reduce and control pollution, if energy storage does not lead to a reduction in environmental pollution, the model is not valid in the eyes of the central manager. In the centralized resource allocation model proposed by [19], we show that undesirable output changes become zero by saving energy. In this paper, we modify their model so that with a reduction in energy consumption, a significant reduction in CO_2 emission is achieved, and show that if the centralized DM considers boundaries for changes in the inputs and outputs, the model may be infeasible, since choosing suitably and feasibly will be a difficult task for the centralized DM. Therefore, the model is modified through GP in a way that makes it feasible.

On the other hand, the reduction of individual desirable outputs due to reductions in the undesirable outputs has the weakness that some undesirable outputs may have been out of the acceptable standard range. In such cases, some undesirable outputs may be reduced without any reduction in the desirable outputs.

What this paper proposes is that since an undesirable output is considered to be a function of the total desirable outputs, if necessary, the changes should be applied to the total desirable outputs. According to the abovementioned, the innovations of this research are:

- Rectifying the infeasibility of the allocation model in cases where unsuitable boundaries are selected for the input/output changes, which are assigned by the DM.
- Modifying the pre-presented model and eliminating the weakness of the respective model in reducing the undesirable outputs.
- Presenting a new model that does not require the reduction of each and every desirable output in the units (production industries) in order to save energy and reduce pollution, since there could be a case where in a given region, some units have a large amount of undesirable outputs due to performance weaknesses, in which case the reduction of a portion of undesirable outputs in the entirety of units may not require a reduction of desirable outputs in all units.

The rest of the paper is organized as follows: In section 1 (Theoretical background), an introduction is provided to the conventional DEA model and the centralized resource allocation models, as well as the method of using GP to solve multi-objective problems. This section also discusses the defects of the previously mentioned model. In section 2 (Proposed model), we present our proposed model for centralized resource allocation with the aim of energy saving and reducing environmental pollution emissions. The advantages to the model are also included in this section. The application of GP in the proposed resource allocation model is illustrated through a numerical example in section 3 (Numerical example). Finally, some conclusions and remarks are provided.

1. Theoretical background

Data envelopment analysis (DEA) is a powerful tool for evaluating the relative efficiency of a set of DMUs that consume multiple inputs to produce multiple outputs. Suppose there are n DMUs that are in need of evaluation, and each one consumes m different inputs to produce s different outputs. Suppose $X_j = (x_{1j}, \dots x_{mj})^T$ and $Y_j = (y_{1j}, \dots y_{sj})^T$, $X_j \ge 0$, $Y_j \ge 0$ are the input and output vectors, respectively. The production possibility set T is defined as:

$$T = \{(x, y) \mid y \textit{ can be produced from } x\}. \quad (1)$$

In [34] is defined the following PPS using the constant returns to scale (CRS) assumption.

$$T_{CCR} = \left\{ (x, y) \in R_{\ge 0}^{m+s} \,\middle|\, \sum_{j=1}^{n} \lambda_j x_{ij} \le x, \right. \\ \left. \sum_{j=1}^{n} \lambda_j y_{rj} \ge y,\ \lambda_j \ge 0,\ j = 1, \dots, n \right\}. \quad (2)$$

The input-oriented model for evaluating DMU_o, $o \in \{1, \dots, n\}$ under the assumption of CRS can be achieved by solving the following ratio programing problem [34].

$$\max \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}}, \quad (3)$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \le 1,$$

$$u_r, v_i \ge \varepsilon \qquad r = 1, \dots, s, \qquad i = 1, \dots, m.$$

Here $\varepsilon > 0$ is a non-Archimedean element defined to be smaller than any positive real number.

GP provides the means for attempting to achieve several objectives simultaneously. Many researchers, including [28, 29, 35], have investigated the relationships between DEA and MOP. Several methods have been developed to solve multi-objective problems (see: [36–38]), one of which is Goal programming [24, 39].

1.1. Resource allocation models

In recent years, various applications of DEA have been seen in most countries around the world for the purposes of evaluating the performance of organizations and other common activities in different areas. In the context of planning and resource allocation, a number of optimization techniques have been introduced, such as multi-objective programming. The purpose of a central unit is to design a reasonable resource allocation mechanism that can bring the greatest benefits for the central organization [7, 40, 41]. In many real-world scenarios, all of the DMUs may be under the influence of a central decision maker who can supervise the resource consumption of these units. The main purpose of resource allocation is to allocate resources in such a way that the general goals of the organization are achieved as far as possible. Unlike conventional DEA models, [42] considered undesirable factors as an important factor in efficiency evaluation. The studies [43–45] suggested an alternative approach in environmental technology in which the desirable outputs increased while the undesirable outputs decreased. The study [19] considered both desirable and undesirable outputs in their evaluation, as there are undesirable outputs in the production process. Their model helped the DM allocate future resources while taking energy saving into account. They combined the energy consumption reduction targets with resource allocation and proposed a multi-objective programming model that not only reduced the undesirable outputs but also decreased the desirable outputs in order to improve the undesirable output production.

They defined the transformation possibility set as follows:

$$F_j = \left\{ \begin{pmatrix} x_j - \Delta x_j \\ y_j^g - \Delta y_j^g \\ y_j^b - \Delta y_j^b \end{pmatrix} \middle| \Delta y_j^g \geq \delta_j y_j^g,\ \Delta y_j^b \leq \delta_j y_j^b \right\}, \quad (4)$$

$$\delta_j = \max\left\{ \frac{\Delta x_{ij}}{x_{ij}} \middle| i = 1,...,m \right\}.$$

Their model, based on the CRS assumption, is formulated as follows:

$$\min \quad \Delta Y^g = \sum_{r=1}^{s_1} \sum_{j=1}^{n} \frac{\Delta y_{rj}^g}{\sum_{j=1}^{n} y_{rj}^g},$$

$$\max \quad \Delta X = \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{\Delta x_{ij}}{\sum_{j=1}^{n} x_{ij}}, \quad (5)$$

s.t.

$$\Delta y_j^g \geq \delta_j y_j^g,\ j = 1, ..., n, \quad (5\text{-}1)$$

$$\Delta y_j^b \leq \delta_j y_j^b,\ j = 1, ..., n, \quad (5\text{-}2)$$

$$\Delta x_j \leq \delta_j x_j,\ j = 1, ..., n, \quad (5\text{-}3)$$

$$y_j^g - \Delta y_j^g \leq Y^g \Lambda_j,\ j = 1, ..., n, \quad (5\text{-}4)$$

$$y_j^b - \Delta y_j^b \geq Y^b \Lambda_j,\ j = 1, ..., n, \quad (5\text{-}5)$$

$$x_j - \Delta x_j \geq X \Lambda_j,\ j = 1, ..., n, \quad (5\text{-}6)$$

$$A_j \leq \Delta y_j^g \leq B_j,\ j = 1, ..., n, \quad (5\text{-}7)$$

$$\Delta Y^b = \sum_{j=1}^{n} \Delta y_j^b \leq M. \quad (5\text{-}8)$$

Where the vectors

$$\begin{pmatrix} X_j - \Delta X_j \\ Y_j^g - \Delta Y_j^g \\ Y_j^b - \Delta Y_j^b \end{pmatrix} \in R_{\geq 0}^{m+s_1+s_2}$$

and the matrices X, Y^g, Y^b are defined as follows:

$$X = [x_1, x_2, ..., x_n] \in R^{m \times n},$$

$$Y^g = [y_1^g, y_2^g, ..., y_n^g] \in R^{s_1 \times n},$$

$$Y^b = [y_1^b, y_2^b, ..., y_n^b] \in R^{s_2 \times n},$$

$$X > 0,\ Y^g > 0,\ Y^b > 0.$$

ΔX_j represents the saving amount of inputs in DMU_j, any Δy_j^g, Δy_j^b denote the reduction amounts of desirable and undesirable outputs in DMU_j, respectively. F_j (transformation possibility set) represents the capacity of input and output changes for DMU_j. $[A_j, B_j]$ indicates the capacity of desirable output changes, and M is the maximum emission reduction, which is determined by the DM.

2. Proposed model: resource allocation models based on goal programming

In Model (5), independent of what the value of δ_j^* (positive or zero) is in the optimal solution, in the constraints (5-2) and (5-8), $\Delta y_j{}^b = 0$ is true. It has also already been established that $\Delta y_j{}^b = 0$ is true in constraint (5-5). Therefore, in all constraints, $\Delta y_j{}^b = 0$ ($j = 1,..., n$) is a solution, and since it does not exist in the objective function, then $\Delta y_j{}^b = 0$ is always true, which indicates a defect in Model (5). Let us also assume that the manager considers the following goals:

$$A_j \leq \Delta x_j \leq B_j,\ C_j \leq \Delta y_j^g \leq D_j,$$

$$\sum_{j=1}^{n} \Delta y_j^b \geq M,\ A_j, B_j \in R_{\geq 0}^m,$$

$$C_j, D_j \in R_{\geq 0}^{s_1},\ M \in R_{\geq 0}^{s_2}.$$

If A_j, B_j, C_j, D_j, M for $j = 1,..., n$ are not chosen pro-perly, Model (5) will be infeasible. In this paper, this model is modified using GP in a way that it becomes feasible and $\Delta y_j^{\,b} > 0$ is obtained.

Therefore, we define F_j as follows.

$$F_j = \left\{ \begin{pmatrix} x_j - \Delta x_j \\ y_j^g - \Delta y_j^g \\ y_j^b - \Delta y_j^b \end{pmatrix} \middle| \Delta y_j^g \geq \delta_j y_j^g,\ \Delta y_j^b \geq \delta_j y_j^b \right\}, \quad (6)$$

$$\delta_j = \max \left\{ \frac{\Delta x_{ij}}{x_{ij}} \middle| i = 1, \ldots, m \right\}.$$

And assuming that the production possibility set remains unchanged in each step,

$$T = \left\{ \left(x, y^g, y^b\right) \in R_{\geq 0}^{m+s_1+s_2} \middle| \begin{array}{l} x \geq \sum_{j=1}^{n} \lambda_j x_j, \\ y^g \leq \sum_{j=1}^{n} \lambda_j y_j^g, \\ y^b \geq \sum_{j=1}^{n} \lambda_j y_j^b, \\ \lambda_j \geq 0, j = 1, \ldots, n \end{array} \right\}, \quad (7)$$

$$\Delta X = \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{\Delta x_{ij}}{\sum_{j=1}^{n} x_{ij}}, \quad \Delta Y^g = \sum_{r=1}^{s_1} \sum_{j=1}^{n} \frac{\Delta y_{rj}^g}{\sum_{j=1}^{n} y_{rj}^g}. \quad (8)$$

Now, the resource allocation model is presented using GP as follows:

$$\min \quad Z_1 = \sum_{j=1}^{n} (n_j^1 + n_j^2) + \sum_{j=1}^{n} (p_j^1 + p_j^2) + L,$$

$$\min \quad Z_2 = \Delta Y^g, \quad (9)$$

$$\min \quad Z_3 = \Delta X.$$

s.t.

$$x_{ij} - \Delta x_{ij} \geq \sum_{l=1}^{n} \lambda_{jl} x_{il},$$
$$j = 1, \ldots, n,\ i = 1, \ldots, m, \quad (9\text{-}1)$$

$$y_{rj}^g - \Delta y_{rj}^g \leq \sum_{l=1}^{n} \lambda_{jl} y_{rl}^g,$$
$$j = 1, \ldots, n,\ r = 1, \ldots, s_1, \quad (9\text{-}2)$$

$$y_{pj}^b - \Delta y_{pj}^b \geq \sum_{l=1}^{n} \lambda_{jl} y_{pl}^b,$$
$$j = 1, \ldots, n,\ p = 1, \ldots, s_2, \quad (9\text{-}3)$$

$$\Delta x_{ij} \leq \delta_j x_{ij}, j = 1, \ldots, n, i = 1, \ldots, m, \quad (9\text{-}4)$$

$$\Delta y_{rj}^g \geq \delta_j y_{rj}^g, j = 1, \ldots, n, r = 1, \ldots, s_1, \quad (9\text{-}5)$$

$$\Delta y_{pj}^b \geq \delta_j y_{pj}^b, j = 1, \ldots, n, p = 1, \ldots, s_2, \quad (9\text{-}6)$$

$$\Delta y_j^g \geq C_j - n_j^1,\ j = 1, \ldots, n, \quad (9\text{-}7)$$

$$\Delta y_j^g \leq D_j + n_j^2,\ j = 1, \ldots, n, \quad (9\text{-}8)$$

$$\Delta x_j \geq A_j - p_j^1,\ j = 1, \ldots, n, \quad (9\text{-}9)$$

$$\Delta x_j \leq B_j - p_j^2,\ j = 1, \ldots, n, \quad (9\text{-}10)$$

$$\sum_{j=1}^{n} \Delta y_j^b \geq M - L, \quad (9\text{-}11)$$

$$\Delta y_j^g \leq y_j^g, j = 1, \ldots, n, \quad (9\text{-}12)$$

$$\lambda_{jl} \geq 0,\ j = 1, \ldots, n,\ l = 1, \ldots, p,$$

where ΔY^g and ΔX are as defined in equation (8), and

$$n_j^1, n_j^2 \in R_{\geq 0}^{s_1},\ p_j^1, p_j^2 \in R_{\geq 0}^{m},\ L \in R_{\geq 0}^{s_2},$$
$$\Delta x_j = [\Delta x_{1j}, \Delta x_{2j}, \ldots \Delta x_{mj}],$$
$$\Delta y_j^g = \left[\Delta y_{1j}^g, \Delta y_{2j}^g, \ldots, \Delta y_{s_1 j}^g\right],$$
$$\Delta y_j^b = \left[\Delta y_{1j}^b, \Delta y_{2j}^b, \ldots, \Delta y_{s_2 j}^b\right].$$

Constraints (9-1) – (9-3) in model (9) indicate that the reduced outputs and inputs belong to the PPS. Constraints (9-4) – (9-6) ensure that the changed output and input values for each DMU belong to its own transformation possibility set. In constraints (9-7) and (9-8), if the management's expectation for $\Delta y_j^{\,g}$ to fall within the interval of C_j, D_j is unattainable, the deviation variables n_j^1, n_j^2 will modify it and make the problem feasible. This is also true for constraints (9-9) – (9-11).

The optimal values of this model can be obtained in two steps. The first step is to obtain the minimum of the total deviation variables for the goal considered by the central manager, which is considered as the first priority for the problem to be feasible, and then obtain the optimal solution to this model using the lexicographic method. The second step is to obtain the weighted sum of the two next objective functions in order to minimize the desirable output reduction and maximize energy saving in the optimal solution obtained from the first step.

Theorem. $\Delta y_j^{\,b} > 0$ is true for all $j = 1,..., n$ that have a positive Δx_j.

Proof: Since $x_j > 0$ and $\Delta x_j > 0$ in constraint (9-4), $\delta_j > 0$ is true. On the other hand, based on constraint (9-6) and the fact that $y_j^{\,b} > 0$ and $\delta_j > 0$, we arrive at $\Delta y_j^{\,b} > 0$.

On the other hand, since an undesirable output is a function of the total desirable outputs, if necessary, the required changes shall be applied to the totality of the desirable outputs. Therefore, reducing individual desirable outputs is not logical, as some of the undesirable outputs may have been out of the acceptable standard range. For example, the carbon monoxide gas produced in industrial plants in a geographical region would cause pollution in that region. However, reduced pollution may be achieved by a reduction in any one of the factories, so all factories are not necessarily forced to reduce their emissions. In this regard, the transformation possibility set defined in this paper will, in addition to energy saving, reduce the undesirable outputs following a minimum reduction in the total desirable outputs. Therefore, the set F is defined as a transformation possibility set for the total inputs and outputs as follows:

$$F = \left\{ \left(\begin{array}{c} \sum_{j=1}^{n}(x_j - \Delta x_j) \\ \sum_{j=1}^{n}(y_j^g - \Delta y_j^g) \\ \sum_{j=1}^{n}(y_j^b - \Delta y_j^b) \end{array} \right) \middle| \begin{array}{l} \sum_{j=1}^{n} \Delta y_{rj}^g \ge \delta \sum_{j=1}^{n} y_{rj}^g, \\ \sum_{j=1}^{n} \Delta y_{pj}^b \ge \delta \sum_{j=1}^{n} y_{pj}^b \\ r = 1,...,s_1,\ p = 1,..., s_2 \end{array} \right\}, \quad (10)$$

$$\delta_j = \max\left\{ \frac{\Delta x_{ij}}{x_{ij}} \middle| i = 1,...,m \right\},$$

$$\delta = \min_j \delta_j.$$

Now, by considering a tradeoff of reductions in the desirable and undesirable outputs and using GP, the centralized resource allocation model is presented as follows:

$$\min \quad Z_1 = \sum_{j=1}^{n}(n_j^1 + n_j^2) + \sum_{j=1}^{n}(p_j^1 + p_j^2) + L, \quad (11)$$

$$\min \quad Z_2 = \Delta Y^g, \max \quad Z_3 = \Delta X,$$

s.t.

$$\sum_{j=1}^{n}(x_{ij} - \Delta x_{ij}) \ge \sum_{j=1}^{n}\sum_{l=1}^{n} \lambda_{jl} x_{il},\ i = 1, ..., m, \quad (11\text{-}1)$$

$$\sum_{j=1}^{n}(y_{rj}^g - \Delta y_{rj}^g) \le \sum_{j=1}^{n}\sum_{l=1}^{n} \lambda_{jl} y_{rl}^g,\ r = 1, ..., s_1, \quad (11\text{-}2)$$

$$\sum_{j=1}^{n}(y_{pj}^b - \Delta y_{pj}^b) \ge \sum_{j=1}^{n}\sum_{l=1}^{n} \lambda_{jl} y_{pl}^b,\ p = 1, ..., s_2, \quad (11\text{-}3)$$

$$\Delta x_{ij} \le \delta_j x_{ij},\ j = 1, ..., n,\ i = 1, ..., m, \quad (11\text{-}4)$$

$$\sum_{j=1}^{n} \Delta y_{rj}^g \ge \delta \sum_{j=1}^{n} y_{ri}^g,\ r = 1, ..., s_1, \quad (11\text{-}5)$$

$$\sum_{j=1}^{n} \Delta y_{pj}^b \ge \delta \sum_{j=1}^{n} y_{pj}^b,\ p = 1, ..., s_2, \quad (11\text{-}6)$$

$$\delta \le \delta_j,\ j = 1, ..., n, \quad (11\text{-}7)$$

$$\Delta y_j^g \ge A_j - n_j^1,\ j = 1, ..., n, \quad (11\text{-}8)$$

$$\Delta y_j^g \le B_j + n_j^2,\ j = 1, ..., n, \quad (11\text{-}9)$$

$$\Delta x_j \ge C_j - p_j^1,\ j = 1, ..., n, \quad (11\text{-}10)$$

$$\Delta x_j \le D_j + p_j^2,\ j = 1, ..., n, \quad (11\text{-}10)$$

$$\sum_{j=1}^{n} \Delta y_j^b \ge M - L, \quad (11\text{-}12)$$

$$\begin{array}{c} x_j - \Delta x_j \ge 0,\ y_j^g - \Delta y_j^g \ge 0, \\ y_j^g - \Delta y_j^g \ge 0,\ j = 1,...,n, \end{array} \quad (11\text{-}13)$$

$$\lambda_{jl} \ge 0,\ j = 1, ..., n,\ l = 1, ..., p.$$

Constraints (11-1) – (11-3) in model (8) indicate that the total reduced outputs and inputs belong to the PPS. That is to say,

$$\begin{pmatrix} \sum_{j=1}^{n}(x_j - \Delta x_j) \\ \sum_{j=1}^{n}(y_j^g - \Delta y_j^g) \\ \sum_{j=1}^{n}(y_j^b - \Delta y_j^b) \end{pmatrix} \in T$$

and constraints (11-4) – (11-7) indicate that

$$\begin{pmatrix} \sum_{j=1}^{n}(x_j - \Delta x_j) \\ \sum_{j=1}^{n}(y_j^g - \Delta y_j^g) \\ \sum_{j=1}^{n}(y_j^b - \Delta y_j^b) \end{pmatrix} \in F.$$

In other words, it is guaranteed that the total changed values of inputs and outputs belong to the transformation possibility set for all inputs and outputs. Constraints (11-8) – (11-12) are conditions set by the central manager. The model above is converted to a model under variable returns to scale (VRS) assumption by adding $\sum_{l=1}^{n}\lambda_{jl} = 1$. The optimal values of model (11) can beobtained through prioritization.

Lemma 1. Models (9) and (11) are always feasible regardless of the goals set by the manager.

Proof: In Model (9), by choosing $\forall j, \forall l \quad \lambda_{jl} = 0$, $x_j = 0, \Delta y_j^{\,b} = y_j^{\,b}, \Delta y_j^{\,g} = y_j^{\,g}, n_j^{\,1} = A_j, n_j^{2} = y_j^{\,g}, p_j^{\,1} = C_j$, $p_j^{\,2} = 0$, $L = M$, $\delta_j = 0.2$ we have a feasible solution to the model. Similarly, Model (11) is also feasible.

Lemma 2. If the first objective function receives a positive value in optimality, it means that the goals set by the manager are unreachable and deviation variables play an important role in the feasibility.

For the computational comparison of models (5) and (11), the conditions considered for changes in the inputs and outputs can be discarded, because in each problem, depending on the opinion of the central manager, these conditions may or may not apply. When the conditions imposed by the central manager are set aside in both models (constraints (5-7) and (5-8) in model (5), and constraints (11-8) and (11-13), then in model (11), we will have only the second and third objective functions, which are equivalent to both objective functions in model (5). As can be seen in the calculations *Table1*, model (11) has less computational volume than model (5).

Even if the conditions imposed by the central manager are considered the same in each mod-

Table1.

Comparison of the constraints of model (5) and model (11)

Model (5)	Number of constraints	Model (11)	Number of constraints
(5–1)	$s_1 \times n$	(11–1)	m
(5–2)	$s_2 \times n$	(11–2)	s_1
(5–3)	$m \times n$	(11–3)	s_2
(5–4)	$s_1 \times n$	(11–4)	$(m \times n)$
(5–5)	$s_2 \times n$	(11–5)	s_1
(5–6)	$m \times n$	(11–6)	s_2
		(11–7)	n
Total:	$(2s_1 + 2s_2 + 2m) \times n$	Total:	$2s_1 + 2s_2 + mn + m + n$

el, for model (5) to be always feasible, the first objective function of model (11) must be added to model (5), in which case since the model is solved by lexicography's prioritization method, the computational volume in both cases will be doubled, which again makes model (11) computationally eco-nomical, especially when the number of units is significant.

Advantages of model (11) compared with model (5):

1. While in model (5), $\Delta y^b = 0$ is obtained along with the reduction of energy, model (11) was changed so that Δy^b can receive a positive value (these have been proven at the beginning of part 2 and the theorem). That is, model (11) can reduce environmental pollution by reducing energy consumption, while model (5) cannot.

2. Even if the parameters are chosen inappropriately, the proposed model (11) is always feasible (due to the existence of deviation variables, while these variables do not exist in model (5)).

3. Since the undesirable outputs may not be within the acceptable standard range, Model (11) is not forced to reduce each desirable output individually. Thus, the required changes are applied to the totality of the desirable outputs and inputs.

4. The number of constraints is significantly reduced in model (11).

3. Numerical example

In this section, we apply Models (9) and (11) to a numerical example for the purposes of analysis. *Table 1* exhibits a simple data set for six DMUs that produce two outputs using one input (desirable and undesirable), which are under the supervision of a central management. We solve Model (9) and Model (11) under CRS and VRS assumptions by lexicography's prioritization method. The first objective function is considered as the first priority for the problem to be feasible. In other words, $Z_1^* > 0$ means that the deviation variable makes the problem feasible, and if we had not considered the problem as GP, then it would be infeasible. The second step is to obtain the sum of the next two weighted objective functions in order to minimize desirable output reduction and maximize input saving in the optimal solution, which is obtained from the first step. *Table 2* shows the input and output data for the 6 DMUs. The following *Tables 3* and *4* provide the results of solving the model (9) using Gams software under CRS assumption and entering the parameters as $A_j = 0$, $B_j = 0.6x_j$, $c_j = 0$, $D_j = 0.3y_j^g$, $M = 0.8\sum_{j=1}^{n} y_j^b$.

By solving the model (9), the optimal value obtained for the first objective function is $Z_1^* = 3.16$; this means that the deviation variables have played an important role in making the problem feasible, and if we did not consider the problem as a GP, then it would be infeasible. *Table 3* shows the reduced values of inputs and outputs, as well as the reduction proportion of each one. In general, the reduction proportion of inputs is 0.19, the reduction proportion of desirable outputs is 0.38, and the reduction proportion of undesirable outputs is 0.75, which shows that overall, the reduction proportion of undesirable outputs is larger than the reduction proportion of desirable outputs. *Table 4* presents the values allocated to the inputs and outputs (desirable and undesirable) after energy

Table 2.

Input and output data for illustrating the proposed models

Unit	x	y^g	y^b
A	3.00	2.00	2.00
B	4.20	3.00	7.10
C	2.70	4.00	5.00
D	5.00	6.00	4.50
E	6.00	4.00	2.00
F	3.80	2.00	5.00
Total	24.7	21	25.6

Table 3.

Reduction amounts of inputs and outputs under CRS assumption in model (9)

Unit	Δx	Δy^g	Δy^b	Reduction proportion		
				x	y^g	y^b
A	0.90	0.60	1.30	0.30	0.30	0.65
B	1.05	0.90	6.05	0.25	0.30	0.01
C	0.00	2.20	4.10	0.00	0.55	0.82
D	0.00	2.66	2.83	0.00	0.44	0.62
E	1.80	1.20	0.60	0.30	0.30	0.30
F	1.14	0.60	4.30	0.30	0.30	0.86
Total	4.89	8.16	19.18	0.19	0.38	0.75

saving and reducing environmental pollutions for the purposes of providing recommendations to the central decision maker. Furthermore, the amount of reduction and the reduction proportion of inputs and outputs under VRS assumption model (9) are shown in *Table 5.*

As can be observed, in some DMUs, the reduction proportion of desirable outputs exceeds the proportion that was considered, and the reduction proportion of undesirable outputs is less than the lower bound that was set. This is due to the existence of deviation variables that make the problem feasible. To compare model (9) with model (5), the results obtained by placing the above parameters in model (5) are given in *Table 6* (we even set the conditions for Δx to be the same conditions for both models). As can be seen from the results of *Table 6*, the amount of reduction in the undesirable outputs for each unit is zero. This is the weakness of the respective model, which does not allow the reduction of undesirable outputs by reducing the desirable outputs and desirable outputs of the model.

By solving Model (11), the optimal value obtained for the first objective function is $Z_1^*=2.23$. In general, the reduction proportion of inputs is 0.10, the reduction proportion of desirable outputs is 0.30, and the reduction proportion of undesirable outputs is 0.71 (according to *Table 7*).

Table 8 provides the values allocated to the inputs and outputs (desirable and undesirable) after energy saving and reducing environmental pollution by considering a tradeoff of reductions in the inputs and outputs. Now we analyze our model through a real example of 20 Chinese regions. The values regarding China's total fossil fuel energy consumption (i.e., raw coal, clean coal, briquettes, coke, coke oven gas, crude oil, gasoline, kerosene, fuel oil, diesel oil, refinery gas, liquefied petroleum gas and natural gas), non-fossil fuel consumption, CO_2 emissions and regional GDP were collected from [46]. These values are listed in *Table 9.*

Table 4.

Allocated values for inputs and outputs under CRS assumption in model (9)

Unit	$x-\Delta x$	$y^g-\Delta y^g$	$y^b-\Delta y^b$
A	2.10	1.40	0.70
B	3.15	2.10	1.05
C	2.70	1.80	0.90
D	5.00	3.33	1.66
E	4.20	2.80	1.40
F	2.66	1.40	0.70

Table 5.

Reduction amounts of inputs and outputs with VRS assumption model (9)

Unit	Δx	Δy^g	Δy^b	Reduction proportion		
				x	y^g	y^b
A	0.00	0.00	0.00	0.00	0.00	0.00
B	1.05	0.90	5.10	0.25	0.30	0.72
C	0.00	0.00	0.00	0.00	0.00	0.00
D	0.00	1.80	1.68	0.00	0.30	0.37
E	0.00	0.00	0.00	0.30	0.00	0.00
F	0.80	0.42	3.00	0.21	0.21	0.60
Total	1.85	3.12	9.78	0.07	0.14	0.38

Table 6.

Reduction amounts of inputs and outputs under CRS assumption in model (5)

Unit	Δx	Δy^b	Δy^g
A	0.90	0.60	0
B	1.26	0.90	0
C	0.00	0.00	0
D	0.00	0.00	0
E	1.80	1.20	0
F	1.14	0.60	0
Total	5.10	3.30	0

As can be observed in *Table 10*, Model (11) has changed a number of inputs and outputs, not necessarily all of them. In general, for a 0.44 reduction in total energy consumption and a 0.04 reduction in non-fossil fuel consumption, we will have a 0.62 reduction in environmental pollution, whereas the desirable outputs are reduced by 0.30. These results provide important information to the decision maker, namely to reduce CO_2 emission by about 0.62 through saving energy in fossil fuel energy consumption by 0.44 and saving energy in Non-fossil fuel energy consumption by 0.04. This reduces the desirable output (GDP) by 0.30.

Table 7.

Reduction amounts of inputs and outputs with CRS assumption model (11)

Unit	Δx	Δy^g	Δy^b	Reduction proportion		
				x	y^g	y^b
A	1.80	0.60	2.00	0.60	0.30	1.00
B	0.85	0.90	7.10	0.20	0.30	1.00
C	0.00	1.20	5.00	0.00	0.30	1.00
D	0.00	1.80	4.15	0.00	0.30	0.92
E	0.00	1.20	0.00	0.00	0.30	0.00
F	0.00	0.60	0.00	0.00	0.30	0.00
Total	2.65	6.30	18.25	0.10	0.30	0.71

Table 8.

Results of Allocated value for inputs and outputs with CRS assumption model (11)

Unit	$x-\Delta x$	$y^g-\Delta y^g$	$y^b-\Delta y^b$
A	1.20	1.40	0.00
B	3.35	2.10	0.00
C	2.70	2.80	0.00
D	5.00	4.20	0.35
E	6.00	2.80	2.00
F	3.80	1.40	5.00

Conclusion

Controlling the pollution from manufacturing industries in developed and developing countries has become a common concern among researchers and governments. The use of DEA-based models as a powerful tool in problems of pollution reduction and energy consumption has attracted the attention of researchers. This also relates to the allocation of resources in organizations that have a central decision maker, such as the Ministry of Health, the Ministry of Education, and the World Health Organization, which are able

Table 9.

The data set are compiled from 30 regions of China in 2005 [51]

Unit	Total fossil fuel Energy consumption (million tce)	Non-fossil fuel consumption (million tce)	GDP (billion RMB at 2005) (million tce)	CO_2 emissions (million tone)
1	55.2	2.6	697.0	110.5
2	41.2	0.5	390.6	99.3
3	197.5	3.7	1001.2	507.1
4	123.1	1.8	423.1	307.1
5	96.4	1.2	390.5	266.5
6	146.9	4.3	804.7	334.2
7	59.6	3.8	362.0	162.7
8	80.3	2.7	551.4	172.2
9	80.7	1.4	924.8	179.7
10	169.0	2.1	1859.9	425.0
11	120.3	14.1	1341.8	254.4
12	65.2	1.0	535.0	162.7
13	61.6	10.3	655.5	133.4
14	42.9	3.5	405.7	104.1
15	236.1	2.6	1836.7	579.3
16	146.3	3.0	1058.7	337.2
17	98.5	11.3	659.0	197.2
18	91.1	10.9	659.6	191.6
19	177.7	19.5	2255.7	352.8
20	49.8	8.5	398.4	112.1
Total	2139.4	108.8	17211.3	4989.1

Table 10.

Results of Allocated value for inputs and outputs with model (11)

Unit	Allocation value				Reduction proportion			
	Total fossil fuel Energy consumption (million tce)	Non-fossil fuel consumption (million tce)	GDP (billion RMB at 2005) (million tce)	CO_2 emissions (million tone)	x_1	x_2	y^g	y^b
1	22	1.04	490	0.00	0.59	0.60	0.30	1.00
2	16	0.35	270	0.00	0.60	0.29	0.30	1.00
3	79	1.48	700	0.00	0.60	0.60	0.30	1.00
4	49	1.80	300	0.00	0.60	0.00	0.30	1.00
5	39	0.48	270	0.00	0.60	0.60	0.30	1.00
6	59	4.30	560	0.59	0.59	0.00	0.29	1.00
7	24	3.80	250	0.00	0.60	0.00	0.30	1.00
8	32	2.70	390	0.00	0.59	0.00	0.30	1.00
9	32	1.40	650	0.00	0.59	0.00	0.30	1.00
10	68	2.10	130	0.00	0.59	0.00	0.30	1.00
11	48	14.1	940	0.00	0.59	0.00	0.29	1.00
12	26	1.0	370	0.00	0.59	0.00	0.30	1.00
13	25	10.3	655.5	0.00	0.60	0.00	0.30	0.89
14	17	3.50	460	104.1	0.60	0.00	0.29	0.00
15	190	2.60	280	579.3	0.20	0.00	0.30	0.00
16	59	3.00	130	337.2	0.60	0.00	0.30	0.00
17	39	11.30	740	197.2	0.59	0.00	0.30	0.00
18	36	10.90	460	191.6	0.60	0.00	0.30	0.00
19	71	19.50	1600	352.8	0.62	0.00	0.30	0.00
20	20	8.50	280	112.1	0.60	0.00	0.30	0.00
Total					0.44	0.04	0.30	0.60

to implement policies for their subdivisions. In these systems, the central manager is interested in evaluating all units individually at the same time, so that total input consumption is minimized or total desirable output production is maximized, or to achieve two or more goals as multi-objective functions. When energy consumption is reduced, it will affect both the desirable and undesirable outputs. Regarding environmental pollution control policies, if energy storage does not lead to a reduction in environmental pollution, this indicates that the model has a weakness and needs to be modified. A model had already been proposed that did not reduce environmental pollution by reducing energy consumption, and hence, we modified the model to reduce environmental pollution. Depending on the decision of the central manager to adopt a policy based on energy saving and reduced environmental pollution emissions, in this paper we developed two new general centralized resource allocation models that the manager can choose from. The first model is modified such that Δy^b can receive a positive value and become feasible. The second model is defined based on the idea that the required changes should be applied to the totality of the desirable outputs. It is not logical to reduce individual desirable outputs, as the reduction of undesirable outputs may not be within the acceptable standard range. In each of the presented models, the undesirable outputs are changed by a larger proportion than the desirable outputs. We added goal programming to the problem so as to prevent the infeasibility of the problem. We also analyzed our model through a real example of 20 Chinese regions. The results showed that the proposed methods significantly reduced the CO_2 emissions compared with the competing model. These models can be effective in preventing energy waste and protecting the environment. The second EU (European Union) clean air outlook report looks at the prospects for EU member states' air quality up to 2050. According to the European Commission targets, by 2030, the amount of greenhouse gases in EU member states will be reduced by 55% compared with 1990 [47]. To achieve this target, manufacturing industries in the EU must purchase permits to produce a certain amount of greenhouse gases. Any industrial unit that produces less harmful gas than its allowed amount can sell its remaining permits to other units and benefit from it. Any plant that produces more harmful gas than its allowed amount will have to buy more permits. In other words, there is a trade-off between industrial units. Therefore, the authors suggest the model presented in this paper to reduce pollution in industrial units under the supervision of the EU. The total amount of permits issued can be considered as the amount obtained after reallocation for environmental pollution in model (11). This means that the allowable amount of pollution considered for all industrial units should be equal to the allocated amount of undesirable outputs from model (11), and the same number of permits should be issued. Furthermore, the proposed models are applicable to any similar system to reduce pollution and save energy. ■

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