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Evaluation of energy performance of drinking water treatment plants: Use of energy intensity and energy efficiency metrics

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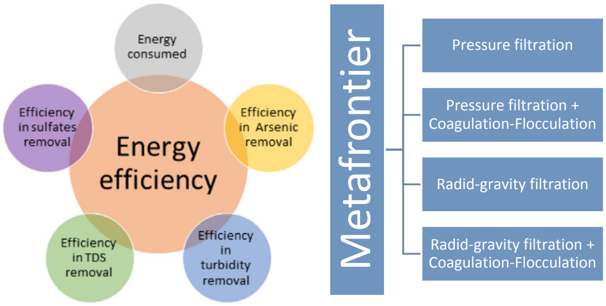
HIGHLIGHTS

- Energy efficiency metric is proposed to evaluate energy performance of drinking water treatment plants.
- Energy efficiency integrates in a synthetic index the energy consumed, the volume of water treated and its quality.
- Energy efficiency of four technologies for treating water is compared.
- Energy intensity and energy efficiency estimates lead to opposite results.

GRAPHICAL ABSTRACT



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ABSTRACT

One of the United Nations Sustainable Development Goals is to provide access to safe and clean drinking water. However, treating raw water in facilities currently involves using a non-negligible amount of energy, and the fossil fuels used are both expensive and emit greenhouse gases when combusted. Previous studies have evaluated the energy performance of drinking water treatment plants by estimating the amount of energy consumed per volume of water. However, such studies have not accounted for differences between treatment technologies and have assumed a common standard water treatment technology. To overcome these limitations, this study employed metafrontier data envelopment analysis to evaluate and compare the energy performance of four types of treatment technologies. This approach integrates energy intensity with pollutant removal efficiency into a single, synthetic index to deliver an energy-efficiency score. A comparison of the four treatment technologies showed that facilities using rapid-gravity filtration and coagulation-flocculation processes provided the highest energy efficiencies. However, energy intensity and energy efficiency metrics delivered contradictory results, which thus illustrates the importance of including pollutant removal efficiency data in performance assessments. This study provides valuable information for policy-makers when planning and developing new drinking water treatment plants and for water utility managers when identifying energy reduction opportunities in plants.

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Acronym list

CF	Coagulation-flocculation	DWTPs	Drinking water treatment plants
CRS	Constant returns-to scale	PF	Pressure filtering
DEA	Data Envelopment Analysis	QAOs	Quality-adjusted outputs
DMUs	Decision making units	RGF	Rapid-gravity filtering
		TGR	Technological gap ratio
		VRS	Variable returns-to scale

1. Introduction

Urban water supply utility plants use energy to extract, convey, treat, and distribute drinking water, and this produces a considerable amount of greenhouse gas emissions. In addition, energy costs currently account for up to 40% of the operating budget of a utility plant, and this percentage is expected to rise as water supplies become increasingly scarce and stricter water quality standards are imposed [1]. Chen et al. [2] reported that approximately 7% of the energy produced worldwide is currently used to enable the anthropogenic water cycle, which includes providing a drinking water supply and treating wastewater.

Dai et al. [3] conducted a literature review and determined an increase in the number of scientific and policy-related studies focusing on the topic of water-energy nexus. It is clear that future efforts will be required to adapt water systems to meeting the increasing demand for water, in addition to ensuring conformity with associated regulatory requirements and mitigating the effects of climate change, and such adaptations will impose additional economic, environmental, and social challenges to water utility companies. In this context, Parkinson et al. [4] proposed a multicriteria model to integrate several objectives when planning energy and water supply infrastructure.

One of the 17 Sustainable Development Goals adopted by the United Nations in 2015 (Goal 6) is to achieve universal and equitable access to safe and affordable drinking water for all by 2030 [5]. However, according to WHO-UNICEF [6], 844 million people still lack basic drinking water services, and 159 million people still collect drinking water directly from surface water resources. It will thus be necessary to construct many more water treatment facilities in the near future to achieve Goal 6, which will unquestionably increase the amount of energy required for drinking water supplies worldwide, and thus also increase greenhouse gas emissions.

Given the economic and environmental significance of using energy for treating and distributing water, a number of studies have focused on the amount of energy used by urban water systems in supplying drinking water to major cities. In this respect, the study of Gude et al. [7] focused on the benefits of reducing energy use in water and wastewater treatment systems, and reported a range of energy intensity values for water supply systems. In addition, a review by Sowby and Burian [8] focused on the energy requirements for supplying water to 109 cities in the United States. The study of Lee et al. [9] evaluated 25 urban water supply systems in 12 countries, in addition to estimating the energy intensities of urban water systems and their greenhouse gas emissions, and the study of Wakeel et al. [10] also focused on the same topic but evaluated the energy intensity of the urban water cycle at state and/or regional levels. These studies, therefore, focused on estimating the energy intensity of water supplies.

However, to supply reliable and high-quality drinking water, it is necessary to firstly treat raw water in drinking water treatment plants (DWTPs), and this process requires most of the energy used in the water supply chain. In this respect, energy studies relating to DWTPs have also been conducted. For example, Miller et al. [11] compared the energy intensities of several water treatment facilities located in India and the United States. As a previous step to conducting a life cycle assessment, Loubet et al. [12] reported notable differences in the energy usage between a sample of DWTPs. Recently, Lam et al. [13] compared the energy intensity involved in treating raw water in 17 cities, and analyzed influential factors such as climate, topography, water use patterns, and operational efficiencies.

These studies have compared energy use among DWTPs using "energy intensity" as an overarching metric to describe the energy required by a DWPT to treat water, where energy intensity is defined as the energy consumed (kWh) per unit volume (m^3) of drinking water processed (expressed in kWh/m^3) [9]. However, as the amount of energy consumed in processing (treating) water is determined not only by the specific treatment processes applied, but also by the quality of the raw water to be processed [14,15], using the energy intensity metric alone is inadequate when comparing the performances of DWTPs [8]. In other words, energy intensity does not reflect the quality of the raw water being processed, and raw water that has a poorer quality requires more energy per unit volume to meet mandated drinking water quality standards than raw water of a superior quality. Therefore, a broader concept than energy intensity is required: a concept that integrates pollutant removal efficiency rates with the energy required to process the water. We therefore propose the use of "energy efficiency" as a metric for comparing energy performances of DWTPs, which is defined as a synthetic index that incorporates both the quality of the raw water being processed and the energy required to treat it.

Prior studies estimating the energy efficiency of wastewater treatment plants [16–18] have consistently shown that the energy efficiency approach is reliable for benchmarking the energy performance and identifying potential energy-saving opportunities. However, only the study of Molinos-Senante and Guzmán [19] benchmarked energy performances to estimate energy efficiencies of DWTPs (n = 42 plants compared). This was achieved this by computing energy efficiency scores for each facility using a data envelopment analysis (DEA) method. DEA is a well-known, robust, reliable and widely applied method used to estimate efficiency scores for various types of decision-making units (DMUs) [20], and is a mathematical programming technique that allows users to build an efficient production frontier based on inputs (e.g. energy) and outputs (e.g. treated water) for DMUs (e.g. DWTPs) [21]. The recent study conducted by Molinos-Senante and Guzmán [19] is very useful for providing a real-world example of how the performances of DWTPs can be compared relative to their energy efficiencies. However, in their examples, the authors assumed that all treatment technologies used by DWTPs have equally efficient potentials. By ignoring variations in these potential efficiencies between treatment technologies, they also assumed that the type of treatment technology employed would not affect the energy efficiency, and thus, assumed that all DWTPs have the same efficiency production frontier [22]. As treatment technologies differ in their intensity of energy use, this implies that both their assumption and their direct cross-comparison of energy efficiencies across DWTPs are inappropriate.

To appropriately compare energy efficiencies among DWTPs that use different treatment technologies, we applied the metafrontier concept proposed by Hayami (1961). This approach has been used previously to evaluate and compare efficiencies of water utilities in various countries [22,23], among concessionary and private water companies [24] and as a component used in other assessments of urban water systems. The metafrontier approach subsumes all possible efficiency frontiers that may arise due to the technological heterogeneity of DWTPs; therefore, it enables the energy efficiencies of all DWTPs to be simultaneously benchmarked, even when they employ different raw water treatment technologies.

This study has two objectives and an ultimate aim of gaining an improved understanding of how to most-appropriately compare the performances of DWTPs. The first objective is to evaluate the energy performance of a large number of DWTPs (n = 146) using a synthetic index approach (energy efficiency scores). The index integrates the energy used in treating water and the volume of the raw water treated as an energy intensity metric (kWh/m^3) with other variables relative to the energy efficiency (such as pollutant-removal efficiency rates). The second objective is to compare energy efficiencies across four groups of DWTPs that employ different types of raw water treatment technologies. By applying the metafrontier concept, our study provides comparisons of performance relative to energy efficiency that are more accurate, reliable, and appropriate than those previous proposed.

This study contributes to current scientific literature relating to the water–energy nexus in two ways. First, the energy performance of DWTPs is compared using a synthetic indicator known as the energy efficiency index, which, unlike the energy intensity metric used in most previous studies, also explicitly integrates the quality of both raw and treated water. Hence, the methodology proposed in this study avoids biased energy efficiency comparisons that occur because of differences between plants in their pollutant removal efficiencies from raw water. Second, no studies to date have investigated the effect of different treatment technologies on the energy efficiency of DWTPs by integrating technological components when benchmarking energy efficiency. Hence, this study provides a novel approach to assessing and comparing the energy efficiencies of DWTPs in relation to the types of technologies employed.

2. Methods

Initial studies using the metafrontier approach applied both parametric and non-parametric methods to calculate a concave metafrontier, from which they then compared the efficiencies of DMUs using different technologies (e.g. [25,26]). This approach firstly involved conducting an estimation of the production frontier of each technology involved in the assessment, and a metafrontier was then obtained from all these production frontiers by pooling the data relating to technologies and repeating the procedure [27]. However, the resulting concave metafrontier thus encompassed infeasible input and output combinations for any of the compared technologies [28] (Fig. 1a). To solve this problem, Tiedemann et al. [29] proposed applying a non-concave metafrontier; this envelops only the input–output combinations that are part of a delineated technology set of at least one of the technologies. As shown in Fig. 1b, the use of a non-concave metafrontier approach avoids the problem of infeasible input–output combinations [23].

In this study, we applied the non-concave metafrontier approach to evaluate and compare the energy efficiencies of a population of DWTPs that employed a variety of water treatment technologies. The application of the approach required two steps. First, we estimated the energy efficiency scores for each DWTP based on the efficient production frontier technology to which it belongs. Second, we estimated the energy efficiency of each DWTP relative to the frontier of the alternative technologies. This step then enabled us to determine whether the energy-efficiency score for a DWTP would be lower if an alternative technology was used instead of the existing technology. If this was the case, it was determined that the energy consumption (input) of the assessed DWTP could be reduced by employing the alternative technology (under conditions where the magnitude of the pollutant removal efficiency (output) was constant).

Either parametric or non-parametric methods can be applied to estimate the energy efficiency of a DWTPs. Although both methods provide advantages and disadvantages, we used the non-parametric DEA method to estimate energy efficiency scores in this study and employed both technology production frontier and the metafrontier approaches. The DEA method provides several advantages over parametric approaches. First, unlike parametric methods, it does not require any prior assumptions about the function used to represent a production frontier. Second, the DEA evaluates the efficiency of DMUs relative to multiple inputs and outputs, and each is expressed in different measurement units [17]. Because of these advantages, the DEA has been used extensively to evaluate efficiencies in the water industry [30].

With respect to methods used by DEA models to combine inputs or obtain a set of outputs, they can either display constant returns-to-scale (CRS) [31] or variable returns-to-scale (VRS) [32]. CRS depicts conditions in which outputs increase in proportion to inputs and assumes that producers can linearly scale inputs and outputs without increasing or decreasing efficiency [33]. In contrast, a DEA model uses VRS if the outputs increase by larger or smaller percentages than the inputs. As previous studies have shown that energy consumed by DWTPs is not linearly affected by the pollutants removed from raw water [13,8,15], we used a DEA model in this study that incorporated a VRS approach. As the aim of treatment facilities is to produce an effluent (drinking water) that meets water quality standards while also minimizing energy consumption, we input the orientation of the DEA model to evaluate the energy efficiency of DWTPs.

To estimate an energy efficiency score for each DWTP relative to the metafrontier (EE) and group k (EE_k) technology, the following linear programming problem was solved for each DWTP assessed,

$$
\begin{aligned}
& Min\theta \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leqslant \theta x_{i0} \quad i = 1, \ldots m \\
& \sum_{j=1}^{n} \lambda_j y_{ij} \geqslant y_{r0} \quad r = 1, \ldots s \\
& \sum_{j=1}^{n} \lambda_j = 1 \\
& \lambda_j \geqslant 0 \quad j = 1, \ldots, n
\end{aligned}
\tag{1}
$$

where x_{ij} and y_{ij} are the quantity of inputs ($i = 1, \ldots, m$) and outputs ($r = 1, \ldots, s$) for each DWTP ($j = 1, \ldots, n$); x_{i0} and y_{r0} are the values (inputs and outputs) of the DWTP being evaluated; and λ_j is the weight of inputs and outputs for each DWTP ($j = 1, \ldots, n$). The objective function of the optimization problem in Eq. (1) involves minimizing inputs (energy use) for a given level of outputs produced. Thus, θ represents the energy efficiency score of a given DWTP, where $\theta \in (0, 1]$. A DWTP is energy efficient if (and only if) $\theta = 1$. If the energy efficiency score of a DWTP is lower than one ($\theta < 1$), then the DWTP has the potential to reduce energy use while also maintaining a constant pollutant-removal efficiency relative to other DWTPs being evaluated. Thus, the difference between an energy-efficiency score < 1.0 and unity represents the potential of a given DWTP to reduce the quantity of energy it consumes while still removing the same quantity of pollutants from raw water.

As shown in Fig. 1b, the non-concave metafrontier envelops k technology frontiers. This means that problems restricting various technologies are represented as constrained subsets of the metafrontier problem; therefore, the energy efficiency score for each technology

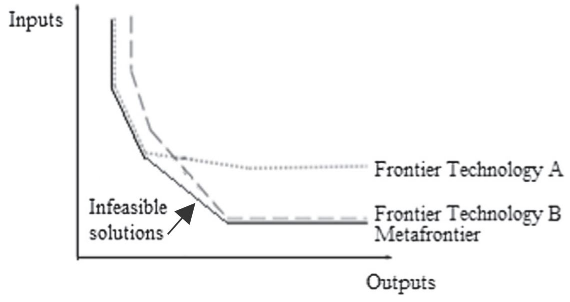

Fig. 1a. Concave metafrontier. Source: Own elaboration based on Tiedemann et al. [29].

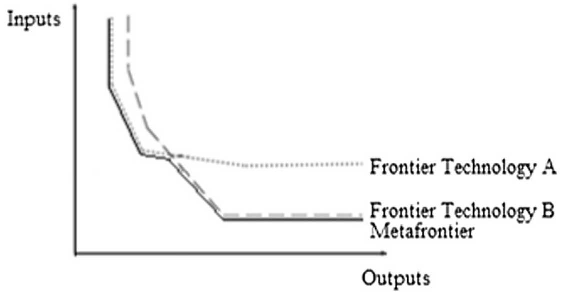

Fig. 1b. Non-concave metafrontier. Source: Own elaboration based on Tiedemann et al. [29].

(EE_k) cannot be smaller than the energy efficiency score with respect to the metafrontier (EE) [34]. A measure of the distance of the technology- k frontier to the metafrontier can be estimated when there is a strict inequality between the technology-k distance function to the metafrontier function [35]. In this context, Battese et al. [26] defined the technological gap ratio (TGR) for technology- k DMUs as follows,

$$TGR^k = \frac{EE}{EE^k}, \tag{2}$$

where the value of TGR^k is between zero and one. A TGR^k closer to unity (1.0) indicates that the minimum input (energy use) by the DWTPs belonging to technology k is closer to the metafrontier input value. When the values are very close, the technological gap between technology k and the metatechnology is also very small [36].

3. Sample description

Chile is a middle-income country in Latin America that has achieved almost universal access (99.9%) to drinking water in urban areas. This has been accomplished through the work of private water companies that are regulated and monitored by the Chilean national water regulator, namely the Superintendencia de Servicios Sanitarios [37]. Chile is a geographically and climatically diverse country, and the quality of raw water processed by the various DWTPs therefore varies considerably across the country [38]. In spite of these differences in raw water quality, the effluent of all DWTPs must meet drinking water quality standards imposed by the Chilean Ministry of Health (NCh 409), which are based on guidelines for drinking water quality published periodically by the World Health Organization [37]. Both water companies and water regulators monitor the quality of drinking water provided to its citizens.

We inventoried 169 DWTPs located across Chile to evaluate their relative energy efficiencies. Prior to assessing the data, we employed outlier analysis [39] to detect and exclude unusual data; 23 DWTPs were subsequently excluded from the sample and a total of 146 DWTPs remained for comparison. Following the methods of Molinos-Senante and Guzmán [19], energy used for groundwater pumping and drinking water transport was not included in our evaluations of DWTP energy efficiencies. The water treatment trains of the 146 DWTPs evaluated were not equal (they did not use a common technology to treat raw water), but they could be categorised into four basic groups with respect to the similar technologies employed (Table 1). The DWTPs evaluated used two different water-filtering technologies, namely pressure filtering (PF) and rapid-gravity filtering (RGF). Pressure filtering requires the application of pressure to force raw water through filters, whereas RGF operates at atmospheric pressure and relies on gravity to force water through filters. The other two (of the four) DWTP technologies were coagulation-flocculation (CF) processes, which are physical–chemical processes commonly used to reduce turbidity and remove arsenic (a common pollutant is some regions of Chile [40]) in raw water.

The selection of input and output variables was influenced by the sample size (i.e. number of DWTPs in each technological group) and the availability of data. To avoid bias problems in efficiency assessments when using the DEA method, we applied Cooper's Rule, which requires that the number of DMUs (DWTPs) in each technological group must be larger than or equal to $max\{mxs;3(m+s)\}$, where m is the number of inputs and s is the number of outputs involved in the efficiency evaluation [33]. Taking this premise into account, and given that the aim of this study was to evaluate and compare energy efficiencies of various DWTP technologies, the energy consumed to treat the raw water (expressed in kWh/year) was selected as the input variable. In addition, minimization of energy consumed maximises the energy efficiency of a given DWTP.

Following the methods used in previous studies [41–43], we considered four quality-adjusted outputs (QAOs) to evaluate the energy efficiency of DWTPs, which are defined as

$$QAO_k = V\cdot\left(\frac{P_{kin}-P_{kef}}{P_{kin}}\right), \tag{3}$$

where V is the volume of drinking water produced (m^3/year); P_{kin} is the concentration of pollutant P_k in the influent (raw water); and, P_{kef} is the

Table 1
Unitary processes involved in each drinking water treatment plant (DWTP) technological group and average and standard deviation (Std. Dev.) of its main variables. Source: Own elaboration from Superintendencia de Servicios Sanitarios data.

Processes and variables		DWTP technology 1 (PF)	DWTP technology 2 (PF + CF)	DWTP technology 3 (RGF)	DWTP technology 4 (RGF + CF)
Pressure filtration		X	X		
Rapid gravity filtration				X	X
Coagulation			X		X
Flocculation			X		X
Number of DWTPs		46	24	26	50
Water treated (m^3/year)	Average	601,879	779,073	5,337,402	47,376,420
	Std. Dev.	543,496	1,494,327	7,508,055	98,325,709
Energy consumed (kWh/year)	Average	126,451	137,924	348,053	408,814
	Std. Dev.	238,063	221,101	286,811	639,546
Energy intensity (kWh/m^3)	Average	0.21	0.18	0.07	0.09
	Std. Dev.	0.44	0.15	0.04	0.07
Efficiency in arsenic removal (%)	Average	60.0	67.5	50.7	63.4
	Std. Dev.	26.2	10.5	21.4	26.1
Efficiency in turbidity removal (%)	Average	54.2	47.2	53.2	63.4
	Std. Dev.	21.3	20.6	31.4	11.1
Efficiency in TDS removal (%)	Average	49.3	46.2	53.1	51.8
	Std. Dev.	31.5	31.3	26.3	27.2
Efficiency in sulfates removal (%)	Average	55.6	72.3	29.0	48.9
	Std. Dev.	26.8	20.9	18.0	33.2

concentration of pollutant P_k in the effluent (treated water). We measured four pollutants (P_k) in our assessments, which are the main pollutants affecting the level of energy intensity treatment required when treating water in Chilean DWTPs [15] and are as follows: turbidity, arsenic, total dissolved solids, and sulfates. Therefore, four QAOs were considered in our energy efficiency assessment.

Table 1 shows the main statistics obtained for the variables used with the four DWTPs technologies that we evaluated. The average energy intensity ranged from 0.07 and 0.21 kWh/m^3, which is consistent with the energy intensity values reported for DWTPs worldwide [11,13]. Our data showed that larger DWTPs use rapid-gravity filtration systems, whereas smaller facilities use pressure filtration systems. However, for both types of filtrations systems, DWTPs using coagulation-flocculation processes were more efficient at removing arsenic and sulfates than the others examined.

4. Results and discussion

The metafrontier concept assumes that the inputs and outputs of each assessed treatment technology have a different functional relationship. To test whether the four groups of DWTPs evaluated in this study verified this assumption, five Kruskal-Wallis tests were performed, one for each variable involved in the energy efficiency assessment. This non-parametric test is used to determine if samples originate from the same distribution [44]. In this study, the null hypothesis (H_0) was that k technological groups belonged to the same population, and a p value of ≤ 0.05 meant that the null hypothesis could be rejected at a statistically significant level of 95%. The results of the Kruskal-Wallis tests are shown in Table 2, and these show that for the input (energy used) and the four QAOs (efficiency in pollutant removal), the null hypothesis was rejected. This result means that of the four technologies analyzed, all variables used in the energy efficiency assessments differed significantly between the technologies employed. This supports our assumption that a conventional DEA approach cannot be used to compare energy efficiencies of DWTPs that use dissimilar technologies.

Table 3 shows descriptive statistics of energy efficiency estimates for each of the 146 DWTPs relative to each technology-k frontier (EE^k) and metafrontier (EE). Average energy efficiency scores ranged from a minimum of 0.510 for DWTPs using pressure filtration (PF) to a maximum of 0.629 for DWTPs using rapid-gravity filtration (RGF). While the differences in average energy efficiencies among the DWTP technologies assessed appear slight, the energy performances differed substantially between the four groups of technologies evaluated (Figs. 2a–2d). For DWTPs using both RGF and a coagulation-flocculation (CF) process, the minimum energy efficiency score was 0.227, whereas efficiency scores for plants using RGF, PF, and both PF and CF were 0.123, 0.033 and 0.069, respectively. This means that from an energy point of view, DWTPs using a combined RGF and CF treatment technology have a more similar energy efficiency than DWTPs using any of the other three treatment technologies types (i.e. the efficiency scores within those groups were more variable).

When evaluating the energy efficiencies of DWTPs belonging to the same technological group (i.e. those using a similar treatment technology), it is useful to determine the percentage of treatment plants that are energy efficient. A facility is deemed to be energy-efficient if its scores are close to those of its energy-frontier. Table 3 shows that in the sample of treatment plants assessed in this study, the percentage of facilities that were energy efficient was low for all four technological groups and ranged from a minimum of 19.6% for DWTPs using PF technology to a maximum of 25.0% for DWTPs using both PF and CF technologies. This implies that approximately 75% to 80% of plants using these technologies could reduce their energy use while maintaining their current pollutant removal efficiencies.

An energy efficiency score enables the calculation of potential energy reductions that could be made if the DWTP achieved the same efficiency as the best-performing facilities (DWTPs with energy efficiency scores of 1.0) that use a similar treatment technology. Based on our sample of DWTPs, it was found that most of the facilities (irrespective of the treatment technology employed) could potentially reduce their energy consumption by between 37% and 49.0% (Table 3). Specifically, the 115 energy inefficient DWTPs in our sample (facilities with energy efficiency scores of < 1.0) could potentially save 9,350,077 kWh/year, which is 43.3% of the amount of energy currently consumed annually (21,599,121 kWh/year) by all 146 DWTPs evaluated. This finding illustrates the importance of assessing energy efficiency relative the most-efficient plants using the same technology (benchmarking).

It is relevant for water managers to use energy efficiency evaluations with respect to group frontiers, as it enables them to identify facilities that are the most energy efficient and which can potentially be emulated. In this context, Figs. 2a–2d show the potential energy savings of each DWTP evaluated by making a comparison with energy efficient facilities. According to EPA [45], this assessment is the first step to implementing programs that improve the energy efficiency of water utilities, and managers of inefficient facilities need to consider adopting measures to reduce energy consumption. Improvements could be achieved by using basic methods such as adopting variable frequency drive motors to match pump speeds to load requirements, automating controls and replacing standard efficiency motors with premium ones [45].

As expected, energy efficiency scores computed with the metafrontier as a reference showed that for all DWTPs, energy efficiency scores relative to the metafrontier were lower than scores computed for any DWTP located on its own group frontiers (Table 3, Fig. 3). However, this lack of energy inefficiency was not equally pronounced for all types of treatment technologies. The lowest average energy efficiency (0.231) occurred in DWTPs using RGF technology. This was the worst performing treatment technology, and it was determined that a 76.9% reduction in energy consumption could be achieved while maintaining the same pollutant removal efficiencies. In fact, none of the 26 DWTPs within this RGF group were found to be energy efficient relative to facilities using other treatment technologies. For example, DWTPs using combined RGF and CF treatment technology had the highest energy performance, even when pollutants removal efficiencies were considered. When energy efficiency was evaluated relative to the metafrontier, only 11 of the 146 DWTPs were identified as energy efficient, and 9 of these 11 efficient facilities used a combined RGF and CF system to treat raw water (Fig. 3). This finding illustrates both the relative energy efficiency of this type of treatment technology and the superiority of using the metafrontier approach.

Assessments of energy efficiency scores with respect to the metafrontier can be used by water regulators to support decision-making processes when selecting the most suitable technology (from an energetic point of view) for use in new DWTPs. Our results show that rapid-gravity filters with coagulation-flocculation are the most energy efficient technology used in treating water; therefore, it is advised that this technology should be adopted by developing countries when constructing new water treatment facilities.

Ranking DWTP technologies by energy efficiency (Table 3) (using the metafrontier approach) differs from ranking using energy intensity

Table 2
Kruskal-Wallis tests for differences in the technologies of drinking water treatment plants (DWTPs).

	Input	Quality-adjusted outputs			
	Energy consumed	Efficiency in arsenic removal	Efficiency in turbidity removal	Efficiency in TDS removal	Efficiency in sulfates removal
p-value	0.004	0.007	0.008	< 0.001	0.004

Table 3
Average energy efficiency scores with respect to group frontiers (EE^k) and the metafrontier (EE) for the four technological groups of drinking water treatment plants.

	Energy efficiency with respect to technological group frontiers (EE^k)			Energy efficiency with respect to the metafrontier (EE)			TGR
	Average	Std. Dev.	% energy efficient	Average	Std. Dev.	% energy efficient	Average
PF	0.510	0.373	19.6	0.378	0.214	2.2	0.741
PF + CF	0.621	0.388	25.0	0.432	0.221	4.2	0.695
RGF	0.629	0.327	23.1	0.231	0.123	0.0	0.367
RGF + CF	0.606	0.296	20.0	0.591	0.304	18.0	0.975

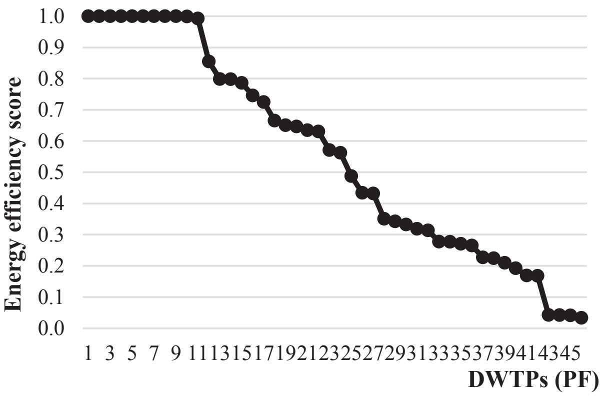

Fig. 2a. Energy efficiency scores (EE^k) for DWTPs using pressure filters.

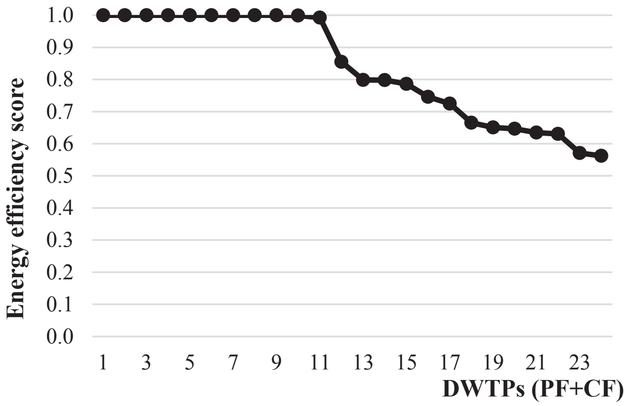

Fig. 2b. Energy efficiency scores (EE^k) for DWTPs using pressure filters and coagulation-flocculation.

(Table 1). For example, the superior energy performance of RGF technology was based on energy intensity only (0.07 kWh/m^3) whereas it ranked as the least energy efficient: RGF used less energy per m^3 of raw water processed, but the other treatment technologies were more energy efficient when the quality of the processed water was also considered. Therefore, the energy intensity and energy efficiency estimates conducted for the DWTPs in this study provided contradictory results. This result shows that energy-intense treatment technologies are highly efficient in removing pollutants (arsenic, sulfates, turbidity and total dissolved solids), thus making them relatively highly energy efficient, and demonstrates the importance of integrating pollutant removal efficiency into DWTP energy performance comparisons rather than using a more simplistic indicator based solely on energy consumption.

When evaluating the proximity of each DWTP technology to the metafrontier (which describes the best performance relative to energy use), it was found that the combined RGF and CF treatment technology had the highest average technological gap ratio (TGR) of 0.975, which makes it the best performing technology (on average) for removing pollutants, as it is closest to the metafrontier (Table 3). In fact, 28 of 50 DWTPs using this technology had a TGR at unity (Fig. 3), which indicates that this treatment technology is the most efficient pollutant remover: it uses the least amount of energy when removing the largest amount of pollutants. In contrast, RGF technology had the lowest average TGR (0.367), indicating that DWTPs using this treatment technology could potentially reduce (on average) their energy use by 63.3% while removing the same pollutant concentration.

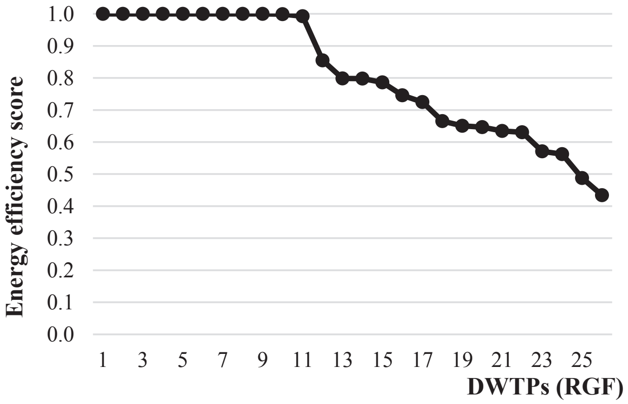

Fig. 2c. Energy efficiency scores (EE^k) for DWTPs using rapid gravity filters.

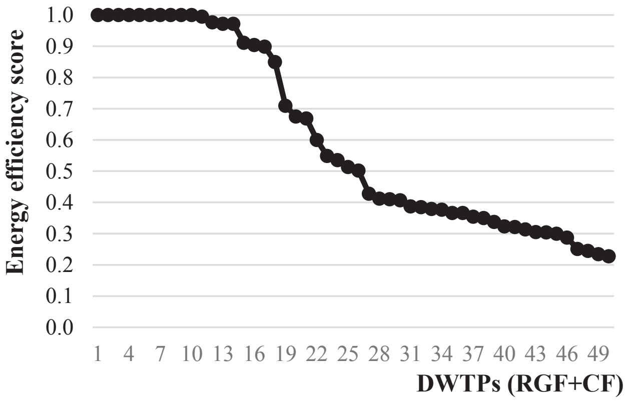

Fig. 2d. Energy efficiency scores (EE^k) for DWTPs using rapid gravity filters and coagulation-flocculation.

This study shows that it is insufficient to use benchmarking when conducting an energy performance of DWTPs solely based on energy intensity (kWh/m^3), as the pollutant removal efficiency is not considered: in other words, energy intensity ignores the quality of the raw water in energy performance benchmarking. The results of this study are consistent with those of recent studies [13,8] showing that raw water quality affects the energy intensity of water treatment.

It is essential to improve the energy efficiency of DWTPs from both economic and environmental perspectives; therefore, our results will be extremely useful for managers and policy makers intent on both minimizing energy costs relative to the quality of raw water processed and reducing greenhouse gas emissions. Comparing DWTPs by energy efficiency metrics related to specific water treatment technologies will assist managers in setting appropriate industry standards relating to the energy use per volume of water processed. As this study considers differences in technological efficiencies when removing pollutants from water, it thus provides insights that can be used by decision-makers to select drinking water treatment technologies that exhibit the best performances relative to energy efficiency.

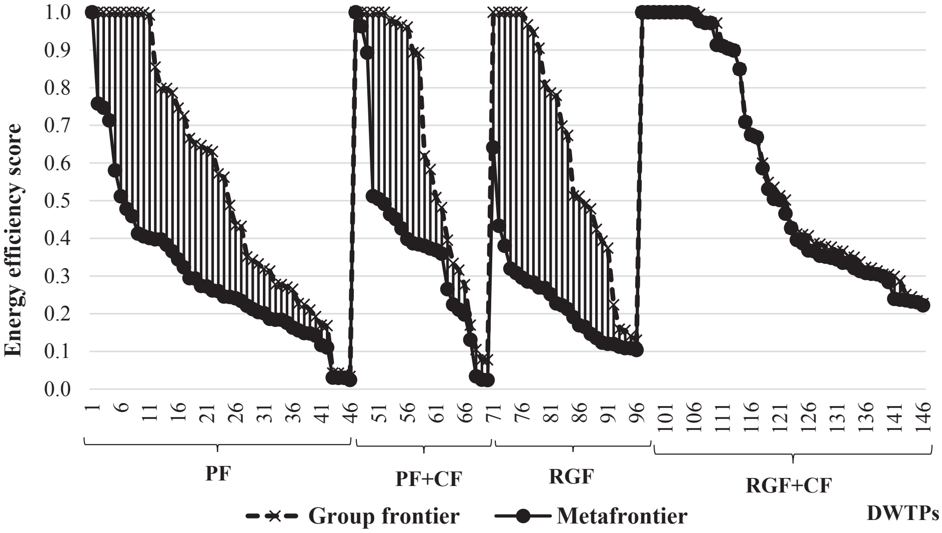

Fig. 3. Energy efficiency scores with respect to group frontiers (EE^k) and the metafrontier (EE) for each drinking water treatment plant evaluated.

We also consider that the methods used and associated results will be of great interest to managers and policy makers of DWTPs, as the energy efficiency comparisons made enable the quantification of potential energy reductions that could be achieved at any given DWTP. As such, this study can be used by managers to make sound economic and environmental decisions. Furthermore, the ability to appropriately compare the energy efficiencies of different types of DWTP technologies can enable policy-makers to identify the most suitable technology for use (from an energetic perspective) when designing and building new DWTPs.

5. Conclusions

Benchmarking using energy efficiencies of drinking water treatment plants provides information that can be used by water regulators and water utility managers who need to identify energy saving methods when treating water for domestic use. In this respect, reducing energy consumption will reduce greenhouse gas emissions and production costs. Previous studies have estimated the energy intensities of water treatment plants to assess energy efficiencies; however, although this simple metric accounts the energy consumed in treating a unit volume of drinking water (kWh/m^3), it does not consider differences between the quality of water that needs to be treated and the associated differences in the energy required to expedite this (as treating lower-quality water requires more energy). These are important limitations, because it is well-known that the energy consumption of drinking water treatment plants is affected by the concentration of pollutants to be removed from raw water and the associated mandated standards. To overcome these limitations, our study evaluates the performance of a large sample of water treatment plants by comparing their performances using a method that incorporates both the energy intensity and pollutant-removal efficiency of the plant into a single synthetic indicator. Our paper is the first to compare the energy efficiencies of four treatment technology types by applying the data envelopment analysis metafrontier approach and integrating technical differences by benchmarking (standardizing) energy efficiencies.

The results of our empirical application provide the following primary conclusions. First, differences were statistically significant among model variables used for estimating the energy efficiency of technological groups associated with drinking water treatment plants (energy consumed, volume of water, and pollutant removal efficiency). This result supported our assumption that the metafrontier data envelopment analysis method is the most appropriate approach for use in comparing water treatment facilities that employ different processes (technologies) when treating raw water. Second, within each technological group, the facilities evaluated have the considerable potential to reduce energy consumption (43% below current consumption) while maintaining their existing pollutant removal efficiencies. Facilities using rapid-gravity filtering technology are the most energy efficient and facilities using pressure filtering are the least energy efficient. Third, a comparison of energy efficiencies among technological groups based on the metafrontier approach illustrates that water treatment plants using combined rapid-gravity filtering and coagulation-flocculation technology are the most energy efficient, followed by those using combined pressure filtering and coagulation-flocculation. This result shows that the higher energy consumption used in the coagulation-flocculation process is compensated for by its higher efficiency in removing pollutants. Fourth, there are greater differences in the ranking of water treatment technologies when performance is evaluated using only energy intensity as a metric. This finding illustrates the importance of integrating pollutant removal efficiency and energy intensity when assessing the performance of a water treatment plant, as this provides a better understanding of all factors that affect energy use in facilities.

The methodology applied in this study and our results provide insights with respect to two main policy issues. First, the energy efficiency index was shown to be a robust, synthetic metric for benchmarking the energy performance of drinking water treatment plants, and the information it provides can be used to identify energy saving opportunities, which may in turn contribute to improvements in the environmental and economic performances of water utilities. Second, our approach for identifying the most energy efficient water treatment technology among a suite of potential technologies (even when there are variations in raw water quality) provides essential information for use when planning new facilities. This is especially relevant for achieving the United Nations Sustainable Development Goals, because many developing countries face economic challenges when designing and constructing drinking water treatment infrastructure.

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