Monitoring and diagnosis of energy consumption in wastewater treatment plants. A state of the art and proposals for improvement

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Abstract

In response to strong growth in energy intensive wastewater treatment, public agencies and industry began to explore and implement measures to ensure achievement of the targets indicated in the 2020 Climate and Energy Package. However, in the absence of fundamental and globally recognized approach evaluating wastewater treatment plant (WWTP) energy performance, these policies could be economically wasteful. This paper gives an overview of the literature of WWTP energy-use performance and of the state of the art methods for energy benchmarking. The literature review revealed three main benchmarking approaches: normalization, statistical techniques and programming techniques, and advantages and disadvantages were identified for each one. While these methods can be used for comparison, the diagnosis of the energy performance remains an unsolved issue. Besides, a large dataset of WWTP energy consumption data, together with the methods for synthesizing the information, are presented and discussed. It was found that no single key performance indicators (KPIs) used to characterize the energy performance could be used universally. The assessment of a large data sample provided some evidence about the effect of the plant size, dilution factor and flowrate. The technology choice, plant layout and country of location were seen as important elements that contributed to the large variability observed.

Keywords:

Wastewater treatment; energy efficiency; benchmarking; KPI; OLS; DEA

Highlights

- A review of WWTP energy-use and benchmarking systems is performed
- Energy data from more than 600 WWTPs were inventoried
- Energy KPIs found are often not representative of the overall energy consumption
- Benchmarking method selection is linked to data availability and purpose of study

- Further research is required on the field of energy efficiency at WWTPs

1. Introduction

The proper treatment and sanitation of wastewater is crucial for protecting public health and environment. To achieve these important goals, water and wastewater systems are relevant energy consumers, demanding not only a large amount of energy onsite, such as electricity used for pumping and aeration, but also offsite for producing and transporting building materials and chemicals for treatment. Data from Germany [1] as well from Italy [2] show that electricity demand for wastewater treatment accounts for about 1% of total consumption of the country, which may be a good estimation for other European countries. In Spain, some studies suggest that domestic and industrial water cycles account for 2-3% of total electric energy consumption and considering water management and agricultural demand, could reach 4-5% [3]. In the United States, it has been estimated that roughly 4% of the electricity demand is employed for potabilization and distribution of water as well as collection and treatment of wastewater, by public and private stakeholders [4].

As the number of WWTPs increases worldwide and the effluent quality requirements become more demanding, the issue of energy efficiency has been attracting increasing attention from an environmental and economic point of view [5]. Water agencies and wastewater treatment plant operators show a growing interest in the use of tools and methodologies to save energy, such as benchmarking and energy audit procedures [2,6,7]. Energy audit is the general term used for a systematic procedure to obtain adequate knowledge of the energy consumption profile of an industrial plant. One of the aims of an energy audit is the determination of energy baseline regarding the reference consumption of individual devices and installation. By a careful analysis of energy data it is possible to identify the best opportunities for improvement. From a regulatory perspective, companies with more than 250 employees and with annual trading volume greater than € 50 million or whose annual balance sheet exceeds € 43 million are obliged to perform energy audit every four years from December 2015, as established by EU Directive 2012/27/EU [8]. Water utilities often fulfil these criteria.

Several reviews have been published on energy benchmarking methodologies in various fields, most of them dealing with energy efficiency of building. Chan [9] analysed the mathematical methods employed for benchmarking the use of energy in buildings, comprehensively discussing the advantage of each method. Li et al. [10] focused on the revision of tool for benchmarking building energy consumption, including black box methods, grey box methods and white box methods. Zhao and Magoulès [11] reviewed work related to the modelling and prediction of building energy consumption, including engineering, statistical and artificial intelligence methods. Pérez-Lombard et al. [12] examined concepts such as benchmarking tool, energy ratings and energy labelling within the framework of building energy certification schemes. Some general findings made in previous works in the building sector can also be useful to the wastewater industry. However, due to the complexity of WWTPs, additional case-specific considerations have to be done.

To the best of our knowledge, there currently exists no standard approach to evaluate a WWTP energy performance. Moreover, no document is available providing a complete and comprehensive review of benchmarking methodologies applied in the field of wastewater treatment. In this paper, we describe the challenges inherent to energy benchmarking in WWTP. The goal of this study is to perform a critical review of relevant papers published on the topic that can help practitioners, plant managers and operators or researchers select the most appropriate methods for each case. By assessing the literature of WWTPs energy-use performance and the benchmarking systems, this paper represents a first step in the development of a systematic methodology for evaluation and improvement of energy performance in WWTPs operation. Such a methodology is the main objective of the ENERWATER coordinated support action, a three-year activity within the Horizon 2020 programme with 9 partners from 4 European countries (the reader is referred to www.enerwater.eu for further information).

The present contribution intends to address the following specific questions related to monitoring and diagnosis of energy consumption in WWTPs: i) which are the sources of information, ii) what kind of energy data are reported in the literature, iii) how are energy data reported in the literature and, iv) what type of methodologies are used for the assessment of energy efficiency in WWTPs. An energy audit requires a clearly stated and accepted methodology beyond common knowledge. Therefore, one of the goals of this manuscript is establish generally accepted principles and good practices that must be included in a standard energy performance auditing.

This paper is structured as follows. First, section 2 presents major features of research available in the literature. The methodology applied for the literature review carried out is explained and how data were collected, treated and classified is also discussed. Then in section 3.1, energy key performance indicators (KPIs) reported in the literature are presented and critically assessed, pointing out the limits to their validity. A comparison of various benchmarking methodologies employed for energy efficiency assessment in WWTPs is presented in section 3.2. Section 3.3 looks at energy datasets, together with the methods for synthesizing the information; energy data are there discussed, describing the availability of data in open literature and allowing to draw conclusions on the main factors affecting the energy consumption in WWTPs. Differences in scale, treatment technology, and operating conditions were evaluated by benchmarking the electric power consumption. Section 3.4 reports some technology-based examples for improving energy efficiency in WWTPs. Finally, an overlook of energy management tools is presented and a hint for the future developments is discussed in section 3.5. Section 4 offers concluding observations.

2. Methods

2.1. Literature review

A thorough review of the literature on WWTP energy-use performance and related benchmarking methods was carried out using different combinations of the following keywords: ‘wastewater’, ‘WWTP’, ‘energy’, ‘energy consumption’, ‘energy performance’, ‘energy efficiency assessment’, ‘energy benchmarking’, ‘life cycle assessment’, and ‘LCA’, in web search engines. Peer-reviewed journal articles were the primary source in relation to the methods used for benchmarking. Information on WWTPs energy consumption published in peer-reviewed journals is limited while a considerable number of references have been found in other non-peer-reviewed publications, such as research books, on-line publications/articles, and technical reports. Furthermore, energy data from regional water agencies (in particular from Germany and Spain) collected by private communications were also included in the analysis.

2.2. Data collection and sample

A thorough search was carried out to identify available sources and databases offering energy data of WWTPs. Energy consumption was gathered together with data related to the operation, influent and effluent characteristics, namely: population equivalent (PE) load basis, both the designed value and the actually served value; flow rate (design and average); influent and effluent wastewater characteristics, i.e. chemical oxygen demand (COD), biochemical oxygen demand (BOD), total suspended solids (TSS), total nitrogen (TN) and total phosphorus (TP). The energy consumption of major pieces of equipment, such as blowers, mixers, pumps, aeration systems and filters was found in a number of cases. Additionally, more general data on energy consumed by the buildings for lighting and heating were also reported.

A total of 601 WWTPs were inventoried for the evaluation of the energy consumption. However, some plants were omitted from the analysis due to important data gaps (i.e. whenever influent and effluent wastewater characteristics or plant treatment technology were unavailable). Additionally, most of the Canadian plants were not included in the analysis due to extremely diluted influent wastewater (COD < 50 mg/L) in order to avoid misleading conclusions. The final sample consisted of 388 WWTPs, which represents the treatment of about 15.7 million PE corresponding a total electric energy consumption of 1.72 GWh/day and distributed as follow: 2.62 million PE (16.6%) in North America, 3.22 million PE (20%) in Asia and the remaining 9.86 million PE (62.8%) in Europe (see section 2 of supplementary material for the dataset used for the analysis).

2.3. Data treatment

According to the literature review and the level of detail of the data collected, three energy key performance indices (KPI) were defined, referred to volume of treated wastewater, PE and kg of COD removed:

$$\mathrm{KPI}_1 = \frac{electric\ energy\ consumption}{volume\ of\ treated\ wastewater}\ [kWh/m^3] \qquad \text{(Eq. 1)}$$

$$\mathrm{KPI}_2 = \frac{electric\ energy\ consumption}{served\ PE}\ [kWh/PE\ year] \qquad \text{(Eq. 2)}$$

$$\mathrm{KPI}_3 = \frac{electric\ energy\ consumption}{COD\ load\ removed}\ [kWh/kg\ COD_{removed}] \qquad \text{(Eq. 3)}$$

It should be noted that the definitions and equivalences of PE can differ between countries. In this study 12 gN/PE·d was taken as an equivalence (following Directive 91/271/EEC [13]). When N values were not available, PE calculation was done on BOD or COD basis, considering 60 gBOD/PE·d or 120 gCOD/PE·d.

In the case of North American plants, the conversion was done considering 80 gBOD/PE·d or 160 gCOD/PE·d for load-based PE or 400 L/PE·d for wastewater volume-based PE [14].

From the analysis of the collected data presented in section 3.3 two WWTP operational indices were defined: i) dilution factor (DF), and ii) load factor (LF), and calculated as follow:

$$DF = \frac{daily\ influent\ flowrate}{served\ PE} \quad [L/PE \cdot d] \qquad \text{(Eq. 4)}$$

$$LF = \frac{served\ PE}{design\ PE} 100 \quad [\%] \qquad \text{(Eq. 5)}$$

DF is mainly function of the sewer network design, age and materials; parasite water negatively affects treatment performance by dilution and hydraulic overloading. LF represents the capacity utilization of the plant compared to the design capacity, showing then if a plant is under or over-designed.

Given the high variability of the sampled values, the mean was found as an unsuitable indicator as it is particularly influenced by extreme values. It was therefore considered more useful to take as reference a more robust indicator such as the median. To represent graphically the data variability, collected energy data are presented by the use of box plots. There, a box is used to indicate the positions of the upper and lower quartiles; the interior of this box indicates the interquartile range, which is the area between the upper and lower quartiles and consists of 50% of the distribution. Finally, the crossbar intersecting the box represents the median of the dataset.

2.4. Data classification

Dataset was classified according to five different WWTP class sizes as defined in [15]: PE < 2 k; 2 k < PE < 10 k; 10 k < PE < 50 k; 50 k < PE < 100 k; PE > 100 k, where k stands for 1000. In addition, datasets were further classified based on a country scale and secondary treatment technology. As a large number of configurations are described, different types of secondary treatment (i.e. Ludzack-Ettinger, modified Ludzack-Ettinger (MLE), Bardenpho, anaerobic-oxic (A/O) or anaerobic-anoxic-oxic (A2/O)) have been grouped under the general treatment technology category biological nutrient removal (BNR). Likewise, all the combinations of membrane filtration process with a suspended activated sludge bioreactor have been clustered under the category membrane bioreactor (MBR). Other treatment technologies under study are aerated ponds (AP), biodiscs (BD), conventional activated sludge (CAS), extended aeration (EA), oxidation ditch (OD), sequential batch reactor (SBR), and trickling filter (TF). Finally, unspecified secondary treatment (UST) category was assigned when no detailed information about the secondary treatment technology, although present, was reported.

3. Results and discussion

3.1. Description of key performance indicators found and critical discussion about their validity

Common definition and measure of energy efficiency is the ratio of energy use input (e.g. electricity consumption) to energy service output (a certain service that a WWTP provides, e.g. the amount of wastewater treated or pollutions removed). Traditionally, energy consumption in WWTPs has been reported as referred to the volume of treated wastewater (kWh/m^3) [16,17] or unit of population equivalent (kWh/PE) on annual basis [18,19]. As a result, the energy consumed (due to aeration, mixing, pumping, sludge treatment, etc.) was considered to be proportional to the flow of wastewater treated or the pollution load coming into the WWTP. Although these approaches are very simple and can easily provide calculated energy consumption indicators, they have significant limitations when it comes to energy benchmark exercises and standardisation methodologies. By comparing the energy consumption in kWh/m^3 or kWh/PE it is assumed that pollutant concentrations in the influent (solids, organic matter, nitrogen and phosphorus) do not vary significantly between WWTPs or that effluent qualities are also similar, hence restricting the application of these approaches. Studies reporting the WWTP energy consumption in kWh/m^3 often result in values that are influenced by the degree of dilution of the wastewater. For example, plants treating wastewater from combined sewer overflows often show higher energy efficiency, which is caused by the higher dilution of the pollutants in the influent [20,21]. Calculation of energy efficiency based on the pollutant load entering WWTPs (i.e. kWh/PE) provides a greater accuracy, but in this case N should be favoured as a basis to calculate PE load instead of BOD and COD [22]. In the case of combined sewer systems, inert COD can be carried to the WWTP by rainwater showing a higher load than the real one.

Moreover, as most nitrogen is present in wastewater as soluble ammonium, it is less prone to sedimentation in the sewer system than organic matter.

A sensible approach is to report the energy consumption in WWTPs per unit of pollutant removed, i.e. TSS, BOD, COD, N and/or P removed, depending on the object of the study and plant treatment scheme. Several authors have used kWh/kg $TSS_{removed}$, kWh/kg $BOD_{removed}$ and kWh/kg $COD_{removed}$ [20,21,23], kWh/kg $N_{removed}$ in the case of nitrogen removal processes on annual basis [24] or a combination of these indicators where both organic matter and nutrients (N, P) are merged and converted in terms of a reference unit such as PO_4^{3-} equivalent [25]. The advantage of reporting the energy consumption per unit of pollutant removed relies in the fact that the removal of organic matter and nutrients are major contributors of energy consumption in WWTPs. In this case, a KPI that may include all the main pollutants (i.e. TSS, COD, N and P) in a single variable should be preferred. This concept was first proposed in 1996 by Vanrolleghem [26] and then refined by others authors (see [27] and [18] as examples) for the evaluation of general cost performance of WWTPs. In this method, the overall pollution removal of a WWTP (in kg pollution units) is calculated by a weighted sum of the compounds that have a major influence on the quality of the receiving water body. A list of possible weights for the calculation of the overall pollution removed by the plant is reported in Table S.1 of the supplementary material.

It should be noted that WWTPs perform different functions, i.e. removing of COD, removing of N and/or P, energy and material recovery, producing an effluent free of pathogens. Although current legislation in Europe only requires the reduction of N and P for the treated effluents returned to sensitive areas [25], the objectives of a WWTP are expected to become broader in the future and include, e.g. the removal of micro- and nanopollutants [28] or the production of reusable water [29]. Even more, it becomes obvious that general energy consumption KPI (i.e. kWh/m^3or kWh/kg $COD_{removed}$) has little value, as it does not provide a suitable overview of the different WWTPs currently in operation. There is a clear need to establish suitable KPIs within the WWTP that allow a comparable, realistic and universal form of reporting the energy data. The choice of the proper KPI should be related to the function of the WWTP. A list of most common KPI and recommendations for their use is reported in table 1.

Table 1. Comparison of most used KPIs. Legend: ✓✓ = universally suitable, ✓= not universally suitable, ✗ = not suitable.

KPI	Overall	Preliminary treatment	Primary treatment	Secondary treatment	Tertiary treatment	Sludge treatment	Comments
kWh/m^3	✗	✓✓	✗	✗	✓	✗	Does not take into account influent dilution; Does not represent the removal of pollutants
kWh/PE year	✗	✗	✗	✗	✗	✗	Does not represent the removal of pollutants
kWh/kg $COD_{removed}$	✓	✗	✓	✓	✗	✗	Limited to plants with same function
kWh/kg $TSS_{removed}$	✗	✗	✓✓	✗	✗	✓✓	Limited to primary and/or sludge treatment
kWh/kg $N_{removed}$	✓	✗	✗	✓	✗	✗	Limited to WWTPs where N removal is implemented
kWh/kg $TPUs_{removed}$	✓✓	✗	✗	✓✓	✓✓	✗	Allow the comparison of WWTPs regardless of treatment intensity

3.2. Energy benchmark approaches

Energy efficiency has been summarised with the idea of "doing more using less" [30]. A widely favoured approach in assessing potentials for efficiency improvement is to establish benchmarks for efficient operation. Energy benchmarking is defined as the continuous and systematic process of comparison of the energy efficiency against a reference performance, thereby identifying the most efficient units and best practise. A comparison can then be carried out between the less efficient units against both the reference and the best practice for any given indicator [31]. The benchmarking results can help wastewater utilities and operators determine how well each plant in the benchmarking study is performing. It also highlights the worst and the best energy users, revealing which WWTPs would achieve the greatest energy savings from implementing energy conservation measures.

There exists wide range of methods to measure the relative efficiency of plant in relation to a sample (Fig. 1). The simplest methods consist on pairwise comparisons by selecting a KPI (hence index methods) and normalizing the performance with respect to the reference or best available one [16-19,21,32]. They provide easily understandable results but they rely on having a large sample of plants to provide a sound benchmark.

Several partial indicators may be needed to compare plants with different layouts. Frontier analysis relies on the definition of a contour (a frontier) that describes an average or a best performance for a given set of inputs (i.e. operational and design data). Within frontier analysis, statistical techniques can be used to describe and infer the performance of a population by analysing a subset (a sample) [33,34]. Programming methods will use an optimisation based on the gathered data to define an optimal contour, which can be subsequently used for comparison [35-39]. The choice of the benchmarking techniques used by individual utilities depends partly on the data available and purpose of the benchmarking exercises and can have impact on the determination of efficiency score. An illustration of the variety of techniques used for this purpose is given in Table 2.

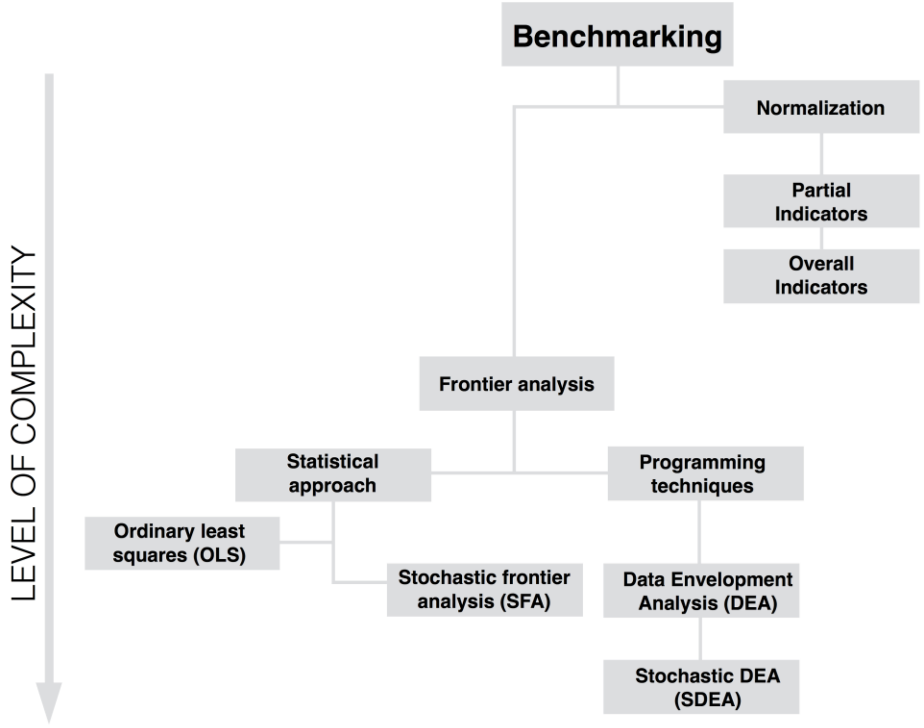

Figure 1. Benchmarking approaches. (Arrow direction means increasing level of complexity). [We suggest 1.5 column width]

Table 2. Summary of WWTP energy benchmark studies. Note: OLS = ordinary least squares; DEA = Data Envelopment Analysis; LCA = Life Cycle Assessment.

Reference	Method	Year	Sample and location	Inputs	Outputs	Main Conclusions

[18]	Normalization	2000	5 WWTPs in North Europe	Electricity consumption; Chemical consumption; Manpower	Population served	Energy costs account for about 25% of total net costs. Ranking highly dependent on the criteria used
[32]	Normalization	2009	1856 WWTPs in China	Electricity consumption	Influent flowrate; COD removed; Air provided for aeration	Energy consumption in WWTPs decreased with the increase of scale and operation load rate.
[17]	Normalization	2010	985 WWTPs in Japan	Electricity consumption	Influent flowrate	Energy intensity is assumed to be more related to scale of plants than wastewater treatment process.
[16]	Normalization	2010	559 WWTPs in China	Electricity consumption	Influent flowrate; Total Pollution Units removed; Influent pump unit; Air provided for aeration; amount of sludge treated.	Energy benchmark is applicable and helpful for plants to recognize energy saving potential. All plants have a potential of energy saving, especially in aeration.
[19]	Normalization	2013	24 WWTPs in Australia	Electricity consumption	Population served	Main reason for higher specific energy consumption of plants in Australia is reuse infrastructure (reuse pump stations, ultraviolet (UV) disinfection, etc.)
[21]	Normalization	2013	51 large WWTPs and 17 rural WWTPs in Slovakia	Electricity consumption; Electricity production from biogas	Influent flowrate; kg of BOD removed	Energy benchmarks are reported for plant class sizes.
[20]	Normalization	2013	289 WWTPs in Italy	Electricity consumption	Influent flowrate; Population served; COD removed	Plant size and type of sewer system impact on energy efficiency.
[6]	Normalization	2014	2 WWTPs in UK	Electricity consumption	Influent flowrate	Benchmarking exercise was useful to identify the most energy-consuming assets and their respective limitations.
[33]	OLS	2007	266 WWTPs in USA	Energy consumption (Electricity, Natural Gas, Fuel Oil, Propane)	Design Daily Flow, Current Daily Flow, Average Influent and Effluent BOD, Fixed Film process (Yes/No), Treatment Nutrient Removal (Yes/No)	The regression model predicts the average energy use for a specific set of characteristics. Only 25% of the plants use less energy of the predicted energy consumption.

[34]	OLS	2012	35 WWTPs in Canada	Energy consumption (Electricity, Natural Gas, Fuel Oil, Propane)	Design Daily Flow, Current Daily Flow, Average Influent and Effluent BOD, Fixed Film process (Yes/No), Treatment Nutrient Removal (Yes/No)	Energy Star method is a valid tool for benchmark energy efficiency even if is not a diagnostic tool.
[38]	DEA	2011	99 WWTPs in Spain	Total cost	COD, N and P in the effluent;	The results indicate that mean efficiencies are relatively high and uniform across the different technologies. Techno-economic efficiency is optimal for WWTPs operating with activated sludge in comparison with other technologies.
[35]	DEA	2011	177 WWTPs in Spain	Electricity consumption; Staff; Chemicals; Maintenance; Waste management; Other	TSS removed; COD removed	Plant size, quantity of eliminated organic matter, and bioreactor aeration type are significant variables affecting energy efficiency of WWTPs.
[39]	DEA	2012	45 WWTPs in Spain	Total cost	COD, N and P in the effluent;	The most efficient and innovative facilities are identified as references.
[37]	DEA	2014	8 WWTPs in the Middle East	Electricity consumption; N. of engineers; N. of technicians; N. of workers	BOD removal efficiency; SS removal efficiency	The flexibility of DEA adds a sort of competitive advantage over other tools and techniques.
[36]	DEA + LCA	2014	60 WWTPs in Spain	Total cost	SS, COD, N and P in the effluent; GHG	The best functioning WWTPs to be used as references were identified, and the potential for GHG reductions were quantified.
[40]	DEA + LCA	2015	113 WWTPs in Spain	Electricity consumption; chemical consumption; sludge production	Net environmental benefit	Smaller WWTPs, which unlike large WWTPs, lack continuous monitoring, have a relevant potential for improving their environmental profile if they were to benefit from stricter supervision.

3.2.1. Normalization approach

The normalization approach consists in the evaluation of WWTPs energy efficiency based on normalized energy performance indicators and ratios. This approach is the most widely used by plant operators, water companies and agencies and all the other stakeholders, due to its simplicity in the implementation and interpretation. Energy-efficiency indicators are usually employed and obtained by simply normalizing the energy use based on a given level of output or activity (section 3.1). In order to perform a benchmark study between different WWTPs, the energy consumption has to be expressed based on certain guidelines and equal dimensions, i.e. the volume of wastewater treated, the unit per capita loading as PE or unit of pollutant removed. These partial measures are generally available, and provide the simplest way to perform a comparison. Researchers and practitioners often combine Partial KPIs to create an Overall KPI, generally using a weighted average of Partial KPIs. As a drawback, benchmark methods based on single KPI representing the whole energy consumption of a plant are too simplistic because they assume that the entire population of plants (e.g. with their different type, size, and location) is comparable with only one metric. Indeed, WWTPs feature complex processes composed by several subsystems (stages), i.e. preliminary, primary, secondary, tertiary and sludge treatment, each one with different function and as a result specific partial KPIs seem to be more appropriate to be used for treatment stage(s) with different function. As for instance, kWh/m^3 does not represent necessarily the overall plant performance since, i.e., in the case of mixed sewer system this KPI is affected by dilution of the wastewater. However, it could be suitable, as KPI for hydraulic-based stages (e.g. preliminary treatment), which are designed using hydraulic loads and typically equipped with pumps, screens, sieving, scrappers, and filters, in which energy depends on the volume of the influent wastewater processed.

The commonly used normalization approach based on one or more KPIs presents important drawbacks due to some implicit assumptions. First, when we compare a small plant with a large plant, we implicitly assume that we can scale linearly input and output, i.e. we assume constant returns to scale (CRS). A second limitation is that it typically involves only partial evaluations. One KPI may not fully reflect the purpose of the plant. We could have multiple inputs (i.e. electricity and chemicals consumption) and several outputs (i.e. volume of treated wastewater, amount of organic carbon removed and/or amount of pollutants removed based on the treatment intensity). To overcome these two limitations, practitioners usually restrict normalization approaches for the performance evaluation of WWTPs within similar size and/or characteristics.

3.2.2. Statistical approach

The concept of statistical frontier analysis can be easily explained in terms of standard linear regression model, such as ordinary least squares (OLS). Given data on energy use (or any equivalent KPI) and using operational or design data as inputs (Y), the parameters α and β can be fit via a simple linear regression model.

$$E = \alpha + Y\beta + \varepsilon_i \qquad \text{(Eq. 6)}$$

where E (N x 1) is the energy use of N plants, Y (N x m) represents the operational or design data and β (m x 1) are slope coefficients for m different inputs and data on N plants, and ε_i is the error term that defines the relative inefficiency. OLS allows estimating the functional form (regression line), which represents the average efficiency level. Interpretation of results from an OLS can shows that all plants with ratings above the average can be considered inefficient while those with ratings below are efficient [9].

An example of regression-based benchmarking tool is Energy Star method [33], which used the measured plant data of 257 facilities from throughout the USA to develop a regression model that can then be used to predict the annual energy consumption given plant characteristics. Benchmarking scores are calculated by comparing the utility's actual energy use with the energy use predicted by OLS model. In order to develop the regression model in Energy Star method stepwise regression approach was employed to find the significant input variables. The parameters included in model are: (1) average influent flow rate; (2) influent BOD; (3) effluent BOD; (4) plant load factor; (5) whether the plant presents filtration; and/or (6) nutrient removal. A benchmark system is developed based on the distribution of residuals of the regression model. The residual is the difference between the actual and the predicted energy consumption. Thus, the residuals are treated as measures of inefficiency. Negative residual means that the plant uses less energy than similar plant with same characteristics. Moreover, the distribution of sample residuals from the regression model can be used to construct the corresponding benchmark table.

By comparing this predicted energy usage with the actual energy use, the utility obtains a score. The benchmarking score represents a percentile: e.g. a 55 score means the utility is more efficient that 55% of the utilities with similar characteristics. The major criticisms of this approach are: i) a large dataset is necessary in order to obtain reliable results; ii) regression results are sensitive to the functional form, iii) that as all the indicators are merged into a single one, it is possible to offset the inefficiency in one variable by another, e.g. high BOD removal can compensate not removing nutrients.

Stochastic frontier analysis (SFA) is another statistic approach that estimates the efficient frontier and efficiency score of the firms but, unlike OLS, SFA considers deviation from the efficiency frontier as two distinct terms, since it separates error components from inefficiency components. SFA particularly requires separate assumptions on the distributions of the inefficiency and error components, potentially leading to more accurate measures of relative efficiency [9]. In SFA the error term ε_i is defined as follows:

$$\varepsilon_i = v_i - u_i \qquad \text{(Eq. 7)}$$

where the $v_i$represents the random errors, a priori assumed to be independent and identically distributed, and u_i represents the non-negative technical inefficiency components. The random error term allows to encompass random effect of measurement error in output, observation, statistical noise and effect of stochastic factors that are beyond the firm control, i.e. seasonality, weather, human factor. However, the estimation results are sensitive to distributional assumptions on the error terms, and the model requires large samples for robustness.

3.2.3. Programming techniques

The majority of the research conducted to date has analysed the efficiency of WWTPs using non-parametric models, such as data envelopment analysis (DEA) in one of its multiple variants. Basically, DEA is a mathematical programming technique that allows building an envelopment surface or efficient production frontier to assess the efficiency of a set of decision-making units (DMUs), i.e. WWTP in this case. Thus, those DMUs that establish the envelopment surface are considered efficient and those that do not rest on the surface are considered inefficient. A unit is considered to be efficient if and only if i) it is not possible to improve its outputs while its inputs are fixed, and ii) it is not possible to do change its inputs without altering the resulting outputs.

DEA can involve the imposition of differing scale assumptions. The return to scale concept (RTS) [41] refers to the rate by which output changes if all inputs are changed by the same factor. Let α represent the proportional input increase and β represent the resulting proportional increase of the single output. Constant returns to scale (CRS) prevail if $\beta = \alpha$, increasing returns to scale (IRS) prevail if $\beta > \alpha$, and decreasing returns to scale (DRS) prevail if $\beta < \alpha$. Due to the fact that energy consumption of WWTPs is affected by economies of scale, in particular energy efficiency increase with increasing plant size, IRS assumption need to be applied to DEA models [36,39] (see section 3.3.1 for further discussion on economy of scale in WWTPs). The DEA efficient frontier defines a convex space that requires a minimum number of data to be determined. For instance, Cooper's rule [42], establishes that the number of DMUs analysed must be at least two times the product of the number of inputs and number of outputs defined.

DEA offers major advantages over parametric models such as does not need to employ an assumption for the functional form of the frontier as the functional form may change when new DMUs are added to the sample set. Consequently, there is no danger of wrong model specification for the frontier. DEA allows the analysis of processes that involve various inputs generating multiple outputs at the same time, comparing each DMU with itself and the rest. In this context, DEA approach has recently attracted special interest for the task of assessing the technical and economic efficiency of WWTPs. For instance, Hernandez-Sancho and Sala-Garrido [43] applied DEA for the assessment of the technical and economic efficiency of a group of WWTPs, considering five inputs (costs for energy, labour, waste management, chemicals and others) and three outputs (the amount of TSS, COD and BOD removed). In other cases, outputs related to the environmental impact, as estimated by LCA, were analysed together with the economic performance [36,40] proving that the combined use of LCA + DEA can be a valuable method for the performance evaluation of WWTP from a broader perspective.

However, there are also a number of disadvantages that must be taken into consideration. Since the analysis relies heavily on the initial choice of inputs and outputs, the efficiency score tend to be sensitive to the choice of input and output variables. Misspecification of variables can lead to wrong results, as consequence of less efficient firms defining the frontier [42]. Thus care needs to be taken to the selection of input and output. As for example, some authors [35,40] selected kWh/m^3 as input for electricity use in their DEA matrices. The variables should, as far as possible, reflect the main aspects of resource-use in the activity concerned. On the contrary, as seen previously (see section 3.1), the KPI kWh/m^3 does not represent necessarily the plant performance.

DEA measures global efficiency for each DMU. That is, it measures the maximum radial (proportional) reduction in all inputs that would raise the DMU efficiency to the level of the most efficient DMUs in the study set [44]. Hence, a shortcoming of this approach is that the DEA frontier does not necessarily coincide with Pareto optimal frontier [45]. However, taking into account that a WWTP is viewed as a multiple input and outputs unit, the shortcoming of DEA models is that they do not provide information on the efficiency of specific inputs, but rather only measures global efficiency. To solve this problem non-radial DEA have also been applied [35,46]. This approach puts aside the assumption of proportionate contraction in inputs or outputs and it allow the isolation of the specific inputs or outputs to act to increase the efficiency of the DMUs being studied [46]. Thus, this type of model provides an efficiency indicator for each of the variables in the process.

Like the OLS, DEA relies on the assumption of deterministic energy efficiency scores, ignoring the fact that energy consumption has a significant stochastic component, affected by factors such as seasonality and weather. Because DEA is highly adaptive to data, efficiency estimates based on single measurements are very biased and unreliable if reported without estimating their error distributions. Literature shows that there are some stochastic extensions to DEA that can improve its robustness to data errors and outliers, i.e. stochastic DEA (SDEA) model [47]. This approach involves smart meter data set (repeated measurements, every 10 min in this case, of energy consumption). By using repeated measurements of energy consumption to estimate bias-corrected and confidence intervals for the efficient frontier the authors were able to estimate the uncertainties in the energy efficiency scores.

3.2.4. Discussion and comparison of different approaches

The above discussion on the different approaches has raised advantages and disadvantages to each, and a comparison of these is given in Table 3.

Table 3. Comparison of various benchmarking approaches. Methods specifically applied for the evaluation of energy efficiency in the field of wastewater treatment are highlighted in blond.

Benchmarking Approaches	System	Method	Approach	Model	Key characteristics	Pros	Cons

Normalization	Public	Non-Frontier	Deterministic	-	Based on relative simple performance indicators, and ratios of single input and output	Relative inexpensive; Easy to implement and interpret	It assume that the entire population of plants is comparable universally and with only one metric
OLS	Public	Frontier	Deterministic	Parametric	Estimates the average trend over the entire population, and then compare each plant with that overall trend.	Computationally easy and straightforward; Suitable for public users	Residuals are treated as measures of inefficiency, even if they actual reflect a combination of different factors; Sensitive to outliers; Difficult to implement on small samples
SFA	Public	Frontier	Stochastic	Parametric	Statistical approach that estimates a production frontier, and shifts this to reflect the efficiency of the most efficient firm to determine the frontier	The impact of measurements errors and other random effects is taken into account	Requires specification of a production frontier. Difficult to implement on small samples
DEA	Internal	Frontier	Deterministic	Non-Parametric	Non-parametric approach that calculates, rather than estimates, the frontier using programming techniques	No assumption or specification of energy function is required; Can incorporate uncontrollable (or unpredictable) factors (e.g. environmental)	Sensitive to choice of input and output variables; No allowance for stochastic factors and measurement errors
SDEA	Internal	Frontier	Stochastic	Non-Parametric	Linear programming model, such DEA, but it extended to account for the influence of statistical noise	Flexible and precise in the noise separation	Large dataset need Requires a prior assumption to describe the stochastic variations

Benchmarking approaches are fundamentally different from each other and therefore it is quite likely that they yield different results. Each approach can provide insights on aspects of WWTPs energy performance. The process of model specification and technique selection process depends on benchmarking objectives, data availability, and the user willingness to adopt specific assumptions for each type of model. Hence, the benchmarking user may need to draw upon professional consultants or specialists at research institutions before moving for more sophisticated models.

One of the main conclusions of this review is that each method is adapted to a particular goal, as all of them face their own drawbacks both on the theoretical and the practical side. This implies that the final efficiency estimates should not be interpreted as being definitive measures of inefficiency. By contrast, a range of efficiency scores may be developed and act as a signalling device rather than as a conclusive statement.

One of the main problems for benchmarking techniques is that there are usually only a small number of observations available relative to the number of explanatory variables. Energy efficiency depend upon a large number of factors, including the geographical characteristics of its service territory, weather condition, the influent load characteristics, electricity price or others factors, such as the human factor. None of these factors could be fully described without using a multitude of variables.

Normalization approach combines partial metrics and provides information time trends and patterns across WWTPs. Statistical techniques such as regression analysis results in an equation that is linear in explanatory variables which can be easily interpreted; each of the regression coefficients indicates the variation of the dependent variable (most often energy consumption) with respect to each explanatory variables, all other variables remaining constant. Furthermore, regression analysis is relatively simple to carry out and its conclusions are rather robust to experimental noise and outliers. DEA is very well adapted to determining the efficiency of a plant with respect to different inputs and outputs, as it is the case of WWTPs. It must be noted though that DEA efficiency scores are dependent on the input variables selected, potentially leading to different conclusions if the inputs are chosen on a different basis. As a consequence, the selection of input variables needs to be checked by other techniques, including linear regression. Finally, SDEA combines the flexible structure of non-parametric model but it is extended to account for the influence of statistical noise. The problem however is that the estimation task become bigger, the data need larger (repeated energy consumption measurement are necessary) and still cannot be avoided a series of strong assumptions about the distributions of the noise terms [48].

Regarding the end-user of the benchmarking system, methods can be well suited to common public (‘user friendly methods’) or rather aimed at internal benchmarking. For DEA, testing a new item requires solving the model again for the whole set of observations, with potential changes in the established ranking. Therefore, DEA based tools are aimed at internal benchmarking for companies, regulatory agencies, etc. On the other hand, new observations can be benchmarked directly with the benchmarking table generated by

OLS and normalization approaches. In effect, it is not necessary to solve the model to obtain the benchmarking score. These methods then become suitable for public users.

3.3. Analysis of collected energy data

Table 4 shows an overview of the consulted studies used in this article for collection of WWTPs energy data. The sources provide very heterogeneous data: from highly detailed to a generic overview of the energy consumption. As shown in Fig. 2, in most of the studies analysed (about 90%), WWTP energy consumption is reported as the average overall consumption (aggregated data), and stated as total electricity consumption (in kWh) or referred to the volume of treated wastewater (kWh/m^3); less frequently aggregated energy data are reported referred to the amount of COD and BOD eliminated or to plant load entering the plant (PE). Those data are usually collected from the energy bills and based on annual or daily average. Less frequently they are results of actual electric energy metering [6,49]. Disaggregated published data (i.e. energy consumption of each of the process and sections of a WWTP) are considerably scarcer in the literature. Those data are always reported as kWh or kWh/m^3, and will be reported and discussed separately bellow (section 3.3.2).

Table 4. Overview of the reviewed studies (see section 2 of the supplementary material for the dataset used for the analysis).

Reference	Type of energy data	Year	Country	N. of case studies	Type of technology[a]	Type of study	Source
[50]	Aggregated	1995	Canada	93	AP; BD; CAS	Energy benchmarking	Technical report
[51]	Aggregated	2009	France	31	BNR	Energy benchmarking	Technical report
[17]	Aggregated	2010	Japan	4	CAS	Energy benchmarking	Research article
[16]	Aggregated	2010	China	3	BNR; SBR	Energy benchmarking	Research article
[25]	Aggregated	2011	Spain	24	BNR; CAS; OD; UST	LCA study	Research article
[34]	Aggregated	2012	Canada	7	CAS; TF	Energy benchmarking	Research article
[52]	Aggregated	2013	Spain	1	BNR	LCA study	Research article
[53]	Aggregated	2013	Spain	7	BNR; MBR	LCA study	Book

[54]	Aggregated	2015	Germany	63	BNR; SBR; UST	Energy benchmarking	German regional agency
[55]	Aggregated	2015	Spain	79	AP; BD; BNR; CAS; EA; MBR; OD; UST	Energy benchmarking	Spanish regional agency
[56]	Aggregated/ Disaggregated	1998	USA	6	UST	Energy audit	Technical report
[57]	Aggregated/ Disaggregated	2004	Spain	1	BNR	LCA study	Research article
[58]	Aggregated/ Disaggregated	2007	Italy	1	MBR	Energy audit	Research article
[59]	Aggregated/ Disaggregated	2008	Spain	13	EA; BNR	LCA study	Research article
[20]	Aggregated/ Disaggregated	2013	Italy	5	CAS	Energy audit	Book
[6]	Aggregated/ Disaggregated	2015	UK	2	OD	Energy benchmarking	Research article
[60]	Disaggregated	1973	USA	9	CAS; TF	Energy audit	Technical report
[50]	Disaggregated	1995	Canada	24	AP; BD; CAS	Energy benchmarking	Technical report
[61]	Disaggregated	2008	USA	7	BNR; CAS	Energy audit	Technical report
[49]	Disaggregated	2009	USA	1	CAS	Energy audit	Technical report
[62]	Disaggregated	2013	USA	7	CAS; MBR; SBR; TF	Energy audit	Book

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[a] AP – Aerated pond; BD – Biodiscs; BNR – Biological nutrient removal; CAS – Conventional activated sludge; EA – Extended aeration; MBR – Membrane bioreactor; OD – Oxidation ditch; SBR – Sequencing batch reactor; UST - unspecified secondary treatment; TF – Trickling filter.

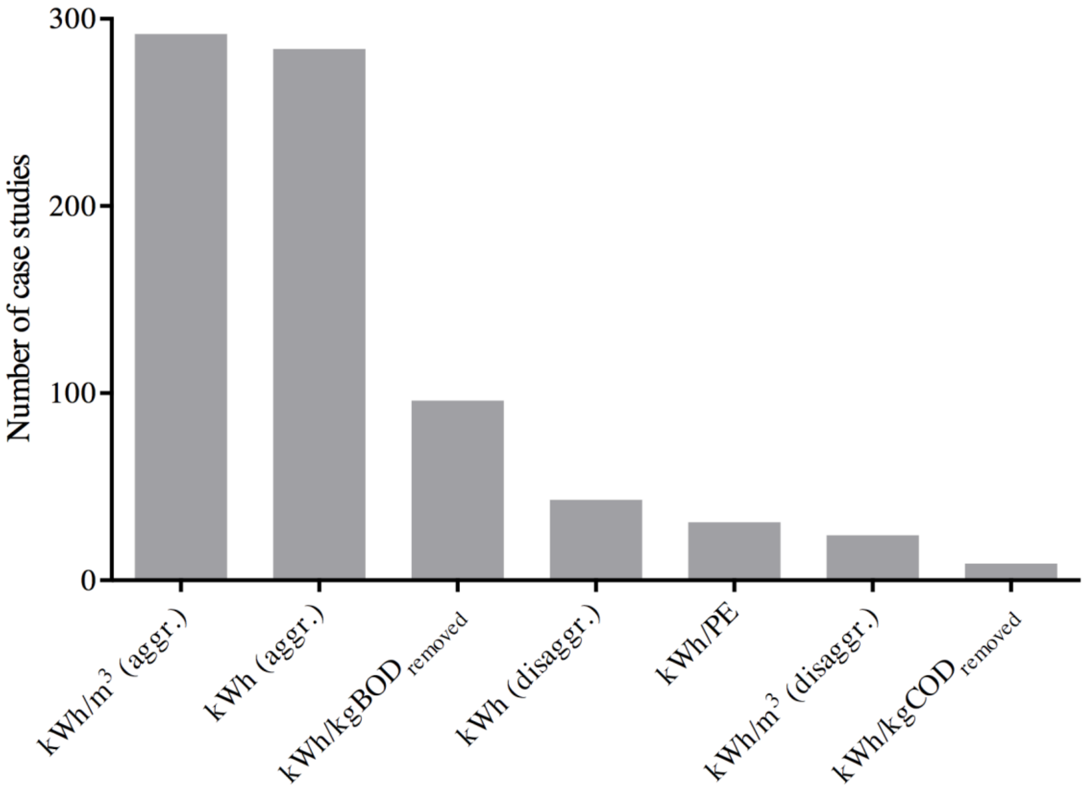

Figure 2. Statistics frequencies of how energy data are reported in the literature. [We suggest 1 column width]

Energy data are reported in literature for two main reasons. On the one hand, energy data are usually reported as part of energy benchmarking exercises and, although more rarely, in detailed energy analysis such as energy audits [56,60]. On the other hand, it is not uncommon to find energy data reported as part of broader analysis such as LCA studies of WWTP, where energy consumption is normally provided as part of the inventory and then transformed and discussed in terms of potential impacts [25,63].

Regarding the sources where energy data are available, the majority of case studies were found on technical reports and book as part of benchmark study or energy audit. Research articles were found to be a primary source in the case of LCA studies. Furthermore, energy data from regional water agencies (in particular from Germany and Spain) collected by private communications were also included in the analysis.

3.3.1. Energy consumption respect to scale, type of treatment and country

In this section the collected and processed data on overall (aggregated) WWTP energy consumption is presented. As discussed previously, the analysis is carried out using energy per COD removed as KPI. In order to elucidate the influence of individual variables on the energy performance, Fig. 3 reports the data variability as described in section 2.4 classified by class size (3.A), technology (3.B) and country (3.C).

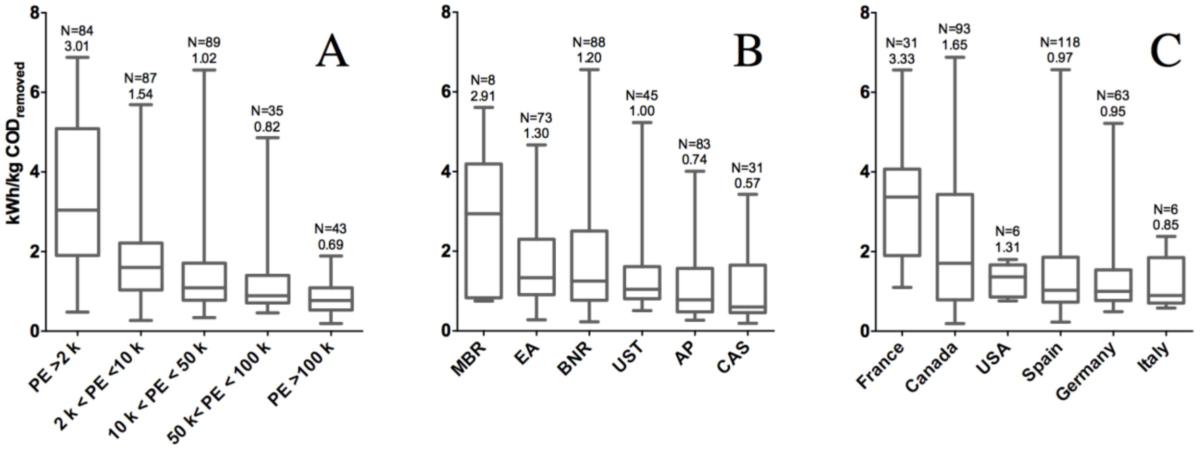

Figure 3. Total WWTPs energy consumption per: (A) class size, (B) type of treatment and (C) country. Note: numbers above the bars are sample size and average. Samples whose N < 5 are not shown, this is the reason why total sample sizes differ among Fig. 3.A, 3.B and 3.C. MBR = Membrane Bio-Reactor; EA = Extended Aeration; BNR = Biologic Nutrient Removal; UST = Unspecified Secondary Treatment; AP = Aerobic Pond; CAS = Conventional Activated Sludge. [We suggest 2 columns width]

Energy consumption respect to scale. According to figure 3.A, it can be seen that the energy consumption decreases when increasing the population equivalent. Considering median values, specific energy consumptions of 3.01, 1.54, 1.02, 0.82 and 0.69 kWh/kg $COD_{removed}$ were obtained moving up from the class size PE < 2 k to the class size PE > 100 k, respectively. According to the literature, large plants (more than 100,000 PE) are normally more energy efficient [17,43,64]. This can be due to: i) exploiting economies of scale, by using large and generally more efficient equipment, in particular larger pumps and compressors; ii) ensuring that the process operates at more stable conditions, which is reflected on a more regular operation of electromechanical equipment and avoiding energy-intensive transitional periods; iii) providing the automation for the treatment process (for example, regulation of the oxygen levels by controlling the operation of the aeration pumps); iv) more and especially better trained staff operating large plants, which is seldom the case for small WWTPs. However, in contrast with these results, some authors reported that smaller plants can, in principle, operate as energy efficiently as larger plants [65], or with diverse energy efficiencies [59]. Thus, to provide more reliable statements on this subject, additional research is required.

Energy consumption respect to type of treatment. The type of treatment has impact on the energy consumption of WWTPs. In Fig. 3.B a general overview of the energy consumption is reported for the sample analysed and different technology. According to the box plot graph, plants that carry out CAS and AP process showed the slowest energy consumption, while as expected MBR system are characterized by the highest energy consumption, being 2.3 times that of BNR system. MBR systems, due to intensive membrane aeration rates required to manage the fouling and clogging, are well known higher energy consuming process, being its energy consumption up to three times higher when compared with CAS systems combined with advanced treatment techniques such as tertiary filtration [66,67]. However, reporting energy in term of kg of $COD_{removed}$ does not take into account the additional complexity of BNR systems to remove N and/or P (i.e. higher volume of mixed liquor to be mixed and/or to be recirculated and higher air to be supplied), thus it is plausible expect higher energy consumption compared with AP and CAS system (that are characterized by a lower intensity of treatment.

Fig. 4 combines scale effect and technology (in particular CAS, BNR and AP, due to a lack of data for the other treatment technologies). The same tendency reported for the whole sample, i.e. the bigger the plant capacity the lower the energy consumption is also visible for these individual treatments. It is possible to observe that AP system is in general the lowest energy consumption treatment option (being the most efficient one in 3 out of the 5 plant size class) and that CAS process appears to be the worst alternative in terms of energy use (being the less efficient one in 4 out of the 5 plant size class). On the contrary BNR systems shows alternating results among the different size class that could be due to the fact that BNR category includes different configuration such as LE, MLE, Bardenpho, A/O or A2/O, hence WWTPs with different functions. However, apparently the possibility of BNR system to implement more efficient equipment, better performing automation and regulation compared to CAS system it allows to perform better despite its higher treatment intensity.

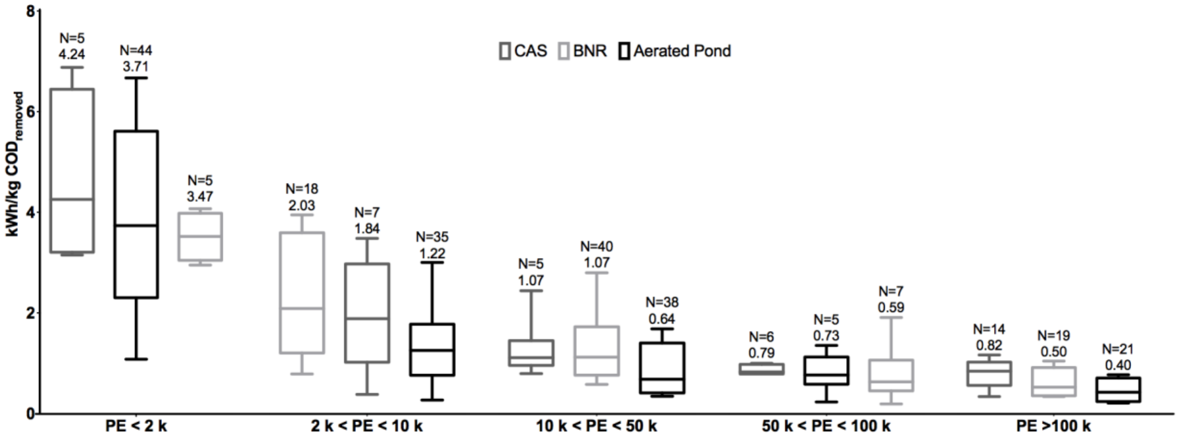

Figure 4. Specific energy consumption per type of treatment and plant size class. Note: numbers above the bars are sample size and average. [We suggest 2 columns width]

Energy consumption respect to country. As seen in the previous section the type of treatment used influences energy consumption. Therefore, it is reasonable to expect differences between different countries, where for economic and/or environmental reasons a particular type of treatment might prevail. With the exception of France and Canadian WWTPs, which turned out to have a particular high-energy consumption (3.33 and 1.65 kWh/kg $COD_{removed}$, respectively), similar values were found among countries (Fig. 3.C). Considering the median values, Spanish, German and Italian samples showed to be the most efficient countries of the sample analysed, with an energy consumption of 0.97, 0.95 and 0.85 kWh/kg $COD_{removed}$, respectively. USA sample, as opposite to the rest of the countries, showed a very low variability due to the smaller sample composed by medium-big size plants and reports a median value of 1.31 kWh/kg $COD_{removed}$. Aside form treatment technology and scale, other factors, such as electric energy price, are likely to influence WWTP energy consumption among the various countries. Higher prices could provide stronger incentives for energy efficiency measures. For example electricity in France is especially cheap for industry (0.079 €/kWh in France instead of 0.120 €/kWh in Spain, 0.130 €/kWh in Germany or 0.178 €/kWh in Italy [68]. A number of barriers can inhibit proactive energy management to address energy efficiency issues at WWTPs. Some of them are deeply rooted in the governance of the sector, referred to as institutional and regulatory issues: politicizing of water and wastewater tariffs, low electricity prices can influence energy efficiency at WWTPs. The reader is referred to [69] for a list of main barriers to improving energy efficiency in water and wastewater utilities and commonly observed barrier removal actions. In addition to this, Rieger and Olson pointed out that the human factor is often neglected when looking at WWTPs performance [70] and in this sense they argue that the lack of or the existence of misleading incentives for plant stakeholders involved (which include the public, federal agencies, state or provincial agencies, local political, plant managers, chief operators and operators) can considerably influence plant performances.

Fig. 5 summarises energy consumption of WWTPs, grouped by country and secondary treatment type of technology plotted against plant size (stated in terms of PE).

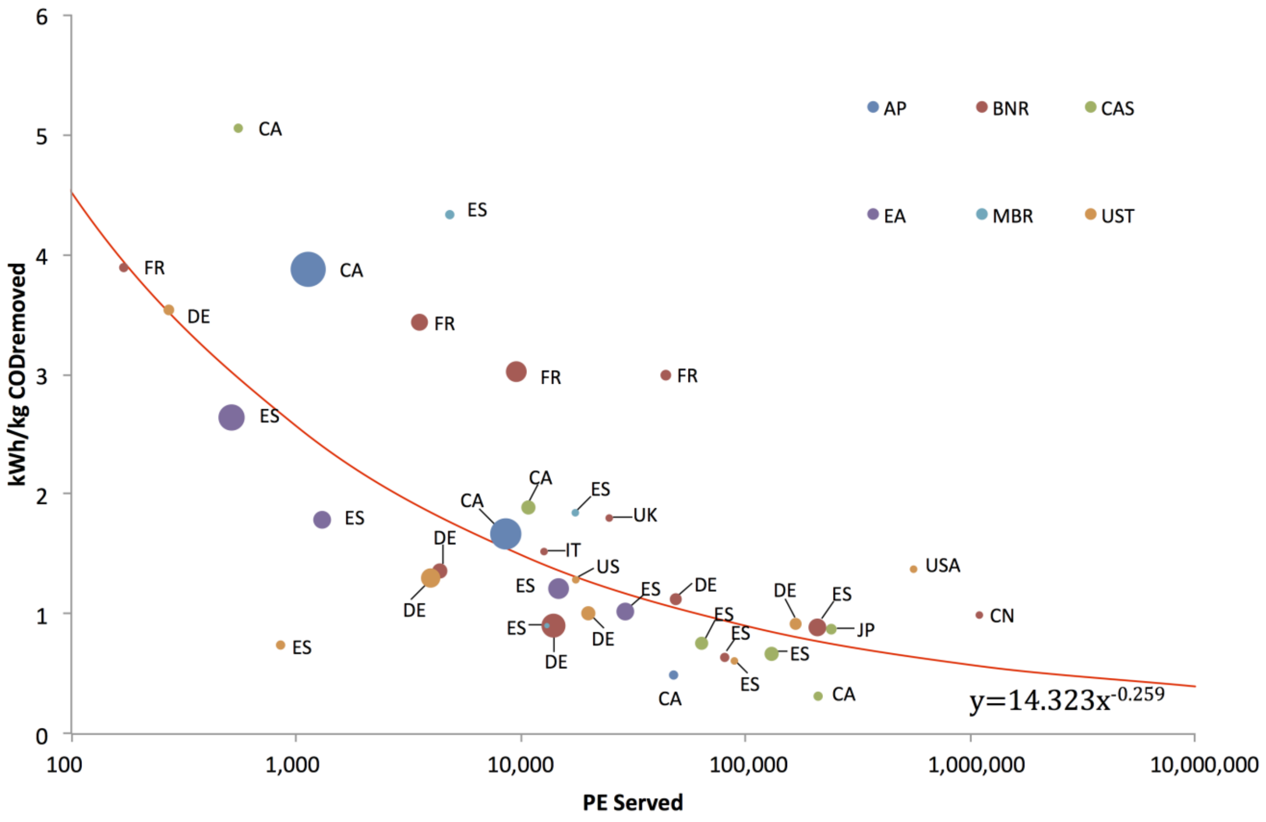

Figure 5. WWTPs specific energy consumption per country and type of treatment (bubbles size by sample size). Note: CN = China; CA = Canada; FR = France; DE = Germany; IT = Italy; JP = Japan; ES = Spain; UK = United Kingdom; US = United States of America. (Colours stand for the type of treatment; the reader is referred to the web version of this article). [We suggest 1.5 column width]

A correlation between specific energy consumption and plant size has been found. Increasing the capacity of the system, its specific energy consumption decreases according to the power law shown in the figure. For a given amount of PE served, a plant located above the regression line performs worse than its peers (and vice-versa). Two main observations can be made: i) there is no clear trend based on technology and location classification, rather there is a certain heterogeneity; ii) there are some countries that in general, regardless of the technology used, show better (Spain and Germany) or worse (France) energy efficiency compared to the expected one, which may be due to several factors such as the influent load, the effluent regulations or other plant operational conditions. In effect Spanish and German samples show a very low dilution factor (data not shown), which make them more energy efficient regardless of their type of treatment. On the contrary French WWTPs are characterized by excessive energy consumption. The influence of operational conditions is also the reason why contrasting results within the different type of treatment were found in the various countries, i.e. CAS systems (represented in green in the figure) result to be efficient in the case of Spain and the opposite in Canada.

3.3.2. Impact of operational conditions on energy consumption

Possible correlations between energy consumption and plant characteristics have been investigated and correlations with dilution and load factors (Eq. 4 and 5) have been identified and described here (Fig. 6). Other plant characteristics, such as sewer system design (mixed rather than separated), possible presence of tertiary treatment (UV or ozone disinfection and tertiary filtration) and sludge treatment layouts, have not been investigated due to the lack of data.

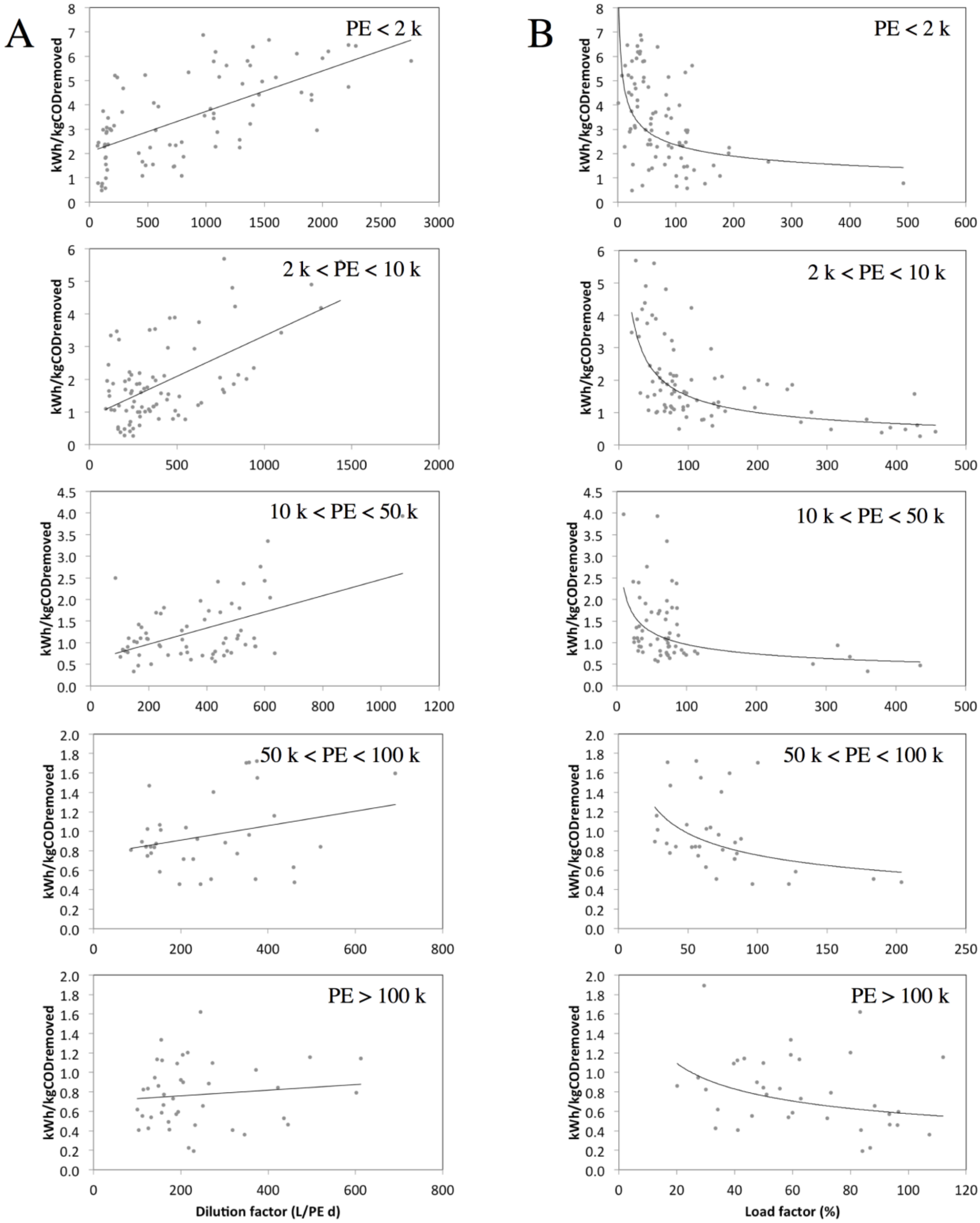

Figure 6. Variation of specific energy consumption with (A) influent wastewater dilution factor and (B) plant load factor. Note: Scale of x- and y-axis decreases with increasing plant class size. [We suggest 1.5 column width]

In case of combined sewer systems, the influent wastewater may be subjected to dilution due to infiltration of rainwater. From the analysis of the data it is clear that the specific consumption achieving wide high values in systems with a high degree of dilution of the wastewater. How it can be observed in Fig. 6.A energy consumption increases when increasing the dilution factor.

WWTP influents are characterised by several sources of variability in flowrate and loadings, with diurnal, weekly and seasonal patterns. Therefore, large design margins are needed, resulting in oversized WWTP [71] that can turn into inefficiencies from the energy point of view, as a result of the installation of equipment with greater power than required (Fig. 6.B). Specific energy consumption can be correlated with the load factor (Fig. 6B): plants receiving lower loads compared to design values present a significantly worse energy performance (not including the obvious excess in capital cost due to oversizing), energy consumption decreases when approaching the optimal value of 100% (as already reported by other authors [20,72]) and keeps decreasing for overloaded plants. It should be noted that in severely undersized plants malfunctions are likely to take place, leading to effluent quality deterioration and non-compliance with effluent requirements.

As a conclusion, WWTPs that receive wastewater diluted are more energy-intensive. However, if specific energy consumption is reported per volume of wastewater treated, the opposite results are achieved (Fig. 7) and so this KPI does not represent necessarily the plant performance. Due to the need to make reference to precautionary conditions at the design stage, a certain oversizing of the plants is necessary. However, an excessive oversizing of the plant involves an increase in specific energy consumption. Moreover, the impact of influent dilution and plant load factor on energy consumption decrease increasing the size of the plant (Fig. 6.A and 6.B). This can explains the greater variability of specific energy consumption of small plants compared to bigger one.

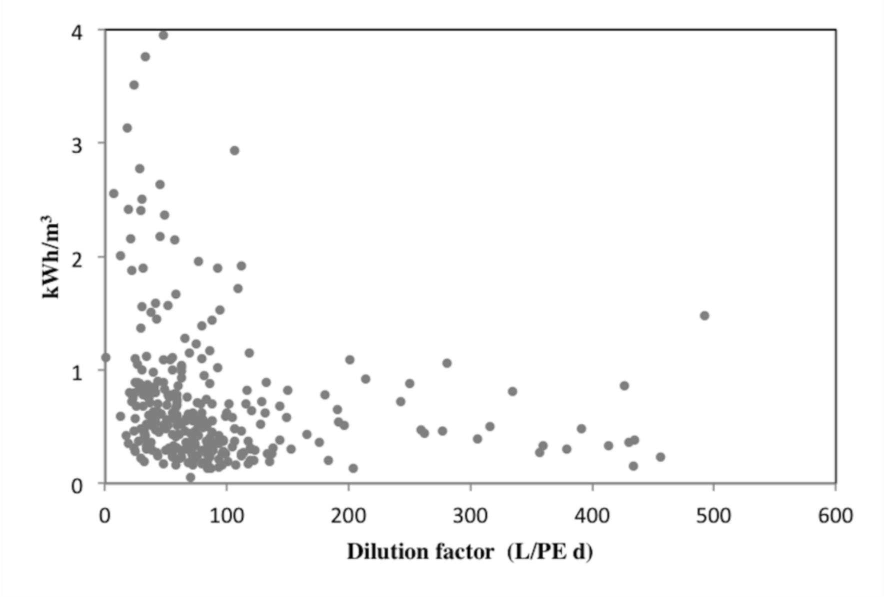

Figure 7. Variation of energy consumption for different influent wastewater dilution factors. [We suggest 1 column width]

3.3.3. Energy consumption per plant section

WWTPs are complex processes composed by several subsystems (stages) (i.e. preliminary, primary, secondary, tertiary, sludge treatment), each one with different function. Each of these stages presents a very different energy consumption rate as summarised in the data presented in this section.

Table 5 shows a list of electromechanic equipment that can be present in a common WWTP divided per plant section and class size. Not all the WWTPs present the same plant sections, depending on the layout, plant size and treatment intensity required. As the literature review has shown that disaggregated energy data are always reported as kWh/m^3 (see Fig. 2), in this section energy data will be discussed using this KPI.

The energy consumption, in general, achieves wide ranges for the various sections of the plant, since each system install different types of equipment, even if they belong to the same compartments of treatment. However, there are typical behaviours, such as for example the increased consumption is due to aeration of the activated sludge or the minimum energy consumption related to the pre-treatment and primary treatments. So, it is generally assumed that for medium to large plants, the treatment sections characterized by higher energy consumption are biological oxidation, lifts (pumping and sludge recirculation) and generally mechanical dewatering of sludge and/or aerobic sludge digestion if present.

Table 5. Disaggregated energy data reported in the literature (stated as kWh/m^3). Sources of disaggregated data are listed in Table 4.

Size classification	PE < 2 k	2 k < PE < 10 k	10 k < PE < 50 k	50 k < PE < 100 k	PE > 100 k
Number of plants	3	6	18	13	36
Average flow rate (m^3/d)	102	1303	4966	18713	188464
PRELIMINARY TREATMENT					
Influent pumping		$2.2\cdot10^{-2}$	$3.9\cdot10^{-2}$	$4.2\cdot10^{-2}$	$4.1\cdot10^{-2}$
Micro screening			0.023		$4.2\cdot10^{-3}$
Screening	$1.3\cdot10^{-2}$	$3.8\cdot10^{-3}$	$1.4\cdot10^{-3}$	$1.0\cdot10^{-4}$	$2.9\cdot10^{-5}$
Comminutors			$3.9\cdot10^{-3}$		
Degritting		$1.1\cdot10^{-5}$	$6.6\cdot10^{-3}$	$5.4\cdot10^{-3}$	$2.7\cdot10^{-3}$
PRIMARY - TREATMENT					
Primary settling			$7.1\cdot10^{-3}$	$4.8\cdot10^{-3}$	$4.3\cdot10^{-3}$
SECONDARY TREATMENT					
Trickling filter			$8.0\cdot10^{-2}$	0.14	0.18
Mixer anoxic		$5.3\cdot10^{-2}$	$6.8\cdot10^{-2}$	$7.0\cdot10^{-2}$	0.16
Mixed liquor recirculation		$1.0\cdot10^{-2}$		$4.7\cdot10^{-2}$	
Blowers oxidation	0.8	0.21	0.18	0.22	0.19
Mixer aerobic oxidation					$2.0\cdot10^{-3}$
Final settling		$1.2\cdot10^{-2}$	$5.5\cdot10^{-3}$	$7.1\cdot10^{-3}$	$8.4\cdot10^{-3}$
Sludge recirculation	0.23	$7.9\cdot10^{-2}$	$2.9\cdot10^{-2}$	$1.1\cdot10^{-2}$	$7.9\cdot10^{-3}$
Bio-filtration			$7.1\cdot10^{-2}$	$6.9\cdot10^{-2}$	$5.5\cdot10^{-3}$
Membrane Bio-Reactor			0.63	0.72	0.38
Sequential Bio-Reactor			0.22	0.29	0.15
TERTIARY TREATMENT					
Chemicals			$1.1\cdot10^{-2}$	$1.5\cdot10^{-2}$	$9.0\cdot10^{-3}$
Chlorine disinfection			$2.0\cdot10^{-4}$	$2.7\cdot10^{-4}$	$8.8\cdot10^{-4}$
Pump tertiary filtration			$2.9\cdot10^{-2}$	$5.9\cdot10^{-2}$	$1.4\cdot10^{-2}$
Tertiary filtration			$2.7\cdot10^{-2}$	$1.3\cdot10^{-2}$	$7.4\cdot10^{-3}$
Ultra-Violet lamps			$4.5\cdot10^{-2}$	$6.2\cdot10^{-2}$	0.11
SLUDGE TREATMENT					
Sludge primary settler			$1.7\cdot10^{-4}$		$1.8\cdot10^{-4}$
Excess sludge pumping		$1.6\cdot10^{-2}$	$4.5\cdot10^{-3}$		$7.3\cdot10^{-4}$
Gravity thickening	$9.2\cdot10^{-3}$	$3.7\cdot10^{-3}$	$2.7\cdot10^{-3}$	$2.1\cdot10^{-3}$	$1.9\cdot10^{-3}$
Centrifuge thickening			$1.6\cdot10^{-2}$	$1.5\cdot10^{-2}$	$1.8\cdot10^{-2}$
Floating thickening			$1.4\cdot10^{-2}$		$3.5\cdot10^{-2}$

Mixer aerobic stabilization		$2.6\cdot10^{-2}$			
Blowers aerobic stabilization	0.53	$4.5\cdot10^{-2}$	0.17	0.15	$2.4\cdot10^{-2}$
Anaerobic stabilization				$2.9\cdot10^{-2}$	$3.2\cdot10^{-2}$
Motor gas recirculation			$1.9\cdot10^{-2}$		$3.1\cdot10^{-3}$
Heating sludge			$3.5\cdot10^{-3}$		$2.4\cdot10^{-3}$
Vacuum filter			$1.5\cdot10^{-2}$		$9.8\cdot10^{-3}$
Incineration			$1.2\cdot10^{-2}$		$0.7\cdot10^{-3}$
Centrifuge dew		$1.8\cdot10^{-2}$	$2.0\cdot10^{-2}$	$2.3\cdot10^{-2}$	$2.7\cdot10^{-2}$
Belt filter press				$1.2\cdot10^{-2}$	$1.0\cdot10^{-3}$
Screw press			$4.0\cdot10^{-3}$	$4.8\cdot10^{-3}$	$4.9\cdot10^{-3}$
Fermentation			$3.0\cdot10^{-2}$	$9.5\cdot10^{-3}$	$1.6\cdot10^{-4}$

Preliminary treatment. The steps most commonly used in the pretreatment of wastewater are 1) the pumping of wastewater, 2) screening, 3) grit removal and 4) comminutors (grinding residues screenings). Generally, apart from pumping, these various steps are responsible for only a small portion of the total electric energy consumption of WWTPs. The electrical energy consumed for pumping the wastewater to sewage infrastructure depends on the structure and location of the sewer system. Consumption of between $2.2\cdot10^{-2}$ and $4.2\cdot10^{-2}$ kWh/m^3 were found, which represents, depending on the size of the plant and intensity of the treatment, between 5 and 18% of the total electricity use. The energy consumption associated with the screening step is mainly attributable to the gates cleaning phase. According to the data collected, this processing step has an electrical expenditure of between $2.9\cdot10^{-5}$ and $1.3\cdot10^{-2}$ kWh/m^3, with an inversely proportional relation to the hydraulic flow. In general, such an energy intake represents less than 1% of the total power consumption. Several grit removal techniques are used in sewage treatment plants. Generally aerated or not-aerated processes can be found. This processing step may be between 1.3 and 2.7% of electricity consumption.

Primary treatment. The primary treatment is, in most cases, a simple separation step in circular settling tanks equipped with mechanized scrapers. The primary settling stage requires about $4.3\cdot10^{-5}$ -$7.1\cdot10^{-5}$ kWh/m^3, which is obviously a very small portion of the overall energy use.

Secondary treatment. The secondary treatment is responsible for a significant proportion of the amount of electrical energy consumption. However, the required amount of electricity can vary for different types of treatment. The most energy consuming process is the aeration system. Generally, the consumption for aeration is between 0.18 and 0.8 kWh/m^3. Aeration is an essential process in the majority of WWTPs and accounts for the largest fraction of plant energy costs, ranging from 45 to 75 % of the plant energy expenditure [73]. Because of the high-energy use associated with aeration, energy savings can be gained by designing and operating aeration system to match, as closely as possible, the actual oxygen demands of the process. The most important process parameter to affect aeration efficiency is the mean cell retention time (MCRT) [74]. MCRT is directly related to the biomass concentration, and dictates oxygen requirements. Aeration efficiency and alpha factor (ratio of process-water to clean-water mass transfer) are higher at higher MCRTs. Literature studies [75,76] showed that the oxygen transfer efficiency is directly proportional to MCRT, inversely proportional to air flow rate per diffuser, and directly proportional to geometry parameters (diffuser submergence, number and surface area of diffusers).

The separation of the sludge produced is usually carried out by a gravity-settling step in decanters equipped with mechanized scrapers. As with the primary settling, a small amount of energy is associated with this process, between $8.4{\cdot}10^{-3}$ and $1.2{\cdot}10^{-2}$ kWh/m^3 or 0.5 to 1.5% of the overall electricity consumption, depending to plant size. Secondary sludge recirculation pumping results in an energy consumption of about $4.7{\cdot}10^{-2}$ to $1.0{\cdot}10^{-2}$ kWh/m^3. This energy consumption is between 1.5 and 3.5% of the electricity consumed in the whole plant. Another energy consuming process is mixing, in particular for anoxic reactors, ranging between $5.3{\cdot}10^{-2}$ and 0.12 kWh/m^3. As the energy required for mixing increases superlinearly with the size of the tank, the contribution of mixing to the overall energy consumption can become comparable to other aerated processes for large plants [77].

Tertiary treatment. Tertiary treatments increase not only effluent quality but also energy consumption. The values depend on the particular technology, going from $4.5{\cdot}10^{-2}$-0.11 kWh/m^3 for UV disinfection, or $9.0{\cdot}10^{-3}$-$1.5{\cdot}10^{-2}$ kWh/m^3 for mechanic equipment required for the dosage of chemicals (aluminium or iron salts, chlorinated reagents, etc.), to $7.4{\cdot}10^{-3}$-$2.7{\cdot}10^{-3}$ kWh/m^3 for tertiary filtration.

Sludge treatment. The energy consumed at different stages of treatment and final disposal of sludge may represent a major fraction of the overall electricity balance for a plant. Aerobic sludge stabilization is the most energy consuming sludge treatment process, since its energy demand is comparable to aeration system in the water line. Anaerobic digestion is more energy efficient options as, though its feasibility is often linked to the plant's size, the energy production may significantly improve the WWTP performance with respect to energy costs and self-sufficiency. Depending on the wastewater characteristics and on the removal efficiencies, $7.4 \cdot 10^{-2}$ - 0.15 kWh/m^3 (production) are reported in the literature [72], and may ensure or even exceed the plant requirements [78]. Finally, a significant portion of energy consumption is normally accounted for sludge dewatering, where mechanical centrifugation was found to be the most energy demanding process ($1.8 \cdot 10^{-2}$-$2.7 \cdot 10^{-2}$ kWh/m^3).

3.4. Examples of energy efficiency improvements

Energy saving measures available for implementation are reported here, focusing on the most energy consuming stages, i.e. pumping, aeration and sludge line. These actions can range from operating conditions upgrade to the implementation of new processes.

Process optimization can substantially increase energy efficiency with very low investments and short payback times. As an illustration, considerable savings in energy have been achieved by reducing the number of active mixers in the biological treatment based on a retrofit of the designed plant [79]. Or, savings up to 10-15% of the total consumption were achieved at Hoensbroek WWTP (Netherlands) only by regulating MLSS concentration based on activated sludge temperature [80].

Energy conservation measures for pumping are conventional and do not represent an area of recent technology innovation. However, they are still extremely important to reducing and optimizing energy use at WWTPs. Simple savings are possible where the pumping operational set up has been changed from the design condition. Together with applying variable frequency drives and adopting energy-efficient pumps, gains of between 5 and 30% of electricity for influent pumping may be realised [81].

Because of high-energy use associated with aeration, energy savings can be gained by operating aeration systems to match, as closely as possible the oxygen demands. DO control has been common practice in process control for many decades. As an example, savings of 26% of air flowrate were reported at Käppala WWTP (Sweden) after the installation of online DO control [82]. More advanced DO set-point control (based on on-line influent measurements and process data) resulted in total energy savings of around 19% [83] and 15% [84]. As a counterpart, the application of measuring and control systems requires greater knowledge and effort on the part of operators, such as maintenance and monitoring of online sensors. The lack of a systematic maintenance and monitoring of sensors can lead, in fact, to drive the process further away from the optimum state [85]. The introduction of direct-drive, high-speed, turbo blowers to the wastewater market have been of great interest with respect to potential energy savings. Investigations conducted at various WWTPs suggest that replacing conventional blower with turbo blowers can easily result in a reduction of energy power in excess of 30-35% [86]. A demonstration test conducted at Franklin WWTP in New Hampshire (USA) has shown that projected energy savings could be as much as 35% [87]. Recent advances in membrane materials have led to ultra-fine bubble diffusers by which energy savings between 10 and 20% have been reported in comparison with traditional ceramic and elastomeric membrane diffusers configurations [88]. Technological advances are also progressing in the area of diffuser cleaning. Larson [89] documented the development of a new online monitoring device to help predict when diffuser air systems require cleaning. The energy efficiency improvement due to the prototype analyser installation has been estimated in 15%.

With regard to the sludge line, the side-stream treatment of nutrient rich reject water deriving from dewatering of digested sludge can lead to consistent energy savings. Within the last decade several partial nitritation/anammox technologies have been developed and successfully implemented in full scale, e.g. sequencing batch reactors, granular reactors, and moving bed biofilm reactors. The energy demand of side-stream treatment systems ranged from as low as 0.8 kWh/kg $N_{removed}$ to around 2 kWh/kg $N_{removed}$ [24]. Similar values of 1.2 kWh/kg $N_{removed}$ have been reported previously by Wett et al. [90]. Compared to a conventional nitro/denitro side-stream treatment with an energy demand of approximately 4.0 kWh/kg $N_{removed}$ [24], the savings of partial nitritation/anammox processes are at least 50%, and depend largely on aeration system. Finally, current research trend is focusing on the pretreatment of sewage sludge, such as thermal pre-treatments or ultrasounds, to be implemented in an anaerobic digester with the aim to produce an increase in the biogas recovery. Ultrasounds applied in full-scale plants can increase the biogas production compensating the extra energy expenditure [91]. Thermal hydrolysis also presents high potential to be fully integrated in WWTP with a complete energy recovery and self-sufficiency [92].

Concluding, overall energy savings result from operational optimization and technology improvements of between 5 and 30% seem reasonable. Area with most potential is aeration systems. Examples include on line aeration control, energy-efficient bubble aerators and updating of sludge line with separate side-stream of rejected water from anaerobic digestion.

3.5. Energy management tools

For WWTPs that have not embarked on a systematic program to manage energy use, initial steps can be taken to organize and gradually ramp up energy management programs, starting with internal energy data collection, reporting and analysis and implementing small/low cost energy conservation measures. Learning from peer WWTPs that have established successful energy management practices it is also important. However, in order to address broader issues and scale up results, wastewater utilities can take advantage of the following energy management actions: i) conduction of a more comprehensive energy audits, ii) further strengthening data collection and analysis via automated systems for energy use and monitoring and data acquisition, analysis and reporting and, iii) looking outside the utility for technical expertise by involving an energy service company (ESCo).

3.5.1. Energy management systems and energy audits

An effective energy efficiency program needs to adopt a structured approach in energy management. The international standard ISO 50001 for enterprise Energy Management Systems [93] offers useful guidance for good energy management by specifying requirements for establishing, implementing, maintaining and improving an energy management system, whose purpose is to enable an organization to follow a systematic approach in achieving continual improvement of energy performance, including energy efficiency, energy use and consumption. The procedure lays on the Plan-Do-Check-Act iterative process, a circular evolving process that focuses on continual improvement over time and that enables utilities to establish and prioritize energy conservation targets (Plan), implement specific practices to meet these targets (Do), monitor and measure energy performance improvements and cost savings (Check), and periodically review progress and make adjustments to energy programs (Act). On this approach is based the Energy Management Guidebook for Water and Wastewater Utilities of US Environmental Protection Agency (USEPA) [94], which describes a systematic approach to reducing energy consumption and energy cost. To do so, the KPI kWh/gallon is suggested to measure progress towards established energy efficiency targets. The guide also includes information on energy auditing and how to use the Energy Star Benchmarking Tool (see section 3.2.2).

The energy audit is an essential step in energy management efforts. Energy audit helps the facility target the most inefficient aspects of its operations. Simple energy audits, which are necessary for gaining a basic understanding of a WWTP energy use and are fairly inexpensive, generally involve a walk-through of facilities (handheld measuring devices may be used) and a quick desk analysis of available energy use and costs data. While walk-through audits lack a detailed analysis of potential energy efficiency measures, they are useful to implement relatively simple and immediately affordable recommendations, such as change in operation timing, and upgrades to lighting, heating and air conditioning, and pumping equipment. The plant operators themselves can usually complete this type of audits during a working day. Detailed process audits require a more in depth conversation between the facility and professional auditors experienced in wastewater systems. This type of audit often involve equipment field tests, inventorying equipment energy performance data, creating energy profiles for equipment and systems, discussing potential energy conservation measures. Detailed process audits provide comprehensive information on the payback periods associated with the recommended measures.

As energy audit normally uses KPI to evaluate the process efficiency, proper measurement and treatment of operation data is essential to ensure the soundness of the audit conclusions. For instance, composite samples are often used to determine the pollutant loading over a given period of time. The simplest form is time-related composites, which are characterized by sub samples of equal volume taken at specific time intervals (e.g. sub samples every hour). If a more accurate loading estimation is needed, flow proportional sampling can be used [95]. This method consists in taking a number of samples proportional to the flowrate thereby leading to a better estimate of the total loading over a period of time.

3.5.2. Energy monitoring and targeting system

Various methodologies have been used to estimate energy consumption in WWTPs, including utilization of the equipment specification (power and usage time), power loggers and modelling. In Europe, however, estimation of energy consumption based on instantaneous power and operating time is still widely used [2,7]. In order to improve the energy efficiency of WWTPs, an energy monitoring and targeting (M&T) system can be implemented. An M&T system is a hardware and software system used to track and manage energy consumption. It may include a set of sub-meters, a connection to the main utility meter, controls for certain systems, and a program to display energy consumption and adjust certain parameters. It is scalable and can be tailored to a single or multiple facilities, providing a good starting point for WWTPs to begin a structured and data based energy management process [69]. Energy M&T is likely to gain acceptance and use among WWTPs where energy cost is a major management concern and there is already a corporate effort underway to optimize energy use. Energy M&T may also serve as a useful engagement platform to introduce energy management practices to WWTPs. These systems vary considerably in their complexity and capability. For example, supervisory control and data acquisition (SCADA) systems become more widely adopted at WWTPs, to help utilities reduce energy costs and save money, being reported as a very cost-effective tool with payback period of 2-4 years [94]. SCADA system can be designed to measure a multitude of equipment operating conditions and parameters, such as flowrate and water quality parameters, and respond to changes in those parameters either by alerting operators or by modifying system operation through automations. Finally, SCADA systems, being able to provide constant, real-time data on processes and equipment energy consumption, can compute KPIs and thus serve as online benchmarking tool letting WWTP operators understand which processes to focus on for energy conservative measurements..

3.5.3. Energy savings performance contracts

Although implementing actions to improve the energy efficiency can be economically sound in the long term, a number of drawbacks prevent their universal application, in particular that the payback time can be too long for some stakeholders. Specialized intervention or trained technicians may be needed, as public bodies increasingly require the need of energy audits and efficiency actions. Specialized companies in energy efficiency actions, ESCo (Energy Service Company), have expanded radically with the aim of reducing energy costs and accompany the client through the efficiency process of the water and wastewater utilities taking upon himself the risk and relieving the client from any organizational effort and investment [97]. Full ESCo services may include financing for the energy efficiency upgrades, disencumbering the host facility from the burden of securing upfront capital. The use of energy savings performance contracts (ESPCs) in water company is fairly common in North America, where the energy service industry is mature and business contracts are well enforced [69]. In the United States, for example, after an ESCo is selected to perform investment grade energy audits, a water utility will arrange its own financing through loans from revolving funds or municipal bonds. Funds can include partial government grants and some bonds have tax exemption status. The water utility will contract the ESCo to implement projects on a performance basis, often with guaranteed savings. If energy savings from the projects are not fully realized, the ESCo payments can be reduced.

4. Conclusion

This paper reviews municipal WWTPs energy-use and benchmarking techniques and provides an overview of the main approaches available. Recommendations and challenges are highlighted on how to conduct energy analysis of WWTPs. It is concluded that benchmarking methods must be chosen depending on the purpose and extent of the analysis, as their range of validity and applicability is different:

- Normalisation approaches, based on single KPIs, can be suitable for similar conditions, similar WWTPs or similar technologies/processes but not for overall assessment of complex plants in different environments, e.g. climate;
- Regression-based techniques such as OLS can control the effect of other variables (flowrate, size, loading) and extend the range of validity. Provided that a representative set of samples was available when building the regression line, the resulting equation can be used in benchmarking by external users;
- DEA can be used to reconcile multiple inputs and outputs in the benchmark assessment. As a consequence, the results depend greatly on the proper selection of input and output variables. DEA would be rather restricted to internal benchmarking procedures, as the inclusion of a new sample lying in the efficient frontier would change the obtained model.

In any case, the various benchmarking methods applied so far are mainly diagnostic tools that fail at prescribing any improvement strategy to make inefficient WWTPs efficient. Such strategies must be studied and implemented by managers through a better understanding of the plant operations. The results of the on-going ENERWATER project are expected to contribute to the development of a methodology able not only to quantify WWTPs energy efficiency but also to identify energy inefficiencies in order to help wastewater utilities to comply with requirements of the EU Energy Efficiency Directive.

The assessment of a representative data sample has provided some evidence about the variables that have a largest effect on energy consumption: plant size, dilution factor and flowrate. The technology choice, plant layout and country of location were seen as important elements that contributed to the large variability observed. The large dispersion of the results shows that there is considerable room for improving the efficiency of WWTP operation, which will require, not only the reviewed techniques for benchmarking but also diagnosis. To achieve this aim, detailed monitoring of the WWTP operation is crucial and is expected to be more frequently carried out in the upcoming years.

Further actions to spread efforts for energy efficiency at WWTPs could need external specialists assistance, by: i) further strengthening data collection and analysis via automated systems for energy use monitoring and data acquisition, and customized analysis and reporting; ii) conducting a more comprehensive energy assessment and developing standard procedures and checklists; iii) looking outside the utility for technical expertise lacking in-house, such as twinning with other better-performing utilities, contracting with ESCo, and accessing national associations.

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Nomenclature

A/O anaerobic-oxic
A2/O anaerobic-anoxic-oxic

AP aerated ponds
BD biodiscs
BNR biological nutrient removal
BOD biochemical oxygen demand
CAS conventional activated sludge
COD chemical oxygen demand
CRS constant returns to scale
DEA data envelopment analysis
DF dilution factor
DMU decision making unit
DRS decreasing returns to scale
EA extended aeration
ESCo energy service company
ESPC energy savings performance contract
IRS increasing returns to scale
KPI key performance indicator
LCA life cycle assessment
LF load factor
M&T monitoring and targeting
MBR membrane bioreactor
MCRT mean cell retention time
MLE modified Ludzack-Ettinger
OD oxidation ditch
OLS ordinary least squares
PE population equivalent
RTS return to scale
SBR sequential batch reactor
SCADA supervisory control and data acquisition
SDEA stochastic DEA
SFA stochastic frontier analysis
TF trickling filter
TN total nitrogen
TP total phosphorus
TSS total suspended solids
UST unspecified secondary treatment
UV ultraviolet
WWTP wastewater treatment plant