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Review

Energy efficiency in wastewater treatment plants: A framework for benchmarking method selection and application

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A R T I C L E I N F O

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A B S T R A C T

Utilities produce and store vast amount of data related to urban wastewater management. Not yet fully exploited, proper data analysis would provide relevant process information and represents a great opportunity to improve the process performance. In the last years, several statistical tools and benchmarking methods that can extract useful information from data have been described to analyse wastewater treatment plant (WWTP) energy efficiency. Improving energy efficiency at WWTPs is however a complex task which involves several actors (both internal and external to the water utility), requires an exchange of different types of information which can be analysed by a broad selection of methods. Benchmarking method therefore must not only be selected based on whether they provide a clear identification of inefficient processes; it must also match the available data and the skills of those performing the assessment and objectives of stakeholders interpreting the results. Here, we have identified the requirements of the most common benchmarking methods in terms of data, resources, complexity of use, and information provided. To do that, inefficiency is decomposed so that the analyst, considering the objective of the study and the available data, can link each element to the appropriate method for quantification and benchmarking, and relate inefficiency components with root-causes in wastewater treatment. Finally, a framework for selecting the most suitable benchmarking method to improve energy efficiency in WWTPs is proposed to assist water sector stakeholders. By offering guidelines on how integrates and links data, methods and actors in the water sector, the outcomes of this article are expected to move WWTPs towards increasing energy efficiency.

1. Introduction

Thanks to new developments in the field of information technology, cheaper sensors, and increasingly common supervisory control and data acquisition system (i.e. SCADA systems), there is a vast amount of data on urban wastewater management, which has been not fully exploited yet and constitutes a resource to improve the process performance. Some of these data are collected and held by water management actors including utility operators and different level of environmental authorities for different purposes, without a common format or storage method. Overall, large amounts of data from wastewater treatment plants (WWTPs) are being generated which need to be properly transformed into knowledge for enhancing their operation (Corominas et al., 2018).

In current practice, plant operators often have an overwhelming amount of data at their hands, which are very difficult to process and analyse in a timely manner. Methods and tools that enable systematic extraction of information from data sets would assist in optimising the plant, eventually helping to further increase the effluent quality, to reduce the consumption of energy and other resources and to foster the operator's knowledge on the plant processes (Yoo et al., 2008). Out of the many processes through which data can be transformed in knowledge such as classification, clustering, prediction, neural networks, machine learning (Corominas et al., 2018), this work/paper focuses on benchmarking techniques as a primary strategy for data management in WWTPs and its application to the evaluation of energy efficiency.

As WWTPs are large energy consumers, energy efficiency is relevant for virtually all water utilities. Besides, current regulation imposes energy efficiency audits in water utilities larger than a certain size. Indeed, Directive 2012/27/EU on energy efficiency (European Commission, 2012) specifies, through its national transpositions, that European large companies must be audited in terms of energy efficiency. However, the

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Directive does not specify important elements such as a clear definition of energy efficiency for WWTP (Longo et al., 2019) or the methods to be used in the compulsory energy efficiency audits. As discussed later, benchmarking methods can be suitable for energy efficiency provided that the right method is chosen, and this selection must not only be based on whether they provide a clear identification of inefficient processes but also on the proper match between the available data and the skills as well as objectives of those performing the assessment.

Energy benchmarking concerns a variety of people, from plant operators, managers, regulators, technology providers, consumers, etc., with different capabilities and interests which should be reflected on the election of the right tool (Walker et al., 2021). A common characteristic of the methods developed for wide standardised benchmarking is their simplicity, as they are intended for diverse actors. Examples of such methods include the Energy Check developed by DWA in Germany (DWA - German Association for Water Wastewater and Waste, 2015), the Energy Star sponsored by the Awwa Research Foundation in the USA (Carlson and Walburger, 2007) or the Standard CEN/TR 17614 developed with the support of the H2020 framework programme (Longo et al., 2019). The International Benchmarking Network for Water and Sanitation Utilities (IBNET, 2022), a World Bank sponsored initiative, counts a large number of indicators for benchmarking which, in the case of WWTP energy efficiency is based on a single indicator: the energy used per unit volume of wastewater, usually reported in kWh/m^3 (Walker et al., 2021). Differently, more detailed analyses (based on data envelopment analysis, regression analysis, etc.) by technical actors require more sophisticated and data-intensive tools.

First, a detailed overview of the methods is given in section 2 which may be skipped for the experienced reader. Section 3 presents a comparison of the methods and how they can provide a decomposition of energy inefficiency. Section 4 is devoted to establishing which method is suitable for each actor. Lastly, section 5 presents an integrated framework that links data, methods and the main actors involved, describing the flow of information leading to decision making from data and hence into energy efficiency investments. It is concluded highlighting the importance of method selection by each actor for an effective promotion and communication of energy efficiency information in the wastewater sector.

2. Overview of benchmarking methods for WWTP energy efficiency

Efficiency is commonly defined as “the relationship between the production of a service, good or energy” and its resource demand (European Commission, 2012). In the case of energy efficiency, the resource is the energy demand, including other resources that can be ultimately converted into a useful form of energy. Regarding WWTPs, defining the service delivered is somewhat more complex. “Cleaning wastewater” or “recovering resources” are not readily quantifiable and must therefore be decomposed in the different functions of a WWTP which may include, among others, “eliminate nitrogen”, “reduce the number of pathogens”, “remove phosphorus from the liquid streams”, “produce biogas from organic carbon”, etc. depending on the influent, location of discharge point and the requirements of the effluent. Therefore, the first step in energy benchmarking is specifying the function(s) provided by the WWTP and, then, relate them with the energy demand. As covered in detail in the following subsections, all the benchmarking methods require this definition of energy (or “inputs”) and services provided (or “outputs”).

2.1. Key Performance Indicators and ratios

Directly based on the definition of efficiency, Key Performance Indicators (KPI) are the simplest benchmarking method. A KPI is often a ratio of an input and an output, which can be obtained by normalizing the energy use based on the unit activity or service provided. Based on the definition of KPIs, several WWTPs can then be compared using input-output data (Fig. 1).

Regarding COD, the plant with highest efficiency is the one with the lowest ratio of input and output (i.e. WWTP 1), and its efficiency level is shown as the dashed line (Fig. 1). For WWTPs, which usually operate close to the discharge limits, the inefficiency would be the vertical distance to the dashed line, i.e., the energy that can be saved while removing the same amount of COD.

The specific energy consumption has been used to roughly characterise the energy efficiency of a WWTP and is reported in large datasets such as Mizuta and Shimada (2010, 985 WWTPs in Japan), Yang et al. (2010, 599 WWTPs in China), Krampe (2013, 24 WWTPs in Australia), Vaccari et al. (2018, 241 WWTPs in Italy), Ganora et al. (2019, 300 WWTPs in Europe), Luo et al. (2019, 2022 WWTPs in China). However, a direct comparison based only on the specific energy consumption misses indeed many details in the plant operation and makes comparison only possible when the WWTPs are very similar, i.e. similar layout, technology, climate, influent, etc.

The obvious advantage of KPIs is that they are relatively inexpensive to obtain, and easy to implement and understand. However, this approach is limited in scope as it involves only partial evaluations. As an example, Panepinto et al. (2016) in a thorough study on Turin WWTP energy efficiency, used four KPIs (energy per person equivalent, per m^3 of water, per kg of COD removed and per kg of N removed) as, in effect, one KPI may not fully reflect the purpose of the plant. A WWTP could have multiple functions, e.g. removing COD, nitrogen, phosphorus, and pathogens, or producing energy or material like biogas and fertilizers. As an example, evaluating the efficiency of WWTPs in removing COD and nitrogen would require two KPIs. WWTP 1, in Fig. 1, has high efficiency in removing COD but low efficiency in removing nitrogen. Conversely, WWTP 2 is the most efficient in nitrogen removal but has a poor COD removal performance. As both nitrogen and COD are important objectives, WWTP 3 could be preferred as it performs well in both dimensions. In this case, weighting between the two plant’s objectives would be necessary.

As a conclusion, partial benchmarks such as simple ratios and KPIs often make misleading comparisons and therefore other strategies should be recommended for effective energy benchmarking beyond a first approximation. In this regard, a proper measure of WWTP energy efficiency should reflect a multidimensional concept by considering the different functions of the plant.

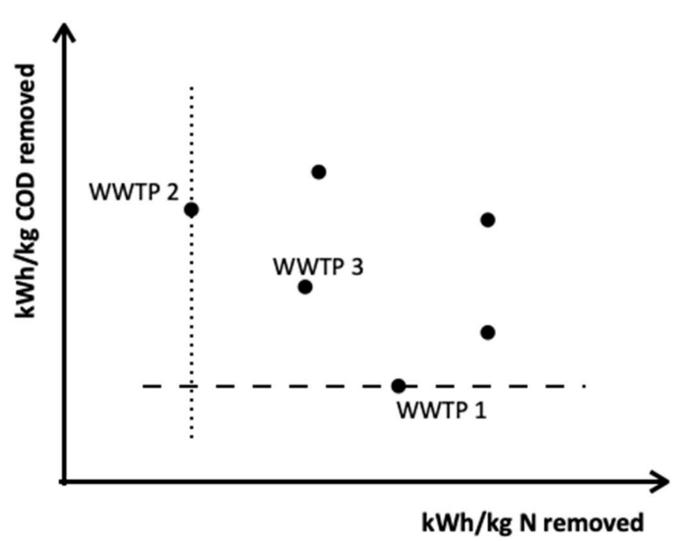

Fig. 1. Input-output combinations for several WWTPs. Dotted line and dashed line indicate the best performance in nitrogen and COD removal, respectively.

2.2. ENERWATER methodology

With the aim of representing the multifunctional nature of WWTP endeavour, a methodology was developed in the framework of the ENERWATER Coordination Support Action[2] to systematically determine the energy efficiency of a particular WWTP. As a result of the application of the methodology stems the Water Treatment Energy Index (WTEI), which is a composite index stemming from the aggregation of several KPIs (Mauricio-Iglesias et al., 2020).

The full methodology is described in detail elsewhere (Longo et al., 2019) and briefly summarised here for completeness. The approach basically consists of 1) measuring energy use and WWTP outputs in terms of flowrate treated, COD and nutrient removal, sludge disposal and pathogen load reduction; 2) determining or estimating KPIs that represent the efficiency of the different WWTP functions (Table 1) as carried out in different stages; 3) expressing the KPIs in a single index (i.e. the WTEI) that can be used for benchmarking energy efficiency of different WWTPs and 4) assigning a label (A, B, C …) for ease of communication to a broad public.

There are two versions of the methodology that differ mainly on the level of detail of the information required:

i) The Rapid Audit (RA) methodology determines the WTEI for benchmarking using routine energy measurement and effluent sampling, hence providing a quick benchmarking;
ii) The Decision Support (DS) methodology requires an intense sampling campaign with analyses of influent and effluent of different plant sections. It provides not only the WTEI but also a diagnosis of the inefficient spots in a plant allowing the user to propose corrective actions.

The results of applying the RA and the DS methodologies are then represented as labels, common in other energy efficiency evaluations, so that they can be easily understood as well by a broad public (Fig. 2).

After having been subjected through the complete revision, update and voting process by the members of the European Committee for Standardization (CEN) the ENERWATER methodology became the core of the new standard CEN/TR 17614 *Standard method for assessing and improving the energy efficiency of wastewater treatment plans*, approved in January 2021 as the European standard for defining and measuring energy efficiency in wastewater treatment plants. As a CEN standard can be subjected to further modifications, the remaining of this discussion will refer to the ENERWATER methodology noting that it can be partially applicable to the CEN/TR 17614.

Table 1
Definition of KPIs used in the Rapid Audit methodology.

Stage	KPI	KPI units	Meaning/function
Stage 1	KPI_1	kWh/m^3	Energy for pumping wastewater through the WWTP
Stage 2	KPI_2	kWh/kg TS_{proc}	Energy for removing solids in primary treatment
Stage 3	KPI_3	kWh/kg TPE_{rem}[a]	Energy for removal of COD, nitrogen and phosphorus
Stage 4	KPI_4	kWh/(logRed·m^3)	Energy for removal of pathogens in tertiary treatment
Stage 5	KPI_5	kWh/kg TS_{proc}	Energy for treatment of sludge and removal of solids

[a] Where the total pollution equivalent TPE = COD (kgCOD) + 20 TN (kgTN) + 100 TP (kgTP) as defined by (Benedetti et al., 2008).

[2] https://cordis.europa.eu/project/id/649819.

2.3. German standard DWA-A 216

The German Water Association (DWA) has devoted a considerable effort in the last two decades in the development of a standard for energy efficiency improvement at WWTPs (Clos et al., 2020). The proposed guideline, the German standard DWA-A 216 (2015), consists of a dual approach. A first simple assessment called Energy Check (EC) is based on the comparison of aggregated energy consumption KPI (i.e. kWh/PE year) and quickly screening out plants where energy waste is present, hence in need of a more in-depth analysis. This second approach, which is called Energy Analysis (EA), consists of breaking down the plant to the level of individual equipment and comparing the energy consumption versus ideal performance values estimated at medium load for energy-consuming equipment such as pumps, blowers, compressors, agitators, sludge heating but also "minor" equipment such as rakes, scrapers, etc. As the EA requires a lot of operational data as input for the requested calculations, the whole process of an EA may last for several months. The amount of work depends on reliability of data, the number of machines and processes to be evaluated and the number of identified actions. It can vary from a few days for a simple pumping station to several weeks for a complex wastewater treatment plant (WWTP). Usually a hydraulic engineer and an electrical engineer shall be involved in the EA.

This approach is certainly data-intensive, but it is very well-suited for the mechanical revision of the WWTP, proposals for equipment renewal and comparison. The main drawback is, perhaps, that the whole-process information is not used, e.g. even though a blower is operating optimally, over-aerating by setting the dissolved oxygen setpoint too high is a decision that would turn the process inefficient while it would not be captured by the equipment-by-equipment analysis.

2.4. Data envelopment analysis

Data Envelopment Analysis (DEA) is a multi-factor productivity analysis model used for estimating the relative efficiencies of a homogeneous set of firms (or decision-making units in the context of the DEA literature). In general, DEA applications can be classified in single- and two-stage DEA, based on whether efficiency estimation is conducted in i) one stage considering only input and output variables, or ii) in two stages including a second regression procedure that takes into account for the possible effect of exogenous influences on efficiency such as e.g. climate or technology.

2.4.1. Single-stage DEA

Intuitively, this deterministic technique can be understood as an extension of KPI analysis for multiple inputs and multiple outputs, thereby representing an attractive tool for performance assessment (Cook and Seiford, 2009). Using the example of COD and nitrogen removal (Fig. 1), a simple illustration of how DEA estimates efficiency is given in Fig. 3.

From the definition of efficiency, WWTPs are more efficient if they use less input for the same output, and/or produce a higher output with the same input. We therefore identify the line connecting WWTP E, D and C as the efficient frontier; no point on this frontier line can improve in one of the efficiency dimensions (or performance dimensions) without worsening in the other. The method's name comes from this property as the frontier is said to "envelop" these points. The efficiency of WWTPs not on the frontier line can be measured by evaluating the distance to the frontier line (Amaral et al., 2022). For example, the inefficiency of A can be evaluated by the ratio OP/OA, where OA, the line from zero to A, crosses the frontier line at P (Fig. 3). An increase in efficiency can be achieved that is by reducing inputs or increasing outputs. Since amount of pollutants to be removed by the plant is usually fixed by the effluent quality requirement and the influent composition, in general the only reasonable improvement of a WWTP consists in input minimization. In this case we talk of input-oriented DEA model, in contrast to the output oriented where the objective is output maximization.

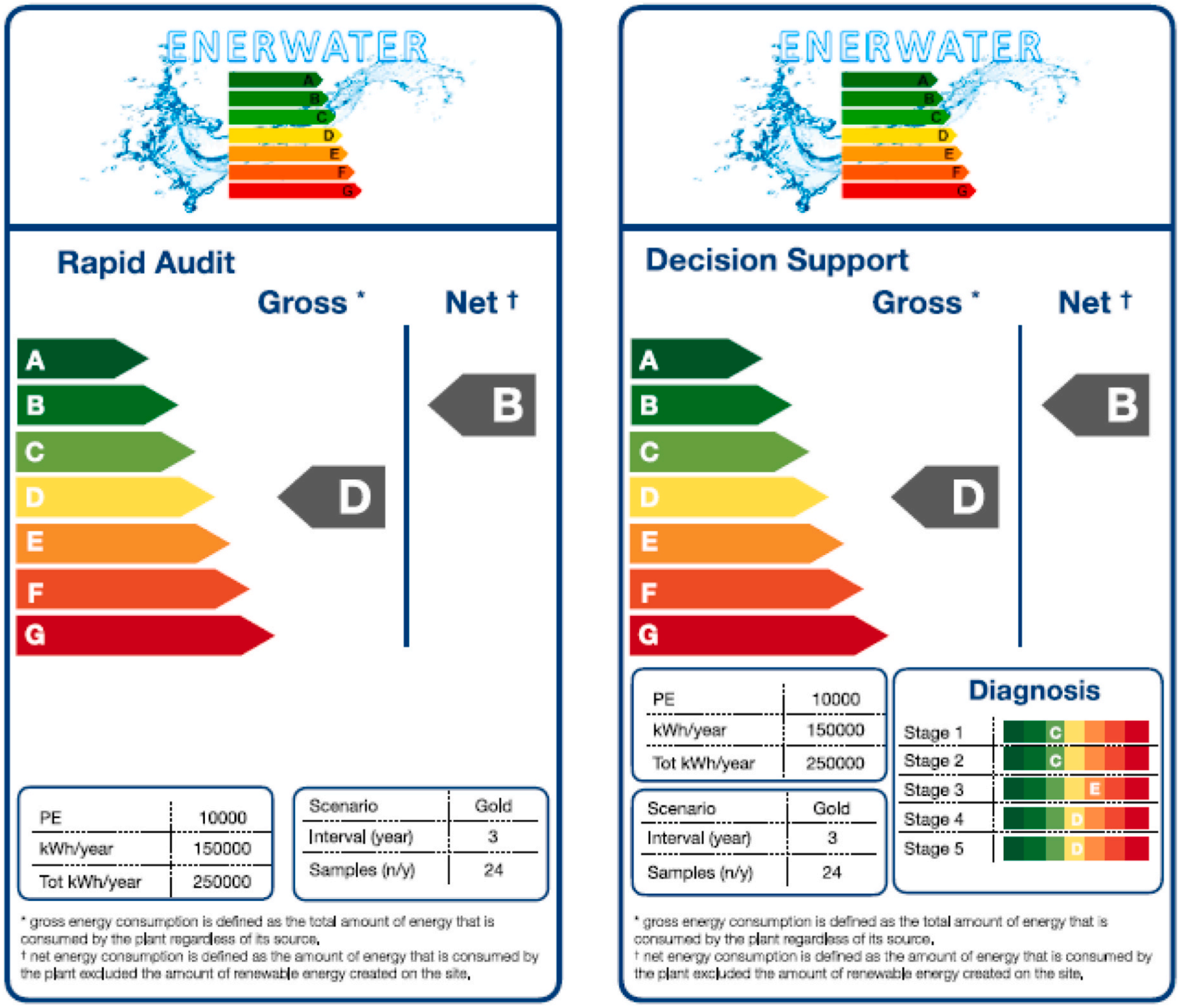

Fig. 2. Representation of energy efficiency information by the WTEI and the ENERWATER methodology (from Longo et al. (2019)).

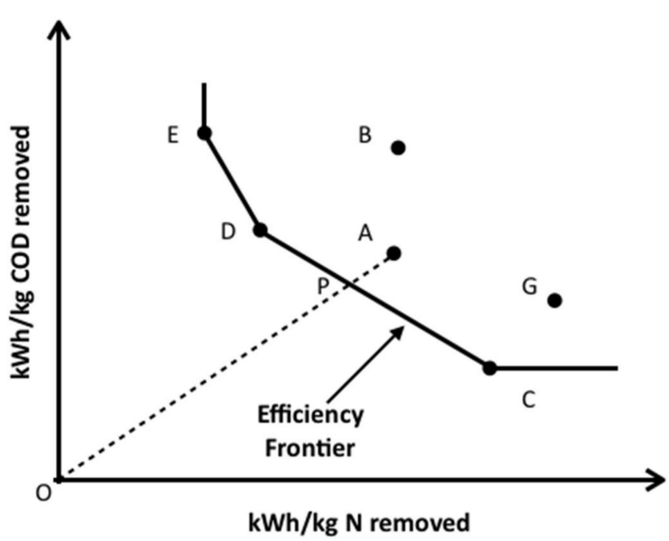

Fig. 3. Efficiency as estimated by DEA for two outputs (COD and N removal) and one input (energy consumption).

Formally, the efficiency of a set of WWTPs can be estimated by the CCR DEA (Charnes et al., 1978). For p inputs, q outputs and n WWTPs, we can determine the input-oriented efficiency of the data matrix of input and output vectors (X, Y), by solving for each observation the following constrained linear programming problem:

$$\begin{aligned} & \min_{\theta,\lambda} && \theta \\ & \text{subject to} && \theta x_k \geq X\lambda \\ &&& Y\lambda \geq y_k \\ &&& \lambda \geq 0. \end{aligned} \tag{1}$$

where the index k represents a given observation, X is the matrix of inputs, Y is the matrix of outputs, and λ is vector of weights given to each observation. Problem (1) can be interpreted as combining WWTPs (by weights λ) to produce an output level at least equal to plant k ($Y\lambda \geq y_k$) and then selecting the combination with the minimum input level ($\theta x_k \geq X\lambda$ for minimum θ). Solving the linear programming problem (1) n times generates the efficiency indices θ_k, one for each WWTPs. WWTPs with efficiency scores $\theta_k < 1$ are inefficient, since they would be capable of reducing their input(s) without affecting the amount of output(s). Efficient WWTPs receive efficiency score $\theta_k = 1$.

Thanks to its capability to include several inputs and outputs, DEA has been very popular in academic research on WWTP efficiency during the last years. For example, studying a set of 77 Spanish WWTPs, Hernández-Sancho et al. (2011) showed that plant size, COD removed and aeration were determinant in energy efficiency; Dong et al. (2017) reached similar conclusions analysing 736 Chinese WWTPs, highlighting as well the importance of the climate type thanks to the broadly distributed sample. With a broader perspective, Amaral et al. (2022) studied 120 wastewater service providers (not just WWTPs) in Portugal finding a general increase of efficiency from 2015 to 2019, in particular related to energy consumption.

The rationale of DEA is that the plant manager knows best the preferred objectives for the operation. Therefore, instead of comparing several indexes (i.e. KPIs) or estimating the expected energy consumption based on the several outputs to be fulfilled, a plant receives the best possible score regarding its performance in each of several plant objectives.

2.4.2. Two-stage DEA

When applying DEA to WWTP benchmarking, several authors have highlighted the importance of accounting for exogenous factors (in principle, any factor that is not under the direct control of the management). Carvalho and Marques (2011) warned on the danger of misattribution of efficiency (or inefficiency) to managerial decisions if exogenous variables are not taken into account in the water sector, including indeed wastewater. Due to the complexity of the analysis of exogenous variables, Longo et al. (2018) proposed a systematic method to apply DEA specially tailored for the analysis of energy efficiency in WWTPs (i.e. two-stage DEA). In this approach, firstly proposed within the wastewater sector by Guerrini et al. (2017), the basic idea is to estimate efficiency scores in the first stage considering only the space of inputs and outputs, ignoring the exogenous factors. Then in the second stage, a bootstrap-based algorithm is used to assess the impact of the exogenous factors and obtain valid and accurate inference for bias correction of the efficiency estimates. The specification used for bias correction being:

$$\theta_k = \beta_0 + \beta_{COUNTRY} COUNTRY_k + \beta_{SECONDARY} SECONDARY_k + \beta_{TERTIART} TERTIARY_k + \beta_{SIZE} SIZE_k + \beta_{LF} LF_k + \beta_{DF} DF_k + \beta_{TEMP} TEMP_k + \varepsilon_k; \tag{2}$$

where *COUNTRY* is categorical variable indicating the country location of the plant, *SECONDARY* end *TERTIARY* are categorical variables indicating the type of technology used in the plant as respectively secondary and tertiary treatment, *LF* is the natural logarithm of the load factor, *DF* is the natural logarithm of dilution factor, *TEMP* is the natural logarithm of the annual average outdoor temperature, and ε is the random term. The results obtained by Longo et al. (2018) confirm that apart from the amount of pollutants removed during the wastewater treatment, there exist a number of exogenous determinants of the plant energy demand that wastewater operators cannot control, e.g. the temperature the plant is operated. Energy variation due to those factors can be misattributed to changes in efficiency. Adjusting for the effect of those factors can lead to substantial changes in efficiency estimates depending on the adverse or favourable environmental conditions a WWTP is operating.

2.5. Parametric approaches

Parametric approaches to benchmarking in the contest of wastewater treatment is relatively new in comparison to e.g. KPI and DEA approaches. The parametric approach consists on statistical analysis that based on the technique can be divided in i) simple regression analysis, e.g. Ordinary Least Squares (OLS) or Corrected OLS (COLS), and ii) Stochastic Frontier Analysis (SFA).

2.5.1. Regression analysis

A linear regression model, such as the very popular ordinary least squares (OLS) (Kutner et al., 2005), can be used to estimate the energy use of a system. If plant data are available, parameters β can be found that relate energy use, E, and a matrix of variables of plant and operation characteristic, X, for $i = 1\ldots n$:

$$E_i = X_i\beta + \varepsilon_i; \quad \varepsilon \sim N(0, \sigma^2). \tag{3}$$

The dependent variable (E) is also called the response variable. Independent variables (X) are also called explanatory or predictor variables. An OLS model provides the expected average energy use for a plant given its operating characteristics such the amount of pollutants removed. The result of such estimation, in the simplest case, can be a regression function with just one variable (OLS in Fig. 4).

In contrast with DEA, which establishes an efficient frontier (representing best performance), the regression function estimated by Eq. (2) represents the average performance. The residuals are defined as the distance from each data point to the regression line, which can be positive or negative, if the data points lie, respectively, above or below the line.

The application of OLS to benchmarking is based on comparing the performance of a WWTP with the average performance. As the residual is the difference between the actual energy use and the predicted energy use for a given service (or output), residuals can be treated as measures of inefficiency. If the actual energy use of a given WWTP is less than the predicted energy use (negative residual), it means that the WWTP uses less energy than the average WWTP described by the regression line. Therefore, WWTPs with ratings above the average can be considered inefficient while those with ratings below are efficient.

A regression energy demand exponential function is developed in Niu et al. (2019). The model is expressed as follows:

$$E = e^{\alpha} \times W^{\beta} \times Y^{\delta} \times S^{\omega} \times M^{\theta} \times P_{in}^{R_{in}} \times P_{out}^{R_{out}} \tag{4}$$

where E is the electric energy consumption, e is the base of the natural logarithm, W is the flow rate, Y is the age of the plant facility, S is the wastewater collection area of the pipe network, M is the amount of sludge produced and processed, P_{in} and P_{out} are COD concentration in the influent and effluent, respectively; β, δ, ω, θ, R_{in} and R_{out} are all regression coefficients; and α captures the impact of categorical variables including treatment technology, operating conditions, topography, and other regional variables.

The regression approach can be complemented with establishing a distribution of residuals, which can assign a performance percentile to each WWTP. This approach was followed by the Energy Star method (Carlson and Walburger, 2007), launched in the USA in 2007 as part of a broader initiative of the Environmental Protection Agency (EPA). This method is based on linear regression function developed using data of 257 WWTPs throughout the USA. The prediction of the average plant consumption is done using as inputs the average influent flow rate, the influent and effluent BOD concentration, the plant load factor and two binary variables accounting for whether the plant presents filtration and/or nutrient removal. Then, the actual benchmarking score can be

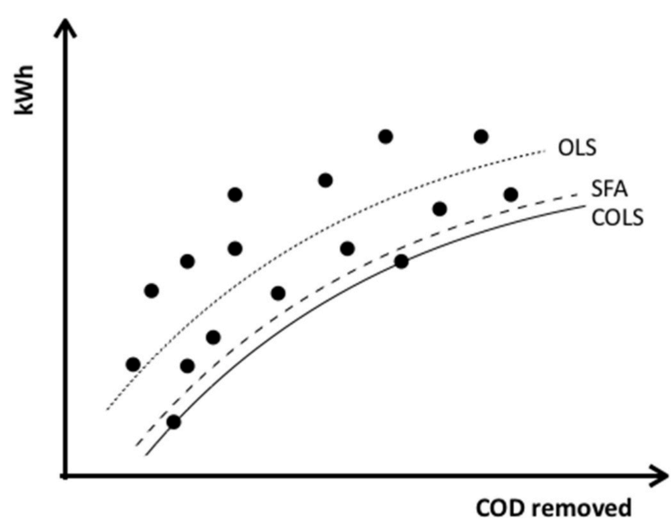

Fig. 4. Comparison of the referenced performance: efficient frontiers (SFA, COLS) and average performance (OLS).

obtained by comparing the difference between the actual consumption and the prediction (the residual) with a distribution of residuals. Negative residual means that the plant uses less energy than expected and vice-versa. Spruston et al. (2014) checked the validity of the Energy Star method on 35 Canadian WWTPs concluding that it was a valid method for energy benchmarking although it was not fully adapted to Canadian specificities and for certain types of WWTPs.

A consequence of using a parametric approach such as OLS is that the residuals are treated as a measure of inefficiency while they can partially represent variables not included in the regression function. For example, in the Energy Star function, the variation in energy use due to nutrient removal is modelled as a categorical variable (either yes or no) when in reality it is the amount of nutrients removed that will impact the energy demand. Then, much of the variation in efficiency scores may remain unexplained by not including the right explanatory variable (the amount of nutrient removed).

An extension of OLS which provides a demand frontier, instead of an average performance line, is the Corrected Ordinary Least Squares (COLS). This method is a two-stage procedure: i) the regression line is first estimated through OLS and ii) then the regression line is shifted downwards such that the resulting regression line (called the COLS frontier) envelops all data. Hence, all the residuals are positive, except for the WWTPs that are found to be efficient (where the residual is zero). Therefore, COLS assumes that all residuals are due to inefficiencies (Fig. 4).

While the COLS method has its appeal in terms of simplicity, a more realistic view is that not all the differences between the actual data and the frontier are due to efficiency. This is especially relevant in wastewater application where significant data uncertainty may be present both in data gathered under either compulsory monitoring or reporting requirements under law (Yoshida et al., 2014). Furthermore, as the COLS frontier is meant to envelop all the points, it is very sensitive to outliers which can move the frontier away from the regular data points.

2.5.2. Stochastic Frontier Analysis

The COLS approach implies that the residual is due solely to inefficiency. Alternatively, the residual can be considered as composed by a random (stochastic) error term and an inefficiency term, which may be composed itself of several contributions. The econometric technique known as Stochastic Frontier Analysis (SFA) has been developed to provide separate estimates of these two components. A general version of the stochastic frontier model can be described as:

$$E_i = f(X_i;\beta) + \varepsilon_i; \quad \varepsilon_i = u_i + \nu_i,; \; \nu_i \sim N\left(0, \sigma_\nu{}^2\right); \quad u_i \sim N^+\left(0, \sigma_u{}^2\right), \tag{5}$$

where E is energy use, X is a vector of variables influencing energy use, including plant characteristics and external factors, and β includes all the parameters to be estimated. Energy use residuals are now captured by two random terms, u and ν. The noise term ν in (5) is assumed to be normally distributed while the non-negative random term u, which represents inefficiency, is generally assumed to follow a half-normal (N^+) or other positive distributions. It is then possible to estimate parameters β, σ_ν and σ_u using maximum likelihood methods (Kumbhakar and Lovell, 2003). A comparison of the stochastic frontier, the COLS and OLS models is provided in Fig. 4.

Environmental factors can be represented as a function of some observable variables but many relevant aspects that cause heterogeneity are unobserved or not known a priori. If panel data are available, that is, each unit is observed at several different points of time, part of these unobserved heterogeneity can be estimated as it does not change with time (Wooldridge, 2010). The simplest SFA model for panel data hence can be rewritten as:

$$E_{it} = f(X_{it};\beta) + \varepsilon_{it}; \quad \varepsilon_{it} = \nu_{it} - u_i; \quad u_i \geq 0; \; i = 1, \ldots N; \; t = 1, \ldots, T, \tag{6}$$

where $f(X_{it};\beta)$ is a linear function of the variables in the vector X_{it}, index t indicates different time points and $u_i \geq 0$ is the energy term of plant i.

The model in (6) can be estimated assuming either u_i is a fixed parameter (the fixed-effects model) or a random variable (the random-effects model). This approach no requires distributional assumptions on u_i and is, thus, labelled as distribution-free (Schmidt and Sickles, 1984). Another important advantage of using panel data over cross-section is that it is possible to think of the inefficiency term as comprised by two components: persistent (i.e. time-invariant) and transient (i.e. time-varying) (Filippini and Greene, 2016; Tsionas and Kumbhakar, 2014). The persistent component corresponds to the presence of structural problems such as inefficient equipment or design limitations that prevent the plant from minimize the use of energy; the transient component may be caused by the presence of non-systematic difficulties that can be solved in the short term such as adaption of wrong operational strategies due to e.g. too infrequent sampling.

To the best of our knowledge, the first application of SFA to efficiency in WWTP was carried out by Longo et al. (2020), who studied panel data from 183 Swiss WWTPs during 15 years. The WWTP energy demand function for panel data is described as follows:

$$\begin{aligned} \ln E_{it} = {} & \alpha_0 + \alpha_P \ln P_t + \alpha_{FLOW} \ln FLOW_{it} + \alpha_{CAP} \ln CAP_i + \alpha_{COD} \ln COD_{it} \\ & + \alpha_{NH4} \ln NH4_{it} + \alpha_{NO3} \ln NO3_{it} + \alpha_{TEMP} \ln TEMP_{it} + \sum_{j=1}^{6} \alpha_{TECH_j} TECH_{ij} \\ & + \alpha_{DEW} DEW_{it} + \nu_{it} - u_i - \tau_{it} \end{aligned} \tag{7}$$

where E is energy consumption, P is the real price of energy, $FLOW$ is the volume of wastewater treated, CAP is the plant capacity expressed as design flow rate, COD, $NH4$ and $NO3$ are the pollutants concentration removed from wastewater, $TEMP$ is the average temperature, $TECH$ represents dummy variables to control for the effect of the type of secondary treatment, DEW is a dummy indicating whether the plant also carries out sludge dewatering.

In this specification, the random error term ε is decomposed as $\varepsilon_{it} = \nu_{it} - u_{it}$, where u_{it} is the inefficiency and ν_{it} is statistical noise. The inefficiency part is further decomposed as $u_{it} = u_i + \tau_{it}$ where u_i is the persistent component and τ_{it} is the transient component of inefficiency. The former is only plant-specific, while the latter is both plant- and time-specific. In addition to that, SFA can be also extended to take into account for unobserved heterogeneity[3] and to include variables that are direct determinants of efficiency level such as e.g. the age of the WWTP, as previously reported by Castellet-Viciano et al. (2018) and Niu et al. (2019). Thanks to that, it is possible to estimate inefficiency related to WWTP obsolescence and, therefore, how much energy can be saved when a WWTP equipment is renewed.

The application of SFA to WWTPs whenever panel data is available is a novel and promising approach able to distinguish whether inefficiency that originates in inefficient equipment or from the inefficient use of (in) efficient equipment. Hence, SFA represents a useful tool to deduce energy diagnosis from common operational data.

3. Comparison of benchmarking methods

From the description of the benchmarking methods is easy to infer that they differ in complexity, scope, sensitivity to outliers, data requirement, efficiency interpretation etc. as summarised in Table 2. It becomes clear that no method can provide a universal solution to benchmarking, as all of them face their own problems 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. Rather, a range of efficiency scores may be developed and act

[3] I.e. those effects that are not easily measurable or quantified such as the topography of the serviced area which may require the use of additional pumping stations or in general design structural problems.

Table 2
Summary of comparison of different benchmarking methods.

	Advantages	Disadvantages
KPIs	- Simple and already used in the wastewater treatment sector. - Can be adapted for different WWTPs and objectives. - Minimal data requirements.	- Being based on KPIs, it implicitly assumes constant return to scale. - Does not account for exogenous factors, beyond WWTP control. - Difficult interpretation for multiple inputs/outputs. - No diagnosis/corrective actions.
ENERWATER	- A composite indicator can summarize the multi-objective purpose of a WWTP. - It can be applied to different plant layouts. - Being equivalent to percentile it is easily interpretable. - Rapid Audit version requires simple and common routine data normally available in all water utility. - Decision Support can be used to do diagnosis of inefficient stages/functions of a WWTP.	- Being based on KPIs, it implicitly assumes constant return to scale. - The database on which the benchmarking system is developed covers mostly WWTPs of medium size and located in Europe. - Composite indicators cannot directly account for exogenous factors, beyond the WWTP control. - Decision Support requires detailed energy monitoring and sampling campaign. - Not ready for multiple outputs (ready though for biogas production).
Standard DWA-A 216	- Energy Check version used common and widely KPI (kWh/PE). - Energy Analysis version is very useful for analysing single equipment energy consumption.	- Energy Check version is limited to plants with similar characteristics (not applicable to other countries). - Energy Analysis version is very data-intensive (i.e. equipment technical sheets are required) and time requiring.
OLS/COLS	- OLS is intuitive and widely used. - Easy to account for exogenous factors. - A distribution function of the residuals can be used to assign performance percentiles.	- It provides an average performance as benchmark (OLS). - Extremely sensitive to outliers and measurement error (COLS). - Does not lead to diagnosis or corrective actions. - Cannot be used for multiple outputs.
DEA	- DEA is easy to extend to multiple outputs and inputs. - DEA can be implemented on a relatively small dataset in comparison to regression analysis. - Once the input and output variables have been selected, DEA is quick and straightforward to implement. - It doesn't require assumptions about the frontier function. - Two stage DEA can account for factors that are beyond the control of the WWTPs.	- Corrective measures are difficult to identify from DEA outcomes. - Efficiency scores are sensitive to the choice of input and output variables. - It is very sensitive to outliers which can move the frontier away. - For DEA, testing a new WWTP requires solving the model again for the whole set of observations. - As more inputs and outputs are considered, the number of WWTPs on the frontier increases and the discrimination power decreases accordingly.
SFA	- SFA distinguishes persistent and transient inefficiency; thus, it can be used as a diagnosis tool. - Using panel data, it can take into account unobserved/ unmeasured factors. - SFA allows statistical inference about which parameters to include in the frontier estimation. - Environmental variables can be directly included in the regression model as regressors. - SFA incorporates the possibility of separate measurement error and stochastic factors, being robust to outliers.	- High data requirements. Panel data required to distinguish between unobserved heterogeneity and inefficiency, as well as persistent and transient inefficiency. - Requires a priori assumptions, e.g. specifying a functional form and statistical distributions for the inefficiency terms. - Can be difficult to implement due to the complexity of algorithm required - Cannot be used for multiple outputs.

as a signalling driver rather than as a conclusive statement.

A relevant point highlighted in the method characterisation and comparison reported in Table 2 is the capability to handle exogenous factors, understood as any factor that is not under the direct control of the management, therefore exogenous to the WWTP system, such as influent characteristics. Labelling a factor as exogenous might, however, be a debatable issue and in fact there is certain controversy around which factors are legitimate uncontrollable influences on performance and which ones should and/or can be controlled and by whom.[4] A factor can be uncontrollable for one stakeholder but not for another. An example is the plant size. Inefficiency due to scale is exogenous to the plant operator but may be endogenous for the water utility management, who may decide to merge two close plants in order to operate only one bigger plant. Furthermore, there may be factors, such as the load factor, that depending on the context may have different interpretations. Oversizing may be a solution to seasonal variation in the load entering the plant in case of e.g. a plant operating in a touristic area but may also be due to erroneous design estimation. In this case, inefficiency due to oversizing is beyond the control of an operator but can be eliminated by a water utility by e.g. dividing the plant in different treatment lines in order to modulate the load. Furthermore, since energy efficiency is only a secondary, although important, objective for water utilities that should never jeopardize the primary objective to clean water, it may be preferred higher energy consumption and a more robust WWTP. In practice in the short run, very little may be controllable by plant operators, whilst in the longer-term inefficiency due to factors such as plant size or load factor can be solved.

The main difference between one method and another is how each method highlights differences in energy consumption between DMUs, i.e. inefficiencies. Comparing efficiency scores for different DMUs within methods provides better indications than comparing efficiency scores inter methods. In this regard, relating the inefficiencies between the different methods can be particularly useful as it can provide a plausible framework for interpretation and driving decisions, which otherwise would be difficult when using just benchmarking method. For example, despite the popularity in academic circles of tools such as DEA, due to its ability to aggregate multiple inputs and outputs in a single efficiency measure, it is plausible that, from a managerial point of view, this is a weakness, as it distracts attention from the question of where the problems actually lie and where one should search for ideas for improvement.

Before thinking about solutions to energy efficiency problems, the logical first step is to diagnose where the problem, i.e. the inefficiency, is located. Inefficiencies may come from factors beyond the control of the management or internally e.g. due to old and inefficient equipment or due to an inefficient use of the equipment itself. Within the plant boundaries, plant managers may discover that a plant provides aeration with an inefficient blower or diffusers. Alternatively, they may discover efficiency problems through internal monitoring of their own

[4] Four stakeholder events were organised during by the project ENERWATER in UK, Italy, Germany and Spain, accounting in total 250 attendants. Raising the question whether a benchmarking methodology should compensate for exogenous factors invariably led to heated arguments between the different stakeholders.

performance. In this context, efficiency metrics that treat the WWTP as a black box have limited utility as they do not pinpoint where to target the intervention. Ultimately, in order to identify inefficiencies and, as a result, proper improvement strategies, the analyst must be aware of the specific methods which are helpful to identify a particular type of inefficiency. To do that, inefficiency needs to be decomposed (Fig. 5) so that the analyst, considering the objective of the study and the available data, can link each element to the appropriate method for efficiency quantification and benchmarking.

The inefficiency decomposition presented in Fig. 5 is then particularly useful for defining better improvement strategies and diagnosis of inefficiency. In fact, the application of such mapping of efficiency is fundamental to understand what type of inefficiency a plant is affected and therefore to design specific improvement strategies. If one does not pinpoint the fundamental problem, corrective actions and improvements are not possible. Inefficiency need to be understood and a consensus on where exactly it comes from need to be reached before to move forward. With the problem identified and the data collected to substantiate it, the problem can be traced to its various causes. With this analysis completed, it can be prioritized which problems should be addressed promptly and in what order considering their costs.

4. Actor analysis in WWTPs

Many actors are involved in the wastewater treatment sector, from WWTP operators to CEOs, including researchers or policy makers, among others, with different working environment, type of decisions to confront or to take. Unlike academic researchers, operators typically spend a significant part of their time facing unexpected and urgent problems. In contrast to policy makers, plant operators have relatively limited and weak levers for driving and securing change as their main objective is to guarantee the operation of the plant within the existing regulatory framework, and communicate with stakeholders at different levels, including institutions. In short, with very limited time and capacity, operators must take informed decisions based on available knowledge.

Selecting a benchmarking method is indeed a complex task that this section tries to address by answering the following questions:

- Who is performing the benchmarking (“actor”)?
- What is the goal of the benchmarking (“task”)?
- What method is best suited for both the task and the actor?
- What is the nature of the available data?

To guide the selection process to the best benchmarking method to be used, the motivations of the involved stakeholders, their interest and pressures must be examined (Rieger and Olsson, 2012). A comparison of the different objectives to assess energy efficiency for the different stakeholders is given in Table 3 and further explained below.

4.1. Plant manager

The plant manager’s main goal is to operate the plant within the effluent limits; secondly, to ensure that the treatment is carried out efficiently with the minimum use of resources. Plant managers are usually in charge of monitoring specific processes, which are the object of assessment and optimization by the operation managers. They therefore use KPIs in order to monitor e.g. the energy consumption for the secondary treatment using e.g. kWh/kg $TPE_{removed}$.

4.2. Operations manager

The operations manager’s main objective is to ensure that the treatment is carried out efficiently with the minimum use of resources and to translate these objectives into specific tasks for the plant manager. They are in charge for plant wide evaluation and optimization and have access to all the plant operational data from different plants. Several methodologies can be applied with these objectives. They will preferably need quick estimation of energy efficiency (ENERWATER RA). Other perspectives can be obtained from the application of the ENERWATER DS, where each stage/function of the plant is evaluated separately, and efficiency information can be obtained individually. Operation managers may wish also to focus on operational efficiency excluding the impact of exogenous influences on energy consumption. In this case methodologies such as Energy Star or two-stage DEA may be also adequate.

4.3. Engineering manager

The engineering manager coordinates all capital improvement programs for the wastewater department of a water utility. The major areas of responsibility include maintenance projects that improve and expand existing facilities or providing recommendations concerning new treatment processes. As his/her focus rather lies on equipment efficiency assessment in order to optimize specific units or to identify equipment that needs substitution, the Energy Analysis (equipment per equipment) developed by the DWA may be the best instrument.

4.4. Chief of operations

Chief of operations have large access to plants operational data from different plants. The higher data availability means that they can use more complex benchmarking methodologies. The chief of operations’ main objective is to make inferences about inefficient equipment, operational strategies, sensor failure etc, and to examine the best use of utility financing resources to improve the wastewater operations. Hence, they can use the SFA approach and panel data to identify appropriate energy inefficiency diagnosis. Thanks to the fact that using this approach plants inefficiency can be decomposed into a persistent and a transient component, associated respectively with structural and operational problems, the chief of operations can decide where to allocate efforts to improve wastewater operations.

4.5. Energy manager

An important role for a water utility to achieve its energy efficiency objectives is played by the energy management department. An energy manager has in charge the monitoring of the energy use within the company, the compliance of the company with the energy management systems such as the ISO 50001 standard and communicating efficiency performance to the regulator. The best instrument in this case is represented by the ENERWATER methodology thanks to the fact that it uses standardized information.

4.6. CEO

One of the activities of CEOs is the identification of innovative tools for financing investments in sustainability projects. For publicly traded water utilities, one possible option is the emissions of green bonds in order to dispose of funds for financing e.g. new energy efficiency projects (Hera, 2019). As a CEO needs to illustrate to investors and analysts the destination, objectives and results of the resources used within the water utility to non-technical public, universally understandable indicators such as the ENERWATER label may be useful to communicate utility-level efficiency information.

4.7. Regulator

Many efficiency studies are conducted from the perspective of a regulator such as OWFAT in the UK (Dassler et al., 2006). The regulator is interested in assessing wastewater utilities technical quality and efficiency using standardized methods, hence the ENERWATER or the

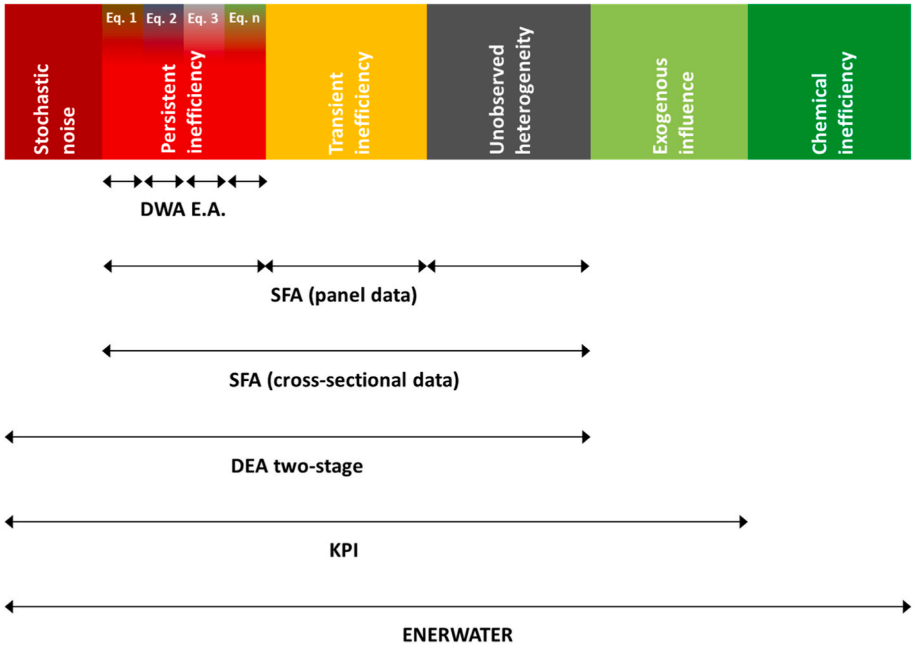

Fig. 5. Inefficiency decomposition by different methods.

Table 3
Elements to be taken into account for benchmarking method selection.

Actor	Task	Method	Data
Plant manager	Process monitoring	KPIs	Routine analyses
Operations manager	Efficiency evaluation	ENERWATER RA	Routine analyses
	Process optimization	ENERWATER DS	Detailed energy monitoring and sampling campaign
		OLS (Energy Star)	Routine analyses
Engineering manager	Diagnosis	DWA Energy Analysis	Equipment technical data sheets
Chief of operations	Planification	SFA	Panel data
Energy manager	Energy savings verification	ENERWATER RA	Routine analyses
CEO	Communication with stakeholders	ENERWATER RA	Routine analyses
Regulator	Control	ENERWATER RA	Routine analyses
	Designing incentives	Two-stage DEA	Cross-sectional data
		SFA	Panel data
Academic researcher	Testing hypothesis	Two-stage DEA	Cross-sectional data
		SFA	Cross-sectional data
		SFA	Panel data
Technology provider	Equipment efficiency verification	DWA Energy Analysis	Equipment technical data sheets
	Process improvement verification	ENERWATER DS	Detailed energy monitoring and sampling campaign

DWA method can be preferred. In this context, the WTEI labels can be also particular useful when defining minimum levels of quality-of-service standards regarding energy efficiency. Regulatory institutions are also in charge for designing incentives frameworks. In this case, the regulator's objective is to control for exogenous factors before making judgements about the level of effort expended by utilities. A limitation for regulators is the availability of data from different utilities leading to proper representation of the wastewater treatment sector in a given area. Depending on the availability of data and the objective of the analysis they can make use of parametric and non-parametric for cross-sectional and panel dataset. For example, a regulator may be interested in fostering investments in new equipment (i.e. reduce permanent inefficiency). Panel data and SFA models would be required in this case.

4.8. Technology providers

The goal of technology providers is to achieve certain metrics or specifications for a piece of equipment such as kWh/kgO_2 supplied for a blower or kWh/m^3 of sludge thickened for a centrifuge. The German standard DWA-A 216 characterises the individual process steps which can be used by technology providers to show better metrics than their competitors. It is worth mentioning automation, monitoring and control software providers, whose main goal is to optimize the different processes in the plant. On the other side, ENERWATER methodology uses KPIs related to what the plant actually does (e.g. kWh/kgCOD removed). Therefore, it is suitable for demonstrating the increase in efficiency of a given process or the whole WWTP and can be adapted for monitoring and control software solutions.

4.9. Academic researchers

Researchers use benchmarking methodologies and more in general data analysis techniques, to test hypotheses and answer questions. Examples are testing for relevant and irrelevant variables, understanding differences between different groups of plants in terms of efficiency or whether efficiency depends on external factors. DEA is often classified as a non-statistical or deterministic approach that does not easily allows genuine hypothesis testing (Bogetoft and Otto, 2010) although this limitation can be partially overcome by a second stage analysis (Longo et al., 2018). On the contrary, SFA and in general parametric approaches are much better suited for academic research, thanks to the fact that variables can be included in the model allows statistical testing of hypotheses concerning the relationship between these factors and efficiency and provide a quantification of inefficiency in terms of energy (Longo et al., 2020).

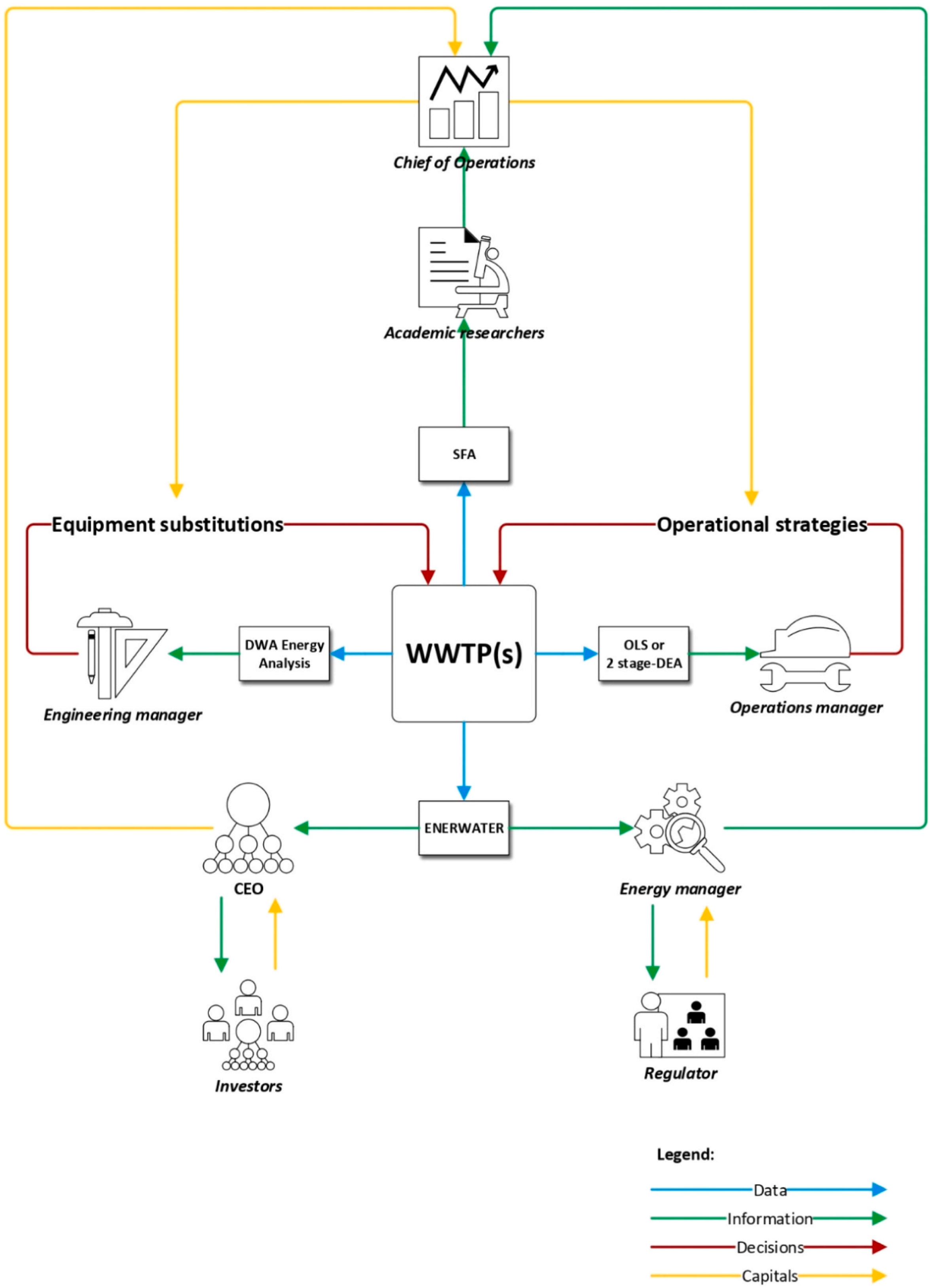

Fig. 6. Integrated framework for energy efficiency improvement in WWTP.

4.10. Investors

Although financial investment decision making is in general driven by business financial performance metrics that display measurable values and show progress of the business goals such as the return on Assets or the operating Cash Flow, sustainability metrics are always more spread among water utilities to report results to investors (Thames Water, 2018). Internationally shared and standardized metrics such as the energy label of the Standard CEN/TR 17614 can make it easier for an investor to evaluate water utility environmental performance resulting from funded projects.

5. Proposed framework for energy efficiency improvement

It is clear from the previous sections that improving energy efficiency at WWTPs is a complex task which involves several actors (both internal and external to the water utility), requires an exchange of different types of information and can be analysed by a broad selection of methods. Furthermore, even though the aforementioned actors may have the common aim of improving the energy efficiency at WWTPs, how to approach this objective differs in their means and time horizon (short- versus long-term). Without an effective framework able to promote the right exchange of information between actors, the sustained application of any energy efficiency policy might be jeopardized and their objectives misaligned. This final section proposes a holistic framework that integrates and links data, methods and actors (Fig. 6). This framework describes the rationale that, starting from data, leads to useful information for decision-making.

The WWPT(s), object of the efficiency improvement process, is represented at the centre of the framework in the figure. The WWTP(s) is the source of data that once processed by the methods described previously is converted into information and successively, depending on the type of data and the method applied, into knowledge for improving energy efficiency.

Energy efficiency analyses are usually done at plant level by operations managers and/or by an engineering unit. Operations managers are interested in improving operational strategies in the short term (e.g. implementing more efficient control strategies) while the work of the engineering manager is more focused on the long-term strategies (e.g. identify inefficient equipment that need substitution). Both types of analysis require different types of data and different methods: OLS methods such as the Energy Star or the 2 stage-DEA in one case (depending on data availability), and per-equipment analysis such as the Energy Analysis described in the DWA standard, in the other.

In order to be implemented, both types of energy saving measures require funding (e.g. for implementing automatic control and/or for substitution of old and inefficient equipment) being the latter usually more costly. Raising investment to support a wastewater utility business plan is generally carried out by CEOs which can make use of simple metrics to communicate objectives and results to investors. In this context the ENERWATER label represents the preferable tool when communicating WWTP energy efficiency information as it can be easily understood by non-technical stakeholders. Funds raised can be then used to finance energy efficiency projects based on the needs of the individual plants, as identified by more specific analyses.

The types of projects and the plants more in need of energy efficiency investment are identified by the chief of operations. He or she is in general a technical profile in charge of monitoring a large sample of plants (depending on the area covered by a water utility). This implies the need for the chief of operations to use more data intensive methods to identify the type of measure to be implemented in each plant, such as e.g. SFA. In practice, lack of data or adequate skills for the application of such more complex methods may require water utilities to make use of external support, from e.g. data scientists, to translate business goals into data-driven information. At the end of this process that provides the chief of operations with the information about the type of inefficiency present in a given plant, i.e. transient or persistent inefficiency or both, he/she can finally decide on the type of energy saving measure to be financed and to be successively implemented.

Energy savings resulting by the implementation of energy efficiency projects are usually certified by an energy manager and the results communicated both internally and externally: withing the utility, to the chief of operations as internal energy management procedure for the continuous efficiency improvement, externally to the regulator for e.g. demonstrating compliance with technical quality and efficiency objectives. National regulation authorities can have positive direct effects on energy efficiency. The adoption of measures to support the development of circular economies by means of setting energy saving objectives by the regulator can constitute a real boost for the promotion of the energy efficiency in the wastewater sector (Guerrini and Manca, 2020). Those objectives or efficiency targets should be based on universal and standardized metrics that would be easily represented the energy label as proposed in ENERWATER. A relevant challenge in regulation is to obtain a proper representation of the wastewater treatment sector in an area. For this endeavour, data from different utilities[5] are needed which would require benchmarking methods of limited complexity and with limited data requirements.

As described along this paper and illustrated in this final section, greatly varying objectives and demands of the different actors involved at all levels must be taken into consideration in a successful WWTP framework for energy efficiency promotion. Goal setting, together with detailed and robust analysis and communication among various actors can helps everyone in the overall common goal to increase the efficiency in the use of energy, hence achieving the object of both economic and environmental performance improvement.

6. Conclusions

The joint increased availability of data and computer methods has opened the door to many techniques to utilize measurements in wastewater treatment. It was seen that each benchmarking method offers different insights on the performance of the WWTP, and the outcomes may well have different interpretations. Although the methods discussed in this article allow identifying, quantifying and explaining (in) efficiency, decision-making is the outcome of putting together many sources of information and the proper selection of the benchmarking method. Focusing in wastewater treatment, and particularly regarding energy efficiency, we have identified the requirements of the most common benchmarking methods in terms of data, resources, complexity of use, and information provided. This analysis has allowed relating each method with different stakeholders in the water sector and benchmarking objectives. Furthermore, as the inefficiency estimated by each method has a different origin, it was possible to link inefficiency components with root-causes in wastewater treatment. Hence, we proposed a framework to assist water sector stakeholders in selecting the most suitable benchmarking method to improve energy efficiency in WWTPs.

Declaration of competing interest

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

Data availability

Data will be made available on request.

[5] Note that benchmarking initiatives have been put in place in the water sector to provide representative data across utilities such as the European Benchmarking Cooperation (www.waterbenchmark.org/).

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