# UNDESIRABLE OUTPUT IN EFFICIENCY: EVIDENCE FROM WASTEWATER TREATMENT PLANTS IN CHINA

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**Abstract.** This study focuses on sewage sludge treatment and applies the Bad Output model to deal with desirable and undesirable outputs independently. This approach provides an objective way to assess the technical efficiency of wastewater treatment plants in eastern China and provides a reference for the development of the Midwest. The efficiency score results of 518 plants show some volatility - the average efficiency score is 0.29; 27 plants' efficiency scores are close to 1; 146 plants have an efficiency score of between 1 and the average efficiency score. The higher efficiency score regions are Hainan, Guangdong, Fujian, and Beijing, while by contrast, Hebei, Shanghai, and Tianjin have average efficiency scores lower than the other regions. The results of the adjustment ratio in wastewater treatment or sewage sludge water contents illustrate that most regions exhibit efficiency volatility, and some regions can no longer can support wastewater treatment or sewage sludge water contents.

**Keywords:** *data envelopment analysis (DEA), undesirable outputs mode, wastewater treatment efficiency, sewage sludge water contents* 

#### Introduction

Ever since the initiation of market reforms and opening up in China, its economy has developed very rapidly. In 2014, China's GDP hit US\$ 10.36 trillion, accounting for 13.3% of the world's total GDP. At the same time, energy consumption has also grown rapidly with economic growth, accounting for 21.09% of global energy consumption in 2014 (National Bureau of Statistics, 2015). It has also brought about serious environmental pollution, in order to promote economic development China has proposed the binding target of "energy conservation and emission reduction" during the "11th Five-Year Plan". For the "12th Five-Year Plan", the target is to cut the country's energy consumption per unit of GDP by 18.4%. China's State Council's "Thirteenth Five Energy-saving Emission Reduction Comprehensive Work Plan" stated that by 2020, energy consumed should only be 15% of China's GDP level in 2015.

The sewage treatment process requires a lot of energy, and thus the sewage treatment industry is also an "energy saving" binding indicator for the integrated source of pollution in the area of intensive treatment. Under the increase of industrialization and an improvement in people's environmental awareness, the wastewater treatment industry in China has developed quite strongly. At the end of 2014, China had a total of 3362 urban wastewater treatment plants (WWTPs) with a total capacity of 160 million tons / day and a total wastewater treatment volume of 47.6 billion tons. Due to the continuous improvement of effluent quality requirements of WWTPs, the energy consumption cost of these plants accounts for 40%-80% of its operation and

maintenance costs, with the power consumption of wastewater treatment increasing to 0.3 kwh/m<sup>3</sup>. Moreover, at least 83% of WWTPs consume more energy than found in the data, which is more than 0.45 kwh/m<sup>3</sup>. Compared to other developed countries, the difference is significant (Pan, 2014). Wastewater treatment costs are now averaging at US\$ 0.8/m<sup>3</sup>, and high energy problems have become major urban wastewater treatment operating efficiency constraints.

Due to the high operating costs of sewage treatment plants, low load rates, and other issues, some municipal wastewater treatments plants cannot operate normally, or even operate inefficiently for a long time, or even are left unused, thus resulting in the failure of WWTPs to play the role of water protection and also causing waste of huge investment capital. Studies on the efficiency of WWTPs may help to significantly reduce costs, improve environmental improvements, and also maintain the sustainability of WWTPs (Guerrini et al., 2013; Georgieva, 2017).

The operation of a wastewater treatment plant is accompanied by a large amount of sludge. With the improvement of wastewater treatment capacity and improvement of effluent quality in China, the amount of sludge is increasing at an annual rate of 15%. Sludge disposal has therefore become an increasingly prominent environmental problem in the country. Sludge treatment also affects the entire wastewater treatment plant operation results. While a reasonable and safe disposal of sludge is an important part of the municipal wastewater treatment process, unfortunately, for the reasons of a lack of capital in China, insufficient knowledge, and limited technology and policy, the disposal of sludge has not been paid enough attention. The existence of the hidden danger of secondary pollution caused by the sludge problem greatly reduces the environmental benefits produced by WWTPs and has caught the nation's concern (Dai, 2012). Assessing the efficiency of WWTPs but ignoring the sludge indicator will produce an unbiased result and also departs from the actual problem of these plants in China. However, traditional efficiency measures of WWTPs focus only on the desirable outputs and fail to consider environmentally undesirable by-products of the production processes.

Within the extensive literature on data envelopment analysis (DEA), comparatively little research has focused on the relationship between desirable and undesirable output. Some studies that have include Yang and Pollitt (2009), Emrouznejad et al. (2010), Sueyoshi and Goto (2011), Wang et al. (2012), and Chiu et al. (2016). This literature provides a good research perspective and analysis approach for our own study to bring the sludge indicator in as an undesirable output.

In view of the problems mentioned above, the purpose of this study focuses on analyzing the efficiency of WWTPs by incorporating the results in Tone (2001) who advocate an undesirable output in the variable-returns-to- scale envelopment models. After its market reforms and opening up, economic growth in eastern China has always been higher than in the central and western regions. By the end of 2014, the eastern region's GDP accounted for 55.34% of the national total, far exceeding the total from the central and western regions. Economic development has been accompanied by resource consumption and environmental pollution, so that at the end of 2014, the eastern region's industrial wastewater emissions and urban domestic sewage emissions accounted for 53.24% of the country's total, respectively. At the same time, the eastern region's industrial wastewater treatment investment is also far higher than that in the central and western regions, accounting for over 55% of the national total. Therefore, analyzing wastewater treatment in the eastern region is of great significance

for China to achieve its goal of "energy conservation and emission reduction" and to build a resource-saving and environment-friendly society. This can also be a reference for the development of the Midwest.

The remainder of this study is the following. Section 2 is the literature review. Section 3 is the research method. Section 4 is the empirical results. Section 5 is the conclusions.

The performance measurement of WWTPs in the past has focused on improving the technical indicators to obtain good effluent quality (Wen et al., 2009; Bolong et al., 2009; Santos et al., 2011; Zanetti et al., 2012; Luo et al., 2014; Zhang et al., 2016). As the research has deepened in this field along with the development of analysis methods, scholars have proposed integrated performance indicators that are technical, economic, and environmental in quantitative analysis (Yang, 2017).

Stochastic frontier analysis (SFA) and Data Envelopment Analysis (DEA) are two main approaches for efficiency assessment - namely, parametric and non-parametric methods (Tiedemann et al., 2010; Ferro et al., 2014). Both of these two methods have been widely used to estimate the efficiency of water utilities (Guerrini et al., 2011; Portela et al., 2011; Guerrini et al., 2013; Carvalho and Marques, 2014; Lannier and Porcher, 2014).

Many studies document the usefulness of the efficiency assessment of WWTPs and measure the so-called efficiency in order to save operational cost and improve sustainability (Hernández-Sancho et al., 2011; Sala-Garrido et al., 2012; Molinos-Senante et al., 2014, 2015b; Chen et al., 2015; Guerrini et al., 2015). Yang (2017) adopts the DEA-SBM model to measure the TFE of wastewater control in 39 industrial sectors in China from 2003 to 2014. However, these studies above only set positive inputs and outputs, and most scholars focus on sludge treatment like sludge stabilization with various physical, chemical, and biological technologies (Zhang et al., 2007; Kelessidis and Stasinakis, 2012; Yu et al., 2013; Yang et al., 2015; He et al., 2018;) and sludge disposal methods such as sanitary landfill, incineration, land application, and building materials (Cai et al., 2007; Hale et al., 2012; Wang et al., 2012). Few studies in the literature look at sludge efficiency in an economic way. Sewage sludge as an inevitable by-product of the wastewater treatment process, which may result in secondary pollution, presents a number of environmental concerns, but no study adopts a sewage sludge indicator as an undesirable output to comprehensively assess the efficiency of WWTPs.

Various approaches recently have enabled DEA to deal with undesirable outputs. They can be summarized into four types as follows (Gomes and Lins, 2007; Chiu et al., 2016). The first method uses a reciprocal of undesirable output to evaluate the efficiency (Golany and Roll, 1989; Lovell et al., 1995; Scheel, 2001). The second method considers the undesirable outputs as inputs (Hailu and Veeman, 2001). The third one is the data transformation function approach (Seiford and Zhu, 2002, 2005). The last type is the directional distance function approach (Chung et al., 1997). Alternatively, Tone (2001) proposes a slacks-based measure of efficiency, which is non-radial and non-oriented, and deals with input/output slacks directly. Following this is Sharp et al. (2007), who modify the slacks-based measure to overcome the lack of translation invariance by drawing on the ideas from the range directional model.

These articles have been recently extended to energy and environment studies, but do not evaluate the efficiency of WWTPs. Evaluating the efficiency of WWTPs without considering the sludge problem, which may cause secondary pollution, will be biased. The reasonable and safe disposal of sludge has especially become an important bottleneck, actually restricting the healthy and benign development of WWTPs in China. Therefore, our study comprehensively considers the economic and environmental benefits of WWTPs and constructs a DEA model with sludge disposal as an undesirable output in order to objectively evaluate the efficiency.

Because of the different economic development levels, urbanization process, and natural geographical conditions in the different regions and provinces of China, there are some obviously differences about wastewater treatment, such as wastewater emissions and the total volume of disposal wastewater and utilization rate of WWTPs between eastern and western cities. Since the eastern region is the most developed area of China, it contributes more than 50% to economic volume. Thus, the development of WWTPs in eastern China is also in the leading position along with serious sludge treatment, and hence our study focus on the eastern region to evaluate the efficiency of WWTPs and uses anundesirable output DEA model. The results provide effective suggestions for China.

# Materials and methods

#### **DEA** method

Data Envelopment Analysis (DEA) is a method for measuring the relative efficiency of a set of Decision Making Units (DMUs), which apply multiple inputs to produce multiple outputs over a period of time. DEA was originally developed by Charnes et al. (1978) under the assumption of constant returns to scale (CCR model). Banker et al. (1984) extend the CCR model to include variable returns to scale and develop the BCC model.

In the Banker et al. (1984) model, we denote the set of DMUs as J, where each DMU  $j \in J$ . Let us define the following variables:  $Y_i$  is the output of the DMU,  $X_i$  is the input of the DMU,  $Z_j$  is the weight of DMU, and  $s_j^-$  and  $s_j^+$  are the input slacks and the output slacks, respectively. Here,  $\theta_i$  is the score of the DMU. We set up the input-oriented BCC method used to calculate technical efficiency as:

$$\max: \theta$$
  
s.t. 
$$\sum_{j=1}^{n} z_j x_j + s^- = x_0$$
$$\sum_{j=1}^{n} z_j y_j - s^+ = \theta y_0$$
$$\sum_{j=1}^{n} z_j = 1$$
$$z_j \ge 0, j = 1, \dots, n$$

Though CCR and BCC mainly focus on desirable output or input, in the real world the production process or the content of output may not be a desirable output. In an actual production process, unwanted by-products may appear during input and output conversion, such as wastewater, exhaust gas, and carbon dioxide. In the traditional DEA model, if the relative inefficient DMUs have desirable (good) and undesirable (bad) inputs/outputs to adjust, then they increase or decrease simultaneously, because they cannot just increase the desirable output yet not decrease the undesirable output.

To address the above problem, Tone (2001) applies the undesirable DEA model, which classifies output items into desirable and undesirable outputs. Both kinds of outputs have no inter-relationship, which is different from the undesirable output model where a reduction of bad outputs inevitably reduces desirable outputs. Hence, this situation can be improved.

### Undesirable outputs model

In light of the environmental protection consciousness in modern society, undesirable outputs of production and social activities, e.g., hazardous wastes and air pollutants have been strongly recognized as societal maladies. Thus, the development of technologies with less undesirable outputs is the main subject in every area of production. DEA usually assumes that producing more outputs relative to less input resources illustrates a standard of efficiency. In the presence of undesirable outputs, nevertheless, technologies with more desirable outputs and less undesirable outputs relative to less input resources should be recognized as being efficient.

This model deals with the same problem by applying a slacks-based measure of efficiency (SBM). SBM is non-radial and non-oriented and utilizes input and output slacks directly in producing an efficiency measure. This paper applies the Bad Output model to deal with desirable and undesirable outputs independently. We decompose the output matrix Y into  $(Y^g, Y^b)$ , where  $Y^g$  and  $Y^b$  denote desirable and undesirable output matrices, respectively. For a DMU  $(x_o, y_o)$ , the decomposition is denoted as  $(x_o, y_o^g, y_o^b)$ .

We conceptualize the production possibility set defined as *Eq.1*:

$$\mathsf{P} = \left\{ \left( \left( x, y^{\mathsf{g}}, y^{\mathsf{b}} \right) \middle| x \ge X\lambda, y^{\mathsf{g}} \le Y^{\mathsf{g}}\lambda, y^{\mathsf{b}} \ge Y^{\mathsf{b}}\lambda, L \le e\lambda \le U, \lambda \ge 0 \right) \right\} \quad (Eq.1)$$

Here,  $\lambda$  is the intensity vector, and L and U are the lower and upper bounds of the intensity vector, respectively. We define the efficiency status in this framework as follows.

A DMU  $(x_o, y_o^g, y_o^b)$  is efficient in the presence of bad outputs, if there is no vector  $(x_o, y^g, y^b) \in P$  such that  $x_o \ge x, y_o^g \le y^g, y_o^b \ge y^b$  with at least one stringent inequality.

According to the definition, SBM runs as *Eq.2*:

$$\theta^* = \min \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_{io}^-}{x_{io}}}{1 + \frac{1}{s} \left( \sum_{r=1}^{s_1} \frac{s_r^{g}}{y_{ro}^{g}} + \sum_{r=1}^{s_2} \frac{s_r^{b}}{y_{ro}^{b}} \right)}$$

subject to

$$\begin{array}{ll} x_{o} = X\lambda + s^{-} \\ y_{o}^{g} = Y\lambda - s^{g} \\ L \leq e\lambda \leq U \end{array} \hspace{1cm} y_{o}^{b} = Y\lambda + s^{b} \hspace{1cm} (Eq.2) \\ s^{-}, s^{g}, s^{b}, \lambda \geq 0 \end{array}$$

APPLIED ECOLOGY AND ENVIRONMENTAL RESEARCH 17(4):9279-9290. http://www.aloki.hu ● ISSN 1589 1623 (Print) ●ISSN1785 0037 (Online) DOI: http://dx.doi.org/10.15666/aeer/1704\_92799290 © 2019, ALÖKI Kft., Budapest, Hungary The vectors  $\mathbf{s}^-$  and  $\mathbf{s}^{\mathbf{b}}$  correspond to excesses in inputs and undesirable outputs, respectively, while  $\mathbf{s}^{\mathbf{g}}$  expresses shortages in desirable outputs. Here,  $\mathbf{s}_1$  and  $\mathbf{s}_2$  denote the number of elements in  $\mathbf{s}^{\mathbf{b}}$  and  $\mathbf{s}^{\mathbf{g}}$ , and  $\mathbf{s} = \mathbf{s}_1 + \mathbf{s}_2$ . Let an optimal solution of the above program be  $(\theta^*, \mathbf{s}^-, \mathbf{s}^{\mathbf{g}^+}, \mathbf{s}^{\mathbf{b}^+})$ . We can then illustrate that the DMU  $(\mathbf{x}_0, \mathbf{y}^{\mathbf{g}}_0, \mathbf{y}^{\mathbf{b}}_0)$  is efficient in the presence of undesirable outputs if and only if  $\theta^* = 1, \mathbf{i}, \mathbf{e}, \mathbf{s}^{-*} = 0, \mathbf{s}^{\mathbf{g}^+} = 0$ . If the DMU is inefficient, i.e.,  $\theta^* < 1$ , then it can be improved and become efficient by deleting the excesses in inputs and undesirable outputs and increasing the shortfalls in desirable outputs by the following projection Eq.3.

In the Undesirable (Bad) Output model, we set weights upon undesirable and desirable outputs through the keyboard before running the model. If we supply  $w_1 (\ge 0)$  and  $w_2 (\ge 0)$  as the weights to desirable and undesirable outputs, respectively, then the model calculates the relative weights as  $W_1 = \frac{sw_1}{(w_1 + w_2)}$  and  $W_2 = \frac{sw_2}{(w_1 + w_2)}$ , W2 =sw2(w1 +w2), and the objective function is then modified to *Eq.4*:

$$\theta^{*} = \min \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s_{i_{0}}^{-}}{x_{i_{0}}}}{1 + \frac{1}{s} \left( w_{1} \sum_{r=1}^{s_{1}} \frac{s_{r}^{p}}{y_{r_{0}}^{p}} + w_{2} \sum_{r=1}^{s_{2}} \frac{s_{r}^{b}}{y_{r_{0}}^{b}} \right)}$$
(Eq.4)

The defaults in Eq.4 are  $w_1 = 1$  and  $w_2 = 1$ . In accordance with the degree of stress on undesirable outputs evaluation, you can put a large  $w_2$  against  $w_1$ , and vice versa.

#### Results

The research samples cover the 518 WWTPs in eastern China according to the China Energy Statistical Yearbook dataset in 2015. We use ten regions and five variables here, as shown in *Table 1*: the regions are Shanghai, Shandong, Guangdong, Tianjin, Beijing, Jiangsu, Liaoning, Hebei, Hainan, and Fujian. The five variables include two as output variables and three as input variables. The output variables are wastewater treatment and the undesirable output of sewage sludge water contents; the input variables are equipment investment, electricity usage, and employees. This study concludes with implications for theoretical research. These variables may lead to a better understanding and merging with input variables are shown to be significantly related.

In order to clarify the influence of the regions, we conduct an analysis of Shandong, Guangdong, and the other regions, with *Table 2* presenting the descriptive statistics of the input and output variable data for them as follows.

(1) Wastewater treatment: The wastewater treatment average of all plants is 18.335 million m<sup>3</sup>, where Shandong is 18.171 million m<sup>3</sup>, and Guangdong is 25.257 million m<sup>3</sup>. The max wastewater treatment plant is 328.5 million m<sup>3</sup> from Beijing, while the lowest wastewater treatment plant is 10.95 million m<sup>3</sup> from Shandong.

(2) Sewage sludge water contents: In general, for the water content of sewage sludge, a lower value is better. The average sewage sludge water contents from the 518 plants

are 76.36%. Shandong is 77.65%, Guangdong is 75.71%, and the other regions are 76.14%. The average sewage sludge water content is higher by 1.28% at Shandong versus Guangdong is lower 0.65%, other regions lower 0.23%. The lowest sewage sludge water content plant is 0.8% from Jiangsu, while the highest sewage sludge water content is better. Guangdong and other regions have lower sewage sludge water contents than Shandong in 2014 -that is, Shandong must improve versus the other regions in terms of controlling sewage sludge water content.

(3) Equipment investment: Equipment investment increased at an average rise of CNY 16.417 million. The highest equipment investment is CNY 6.818 billion in Jiangsu, with the lowest equipment investment at CNY 0.156 in Guangdong.

(4) Electricity usage: The average electricity usage of all plants is 4,487,008.87 kwh, where Shandong is 4,749,826.54 kwh, and Guangdong is 5,364,878.92 kwh. The highest electricity usage plant is at 96,054,400 kwh in Guangdong, while the lowest electricity usage plant is at 47.46 kwh in Hainan.

(5) Employees: The average number of employees of all plants is 62.64 persons, where Shandong is 71.56 persons and Guangdong is 78.75 persons. The plant with the most employees is in Shandong at 575 persons, while Fujian, Guangdong, and Liaoning have 6 persons in their plants, representing the least number of employees.

Region	Output Variable	Input Variable		
<ol> <li>Shanghai 2. Shandong 3. Guangdong 4. Tianjin 5. Beijing 6. Jiangsu7.Liaoning8. Hebei 9.Hainan10.Fujian</li> </ol>	<ol> <li>1. wastewater treatment</li> <li>2. sewage sludge water contents</li> </ol>	<ol> <li>equipment investment</li> <li>electricity usage</li> <li>employees</li> </ol>		

Table 1.	Regions	and input	and output	variables
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Region		Output V	Variable	Input Variable			
		Wastewater Treatment	Sewage Sludge Water Content	Equipment Investment	Electricity Usage	Employee	
	Region	117	117	117	117	117	
	Max	11059.50	85.00	8225.00	23806880.	574.72	
Shandong	Min	10.95	40.00	3.75	72.00	8.18	
-	Average	1817.10	77.65	503.54	4749826.54	71.56	
	Stdev	1629.22	6.30	1276.24	4724107.43	77.87	
	Region	142	142	142	142	142	
Guang-	Max	22861.26	86.00	4523.00	96054400.00	553.01	
	Min	16.26	20.00	0.02	35310.00	5.82	
dong	Average	2525.75	75.71	198.96	5364878.92	78.75	
	Stdev	3094.67	8.34	502.68	10424243.63	90.84	
1	Region	259	259	259	259	259	
	Max	32850.00	280.00	681822.00	75712596.00	468.30	
Others	Min	14.60	8.00	0.40	47.46	5.58	
	Average	1461.42	76.14	2946.89	3886981.02	49.77	
	Stdev	2635.92	16.39	42362.80	6234240.36	63.07	
10Region s	Region	518	518	518	518	518	
	Max	32850.00	280.00	681822.00	96054400.00	574.72	
	Min	10.95	8.00	0.02	47.46	5.58	
	Average	1833.52	76.36	1641.72	4487008.87	62.64	
	Stdev	2619.64	12.73	29933.05	7371638.54	75.88	

#### Table 2. Descriptive statistics

Data source: Authors' Collection

#### Discussion

The wastewater treatment of China was 71.617 billion  $m^3$  in 2014, with 37.727 billion  $m^3$  from the eastern region. By contrast, this area value GDP, water resources and wastewater treatment highly with other area.

We use DEA-Solver software to evaluate the 518 WWTPs' efficiency and analyze each plant's ranking. From the undesirable model, we find that 27 plants have efficiencies equal to 1. More plants from Guangdong have an efficiency score equal to 1.

*Table 3* shows the differences between the average efficiency score and the higher/lower average efficiency score of each region. The average efficiency score is 0.29 for the 518 plants, and the higher efficiency score regions are Hainan, Guangdong, Fujian, and Beijing. Hainan and Beijing have a greater percentage of efficiency scores close to 1 versus the other regions. The plants' average efficiency score between 1 and average efficiency score was 146 plants in 2014 and the major regions were form Guangdong, Fujian and Shandong. In some regions, the average efficiency score is lower, because, they no longer are able to support wastewater treatment or sewage sludge water contents. For example, Hebei, Shanghai, and Tianjin, their average efficiency scores are lower than the other regions.

Region			Over all	Between 1 and Average Efficiency Score				
	Total	Average	Score=1	Percentages of the score=1	Higher Average Percentage	Total	Average	Percentages
Guangdong	142	0.37	13	9.15%	52.11%	61	0.41	42.96%
Shandong	117	0.26	5	4.27%	50.00%	20	0.46	17.09%
Hebei	81	0.24	1	1.23%	50.00%	16	0.38	19.75%
Jiangsu	62	0.24	1	1.61%	30.77%	14	0.37	22.58%
Fujian	50	0.35	3	6.00%	25.00%	22	0.40	44.00%
Liaoning	39	0.28	1	2.56%	24.19%	11	0.39	28.21%
Shanghai	11	0.14		0.00%	21.37%			0.00%
Hainan	8	0.43	2	25.00%	20.99%	2	0.35	25.00%
Tianjin	4	0.12		0.00%	0.00%			0.00%
Beijing	4	0.33	1	25.00%	0.00%			0.00%
total	518	0.29	27	5.21%	33.40%	146	0.41	28.19%

Table 3. Efficiency score results of each region

Data source: Authors' Collection

*Table 4* lists the ten regions' efficiency score and improvement by the undesirable model. We note that there are several issues between regions and their efficiency score. For example, in Fujian, Guangdong, Liaoning, and Hainan, their average efficiency scores are higher than the other regions. In other words, each region has too much investment into the input variables; Jiangsu by CNY 699,193; Shandong by CNY 56.59 million; and Guangdong by CNY 23.35 million on equipment investment. Guangdong exceeds electricity usage by 405,729,807 kwh; Shandong by 394,761,772 kwh; and Jiangsu by 178,827,079 kwh. By contrast, the output variables should be increased in each region. Jiangsu should increase 4,973 thousand m<sup>3</sup>, Jiangsu should be increase 2,061 thousand m<sup>3</sup> in the wastewater treatment, and the sewage sludge water contents should be decrease 602 percentages in Guangdong, 355 percentages in Jiangsu and 336 percentages in Fujian.

	Total	Avg. Score		Slack Excess	Slack Shortage		
Region			Equipment Investment	Electricity Usage	Employee	Wastewater Treatment	Sewage Sludge Water Contents
Guangdong	129	0.30	23,354	405,729,807	7,328	1,757	602
Shandong	112	0.23	56,590	394,761,772	6,438	119	243
Hebei	80	0.23	19,826	167,187,348	2,536	2,137	297
Jiangsu	61	0.22	699,193	178,827,079	2,637	4,973	355
Fujian	47	0.31	8,319	46,420,398	1,128	2,061	336
Liaoning	38	0.26	2,574	108,908,648	1,308	-	62
Shanghai	11	0.14	6,814	58,625,773	1,161	-	76
Hainan	6	0.25	11,985	15,853,913	297	-	10
Tianjin	4	0.12	3,248	13,232,191	200	1,924	-
Beijing	3	0.10	6,686	35,327,785	301	356	18
Total	491	0.25	838,588	1,424,874,714	23,334	13,326	1,997

 Table 4. Inefficiency scores and improvement of each region

Data source: Authors' Collection

# Conclusion

The GDP of China is US\$ 10.36 trillion, making upto 13.3% of global GDP and 21.09% of global energy consumption. Environmental topics in recent years have become more popular in the world, but few scholars have discussed wastewater treatment efficiency and the effects of sewage sludge water contents. Some regions in China have spent a lot of resources into increasing wastewater treatment or reducing sewage sludge water contents, while some regions have lower efficiency scores versus others. Some regions' efficiency score has fallen in order to control electricity usage or equipment investment.

This research reports the efficiency scoresof regions in China by the Tone (2001) undesirable DEA Model. After evaluating ten regions and data on 518 plants in eastern China, we provide the following conclusions below.

(1) The efficiency scores from the 518 plants exhibit some volatility: 27 plants have efficiency scores close to 1; 146 plants have efficiency scores between 1 and 0.

(2) The average efficiency score is 0.29 from the 518 plants, with higher efficiency scores coming from Hainan, Guangdong, Fujian, and Beijing. By contrast, Hebei, Shanghai, and Tianjin have average efficiency scores that are lower than the other regions.

(3) There are 491 inefficient plants, whose average efficiency score is 0.25. The inputs including equimpment investment, electricity usage and employee of WWTPs performed invest too much, which need to be decreased by different level. The equimpment investment excess the optimum level of CNY 838,588, the exctricity usage with the excess consumption of 1,424,874,714 kwh, and the employee with the excess of 23,334 persons. The wastewater treatment volume need to be increase 13,326 thousand m<sup>3</sup> and sewage sludge water contents will be decrease 1,997 percentages.

The efficiency results of wasteter treatment assessment will be different while considersing the sludge problem or not. As a by-product, sludge in WWTPs is harmful to the environment, which is urgent to strenthen the treatment and disposal. At present, 90% WWTPs in China have realized sludge dewatering and reduction treatment, but the proportion of WWTPs that have achieved sludge biological stabilization treatment is

less than 3%. Most of the sludge has not been stabilized and landfill directly, and less than 20% sludge has been safely treated and disposed (Kan Liao et al., 2019). The efficiency of WWTPs can be evaluated comprehensively and objectively by building the index system with sludge indicator in. In order to impove the efficiency of WWTPs, it is necessary to regularly maintain the machineryandequipmentand improve its utilization efficiency, also control the electricity consompution to reduce electricity charges, and reasonably allocate the staff to control labor costs.

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