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A comprehensive assessment of energy efficiency of wastewater treatment plants: An efficiency analysis tree approach

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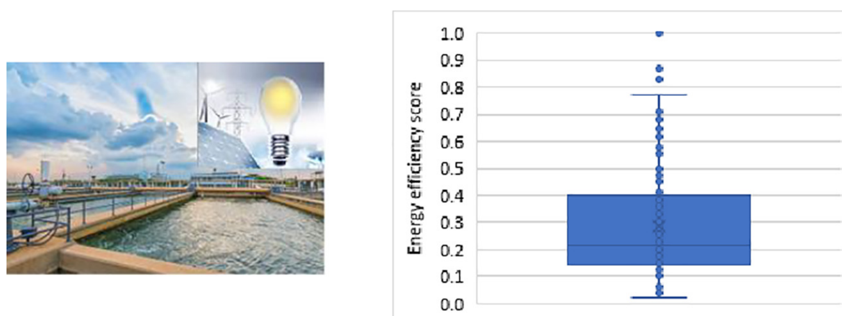
HIGHLIGHTS

- Efficiency analysis tree was used to evaluate the energy efficiency of wastewater treatment.
- The average energy efficiency of evaluated wastewater treatment plants is 0.287.
- Energy efficiency is influenced by the age and technology of the facility.

GRAPHICAL ABSTRACT



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ABSTRACT

Wastewater treatment plants (WWTPs) are energy intensive facilities. Controlling energy use in WWTPs could bring substantial benefits to people and environment. Understanding how energy efficient the wastewater treatment process is and what drives efficiency would allow treating wastewater in a more sustainable way. In this study, we employed the efficiency analysis trees approach, that combines machine learning and linear programming techniques, to estimate energy efficiency of wastewater treatment process. The findings indicated that considerable energy inefficiency among WWTPs in Chile existed. The mean energy efficiency was 0.287 suggesting that energy use should cut reduce by 71.3 % to treat the same volume of wastewater. This was equivalent to a reduction in energy use by 0.40 kWh/m^3 on average. Moreover, only 4 out of 203 assessed WWTPs (1.97 %) were identified as energy efficient. It was also found that the age of treatment plant and type of secondary technology played an important role in explaining energy efficiency variations among WWTPs.

1. Introduction

Evaluating the sustainability of urban water services has become a relevant issue during the last twenty years (Molinos-Senante et al., 2016). Sustainability is usually associated with the triple bottom line framework, i.e., social, economic and environmental dimensions (Marques et al., 2015). However, after the Paris Agreement adopted at 21st Conference of the Parties to the United Nations Framework Convention on Climate Change (COP21), energy and greenhouse gas emissions related issues have acquired special attention. In this context, reducing the carbon footprint of urban water utilities would contribute to meet the objectives of the Paris Agreement in the medium-term.

Wastewater needs to be treated at high standards before it is discharged back to the environment or its reuse (Feng et al., 2022). On average, high-

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income countries treat about 70 % of the wastewater they generate whereas in upper-middle and lower-middle income countries this ratio drops to 38 % and 28 %, respectively (UNESCO, 2017). Untreated wastewater will lead to a deterioration on the ecological status of water bodies such as rivers and lakes (Miller et al., 2013; Ganguly and Dewan, 2020). Hence, in the coming years, the number of wastewater treatment plants (WWTPs) will increase to achieve the targets defined by the Sustainable Development Goals (Goal 6) (United Nations, 2015).

An importance resource, from an economic and environmental perspective, for the operation of WWTPs is energy. Previous studies estimated that the treatment of wastewater requires up to 4 % of electric energy in United States and 0.70 % of electricity consumption in China (Longo et al., 2016, 2020; Niu et al., 2019). In Europe, energy use for treating wastewater could explain for >1 % of consumption (Walker et al., 2021). The energy intensity of wastewater treatment process pushes up companies' production costs. Previous studies concluded that energy costs account for >60 % of water companies' operating expenditure (Gu et al., 2017). Moreover, energy use leads to the generation of greenhouse gas emissions (GHG) which could have a negative impact on people and environment (Wang et al., 2018; An et al., 2018; Cardoso et al., 2021). Thus, the transition towards a sustainable and carbon efficient wastewater treatment process is of great interest to policy makers. The above challenges and objectives give rise to the measurement of the energy performance of WWTPs and the need to get a better understanding on what drives energy efficiency when treating wastewater (Venkatesh et al., 2014; Torregrossa et al., 2018; Molinos-Senante and Maziotis, 2022).

Based on the traditional definition of efficiency, which (in an input-oriented case) measures the ability of a decision-making unit (DMU) to produce the same level of outputs using less inputs (Coelli et al., 2005), in the framework of WWTPs, energy efficiency is defined as a synthetic index that integrates the volume of wastewater treated, the amount of pollutants removed and the energy required to treat wastewater (Hernández-Sancho et al., 2011). Hence, energy efficiency is a metric for benchmarking energy performances of WWTPs (Longo et al., 2016). This approach differs from the energy intensity concept defined as the energy consumed per unit volume of wastewater treated (kWh/m^3) which ignores the main function of a WWTP, e.g., removing pollutants from wastewater (Castellet-Viciano et al., 2018).

From a methodological point of view, there are two main techniques to measure efficiency of DMUs, i.e., parametric (econometric) and non-parametric (linear programming). Both approaches compare inputs and outputs of DMUs and derive relative efficiency measures. Data envelopment analysis (DEA), a non-parametric approach, can be used to evaluate the energy efficiency of WWTPs (Cardoso et al., 2021) because of its ability to integrate multiple inputs and outputs in a single composite indicator (Guerrini et al., 2016). DEA relies on the construction of the efficient production frontier using observed data on inputs and outputs of the units evaluated, i.e., efficiency is not estimated econometrically (Yadav et al., 2022). DEA builds a piecewise and linear frontier and assumes that deviations of DMUs from the frontier are due to inefficiency only.

Past research evaluating the energy efficiency of WWTPs is limited and focused on the use of DEA method. Hernández-Sancho et al. (2011) and Hernández-Chover et al. (2018) used a non-radial DEA model, to estimate energy efficiency of a sample of Spanish WWTPs. Guerrini et al. (2017) applied a double bootstrap DEA model to assess the energy efficiency of Italian WWTPs. The objective of the paper by Molinos-Senante (2018) was to compare the energy efficiency among wastewater treatment technologies using a metafrontier DEA model. Longo et al. (2016) used the DEA-CCR (Charnes, Cooper and Rhodes) and DEA-BCC (Banker, Charnes and Cooper) models to assess the energy efficiency of WWTPs from different countries. The same DEA models were used by Yang and Chen (2021) to estimate the energy efficiency of Chinese WWTPs. Longo et al. (2018) proposed a robust energy efficiency DEA to estimate bias-corrected EE scores of WWTPs.

Despite the positive features of DEA to estimate energy efficiency of WWTPs, it is a deterministic approach which means that it is sensitive to outliers. Moreover, it suffers from overfitting suggesting that efficiency estimates may not be accurate (Esteve et al., 2020). This is because technical inefficiency score for each unit is estimated as the deviation of each activity or production plan from the frontier of the production possibility set. The WWTPs´ energy efficiency estimations by Molinos-Senante and Maziotis (2022) might suffer from overfitting problem as well because they used stochastic parametric envelopment of data (StoNED) method which is a combination of DEA and stochastic frontier analysis approaches. To deal with overfitting issues in efficiency estimation and improving the robustness of the results, Esteve et al. (2020) developed a newly technique, called efficiency analysis trees (EAT) which brings together machine learning and linear programming techniques. EAT overcomes the overfitting problem by applying a pruning procedure based upon cross-validation. It allows determining efficiency evaluation out-of-sample for the assessed units (WWTPs) and therefore, estimating the optimal levels of energy use for WWTPs. Esteve et al. (2020) demonstrated that the EAT method outperforms against other non-parametric techniques. Therefore, it provides reliable efficiency scores being appropriate for benchmarking analysis and policy decision making.

Against this background, the main objective of this study is to provide a comprehensive assessment of the energetic performance of a sample of WWTPs based on the EAT method. This approach allows quantifying the optimal level of energy that could be used to treat wastewater based on different pollutants quality-adjusted volume thresholds. Because energy efficiency is estimated at WWTP level, potential energy savings if WWTPs were efficient are also quantified. Finally, we investigate the influence of the age and secondary treatment technology on the energy efficiency of WWTPs.

Our study extends the current strand of literature as follows. To the best of our knowledge, this is the first time that an approach that combines both machine learning and linear programming techniques is used to measure energy performance of wastewater treatment process. The use of EAT method to estimate energy efficiency scores of WWTPs overcomes the limitations of DEA approach previously used by the literature. Moreover, for the first time, the optimal level of energy use of WWTPs is estimated. This information is very relevant for the water regulator and water companies to define targets that could progressively be met. This novel piece of work was applied to a sample of Chilean WWTPs.

2. Methodology

In this section we present the methodology used to assess the energetic performance of several WWTPs. It is based on three stages. The first and second stages are related to the application of the EAT method whereas the third stage focuses on identifying factors influencing the previously estimated energy efficiency scores. In the first stage, the EAT approach uses regression (decision) trees to derive the predicted value of the response variable (i.e., energy use in this case study). This value is derived after separating the whole sample into several non-overlapping regions based on a set of rules (thresholds) of the predictor variables (i.e., volume of wastewater treated to remove several pollutants in this case study) (Rebai et al., 2019) (see Fig. 1). The EAT approach incorporates the concept of free disposability (Esteve et al., 2021) and therefore, the predicted value of the response variable is not the average value but the optimal (or maximum) one, which in our study allows us to estimate the optimal use of energy by WWTPs.

In the second stage, production frontiers and energy efficiency scores are estimated using linear programming techniques. The estimated production frontier takes the shape of a step function (Esteve et al., 2020) (Fig. 2). In the third stage, bootstrap truncated regression techniques are applied to statistically identify characteristics of the WWTPs influencing their energy efficiency.

Let's assume that there is a vector of predictor variables defined as $x_1, \ldots, x_m$ with $x_i \in R^m$. This set of variables is employed to predict a vector of response variables defined as $y, \ldots, y_n$ with $y_i \in R^n$. The EAT method splits the observations into two nodes, t_R and t_L by selecting a predictor variable j and a threshold $s_j \in S_j$ where S_j captures the set of likely

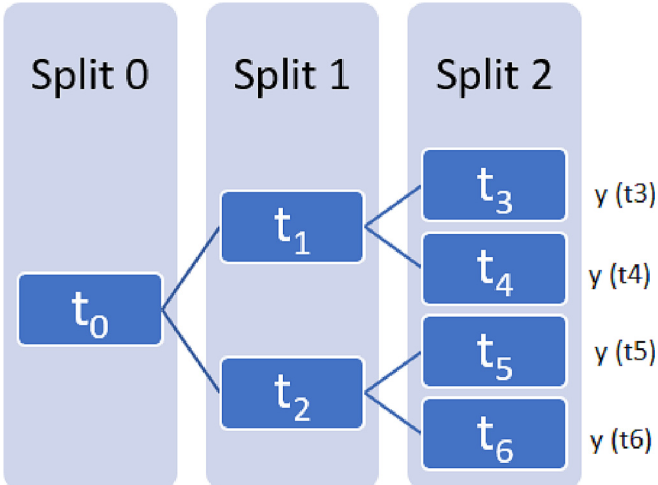

Fig. 1. Example of a regression tree.

thresholds for the variable j to split the data into (Esteve et al., 2022). The separation of the observations into several regions based on thresholds from the response variables is done by minimizing the sum of the mean squared of error. Its mathematical form is as follows:

$$R(t_L) + R(t_R) = \frac{1}{n}\Sigma_{(x_i,y_i)\in t_L}(y_i - y(t_L))^2 + \frac{1}{n}\Sigma_{(x_i,y_i)\in t_R}(y_i - y(t_R))^2 \quad (1)$$

In Eq. (1) t is the node of the regression tree; $R(t_L)$ and $R(t_R)$ are the mean squared error of left node and right of the tree, i.e., t_L and t_R, respectively; n is the size of the sample and $y(t_L)$ and $y(t_R)$ are the predicted values of the response variable that are estimated on the left and right node of the tree, respectively. The regression tree can be visualized in Fig. 1.

The predicted values of the response variable in the left and right node of the regression tree are derived from the following equations:

$$y(t_L) = max\left\{ max\{y_i : (x_i, y_i) \in t_L\}, y\left(I_{T(k|t^* \to t_L, t_R)}(t_L)\right)\right\} \quad (2a)$$

$$y(t_R) = max\left\{ max\{y_i : (x_i, y_i) \in t_R\}, y\left(I_{T(k|t^* \to t_L, t_R)}(t_R)\right)\right\} \quad (2b)$$

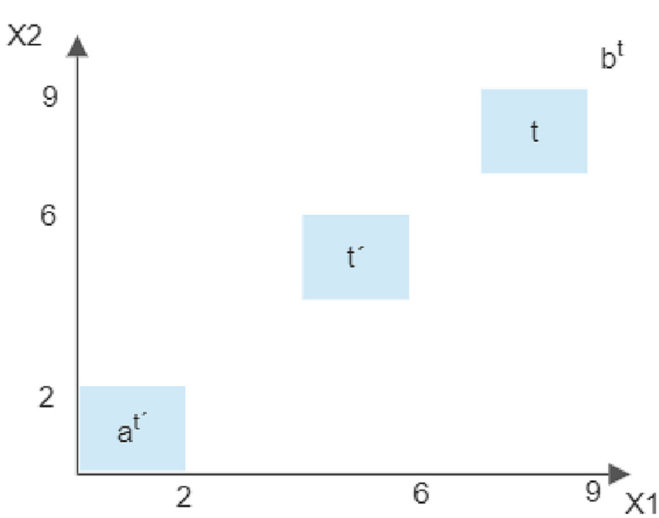

Fig. 2. Pareto-dominance nodes.

where T denotes the sub-tree that is formed utilizing the EAT technique and the number of splits is shown by k. Moreover, $y\left(I_{T(k|t^* \to t_L, t_R)}(t_L)\right)$ and $y\left(I_{T(k|t^* \to t_L, t_R)}(t_R)\right)$ show the set of leaf nodes of the tree created after achieving the k-th split that Pareto dominates node t_L and t_R (Esteve et al., 2020, 2021, 2022). The concept of Pareto dominance is illustrated in the Fig. 2 where a case of two inputs, x_1 and x_2 is considered. In Fig. 2 node t′ Pareto-dominates node t because $a^{t'} = (2,2) < b = (9,9)$ where a and b present points of nodes t' and t, respectively. Node t' "is preferable to" node t because it employs less inputs than node t (Esteve et al., 2020).

As part of the second stage of the methodology applied, the production frontier that the EAT approach estimates is presented by the following equation:

$$\widehat{PT_{T_k}} = \left\{(x, y) \in R_+^{m+1} : y \le d_{T_k}(x)\right\} \quad (3)$$

where $d_{T_k}(x)$ is the predictor estimator regarding the sub-tree T_k.

The energy efficiency score for each unit assessed (i.e., WWTP) is measured by solving the following linear programming:

$$\begin{aligned}
&\varphi(x_k, y_k) = \min \varphi \\
&s.t. \\
&\Sigma_{t \in \tilde{T}^*}\lambda_t a_j^t \le \varphi x_{jk}, j = 1, \ldots, m \\
&\Sigma_{t \in \tilde{T}^*}\lambda_t d_{rT^*}^t(a^t) \ge y_{jk}, r = 1, \ldots, p \\
&\Sigma_{t \in \tilde{T}^*}\lambda_t = 1 \\
&\lambda_t \in \{0, 1\}, i = 1, \ldots, n
\end{aligned} \quad (4)$$

In Eq. (4) φ denotes the energy efficiency score, $(a^t, d_{T^*}(a^t))$ are input-outputs points for all $t \in T^*$ where * is the final sub-tree, and λ are intensity variables that are used to estimate the production frontier (Esteve et al., 2020). It is noted that the energy efficiency score can take any value between zero and one. A WWTP that has an energy efficiency score equal to one ($\varphi = 1.0$) means that it is 100 % energy efficient. A WWTP that obtains an energy efficiency score less than one ($\varphi < 1.0$), means that it is energy inefficient and can reduce energy use to become more efficient. We quantify the potential energy savings using the following equation:

$$Energy_s = Energy_c * (1 - \varphi) \quad (5)$$

where $Energy_s$ denotes the potential savings in energy use if the WWTP was energy efficient and; $Energy_c$ is the actual level of energy use for each WWTP evaluated.

The third step of our analysis is to get a better insight of what could drive energy efficiency of WWTPs. In doing so, we regress the energy efficiency score of each WWTP assessed using the EAT approach (φ) against a set of structural characteristics of the facilities. Since the energy efficiency score takes a value between zero and one, we employ truncated regression. In particular, we utilize bootstrap truncated regression techniques developed by Simar and Wilson (2007). The regression model takes the following form:

$$\varphi_i = \delta_0 + \delta_i \mu_i' + \varepsilon_i \quad (6)$$

where φ_i is the energy efficiency score; δ_0 is the constant term; μ_i' is the set of structural characteristics of each WWTP i assessed, and δ_i are parameters that the regression model estimates. Finally, ε_i is the error (noise) term which follows the standard normal distribution (Simar and Wilson, 2007).

3. Case study description

The identification of outliers and/or atypical observations becomes fundamental in non-parametric methods (De Witte and Marques, 2010a). A peer index approach[1] (De Witte and Marques, 2010b) was applied to the original database, which embraces 238 WWTPs, to identify atypical

[1] Other methods for identifying outliers are leverage, super-efficiency and order-m (De Witte and Marques, 2010b).

observations. As a result, 35 WWTPs were removed from the database leading to a total of 203 WWTPs whose energy efficiency was evaluated. The 203 WWTPs operate in Chile and use five different secondary treatment technologies: i) conventional activated sludge (CAS) (n = 79); ii) extended aeration (EA) (n = 43); iii) aerated lagoon (AL) (n = 16); iv) trickling filter (TF) (n = 20); and v) rotating biological contactor or biodisk (BD) (n = 45). All WWTPs are operated by private water companies because the Chilean water industry was almost full privatized between 1998 and 2004 (Molinos-Senante, 2018). Nevertheless, the Chilean urban water regulator, i.e., the "Superintendencia de Servicios Sanitarios" (SISS), is in charge of monitoring the quality of the wastewater (effluent) before it is safely charged to the environment. The data used in this study come from the regulator and is for 2017.

Choosing the input and output variables is the most important stage in efficiency assessment as the results are highly influenced by this choice (De Witte and Marques, 2010b). Because we are interested in assessing the energetics of WWTPs, the input (or response variable in this study) variable was the electricity consumed by each WWTP expressed in kWh/year (Rodríguez-García et al., 2011; Bodik and Kubaska, 2013; Longo et al., 2016; Molinos-Senante, 2018). It involves all electricity used to treat wastewater regardless if it is from renewable or non-renewable sources. Unfortunately, this information is not publicly available and therefore, any environmental impact analysis about electricity used by WWTPs could not be conducted. According to Wakeel et al. (2016) and Longo et al. (2019), the largest amount of energy consumed in WWTPs is in form of electricity.

The main objective of the WWTPs is to remove pollutants from wastewater to meet effluent discharge thresholds defined by the regulation (Dong et al., 2017). Based on previous research (Hernández-Sancho et al., 2011; Gómez et al., 2017; Hernández-Chover et al., 2018; Longo et al., 2018; Huang et al., 2021), pollutant quality-adjusted outputs, estimated according to Eq. (7), were used as outputs (or predictor variables in this study) in the energy assessment of WWTPs.

$$Quality\ adjusted\ output_p = Volume_{ww} \times \left(\frac{C_{pin} - C_{pef}}{C_{pin}}\right) \tag{7}$$

where $Volume_{ww}$ presents the volume of wastewater treated measured in cubic meters per year. C_{pin} is the concentration of pollutant p in the influent and C_{pef} is the concentration of pollutant p in the effluent. Hence, the volume of wastewater treated by each WWTP was modified to consider the efficiency in removal of each pollutant p. Our case study takes into account three pollutants: i) biochemical oxygen demand (BOD); ii) suspended solids (SS) and iii) phosphorus (P). Therefore, we used three quality-adjusted outputs to assess the energetic performance of WWTPs.

Finally, to explore the impact of structural characteristics on the energetic performance of WWTPs, we considered the following variables in our analysis: i) the age of treatment facility measured in total number of years; ii) the type of treatment technology, a categorical variable that considers the available secondary treatment technologies. Table 1 reports the descriptive statistics of the variables used in the case study.

4. Results and discussion

4.1. Optimal level of energy use in wastewater treatment plants

To estimate the level of energy use in WWTPs based on pollutant quality-adjusted volume of wastewater treated, the EAT algorithm was solved (Fig. 3). Within the three quality-adjusted outputs based on the pollutants removed from wastewater (BOD, SS and P), it is evidenced that P quality-adjusted output determines the maximum level of energy use in WWTPs. This is because, as it is shown in Table 1, P is the pollutant whose removal efficiency varies more among the WWTPs evaluated. By contrast, the standard deviation of BOD and SS quality adjusted outputs is more bounded which means that the performance of the WWTPs evaluated in the removal of these pollutants is more homogenous than for P pollutant.

Fig. 3 shows that for those WWTPs whose P quality-adjusted output is more 2,267,961 m^3/year of wastewater, the maximum energy consumption is 6,711,383 kWh/year which involves that the maximum energy consumption is 2.95 kWh per cubic meter of wastewater treated adjusted by P efficiency removal. When P quality-adjusted output is between 35,624 and 2,267,961 m^3/year, then the maximum level of energy use could be at 915,708 kWh/year. If the WWTP annually treats <35,624 m^3 of P quality-adjusted volume of wastewater, then energy consumption could reach the level of 213,620 kWh/year. Overall, the results demonstrated that wastewater treatment is energy intensive. As a result, we need to further understand how efficient the energy performance of wastewater treatment process is.

4.2. Energy efficiency assessment of wastewater treatment plants

The statistics of the energy efficiency scores estimated for the 203 WWTPs evaluated are reported in Fig. 4. It is shown that, on average the energy efficiency of WWTPs was 0.287 which means that the evaluated facilities could cut down energy use by 71.3 % to treat the same level of wastewater to remove pollutants. It reveals that the energetic performance of wastewater treatment process is poor. This figure is lower than the average energy efficiency scores estimated by past research. For Spanish WWTPs, Hernández-Sancho et al. (2011) and Hernández-Chover et al. (2018) found an average energy efficiency of 0.310 and 0.460, respectively. For Chilean WWTPs, Molinos-Senante (2018) estimated an average energy efficiency score of 0.511. A similar average energy efficiency (0.458) was reported by Guerrini et al. (2017) for a sample of Italian WWTPs. Finally, Longo et al. (2018) found average energy efficiency scores between 0.12 and 0.40 for a large sample of WWTPs from different European countries. It should be noted that these previous studies used DEA methods to estimate energy efficiency scores which has some limitations, whereas our study estimated energy efficiency scores using the EAT approach. Hence, differences in results among studies might be due to methodological approached used for energy efficiency estimations.

According to our estimations, only 4 out of 203 WWTPs, i.e., 1.97 % of the sample, are energy efficient (Table 2). These four facilities are identified as the best performers in terms of energy use. Two of them, i.e., WWTP66

Table 1
Descriptive statistics of the variables used to estimate energy efficiency scores of wastewater treatment plants.

Variables	Unit of measurement	Mean	Std. Dev.	Minimum	Maximum
Electricity consumption	kWh/year	337,563	855,810	443	6,711,383
Wastewater volumes BOD removed	m^3/year	667,766	1,657,445	461	13,078,100
Wastewater volumes SS removed	m^3/year	649,010	1,620,520	445	13,182,505
Wastewater volumes P removed	m^3/year	472,332	1,300,256	9	11,927,636
Removal efficiency BOD	%	90.58	9.66	28.86	98.93
Removal efficiency SS	%	88.33	10.81	23.5	99.80
Removal efficiency P	%	56.63	19.62	1.16	96.06
Age of facility	Years	19	6	5	40
Type of treatment technology (CAS = 1, EA = 2, AL = 3, TF = 4, BD = 5)	Categorical	3	2	1	5

Observations: 203.

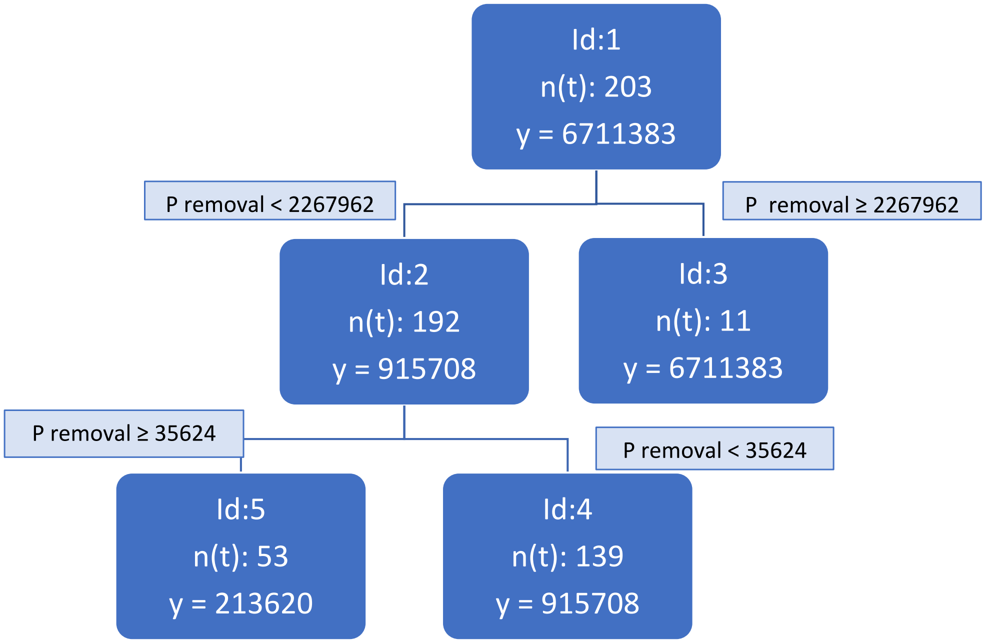

Fig. 3. Efficiency analysis tree (EAT) for estimating use of energy in wastewater treatment plants, where: P removal denotes phosphorous (P) quality adjusted output (Eq. (7)) in m^3/year; Id is the node; n(t) is the number of observations and *y* is the maximum energy use in kWh/year.

and WWTP96, were of bigger size compared to the other ones as shown by the high levels of pollutants removed and energy use. These WWTPs are relatively old plants with a construction age of 27 and 24 years old and use CAS and EA technology, respectively. The other two fully energy efficient facilities are relatively newly built with a life that does not exceed the 15 years and use TF and BD technologies to treat lower levels of wastewater. This finding evidences that WWTPs with different characteristics, i.e., age and technology could be energy efficient.

The rest of WWTPs within the top 10 of facilities showed an energy efficiency score which ranged between 0.70 and 0.870. The type of treatment technology used among this group of facilities varied but there is representation of all technologies considered in this study. Hence, the type of secondary treatment used to treat wastewater is not a technical limitation to achieve relatively good energy efficiency.

As far as the worst performers are concerned, it is found that the average energy efficiency score ranged between 0.020 and 0.070 (Table 2). This indicates that this group of facilities needs to make considerable savings in the energy use to catch-up with the most energy efficient ones. The majority of worst performers are old WWTPs with an average construction age of 19.6 years. This group of WWTPs is characterized by using CAS, EA and AL technologies to treat wastewater. By contrast, none of the bottom 10 energy efficiency WWTPs uses TF and BD as secondary treatment. More details about the impact of technology and age on the energetic performance of WWTPs are reported in Section 4.3.

In order to further analyze the variability in the energetic performance of the 203 WWTPs assessed, Fig. 5 shows the distribution of the estimated energy efficiency scores among WWTPs. It is shown that the majority of the WWTPs are inefficient from an energy perspective. In particular, 99 out of

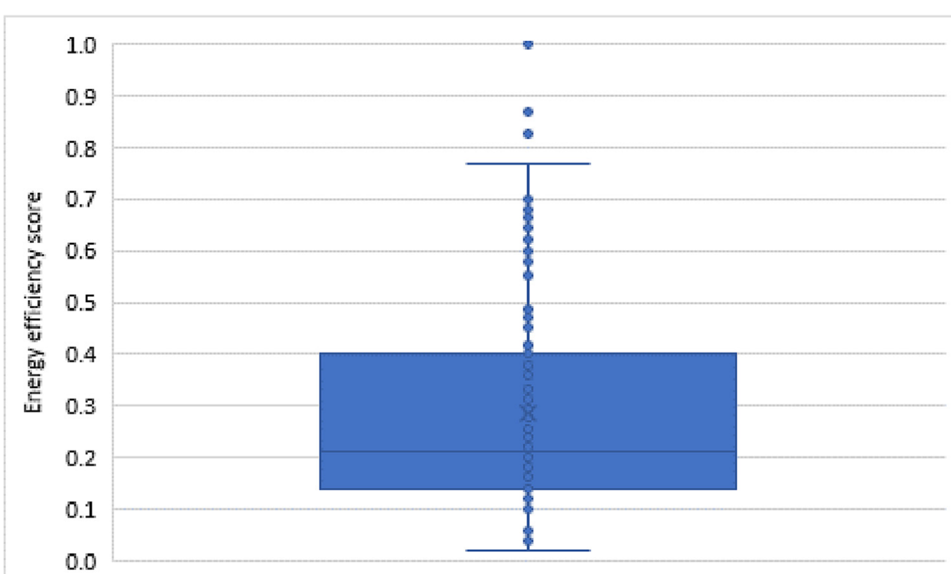

Fig. 4. Statistics of the energy efficiency estimations for assessed WWTPs.

Table 2
Top 10 and bottom 10 energy efficient WWTPs.

WWTP identification		Energy efficiency score	Energy saving potential (kWh/year)	Actual energy (kWh/year)	BOD quality-adjusted volume	SS quality-adjusted volume	P quality-adjusted volume	Age	Technology
Top 10 energy efficient units	WWTP66	1.000	0	869,880	44,051	45,313	35,624	27	CAS
	WWTP96	1.000	0	1,340,569	2,567,717	2,535,503	2,267,962	24	EA
	WWTP158	1.000	0	1097	461	445	393	15	TF
	WWTP194	1.000	0	1572	5234	5235	9	9	BD
	WWTP157	0.870	923	7103	5299	5240	3874	18	TF
	WWTP120	0.827	639,915	3,698,930	5,802,318	5,430,766	2,741,136	15	EA
	WWTP197	0.770	2011	8744	6014	5841	5052	10	BD
	WWTP111	0.710	126,692	436,869	677,122	642,038	503,489	23	EA
	WWTP71	0.700	25,092	83,639	72,041	61,653	63,742	14	CAS
	WWTP123	0.700	241	803	69,089	90,586	91,665	11	AL
Bottom 10 energy efficient units	WWTP23	0.070	38,957	41,889	65,065	62,060	38,491	17	CAS
	WWTP133	0.069	417,554	448,500	651,829	494,116	517,640	31	AL
	WWTP13	0.064	216,439	231,238	675,648	692,818	559,040	12	CAS
	WWTP119	0.061	420,877	448,218	676,596	641,377	581,390	23	EA
	WWTP80	0.058	280,471	297,740	675,544	677,261	612,112	12	EA
	WWTP129	0.058	584,746	620,749	1,490,316	1,538,891	618,420	22	AL
	WWTP7	0.045	254,330	266,314	1,078,200	1,084,140	785,366	16	CAS
	WWTP10	0.042	676,293	705,943	1,421,667	1,419,844	858,325	19	CAS
	WWTP105	0.039	510,772	531,500	953,003	942,167	912,534	22	EA
	WWTP102	0.020	747,810	763,071	2,486,964	2,370,157	1,822,024	22	EA

203 WWTPs (48.8 %) were found to have an energy efficiency score which varied between 0 and 0.20. This means that on average these facilities need to cut down energy use by >80 %. Additionally, there were 64 facilities (31.5 %) with an energy efficiency score which ranged between 0.21 and 0.40. Therefore, the energy saving potential among these WWTPs could range between 60 % and 80 %. Only 40 out of 203 facilities, i.e., 19.7 % of the sample, present an energy efficiency score larger than 0.41. Overall, the findings demonstrate that considerable energy inefficiency exists in the wastewater treatment process among the assessed facilities.

The estimated energy efficiency involves that the assessed WWTPs could save energy to produce the same quality-adjusted outputs, i.e., to treat the same volume of wastewater with the same pollutants' removal efficiency. Based on the energy efficiency scores for the 203 WWTPs and their current energy use, potential energy saving was estimated to be 42,465,302 kWh/year which is equivalent to an average of 0.40 kWh/m^3. Fig. 6 reveals that potential energy savings are heterogenous among the evaluated WWTPs. The median value is 0.32 kWh/m^3 whereas the 25th and 75th percentiles are 0.19 kWh/m^3 and 0.53 kWh/m^3, respectively. The extreme values correspond to those WWTPs with the lowest energy efficiency scores.

Controlling energy use could have positive benefits for people and environment. First, by reducing energy use in the operation of WWTPs, water companies could reduce operating costs which could be further passed on to customers in terms of lower bills. The average electricity price of Chile in 2017 was 65.05 €/MWh (CNE (Nacional Energy Commission), 2020). Hence, based on the volume of wastewater treated by the assessed WWTPs, they could save around 2,762,368 €/year if they were energy efficient. It is equivalent to 0.026 €/m^3 of wastewater treated. Second, energy savings may lead to a considerable reduction in GHG emissions. The use of renewable energy in treating sewage could lead to lower emissions released in the atmosphere. Based on the electrical production mix of Chile in 2017, the GHG emission factor was 449.73 KgCO2eq/MWh (ME (Chilean Ministry of Energy), 2022). If the WWTPs evaluated were energy efficient, they could save 19,098 tons CO_2eq/year. According to the World Bank (2022) database, the average annual carbon emission per capita in Chile in 2017 was 4.7 tons of CO_2eq. Hence, if the WWTPs assessed were energy efficient,

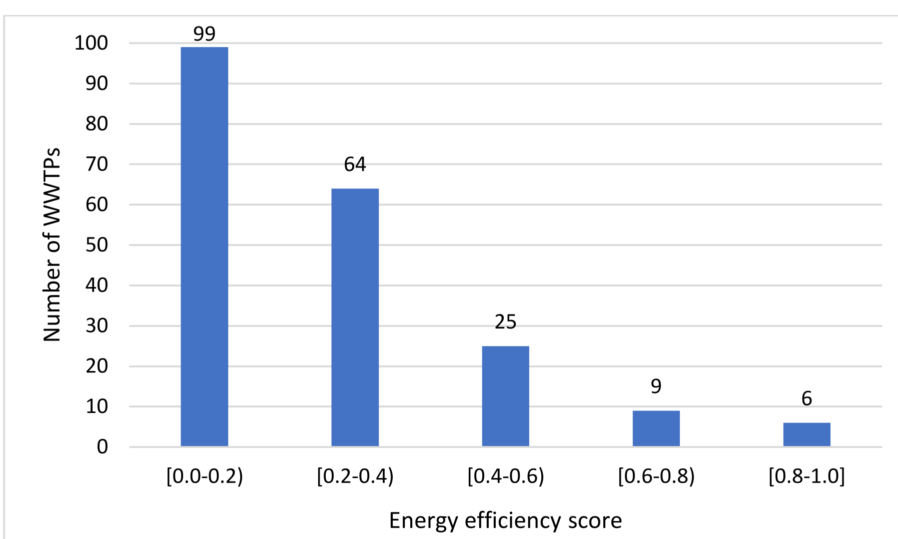

Fig. 5. Energy efficiency scores of WWTPs evaluated.

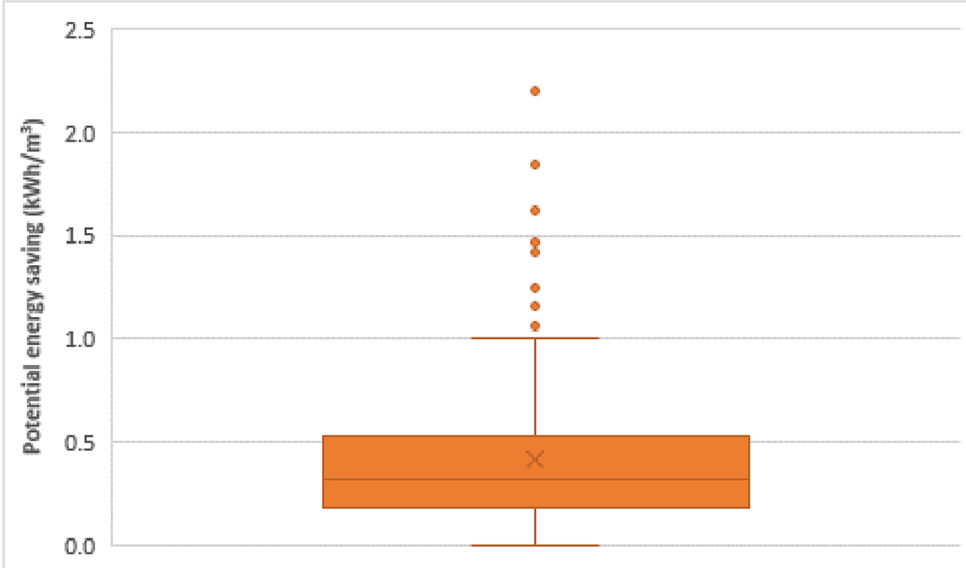

Fig. 6. Statistics of the potential energy savings for assessed WWTPs.

potential savings in GHG emissions would be equivalent to the annual GHG emitted by 4063 Chilean people.

4.3. Factors influencing energy efficiency

In order to get a better understanding on what drives the energy efficiency of wastewater treatment process we need to look at the results reported in Table 3. The regression findings demonstrate that the age of the WWTPs and the type of secondary treatment technology had an important part in explaining energy efficiency variations across facilities. The age of treatment plant had a negative sign and was statistically significant. This means that the older the WWTP is, the lower its energy efficiency could be. The result indicates that an increase in the age of treatment plant by one year could lead to a reduction in its energy efficiency by 0.101 % on average. This might be explained by the fact that older facilities present less energy efficient pumps and aeration systems in the biological process. It should be noted that aeration accounts for the largest fraction of WWTPs´ energy costs, ranging from 45 % to 75 % of total operational costs (Longo et al., 2016). Evidence on the influence of the age of WWTPs on energy efficiency is inconclusive. On the one hand, Hernández-Sancho et al. (2011); Molinos-Senante et al. (2014) and Guerrini et al. (2017) found that energy efficiency of WWTPs was not affected by the age of the facilities. By contrast, Molinos-Senante and Maziotis (2022) concluded the opposite because they found that WWTPs younger than 10 years old presented the largest energy efficiency scores.

Fig. 7 shows the distribution of energy efficiency scores based on the age of WWTPs. The results indicate that the older facilities are less energy efficient than new ones. In particular, WWTPs that have a life of 1 to 10 years showed an average energy efficiency score of 0.339. In contrast, facilities that have a life of >10 years showed an average energy efficiency score of 0.263. Overall, the results suggest that the recently built WWTPs can be more energy efficient than older ones. However, on average the evaluated facilities are characterized by high levels of energy inefficiency. Hence, there is room for considerable improvement in energy performance for newly and older built plants.

Looking at the type of secondary treatment technology, Table 3 shows that in the regression analysis, this variable had a positive sign and was statistically significant. This means that on average the WWTPs that operated based on EA, AL, TF, and BD technologies were found to be more energy efficient than those facilities using CAS technology. Whereas CAS technology has been widely adopted worldwide to treat domestic wastewater, it is now being recognized as lacking economic and environmental sustainability, especially with respect to the inefficient use of energy (Sheik et al., 2014; Garrido-Baserba et al., 2018). This conclusion was also evidenced by past studies (Molinos-Senante, 2018; Molinos-Senante and Maziotis, 2022) who focused on comparing the energy efficiency of WWTPs using different secondary treatment technologies.

We next discuss the relationship between energy efficiency, energy savings potential and the type of technology used. This is shown in Table 4. The results highlight that plants that use CAS technology are less energy efficient than the ones that use other types of treatment technologies. There were 79 plants that use CAS technology and reported an average energy efficiency score of 0.228. This means that these facilities could become more energy efficient by reducing energy use by 77.2 % on average. The potential savings in energy use could be 0.494 kWh/m^3 on average. By contrast, it was found that facilities who used EA and TF treatment technologies reported higher levels of energy efficiency scores. The average energy efficiency for plants that use EA and TF technologies were 0.346 and 0.364, respectively. Although their energy performance was better than the plants that use CAS technology, the potential savings in energy use are substantial. It is estimated that energy potential savings could reach the level of 0.434 kWh/m^3 and 0.296 kWh/m^3 when facilities use EA and TF technologies, respectively. It should be noted that WWTPs using BD technology are those with the lowest potential to save energy (0.270 kWh/m^3) although they are not the most energy efficient. This is because, currently, this type of facilities is using less energy than the others based on CAS, EA, AL and TF technologies.

Overall, the results indicate that energy performance of WWTPs is influenced by its age and the secondary treatment technology it uses. Older facilities are less energy efficient than newly built ones. Plants that use

Table 3
Factors influencing the energy efficiency of WWTPs. Estimates of bootstrap truncated regression.

Variables	Coeff	Std. error	z-stat	p-value
Constant	3.310	0.121	**27.355**	0.000
Age of facility	−0.101	0.041	**−2.463**	0.013
Type of technology	0.121	0.031	**3.903**	0.000
sigma	0.251	0.056	**4.482**	0.000
X^2 (3)	**71.54**			
p-value	0.000			

Observations: 203.
Bold statistics are statistically significant at 5 % significance level.

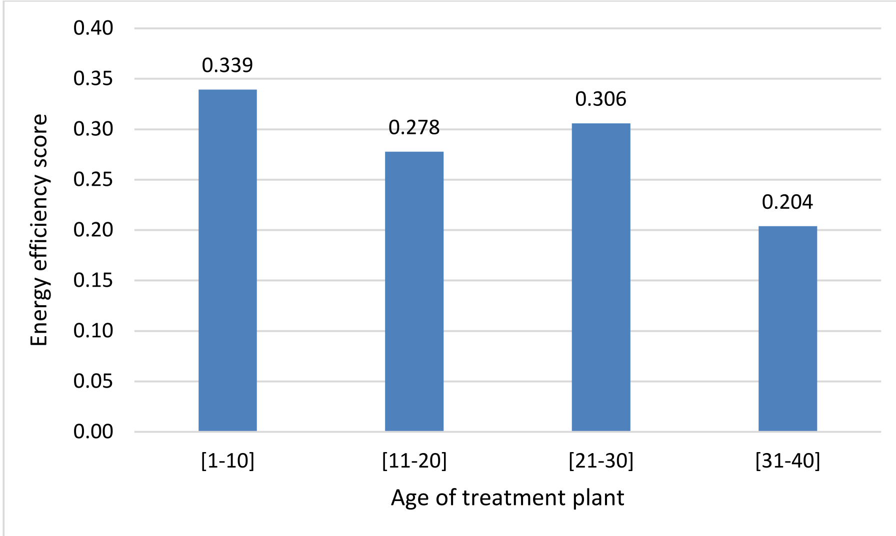

Fig. 7. Average energy efficiency according to groups of wastewater treatment plants by age.

CAS technology may require high levels of energy use and thus could be less energy efficient than those using other types of secondary treatment technologies.

Past research (e.g., Carvalho et al., 2012; Hernández-Chover et al., 2018; Cardoso et al., 2021) has evaluated the presence of economies of scale in the performance of water and wastewater utilities leading to mixed results. To better understand the influence of the volume of wastewater treated, i.e., economies of scale, on the energy efficiency of WWTPs, Fig. 8 shows the estimated energy efficiency score of each facility evaluated against its volume of wastewater treated. No direct relationship among both variables was evidenced. The Pearson correlation coefficient between energy efficiency score and volume of wastewater treated was 0.156 which means that both variables are not related. Moreover, Fig. 8 shows that the largest facility treating 13,596,615 m^3 of wastewater per year presents an energy efficiency score of 0.19. Hence, potential diseconomies of scale are identified for this (and other) evaluated WWTPs.

The 203 assessed WWTPs were categorized in three groups: i) WWTPs treating <100,000 m^3/year; ii) WWTPs treating between 100,000 and 500,000 m^3/year and; iii) WWTPs treating >500,000 m^3/year (Hernández-Sancho et al., 2011).[2] The average energy efficiency for each group of facilities was 0.312, 0.259 and 0.303, respectively. A Kruskal-Wallis test was conducted to verify whether the differences between energy efficiency scores are statistically significant (Hernández-Chover et al., 2018). The p-value was larger than 0.05 which means that differences in average energy efficiency among groups of WWTPs are not statistically significant.

5. Conclusions

The removal of pollutants from wastewater to avoid environmental damage is an energy intensive process. Control of energy use could have a positive influence for people and environment. Understanding the optimal use of energy during the operation of WWTPs and what drives energy requirements is of great interest to policy makers and water companies´ managers. A relevant tool of energy use improvements in WWTPs is benchmarking its energy efficiency. In doing so, reliable and robust methodological approaches should be used. Hence, in this study, for the first time, the efficiency analysis tree (EAT) method was employed to comprehensively evaluate the energy efficiency of a sample of WWTPs. EAT brings together machine learning and linear programming techniques overcoming the limitations of DEA method, which is the most common method used in the literature to assess energy efficiency of WWTPs.

The main findings of this study are as follows. First, it is found that the efficiency in the removal of P significantly influences the use of energy by WWTPs. Second, only 4 out of 203 assessed WWTPs (1.97 %) were energy efficient whereas the other facilities present room to save energy. The average energy efficiency was 0.287 meaning that on average WWTPs should cut down energy use by 71.3 % to treat the same volume of wastewater. This is equivalent to a reduction in energy use by 0.40 kWh/m^3. Third, it has been demonstrated that the age of the facility and the secondary treatment technology used to treat wastewater significantly influence on the energy efficiency of the WWTPs. Facilities using CAS were identified as the less energy efficient evidencing the lack of economic and environmental sustainability of this technology.

This research provides scientific guidance for benchmarking the energy efficiency of WWTPs and therefore, for the efficient operation of the wastewater treatment industry that can benefit people and the environment. This study evidences the poor energy efficiency of the WWTPs assessed and therefore, reveals the need to develop policies and implement actions by water regulators and water companies to improve the energy efficiency of WWTPs. In particular, WWTPs could reduce energy consumption and increase energy efficiency by adopting several measures such as: i) optimization of processes by installing smart meters and developing control systems for the optimal operation of pumps and aeration systems and; ii) recovery of the energy from wastewater such as heat or electricity from sewage sludge. This energy could contribute to the reduction in the overall energy requirements of the facility. Given the economic and

Table 4
Energy efficiency scores and energy potential saving of the assessed WWTPs by type of technology.

Technology	Energy efficiency scores (indicator)				Potential energy savings (kWh/m^3)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
CAS	0.228	0.147	0.042	1.000	0.494	0.359	0.000	1.841
EA	0.346	0.230	0.020	1.000	0.434	0.404	0.000	2.200
AL	0.278	0.180	0.058	0.700	0.465	0.277	0.002	0.790
TF	0.364	0.240	0.100	1.000	0.296	0.204	0.000	0.663
BD	0.302	0.203	0.100	1.000	0.270	0.200	0.000	1.060

[2] WWTPs were categorized based on alternative volume of wastewater treated without finding p-values lower than 0.05 in any case.

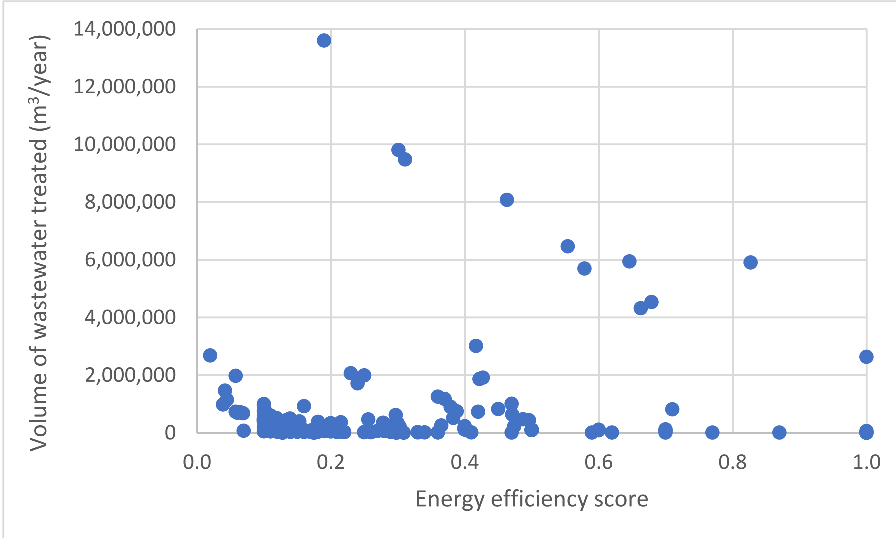

Fig. 8. Energy efficiency score of each WWTP and volume of wastewater treated.

environmental relevance of the use of energy issues, enhancing the energy efficiency of WWTPs should be a priority for regulators. In this context, water regulators should define obligatory actions for water companies to reduce their carbon footprint such as periodically conducting energetic audits, treating sewage sludge through anaerobic digestion to produce biogas when the WWTP is larger than a predefined size, economically incentivize the use of renewable energy, etc. Moreover, water companies should also be transparent regarding the energy used for treating wastewater through the use of carbon footprint labels which could be shared with customers via water bills and in the webpage of the water regulator.

Although this study provided a novel methodological approach to benchmark the energetic performance of WWTPs, it is not exempt of limitations with respect to exogenous variables which might influence estimated energy efficiency scores. Firstly, the variable age considered in this study corresponds to the year in which each WWTP started to operate. Therefore, it does not consider potential upgrades made to them since this year. Second, the response variable "electricity used" integrates all electricity used in the WWTP. Therefore, it embraces electricity used to treat wastewater and sewage sludge. Because different technologies could be used in WWTPs to treat sewage sludge, achieving different treated sewage in terms of quality might also influence energy efficiency of WWTPs. Finally, there are other potential exogenous variables such as load factor, dilution factor and wastewater temperature that might influence energy efficiency of WWTPs. Due to the lack of public available information, these variables were not included in the energy efficiency assessment conducted in this study. In other words, the main limitation of this study is related to the lack of available data. Additional information on exogenous variables influencing energy efficiency of WWTPs must be considered to get a better understanding on the energetic performance of WWTPs and support individual WWTP energy efficiency optimization.

CRediT authorship contribution statement

Alexandros Maziotis: Conceptualization; Writing-Original Draft; Supervision.
Ramón Sala-Garrido: Formal analysis; Methodology.
Manuel Mocholi-Arce: Methodology; Validation.
María Molinos-Senante: Conceptualization; Writing-Original, Supervision.

Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

An, M., He, W., Degefu, D.M., Liao, Z., Zhang, Z., Yuan, L., 2018. Spatial patterns of urban wastewater discharge and treatment plants efficiency in China. Int. J. Environ. Res. Public Health 15, 1892.
Bodik, I., Kubaska, M., 2013. Energy and sustainability of operation of a wastewater treatment plant. Environ. Prot. Eng. 39 (2), 15–24.
Cardoso, B.J., Rodrigues, E., Gaspar, A.R., Gomes, Á., 2021. Energy performance factors in wastewater treatment plants: a review. J. Clean. Prod. 322, 129107.
Carvalho, P., Marques, R.C., Berg, S., 2012. A meta-regression analysis of benchmarking studies on water utilities market structure. Util. Policy 21, 40–49.
Castellet-Viciano, L., Hernández-Chover, V., Hernández-Sancho, F., 2018. Modelling the energy costs of the wastewater treatment process: the influence of the aging factor. Sci. Total Environ. 625, 363–372.
CNE (Nacional Energy Commission), 2020. Annual energy statistics report. Available at: https://www.cne.cl/wp-content/uploads/2021/12/AnuarioCNE2020.pdf.
Coelli, T.J., Rao, D.S.Prasada, O'Donnell, C.J., Battese, G.E., 2005. An Introduction to Efficiency and Productivity Analysis. Kluwer Academic Publishers, Boston.
De Witte, K., Marques, R.C., 2010a. Influential observations in frontier models, a robust non-oriented approach to the water sector. Ann. Oper. Res. 181 (1), 377–392.
De Witte, K., Marques, R.C., 2010b. Designing performance incentives, an international benchmark study in the water sector. CEJOR 18 (2), 189–220.
Dong, X., Zhang, X., Zeng, S., 2017. Measuring and explaining eco-efficiencies of wastewater treatment plants in China: an uncertainty analysis perspective. Water Res. 112, 195–207.
Esteve, M., Aparicio, J., Rodriguez-Sala, J.J., Zhu, J., 2022. Random forests and the measurement of super efficiency in the context of free disposal Hull. Eur. J. Oper. Res. 304 (2), 729–744.
Esteve, M., Aparicio, J., Rabasa, A., Rodriguez-Sala, J.J., 2020. Efficiency analysis trees: a new methodology for estimating production frontiers through decision trees. Expert Syst. Appl. 162, 113783.
Esteve, M., Rodriguez-Sala, J.J., Lopez-Espin, J.J., Aparicio, J., 2021. Heuristic and backtracking algorithms for improving the performance of efficiency analysis trees. IEEE Access 9, 17421–17428.
Feng, Z., Liu, X., Wang, L., Wang, Y., Yang, J., Wang, Y., Huan, Y., Liang, T., Yu, Q.J., 2022. Comprehensive efficiency evaluation of wastewater treatment plants in Northeast Qinghai-Tibet plateau using slack–based data envelopment analysis. Environ. Pollut. 311, 120008.
Ganguly, R., Dewan, H., 2020. Application of decision making tool to determine effluent quality index of existing sewage treatment plants. J. Inst. Eng. (India): Ser. A 101 (1), 207–219.

Garrido-Baserba, M., Vinardell, S., Molinos-Senante, M., Rosso, D., Poch, M., 2018. The economics of wastewater treatment decentralization: a techno-economic evaluation. Environ. Sci. Technol. 52 (15), 8965–8976.

Gómez, T., Gémar, G., Molinos-Senante, M., Sala-Garrido, R., Caballero, R., 2017. Assessing the efficiency of wastewater treatment plants: a double-bootstrap approach. J. Clean. Prod. 164, 315–324.

Gu, Y., Li, Y., Li, X., Wu, J., Li, F., 2017. The feasibility and challenges of energy self-sufficient wastewater treatment plants. Appl. Energy 204, 1463–1475.

Guerrini, A., Romano, G., Indipendenza, A., 2017. Energy efficiency drivers in wastewater treatment plants: a double bootstrap DEA analysis. Sustainability (Switzerland) 9 (7), 1126.

Guerrini, A., Romano, G., Mancuso, F., Carosi, L., 2016. Identifying the performance drivers of wastewater treatment plants through conditional order-m efficiency analysis. Util. Policy 42, 20–31.

Hernández-Chover, V., Bellver-Domingo, Á., Hernández-Sancho, F., 2018. Efficiency of wastewater treatment facilities: the influence of scale economies. J. Environ. Manag. 228, 77–84.

Hernández-Sancho, F., Molinos-Senante, M., Sala-Garrido, R., 2011. Energy efficiency in spanish wastewater treatment plants: a non-radial DEA approach. Sci. Total Environ. 409 (14), 2693–2699.

Huang, R., Shen, Z., Wang, H., Zheng, H., Liu, R., 2021. Evaluating the energy efficiency of wastewater treatment plants in the Yangtze River Delta: perspectives on regional discrepancies. Appl. Energy 297, 117087.

Longo, S., d'Antoni, B.M., Bongards, M., Chaparro, A., Cronrath, A., Fatone, F., Lema, J.M., Mauricio-Iglesias, M., Soares, A., Hospido, A., 2016. Monitoring and diagnosis of energy consumption in wastewater treatment plants. A state of the art and proposals for improvement. Appl. Energy 179, 1251–1268.

Longo, S., Hospido, A., Lema, J.M., Mauricio-Iglesias, M., 2018. A systematic methodology for the robust quantification of energy efficiency at wastewater treatment plants featuring data envelopment analysis. Water Res. 141, 317–328.

Longo, S., Mauricio-Iglesias, M., Soares, A., Stefani, L., Hospido, A., 2019. ENERWATER – a standard method for assessing and improving the energy efficiency of wastewater treatment plants. Appl. Energy 242, 897–910.

Marques, R.C., da Cruz, N.F., Pires, J., 2015. Measuring the sustainability of urban water services. Environ. Sci. Pol. 54, 142–151.

ME (Chilean Ministry of Energy), 2022. Greenhouse gas emissions factors in Chile. Available at https://energia.gob.cl/indicadores-ambientales-factor-de-emisiones-gei-del-sistema-electrico-nacional.

Miller, L.A., Ramaswami, A., Ranjan, R., 2013. Contribution of water and wastewater infrastructures to urban energy metabolism and greenhouse gas emissions in cities in India. J. Environ. Eng. (United States) 139 (5), 738–745.

Molinos-Senante, M., 2018. Comparative energy efficiency of wastewater treatment technologies: a synthetic index approach. Clean Techn. Environ. Policy 20 (8), 1819–1834.

Molinos-Senante, M., Hernández-Sancho, F., Mocholí-Arce, M., Sala-Garrido, R., 2014. Economic and environmental performance of wastewater treatment plants: potential reductions in greenhouse gases emissions. Resour. Energy Econ. 38, 125–140.

Molinos-Senante, M., Marques, R.C., Pérez, F., Gomez, T., Sala-Garrido, R., Caballero, R., 2016. Assessing the sustainability of water companies: a synthetic indicator approach. Ecol. Indic. 61, 577–587.

Molinos-Senante, M., Maziotis, A., 2022. Evaluation of energy efficiency of wastewater treatment plants: the influence of the technology and aging factors. Appl. Energy 310, 118535.

Niu, K., Wu, J., Qi, L., Niu, Q., 2019. Energy intensity of wastewater treatment plants and influencing factors in China. Sci. Total Environ. 670, 961–970.

Rebai, S., Yahia, F.B., Essid, H., 2019. A graphically based machine learning approach to predict secondary schools performance in Tunisia. Socio Econ. Plan. Sci. 70, 100724.

Rodríguez-García, R., Molinos-Senante, M., Hospido, A., Hernandez-Sancho, F., Moreira, M.T., Feijoo, G., 2011. Environmental and economic profile of six typologies of wastewater treatment plants. Water Res. 45, 5997–6010.

Sheik, A.R., Muller, E.E.L., Wilmes, P., 2014. A hundred years of activated sludge: time for a rethink. Front. Microbiol. 5 (MAR), 47.

Simar, L., Wilson, P.W., 2007. Estimation and inference in two-stage, semiparametric models of production processes. J. Econ. 136 (1), 31–64.

Torregrossa, D., Leopold, U., Hernandez-Sancho, F., Hansen, J., 2018. Machine learning for energy cost modelling in wastewater treatment plants. J. Environ. Manag. 223, 1061–1067.

UNESCO, 2017. The United Nations world water development report 2017. Wastewater the untapped resource report. Available at https://unesdoc.unesco.org/ark:/48223/pf0000247552.

United Nations, 2015. Sustainable development goals. Available at: https://sdgs.un.org/es/goals.

Venkatesh, G., Chan, A., Brattebø, H., 2014. Understanding the water-energy-carbon nexus in urban water utilities: comparison of four city case studies and the relevant influencing factors. Energy 75, 153–166.

Wakeel, M., Chen, B., Hayat, T., Alsaedi, A., Ahmad, B., 2016. Energy consumption for water use cycles in different countries: a review. Appl. Energy 178, 868–885.

Walker, N.L., Williams, A.P., Styles, D., 2021. Pitfalls in international benchmarking of energy intensity across wastewater treatment utilities. J. Environ. Manag. 300, 113613.

Wang, D., Guo, F., Wu, Y., Li, Z., Wu, G., 2018. Technical, economic and environmental assessment of coagulation/filtration tertiary treatment processes in full-scale wastewater treatment plants. J. Clean. Prod. 170, 1185–1194.

World Bank, 2022. Annual carbon emissions per capita. Available at: https://datos.bancomundial.org/indicador/en.atm.co2e.pc?locations=CL.

Yadav, D.V., Parmar, D., Ganguly, R., Shukla, S., 2022. Efficiency evaluation of sewage treatment plants in Delhi, India, using tolerance-based data envelope analysis. Environ. Monit. Assess. 194 (12), 867.

Yang, J., Chen, B., 2021. Energy efficiency evaluation of wastewater treatment plants (WWTPs) based on data envelopment analysis. Appl. Energy 289, 116680.