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RESEARCH ARTICLE

Benchmarking Toronto wastewater treatment plants using DEA window and Tobit regression analysis with a dynamic efficiency perspective

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Abstract

The environmental-economic focus of wastewater treatment and management attracts growing attentions in recent years. The static efficiencies and their dynamic changes are helpful to systematically assess the environmental performance of the water agencies and wastewater treatment plants (WWTPs). Additionally, identifying key factors of efficiencies is critical to improve the operation of WWTPs. In this study, the window method of data envelopment analysis (DEA) was applied to estimate the annual efficiency for four Canadian WWTPs and to explore the variations of annual efficiency under different window lengths. Meanwhile, the Tobit regression analysis was developed to determine the driving forces for WWTPs' efficiency. The empirical results showed that: (i) the selected DEA window length remarkably affected both the average efficiency and the variations; however, it had no impact on the ranking of plants' efficiency; (ii) lower efficiencies were observed in plants with larger capacities due to higher infrastructure and operation investments involved; (iii) both the influent total phosphorus concentrations and influent flow rates had significant effects on the WWTPs' performance. Moreover, the staff and utility expenditures should be reduced to generate greater potential cost savings and efficiency improvement given the treatment technologies employed.

Keywords DEA window analysis · Tobit regression · Wastewater · Dynamic efficiency

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Introduction

Wastewater treatment plants (WWTPs) have been designed and operated worldwide since the late nineteenth century to protect the environmental sustainability and human health. WWTPs are complex systems that involve various biological, physical, and chemical interactions. Moreover, they suffer constant changes in multiple operational inputs including the inflow rates and wastewater characteristics (Ge et al. 2012; Lorenzo-Toja et al. 2015). These complexity and variations challenged the efficiency assessment of the WWTPs and their long-term sustainability (Molinos-Senante et al. 2016; Piao et al. 2016). Therefore, more robust and credible methodologies are required to assess these challenges and thereby to improve the WWTPs' performance.

A large number of efficiency evaluation models and methods have been developed and applied in the wastewater treatment sector, including Performance Measurement System (PMS) (Guerrini et al. 2016a), Data Envelopment Analysis

(DEA) models (Gómez et al. 2017; Molinos-Senante et al. 2016), Meta Frontier approach (Molinos-Senante and Sala-Garrido 2016), Life Cycle Assessment (LCA) (De Feo and Ferrara 2017), and hybrid models (Saha et al. 2017; Wang et al. 2017) (see a summary in Table S1 in Supporting Information). Comparatively, DEA is considered as an effective and most widely used approach for comparing the inputs and outputs of homogenous decision-making units (DMUs), due to less requirements for data and model assumptions (Fuentes et al. 2015; Sun et al. 2017; Yang and Yang 2015; Yang and Yang 2016). Unfortunately, most studies only performed the cross-sectional data analysis and focused on the static efficiency of evaluated WWTPs at a certain time, failing to evaluate the changes in plants' efficiency. Some previous studies tried to obtain the dynamic eco-productivity change by different DEA models, such as the weighted Russell directional distance function Gémar et al. (2018) and the Malmquist productivity index (Fuentes et al. 2015; Molinos-Senante and Sala-Garrido 2016). However, these tools are not suitable for small sample cases.

The dynamic operational efficiencies in different periods of time are also critical to identify the annual performance of the WWTPs and further improve their operation and management. As for small sample evaluations, an extended DEA, namely the DEA window analysis using the moving average method, has been developed/designed to comprehensively describe the dynamic changes of the efficiency of each DMU, both horizontally and vertically. More importantly, the number of DMUs increases with varied window length set. This could enhance the discriminating power when a limited number of DMUs was available (Halkos and Tzeremes 2009). Al-Refaie et al. (2016) assessed the energy efficiency of the industrial sector using the DEA window analysis and Malmquist index. To the best of the authors' knowledge, few studies were reported with this method to evaluate the dynamic efficiency of wastewater treatment facilities. Recently, Lorenzo-Toja et al. (2017) explored the eco-efficiency by using the DEA window model based on the data of 47 WWTPs during 2009–2012, in order to determine the changes in the efficiency of individual plants and the divergences among them. Nevertheless, only the eutrophication net environmental indicator (ENEI) was considered as the output without considering the removal of the pollutants in wastewater.

A wide range of indicators such as the plant size, influent quality, and treatment capacity had significant effects on the efficiency of WWTPs (Dong et al. 2017; Guerrini et al. 2016b; Rodriguez-Garcia et al. 2011; Romero-Pareja et al. 2017). Numerous models were developed to evaluate the factor effects on the WWTPs' efficiencies such as analysis of variance (ANOVA) (Lorenzo-Toja et al. 2017), artificial neural network (ANN) (Güçlü and Dursun 2010), and non-parametric test (Molinos-Senante et al. 2014). Comparatively, the Tobit model was designed to estimate linear relationship among variables when there was either left- or right-censoring in the dependent variables. Therefore, this model was appropriate to conduct the influencing factor analysis for the efficiency of WWTP that was usually constrained in a certain range of 0–1 (Lv et al. 2015). Li et al. (2017b) applied the Tobit model to identify the key influencing factors for the county sewage, ammonia, chemical oxygen demand, and biochemical oxygen demand reduction in China, with the capital, operating costs, labor, and energy consumption as input indices. Studies considering more comprehensive inputs such as the influent characteristics will help understand the relationship between factors and the WWTP efficiency. In addition, most studies compared the efficiency of WWTPs with different treatment technologies in various locations that greatly vary in conditions such as climate, economic levels, and labor markets. These may result in an inaccurate or unreal efficiency evaluation.

In this study, four WWTPs located in Toronto, Canada, that have similar natural, social, and economic conditions were selected. It is strongly believed that the current paper moved forward with four innovative explorations. First, the DEA window analysis was performed to explore the efficiency based on small sample, and the Tobit regression model was applied to identify the key factors affecting the efficiency. Second, the efficiency values and their dynamic changes of both individual plants and the total sample between 2007 and 2016 were presented. Third, this study discussed the development laws of WWTPs' annual average efficiency and variations under different DEA window lengths, which were reported firstly to use this technique in this area. Finally, it determined the driving forces of efficiency and at least partially, the theoretical basis for improving the WWTPs' operational performance in addition to measures for cost savings.

Materials and methods

WWTPs

Four wastewater treatment plants (WWTPs) located in Toronto, Canada, including Ashbridges Bay Treatment Plant (ABTP), Highland Creek Treatment Plant (HCTP), Humber Treatment Plant (HTP), and North Toronto Treatment Plant (NTTP), were inventoried in this study to develop the DEA window and Tobit regression (Table 1).

Built in 1910, ABTP is the largest of four wastewater treatment plants operated by the City of Toronto. HCTP is located in Scarborough, with its construction completed in 1956 and followed by several phases of expansion. HTP is located at 130 The Queensway, at the border of the old City of Toronto and City of Etobicoke. The smallest of the wastewater plants, North Toronto, is located in the Don Valley at 21 Redway Road. Commissioned in 1929, North Toronto was one of the first plants in North America to use the biological activated

Table 1 Configurations of WWTPs evaluated

WWTP	Location	Effluent discharged	Treatment capacity (m^3/day)	Treatment technology	Employees
ABTP	$43^\circ 39'26''N$, $79^\circ 19'15''W$ East Toronto	Lake Ontario	818,000	WAS	174
HCTP	$43^\circ 46'04''N$, $79^\circ 09'01''W$ Northeast Toronto	Lake Ontario	219,000	WAS	67
HTP	$43^\circ 38'00''N$, $79^\circ 28'44''W$ West Toronto	Lake Ontario	473,000	WAS	62
NTTP	$43^\circ 41'58''N$, $79^\circ 21'22''W$ North Toronto	Don River	45,500	WAS	10

sludge process. All four WWTPs were operated with the conventional waste activated sludge process during 2007–2016.

DEA window analysis

DEA model selection

DEA is widely used in measuring relative efficiencies of plants with handling multiple inputs and outputs. It estimates the effective production frontier based on a set of input-output observations. While for the DEA window analysis, it not only makes the DMUs reused to increase the sample size, but also takes different periods of the same DMU as different DMUs (Al-Refaie et al. 2016). In this case, the efficiency of a DMU in a certain period can be compared with both the same period of the other DMUs and the efficiency of this DMU in other periods, to obtain more real efficiency evaluations. In this study, therefore, the annual data of each WWTP is regarded as an independent DMU, which makes the comparison of different WWTPs in the same period feasible as well as of the same DMU in different periods meaningful (Asmild et al. 2004). In particular, the variable return to scale was adopted here because high efficiencies are usually observed in WWTPs with large capacities (Dong et al. 2017). Moreover, the input-oriented approach was implemented that allows for the minimization of input costs rather than maximizing outputs, while maintaining the quality of the effluent. According to Banker et al. (1984), the Banker-Charnes-Cooper (BCC) model assumed variable returns to scale (VRS), where an increase in the input might result in a disproportionate increase in the output. Consider the number of WWTPs evaluated as $n = \{1, 2, \cdots, N\}$, each facility having p inputs and q outputs. The efficiency score for rth units DMU_r can be estimated as the suggested BCC model in Eq. (1).

$$
\begin{aligned}
&Min\ \ \mu \\
&subject\ \ to: \\
&\qquad \mu x_{in} - \sum_{n=1}^{N} \delta_n x_{in} \geq 0, i = 1, \cdots, p \\
&\qquad \sum_{n=1}^{N} \delta_n y_{jn} \geq y_{jr}, j = 1, \cdots, q \\
&\qquad \sum_{n=1}^{N} \delta_n = 1 \\
&\qquad \delta_n \geq 0, n = 1, \cdots, N
\end{aligned}
\tag{1}
$$

The DEA window analysis with the period $\tau = \{1, \cdots, T\}$was constructed. It was assumed that DMU_n^τ denoted an observation n in the period$\tau$with the input X_n^τ to produce the outputY_n^τ, which could be described in Eq. (2).

$$
X_n^\tau = \left[x_n^{1\tau}, \cdots, x_n^{p\tau}\right]' \qquad Y_n^\tau = \left[y_n^{1\tau}, \cdots, x_n^{q\tau}\right]' \tag{2}
$$

The input and output could be further expressed in Eq. (3) when the DEA window began at the time t ($t = 1, 2, \cdots, T$) with the length$l$ ($l = 1, \cdots, T - t + 1$). The DEA window analysis could then be applied for the efficiency assessment when the Eq. (3) was incorporated into the model (1).

$$
X_{tl} = \begin{bmatrix} x_1^t & x_2^t & \cdots & x_N^t \\ x_1^{t+1} & x_2^{t+1} & \cdots & x_N^{t+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{t+l} & x_2^{t+l} & \cdots & x_N^{t+l} \end{bmatrix} \quad Y_{tl} = \begin{bmatrix} y_1^t & y_2^t & \cdots & y_N^t \\ y_1^{t+1} & y_2^{t+1} & \cdots & y_N^{t+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{t+l} & y_2^{t+l} & \cdots & y_N^{t+l} \end{bmatrix} \tag{3}
$$

Determination of input and output

Based on the main findings of input-output variables in studies such as Choubert et al. (2017) and Cossio et al. (2017), four different costs were included as input variables in order to evaluate the efficiency of WWTPs: (i) utility cost, which includes charges on water, hydro, and gas used at the WWTPs); (ii) staff cost, which includes employees' salaries and social expenditure; (iii) chemical consumption, which contains charges on polymer, ferrous chloride, chlorine, and sodium hypochlorite; and (iv) operational cost, which consists of equipment, services, and other costs. Meanwhile, three pollutant removal rates in the effluent were chosen as representatives of outputs: (i) removal rate of suspended solid (*SS*), (ii) removal rate of 5-day carbonaceous biological oxygen demand ($cBOD_5$), and (iii) removal rate of total phosphorus (*TP*). The descriptive statistics of input and output variables are listed in Table 2.

Table 2 The descriptive statistics of input-output variables for DEA window analysis. All the data for variables comes from the annual reports of four WWTPs between 2007 and 2016, which are publicly distributed online at https://www1.toronto.ca/wps/portal/contentonly?vgnextoid=da8807ceb6f8e310VgnVCM10000071d60f89RCRD

Variable	Index	Obs	Mean	SD	Min.	Max.
Input variables	Utility ($)	40	6,318,622	4,892,196	228,061	17,435,419
	Staff ($)	40	7,060,065	5,500,058	751,267	17,525,550
	Chemical ($)	40	1,827,899	1,822,290	61,856	5,667,169
	Operational ($)	40	6,173,927	7,997,029	168,070	23,243,822
Output variables	SS (mg/L)	40	262.21	63.05	158.50	432.90
	$cBOD_5$ (mg/L)	40	186.10	62.46	83.50	312.60
	TP (mg/L)	40	4.61	0.88	3.30	6.80

Obs observational value, *Mean* mean value, *SD* standard deviation, *Min. and Max.* minimum value and maximum value of variables

Tobit regression model

The Tobit model, also known as the sample selection model and the limited dependent variable model, is a kind of limited dependent variable regression. It is expert in dealing with dependent variables constrained in a certain range, which coincides with the calculated efficiency values in our study. The Heckman two-step method is usually used to estimate the Tobit model, that is, to estimate the selection equation first and then to estimate the limited dependent variable model. In the second stage, the Tobit regression analysis was carried out to explore the key impact factors of efficiency. In general, the Hausman test is applied to determine a suitable model between the random effect model and the fixed effect model. Taking the fixed effect model as an example, it can be illustrated by Eq. (4).

$$Eff_{it} = \alpha_i + Z_{it}\beta + \varepsilon_{it} \tag{4}$$

Further, Eq. (4) can be expanded to Eq. (5).

$$\begin{aligned} Eff_{it} = {} & \alpha_i + \beta_1 PE_{it} + \beta_2 ISS_{it} + \beta_3 IcBOD_{it} + \beta_4 ITP_{it} \\ & + \beta_5 Iflow_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

where $Eff_{it}$is the VRS efficiency of WWTP i in the period t; $\alpha_i$indicates the fixed effect; ε_{it}represents the interferences; Z_{it}reflects the explanatory variables (or independent variables). The selected five independent variables included (i) equivalent population (*PE*) representing plant scale, (ii) SS concentration in influent (*ISS*), (iii) $cBOD_5$ concentration in influent ($IcBOD_5$), (iv) total phosphorus in influent (*ITP*) reflecting influent characteristics, and (v) average daily influent flow rate (I_{flow}) as a representative of treatment capacity.

Results

In this section, the WWTPs' annual efficiency was evaluated and compared under different window lengths including $l = 1$, $l = 5$, and $l = 10$ by the DEA window method. Based on these empirical results, the driving factors of WWTP's efficiency were then explored through the Tobit regression analysis.

Efficiency estimation of WWTPs using DEA window analysis

The length of the DEA window should be large enough to ensure sufficient samples to be covered, and as small as possible to minimize or avoid unfair comparisons caused by time factors (Al-Refaie et al. 2016). In this study, four Toronto-located WWTPs serving an average population of 699,250 PE were selected from 2007 to 2016. Without loss of generality, three window lengths were set for the collected input and output data over the 10-year period: $l = 1$, $l = 5$, and $l = 10$.$l = 1$ indicated a cross-section analysis between WWTPs in the same year. On the contrary, $l = 10$denoted a globally intertemporal comparison between WWTPs in 10 continuous years (across the entire study period). However, $l = 5$ implied that each efficiency estimation had a 5-year span (i.e., 2007–2011, 2008–2012, etc.). Detailed information on the window length is summarized in Table S2 and Table S3. The annual average efficiencies for both the individual facility and four WWTPs as a whole are listed in Table 3. The numbers of efficient years and the variations of efficiencies are presented in Fig. 1.

For $l = 1$, ABTP, HTP, and NTTP exhibited similar performance with high efficiencies of 1.000 over the 10 years studied. However, the efficiencies of HCTP were found to be less than 0.8 in the years of 2011, 2012, 2015, and 2016. This resulted in an average efficiency of 0.840 and significant differences between the annual average efficiencies of four WWTPs (Table 3). Specifically, the annual efficiency of HCTP in 2015 was only 0.826, which was as high as 1.000 in both 2007–2010 and 2014–2015 (Table 3). The average efficiency of four WWTPs was 0.960 with the variation of 0.135 (Table 3).

Table 3 The annual efficiency of WWTPs during 2007–2016 based on different window lengths

$l = 1$											
WWTP	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
ABTP	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
HCTP	1.000	1.000	1.000	1.000	0.752	0.797	1.000	1.000	0.306	0.544	0.840
HTP	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
NTTP	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Average	1.000	1.000	1.000	1.000	0.938	0.949	1.000	1.000	0.826	0.886	0.960
$l = 5$											
WWTP	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
ABTP	1.000	0.590	0.844	0.472	0.945	0.863	0.763	0.813	1.000	1.000	0.829
HCTP	0.467	1.000	0.935	1.000	0.352	0.340	0.310	0.414	0.306	0.396	0.552
HTP	0.327	0.532	0.901	1.000	1.000	1.000	0.702	1.000	1.000	1.000	0.846
NTTP	1.000	1.000	1.000	1.000	0.962	1.000	1.000	1.000	1.000	1.000	0.996
Average	0.699	0.781	0.920	0.868	0.815	0.801	0.694	0.807	0.826	0.849	0.806
$l = 10$											
WWTP	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	Average
ABTP	0.614	0.395	0.516	0.301	0.723	0.658	0.583	0.713	1.000	1.000	0.650
HCTP	0.131	0.788	0.187	1.000	0.124	0.140	0.138	0.330	0.306	0.396	0.354
HTP	0.144	0.282	0.621	0.630	1.000	1.000	0.532	1.000	1.000	1.000	0.721
NTTP	1.000	1.000	0.983	0.968	0.900	1.000	1.000	1.000	1.000	1.000	0.985
Average	0.472	0.616	0.577	0.725	0.687	0.699	0.563	0.761	0.826	0.849	0.678

For $l = 5$, NTTP achieved the highest annual efficiency (0.996), and it lasted for 9 years except for 2011 (Fig. 1). Compared to $l = 1$, the numbers of efficient years for HTP, ABTP, and HCTP decreased to 6, 3, and 2 years from 10, 10, and 6 years, respectively, resulting in lower average efficiencies of 0.846, 0.829, and 0.552, respectively (Table 1). The overall average efficiency dropped to 0.806 (Table 3), and the efficiency variance increased up to 0.258 (Fig. 1).

The numbers of the efficient year for WWTPs decreased when the window length was extended to 10. To be specific, NTTP was only operated efficiently for 7 years, followed by HTP (5 years), ABTP (2 years), and HCTP (1 year), respectively (Table 3). Unsurprisingly, the annual efficiencies dropped to 0.985, 0.721, 0.650, and 0.354 for NTTP, HTP, ABTP, and HCTP, respectively. A significant drop (n 0.678 in Table 3) was also observed in the overall average efficiency and the efficiency variation increased again up to 0.328 (Fig. 1).

Contributions of multi-factors to the efficiency based on Tobit model

Compared to the cross-section analysis of $l = 1$ and the global analysis of $l = 10$, the efficiency evaluations of $l = 5$ could reflect the relative performance of WWTPs

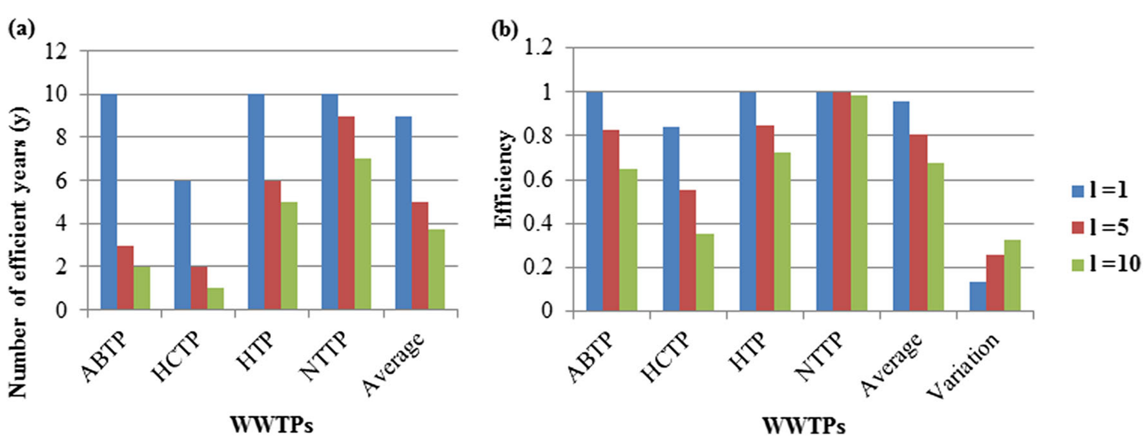

Fig. 1 Comparisons of **a** the number of efficient years during 2007–2016 and **b** the efficiency for WWTPs with different window lengths. The term "Average" corresponds to the average value of 10-year efficiencies of four WWTPs, while the term "Variation", measured by the standard deviation, represents the degree of dispersion relative to the mean value during 2007–2016

better in every 5 years. With the expectation of the best balance of the in formativeness and stability of the efficiency scores, the window length of $l = 5$ was selected to investigate the effects of the plant size and influent pollutant concentrations on the WWTPs' efficiencies. Both the correlation analysis and the Hausman test suggested the establishment of a fixed effect Tobit regression model. The Tobit regression analysis was conducted with a dependent variable (*Eff*) and five independent variables (*PE*, *ISS*, $IcBOD_5$, I_{flow}, and *ITP*). The descriptive statistics of these variables are listed in Table 4. The results of Tobit regression analysis are given in Table 5.

The Tobit regression model showed statistically significant with a value of $P = 0.0000$ (Table 5). Results indicated that at a level of 5%, variables such as *PE*, *ITP*, and I_{flow} had significant influences on the WWTPs' efficiencies. Comparatively, a negative correlation with a coefficient of −3.24e-06 was observed between *PE* and *Eff*. This finding was consistent with the observation of the size effect obtained by the DEA window method (Table 3). Moreover, the WWTP tended to be more efficient with the increase of *ITP* (0.6734) and I_{flow} (0.0047). It was obvious that the influences of *ISS* and $IcBOD_5$ on efficiencies were not significant though their coefficients turned out to be completely opposite signs.

Table 5 Results of Tobit regression model

Eff	Coef.	SD	*T*	P > |t|	[95% Conf. Interval]	
PE	−3.24e-06	9.71e-07	−3.34	0.002	−5.21e-06	−1.27e-06
ISS	0.0034	0.0018	1.88	0.069	−0.0003	0.0070
$IcBOD_5$	−0.0026	0.0016	−1.63	0.112	−0.0059	0.0006
ITP	0.6734	0.1672	4.03	0.000	0.3339	1.0130
I_{flow}	0.0047	0.0020	2.31	0.027	0.0006	0.0089
_cons	−2.038	0.6759	−3.02	0.005	−3.4102	−0.6660
Prob > chi2 = 0.0000						

Discussions

Effect of the DEA window length on the evaluation of WWTPs' efficiencies

First, the DEA window model systematically revealed the dynamic changes of WWTPs' efficiencies. Based on the empirical results, along with the change of the window lengths, obvious regularities could be found in plants' annual efficiency, the average efficiency of the total sample, and their variabilities. It indicated that the DEA window analysis method was suitable for identifying the dynamic characteristics of the sewage plant efficiency. This finding was consistent with the view that the DEA window model was effective for the identification of the operational performance or environmental efficiencies of WWTPs and could handle small samples that failed to meet the 'thumb rule' (Al-Refaie et al. 2016; Hemmasi et al. 2011).

Second, the efficiencies of WWTPs remarkably varied with the window length selected during the DEA window analysis. As the window length increased from 1 to 5, and then to 10, both the individual and overall average efficiencies of WWTPs decreased while the efficiency variations increased. This suggested that the impacts of the window lengths on WWTPs' efficiency presented consistent outcomes. The effects of the window length settings on efficiency were also verified by some of the previous literature (Lorenzo-Toja et al. 2017; Řepková 2014). However, the selected window length did not appear as an important factor for the ranking of WWTPs' annual efficiency. Irrespective of the window lengths ($l = 1$, 5, and 10), similar rankings of annual efficiencies of four WWTPs were obtained (NTTP > HTP > ABTP > HCTP), indicating that the selection of window length had little influence on the relative efficiency scores of WWTPs. This was in accordance with the findings that, regardless of window length, consistent rankings of plants' efficiencies were observed while the efficiency variation for plants varied.

Table 4 The descriptive statistics of dependent and independent variables for Tobit regression analysis

Variable	Index	Obs	Mean	SD	Min.	Max.
Dependent variables	*Eff*	40	0.81	0.26	0.31	1.00
Independent variables	*PE*	40	683,325	530,364.90	55,000	1,524,000
	ISS (mg/L)	40	273.45	63.74	165.50	446.00
	$IcBOD_5$ (mg/L)	40	191.29	63.14	86.60	318.00
	ITP (mg/L)	40	5.24	0.93	3.80	7.50
	I_{flow} (ML/day)	40	279.85	221.40	17.60	697.60

Obs observational value, *Mean* mean value, *SD* standard deviation, *Min. and Max.* minimum value and maximum value of variables

Third, the annual average efficiencies decreased with the increase of the window lengths applied. This decrease was in different degrees, leading to substantial variations in the ranking of WWTP's annual average efficiencies. For instance, the lowest average efficiency for $l = 1$, $l = 5$, and $l = 10$arose in the years 2015, 2013, and 2007, respectively, suggesting that the window length settings had a non-negligible effect on the average efficiencies of individual years. This was also supported by Lorenzo-Toja et al. (2017) who divided the plants into the large, medium, and small size groups and found that the efficiencies of individual plants varied in substantial different degrees with the increases of window lengths under three scale groups, and therefore, the levels of maximum and minimum efficiencies appeared in different years for different window lengths and plant sizes.

Effect of the plant size on the WWTPs' efficiencies

The plant size was an important contributor to the WWTPs' efficiencies according to our empirical results. As observed by the Tobit model, the impact of the plant size on the WWTPs' efficiencies passed the significance test. Meanwhile, both the DEA window and the Tobit regression analysis concluded that WWTPs with larger scale had lower efficiencies. However, the influencing directions of the plant scale on the efficiencies and the efficiency variations were completely opposite. Among NTTP, HTP, and ABTP, the greater the scale was, the lower the efficiencies and the larger the efficiency variations were, respectively. This implied that large WWTPs performed less efficiently than the small ones did.

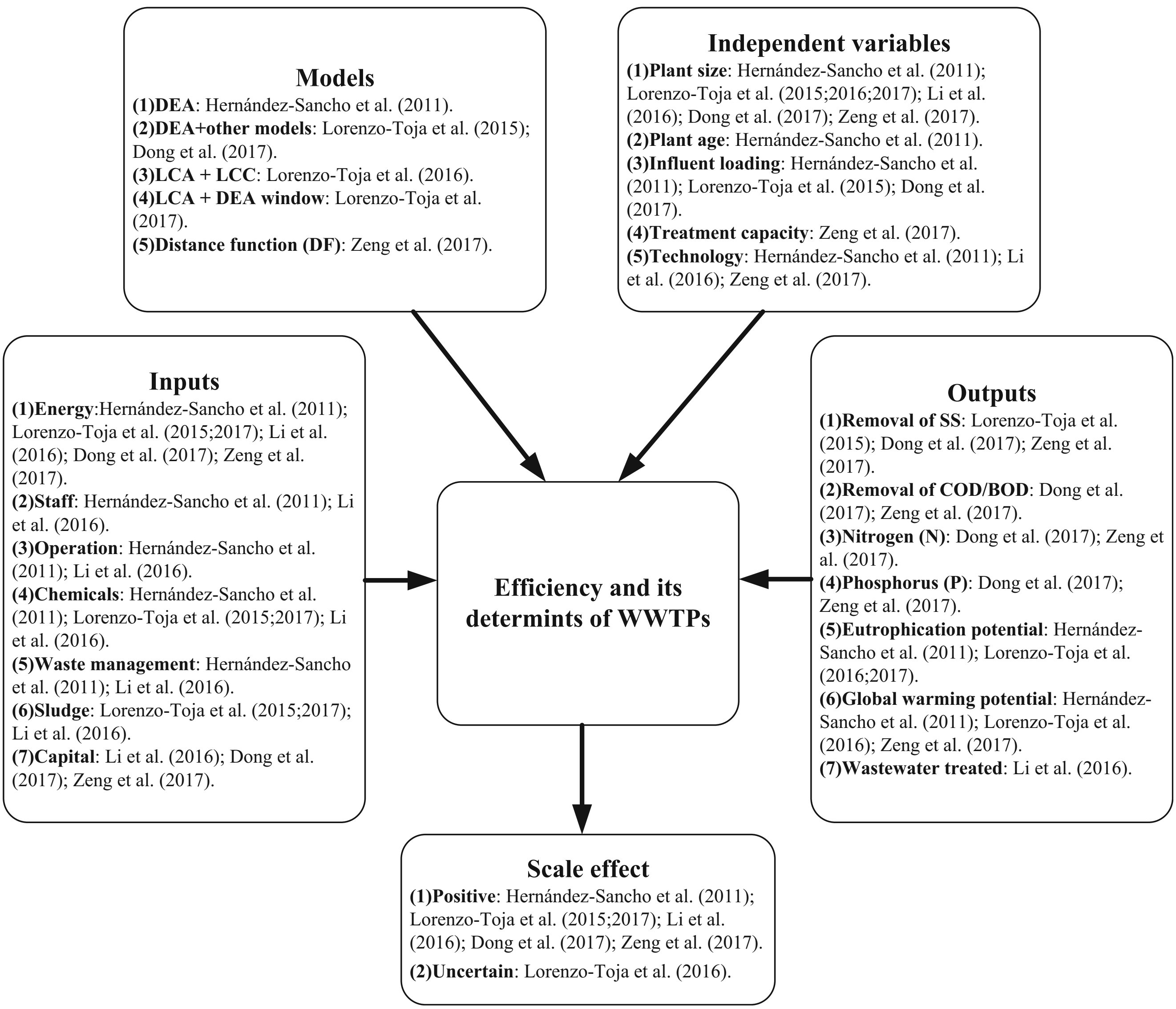

Fig. 2 Research summaries regarding the plant size effects on WWTP efficiencies. LCC refers to life cycle costing

Figure 2 summarizes studies regarding the scale effects on the WWTPs' efficiencies. Most of previous studies pointed out that the facility size had a positive effect on the efficiency (Hernández-Sancho et al. 2011; Lorenzo-Toja et al. 2015, 2017). For example, Dong et al. (2017) and Zeng et al. (2017) believed that large-scale facilities had higher environmental efficiencies. However, these were totally different with what we observed in this study. What is the root cause? The potential reason could be explored by examining deep into the features of WWTPs evaluated in these studies, which reported that the high efficiency obtained in large-scale facilities was usually attributed to the relatively advanced wastewater treatment technologies employed (Li et al. 2017a; Longo et al. 2016). In other words, these plants enjoyed, at least in part, the benefits of the efficiency improvement resulted from the advanced treatment technologies (Laitinen et al. 2017; Panepinto et al. 2016). However, this was not the case in this study where similar conventional activated sludge treatment technologies were adopted in four WWTPs. It could be certainly taken away of the possibility of the wastewater treatment processes for the controversy observation. In fact, it was speculated that the excessive increase of the input costs such as utilities, chemical, staff, and operation (Fig. 3 and Fig. 4, detailed discussion in section "The composition of inputs and cost-saving considerations") in the large-scale WWTPs contributed to the decrease of the efficiencies. In addition, it was argued that the scale effect turned out to be uncertain (Lorenzo-Toja et al. 2016). According to the authors, in terms of operation costs, the small and large WWTPs performed much better than the medium ones. Hence, there was no certain correlation between the economic cost and the plant size. In conclusion, it was necessary to explore further the scale effect under the control of other factors including technological influence.

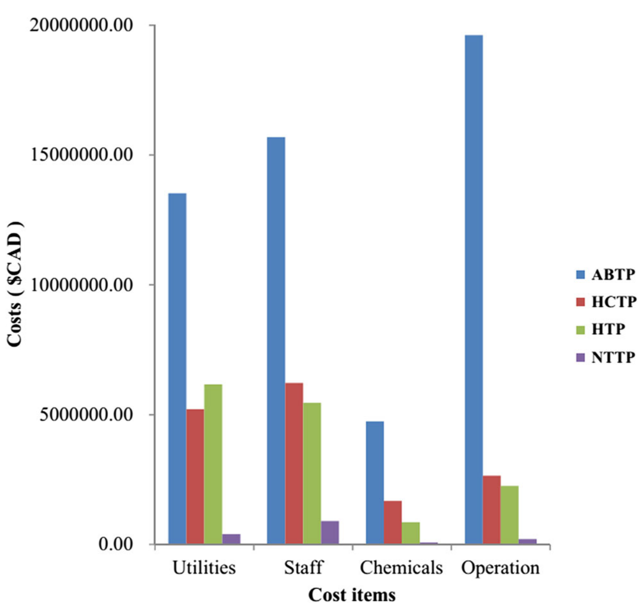

Fig. 3 The comparison on 10-year average costs in inputs among four WWTPs

It is worth noting that the ranking for HCTP was an exception when the efficiency was taken into consideration. Based on our empirical results, with similar scales (*PE*), HCTP presented lower efficiencies (0.84, 0.54, 0.35 under $l = 1$, $l = 5$, $l = 10$, respectively) than HTP did (1.00, 0.90, 0.72 under $l = 1$, $l = 5$, $l = 10$, respectively), because the inputs far exceeded the outputs in HCTP. In 2016 as an example (Table S2), with the similar other inputs such as utilities, staff, HCTP had 1.25-fold higher of chemical consumption and 3.2-fold higher operating costs than HTP did, respectively, whereas the removal rates of pollutants at HCTP in 2016 were far less (230.20, 235.30, and 4.80 for *SS*, $cBOD_5$, and *TP*, respectively) than those at HTP (298.00, 293.30, and 5.10 for *SS*, $cBOD_5$, and *TP*, respectively).

The composition of inputs and cost-saving considerations

It is well known that the input variables are strong driving forces affecting the plant efficiency and its techno-economic viability. Figure 3 describes the differences on average in the four specific input cost items investigated when the outputs were at similar levels in four plants. Obviously, for four types of inputs, ABTP occupied the top positions among four plants, while NTTP held the smallest part in each cost item. Meanwhile, HCTP was higher in three kinds of costs except for the utilities compared to HTP, indicating that the ranking of cost inputs was negatively correlated with the order of the efficiency. Therefore, the cost control might be a useful method to improve the WWTPs' performance.

When analyzing the cost structure of each WWTP during 2007–2016 (Fig. 4), the authors found that chemical expenditure took the least proportions in the total costs of four plants. That was related to the conventional secondary treatment technologies applied. Moreover, it should be noted that the staff salaries were an important contributor for all four plants, which were 29.20% for ABTP, 39.50% for HCTP, 37.14% for HTP, and 57.25% for NTTP, respectively. This suggested that the application of automatic control systems throughout the entire treatment process should be considered to improve the performance of WWTPs and economic operation (Guerrero et al. 2011).

Limitations

DEA is regarded as an efficient method in evaluating the performance of DMUs without strict requirements on the data and hypotheses on model parameters. Therefore, DEA

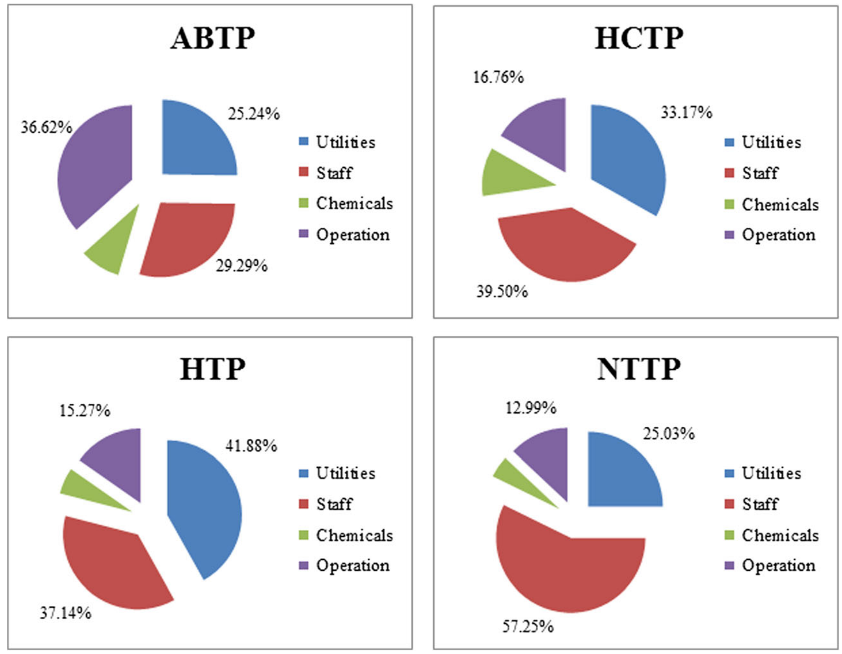

Fig. 4 The comparison on the inputs' composition among four WWTPs throughout the period of 2007–2016

window analysis is suitable for the efficiency assessment with limited data of WWTPs. This guarantees the rationality of the methods applied in this study. However, four Toronto WWTPs studied had similar treatment technologies, climatic features, economic development, and other conditions, and only ten operation years between 2007 and 2016 were considered. This might limit the interpretation and application of the observations obtained here to some extent.

With regard to the cost savings, different cost items should be cut down for individual plants. However, the potentials of cost-cutting for each facility were not estimated, because when inefficient units reduced some cost items, some other characteristics of these units would also change together. Moreover, considering the fact that the plants evaluated in this study applied relatively inefficient treatment technologies throughout the study period, it might be more important to upgrade the technological system in addition to the control of high cost items.

Conclusions

Relying on the flexible data processing and robust results, the DEA window method proved suitable for assessing the cost efficiency of WWTPs. By using the cost items of utilities, staff, chemicals, and operation as input variables, and the removal rates of influent SS, $cBOD_5$, and TP as output variables, dynamic efficiencies of four WWTPs during 2007–2016 were estimated under three window lengths of $l = 1, l = 5$, and $l = 10$. The empirical results showed that the selection of window lengths did not affect the ranking of WWTPs' efficiency. However, the efficiencies for both individuals and the whole sample decreased with the increase of window length. Under the assumption of technical similarity, plants with larger size tended to perform poorly. In addition, Tobit regression analysis showed that three variables including the PE, influent TP, and influent flow rate were found to affect the efficiency at different degrees and in different directions. With the control of other factors such as the technology, operation cost, personnel or utilities significantly contributed to large potentials of the cost savings and efficiency improvement.

Despite the reliability and rationality of the results produced by the models of DEA window and Tobit regression, there were still some limitations on the application of the findings obtained from this study. Therefore, it is strongly suggested that more attention should be paid to integrated effects of the plant size and the treatment technology on the WWTPs' efficiencies, as well as on to the distribution features of the efficiency embodied in different groups of wastewater treatment facilities.

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Appendix

Appendix Table 6 list of abbreviations/nomenclature

abbreviations/nomenclature	full name/connotation	abbreviations/ nomenclature	full name/connotation
ABTP	Ashbridges Bay treatment plant	ISS	SS concentration in influent
ANN	artificial neural network	ITP	total phosphorus in influent
ANOVA	analysis of variance	l	window length
BCC	Banker-Charnes-Cooper	LCA	life cycle assessment
$cBOD_5$	five-day carbonaceous biological oxygen demand	LCC	life cycle costing
DEA	data envelopment analysis	NTTP	North Toronto treatment plant
DMUs	decision-making units	PE	population equivalent
Eff_{it}	efficiency of WWTP i in the period t	PMS	performance measurement system
ENEI	eutrophication net environmental indicator	SS	suspended solid
HCTP	Highland Creek treatment plant	TP	total phosphorus
HTP	Humber treatment plant	VRS	variable returns to scale
$IcBOD_5$	$cBOD_5$ concentration in influent	WAS	waste activated sludge
I_{flow}	average daily influent flow rate	WWTP	wastewater treatment plant

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