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Research Article

Running Efficiency and S&T Contribution to Regional Wastes' Treatment in China based on Parallel and Two-stage DEA models

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Abstract: In this study, we apply parallel and two-stage DEA models to measure the running efficiency and S&T contribution to regional wastes' treatment in China. The process of harshly development in industry often sacrificed natural living environment of human being. Because of greenhouse effect, poor air and water quality, improper disposed solid waste and other environmental pollution problems, regional environment are bearing tremendous pressure. To relieve pressure on environment and keep sustainable development in China, decision makers begin to focus on the optimal measures of ecological environment. A novel parallel and two-stage DEA models were applied to evaluate the efficiency of regional wastes' treatment in China. While the status of wastes can be divided into three types, i.e. waste water, gas and solid wastes, we classified different types of treatments into three modes. Then, the multiple parallel DEA methodology is applied to calculate the treatment efficiency of these three modes of wastes' treatment in 30 provincial regions in China. Taking S&T inputs as a pivotal effect on wastes' treatments, two-stage DEA model was applied to calculate S&T contribution rate to wastes' treatment in 30 provincial regions in China. Based on the calculation results, decision making information can be drawn for each region in China and.

Keywords: Ecological regions, overall efficiency, parallel DEA, sub-system efficiency, treatments of wastes, two-stage DEA

INTRODUCTION

Since 1970s, the old Soviet mode had been applied which mainly enlarged the inputs, especially labor and capital, in China and had already pushed China's economy development. In that process, natural environment and limited resources were sacrificed to pursue economy's rapid development. With the influence of global greenhouse effect and serious pollution, decision makers began to transfer traditional production mode into environmental friendly development mode and emphasis on the capability of wastes' treatments. Generally, based on the status of wastes, we can classify wastes into three different modes, i.e., waste gas, waste water and solid wastes. The treatments of the three types of wastes are pivotal measures to build regions with more environmentally friendly.

Water quality management issues were discussed in Oregon, USA and proposed constructive measures to enhance the capability of waste water's treatment (Sharon *et al*., 1991). At the same time, other two types of wastes, waste gas and solid wastes, also take important roles in ecological environment. A coordination of Energy-Economy-Environment System should be expressed by the close relationship between energy, economy and environment (Heshan *et al*., 2011). The evaluation of wastes' treatment should be applied to identify the development level of ecological optimization. Many statistical methodologies can be applied to calculate ecological indicators (Paul, 1996). In fact, the treatment processes of waste gas, waste water and solid wastes are parallel systems where little interaction exists among those three systems. At the same time, all three processes cover the major aspects of wastes' treatment. Based on the parallel structure of three types of wastes' treatment, we applied parallel DEA to calculate the running efficiency and provide regional information of wastes' treatments to the decision makers. To identify the effect of S&T on wastes' treatment, two-stage DEA model was applied to measure the contribution of S&T to wastes' treatments.

RUNNING EFFICIENCY OF WASTES' TREARMENTS

Structure and indexes of wastes' treatments: In general, we candivide all of wastes in three types, denoted as waste gas, waste water and solid wastes. To optimize the eco-environment, we also should apply

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Table 1: Indexes for each of waste treatments

	Indexes	
Treatment	Inputs	Outputs
Waste gas treatment	Total volume of industrial waste GasEmission (100 million cu.m)	Number of facilities for treatment of waste gas (set)
		Volume of industry sulphur dioxide removed (10 000 tons)
		Volume of industrial Soot Removed (10 000 tons)
		Volume of industrialDust removed (10 000 tons)
Waste water treatment	Total volume ofwaste water discharge in industry (10 000 tons)	Number of facilities fortreatment of waste water (set)
	Consumption waste water discharge (10 000 tons)	Industrial waste water meeting dischargeStandards (10 000 tons)
Solid wastes treatment	Volume of industrial solid wastes Produced (10 000 tons)	Volume of industrial solid wastes utilized (10 000 tons)
		Volume of industrial solid wastes in stocks (10 000 tons)
		Volume of industrialsolid wastes treated (10 000 tons)

corresponding treatment measures in these three types wastes (Xiong *et al*., 2007; Kai-ya *et al*., 2005). Because three types of wastes are existed in different forms, the treatment of them is expressed as parallel measures. Then, we divided the optimization of eco-environment into three parallel processes, i.e., waste gas treatment, waste water treatment and solid wastes' treatment (Yong and Qing, 2005). If we take each of waste treatment as a sub-system, there are multiple indexes can be listed to measure the efficiency of each process of waste treatments (Yao-bin *et al*., 2005) in the view of multiple inputs and outputs. The indexes can be shown on Table 1.

For waste gas treatment, we use 1 input and 4 outputs index to interpret the sub-system's efficiency. For waste water treatment, we design 2 inputs and 2 outputs to explain the efficiency of sub-system. For solid wastes' treatment, we apply 1 input and 3 outputs to measure the sub-system's efficiency.

Multiple parallel DEA model: DEA model CCR (Charnes *et al*., 1978) was applied an optimal linear programming formula to calculate efficiency of DMUs. Suppose we have *n* DMUs and that *k*th DMU_k (k = 1, 2, …, n) has m inputs, denoted as x_{ik} (i = 1, 2, …, m) and s outputs, denoted as y_{rk} (r = 1, 2, …, s). The traditional CCR DEA model can be expressed by the following formula (1):

$$\mathrm{E}_k = \max \sum_{r=1}^{s} u_r y_{rk}$$
$$s.t. \begin{cases} \sum_{i=1}^{m} v_i x_{ik} = 1 \\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, j = 1,...,n \\ u_r, v_i \ge \varepsilon, r = 1,...,s; i = 1,...,m \end{cases} \quad (1)$$

By calculating with DEA models, the optimal weights can be allocated for each DMU, denoted as $v_i^* = (v_{1j}^*, v_{2j}^*, ..., v_{mj}^*)$, $u_r^* = (u_{1j}^*, u_{2j}^*, ..., u_{sj}^*)$, which guarantee the *k*th DMU with the maximum efficiency value. If the objection of model (1) equals to 1, then the DMU is denoted as DEA efficient DMU. If the objection of model (1) is less than 1, then the DMU is denoted as DEA inefficient DMU. DEA models have obvious advantages in measure the performance of multiple inputs and outputs system. However, traditional DEA models take system as a black box and ignore the internal structure of system.

In general, the inside of DMU can be classified in different structures and the internal structure can affect the overall efficiency of whole system. For each of sub-systems, its efficiency has close relationship to overall efficiency. In this study, we will use the DEA model to deal with parallel sub-system structures.

To overcome the shortcomings of traditional DEA models, parallel DEA model (Chiang, 2009) was proposed for measuring the relationship between sub-systems and DUM. Firstly, we will explain the parallel structure. For each of DMUs, there are q sub-systems, denoted as sub-system 1, sub-system 2, ..., sub-system q. For each of sub-systems, we use X_{ik}^p and Y_{rk}^p to express the *i*th input and *r*th output, respectively, of the *p*th sub-system. The relative inefficiency of a set of *n* DMUs, each has q parallel sub-systems can be calculated by following formula:

$$\min \sum_{p=1}^{q} s_k^p$$
$$s.t. \begin{cases} \sum_{i=1}^{m} v_i X_{ik} = 1; \sum_{r=1}^{s} u_r Y_{rk}^p - \sum_{i=1}^{m} v_i X_{ik}^p + s_k^p = 0 \\ \sum_{r=1}^{s} u_r Y_{rj}^p - \sum_{i=1}^{m} v_i X_{ij}^p \le 0 \\ u_r, v_i \ge \varepsilon; p = 1,2,...,q; \\ j = 1,...,n; j \ne k; r = 1,...,s; i = 1,...,m \end{cases} \quad (2)$$

The above model (2) should be calculated for n times to obtain the inefficiency slacks of systems as well as their sub-systems. However, the inefficiency slacks is not equal to inefficiency scores because is not equal to 1 for *k*th DMU with *w*th sub-systems. Therefore, the inefficiency score should be calculated by S_k^wshould be divided by $\sum_{i=1}^{m} v_i X_{ik}^w$and the efficiency score should be:

$$1 - \left(s_k^w \Big/ \sum_{i=1}^{m} v_i X_{ik}^w \right)$$

Calculation and results: Based on those indexes listed on Table 1, we collect 30 provinces corresponding

Table 2: Efficiencies of 30 regions in wastes' treatments

Regions	Inefficiencyscore	Efficiency score	CCR efficiency
Beijing	0	1	1
Tianjin	0	1	1
Hebei	0.0029	0.9971	1
Shanxi	0.0389	0.9611	1
Inner Mongolia	0.0888	0.9112	1
Liaoning	0.0704	0.9296	1
Jilin	0	1	1
Heilongjiang	0	1	1
Shanghai	0.0107	0.9893	1
Jiangsu	0.0079	0.9921	1
Zhejiang	0	1	1
Anhui	0.0130	0.987	1
Fujian	0	1	1
Jiangxi	0	1	1
Shandong	0.0038	0.9962	1
Henan	0.0057	0.9943	1
Hubei	0.0270	0.973	1
Hunan	0.0350	0.965	1
Guangdong	0.0501	0.9499	1
Guangxi	0.0110	0.989	1
Hainan	0	1	1
Chongqing	0.0473	0.9527	1
Sichuan	0.0257	0.9743	1
Guizhou	0	1	1
Yunnan	0.0706	0.9294	1
Shaanxi	0	1	1
Gansu	0	1	1
Qinghai	0	1	1
Ningxia	0	1	1
Xinjiang	0	1	1

statistic data from "China Statistic Year Book 2011". Taking 30 provinces as DMUs and three treatments as sub-systems, we can calculate the CCR DEA efficiency and overall efficiency for each system. The calculation results can be shown on Table 2. By using traditional CCR DEA model to calculate CCR efficiency for each region, we can get all of efficiencies are equal to 1, i.e., all of DUMs are efficient. Therefore, we can't identify the performance of eco-environment optimization in each of regions. When we use parallel structure DEA model, we can get all of DUMs overall efficiency based on inefficiency score calculated by model (2).

There are 14 regions, occupied 47%, who reached 1 as overall efficiency value. Those regions are executed well in the eco-environmental optimization. Among these efficient regions, Beijing, Tianjin and Zhejiang are advanced developed regions which have large amount of inputs in treatments process, i.e., emission of waste gas, discharged waste water and produced solid wastes. The main reason of high performance of eco-environmental optimization in the three regions is the capability of treatments for those three types of wastes. Therefore, the three regions have the characteristics of large inputs and lager outputs.

For Jilin, Heilongjiang, Fujian and Hainan, they are efficient regions too. Those regions are middle developed regions. Heilongjiang and Jilin locate in the northeast part of China. Although these regions are industry basement in 1980s, the center of industry development has transferred into coastal regions. Therefore, the transformation relieved the pressure of eco-environment in that region. Fujian and Hainan are coastal provinces, who are not industry centers or basements. Therefore, the pollution in Fujian and Hainan are relatively less than other coastal regions.

The other 7 regions, i.e., Jiangxi, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang, located on the west part of China. Those regions' development of industry is lagged comparing to other eastern regions.

S&T CONTRIBUTION TO WASTES' TREATMENTS

With the rapid change and development of society, S&T has become the pivotal power for pushing the development of regional economy. However, the traditional regional strategy was focus on the development of industry but ignore the protection of environment. Therefore, the traditional S&T inputs were designed for stimulate the development of industry (Wang *et al*., 1997). With the development of regional eco-construction, more of S&T inputs for optimizing eco-environment are proposed. In the view of regional eco-construction, the impact of S&T inputs on environmental emission and treatment were measured in this study. Based on the chain relationship between S&T inputs, environmental emission and environmental treatment, addictive two-stage DEA model was applied to calculate the impact efficiency of S&T inputs on environmental emission and treatment (Rongchao, 2007).At the same time, we can obtain the impact relationship between S&T inputs and regional eco-environmental optimization.

Basic structure of S&T's effect on wastes' treatment: To identify the influence of S&T to eco-environment optimization, we divided the whole process into two connected stages. Taking related S&T indexes as inputs and wastes emission indexes as outputs in the first stage, we can identify the "wastes producing stage" the first stage. Then, the second stage is "wastes' treatments stage" which takes wastes emission as inputs and treated wastes as outputs and corresponding indexes is same as the indexes mentioned in Section II. The wastes emission indexes are same as the inputs on Table 1. Therefore, the two stages are connected by intermediate indexes. The structure can be shown in Fig. 1.

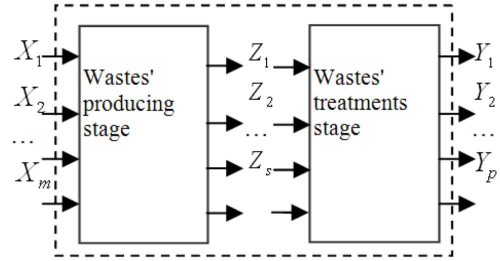

Fig. 1: Two-stage DEA model structure

Table 3: Indexes for S&T's effect to waste treatments

Inputs	Intermediate indexes	Outputs
Effective patents and inventions (item)	Total volume of industrial waste gas emission (100 million cu.m)	Number of facilities for treatment of waste gas (set)
		Volume of industry sulphur dioxide removed (10 000 tons)
		Volume of industrial soot removed (10 000 tons)
R&D expenditure (million RMB)		
		Volume of industrial dust removed (10 000 tons)
Full-time equivalent of R&D Personnel (10 000 man-years)	Total volume of waste water Discharge in Industry (10 000 tons)	Number of facilities for treatment of waste water (set)
R&D Project (item)	Consumption waste water discharge (10 000 tons)	Industrial waste water meeting discharge standards (10 000 tons)
The number of national science and technology achievement award (item)	Volume of industrial solid wastes produced (10 000 tons)	Volume of industrial solid wastes utilized (10 000 tons)
		Volume of industrial solid wastes in stocks (10 000 tons)
Technical contracts number (item)		Volume of industrial solid wastes treated (10 000 tons)

Because the intermediate indexes and outputs have been identified on Table 3, we will propose S&T indexes as inputs. Based on the principle of scientific, comprehensive, operational and obtainable and referenced on related references, six indexes can be listed as the S&T indexes in the left column on Table 3.

Two-stage DEA methodology: We suppose there are n DMUs and each DMU_j (j = 1, 2, …,n) has m inputs, denoted as x_{ij}(i = 1, 2, …, m). Through the first stage, we get s outputs, denoted as z_{tj}(t = 1, 2, …,s). Because the second system follows the first system, the outputs of the first system become the inputs of the second system. Through the second system, there are p outputs produced, denoted as y_{kj}(k = 1, 2, …, p).

A two-stage DEA model was proposed based on CRS (Constant Return to Scale) model (Chen *et al*., 2009; Sexton and Lewis, 2003), which can be expressed as follow for DMU_{j0} as formula (3), where w_1 and w_2 are user-specified weights for subsystem 1 and subsystem 2 respectively and $w_1 + w_2 = 1$. The value of v_i, η_t and u_k are the rational assumption weights for x_{ij},z_{tj} and y_{kj} separately:

$$Max\left(\sum_{k=1}^{p}\mu_k y_{kj_o}+\sum_{t=1}^{s}\pi_t z_{tj_o}\right)$$
$$s.t.\begin{cases}\sum_{t=1}^{s}\pi_t z_{tj}-\sum_{i=1}^{m}\omega_i x_{ij}\le 0\\ \sum_{k=1}^{p}\mu_k y_{kj}-\sum_{t=1}^{s}\pi_t z_{tj}\le 0\\ \sum_{i=1}^{m}\omega_i x_{ij_o}+\sum_{t=1}^{s}\pi_t z_{tj_o}=1\\ \sum_{i=1}^{m}\omega_i x_{ij_o}\ge\alpha,\sum_{t=1}^{s}\pi_t z_{tj_o}\ge\beta\\ \pi_t,\mu_k,\omega_i\ge 0, j=1,2,...,n\end{cases}\tag{3}$$

By changing the value of α,β, we can study the sensitivity of the overall efficiency scores to α,β. To determine the efficiency for each stage, we propose the following procedure. Chen *et al*. (2009) calculated either the first stage's efficiency (θ^1_j) or the second stage's efficiency (θ^2_j) first, then derive the efficiency of the other stage. The following model determines the first stage's efficiency (θ^1_j) while maintaining the overall efficiency score at θ_o calculated from model (3):

$$\theta_o^1=Max\sum_{t=1}^{s}\pi_t z_{tj_o}$$
$$s.t.\begin{cases}\sum_{t=1}^{s}\pi_t z_{tj}-\sum_{i=1}^{m}\omega_i x_{ij}\le 0\\ \sum_{k=1}^{p}\mu_k y_{kj}-\sum_{t=1}^{s}\pi_t z_{tj}\le 0\\ (1\text{-}\theta_o)\sum_{t=1}^{s}\pi_t z_{tj_o}+\sum_{k=1}^{p}\mu_k y_{kj_o}=\theta_o\\ \sum_{i=1}^{m}\omega_i x_{ij_o}=1,\pi_t,\mu_k,\omega_i\ge 0, j=1,2,...,n\end{cases}\tag{4}$$

The efficiency for the second stage then is calculated as:

$$\theta_o^2=\theta_o-w_1\cdot\theta_o^1\tag{5}$$

For the second stage's efficiency (θ_o^2), we can calculate from model (6):

$$\theta_o^2=Max\sum_{r=1}^{s}\mu_r y_{rj_o}$$
$$s.t.\begin{cases}\sum_{d=1}^{D}\pi_d z_{dj}-\sum_{i=1}^{m}\omega_i x_{ij}\le 0\\ \sum_{r=1}^{s}\mu_r y_{rj}-\sum_{d=1}^{D}\pi_d z_{dj}\le 0\\ \sum_{d=1}^{D}\pi_d z_{dj_o}+\sum_{r=1}^{s}\mu_r y_{rj_o}-\theta_o\sum_{i=1}^{m}\omega_i x_{ij_o}=\theta_o\\ \sum_{d=1}^{D}\pi_d z_{dj_o}=1,\pi_d,\mu_r,\omega_i\ge 0, j=1,2,...,n\end{cases}\tag{6}$$

The efficiency for the first stage then is calculated as:

$$\theta_o^1=\theta_o-w_2\cdot\theta_o^2\tag{7}$$

Calculation and results: Using the corresponding panel data of 30 provincial regions, we can calculate the contribution rate of S&T in both stages, denoted θ^*_1as S&T contribution rate in wastes production stage, θ^*_2as wastes treatment capability and θ^*_0as S&T contribution rate in wastes production stage. All of required statistic data are collected from 2011 China Statistic Year Book, 2011 Chinese Environmental Statistic Year book and 2011 Cities Statistic Year Book in China. By used addictive two-stage DEA model, we can get the calculation results on Table 4.

By using two-stage DEA model, we can get the S&T contribution rate to wastes' production and wastes' treatment. θ^*_1 Expressed the effect of S&T to wastes' production, where the more this value the more influence on environmental pollution. θ^*_0Expressed the effect of S&T to wastes' treatments, where the more

Table 4: S&T contribution rate to wastes' treatments based on two-stage DEA model

		Overall efficiency				Efficiency of the first stage		Efficiency of the second stage	
Regions		θ^*_0	Rank	w1	w2	θ^*_1	Rank	θ^*_2	Rank
DMU1	Beijing	0.849	8	0.502	0.498	0.993	3	0.704	6
DMU2	Tianjin	0.812	10	0.500	0.500	0.998	2	0.626	7
DMU3	Hebei	0.817	9	0.592	0.408	0.690	18	1	1
DMU4	Shanxi	0.763	15	0.711	0.867	0.591	20	0.409	20
DMU5	Inner Mongolia	0.873	7	0.546	0.454	0.831	10	0.923	2
DMU6	Liaoning	0.776	13	0.658	0.987	0.610	19	0.390	21
DMU7	Jilin	0.910	5	0.939	0.885	0.517	23	0.483	16
DMU8	Heilongjiang	0.917	4	1.000	0.834	0.500	25	0.500	12
DMU9	Shanghai	1	1	0.483	0.517	1	1	1	1
DMU10	Jiangsu	0.713	19	0.537	0.463	0.862	7	0.541	11
DMU11	Zhejiang	0.952	2	0.952	0.954	0.513	24	0.487	15
DMU12	Anhui	0.880	6	0.500	0.500	1	1	0.760	3
DMU13	Fujian	0.557	28	0.552	0.448	0.811	11	0.243	27
DMU14	Jiangxi	0.577	27	0.580	0.420	0.725	16	0.374	22
DMU15	Shandong	0.807	11	0.500	0.500	1	1	0.614	8
DMU16	Henan	0.639	23	0.530	0.470	0.886	6	0.362	23
DMU17	Hubei	0.613	25	0.580	0.420	0.723	17	0.460	18
DMU18	Hunan	0.587	26	0.558	0.442	0.794	12	0.326	24
DMU19	Guangdong	0.706	20	0.500	0.500	1	1	0.411	19
DMU20	Guangxi	0.765	14	0.517	0.483	0.933	5	0.586	10
DMU21	Hainan	0.541	30	0.571	0.429	0.751	15	0.262	26
DMU22	Chongqing	0.742	17	0.629	0.371	0.590	21	1	1
DMU23	Sichuan	0.685	21	0.543	0.457	0.843	9	0.499	13
DMU24	Guizhou	0.544	29	0.500	0.500	1	1	0.087	28
DMU25	Yunnan	0.937	3	0.914	0.970	0.524	22	0.476	17
DMU26	Shaanxi	0.732	18	0.511	0.489	0.964	4	0.490	14
DMU27	Gansu	0.684	22	0.571	0.429	0.752	14	0.593	9
DMU28	Qinghai	0.754	16	0.523	0.477	0.783	13	0.722	5
DMU29	Ningxia	0.639	24	0.501	0.499	1	1	0.276	25
DMU30	Xinjiang	0.780	12	0.538	0.462	0.862	8	0.727	4

this value the more influence on environmental purification. Referencing on the results on Table 4, we can get the information as following:

- Based on the value of θ^*_1, there are 25 provinces whose corresponding value larger than 0.6. Because S&T inputs can improve the efficiency of production and enlarge scale in enterprises, the productivity is enhances in multiple aspects. At the same time, emission of wastes is increased in the same process. The most serious provincial regions are Shanghai, Anhui, Shandong, Guangdong, Guizhou and NIngxia. Therefore, for these regions, governments should apply measures on strengthen the pollution treatments and energy saving capability in enterprises
- Based on the value of θ^*_0, Shanghai has the highest value, i.e. 1 and other regions' values are less than 1. θ^*_0 Means the positive effect on wastes' treatment. Therefore, the overall contribution of S&T to wastes' treatment is not high. There are five regions whose values are less than 0.6 where S&T has weak influence on wastes' treatment. To enhance the contribution of S&T to environmental purification, government should propose more S&T project and enlarge investment in regional environmental construction. Moreover, we should increase more S&T human resource and grants in the research filed of environmental science and ecological sciences

CONCLUSION

Based on the parallel DEA calculation results, there are 16 regions' efficiencies are less than 1. To optimize eco-environment and keep sustainable development mode in China, we should empower the wastes' treatments capability in the next few years. At the same time, we also should pay attention to the average level of efficient values that all of efficiency values are more than 0.9. The meaning is the gaps between different regions in eco-environmental optimization are not very huge. Therefore, it is feasible to optimize the overall eco-environment in China. Based on the calculation results of two-stage DEA model, S&T contribution to wastes' treatments in Shanghai is ranked on the top one among 30 provincial regions. Therefore, Shanghai should be the benchmark of other regions.

In the past 30 years, we didn't care too much about our eco-environment which produced some pollution and a lot of wastes. How to enhance the capability of deal with those wastes should be important measures to make our environment friendly. Now, Chinese government has already recognize the importance of protection on eco-environment and increased inputs to support the treatments of wastes. Governments should propose specific measures in different provincial regions based on their corresponding evaluation results. By referencing on the calculation results, government can get eco-environmental optimization levels in 30 regions and make corresponding measures to enhance optimization capability of eco-environment in China.

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