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Technical efficiency assessment of wastewater treatment plants in China based on electricity stress index and DEA model#

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ABSTRACT

China's wastewater treatment plants (WWTPs) have consumed a large amount of electricity, which is threatening the sustainable development of regions with severe energy scarcity. In this paper, we developed a novel framework for evaluating the technical efficiency of WWTPs and identifying the key pathways to save electricity and improve treatment efficiency. First, multiple regional initial and integral electricity scarcity risks were investigated based on the proposed electricity stress index (ESI). Then, an index system covering two inputs (scale and electricity consumption) and six outputs (COD, BOD, SS, NH3-N, TN and TP pollutant removal volumes) was constructed to assess the technical efficiencies of 3776 WWTPs by introducing the multiple electricity scarcity risks into data envelopment analysis (DEA). The results showed that the original average technical efficiency score of investigated samples was 0.340, of which only 28 samples were relatively effective. The remaining WWTPs had different levels of input excesses and over 60% electricity overcapacity, indicating that the substantial potential for technical efficiency improvement and electricity saving. Moreover, regional electricity scarcity risks differed significantly and the technical efficiency changed significantly considering ESI. This paper may present a useful tool for the technical efficiency assessment of WWTPs.

Keywords: electricity efficiency, wastewater treatment, electricity stress index, data envelopment analysis, multi-regional input-output analysis

1. INTRODUCTION

Energy efficiency is important for the sustainable development goals (SDGs) of the whole world. China's WWTPs energy consumption accounted for 1-2% of total social energy consumption [1] and exceeded 1.67 × 1010 kWh of total electricity consumption in 2017[2]. Electricity demand in WWTPs will keep growing due to increasing final consumption demand as population and economic growth. More importantly, electricity scarcity has been recognized as a critical challenge of electricity sustainability. At the same time, there is a strong scientific consensus that the ambitious carbon emission reduction plans of China may influence the energy supply and its security. The increases in wastewater treatment electricity consumption demand and low efficiency (about 0.31 kWh/m^3) may aggravate the energy scarcity crisis.

It is important to measure the energy efficiencies of enterprises and regions to monitor energy consumption sustainability. There are two main methods that have been used to quantify energy efficiency [3]: single-factor energy efficiency and total-factor energy efficiency [4]. There are three main energy efficiency calculation tools: data envelopment analysis (DEA), Life cycle assessment (LCA) and multiple criterion analysis (MCA) [5]. DEA has been widely considered as one of the methodologies to examine the level of sustainability [6] and DEA has been widely applied to investigate energy and environment issues. DEA method evaluates the energy efficiency of decision-making units (DMUs) with multiple inputs and outputs based on linear programming, and energy is one of the input factors [7]. In addition, economic transactions also can redistribute energies among regions, then affecting the entire energy system and energy efficiency.

In recent years, research interests have been found in technical efficiency between different technical groups [8], spatio-temporal difference analysis [3], operating variables investigation for energy efficiency differences and multiple input and output factors analysis [9]. Gao et al. used the DEA model to evaluate

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the efficiencies of wastewater treatment plants and explored the influence factors of the operational efficiency [10]. In addition, the ecological and environmental efficiency of wastewater treatment plants is also a hot spot. Wu et al. analyzed the pollutant emission efficiency of WWTPs in 68 cities from 2006 to 2015 through DEA, determining scale effects and the differences between cities from both temporal and spatial perspectives [11]. Castellet et al. used a non-radial DEA model to compute the efficiency of 49 largest WWTPs [12]. Hernández-Chover et al. evaluated the efficiency of 217 WWTPs in the Valencian to learn the influence of scale economies in wastewater treatment processes [13]. Although some evaluations have considered the carbon emission properties of electricity to investigate the energy sustainability of WWTPs, the heterogeneity of energy scarcity has not been considered to evaluate the energy efficiency of WWTPs.

The deficiency in existing studies is manifested in two aspects. Most of the existing studies tested the energy efficiency in different provinces of China and the differences of electricity scarcity in different provinces are barely studied. In addition, most research assumes that the regions are independent and lack interaction. Few studies consider the wastewater treatment energy efficiency space overflow and diffusion effect in inter-regional economic trade. Thus, in this study, the Multiregional input-output (MRIO) analysis was applied to unveil the interregional and intersectoral economic relationships among regions and reallocate all the energy inputs to different consumers.

This paper introduced the electricity scarcity indicators into the DEA method to provide a novel assessment framework to evaluate the sustainable performance of energy efficiency. In addition, the MRIO method has been applied to identify electricity scarcity and reveal the wastewater treatment electricity interaction among regions in accordance with the level of energy efficiency. The remainder of this paper is structured as follows: Section 2 explained the methods. Section 3 presented the empirical results of 3782 urban wastewater treatment plants in China. Further discussions and conclusions were presented in Section 4. The purpose of this study is to provide a novel assessment framework to evaluate the sustainable performance of WWTPs.

2. MATERIAL AND METHODS

2.1 Data and data processing

The sectoral electricity consumption data and province-level MRIO data were obtained from CEADS. The WWTP operation data was obtained from the Chinese Urban Drainage Yearbook. the regional electricity consumption and generation data were obtained from the Chinese Energy Statistics Yearbook. Notably, the data for Tibet, Hong Kong, Macau and Taiwan were not available.

Based on data availability, 42 sectors in the original MRIO table were aggregated into 31 sectors to match the format of the sectoral electricity consumption data. Based on the construction of the conventional DEA model, each wastewater treatment plant was defined as a DMU. The number of DMUs is required to be more than 2 times the product of inputs and outputs to ensure that the samples are adequate and the efficiency index for each sample is comparable. 8 indicators from 3782 DMUs were obtained, which include two input and six output indicators (shown in Table 1).

To reflect the initial electricity stress levels, the data of the total electricity consumption and import was used to calculate the electricity stress index (ESI). To reflect the integral electricity stress levels, the data of the total electricity consumption and generation were used to calculate the integral energy stress index (VESI). The data of sectoral electricity consumption was used to calculate energy consumption intensity. All the ESI-related electricity data were obtained from China's energy Statistical Yearbook and the results of MRIO analysis.

2.2 Methods

2.2.1 CCR and BCC models

The CCR and BCC model are two basic DEA model. The CCR model evaluate the technical efficiency (TE) which express as a value from 0 to 1. The BCC model assesses the pure technical efficiency (PTE) which represents the effect of production and management on efficiency. The BCC model introduce the intensity variable vector λ, with the constraint that the sum of λ for all DMUs is 1, as in Eq. (1)

$$\boldsymbol{X} = ({x_{1m}}^t, {x_{2m}}^t, \cdots, {x_{nm}}^t)^{\mathrm{T}}$$

$$\boldsymbol{Y} = ({y_{1l}}^t, {y_{2l}}^t, \cdots, {y_{nl}}^t)^{\mathrm{T}}$$

$$\min\varphi \begin{cases} \sum_{j=1}^{n} \delta_j x_{ij} + s^- = \varphi x_0, i = 1,2,\cdots,m \\ \sum_{j=1}^{n} \delta_j y_{rj} - s^+ = y_0, r = 1,2,\cdots,s \\ \sum_{j=1}^{n} \delta_j = 1 \\ \delta_j \geqslant 0, j = 1,2,\cdots,n \end{cases} \tag{1}$$

$$TE = d_{(x,y,CRS)} = d_{(x,y,VRS)} \times \left[d_{(x,y,CRS)}/d_{(x,y,VRS)}\right] = PTE \times SE \tag{2}$$

Table 1 Statistical description of input and output indicators

Indicator	Unit	Min	Max	Mean	Total
Input					
Design scale (X_1)	10^4 m^3/d	0.04	280.00	4.64	17535.01
Electricity consumption（X_2）	kWh	500.00	203399799.00	4293606.00	16234124872.00
Output (amount of pollutant removal)					
COD (Y_1)	kg/kWh	0.84	222004.03	3490.28	13196730.29
BOD (Y_2)		0.36	100803.56	1533.43	5797889.83
SS (Y_3)		0.73	134462.03	2525.30	9548144.94
NH_3-N (Y_4)		0.37	21414.34	333.56	1261189.23
TN (Y_5)		0.26	14799.38	336.24	1271310.42
TP (Y_6)		0.02	2597.35	49.85	188476.78

where φ represents the efficiency value of the DMU (serial number from 1 to *n*). *i* represents the serial number of input indicators from 1 to *m*, and *r* represents the serial number of output indicators from 1 to *s*. The quotient of TE and PTE is scale efficiency (SE), as shown in Eq. (2). SE reflects whether the scale of investment is optimal. only when both the PTE and SE reach effectiveness at the same time is the effectiveness of TE guaranteed.

2.2.2 Initial and integral electricity index

Energy stress index (ESI) was defined to reflect the degree of regional energy shortage. We introduced the electricity stress index (ESI) to quantitatively characterize the scarcity of electricity consumption in WWTPs of each region. Here, we defined the ESI as the ratio of the amount of energy consumption to the total energy consumption, as shown in Eq. (3) and Eq. (4).

$$ESI = EC/EP \tag{3}$$

$$VESI = (VEC + HEC)/EP \tag{4}$$

where ESI presents the energy stress index. $VESI$ presents the integral electricity stress index. VEC is the amount of regional final electricity consumption demand that could be calculated by MRIO analysis. EC is the amount of electricity consumption. HEC is the household electricity consumption and EP is the energy generation.

The MRIOA can track the resource transmission between sectors and regions. the total economic output of sectors in regions can be expressed as Eq.(5).

$$x_i^r = \sum_{s=1}^{n} \sum_{j=1}^{n} z_{ij}^{rs} + \sum_{s=1}^{n} y_i^r \tag{5}$$

where x_i^r represents the total economic output of sector i in province r; z_{ij}^{rs} represents intermediate input from sector i in province r to sector j in province s; y_i^r represents final demand of sector i in province r.

$$A = \left[a_{ij}^{rs}\right]_{n\times n} \tag{6}$$

$$a_{ij}^{rs} = z_{ij}^{rs}/x_j^s \tag{7}$$

where A represents the direct consumption coefficient matrix of the whole study area. The direct consumption coefficient a_{ij}^{rs} represents the amount of input from sector i in province r directly consumed by sector j in province s per unit of economic output; z_{ij}^{rs} represents intermediate input from sector i in province r to sector j in province s; x_j^s represents the total economic output of sector j in province s.

$$X = A \times X + Y \tag{8}$$

$$X = (I - A)^{-1}Y \tag{9}$$

$$L = (I - A)^{-1} \tag{10}$$

where X represents the total economic output column vector; A is the direct consumption coefficient matrix; Y represents the final demand matrix; L is the Leontief inverse matrix.

We first use MRIOA to calculate the direct electricity intensities of each sector in different regions. That we can calculate the VEC of different regions.

$$T = D \times L \tag{11}$$

$$D = \left[d_j^s\right]_{1\times n} \tag{12}$$

$$d_j^s = p_j^s/x_j^s \tag{13}$$

where L denotes the direct coefficient of electricity consumption for sector j; p_j^s denotes direct electricity consumption of sector j; x_j^s denotes the total economic input of sector j.

the calculation formula of them is as follows:

$$W = \widehat{D} \times L \times Y \tag{14}$$

$$V = [v^{rs}]_{n \times n} = \sum_{i=1}^{n} \sum_{y=1}^{5} w_{iy}^{rs} \tag{15}$$

where W represents the final electricity demand matrix. V represents the inter-province transfer matrix of electricity; D^ represents the diagonal matrix of D; L represents the Leontief inverse matrix; and Y represents the final demand matrix. v^{rs} represents electricity transfer from province r to province s; w_{iy}^{rs} represents electricity consumption of sector i in province r driven by final demand y in province s.

We reassessed the technical efficiency using the new input indicators X21 and X22 as the input, as shown in Eq.(16) and Eq.(17) respectively.

$$X21 = ESI \times WEC \tag{16}$$

$$X22 = \mathrm{V}ESI \times WEC \tag{17}$$

where ESI presents the initial electricity stress index; WEC represents the electricity input of WWTPs. $\mathrm{V}ESI$ presents the integral electricity stress index.

3. RESULTS

3.1 Energy efficiency performance

In this study, the CCR model based on VRS was established. The technical efficiency (TE) of 3782 wastewater treatment facilities has been calculated and the result was shown in Fig. 1. We considered that a DMU is efficient when its score is 1. It could be seen that the efficiency levels of TE and PTE for the whole sample were low. More than 90% of the WWTPs showed a PTE score between 0 and 0.600 among them 470 samples with a PTE lower than 0.2. only 38 of the 3782 WWTPs had a PTE score of 1. The average TE and PTE scores of samples were 0.340 and 0.372 which can be concluded that the wastewater treatment facilities studied could save over 60% of their inputs if they operated at the efficiency frontier. Only 28 wastewater treatment facilities were technically efficient (TE=1).

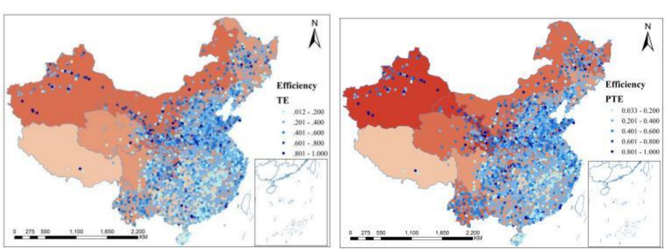

Fig. 1 The TE and PTE scores for each WWTPs.

For recognizing regional efficiency discrepancies, the provincial-level average, maximum and minimum PTE of the 31 provinces was calculated based on the VRS assumption and was showed in Fig 2. Xinjiang (0.544) owned the highest mean PTE and followed by Gansu (0.525) and Beijing (0.517). Shandong and Shanghai with the most WWTPs had PTE of 0.439 and 0.436. Hainan owned the lowest mean PTE score of 0.219, and Jiangxi, Tibet and Hunan had a relatively lower PTE below 0.300. We could also find that these regions showed lower maximum PTE and even Hainan had the maximum score of 0.399. More than 90% of Jiangxi, Hubei and Hunan' WWTPs had PTEs below 0.500, indicating that these regions were significantly inefficiency and had a large potential of energy saving.

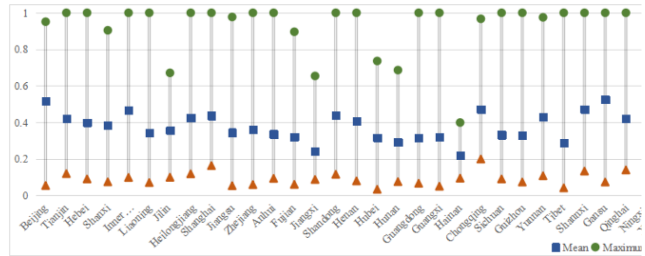

Fig.2 The average, maximum and minimum PTE

3.2 Comprehensive energy efficiency performance

Difference between the original TE and comprehensive TE (TE21 and TE22) which considered the regional electricity scarcity appeared in the basic statistics and was shown in Fig. 3. Xinjiang, Gansu, Beijing were the top three regions in original TE score, Yunnan, Xinjiang, Gansu were the top three regions in TE21 score. Xinjiang, Gansu, Ningxia were the top three regions in TE22 score. Except Yunnan, Ningxia, Shanxi, Sichuan, Anhui, Guizhou and Hubei presented TE21 scores increase, the other 22 regions showed TE21 scores decrease. As for the direct scarcity power technical efficiency (TE21) and virtual scarcity power technical efficiency (TE22), All region's TE22 average scores were lower than TE21 average scores. Jiangxi and Hainan' score rankings were lowest and significantly reduced after considering the power scarcity. Besides Zhejiang, Fujian, Guangxi, Guangdong and Hunan also had a relatively lower technical efficiency and efficiency scores decreased. More importantly, most of these regions were identified as power supply provinces of water production and supply products which cause more inefficient power consumption. On a positive note, the Jiangsu who had lower technical efficiency was identified as the biggest power consumer of water production and supply products and outsourced most of the power consumption demand to higher efficient regions such as Shandong, Jilin and Yunnan, which reduced the use of locally inefficient power (Fig.4).

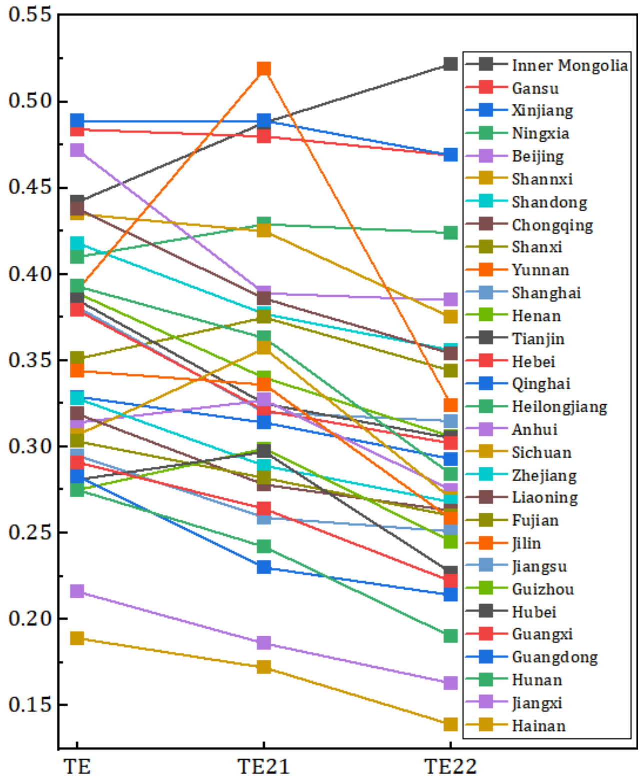

Fig.3 The TE, TE21, TE22 average scores for regions.

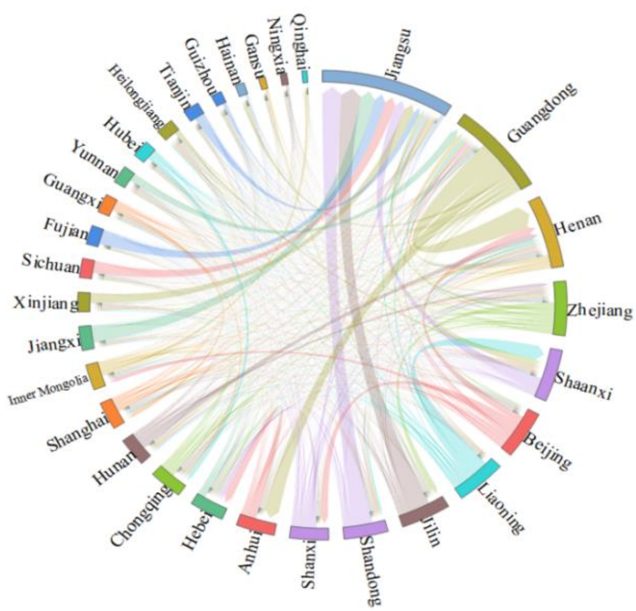

Fig.4 The electricity transitions between regional Production and distribution of tap water sectors.

4. DISCUSSION AND CONCLUSION

In order to comprehensively assess the energy efficiency of WWTPs based on electricity scarcity, a novel method that combines the DEA and MRIO methods is constructed to evaluate the energy performance of WWTPs. The proposed method was applied to test the electricity efficiency and sustainability performance of WWTPs in China. The technical efficiency changed significantly considering ESI. In addition, the analyses showed that rich electricity resource endowment strongly underpinned local WWTPs' good electricity efficiency performance. The power supply provinces who had low original electricity efficiency and observed lower efficiency increased the regional electricity gap. Those regions that have higher energy efficiency and import large amount of products from regions with low energy efficiency for water production and supply could aggravate the risk of energy sustainability nationally.

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