Desalination and Water Treatment
www.deswater.com
doi: 10.5004/dwt.2018.22912

119 (2018) 276–281
July

Energy efficiency evaluation for wastewater treatment plant

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Received 12 December 2017; Accepted 26 June 2018

ABSTRACT

Wastewater treatment plant (WWTP) is one of the energy-intensive industries. Energy efficiency evaluation is critical to energy-saving and emission-reduction. The energy efficiency was closely associated with the influent loads, organic, nutrient and other factors. It is difficult to identify the complex relationships between energy efficiency and wastewater. This article presents grey fixed weight clustering for evaluating the energy efficiency of WWTP. An overall energy efficiency index for WWTP is calculated from the individual energy use device indices. The weights of each devices were according with the energy end use consumption breakdown. The application of this method enabled the identification of device-specific measure to increase the energy use efficiency. In addition, a new grey correlation degree method was used to analyze the relationship between energy efficiency and the influence factors. The results of this study allow wastewater managers to better develop sewage-treatment strategies for wastewater treatment plants.

Keywords: Wastewater treatment plant; Energy efficiency; Grey fixed weight clustering; New grey correlation analysis

1. Introduction

Along with the development of urbanization and population growth, municipal wastewater discharges from domestic and industrial sources are gradually increasing. Today, the surface water and underground aquifers are seriously polluted in many places. Water pollution has seriously affected the health and security of aquatic ecosystems. Wastewater treatment plants can effectively remove the organic pollutant to reduce water pollution. It is one of the energy-intensive industries [1,2]. Energy consumption is one of the main costs for wastewater treatment and a major constraint to the development of wastewater treatment plant (WWTP). Energy consumption and manage are generally inefficient and the application of energy efficient technologies can lead to considerable savings in energy consumption. Energy demand for wastewater treatment would increase in the future due to ageing infrastructure and stricter discharge requirements [3–7]. Thus, a reduction on energy consumption brings important benefits such as improving efficiency and reducing operational costs.

Energy efficiency evaluation is critical to implement target strategies for energy reduction [8,9]. Several studies have been conducted for energy efficiency analysis, such as specific energy consumption, life cycle assessment and so on [10–15]. These methods provided insight of relationship between energy consumption and wastewater. Specific energy consumption (the per cubic meter water electrical consumption index or per kilogram chemical oxygen demand (COD) electrical consumption index) has been widely applied in WWTP as a single index method [16]. The energy consumption was closely associated with nutrient and other factors except influent loads and COD [17–19]. The single index method would ignore the effects of these factors. The energy efficiency evaluation should comprise all the factors. However, the relationship between energy consumption and

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wastewater is uncertainty and fuzziness. Data analysis is a difficult task because it is multidimensional, complex, and nonlinear. The grey fixed weight clustering (GFWC) could calculate an overall energy efficiency index for WWTP and the weights of the individual energy use device indices were according with the energy end use consumption breakdown.

Grey theory was developed by Deng [20–22]. It is widely used system when the information is poor, incomplete and uncertain. The advantage of this theory is that it only requires a limited set of data to estimate the behaviour of unknown system [20–22]. GFWC has drawn widespread interests in recent years. Yuan et al. [23] used the method to evaluate the innovation system construction level of China's provinces. The model also applied to evaluate the urbanization process in Henan province and the result showed that the Henan's urbanization level belonged to the general level in 2012 [24]. Li et al. [25] applied this model in railway transportation and provided a reliable selection plan for heavy haul railway transportation. Although GFWC has already been used in many research domains, the concept has never been applied to evaluate energy efficiency of WWTP.

Grey correlation analysis is often used to analyze the relationship between the behavioural sequence and feature sequences in various systems such as economic, transportation, social, financial, and so on. Meena and Azad [26] employed grey relational analysis to optimize the levels of input parameters in micro-electric discharge machining. Sun et al. [27] presented a new decision-making method based on grey correlation degree. Kung and Wen [28] verified that the significant financial ratio variables drove the financial performance of venture capital enterprises in Taiwan. Kuo et al. [29] used the method solving multiple attribute decision-making problems. Zhang and Zou [30] explored the relationship between the power system and aeration system of WWTP. Based on traditional grey correlation analysis, some new methods are proposed to characterize the relationship among different sequences [31,32]. In this paper, a new grey relational degree was proposed and used to analyze the relationship between energy efficiency and wastewater. We also employed this method to calculate the weight of GFWC. Based on quantitative analysis for the relevant inputs and outputs of wastewater treatment plant, the overall energy efficiency of WWTP is assessed through GFWC.

2. Data sources and research methods

2.1. Research methods

2.1.1. New grey relational method

Wastewater treatment plants represent a portion of the broader relationship between energy and wastewater [7]. It is one of the energy-intensive and complex public service. Energy consumption spent a large portion of the current costs of a WWTP. Thus, the reduction on energy demand brings important benefits to a WWTP system. Energy demand is mainly due to aeration and pumping against gravity. The energy efficiency is strongly dependent on the influent loads, organic, nutrient and other factors. The relationship among them is uncertainty and fuzziness. Grey correlation analysis is a good method to measure the relationship of fuzzy system. It could verify the relationships of variable parameter by measuring the geometrical shapes of curve. In general, the higher grey correlation degree means the individual energy use has a stronger impact on energy efficiency. For convenience, it is necessary to make assumption about the statistical data for Tables 1 and 2 [19]. Suppose a_{i0} and a_{ij} (i = 1, 2, …, 12; j = 1, 2, 3, 4) are feature sequence and behavioural sequence, respectively. Where a_{i0} denotes monthly electricity consumption, a_{ij} (j = 1, 2, 3, 4) represents influent loads, COD, total ammonia nitrogen, and total phosphorus separately in the wastewater monthly. The procedures of grey correlational degree can be concluded as follows:

(1) Normalizing the feature sequence and behavioural sequence by initial value, respectively.

$$a'_{ij} = a_{ij} / a_{1j} \quad \left(i = 1,2,\cdots,12;\ j = 1,2,3,4\right) \tag{1}$$

(2) Performing the minimum difference and maximum difference operation on the normalized sequence, respectively.

$$M = \max_i \max_j \left(\Delta_{ij}\right),\ m = \min_i \min_j \Delta_{ij} \tag{2}$$

where $\Delta_{ij} = \left|a'_{i0} - a'_{ij}\right| \quad \left(i = 1,2,\cdots,12;\ j = 1,2,3,4\right)$

Table 1
Grey clustering coefficients of assessments of energy efficiency at different times

Cluster objective	Integrated cluster coefficients			Grey classes
	I	II	III	
Jan	0.1295	0.3440	0.4115	III
Feb	0.2445	0.3409	0.3718	III
Mar	0.0307	0.1768	0.7515	III
Apr	0.2091	0.2734	0.5667	III
May	0.1773	0.3986	0.3669	II
Jun	0.5010	0.3482	0.1236	I
Jul	0.3237	0.3342	0.1166	II
Aug	0.8688	0	0	I
Sep	0.7934	0.0506	0	I
Oct	0.7783	0.0843	0	I
Nov	0.6204	0	0.2275	I
Dec	0.4474	0.1524	0.1706	I

Table 2
Calculated new grey relational degree and weights

Research objects	Influent loads	COD	Total ammonia nitrogen	Total phosphorus
New grey relational degree	0.5487	0.3763	0.3681	0.3033
Weight	0.3451	0.2367	0.2257	0.1807

(3) Grey correlation coefficient can be calculated by Eq. (3) as follows:

$$r_{ij} = \left(m + q * M\right) / \left(\Delta_{ij} + q * M\right) \tag{3}$$

where $q \in (0,1)$ is discriminating coefficient. It could help to make better distinction between feature sequence and behavioural sequence. q is frequently set as 0.5.

(4) The grey correlation degree is then calculated by averaging the grey relational coefficients:

$$r_{Qj} = \frac{1}{12}\sum_{i=1}^{12} r_{ij} \tag{4}$$

It is obvious that the minimum difference m is equal to 0. So the grey relational coefficient r_{ij} is equivalent to:

$$r_{ij} = \left(q * M\right) / \left(\Delta_{ij} + q * M\right) \tag{5}$$

From Eq. (5), we can conclude that if there is only one behavioural sequence, the grey correlation degree could reflect the relationship between normalized feature sequence and behavioural sequence. However, if there is more than one behavioural sequence, the choice of the maximum difference would ignore the impact of the other behavioural sequence on the system. So it is necessary to consider the impact of other behavioural sequence on the system. Therefore, the maximum difference of system is calculated by averaging the maximum differences of each behaviour sequence.

$$M' = \Delta_{ij} = \sum_{j=1}^{4}\left(\delta_j\right) / 4 \tag{6}$$

The maximum difference of each behaviour sequence is written as:

$$\delta_j = \max_i \left| a_{i0}^{'} - a_{ij}^{'} \right| \quad \left(i = 1,2,\cdots,12;\ j = 1,2,3,4\right) \tag{7}$$

Thus, the grey correlation coefficient is written as Eq. (8).

$$r_{ij}^{'} = \left(m + q * M'\right) / \left(\Delta_{ij} + q * M'\right) \tag{8}$$

The new grey correlation degree can be calculated as follows:

$$r_{Qj}^{'} = \frac{1}{12}\sum_{i=1}^{12} r_{ij}^{'} \tag{9}$$

In this article, the weights of various indexes can be obtained by the meaning of new grey relational degree.

$$w_j = \frac{r_{Qj}}{\sum_{j=1}^{4} r_{Qj}} \tag{10}$$

2.1.2. Grey cluster method with fixed weights

Grey cluster method can convert state variables into performance indices. This method has been widely applied to many fields in recent years. The energy consumption of WWTP depends on many factors. Therefore, grey cluster method is applied to measure the energy efficiency of WWTP. The grey whitening weight function is constructed by observing index and grey classes [17]. In this paper, the energy efficiency is related with influent loads, COD, total ammonia nitrogen and total phosphorus (Table 3). Three performance categories (excellent (I), general (II), and poor (III)) would identify the different level of energy efficiency. Four different grey whitening weight functions are defined for the categories.

The grey whitening weight function for the unit energy consumption of inflow loads definite as Eq. (11).

$$f_1^1\left[3.4, 3.895, -, -\right],\ f_1^2\left[3.252, 3.5, -, 3.7\right],\ f_1^3\left[-, -, 3.252, 3.4\right] \tag{11}$$

where

$$f_1^1(x) = \begin{cases} 0, & x < 3.4 \\ \dfrac{x - 3.4}{3.895 - 3.4}, & 3.4 \le x < 3.895 \\ 1, & 3.895 < x \end{cases}$$

Table 3
Statistical description of the energy consumption parameters

	Inflow loads	COD	Total ammonia nitrogen	Total phosphorus
Unit	(m^3/kWh)	(g/kWh)	(g/kWh)	(g/kWh)
Jan	3.577	1,245	91	17.3
Feb	3.252	1,664	96	21.3
Mar	3.261	1,242	95	17
Apr	3.248	1,303	124	20
May	3.259	1,441	110	21
Jun	3.347	1,764	124	22
Jul	3.350	1,463	118	24
Aug	3.895	1,643	127	25
Sep	3.829	1,612	121	26
Oct	3.796	1,662	117	26
Nov	3.799	1,633	82	27
Dec	3.725	1,612	84	23

$$f_1^2(x)=\begin{cases}0, & x\notin[3.252,3.7]\\ \dfrac{x-3.252}{35-3.252}, & 3.252\le x<35\\ \dfrac{3.7-x}{3.7-3.5}, & 3.5\le x<3.7\end{cases}$$

$$f_1^3(x)=\begin{cases}0, & x\notin[3.252,3.4]\\ 1, & 0\le x<3.252\\ \dfrac{x-3.252}{3.4-3.252}, & 3.252\le x<3.4\end{cases}$$

Similarly, the grey whitening weight functions for other indicators (the unit energy consumption for COD, total nitrogen, and total phosphorus) can be defined as follows:

$$\begin{aligned}&f_2^1[1400,1764,-,-],\\&f_2^2[1242,1350,-,1500],\\&f_2^3[-,-,1242,1350]\end{aligned} \tag{12}$$

$$\begin{aligned}&f_3^1[90,127,-,-],\\&f_3^2[82,100,-,127],\\&f_3^3[-,-,82,90]\end{aligned} \tag{13}$$

$$\begin{aligned}&f_4^1[20,26.9,-,-],\\&f_4^2[17,22,-,25],\\&f_4^3[-,-,17,22]\end{aligned} \tag{14}$$

The cluster coefficients are calculated as:

$$\sigma_i^k=\sum_{j=1}^{4}f_j^k\left(x_{ij}\right)\cdot w_j \tag{15}$$

where InlineEqn(6) is the jth grey weighting function of the kth category. w_j (j = 1, 2, 3, 4) is the jth cluster weight. InlineEqn(7) is cluster coefficients of energy efficiency

The type of the subject can thus be confirmed according to the value of maximization.

$$\max_{1\le k\le 3}\left\{\sigma_i^k\right\}=\sigma_i^{k^*} \tag{16}$$

The k* is the category of subject.

2.2. Data sources

In this paper, the WWTP applies improved carrousel oxidation ditch process, treating municipal sewage and industrial sewage. The daily capacity is 100,000 cubic meters and the inflow loads are 72,000–85,700 cubic meters per day. After treatment, the effluent quality can meet the national integrated discharge standard. The data sets were collected from the wastewater treatment plant from the January 1st, 2011 to November 30th, 2011 [19]. Table 3 descripts the energy consumption parameters, including the energy consumption for unit inflow load, eliminate COD, eliminate total nitrogen and eliminate total phosphorus. It can be seen in Table 3, the range and unit of each parameter are different in data sequence. So, we employed the GFWC method to evaluate energy efficiency of WWTP.

3. Results and discussion

3.1. Relationship between the energy consumption and wastewater

New grey correlation degree analysis and the weights of GFWC are depicted in Table 2. As it can be seen in Table 2, the results show that inflow loads have a significant impact on energy consumption, followed by COD, while total ammonia nitrogen has the weaker, followed by total phosphorus. The weights are obtained according to Eq. (10). It can be seen that the contribution of inflow loads for the total WWTP energy consumption is 34.51%. COD removal and total ammonia nitrogen removal represents 23.67%, 22.57% of energy consumption, respectively. Phosphorus removal contributes (18.07%) the least for energy consumption.

3.2. Evaluation of the energy efficiency of wastewater treatment plant

The performance indices of energy efficiency of WWTP are divided into three categories. They are presented in Table 1. Results show that energy efficiency of WWTP is quite different in various times. There are three typical types.

Type I: "Excellent condition – high energy efficiency of WWTP". In these periods, the energy efficiency is classified as "excellent", as the unit energy consumption could treat more influent loads and pollutants in wastewater, including: Jun, Aug, Sep, Oct, Nov, and Dec. It is easy to see that unit energy consumption for inflow loads and COD on Oct are almost as that on Nov, but on Oct more ammonia nitrogen have to be removed. So, the performance index on Oct is better than that on Nov.

Type II: "General condition – general energy efficiency of WWTP". In such periods, the performance of energy consumption is classified as "good", including: May and Jul.

Type III: "Poor condition – poor energy efficiency of WWTP". In such periods, the performance of energy use is classified as "poor", including: Jan, Feb, Mar, and Apr.

All above results indicate that energy efficiency of WWTP in varying time is different. Energy efficiency has good performance when inflow loads are sufficient and concentration of wastewater is high. Energy efficiency has poor performance when inflow loads are insufficient and contamination of wastewater is low. Results suggest that energy use and management are generally inefficient and application of energy efficient technologies can lead to considerable savings in energy consumption. Sufficient inflow loads and higher concentrations organic contamination are essential for the higher energy efficiency. So, urban sewage centralized treatment is a useful way to ensure the stability and reliability of inflow loads. COD removal and total ammonia are other energy intensive aspects of WWTP. These barriers prevent plants from utilizing high energy efficiency. The plant could reduce their energy consumption by instituting energy efficiency programs. Meanwhile, the new energy intensive technologies to removal COD and total ammonia should be deployed in the plant.

4. Conclusions

This paper presented GFWC method to estimate the overall energy efficiency of WWTP, based on performance estimation of the different indexes. An overall performance index for energy efficiency of WWTP was obtained by weighting the individual performance indices for the energy efficiency. New grey correlation degree was implemented to analyze the relationship between energy consumption and wastewater. This method shows good ability in dealing with fuzzy set. The method also used to calculate the cluster of GFWC. It demonstrates that inflow loads have a significant contribution on energy consumption, followed by COD removal, while total nitrogen removal has the smaller, followed by total phosphorus removal. GFWC is widely used in multi-index estimation. For the energy consumption in wastewater treatment plants, this method could make a comprehensive estimation for the energy efficiency of WWTP. The result of this study and application of the performance efficiency indices could allow WWTP management to identify lower energy efficiency and, subsequently, implement energy demand strategies tailored to certain energy consumption devices. Furthermore, with the strict effluent limitations, wastewater treatment would become more energy intensive.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (No. 51478025).

Authors' contributions

ZhenHua Li, ZhiHong Zou, and Xiaojing Wang designed the study and analyzed the data. All the authors approved the final manuscript for publication.

Conflict of interest

The authors declare no conflict of interest.

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