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A Correction on Data Envelopment Analysis for Environmental Assessment Using Methodological Comparison between Three Efficiency Measurement Models

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ABSTRACT

This study introduces a revised data envelopment analysis (DEA) model to explore a new use of DEA for the environmental assessment in which outputs are classified into desirable (good) and undesirable (bad). Such an output separation is important in the DEA-based environmental assessment. We used a Range-Adjusted Measure (RAM) DEA model that is a kind of non-radial DEA model for combining the two performance measures, operational and environmental performance as an unified measure. Some of the previous studies that are recently published in this context proposed two alternative models of unification for DEA-based environmental assessment, too. Some drawbacks in their models reduce their usefulness. In fact, we revise their models in this study, and then we compare the three types of unification from methodological and mathematical perspectives of environmental assessment. We proposed a DEA based environmental method for evaluating a set of kinds of organizations. Some of the studies believe that for decreasing the amount of undesirable outputs, we should increase the amount of inputs. But the present work revealed that focusing on reducing the undesirable outputs to reach goal is very important than its increase or decrease in the amount of inputs.

KEYWORDS: Revised data envelopment analysis; Environmental assessment; Undesirable outputs

1. INTRODUCTION

Data Envelopment Analysis (DEA) has been long serving as a methodology to evaluate the performance of various organizations or Decision Making Units (DMUs). It was first proposed by Charnes et al. [1]. In DEA literature, the performance evaluation along with the efficiency of the included units of an organization is considered as a crucial fact, affecting the whole performance, either directly or indirectly [2]. This happen is study by Jafarpour et al. [3]. DEA has already been applied in the environmental assessment that has recently become a major policy issue in the world. In the classical production possibility sets, DMUs consume inputs to produce outputs but in the environmental production possibility sets, DMUs consume inputs to produce outputs that may be classified into desirable (good) and undesirable (bad). The main question in this case is "How to deal with undesirable outputs?" Many papers have tried to answer this question. Here, we mention some of them. Fare et al. [5] implemented the nonparametric approach on a 1976 data set of 30 US mills which use pulp and three other inputs in order to produce paper and four pollutants. In their research, they assumed weak disposability for undesirable outputs. Their results showed that the performance rankings of DMUs turned out to be very sensitive to whether or not undesirable outputs were included [8]. Yaisawarng and Klein [20] constructed a DEA model to measure the effects of SO_2 control on the efficiency change of US coal fired power plants in the 1980s. They assumed weak disposability for undesirable outputs, too. Fare et al. [6] introduced an environmental performance indicator by decomposing overall productivity into an environmental index and a productive efficiency index. Hongliang Yang, Michael Pollitt [8] incorporated both undesirable outputs and uncontrollable variables into DEA. They constructed a DEA model to evaluate the performance of Chinese coal-fired power plants. Jahanshahloo et al. [7] proposed a non-radial DEA model in order to improve the performance of an inefficient Decision Making Unit (DMU) in the presence of undesirable outputs, and they supposed that there exist undesirable inputs, too. Toshiyuki Sueyoshi et al. [9] proposed a new DEA approach to evaluate the operational, environmental and both-unified performance (three DEA efficiencies) of US coal-fired power plants. Also, they have developed their own method with several papers [10-19]. Toshiyuki Sueyoshi and Mika Goto [15] proposed two unified (operational and environmental) efficiency measurements for environmental assessment. Then, they compared the two types of

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unification from economic and mathematical perspectives of environmental assessment. Their models have some drawbacks which reduce their usefulness.

This study introduces a non-radial DEA model to explore a new use of DEA for environmental assessment in which outputs are classified into desirable (good) and undesirable (bad). Since reducing the amount of undesirable outputs is the main purpose of environmental assessment, we are looking to find a projection (a benchmark) on the operational efficient frontier for the inefficient DMU that produces fewer undesirable outputs from the DMU under evaluation. To reach this goal, it is not important to increase or decrease the amount of inputs. We used a Range-Adjusted Measure DEA model that was first proposed by Cooper et al. [4] for combining the two performance measures operational and environmental performance as a unified measure. In fact, we have revised the models proposed by Sueyoshi and Mika Goto [15] for measuring the unified efficiency in this study, and then we have compared the three types of unification.

The remainder of this paper has the following structure: In Section 2, we introduce two models for measuring the operational and environmental efficiency scores separately. In Section 3, we first review two unified models proposed by Sueyoshi and Mika Goto [15]. Then, we propose our new model for combining the two performance measures operational and environmental performance as a unified measure. In Section 4, we compare the three types of unification from methodological and mathematical perspectives of environmental assessment. Section 5 illustrates the proposed method using an example. Finally, conclusions are given in Section 6.

1. Operational and environmental efficiency measurements

Consider n decision making units DMU_j, (j=1,2,…,n), each DMU_j consuming input levels $x_{ij}>0$, (i=1,2,…,m) to produce two kinds of desirable (good) outputs $y_{rj}>0$, (r=1,2,…,s) and undesirable (bad) outputs $u_{lj}>0$, (l=1,2,…,h). In the reminder of this section we introduce two DEA models for measuring operational and environmental efficiency scores separately.

1.1 Operational efficiency measurement: This study uses RAM (Range-Adjusted Measure) model proposed by Cooper et al. [4] for determining operational efficiency of the pth organization. The formulation is as follows:

$$
\begin{aligned}
\text{Max } & \textstyle\sum_{i=1}^{m} R_i^x s_i^{xg} + \sum_{r=1}^{s} R_r^g s_r^g \\
\text{s.t } & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{xg} = x_{ip}, && (i = 1,2,\dots,m), \\
& \textstyle\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^g = y_{rp}, && (r = 1,2,\dots,s), \\
& \textstyle\sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \geq 0, && (j = 1,2,\dots,n), \\
& s_i^{xg} \geq 0, && (i = 1,2,\dots,m), \\
& s_r^g \geq 0, && (r = 1,2,\dots,s). \qquad (1)
\end{aligned}
$$

Where superscript (g) specifies desirable (good) outputs. $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)^t$ is a column vector of intensity variables used for connecting the input and output vectors by a convex combination. s_i^{xg}, (i=1,2,…, m) are all slack variables related to inputs, and s_r^g, (r=1,2,…,s) are all slack variables related to desirable outputs. Also, the upper and lower bounds of each desirable output are mathematically expressed by: $\bar{y}_r = Max_j\{y_{rj}\}$, $\underline{y}_r = Min_j\{y_{rj}\}$ and the upper and lower bounds of each input are mathematically expressed by: $\bar{x}_i = Max_j\{x_{ij}\}$, $\underline{x}_i = Min_j\{x_{ij}\}$, respectively.

Then, $R_r^g = \frac{1}{(m+s)(\bar{y}_r - \underline{y}_r)}$ for all r and $R_i^x = \frac{1}{(m+s)(\bar{x}_i - \underline{x}_i)}$ for all i indicate the ranges for desirable outputs and inputs, respectively. An operational efficiency score is measured on the optimality of Model (1) as below: 1-$(\sum_{i=1}^{m} R_i^x s_i^{xg*} + \sum_{r=1}^{s} R_r^g s_r^{g*})$.

Where (*) denotes optimal values in Model (1). Here, the equation indicates the level of efficiency by subtracting the level of inefficiency from unity. In Model (1), an inefficient DMU improves its operational performance by decreasing the amount of its inputs and increasing the amount of desirable outputs as much as possible in a non-radial direction.

1.2 Environmental efficiency measurement: In this section, we introduce a non-radial DEA model to explore a new use of DEA for the environmental assessment in which outputs are classified into desirable (good) and undesirable (bad). We evaluate the environmental efficiency of the pth DMU by using the following Range-Adjusted Measure model:

$$
\begin{aligned}
\text{Max } & \textstyle\sum_{l=1}^{h} R_l^b s_l^b \\
\text{s.t } & \textstyle\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{xg} - s_i^{xb} = x_{ip}, && (i = 1,2,\dots,m),
\end{aligned}
$$

$$\sum_{j=1}^{n} \lambda_j u_{lj} + s_l^b = u_{lp}, \qquad (l = 1,2,\dots,h),$$
$$\sum_{j=1}^{n} \lambda_j = 1,$$
$$\lambda_j \geq 0, \qquad (j = 1,2,\dots,n),$$
$$s_i^{xg} \geq 0, \qquad (i = 1,2,\dots,m),$$
$$s_i^{xb} \geq 0, \qquad (i = 1,2,\dots,m),$$
$$s_l^b \geq 0, \qquad (l = 1,2,\dots,h). \qquad (2)$$

Here, the upper and lower bounds of each undesirable output are mathematically expressed by: $\bar{u}_l = Max_j\{u_{lj}\}$, $\underline{u}_l = Min_j\{u_{lj}\}$ So, the ranges incorporated in Model (2) are specified as follows:

$R_l^b = \frac{1}{h(\bar{u}_l - \underline{u}_l)}$ for all l.

Here, s_i^{xg} and s_i^{xb} (i=1,2,…,m) are all input slack variables related to desirable and undesirable outputs, respectively. s_l^b, (l=1,2,…,h) are all slack variables related to undesirable outputs.

In Model (2), we evaluate environmental performance of DMUp, such that an arbitrary increase or a decrease in inputs can occur as long as undesirable outputs decrease. In fact, Model (2) tries to reduce the undesirable outputs regardless of the amount of inputs. Since the reduction of undesirable outputs in the environmental assessment is important and we believe that between the two organizations that produce the same desirable outputs, one is more efficient that produces fewer undesirable outputs even it consumes more inputs. Therefore, Model (2) focused on reducing them. Also Model (2) projects the DMU under evaluation on the environmental efficiency frontier.

An environmental inefficiency score of the DMUp is measured by Model (2), and it is equal:

$1-(\sum_{l=1}^{h} R_l^b s_l^{b*})$

where the superscript (*) indicates the optimality of Model (2).

2. Unified efficiency measurement

Recently, many studies have been done by Sueyoshi et al. [9-16] in order to calculate unified (operational and environmental) efficiency of organizations that produce two types of desirable and undesirable outputs. In this section, at first we review two basic models proposed by them in their research [15]; and then we propose a new approach for calculating the unified efficiency measure. Finally, we compare all three models in the next section.

***2.1 Unified efficiency model : Type I*:** Type I of unification on the pth organization proposed by Sueyoshi and Goto [15] has the following mathematical structure:

$$\text{Max } \sum_{i=1}^{m} R_i^x s_i^{xg} + \sum_{i=1}^{m} R_i^x s_i^{xb} + \sum_{r=1}^{s} R_r^g s_r^g + \sum_{l=1}^{h} R_l^b s_l^b$$
$$\text{s.t } \sum_{j=1}^{n} \lambda_j^g x_{ij} + s_i^{xg} = x_{ip}, \qquad (i = 1,2,\dots,m),$$
$$\sum_{j=1}^{n} \lambda_j^g y_{rj} - s_r^g = y_{rp}, \qquad (r = 1,2,\dots,s),$$
$$\sum_{j=1}^{n} \lambda_j^g = 1,$$
$$\sum_{j=1}^{n} \lambda_j^b x_{ij} - s_i^{xb} = x_{ip}, \qquad (i = 1,2,\dots,m),$$
$$\sum_{j=1}^{n} \lambda_j^b u_{lj} + s_l^b = u_{lp}, \qquad (l = 1,2,\dots,h),$$
$$\sum_{j=1}^{n} \lambda_j^b = 1,$$
$$\lambda_j^g \geq 0, \qquad (j = 1,2,\dots,n),$$
$$s_i^{xg} \geq 0, \qquad (i = 1,2,\dots,m),$$
$$s_r^g \geq 0, \qquad (r = 1,2,\dots,s).$$
$$\lambda_j^b \geq 0, \qquad (j = 1,2,\dots,n),$$
$$s_i^{xb} \geq 0, \qquad (i = 1,2,\dots,m),$$
$$s_l^b \geq 0, \qquad (l = 1,2,\dots,h). \qquad (3)$$

Where superscripts (g and b) are considered in order to specify desirable (good) outputs and undesirable (bad) outputs, respectively. In this model, there are two kinds of intensity variables and therefore, there are two efficiency frontiers. λ_j^g (j = 1, 2, …, n) indicates the jth intensity variable for desirable (good) outputs and determines the projection on the operational efficiency frontier. In a similar manner λ_j^b (j = 1, 2, … ,n), indicates the jth intensity variable for undesirable (bad) outputs and determines the projection on the environmental efficiency frontier. The ranges incorporated in Model (3) are specified as follows: $R_i^x = \frac{1}{(m+s+h)(\bar{x}_i - \underline{x}_i)}$ for all i indicate the ranges for inputs. $R_r^g = \frac{1}{(m+s+h)(\bar{y}_r - \underline{y}_r)}$ for all r and $R_l^b = \frac{1}{(m+s+h)(\bar{u}_l - \underline{u}_l)}$ for all l indicate the ranges for desirable and undesirable outputs, respectively. Note that other parameters and variables are defined exactly as

before. Model (3) evaluates the unified efficiency (θ_1) of the DMUp as: $\theta_1 = 1 - (\sum_{i=1}^{m} R_i^x s_i^{xg*} + \sum_{i=1}^{m} R_i^x s_i^{xb*} + \sum_{r=1}^{s} R_r^g s_r^{g*} + \sum_{l=1}^{h} R_l^b s_l^{b*})$. Where the superscript (*) indicates the optimality of Model (3).

2.2 Unified efficiency model: Type II: Sueyoshi and Goto [15] offered another model that provides a single set of intensity variables to produce a unified efficiency score for operational and environmental performance. This model of unification on the pth organization has the following mathematical structure:

$$
\begin{aligned}
\text{Max } & \sum_{i=1}^{m} R_i^x s_i^{x-} + \sum_{i=1}^{m} R_i^x s_i^{x+} + \sum_{l=1}^{h} R_l^b s_l^b + \sum_{r=1}^{s} R_r^g s_r^g \\
\text{s.t } & \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x-} - s_i^{x+} = x_{ip}, && (i = 1,2,\dots,m), \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^g = y_{rp}, && (r = 1,2,\dots,s), \\
& \sum_{j=1}^{n} \lambda_j u_{lj} + s_l^b = u_{lp}, && (l = 1,2,\dots,h), \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \geq 0, && (j = 1,2,\dots,n), \\
& s_i^{x+} \geq 0, && (i = 1,2,\dots,m), \\
& s_i^{x-} \geq 0, && (i = 1,2,\dots,m), \\
& s_r^g \geq 0, && (r = 1,2,\dots,s). \\
& s_l^b \geq 0, && (l = 1,2,\dots,h). \qquad (4)
\end{aligned}
$$

Where s_i^{x+} and s_i^{x-} are positive and negative parts of another slack variable like s_i^x. In fact, the two slacks related to the ith input are defined as $s_i^{x+} = \frac{|s_i^x| + s_i^x}{2}$ and $s_i^{x-} = \frac{|s_i^x| - s_i^x}{2}$. Ranges in the objective function are defined as Model (3) and other parameters and variables are defined exactly as before. According to the aforementioned variables, Model (4) is a non-linear programming model. Sueyoshi and Goto [15] suggested the following two alternative methods for solving Model (4).

a. One of the two alternatives is that Model (4) incorporates the nonlinear conditions into Model (4) as side constraints and then we solve Model (4) with $s_i^{x+} s_i^{x-} = 0$, $(i = 1,2,\dots,m)$ as a nonlinear programming problem.

b. The other alternative is that we additionally incorporate the following side constraints: $s_i^{x+} \leq M z_i^+$, $s_i^{x-} \leq M z_i^-$, $z_i^+ + z_i^-, \leq 1$, z_i^+ and z_i^-: binary $(i = 1,2,\dots,m)$ into Model (4) and solve Model (4) with the side constraints as a mixed integer programming problem. Here, M stands for a very large number that we need to prescribe.

Model (4) evaluates the unified efficiency (θ_2 if we use method (a) and θ_3 if we use method (b)) of the DMUp as follows:

$$\theta_2 \, or \, \theta_3 = 1 - (\sum_{i=1}^{m} R_i^x s_i^{x-*} + \sum_{i=1}^{m} R_i^x s_i^{x+*} + \sum_{l=1}^{h} R_l^b s_l^{b*} + \sum_{r=1}^{s} R_r^g s_r^{g*}).$$

Here, (*) indicates the optimality of Model (4).

***2.3 Unified efficiency model: Type III*:** In this section, we propose a new DEA model for determining the unified efficiency measure. We believe that in environmental assessment the amount of undesirable outputs produced by an organization is more important than the amount of desirable outputs, and it is more important than the amount of inputs consumed. Because it is related to human health. To explain further, suppose two organizations that produce the same amount of desirable outputs, in our view between these two organizations one of them is more (environmental and operational) efficient that produces fewer undesirable outputs, even if it consumes more inputs. Based on the above description, we suppose following linear programming model for calculating the unified efficiency score.

$$
\begin{aligned}
\text{Max } & \sum_{l=1}^{h} R_l^b s_l^b + \varepsilon \left(\sum_{r=1}^{s} R_r^g s_r^g + \sum_{i=1}^{m} R_i^x s_i^{xg}\right) \\
\text{s.t } & \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{xg} - s_i^{xb} = x_{ip}, && (i = 1,2,\dots,m), \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^g = y_{rp}, && (r = 1,2,\dots,s), \\
& \sum_{j=1}^{n} \lambda_j u_{lj} + s_l^b = u_{lp}, && (l = 1,2,\dots,h), \\
& \sum_{j=1}^{n} \lambda_j = 1, \\
& \lambda_j \geq 0, && (j = 1,2,\dots,n), \\
& s_i^{xg} \geq 0, && (i = 1,2,\dots,m), \\
& s_i^{xb} \geq 0, && (i = 1,2,\dots,m), \\
& s_r^g \geq 0, && (r = 1,2,\dots,s). \\
& s_l^b \geq 0, && (l = 1,2,\dots,h). \qquad (5)
\end{aligned}
$$

Where all variables and parameters are exactly as defined in Model (3) except for input slack variables. In Model (5) there exists two groups of input slack variables that are named s_i^{xg} (i=1,2,…,m) and s_i^{xb} (i=1,2,…,m) which are related to desirable and undesirable outputs respectively. ε is a non-archimedes parameter. In fact, Model (5) is a kind of two-phase model that in the phase I, we try to decrease the amount of undesirable outputs without any attention to the amount of inputs, maybe they decrease or increase. Then, in the phase II, we try to

increase the amount of desirable outputs and decrease the amount of inputs without any change in the amount of the current level of undesirable outputs and s_i^{xb} (i=1,2,…,m). Model (5) evaluates the unified efficiency (θ_3) of the DMUp as follows:

$$\theta_4 = 1 - \left(\sum_{l=1}^{h} R_l^b s_l^{b*} + \sum_{r=1}^{s} R_r^g s_r^{g*} + \sum_{i=1}^{m} R_i^x s_i^{xg*} \right).$$

Where the superscript (*) indicates the optimality of Model (5). The objective function of Model (5) represents desirable and undesirable output inefficiency.

3. Methodological comparison between three efficiency measurement models

Table 1 summarizes comparison between the three unified efficiency measurements (Type I, II and III).

Table 1. Comparison between three Types of unified efficiency

Unification type	Number of efficiency frontiers	Intensity variables	Computational method	Availability of dual formulation
Type I	Two efficiency frontiers	Two groups	LP	Available
Type II	Two efficiency frontiers	A single group	NLP or MIP	Not available
Type III	Two efficiency frontiers	A single group	LP	Available

LP, NLP and MIP stand for Linear Programming, Non Linear Programming and Mixed Integer Programming, respectively

Comparing Model (3) in Type I with Model (4) and Model (5) in Type II and Type III, we find the following methodological and computational differences.

First, the unification of Type I has two efficiency frontiers for operational and environmental performance, respectively, and it determines two projections for us according to each efficiency frontier. In one of the projections Decision Maker (DM) probably should reduce the amount of inputs and in the other on the contrary must reduce them, and it is clear that it is impossible to do both simultaneously. We know that efficiency analysis is performed not only to estimate the current level of efficiency, but also to provide information on how to remove inefficiency, that is, to obtain benchmarking information. DEA was developed in order to satisfy both objectives and the strength of its benchmarking analysis gives DEA a unique advantage over other methodologies of efficiency analysis, so this problem exactly reduces the usefulness of Type I. The unification of Type II and Type III has also the two efficiency frontiers. However, Type I combines them by two groups of intensity variables, but Type II and Type III use a single group of intensity variables for combination. That is a methodological strength of Type II and Type III.

Second, we can solve Type I and Type III as linear programming, but Type II often needs nonlinear or mixed integer programming; that is, a computational strength of Type I and Type III.

Finally, a major problem of Model (4) in Type II is that it is difficult for us to prepare a dual formulation of Model (4) because it contains the nonlinear conditions. As a result, Model (4) can solve the problem as nonlinear or mixed integer programming. However, we cannot measure the degree and type of RTS (Return To Scale), using Model (3). In contrast, it is easy to prepare the dual formulation of Model (3) and Model (5) in Type I and Type III respectively. Because they are formulated by linear programming. So, we can measure the degree and type of RTS by these two models, that is, a methodological strength of Type I and Type III.

Note that Model (5) in Type III has all of the advantages of alternative models in Type I and Type II. As discussed before, Model (5) uses a single group of intensity variables, the computational method for solving it is LP form and its dual formulation is available.

4. Numerical example

To illustrate our approach, numerical illustration is done regarding the example that was first used by Sueyoshi and Goto [15]. They selected a small example related to Japanese electric power companies which produce more than 25% of CO_2 of the whole Japanese emission. Table 2 summarizes the data set on their performance which consists of two inputs (i.e., the total amount of assets and the number of employees), two desirable outputs (i.e., the total amount of sales and the number of customers) and an undesirable output (i.e., the total amount of CO_2 emission). The Japanese electric power industry consists of nine investor-owned electric power firms, all of which are vertically integrated from generation to retail supply of electricity where the input, output and undesirable variables are defined as follows:

x_1: Input1 Total assets (100 billion JPY) (JPY stands for Japanese Yen).
x_2: Input2 Number of employees (1000).
y_1: Desirable Output1 Total sales (100GWH) (GWh stands for Gigawatt hours).
y_2: Desirable Output2 Number of Customers (100 Thousand).
u: Undesirable Output CO_2 emission (100Thousand ton).

Table 2. Electric power firms

(Electric Power Company) DMU	x_1	x_2	y_1	y_2	U
(Hokkaido) A	15.6	5.7	318.4	39.4	167.8
(Tohoku) B	36.8	1.5	811	76.8	397.9
(Tokyo) C	129.9	4.8	2889.6	284.9	1265.0
(Chubu) D	51.1	1.9	1297.3	104.6	646.7
(Hokuriku) E	14.2	0.5	281.5	20.8	185.2
(Kansai) F	62.4	2.4	1458.7	134	549.9
(Chugoku) G	26.1	1.1	612.2	51.9	430.7
(Shikoku) H	13.5	0.7	287.0	28.3	114.6
(Kyushu) I	38.3	1.4	858.8	84.0	341.0

In Table 3, we show four efficiency scores that are obtained by applying Model (3), Model (4) and Model (5) for the nine electric power companies. The efficiency scores obtained by Model (5) are greater than those obtained by both of the Model (3) and Model (4) for all the DMUs except DMUB. Because the input slack variables (s_i^{xb} or s_i^{x+} (i=1,2,…,m)) related to undesirable outputs have appeared in the objective functions of Model (3) and Model (4), but they have not appeared in the Model (5).

Table 3. Four efficiency score

Unified efficiency	DMUA	DMUB	DMUC	DMUD	DMUE	DMUF	DMUG	DMUH	DMUI
$\boldsymbol{\theta_1}$	0.972	0.935	1.000	0.889	0.955	0.959	0.896	1.000	0.969
$\boldsymbol{\theta_2}$	0.952	0.911	1.000	0.806	0.916	0.930	0.816	0.988	0.963
$\boldsymbol{\theta_3}$	0.952	0.911	1.000	0.806	0.916	0.930	0.816	0.988	0.963
$\boldsymbol{\theta_4}$	0.985	0.924	1.000	0.875	0.930	1.000	0.827	1.000	1.000

5. CONCLUSION

In this paper, we discuss how to apply DEA for environmental assessment. One of the important cases in the environmental assessment is the presence of two types of outputs named desirable (good) and undesirable (bad) in the environmental studies. Because some organizations often produce not only desirable outputs but also undesirable outputs as a result of their production activities. We proposed a DEA based environmental method for evaluating a set of these kinds of organizations. Some of the previous studies that are recently published in this context [9-19] believe that for decreasing the amount of undesirable outputs, we should increase the amount of inputs. But we believe that we should focus on reducing the undesirable outputs and, to reach this goal, it is not important to increase or decrease the amount of inputs.

We also compare our proposed model and two alternative models proposed by Sueyoshi and Goto [15]. Our model has all of the advantages of their models. It uses a single group of intensity variables, the computational method for solving it is LP form and its dual formulation is available.

This study did not discuss how to use Model (5) to change the concept of Return to Scale (RTS) for desirable outputs to the concept of Damages to Scale (DTS) for undesirable outputs. Thus, determining DTS in the presence of undesirable outputs is our future research extension.

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