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Energy intensity of treating drinking water: Understanding the influence of factors

María Molinos-Senante [a,b,c,*], Ramón Sala-Garrido [d]

[a] Departamento de Ingeniería Hidráulica y Ambiental, Pontificia Universidad Católica de Chile, Av. Vicuña Mackenna 4860, Santiago, Chile
[b] Escuela de Arquitectura e Instituto de Estudios Urbanos, Pontificia Universidad Católica de Chile, El Comendador 1916, Santiago, Chile
[c] Centro de Desarrollo Urbano Sustentable CONICYT/FONDAP/15110020, Av. Vicuña Mackenna 4860, Santiago, Chile
[d] Departamento de Matemáticas para la Economía y la Empresa, Universitat de Valencia, Avda. Tarongers S/N, Valencia, Spain

HIGHLIGHTS

- Energy intensity depends on water treatment technology.
- Facilities using rapid gravity filters present economies of scale in energy intensity.
- Factors affecting energy intensity of drinking water treatment plants are identified.

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ABSTRACT

To provide safe drinking water to urban populations, raw water must be treated in drinking water treatment plants, which are energy-intensive facilities. Previous studies have assessed energy intensity (EI: unit of energy required per unit of treated water) of conventional drinking water treatment plants, but they ignored variations related to water treatment trains. By modeling 179 facilities of four water treatment trains, we explored factors potentially affecting energy intensity, such as removal efficiencies of pollutants and treatment capacities of drinking water treatment plants. We also investigated the economies of scale in energy intensity of drinking water treatment plants. Our results illustrated that the energy intensity of water facilities using pressure filter systems is affected by several pollutant removal efficiencies, but not by plant capacity. In contrast, the volume of water treated is the main factor responsible for the energy intensity in plants using rapid gravity filter systems and, therefore, their energy intensities are significantly affected by economies of scale. The results of this study should be useful to policy makers planning new facilities and developing policies to reduce the carbon footprints of urban water treatment plants.

1. Introduction

The provision of clean water requires an energy input [1]. Urban water systems consume a substantial amount of energy and, thus, contribute to climate change [2]. In addition, the energy consumption of the water sector is likely to expand to meet the growing demand for cleaner water and to prevent water shortages in urban and urbanizing areas [3]. Increased energy use may be further exacerbated by population growth, climate change, and the implementation of more restrictive regulatory requirements for improving water quality [4,5,6]. In the near future, new water supply systems will need to be built to provide safe drinking water for populations in developing countries. According to WHO-UNICEF [7], in 2015, 663 million people still lacked safe drinking water. Hence, the energy requirements for safe drinking water in urban areas will likely increase worldwide.

Given the relevance of energy use and greenhouse gas emissions in urban water supply, several recent studies have quantified the energy used in the water supply sector. For example, Smith et al. [8] quantified the energy employed for maintaining an urban water supply in China and analyzed this energy requirement relative to population density and gross domestic product. Detailed studies of energy requirements were developed by Barrios et al. [9], Gerbens-Leenes [10] for the Netherlands and by Sanders and Webber [11] in the United States, which assessed energy consumed relative to water use. Other studies have quantified the energy used to supply urban water to several cities, such as New York [12], Toronto [13], Tampa, Kalamazoo [14], Los Angeles [15]

* Corresponding author at: Departamento de Ingeniería Hidráulica y Ambiental, Pontificia Universidad Católica de Chile, Av. Vicuña Mackenna 4860, Santiago, Chile.
E-mail address: mmolinos@uc.cl (M. Molinos-Senante).

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and Beijing [16,17]. A review of the energy requirements for water supply systems has also been provided by Gude [1], Wakeel et al. [18].

To ensure safe, reliable, and high-quality drinking water to citizens, raw water should be treated in drinking water treatment plants (DWTPs) prior to distribution. Several energy-consuming processes are used by DWPTs to make water potable: coagulation, flocculation, filtration, and sedimentation [19]. Studies have been carried out to assess the electricity consumption of DWTPs, mainly by using a life-cycle assessment tool (for a review, see [20]). Miller et al. [21] used an end-use energy intensity (EI) approach (i.e., unit of energy required per unit of treated water) to compare Indian water treatment facilities with similar facilities in US cities. A more specific study by Santana et al. [22] investigated the influence of water quality parameters on the embodied energy of drinking water treatment facility.

Previous studies analyzing EI approaches for DWTPs have been very useful for evaluating the carbon footprint of water treatment facilities. However, these studies have had three main limitations. First, with the exception of the Santana et al. [22] study, previous studies ignored the quality of the raw water (influent). Water quality affects the choice of treatment options and, therefore, the EI of a given DWTP [10]. In the framework of carbon emissions studies, Mo et al. [23] found that water quality could have a greater effect on energy input than water availability. However, previous studies assessing the EI of DWTPs used the term "conventional" water treatment [20,24], even though their studies involved facilities with various types of water treatment trains (WTTs). Second, most EI assessments focused on only one or a few DWTPs. Thus, their results were very specific to a city or region and not applicable to other water treatment approaches. Finally, despite debate about the sustainability of centralized vs. decentralized urban water systems, to the best of our knowledge, there have been no studies analyzing whether economies of scale of DWTPs affect EI. When planning for the construction and operation of new DWTPs, it is critical to know which WTT types can provide the best economies of scale.

The objective of this paper is to understand how and to what degree the EI of DWTPs is impacted by a facility's capacity, age, and its efficiency in removing pollutants. Moreover, to compare how various WTT technologies might affect carbon emissions we categorized DWPTs into four types of WTTs and determined how much energy was required by the various approaches. We categorized WTTs because grouping all WTT configurations into one "conventional DWTP" category is not sufficiently accurate to determine how to minimize carbon emissions in water treatment.

This paper contributes to the current strand of literature in the field of the water-energy nexus in several aspects. First, to the best of our knowledge, no prior studies have modeled the EIs of a large number of DWTPs (n = 179). Second, the EIs of four different WTTs are compared. Hence, this study provides a pioneering and novel comparison of EI of WTTs. Third, it is explored for each WTT, how and to what degree its EI is influenced for a set of technical variables. Finally, no study to date has investigated variations in economies of scale in EIs among DWTPs. The procedures we applied and the results we obtained will be of great interest to policy makers planning new DWTPs and developing policies aimed at reducing EI and greenhouse gas emissions associated with DWTPs.

2. Materials and methods

2.1. Methods

The EI of a DWTP could be affected by several complex and interrelated factors. Previous studies ([22,23,25,26]) illustrated that statistical analysis is an effective means for understanding the influence of a set of independent variables, or "predictors", on a dependent variable. In this study, we used regression analysis because it explains changes in a dependent variable (EI) when any of the independent variables vary.

A regression model relates Y to a function of X and α as follows:

$$Y \approx f(X, \alpha) \tag{1}$$

where Y is the dependent variable (EI, expressed in kW h/m^3), X is an independent or predictor variable (volume of water treated, age of the facility, efficiency in the removal of pollutants), and α is an unknown parameter.

The first step for selecting independent variables was to test collinearity (i.e., to identify if any of the potential predictors were correlated). Pearson correlation coefficients were estimated among the independent variables. Values closer to 1.0 and -1.0 meant a strongly positive or negative correlation, respectively, between two variables. In these cases, only one of the variables was used in the regression analysis. After the regression analysis was conducted, a condition number test was performed to ensure that there were no multicollinearity problems [27]. A White test was performed to test for heteroscedasticity [28]. By performing these tests beforehand, we ensured that we met the basic statistical assumptions required for regression analysis.

Following Hernandez-Sancho et al. [29], a parametric regression analysis approach was applied (i.e., regression function was defined based on a finite number of unknown parameters estimated from the data). This approach required us to choose the type of function that would best model the conditions. Given the lack of previous studies similar to ours, we could not define a preferential *a priori* form for the function. Santana et al. [22] used linear regression to relate total embodied energy in a set of water quality variables, but did not consider the treatment capacity of the plant; this variable usually has a nonlinear relationship with dependent variables [25,29]. Therefore, we considered both linear (Eq. (2)) and exponential (Eq. (3)) models as potential functions in the regression analysis:

$$Y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \ldots + \alpha_k x_k + \varepsilon \tag{2}$$

$$Y = e^{\sum_{k=1}^{n} \alpha_k \left(\frac{P_{kin} - P_{kef}}{P_{kef}}\right)} * V^{\beta} * A^{\delta} \tag{3}$$

In Eq. (2), α_0 is the intercept, $\alpha_1, \alpha_2, \ldots \alpha_k$ are regression coefficients measuring the influence of each independent variable over the dependent variable (Y), $x_1, x_2, \ldots x_k$ are significant independent variables, and ε is an error term. In Eq. (3), P_k is the k^{th} pollutant ($k = 1, 2, \ldots, n$), P_{kin} is the concentration of pollutant P_k in the influent, P_{kef} is the concentration of pollutant P_k in the effluent, V is the treatment capacity of the DWTP (defined by the volume of water treated annually), A is the age of the plant (years old), and α_k, and δ are unknown parameters.

We used a stepwise regression method (using SPSS software) to identify any significant independent variables. For an independent variable to be significant in modeling the EI of a DWPT, we specified that its p-value must be less than 0.05. Hence, it is a measure of the accuracy to which the regression can predict the dependent variable. The value of R^2 ranges from 0 to 1, with a value of 1 meaning that the adjustment between actual and estimated data is perfect. Regressions with R^2 values larger than 0.5 are typically considered significant.

Budescu's dominance analysis [30] and Johnson's relative weight procedure [31] were used to examine the contribution of each independent variable in modeling the EIs of DWTPs. Both procedures measure the proportional contribution that each