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Analysis of Environmental Efficiency and Marginal Rate of Substitution in the Presence of Undesirable Factors: A DEA-Based Approach

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Abstract

The balance between environmental regulations and economic issues has always been one of the main challenges of governments, because with the growth of industrialization, environmental pollution has also increased. Along with the desired outputs in the production process, may also produce undesirable outputs which have a great impact on organizations efficiency and environmental pollution. On the other hand, dealing with the impact of undesirable factors on the inputs and desirable outputs, valuable information for making strategies and organizational decisions could be achieved. Considering undesirable factors, this paper aims to calculate the relative efficiency and marginal ratios of environmental systems using weak and managerial disposability models of data envelopment analysis (DEA). This study is conducted in two phases. In the first one, the regions were classified into efficient and inefficient groups using a developed DEA model. In the second step, the marginal rate of undesirable outputs on the inputs and desirable outputs in efficient areas were calculated. The results showed that the change in the amount of undesirable outputs has a significant effect on other variables.

Keywords:
Eco-efficiency
Data envelopment analysis
undesirable outputs
Managerial disposability

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INTRODUCTION

Over the last forty years, the world economy has grown from 1.37 to 85.93 trillion dollars. Due to excessive resource consumption and ecological issues, this rapid economic growth has resulted in excessive resource consumption (Huang et al., 2021; Zhang et al.,2021). In addition to measuring and evaluating efficiency at the organizational level, eco-efficiency is analyzed at a national level, used in evaluating industries and regions within a country.The main concern of measuring eco-efficiency, regardless of its level of evaluation, is to reduce the environmental impact and energy usage while simultaneously improving economic performance. Also, the meaning of eco-productivity contrasts to some degree among the researchers who present this idea, however essentially, they shed light on the normal center of "producing appropriate pollutants and energy efficiently" (Lee, 2022). Sustainable development has embraced eco-efficiency as a valid measurement and management tool in recent years (Sun&Wang,2021). Environmental efficiency is gaining interest in many sectors of business, and eco-efficiency evaluations can complement traditional evaluations dominated by technological and economic evaluations (Lee, 2022). Since then, scholars have paid attention to measuring and evaluating eco-efficiency Environmental change because of a worldwide temperature alteration is currently a significant arrangement issue all over the world. Environmental change suggests an expansion in normal worldwide temperature in regards to air, ocean and land on the earth. Regular occasions what's more, financial exercises, including modern turns of events and businesses, add to an expansion in normal worldwide temperature. An environmental change is basically brought about by an expansion in Green House Gases (GHGs) like carbon dioxide (CO2)(Sueyoshi& Goto, 2020).

It is fundamental as far as we're concerned to battle the natural issue by worldwide participation among modern and non-industrial countries as well as innovations in innate science alongside administrative difficulties in business, financial aspects and modern strategy (Gusmao Caiado et al, 2017). An arrangement trouble on a dangerous atmospheric devotion and environmental change is the secret every country keeps a harmony between monetary thriving and decrease of GHG outflow. During this period, it is critical to ensure that the availability of necessary resources, labor, and capital inputs are efficiently utilized for enhancing technology innovation and human wellbeing across the globe. To achieve eco-technology innovation and eco-well-being are required to produce more technology and to improve human well-being while reducing resource consumption and environmental impact (Mavi et al., 2018). Environmental efficiency indicates the capacity to produce more desirable output using fewer resources with decrease environmental damage. In recent years, environmental efficiency has become a focus as an indicator of the balance between environmental protection and economic growth (An et al, 2019). By maximizing economic return with the least amount of resource input and environmental hazards, you can achieve high eco-efficiency. The study of ecoefficiency utilizes a number of methods, such as ecological footprint (Yang and Yang 2019), stochastic frontiers analysis (Deng and Gibson 2019), a material flow analysis (Wang et al., 2016), a life cycle assessment (Martinelli et al., 2020; Alizadeh et al., 2020), and a multimethodology approach (Belucio et al., 2020; Vásquez-Ibarra et al., 2020) The method of data envelopment analysis (DEA) is based on linear programming and measures the efficiency of a set of decision-making units (DMUs) when there are multiple inputs and outputs in a manufacturing process (Charnes et al., 1978). Often, production processes have undesirable outputs, whose reduction improves the process. An undesirable output is overdue debts, which are to be decreased (and not increased). The conventional DEA emphasizes the need to increase desirable inputs and outputs, while decreasing undesirable inputs and outputs. To deal with desirable and undesirable outcomes, Fare, Grosskopf, Lovell, and Pasurka (1989) provided a non-linear DEA model. For DEA under variable returns to scale, Seiford and Zhu (2002) developed a new method. For preserving convexity and linearity. Liu et al (2010) sent off an orderly examination concerning the development of DEA models without moving unfortunate information. Sueyoshi and Goto (2012) described two disposability concepts in DEA environmental assessment. Natural Disposability for Economic Stability, To measure an occurrence of undesirable congestion and Managerial Disposability for Sustainable Economic Growth. , indicates that a firm increases an input vector to decrease the vector of undesirable outputs. Given the increased input vector, the firm increases the directional vector of desirable outputs as much as possible. The managerial disposability implies an adaptive strategy in which the environmental performance of firms is as important as their operational performance.

Liu et al. (2017) presented a strategy for DEA cross-proficiency assessment within the sight of unwanted results and recommended an impartial assessment model for productivity assessment. Toloo and Hanˇclov'a (2020) model genuine issues in which one might experience multi-esteemed measures, which are estimated by different norms, and only one of their qualities is to be chosen. They plan two individual and summative specific directional distance models within the sight of unfortunate results, and they fostered a couple of the multiplier-and envelopment-based selection approaches. Specifically, this study examines another methodology on how the DEA assessment can measure Marginal Rate of Substitution (RS) among production factors.

Tavana et al (2021) proposed a robust cross-efficiency data envelopment analysis model with undesirable outputs. DEA has been widely applied in a scope of uses to assess the general exhibitions of the DMUs in various circumstances and various constructions. Omrani et al. (2022) provided two new DEA models, namely the computational DEA for goal programming and the computational DEA for common weight, to assess the efficencies with significantly fewer computations. The results of each model are different. In order to integrate the results obtained from the four presented models, the TOPSIS approach is used. Maghbouli et al. (2020) proposed a modified model in which both undesirable and negative data are treated to improve the relative efficiency of the DMU under evaluation. The focus of this paper is on treating the negative data on the definition of the two non-negative variables and the decreasing of undesirable outputs.

One exploration issue that has drawn in extensive consideration in DEA is the issue of deciding minimal paces of replacement of data sources and results. Conversation on the best way to ascertain the minimal paces of replacement for the proficient DMUs is a significant and most often concentrated on subject in non-parametric creation financial aspects. Over the most recent twenty years, significant stages toward the improvement of minimal rates utilizing DEA models have been taken by specialists. In what the future held a portion of these examinations.

Huang et al. (1977) were quick to straightforwardly concentrate on the issue of ascertaining the pace of changes of results regarding the progressions of information sources. They have introduced an overall strategy for deciding the paces of progress of results to the contributions along proficient features of DEA boundaries. In their methodology, effective features of the DEA creation innovation assume a significant part. With a similar point of view, Rosen et al.(1998) straightforwardly concentrated on the issue of minimal pace of substation on effective outskirts and introduced an overall system for the computation of compromises between two factors in DEA. Their methodology depends on ascertaining proportions of multiplier values as acquired from duals of envelopment models; here likewise proficient aspects of DEA innovation assume a key part. Cooper et al(2000) nonetheless, have utilized the added substance DEA model to decide the minimal rates and flexibilities of replacement for proficient DMUs. They proposed a calculation to look through the outrageous focuses for cost enhancements on account of given cost or relative loads and steady results and considered non minimal compromises too.

Asmild et al. (2006) had an alternate look toward the issue of assessing minor rates. They applied the envelopment type of BCC model of Banker et al. (1984) to work out the minor paces of replacement. They additionally created techniques for assessing bigger compromises between factors in DEA, as non-minimal paces of replacement. At that very year, Prior and Surroca (2006) involved the DEA created methods for assessing negligible rates to distinguish key gatherings in a Spanish financial industry. One more use of utilizing compromise investigation can be found in Nevo et al. (2007) They inspected the compromises among inner and outer IT capacities.

Khoshandam et al. (2014) fostered a DEA concentrate on which joins minor rates and non-discretionary factors in execution estimation with an application in banking. The proposed strategy makes it conceivable to confirm how an effective unit would act in two unique conditions and figure out how the productivity scores relies upon finding the units in a more or less positive climate. In a comparative report, the principle subject of this work, which is significant from both hypothetical and application perspectives, it to figure out how changing in at least one bothersome element will influence on beneficial results or the other way around? This requirement to lay out a connection between bothersome factors and minimal pace of replacements. Apparently, the past examinations on ascertaining negligible paces of replacements give the minor paces of a particular throughput to a solitary throughput.

Based on the above three aspects, this paper aims to build and present a new DEA model considering undesirable outputs with weak and managerial disposability. In the next step, we develop marginal ratios by considering this two disposability and we examine the effect of Undesirable outputs on desirable outputs and inputs.

The first aspect in this paper is concerned with the undesirable outputs. In recent literature, there have been essentially two different approaches to dealing with undesirable outputs. As compared to the models built by transforming data, this paper tries to follow a SBM to determine the objective function, because SBMs are more flexible and benefit the discovery of production flaws indicated by slacks.

The second aspect this paper is concerned with is weak and managerial disposability. Because the existing literatures cannot distinguish undesirable outputs based upon their specific technical characteristics, the uniform disposability assumption they make may be arbitrary. the other hand, managerial disposability strategy considers changing regulations as a new business position. It is a long-term strategy. The organization should invest in new generation technology. Therefore, the investment cost of the strategy increases in the short term. However, the organization can reduce its operation cost due to the use of new technology. In addition, consumers who are aware of the environment, so organizations reduce the cost of the situation in a long time and increase their income in the short-term and long-term input formula by increasing the amount of desired input and output.

Therefore, in this type of disposability, the total operation cost and average operating costs increase; the position cost decreases and the investment cost increases.

The third aspect this paper is concerned with is marginal rate of substitution. When changing a decision parameter in a production process, it will influence other decision parameters as well. It is important for decision makers to be aware of such trade-offs between inputs and outputs. Hence, production theory emphasizes the importance of estimating marginal substitution rates.

This paper is organized as follows. Section 2 defines the concepts of Technical efficiency models with undesirable factors and managerial disposability, and provides a detailed introduction of the new model as well as the implications. Section 3 Marginal rates of substitution with undesirable outputs and managerial disposability and provides a detailed. Section 4 applies the new models in China's provincial environmental efficiency evaluation. Section 5 is the conclusion.

TECHNICAL EFFICIENCY MODELS WITH UNDESIRABLE FACTORS AND MANAGERIAL DISPOSABILITY

Basic DEA models have the main weakness that, in addition to desirable by-products, they also generate undesirable by-products, such as pollution and waste.(Amirteimoori et al,2014) A variety of factors can have an impact on productivity, including flight delays at the airport, overdue debts in the banking sector, and air pollutants and hazardous waste in the manufacturing industry. It is unavoidable and inevitable that organizations produce these undesirable outputs along with the desired outputs and they significantly impact efficiency and profitability (Toloo & Hanclová,2019). Over the past three decades, modeling undesirable outputs in the DEA literature has been a prominent topic in the field of production efficiency, since basic DEA models can't measure these outputs. Kuosmanen (2006) presents a method for including undesirable outputs of the production process, the weak disposability method. Each unit of production exhibited both a non-uniform contractile factor and a desirable contractile factor (Kao& Nan Hwang,2020).

suppose, x_{io} be the optimal value of i-th input, v_{po} be the optimal value of p-th desirable output and w_{fo} be the optimal value of f-th undesirable output for the under-consideration unit (unit o). Suppose that x_{ij} be the i-th input of the DMU_j, v_{pj} be the p-th desirable outputs of DMU_j and w_{fj}, be the f-th undesirable output of DMU_j. In addition, suppose m_1 is the number of inputs considering managerial disposability, m_2 is the number of inputs considering weak disposability, P is the number of desirable outputs, F is the number of undesirable outputs, J is the number of DMUs, C is the price or weight of inputs, Q is the price or weight of outputs $\overline{x}_i^{(w)}$ is the optimal values of inputs considering weak disposability and $\bar{v}_r$ is the optimal values of desirable outputs considering weak disposability

Production technology is indicated by $Y = \{(x, v, w)\}$. If θ_j representing the reduction of undesirable output is done by reducing the level of activity, the coefficient θ can be defined as the abatement factors. If θ_j is considered the abatement factor of the Jth unit, it is decomposed into two parts to linearize $\theta_j = \mu_j + \lambda_j$. The displayed μ_j component is the part of the output that decreases with the activity level, while the display λ_j component is the part of the output of the j-th unit that remains active Roshdi et al.(2018) Using this notation, the activity analysis technology can be written as:

$$
\begin{aligned}
&T_J\{(x,v,w)\}: \\
&\textstyle\sum_{j=1}^{J}(\mu_j+\lambda_j)x_{ij} \le x_{io}, && i=1,\dots,m \\
&\textstyle\sum_{j=1}^{J}\lambda_j v_{pj} \ge v_{po}, && p=1,\dots,P \\
&\textstyle\sum_{j=1}^{J}\lambda_j w_{fj} = w_{fo}, && f=1,\dots,F \\
&\textstyle\sum_{j=1}^{J}(\mu_j+\lambda_j)=1 \\
&\mu_j,\lambda_j \ge 0 && j=1,\dots,J
\end{aligned} \tag{1}
$$

In determining a unit's efficiency, undesirable outputs are crucial. In unit evaluation, we aim to reduce unwanted effects and increase desired effects by employing a method The concept of managerial disposability, introduced by Sueyoshi and Goto (2012), is intended to reduce undesirable outputs. Under this principle, the company uses technological and managerial innovations to reduce undesirable outputs by increasing inputs.

$$
\begin{aligned}
&T_J\{(x,v,w)\} \\
&\textstyle\sum_{j=1}^{J}\lambda_j x_{ij} \ge x_{io}, && i=1,\dots,m \\
&\textstyle\sum_{j=1}^{J}\lambda_j v_{pj} \ge v_{po}, && p=1,\dots,P \\
&\textstyle\sum_{j=1}^{J}\lambda_j w_{fj} \le w_{fo}, && f=1,\dots,F \\
&\textstyle\sum_{j=1}^{J}\lambda_j = 1 && (2)
\end{aligned}
$$

Kuosmanen's weak disposability model and Sueyoshi and Goto's managerial disposability model differ in two constraints of inputs and undesirable outputs. In weak disposability, inputs constraint is defined by $\sum_{j=1}^{J}(\mu_j+\lambda_j)x_{ij}\le x_{io}$ and aims to reduce the inputs, but in managerial disposability, $\sum_{j=1}^{J}x_{ij}\lambda_j\ge x_{io}$ aims to increase at least one input to reduce the undesirable outputs. Also, undesirable outputs are due to the weak disposability of the boundary zone. Also, the constraint of undesirable outputs $\sum_{j=1}^{J}\lambda_j w_{fj}=w_{fo}$ in weak disposability of the border area is the efficiency of adverse outputs on the convex composition of all observed adverse outputs; in contrast, in managerial disposability, the efficiency boundary area of undesirable outputs is above or below the convex composition of the undesirable outputs observed (Roshdi et al,2018) .therefore Technical efficiency model with undesirable factors and both of managerial and weak disposability is shown as follows:

$$MAX \quad \varphi$$

$$S.T.$$

$$\sum_{j=1}^{J}\lambda_j x_{ij}^{(M)}\ge x_{io}^{(M)}, \qquad i=1,\dots,m_1,$$

$$\sum_{j=1}^{J}(\mu_j+\lambda_j)x_{ij}^{(w)}\le x_{io}^{(w)}, \qquad i=1,\dots,m_2$$

$$\sum_{j=1}^{J}\lambda_j v_{pj}\ge\varphi v_{po}\ , \qquad p=1,\dots,p$$

$$\sum_{j=1}^{J}\lambda_j w_{fj}\le w_{fo}\ , \qquad f=1,\dots,F$$

$$\sum_{j=1}^{J}(\mu_j+\lambda_j)=1 \qquad j=1,\dots,J$$

$$\lambda_j,\mu_j,\ge 0 \quad , (3)$$

It is easy to show that model (11) i feasible. Because, $\lambda_j=0,\ j\ne o,\lambda o=1,\mu_j=0,\forall j, j=1,\dots,J,\varphi=1.$

Constraint $\sum_{j=1}^{J}\lambda_j x_{ij}^{(M)}\ge x_{io}^{(M)}$ ensures th increase in one of the inputs is based on th principle of managerial disposability t reduce undesirable outputs. Constrai $\sum_{j=1}^{J}(\mu_j+\lambda_j)x_{ij}^{(w)}\le x_{io}^{(w)}$, ensures th decrease in one of the inputs is based on th principle of weak disposability. Constrai $\sum_{j=1}^{J}\lambda_j v_{pj}\ge\varphi v_{po}$ shows the increase i desirable outputs. Constrai $\sum_{j=1}^{J}\lambda_j w_{fj}\le w_{fo}$ show the increase i undesirable outputs. Constrai $\sum_{j=1}^{J}(\mu_j+\lambda_j)=1$ represents the retu variable scale, which is calculated from μ and the sum of variables λ equal to 1.

MARGINAL RATES SUBSTITUTION WITH UNDESIRABLE OUTPUTS AND MANAGERIAL DISPOSABILITY

If one decision parameter is altered during the production process, it will affect several other parameters. Decision makers benefit from such tradeoffs between inputs and outputs. It is therefore important in production theory to estimate marginal rates of substitution. The significance of this problem lies in the ability to calculate the effects of changes in one or more throughputs on others(Khoshandam,2015).

In general form we can assume that each DMU uses M inputs to produce s (desirable and undesirable) outputs. So, each $DMU_j$is characterized by a throughput vector $z_j=(-x_0,y_0)^t$ in which $x_j=(x_{1j},\dots,x_{mj})$ and $y_j=(y_{1j},\dots,y_{sj})$.

Considering the efficient (frontier) point $z_0=(-x_0,y_0)$ in the production set, the marginal rate of substitution of the p-th throughput to the q-th throughput at$Z_\circ$ is defined as:

$$MRS_{pq}^{+}(z_0)=\left(\frac{\partial z_{p0}}{\partial z_{q0}}\right)_{z_0^+} \qquad (4)$$

$$MRS_{pq}^{-}(z_0)=\left(\frac{\partial z_{p0}}{\partial z_{q0}}\right)_{z_0^-} \qquad (5)$$

The four-step procedure of Asmild et al.(2006) could be summarized as follows:

i. Choose a small increment h

ii. Solve the following LP problem and obtain the value of X^* (The effect of marginal ratios of adverse outputs on inputs derived from the principle of managerial disposability) and v^* (The effect of marginal ratios of unfavorable outputs on optimal outputs)

$$
\begin{aligned}
& \text{MAX} \quad v^* \\
& S.T. \\
& \sum_{j=1}^{J} \lambda_j x_{ij}^{(M)} \geq x_{io}^{(M)}, && i=1,\ldots,M_1 \\
& \sum_{j=1}^{J} (\mu_j+\lambda_j) x_{ij}^{(w)} \leq x_{io}^{(w)}, && i=1,\ldots,M_2 \\
& \sum_{j=1}^{J} \lambda_j v_{pj} \geq v_{po}, && p=1,\ldots,P,\ p \neq r \\
& \sum_{j=1}^{J} \lambda_j v_{rj} \geq v^* \\
& \sum_{j=1}^{J} \lambda_j w_{fj} \leq w_{fo}, && f=1,\ldots,F,\ f \neq l \\
& \sum_{j=1}^{J} \lambda_j w_{lj} \leq w_{lo} \pm h \\
& \sum_{j=1}^{J} (\mu_j+\lambda_j) = 1 && j=1,\ldots,J \\
& \lambda_j, \mu_j, v^* \geq 0, && (6)
\end{aligned}
$$

$$
\begin{aligned}
& \text{MAX} \quad X^* \\
& S.T. \\
& \sum_{j=1}^{J} \lambda_j x_{ij}^{(M)} \geq x_{io}^{(M)}, && i=1,\ldots,M_1,\ i \neq t \\
& \sum_{j=1}^{J} \lambda_j x_{tj}^{(M)} \geq X^* \\
& \sum_{j=1}^{J} (\mu_j+\lambda_j) x_{ij}^{(w)} \leq x_{io}^{(w)}, && i=1,\ldots,M_2 \\
& \sum_{j=1}^{J} \lambda_j v_{pj} \geq v_{po}, && p=1,\ldots,P \\
& \sum_{j=1}^{J} \lambda_j w_{fj} \leq w_{fo}, && f=1,\ldots,F,\ f \neq l \\
& \sum_{j=1}^{J} \lambda_j w_{lj} \leq w_{lo} \pm h \\
& \sum_{j=1}^{J} (\mu_j+\lambda_j) = 1 && j=1,\ldots,J \\
& \lambda_j, \mu_j, X^* \geq 0, && (7)
\end{aligned}
$$

iii. Calculate the marginal rate of substitution from right as follows:

$$MR_{pq}^{+}(z_0) = \frac{z_{po}^{*} - z_{po}}{h} \qquad (8)$$

iv. Repeat steps (2) and (3) for -h to get the marginal rate of substitution from left.

Model (6) is solved for p Th throughput when the q Th throughput is changed by h. Maximizing z_{po}^{*} is the objective function that ensures being on the frontier point.

AN ILLUSTRATIVE APPLICATION

In this section we examine the efficiencies of 20 regions in China. We point out that we have combined the three waste gasses nitrogen oxide, sulfur dioxide and soot into a single factor namely S as shown in Table 1, and have separated it into treated gasses (S), Consumption of water(W) are undesirable out puts; Population(H), Gross Regional Product by Expenditure Approach (M) are desirable outputs. Cultivated land (E), Water available for use (U) is inputs with weak disposability and Investment (I) is input with managerial disposability. Statistical summary of Indicators are shown in Table 1, after identifying the inputs and outputs of the regions using model (3) which is an approach of the presence of undesirable outputs by combining the principle of weak disposability of Kuosmanen (2005) and the principle of managerial disposability of Sueyoshi and Goto (2012), 20 regions are evaluated. The results of model implementation in GAMS software show which units are efficient and which are inefficient. The software results are shown in Table (2) and MRS_{-}^{+} are shown in Table 3.

Table1: statistical summery

Total volume of Nitrogen oxides, Sulfur dioxide, and Soot (Dust) emission: S	Consumption of water:W	Population:H	Gross Regional Product by Expenditure Approach: M	Investment:I	Water available for useful	Cultivated land:E	
tons	100 million cu.m	10,000 Persons	100 million Yuan	100 million Yuan	100 million cu.m	1000 ha	
4338188	281.9	10594	56805.7	36552.9	552.2	11830.1	Max
338167	15.5	1413	11784.6	6961.2	23.1	231.7	Min
1179153	62.63683	2597.38	13596.73	7967.762	129.3324	2857.111	St.D
2153817	116.4755	5241.3	24155.42	16424.03	229.375	4370.13	Mean

Table2: Efficiency of units and models comparison

unit	Region	New model efficiency	Weak disposability Efficiency (Kuosmanen ,2005)	Managerial disposability Efficiency (Sueyoshi & Goto ,2012),
1	Beijing	1/00000	1/00000	1/0000
2	Tianjin	1/00000	1/00000	1/0000
3	Hebei	0/85985	1/00000	0/7513
4	Shanxi	1/00000	1/00000	0/78684
5	Inner Mongolia	0.35989	1/00000	0/34416
6	Liaoning	1/00000	0/8210	0/66688
7	Jilin	0/59298	0/8478	0/55997
8	Heilongjiang	0/00036	1/00000	0/43493
9	Shanghai	1/00000	1/00000	1/00000
10	Jiangsu	1/00000	1/00000	0/94002
11	Zhejiang	1/00000	1/00000	0/82815
12	Anhui	0/77310	1/00000	0/70751
13	Fujian	0/73057	1/00000	0/72971
14	Jiangxi	0/69396	1/00000	0/66133
15	Shandong	1/00000	1/00000	1/0000
16	Henan	1/00000	1/00000	1/0000
17	Hubei	0/79624	0/92945	0/79617
18	Hunan	0/92421	1/00000	0/92464
19	Guangdong	1/00000	1/00000	1/0000
20	Guangxi	0/81090	1/00000	0/81089

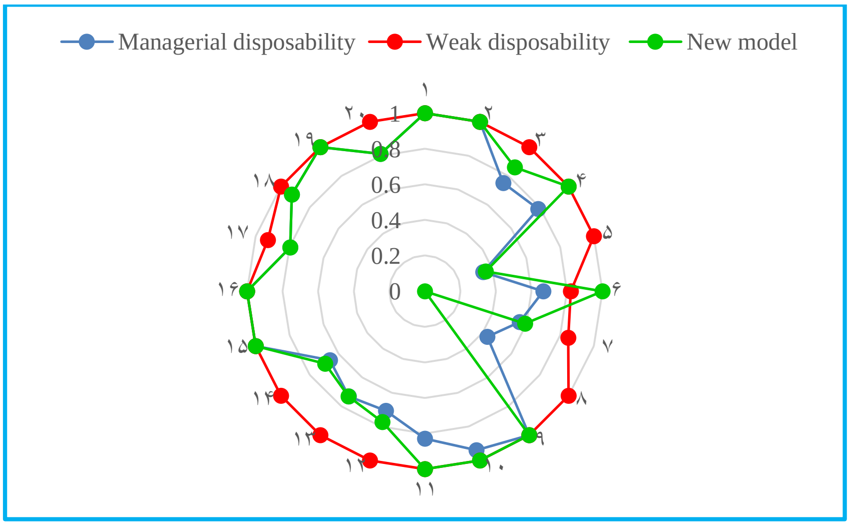

Fig.1.Graphic diagram of models comparison

Table 3: The estimated marginal rates with applying equation (6,7)

DMU		DMU1	DMU2	DMU16	DMU19
I	h= +1000 h=-1000	$\mathrm{MRS}^{+}_{\mathrm{w,I}} = 0$ $\mathrm{MRS}^{-}_{\mathrm{w,I}}$ $= -0.0244$ $I^{*} = 8846.42$	$\mathrm{MRS}^{+}_{\mathrm{w,I}} = 0$ $\mathrm{MRS}^{-}_{\mathrm{w,I}} = 0$	$\mathrm{MRS}^{+}_{\mathrm{w,I}} = 0.0321$ I^{*} =33691.4898 $\mathrm{MRS}^{-}_{\mathrm{w},I} = -0.0321$ $I^{*} = 21677.9983$	$\mathrm{MRS}^{+}_{\mathrm{w,I}} = 0$ $\mathrm{MRS}^{+}_{\mathrm{w},I} = -0.1819$ $I^{*} = 21824.0295$
M		$\mathrm{MRS}^{+}_{\mathrm{w,M}} = 0$ $\mathrm{MRS}^{+}_{\mathrm{w,M}}$ $= -0.0061$ $M^{*} = 337161$	$\mathrm{MRS}^{+}_{\mathrm{w,M}} = 0$ $\mathrm{MRS}^{+}_{\mathrm{w,M}} = 0.0002$ $M^{*} = 641808$	$0\mathrm{MRS}^{+}_{\mathrm{w,M}} =$ $\mathrm{MRS}^{+}_{\mathrm{w,M}} = -0.0016$ $M^{*} = 3500630$	$0.0006\mathrm{MRS}^{+}_{\mathrm{w,M}} =$ $\mathrm{M}^{*} = 9406.6244$ $\mathrm{MRS}^{+}_{\mathrm{w,M}} = -0.0042$ $M^{*} = 2429904$
H		$\mathrm{MRS}^{+}_{\mathrm{w,H}} = 0$ $\mathrm{MRS}^{-}_{\mathrm{w,H}}$ $= -0.0061$ H^{*} =2062.8817	$\mathrm{MRS}^{+}_{\mathrm{w,H}} = 0$ $\mathrm{MRS}^{-}_{\mathrm{w,H}}$ =0.0002 1413.2257H^{*} =	$0.0633\mathrm{MRS}^{+}_{\mathrm{w,H}} =$ $29456.0548\mathrm{H}^{*} =$ $\mathrm{MRS}^{-}_{\mathrm{w,H}} = -0.0016$ H^{*} =9404.3633	$0\mathrm{MRS}^{+}_{\mathrm{w,H}} =$ $\mathrm{MRS}^{+}_{\mathrm{w,H}}$ =-0.0045 10589.4993H^{*} =

According to the results obtained from Table 2, we can see models comparison. The results showed that 10 units (1,2,4,6,9,10,11,15,16,19) have an efficiency of one (efficient) in new model, however we have 17 efficient unit in weak and 7 efficient unit in managerial disposability. cities with financial and managerial capabilities to improve environmental and operational performance. These cities first improved their operational performance, then they tried to improve their environmental performance, which means that environmental performance was their second priority.

They cannot immediately improve their environmental performance even if inhabitants' awareness of environmental factors creates more business opportunities for organizations. Therefor they need to increase capital and then convert it into investment in production technology and management.6 units (1,2,9,15,16,19) are efficient in three models.

After identifying the efficient areas, we are able to calculate the impact of changes in 1000 units of gases produced by the GDP of the region using model (6) and investment input with the principle of managerial disposability using model (7). Due to the impact of 1000 units change in greenhouse gases, areas undergo tangible and intangible changes in investment, GDP and population. In region number one and two, with the increase of the amount of undesirable emissions, none of the values change, but in region 16, with the increase of the amount of undesirable emissions, the amount of investment to reduce these pollutants changes by 0.0321 units. And will reach 33691.4898 million yuan. And in the nineteenth region, the population increases by 0.0006 units to 9406.6244 people.

As the amount of undesirable emissions, which includes greenhouse gases, decreases, the amount of investment, gross product and population in zones one, sixteen and nineteen decreases, but these variables increase in unit two in investment unchanged and in the other two variables.

CONCLUSION

In this study, an optimization model was developed to evaluate the relative efficiency of environmental systems by combining the principle of managerial and weak disposability to simultaneously reduce undesirable outputs and increase optimal outputs. On the other hand, marginal ratios were developed taking into account this two disposability.

Given that traditional methods of data envelopment analysis are not able to measure undesirable outputs, which also has a significant impact on the efficiency of units; Therefore, its developed methods to reduce undesirable outputs appeared by reducing inputs, but this approach leads to short-term follow-up by managers, because reducing inputs also leads to reducing desirable outputs; Therefore, another new approach was introduced which aimed to reduce undesirable outputs by increasing at least one of the inputs.

In previous studies, the method of reducing inputs was used to reduce the undesirable output. Due to these issues, in this study, to evaluate the efficiency of a combined method based on reducing undesirable outputs according to the principle of managerial disposability, which aims to increase an input, was presented.

Given that environmental pollution is one of the problems of global warming, organizations are required to reduce pollution in their centers; one of the ways to reduce adverse outputs is to invest in technology. This study was conducted in 20 regions in China, and after measuring the efficiency of regions that were 10 efficient regions; we examined the marginal ratios of the impact of pollutant gases on investment as input, population and GDP as the optimal input of these regions. The results show that increasing polluting gases increases investment and reduces GDP; also due to increased investment and. Technological development increases the size of the population. But as these pollutants decrease, the amount of investment decreases and the amount of desired emissions changes unchanged or slightly. Therefore, using the available information, the necessary strategies can be adopted to reduce undesirable outputs and increase desirable outputs.

In this sense, future research could investigate how to modify this model by using stochastic data and nondiscretionary in the model. A variety of radial and non-radial DEA models must be developed that can differentiate between desirable and undesirable outputs. A time series aspect and evaluation of returns to scale (RTS)and damage to scale (DTS) can also be included in such an extension.

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