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Review

A Critical Review on Methodologies for the Energy Benchmarking of Wastewater Treatment Plants

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Abstract: The main priority at wastewater treatment plants (WWTPs) is the attainment of a high quality of treated effluent ensuring the highly effective removal of pollutants and protecting the environment and public health. However, WWTPs are made of energy-intensive processes and consequently, they are considered major energy consumers in the public sector. The need to move towards energy neutrality in the wastewater sector was recently pointed out by the proposal of a recast Urban Wastewater Treatment Directive. To date, a comprehensive methodology for energy audits at WWTPs is still missing. The present review aims at discussing the state of the art on energy consumption at WWTPs and at surveying the energy benchmarking methodologies currently available highlighting the main advantages and limitations. It was pointed out that aeration represents the highest energy-intensive compartment in WWTPs (40–75% of total energy). The wide overview provided by key performance indicators (KPIs) might be overcome by applying benchmarking methodologies based on data envelopment analysis (DEA). The latest is properly designed for WWTPs and able to manage multiple inputs and outputs. However, the obtained findings are often limited and fragmented, making the standardization of the methodology difficult. Consequently, future investigations are advised on the development of standard procedures related to data acquisition and collection and on the implementation of online and real-time monitoring. Considering the lack of standardized methodology for the energy benchmarking of WWTPs, the present article will provide essential information to guide future research, helping WWTP utilities to reach the energy audit goals in the accomplishment of incoming EU directives.

Keywords: energy benchmarking; energy consumption; energy audit; key performance indicator (KPI); wastewater treatment plants (WWTPs)

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1. Introduction

The water–energy nexus explains the linkages between water and energy, two resources that are strongly interconnected and their needs are set to increase [1,2]. As extensively documented, the scarcity of one heavily impacts the availability of the other [3,4]. Energy plays an important role in water services, and it generally represents the second-largest share of operating costs along the urban water cycle [5]. Recently, a recast proposal of the EU Energy Efficiency Directive (EED) advised an annual decrease target of 1.7% of energy consumption for all public sectors, including water and wastewater treatment without compromising public health and the environment [6].

Accounting also for the issues related to steadily rising energy costs and climate change, effective energy management in the water sector is mandatory to ensure that utility operations become more sustainable in the future. The energy-saving strategies can produce relevant findings from both economic and environmental perspectives. Indeed, according to Goal 6 of the 2030 Agenda for Sustainable Development, it is paramount to "ensure access to water and sanitation for all" [7].

Across the urban water–wastewater cycle, the water sector involves several energy-intensive processes employed for different purposes such as the production of drinking water, pressurizing water distribution systems, pumping water, and wastewater (WW) treatment [3,4,8]. Although the use of energy may be smaller compared to industrial activities, the energy consumption in the water sector represents nearly 44% of the municipalities' energy costs [2,9]. Moreover, wastewater treatment plants (WWTPs) are considered the major energy users of the urban sector accounting for 1–3% of the total electricity output of a country [1–3,10,11]. These percentages are widely reported in the scientific literature and vary across countries. For instance, in Europe, only the WW sector accounts for ~0.8% of the overall EU energy use [12], while in Sweden, about 1% of national electrical energy use is associated with the water sector. This value is higher (~3–4%) in other countries (such as the USA and UK) [1,4]. Conversely, in countries facing greater water scarcity and those that are closely dependent on desalination processes, such as Israel, the energy demand for water-related processes is even higher (~10%) [4].

Overall, as pointed out by the International Energy Agency (IEA), electricity consumption in the water sector is projected to more than double during the following decades (Figure 1). This finding might be ascribed to the scarcity of freshwater resources which lead to a greater reliance on energy-intensive treatments such as desalination (~345 TWh of electricity consumption in 2040) and advanced WW treatment (~314 TWh of electricity consumption in 2040). Specifically, across the urban water cycle, it is extensively reported that the highest percentage of energy consumption in the form of electricity is for WW treatment [3,13].

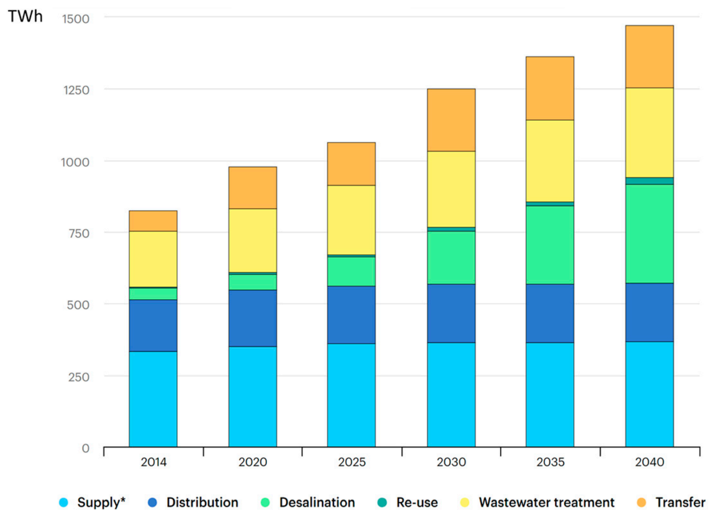


Figure 1. Electricity consumption in water sector, 2014–2020 (* supply includes ground and surface treatment). Source [14].

Furthermore, the increase in energy consumption in WWTPs could be linked to more restrictive limits on the quality of water effluents recently introduced to meet the standard of water reuse both for potable and agricultural purposes [14]. The implementation of additional treatment steps required for removing contaminants of emerging concern (CEC), such as pharmaceutical and personal care products and per- and polyfluoroalkyl substances (PFAS), may undoubtedly imply the increase in the energy demand of WWTPs [3,10,14].

Based on the latest technological advancements, modern WWTPs are expected to have a specific power consumption ranging from 20 to 45 kWh per population equivalent (PE) per year [3,15]. Additional data reveal that energy consumption in the EU varies between 0.3 and 2.1 kWh/m^3 of treated wastewater, while in the United States, the range is from 0.41 to 0.87 kWh/m^3 [3,16].

Undoubtedly, operations in the water sector also pose critical challenges to environmental sustainability due to direct and indirect greenhouse gas (GHG) emissions [2,10,17].

It was pointed out that WWTPs account for ~56% of GHG emissions within the water industry, and globally the water and WW sectors are responsible for 1.5% of CO_2 and ~5–7% of GHG emissions [4,10].

Consequently, any energy efficiency improvements in the water and WW sectors are expected to effectively contribute to reducing global GHG emissions and reaching the goal of carbon neutrality [4,8,18].

Another key aspect of the sustainable development of the water sector is the promotion of circularity in WW management [3,10,19]. Indeed, several recovery potential strategies (e.g., improved sludge management and effective recovery of nutrients) exploit the embedded energy in WW [3,10]. Indeed, the energy efficiency optimization will contribute to achieving energy self-sufficient WWTPs which are becoming very interesting [5,10]. WW includes recoverable resources such as energy and nutrients and recent studies have demonstrated the feasibility of energy and materials recovery from WW [5,20,21]. Indeed, WW contains embedded energy in the form of chemical, thermal, and kinetic ones that, if correctly and effectively recovered, allow for energy-neutral or even net energy producer WWTPs [3,5,10]. Several studies have estimated that the chemical energy content of WW is approximately 10–14 KJ/kg COD (1.67–2.33 kWh/m^3), while the thermal energy potential can yield around 21 MJ/m^3 (5.8 kWh/m^3) and the potential energy can generate just 30 kJ/m^3 (0.008 kWh/m^3) [3,22]. The main available and developing technologies for resource recovery from WW have been recently reviewed with a particular focus on the value-added WW extractable products [21].

The recent recast proposal of the Urban Wastewater Treatment Directive (UWWTD) confirms the need to move towards the energy neutrality of the WW sector [23]. Indeed, it established energy neutrality by 2040 at the national level for all WWTPs above 10,000 PE (population equivalent). To reach this objective, energy audits will be needed for all facilities above 100,000 PE by 2025, and by 2030 (interim target), audits will be needed for all facilities above 10,000 PE [23].

Consequently, the reduction in the energy consumption in water and wastewater treatment plants starts with its assessment through an energy audit previously designed and tuned for the kind of facility under investigation. The energy audit plays a crucial role in assessing the energy consumption and carbon emissions related to wastewater treatment systems [10,24]. Furthermore, it allows for the identification of sustainable strategies for energy efficiency and for performance optimization while contributing to WWTPs' decarbonization [10]. As extensively discussed in the following sections, an energy audit is a systematic methodology to assess the energy consumption profile of an industrial plant and it allows for the identification of the energy baseline as the reference consumption of individual devices and installations. Consequently, based on the obtained results from the energy audit, the best opportunities for improvement could be identified and the related implementations of process management properly designed.

Specifically, the energy audit of WWTPs is useful to identify the main energy consumers (e.g., processes and equipment) including the needed maintenance practices and their lifespan. However, a standardized method for WWTPs is still missing and further investigations are required to develop a comprehensive methodology for energy audits at WWTPs [10,24].

Recent studies have aimed to develop several methodologies to perform energy audits at WWTPs and consequently to develop energy benchmarking [25]. Specifically, benchmarking tools are useful to identify the opportunities for energy savings and to prioritize optimization with targeting measures.

The present review is aimed at discussing the state of the art on energy consumption at WWTPs, highlighting the impact of plant configuration and operational conditions. A particular focus is placed on the energy benchmarking methodologies by critically discussing their main advantages and limitations. Consequently, the currently available methodologies were surveyed in order to point out the challenges and the research needs related to WWTP energy benchmarking. Indeed, considering the lack of a standardized method, the present article will provide essential information to guide future research, helping WWTP utilities to reach the energy audit goals in the accomplishment of the EU directive.

2. Energy Consumption in WWTPs

It is well known that wastewater treatment is energy intensive. Moreover, the stricter regulations on water effluent quality contribute to an increase in the energy demand [2,10]. Undoubtedly, the required effluent quality (and consequently BOD, N, and P removal rates) has an impact on energy consumption since stricter discharge limits lead to a higher consumption of energy and chemicals [2,26].

Indeed, advanced technologies are needed to attain the removal of recalcitrant contaminants posing significant challenges for the effective management and operation of WWTPs.

Several key factors influence the energy consumption in WWTPs such as (i) plant size, age, and climate (that could be grouped as physical-related factors); and (ii) the type of processes and technologies installed and consequently the operation and maintenance practices (grouped as process-related factors).

A discussion of these key factors is reported in the following paragraphs.

2.1. Physical-Related Factors: Plant Size and Age and Climate Conditions

The relationship between plant size and its energy consumption is not necessarily straightforward.

It was demonstrated that the size of WWTPs and specific energy consumption are correlated when energy consumption is expressed in terms of the volume of treated WW or PE served [26–28]. As a whole, large WWTPs are characterized by lower specific energy consumption compared to the smallest ones. This may be ascribed to the volumetric and organic load fluctuations that occurred at small plants [27,28].

Specifically, the small-scale WWTPs (e.g., <2000 PE) are not conventionally equipped with control and monitoring systems and, in the case of conventional energy-consuming technologies being installed, they are characterized by a higher specific energy consumption [27,28]. However, small-scale WWTPs made of nature-based technologies (adopted at small-size agglomerations such as Imhoff tanks combined with constructed wetlands) do not suffer from less frequent optimization and maintenance, and lower specific energy consumption may result due to the less energy-intensive technologies installed [29,30]. Furthermore, it is mentioned that a 1% size increase led to a 0.91% increase in the total energy consumption [2].

Data collected at ~300 WWTPs from Ganora et al. (2019) pointed out that the specific energy consumption tends to decrease with increasing PE served [27]. Other findings showed that the specific electrical consumption expressed as a function of the plant capacity (PE served per year) decreased from more than 60 kWh/PE/y for small WWTPs (<10,000 PE) to less than 45 kWh/PE/y for larger systems (>100,000 PE) [31]. It mainly depends on the technology adopted.

Despite the water treatment process analyzed (trickling filters, activated sludge, and advanced treatments), the electrical consumption always reduces when plant size increases [31]. The specific energy consumption is exponentially reduced when moving from small to larger plants in terms of kWh per kg of COD removed and PE served. It is confirmed that generally for medium-to-large plants, the treatment sections characterized by higher energy consumption are biological oxidation, pumping and sludge recirculation, and mechanical dewatering of sludge or aerobic sludge digestion if present (as extensively discussed in the next section) [32–34]. Undoubtedly, this finding is also supported by the economies of scale which affect energy efficiency [2]. Data collected from small WWTPs (influent flowrate < 300 m^3/d) pointed out an average specific energy consumption of ~0.91 kWh/m^3, while medium-large WWTPs (influent flowrate > 5000 m^3/d) exhibited an energy consumption in the range of 0.33–0.41 kWh/m^3 [2,25]. In the work of Awe et al.

(2016), it is mentioned that a WWTP (flowrate 4000 m^3/d) consumes 0.591 kWh/m^3, while a larger WWTP (flowrate ~378,500 m^3/d) consumes 0.272 kWh/m^3 [35].

However, several debates are still ongoing regarding the optimal plant size (e.g., several decentralized plants or a larger one serving multiple urban settlements) since it should be identified based on energy and economic assessments of both WW treatment and WW reuse [2,26]. Moreover, the WW reuse should be pursued given the climate change scenario of water scarcity and uneven water distribution [2].

The effect of plant age on energy consumption is a controversial debate in the scientific community as demonstrated by contradictory and often fragmentary evidence. For instance, it seems that the energy consumption is lower in new WWTPs and the renovation of old WWTPs (more than 20 years old) leads to a decrease equal to ~3% in energy consumption [1,2]. Consequently, the periodical monitoring of WWTP energy performance is essential to obtain information on obsolete technologies, proper and effective maintenance of equipment, and consequently the service life of the entire plant.

Another physical-related factor is climate since its impact on energy is expected to increase with the increasing occurrence of extreme weather events [2,36,37]. Influent WW temperature affects the performance of the treatment process, in particular the biological ones [2,37,38]. Indeed, any temperature change may affect the energy consumption at WWTPs [2,15,38,39]. For instance, an increase in water temperature led to an increase in biological activities while reducing the oxygen solubility and a subsequent greater energy demand for aeration [2,15,40]. It was reported that high temperatures during the summer season (T = 19.4 °C) led to an energy consumption approximately 5.6% lower than in winter (T = 11.5 °C) [2]. Furthermore, a decrease in pollutant removal efficiency with increasing temperature was observed, which can be attributed to the decrease in oxygen solubility affecting microbial metabolism and biodegradation processes [37,39].

The effect of other weather events (e.g., rainfall intensity and frequency) on energy consumption in WWTPs have been investigated [36,37]. A direct correlation between rainfall intensity and energy consumption was highlighted, and an increase in energy consumption (from 0.36 to 0.52 kWh/m^3) was observed due to the raising of rainfall intensity (from 0.8 to 2.9 mm/min) [36].

2.2. Process-Related Factors: Unit Process and Type of Installed Technology

It is important to note that the energy consumption in WWTPs varies depending on the specific technologies employed in the treatment process. Electricity consumption plays an important role in the environmental performance of WWTPs, and nearly 70% of the energy consumption occurs during the operational phase [41,42].

As a whole, a WWTP encompasses five main stages: preliminary, primary, secondary, tertiary, and sludge treatment [42]. The first one accounts for the smallest percentages (~10%) [2,15].

Energy is mainly consumed during the transportation of wastewater, sludge, and process water (accounting for 10–20% of the total energy consumption); aeration and oxygen supply (accounting for 50–70% of the total energy consumption); and solids and biosolids processing, dewatering, and drying (accounting for 10–25% of the total energy consumption) [2,41]. Aeration is the most important process at biological treatment plants and it accounts for ~45–75% of the energy demand in a WWTP [31,33].

However, those percentages may vary significantly across WWTPs due to different configurations and no standardized methodology for energy benchmarking [3,33].

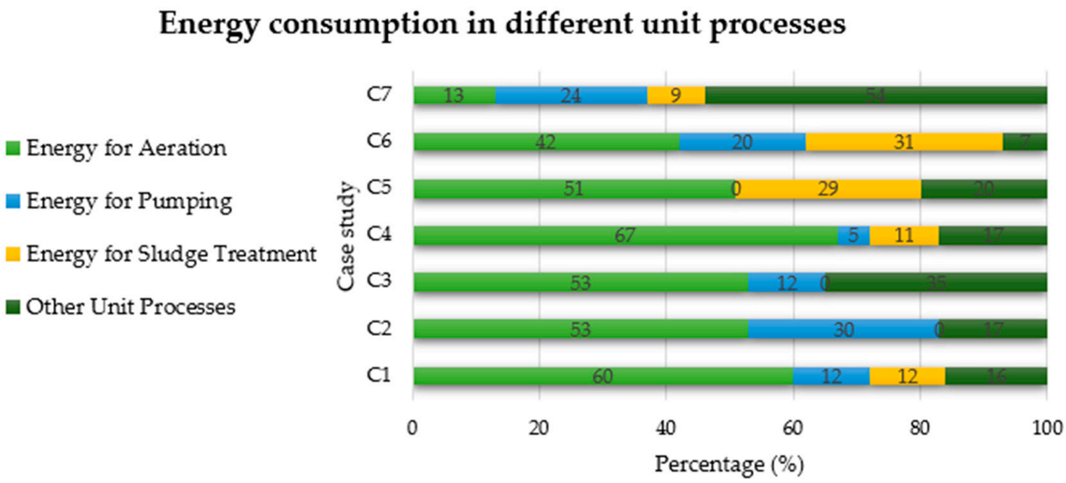
Among sludge treatments, coagulation/flocculation is a proven technology for primary sludge separation and it was recently proposed as an upgrade in a WWTP to enhance the primary sludge removal while reducing the energy consumption [43].

Furthermore, most energy self-sufficient WWTPs are recovering energy for the anaerobic digestion of sludge, highlighting the feasibility of energy recovery [5,44,45].

Aside from the aforementioned energy consumptions, WWTPs indirectly consume energy through various processes and activities associated with WW treatment [3,15,19].

Several features are related to indirect energy consumption at WWTPs such as building and maintaining treatment facilities (e.g., pipelines and pumping stations including materials manufacturing and transportation), the production and transportation of chemicals used in WWTPs (e.g., coagulants and disinfectants), and sludge handling and disposal [2,41]. This energy consumption is considered indirect as it is not directly related to the day-to-day operation of WWTPs. In this regard, the life cycle assessment (LCA) is useful for measuring the environmental footprint of WWTPs including both direct and indirect energy consumption [41,46].

The percentages of energy consumed in relevant unit processes (e.g., aeration, pumping, sludge treatment, and others) are reported in Figure 2 for a selection of case studies.



Case Study	Description	Specific Energy Consumption (kWh/m³)	Reference
C1	Average MBR treatment systems in Singapore	0.985	Gu et al, 2017
C2	250,000 PE advanced WWTP in Poland	0.48	Zaborowska et al, 2017
C3	Benchmarking study on 14 WWTPs in Portugal	N.A.	Henriques et al, 2017
C4	WWTP Bochum-Ölbachtal located in Germany	23 *	Marner et al, 2018
C5	Advanced WWTP in Italy (flowrate = 615,000 m³/d)	0.3	Panepinto et al, 2016
C6	WWTP in Spain (flowrate = 18,500 m³/d)	0.65 **	Aymerich et al, 2015
C7	Advanced WWTP in Singapore (flowarate= 800,000 m³/d)	0.89	Sarpong et al, 2020

N.A.: not available
* value expressed in kWh/(PE·year)
** value calculated based on energy consumption (363 MWh/month) and flowrate (18,500 m³/d)

Figure 2. Selected case studies and related percentages of energy consumption for relevant unit processes (e.g., energy for aeration, pumping, sludge treatment, and other unit processes) [5,34,43,47–50].

Aside from several factors reported above, the energy consumption in WWTPs also varies with the treatment technologies installed. A collection of data related to energy consumption in WWTPs is reported in Table 1 along with a brief description of the water line, population equivalent, WW flowrate (m^3/month), and specific energy consumption (kWh/m^3).

Table 1. Collection of data related to energy consumption in WWTPs (description of water line, population equivalent, WW flowrate, and specific energy consumption).

Water Line	PE	Wastewater Flowrate (m^3/month)	Specific Energy Consumption (kWh/m^3)	References
PreTr-Sed.I-PredeN-dePchim-Ox-Sed.II-Dis	800,000	3.30×10^6	0.58	[51]
PreTr-PreDeN-dePchim-Ox-Sed.II-Dis	36,000	8.12×10^4	0.59	[51]
PreTr-PreDeN-dePchim-Ox-Sed.II-Dis	9500	3.95×10^4	0.65	[51]
PreTr-Primary-Secondary-Terziary-Dis	30,761	3.6×10^5	0.21	[52]
PreTr-AEZ-MBR	130,000	1.17×10^6	0.83	[53]
PreTr-Sed.I-PreDeN-dePchim-Ox- Sed.II-Dis	560,000	2.55×10^6	0.46	[51]
PreTr-Sed.I-PreDeN-dePchim-Ox-Sed.II-Dis	139,000	4.31×10^5	0.36	[51]
PreTr-Sed. I-PreDeN-dePchim-Ox-Sed. II-TerTreat-Dis	197,500	5.44×10^6	0.48	[51]
PreTr-PreDeN-dePchim-Ox-Sed.II-Dis	75,000	5.15×10^5	0.49	[51]
PreTr-PreDeN-dePchim-Ox-Sed.II-Dis	44,000	1.54×10^5	0.60	[51]
PreTr-dePBio-Ox-Sed.II-Dis	12,000	1.10×10^5	0.39	[51]
PreTr-PreDeN-Sed.II-Dis	330,000	3.28×10^6	0.23	[54]

PreTr: pretreatment; AEZ: aeration zone; dePBio: biological phosphorus removal; Sed. I: primary Clarifiers; PreDeN: pre-denitrification; dePchim: chemical phosphorus removal; Ox: oxidation tank; Sed.II: secondary clarifiers; Dis: disinfection; MBR: membrane bioreactor.

3. Overview of Methodologies for Energy Audit at WWTPs

An energy audit represents a systematic procedure to obtain a comprehensive framework of the energy consumption profile of an industrial plant. The energy audit is aimed at identifying the energy baseline regarding the reference consumption of individual devices and installation. Consequently, based on the results of the energy audit, it is possible to identify the best opportunities for improvement.

An energy audit requires a clearly stated and accepted methodology beyond common knowledge. According to EU Directive 2012/27/EU, the energy audit is mandatory for companies including water utilities with more than 250 employees and with annual trading volume greater than EUR 50 million or whose annual balance sheet exceeds EUR 43 million [33].

The following sections summarize the methodologies that are currently available to perform an energy audit of WWTPs, highlighting the main advantages and limitations. The obtained survey helps identify the main principles and good practices that should be included and account for the methodology standardization.

3.1. International Standard ISO 50001 for Enterprise Energy Management Systems

The International Standard ISO 50001:2018 for enterprise Energy Management Systems represents useful and systematic guidance for an organization to achieve a healthy energy management system, reducing energy consumption and environmental impacts and increasing profitability [55].

It might apply to organizations of any size including WWTPs, although it is not specifically designed for the water sector.

It is based on the Plan-Do-Check-Act (PDCA) [55], an iterative process with a circular framework (Figure 3). The PDCA approach encompasses the following consecutive steps:

- Plan: Perform the energy assessment in order to identify the baseline, energy performance indicators, objectives, targets, and action plans.
- Do: Implementation and operation of the energy management action plan.
- Check: Monitor and measure the improvements and determine the energy performance based on the objectives; report the results and cost savings.
- Act: Periodically review progress and make adjustments to energy programs.

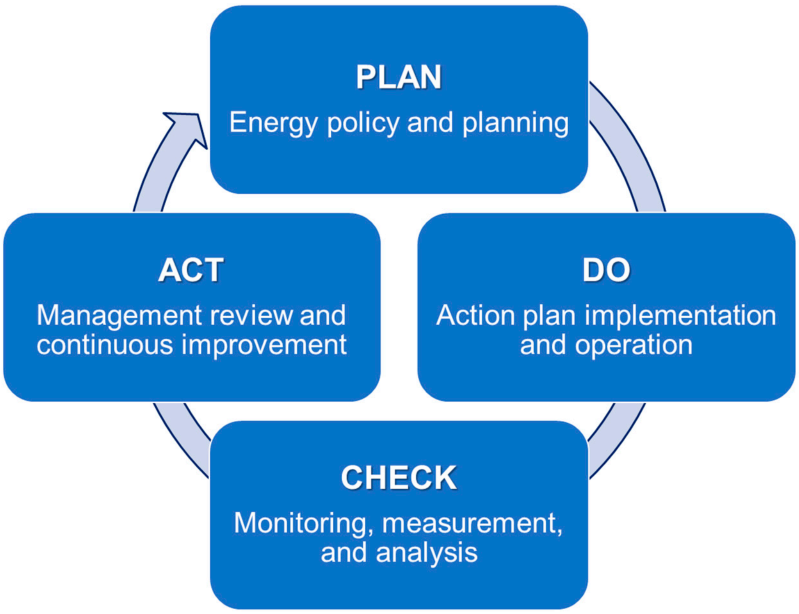


Figure 3. Schematic view of the "Plan-Do-Check-Act (PDCA)" approach according to ISO 50001:2018.

3.2. Key Performance Indicators (KPIs)

In the context of industrial systems, a common approach to evaluating energy performance encompasses the key performance indicators (KPIs) [51,56]. Traditionally, a KPI is a ratio between an input (e.g., energy consumption) and output (e.g., unit activity or service provided) [57]. Specifically, in the WW sector, KPIs have been widely employed to provide an overview of WWTP energy performance, although several limitations have been pointed out [58]. As a whole, KPIs for WWTPs have been developed as the ratio between electric energy consumption and volume of treated WW (kWh/m^3) or unit of population equivalent on an annual basis (kWh/PE year) [33,51,56]. Consequently, they assumed that the energy consumption is proportional to the flowrate of influent WW and that the concentration of pollutants in the influent does not vary significantly between WWTPs [51,59]. Notably, these assumptions limit the wide application of KPIs based on the volume of treated WW and PE for the energy benchmarking of WWTPs. As a result, other KPIs have been developed and applied.

The most used KPIs and their suitability in assessing the energy efficiency of different treatment stages and of the whole WWTP are reported in Figure 4. The criterion for evaluating KPI suitability is derived from the literature [15,33].

KPI	Treatment stage: Preliminary	Primary	Secondary	Tertiary	Sludge	Overall
kWh/m³	US	NS	NS	PS	NS	**NS**
kWh/PE year	NS	NS	NS	NS	NS	**NS**
kWh/kgCODrem	NS	PS	PS	NS	NS	**PS**
kWh/kgTSSrem	NS	US	NS	NS	US	**NS**
kWh/kgTNrem	NS	NS	PS	NS	NS	**PS**
kWh/kgTPUrem	NS	NS	US	US	NS	**US**

US: Universally Suitable; PS: Partially Suitable; NS: Not Suitable

Figure 4. Most used KPIs and their suitability in assessing the energy efficiency of different treatment stages. (US: Universally Suitable; PS: Partially Suitable; NS: Not Suitable; TPU: total pollution units).

Analyzing the collected information reported in Figure 4, it is possible to highlight the limitations of KPIs most used in benchmarking studies of WWTPs. For instance, it is noteworthy that kWh/PE year is an unsuitable indicator either for a single treatment stage (e.g., preliminary, primary, and sludge) or the entire plant. Furthermore, it does not account for the removal of pollutants and consequently, the application of kWh/PE year is very limited.

The KPI related to the volume of treated wastewater (kWh/m^3) is universally suitable for the preliminary treatment, while it is not representative of the entire plant (i.e., overall), it does not represent the removal of pollutants, and it may be affected by the dilution factor [33,60]. The latter influenced the findings from several studies that reported the WWTP energy consumption in kWh/m^3 because the higher energy efficiency of WWTPs is often related to a higher dilution of pollutants, particularly in the presence of WW from combined sewer systems [29].

Another group of KPIs reports the energy consumption per unit of pollutant removed (e.g., kWh/TSSrem, kWh/CODrem, and kWh/TNrem) since the removal of organic matter and nutrients strongly affects the energy consumption in WWTPs, although it often neglects the volume of WW to be treated and other pollutants [20,34,43].

Moreover, as evidenced by Figure 4, considering a single KPI has significant limitations since it does not provide an overview of a WWTP and its main operations. For instance, kWh/CODrem could be feasible for comparing plants with similar configuration, although its application is not recommended for the preliminary, tertiary, and sludge treatment stages (Figure 4).

Moreover, other KPIs related to pollutants such as kWh/TSSrem and kWh/TNrem are suited for specific treatment stages (e.g., primary and sludge treatments) or for WWTPs specifically designed and operated for removing nitrogen.

To overcome the limitations, a KPI expressed as kWh/TPUrem has been developed including all the main pollutants in a single variable. Indeed, the total amount of pollutants removed at a WWTP (expressed in kg of total pollution units, TPU) is calculated based on the sum of compounds influencing the quality of the receiving water body [33]. Consequently, the related KPI (kWh/TPUrem) is universally suitable for the entire WWTP and particularly for secondary and tertiary treatments allowing for the comparison among different WWTPs.

Based on the above, it is clear that a comprehensive assessment of energy consumption in WWTPs is unfeasible using a single KPI. Indeed, a single KPI does not reflect the operation of the entire WWTP, allowing for only partial evaluations [33,61].

Moreover, a direct comparison among WWTPs based on KPIs is feasible only when WWTPs have similar process layouts and treatment technologies [60,61].

Furthermore, as previously mentioned, KPIs are ratios between two variables assuming a linear correlation between, for instance, specific energy consumption and pollutant removal [33,60,61].

However, WWTPs encompass nonlinear biological processes also composed of different interconnected control units [60,61]. Consequently, monitoring and optimization based on KPIs is a complex task. The recently developed benchmarking approaches are based on multiple KPIs and they use different weighting procedures [13,60].

The following section provides the classification of the energy benchmarking according to complexity level and a survey of the recently developed tools employed at WWTPs.

3.3. Energy Benchmarking Approach Classification and Recently Developed Tools for WWTPs

Energy benchmarking is a systematic comparison of energy efficiency in relation to a reference performance, and the identification of the most efficient units and best practices is its main key finding [15].

There are different benchmarking methods and the selection of the most suitable depends on the purpose of the analysis, the data availability, and the expected outcomes.

Table 2 provides an overview of existing benchmarking methodologies classified according to the level of complexity in the normalization approach, statistical approach (e.g., ordinary least squares, OLS, and stochastic frontier analysis, SFA), and programming techniques (e.g., data envelopment analysis, DEA, and stochastic data envelopment analysis, SDEA) [33,51,62].

The simplest one is the normalization approach which is also the most widely employed by water companies and plant operators considering its ease of implementation and interpretation. The normalization approach is generally performed through energy-efficiency indicators such as KPIs and partial indicators which are commonly available. However, this type of benchmarking is mainly suitable for comparing WWTPs having similar characteristics (e.g., processes, technologies, and size) but not for a comprehensive assessment of different WWTPs operated at different conditions [13].

The statistical approach is a conventional linear regression model used to calculate both the efficiency frontier and the efficiency score of the management entities [33,61]. The statistical approach encompasses regression-based techniques such as OLS which mainly use operational and design data (e.g., flowrate, size, and loading) as parameters, and then, to evaluate the efficiency level, each plant is compared with the average values. Although it might be used to predict the annual energy consumption of plants, OLS is sensitive to outliers and needs a large dataset to extend its range of validity [33].

Contrary to OLS, SFA is difficult to implement through a small dataset. Indeed, a robustness model based on SFA requires a large amount of data.

Programing techniques are another group of benchmarking methodologies that include DEA and SDEA. Programming methods involve optimization based on the collected data to establish an optimal boundary or contour, which is utilized for comparing different entities.

Specifically, DEA is a mathematical programming technique method that might be used as a decision support tool in several sectors [63].

It allows for the inclusion of unpredictable factors such as those that are environmental. Consequently, it can be used to merge multiple inputs and outputs in the benchmark assessment; however, the proper selection of input and output variables might affect the obtained findings. The selection of input variables might be verified through other techniques such as linear regression. Furthermore, DEA-based tools are mainly intended for internal benchmarking within companies.

Table 2. Overview of existing benchmarking approaches classified according to their complexity level.

Benchmarking Methodologies		
Level I	**Level II**	**Level III**
Normalization	**Statistical Approaches**	**Programing Techniques**
- Based on normalized energy performance indicators and ratios. - The simplest way to perform a comparison. - The most widely used approach by plant operators and water companies. - It should be applied to plants with similar sizes and characteristics.	*Ordinary least squares (OLS)* - Use operational and design data as input parameters and compare each plant with average values to evaluate the efficiency level. - Might be used to predict the annual energy consumption based on the plant's characteristics. - It is sensitive to outliers, and it needs a large dataset to obtain reliable results.	*Data envelopment analysis (DEA)* - It is a nonparametric model that allows for the analysis of processes with various inputs and multiple outputs at the same time. - The efficiency scores depend on the input variables selected. - The outcomes might be influenced by the choice of input and output variables.
	Stochastic frontier analysis (SFA) - It estimates the efficient frontier and efficiency score and their deviations. - It requires a large amount of data in order to obtain a robustness model. - It takes into consideration the impact of measurement errors and other random effects.	*Stochastic data envelopment analysis (SDEA)* - It includes the flexible structure of a nonparametric model also accounts for the influence of statistical noise. - Large dataset is required.

SDEA is a linear programming model similar to DEA, but its stochastic nature allows for it to account for the influence of statistical noise. Furthermore, it might involve a smart meter dataset made of repeated measurements (e.g., every 10 min). As highlighted in Table 2, the main limitation of SDEA is the need for large datasets [33].

In order to strengthen the development of a standard methodology for the energy benchmarking of WWTPs, the available benchmarking tools recently developed for WWTPs and reported in the scientific literature are surveyed in Table 3. Particularly, per each methodology, a brief description is reported along with the main advantages and limitations for comparison purposes.

Table 3. Summary of recent benchmarking tools developed for WWTPs.

Methodology	Description	Advantages	Limitations	References
The Robust Energy Efficiency DEA (REED)	This approach enhances the reliability of energy measurement in WWTPs, consequently improving the accuracy of efficiency assessments and the overall effectiveness of benchmarking.	Assess the impact of external factors on WWTP energy efficiency. Determine the energy efficiency improvements of losses attributed to these external factors. Establish a ranking system for WWTPs based on their energy efficiency levels.	Addresses the constraints by employing composite indicators to diminish variations and facilitate comparisons within the reference dataset of WWTPs.	[40]

Table 3. *Cont.*

Methodology	Description	Advantages	Limitations	References
Energy Performance Indicator (EPI)	The novel method assesses the energy performance of WWTPs. Novel performance classes are defined by coupling the specific energy consumption indicators with pollutant removal efficiency parameters.	It accounts for the amount of influent pollutants and the removal efficiency of the treatment in the assessment of energy performance. A new classification in classes of performance considering EPI and removal efficiency is provided. This indicator helps to compare the energy performance of plants before and after conducting interventions.	It considers only a single factor, and these indicators neglect the variability in the other properties of WW.	[60]
ENERWATER	Tool for benchmarking and diagnosing the use of energy and formulating improvement actions at WWTPs.	The key novelty is its output, a single energy label that is universally recognizable. Flexibility to adapt to various plant configurations.	The final database was retrieved from the literature, and it includes only European WWTPs.	[13]
Global Energetic Index (GEI)	Used for performance comparisons, classification, and labelling of WWTPs. This methodology gives a rapid WWTP energy balance evaluation.	It is an analyzing procedure that allows for the design of interventions aimed at reducing energy costs and environmental impacts. It highlights the most efficient plant.	A limited number of WWTPs were employed for the development of this methodology.	[51]
Economic efficiency analysis (EEA)	It focuses on the evaluation of financial aspects related to WWTPs, examining capital expenditures and operational expenses.	It involves the assessment of the energy performance ascribed to equipment and systems, leading to better overall operational parameters monitoring and lowering the downtime.	Data collection can be challenging, especially in older facilities with outdated monitoring systems.	[20,64]
Eco-efficiency analysis using LCA + DEA	Combines the DEA methodology with LCA in order to determine both the operational efficiency and the environmental impacts of WWTPs.	The eco-efficiency criteria are verified through the computation of environmental gains linked with results from the DEA model.	Mainly applied to WWTPs with good data quality and without tertiary treatment systems.	[62]
Stochastic non-parametric envelopment of data (StoNED)	Combination of nonparametric methods (nonlinear programming) with stochastic noise (parametric techniques) in order to investigate the influence of the operating environment on the energy performance of WWTPs.	Quantification of energy potential savings provides essential information for supporting the decision process regulations. It could be applied to assess the water–energy–GHG nexus. Potential application also for drinking water treatment plants.	No limitations mentioned in the study.	[18]

Table 3. *Cont.*

Methodology	Description	Advantages	Limitations	References
Plant-wide modeling	A simulation tool to predict WWTPs' performance in terms of energy consumption and WW influent and effluent qualities. Furthermore, it allows for the comparison of different treatment options and management approaches to attain the energy-neutral state.	Offers a comprehensive perspective on the complete WWT procedure, enabling precise forecasts of the facility efficiency across various operational scenarios.	Uncertainties in model parameters, assumptions, and data can affect the accuracy of predictions.	[20,65–67]

Looking at Table 3, several tools and methodologies have been specifically designed and tested at WWTPs.

For instance, ENERWATER is an energy benchmarking model developed by Longo et al. and properly designed for WWTPs [13,27]. The methodology represents a tool for benchmarking and diagnosing the use of energy, also suggesting some improvement actions for reducing energy consumption at WWTPs. It is based on the DEA benchmarking method [40]. The methodology follows a continuous improvement cycle and defines the concept of energy efficiency. It utilizes a comprehensive and comparable measurement approach, known as the Water Treatment Energy Index (WTEI). The WTEI serves as an energy tag, providing information about the energy performance of WWTPs based on defined consumption patterns. However, one limitation of the methodology is the difficulty in accessing data, which hampers the calculation of key performance indicators (KPIs) and the composite energy index (WTEI). ENERWATER accounts for two approaches, "Rapid Audit" and "Decision Support".

"Rapid Audit" is aimed at a rapid estimation of the WTEI of a specific WWTP using existing information. This method uses historical data on energy consumption and existing information such as influent and effluent. After the calculation of WTEI, the obtained values can be compared against a large database.

"Decision Support" is aimed at founding the WTEI of a specific WWTP and providing information that can be used as decision support for an energy efficiency assessment. The online energy data were obtained over extended periods to establish KPIs for each treatment stage. "Decision Support" methodology can be used to provide a WWTP energy benchmark but also to understand the impact of seasonal variations, storm events, changes in maintenance, and the implementation of new equipment (e.g., screens, pumps, blowers, etc.) [13,27].

The Robust Energy Efficiency DEA (REED) utilized by Longo et al. improves the quality of the efficiency estimates and hence the significance of benchmarking. It is meant to guide operators, managers, and engineers through all the steps required to correctly use DEA for comparison of the energy efficiency of WWTPs. It is a case study of 399 WWTPs operating in different countries and under heterogeneous environmental conditions. A novel method is utilized by Di Fraia et al. for assessing the energy performance of WWTPs. The method is based on specific energy consumption indicators, named EPIs, and the removal efficiency parameters. Coupling EPI with the removal efficiency parameter defines the novel performance classes of WWTPs. The most representative indicator observed is EPI_{BOD}, which relates energy consumption to the influent BOD. The partition into classes is derived considering a large database of about 300 WWTPs.

The Global Energetic Index (GEI) is another methodology that implies the KPIs' aggregation, and it is used for WWTP performance comparison, classification, and labeling [51]. The benchmarking analysis for each dimensional group, the differences among WWTPs' energy performances in terms of the “distance” of GEI values, allows us to derive a rough indication of the potential energy efficiency benefits following the definition and the implementation of suitable improvement measures.

Energy Efficiency Assessment (EEA) is another study method that is an indirect method to evaluate energy efficiency. This method supports decision-making in the energy-related aspects of WWTPs. The EEA focuses on three key factors: capital costs, operating costs, and economic benefits. Its primary focus is on energy-related aspects, specifically reducing operating costs through advanced control systems and maximizing economic benefits by enhancing energy recovery, conducted by Guerrini et al. [64].

The study examined environmental impact indicators assessed through LCA alongside economic performance measures. This analysis highlighted that the combined application of LCA and DEA can offer a valuable approach for evaluating the overall performance of WWTPs. It is an integration of methodologies for evaluating the environmental performance and the mathematical method used for evaluating the efficiency and performance of decision-making units with multiple inputs and outputs [62].

The StoNED method, developed by Molinos-Senante and Maziotis, uses a semi-nonparametric approach called the stochastic nonparametric envelopment of data, and its feasibility was evaluated at Chilean WWTPs [18]. It is a combination of parametric (econometric) and nonparametric (nonlinear programming) techniques. This study provides robust and reliable energy efficiency scores and quantifies energy potential savings [18].

Plant-wide modeling is a simulation tool that enables the prediction of WWTP performance and provides detailed information about influent and effluent quality as well as energy consumption [65,66]. Modeling allows for the easy comparison of various strategies to achieve energy-neutral conditions.

The benchmarking approaches exhibit significant variations, resulting in different outcomes regarding the energy performance of treatment infrastructures [33].

Additionally, the choice of model specification and technique relies on the specific benchmarking objectives [33].

Recent studies acknowledged that WWTPs are complex systems with multiple input and output variables [62]. Several factors that impact efficiency, such as the size of the treatment infrastructure, technological complexity, climate, pollutant load in the influent, and operational management practices, have been verified through the studies. The research findings demonstrated that efficiency levels in WWTPs are directly related to their capacity, meaning that smaller plants have a lower potential for improvement. While the study presented valuable insights and contributed to understanding the variations among WWTPs and their environmental profiles, the authors recommended future work to include long-term monitoring for yearly periods. This would enable the examination of patterns and correlations between variations in the parameters analyzed.

Lastly, limited studies have been performed in order to develop decision support tools that could help WWTP managers to identify all possible strategies and actions for optimization.

4. Conclusions and Final Remarks

Assessing the energy efficiency of WWTPs is essential to reduce energy consumption and operational costs while improving environmental sustainability and optimizing WWTPs’ performance. WWTPs are considered major energy consumers in the public sector. Consequently, the energy consumption at WWTPs needs to be accurately evaluated, although a standardized method is still missing.

In the present review article, several methodologies that were properly designed for WWTPs were surveyed, highlighting the main advantages and limitations. The comparison among findings obtained from existing methodologies is barely feasible due to the differences in the WW pollutant loads in terms of the influent and the effluent quality (e.g., carbon-to-nitrogen ratios and discharge limits) which vary widely according to the geographical areas.

The wide overview provided by KPIs might be overcome by applying benchmarking methodologies based on DEA. The latest are specifically designed for WWTPs and are able to manage multiple inputs and outputs. Indeed, benchmarking methods based on a single KPI are suitable for WWTPs operated at similar conditions (e.g., same installed technologies). Moreover, the findings are strongly related to WWTPs' configuration and WW characteristics. Conversely, the findings obtained by applying DEA might depend on the proper selection of input and output variables. The discrepancy between findings from energy benchmarking methodologies applied at WWTPs might be also ascribed to the different units of measure used to report the energy consumption at WWTPs, energy consumption per volume of wastewater treated, per population served (expressed as PE), or the pollutant load.

The following specific research needs can be drawn based on the observed gaps. Firstly, future investigations should address the development of standard procedures for data acquisition and collection. Indeed, the standard method could be easily extended at the international level and be universally suitable. Regarding the data collection, the equipment age and the maintenance schedule should be recorded in order to accurately quantify the energy consumption.

Furthermore, the iterative process based on Plan-Do-Check-Act (PDCA), as reported in the ISO 50001:2018, should be accounted for in the implementation of the novel standard methodology properly designed for WWTPs. Indeed, the periodical review of progress in terms of energy efficiency allows for the adoption of adjustments to the energy programs.

Lastly, the implementation of online and real-time monitoring related to both water quality and energy consumption is needed for the diagnosis of the entire WWTPs without expensive sampling campaigns. The essential information collected here will guide future research, helping WWTP utilities to reach the energy audit goals in the accomplishment of incoming EU directives.

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References

1. Niu, K.; Wu, J.; Qi, L.; Niu, Q. Energy Intensity of Wastewater Treatment Plants and Influencing Factors in China. *Sci. Total Environ.* **2019**, *670*, 961–970. [CrossRef] [PubMed]
2. Cardoso, B.J.; Rodrigues, E.; Gaspar, A.R.; Gomes, Á. Energy Performance Factors in Wastewater Treatment Plants: A Review. *J. Clean. Prod.* **2021**, *322*, 129107. [CrossRef]
3. Capodaglio, A.; Olsson, G. Energy Issues in Sustainable Urban Wastewater Management: Use, Demand Reduction and Recovery in the Urban Water Cycle. *Sustainability* **2020**, *12*, 266. [CrossRef]
4. Olsson, G. Water and Energy Nexus. In *Encyclopedia of Sustainability Science and Technology*; Meyers, R.A., Ed.; Springer New York: New York, NY, USA, 2012; pp. 11932–11946. ISBN 978-0-387-89469-0.
5. Gu, Y.; Li, Y.; Li, X.; Luo, P.; Wang, H.; Robinson, Z.P.; Wang, X.; Wu, J.; Li, F. The Feasibility and Challenges of Energy Self-Sufficient Wastewater Treatment Plants. *Appl. Energy* **2017**, *204*, 1463–1475. [CrossRef]
6. Council of the European Union. *Directive (EU) 2023/1791 of the European Parliament and of the Council on Energy Efficiency and Amending Regulation (EU) 2023/955 (Recast)*; Council of the European Union: Brussel, Belgium, 2023.
7. United Nations Goal 6: Ensure Availability and Sustainable Management of Water and Sanitation for All. Available online: https://sdgs.un.org/goals/goal6 (accessed on 19 December 2023).
8. Ananda, J. Productivity Implications of the Water-Energy-Emissions Nexus: An Empirical Analysis of the Drinking Water and Wastewater Sector. *J. Clean. Prod.* **2018**, *196*, 1097–1105. [CrossRef]
9. Masłoń, A.; Czarnota, J.; Szaja, A.; Szulżyk-Cieplak, J.; Łagód, G. The Enhancement of Energy Efficiency in a Wastewater Treatment Plant through Sustainable Biogas Use: Case Study from Poland. *Energies* **2020**, *13*, 6056. [CrossRef]

10. Nakkasunchi, S.; Hewitt, N.J.; Zoppi, C.; Brandoni, C. A Review of Energy Optimization Modelling Tools for the Decarbonisation of Wastewater Treatment Plants. *J. Clean. Prod.* **2021**, *279*, 123811. [CrossRef]
11. Hamawand, I. Energy Consumption in Water/Wastewater Treatment Industry—Optimisation Potentials. *Energies* **2023**, *16*, 2433. [CrossRef]
12. Directorate-General for Environment. *Commission Staff Working Document Impact Assessment*; EU-Commission: Brussels, Belgium, 2022.
13. Longo, S.; Mauricio-Iglesias, M.; Soares, A.; Campo, P.; Fatone, F.; Eusebi, A.L.; Akkersdijk, E.; Stefani, L.; Hospido, A. ENERWATER—A Standard Method for Assessing and Improving the Energy Efficiency of Wastewater Treatment Plants. *Appl. Energy* **2019**, *242*, 897–910. [CrossRef]
14. International Energy Agency Electricity Consumption in the Water Sector by Process, 2014–2040. Available online: https://www.iea.org/data-and-statistics/charts/electricity-consumption-in-the-water-sector-by-process-2014-2040 (accessed on 1 September 2023).
15. Esteves, F.; Cardoso, J.C.; Leitão, S.; Pires, E.; Baptista, J. Review of Energy Audit and Benchmarking Tools to Study Energy Efficiency through Reducing Consumption in Wastewater Treatment Systems. *Br. J. Ed., Technol. Soc.* **2022**, *15*, 150–165. [CrossRef]
16. Kenway, S.J.; Lam, K.L.; Stokes-Draut, J.; Sanders, K.T.; Binks, A.N.; Bors, J.; Head, B.; Olsson, G.; McMahon, J.E. Defining Water-Related Energy for Global Comparison, Clearer Communication, and Sharper Policy. *J. Clean. Prod.* **2019**, *236*, 117502. [CrossRef]
17. Chen, Z.; Wang, D.; Dao, G.; Shi, Q.; Yu, T.; Guo, F.; Wu, G. Environmental Impact of the Effluents Discharging from Full-Scale Wastewater Treatment Plants Evaluated by a Hybrid Fuzzy Approach. *Sci. Total Environ.* **2021**, *790*, 148212. [CrossRef]
18. Molinos-Senante, M.; Maziotis, A. Evaluation of Energy Efficiency of Wastewater Treatment Plants: The Influence of the Technology and Aging Factors. *Appl. Energy* **2022**, *310*, 118535. [CrossRef]
19. Molinos-Senante, M.; Hernández-Sancho, F.; Mocholí-Arce, M.; Sala-Garrido, R. Economic and Environmental Performance of Wastewater Treatment Plants: Potential Reductions in Greenhouse Gases Emissions. *Resour. Energy Econ.* **2014**, *38*, 125–140. [CrossRef]
20. Maktabifard, M.; Zaborowska, E.; Makinia, J. Achieving Energy Neutrality in Wastewater Treatment Plants through Energy Savings and Enhancing Renewable Energy Production. *Rev. Environ. Sci. Biotechnol* **2018**, *17*, 655–689. [CrossRef]
21. Capodaglio, A.G. Urban Wastewater Mining for Circular Resource Recovery: Approaches and Technology Analysis. *Water* **2023**, *15*, 3967. [CrossRef]
22. Shizas, I.; Bagley, D.M. Experimental Determination of Energy Content of Unknown Organics in Municipal Wastewater Streams. *J. Energy Eng.* **2004**, *130*, 45–53. [CrossRef]
23. Council of the European Union. *Proposal for a Directive of the European Parliament and of the Council Concerning Urban Wastewater Treatment (Recast)*; European Commission: Brussels, Belgium, 2023.
24. Daw, J.; Hallett, K.; DeWolfe, J.; Venner, I. *Energy Efficiency Strategies for Municipal Wastewater Treatment Facilities*; NREL/TP-7A20-53341; National Renewable Energy Lab.(NREL): Golden, CO, USA, 2012; p. 1036045.
25. Strubbe, L.; Dijk, E.J.H.V.; Deenekamp, P.J.M.; Loosdrecht, M.C.M.V.; Volcke, E.I.P. Oxygen Transfer Efficiency in an Aerobic Granular Sludge Reactor: Dynamics and Influencing Factors of Alpha. *Chem. Eng. J.* **2023**, *452*, 139548. [CrossRef]
26. Trapote, A.; Albaladejo, A.; Simón, P. Energy Consumption in an Urban Wastewater Treatment Plant: The Case of Murcia Region (Spain). *Civ. Eng. Environ. Syst.* **2014**, *31*, 304–310. [CrossRef]
27. Ganora, D.; Hospido, A.; Husemann, J.; Krampe, J.; Loderer, C.; Longo, S.; Moragas Bouyat, L.; Obermaier, N.; Piraccini, E.; Stanev, S.; et al. Opportunities to Improve Energy Use in Urban Wastewater Treatment: A European-Scale Analysis. *Environ. Res. Lett.* **2019**, *14*, 044028. [CrossRef]
28. Bodík, I.; Kubaská, M. Energy and Sustainability of Operation of a Wastewater Treatment Plant. *Environ. Prot. Eng.* **2013**, *39*, 15–24. [CrossRef]
29. Foladori, P.; Vaccari, M.; Vitali, F. Energy Audit in Small Wastewater Treatment Plants: Methodology, Energy Consumption Indicators, and Lessons Learned. *Water Sci. Technol.* **2015**, *72*, 1007–1015. [CrossRef] [PubMed]
30. Vaccari, M.; Foladori, P.; Nembrini, S.; Vitali, F. Benchmarking of Energy Consumption in Municipal Wastewater Treatment Plants—A Survey of over 200 Plants in Italy. *Water Sci. Technol.* **2018**, *77*, 2242–2252. [CrossRef] [PubMed]
31. Gandiglio, M.; Lanzini, A.; Soto, A.; Leone, P.; Santarelli, M. Enhancing the Energy Efficiency of Wastewater Treatment Plants through Co-Digestion and Fuel Cell Systems. *Front. Environ. Sci.* **2017**, *5*, 70. [CrossRef]
32. EPRI. *Water & Sustainability: U.S. Electricity Consumption for Water Supply & Treatment—The Next Half Century*; Electric Power Research Institute. Inc.: Palo Alto, CA, USA, 2000; p. 1006787.
33. Longo, S.; d'Antoni, B.M.; Bongards, M.; Chaparro, A.; Cronrath, A.; Fatone, F.; Lema, J.M.; Mauricio-Iglesias, M.; Soares, A.; Hospido, A. Monitoring and Diagnosis of Energy Consumption in Wastewater Treatment Plants. A State of the Art and Proposals for Improvement. *Appl. Energy* **2016**, *179*, 1251–1268. [CrossRef]
34. Panepinto, D.; Fiore, S.; Zappone, M.; Genon, G.; Meucci, L. Evaluation of the Energy Efficiency of a Large Wastewater Treatment Plant in Italy. *Appl. Energy* **2016**, *161*, 404–411. [CrossRef]
35. Awe, O.W.; Liu, R.; Zhao, Y. Analysis of Energy Consumption and Saving in Wastewater Treatment Plant: Case Study from Ireland. *J. Water Sustain.* **2016**, *6*, 63–76. [CrossRef]

36. Ranieri, E.; D'Onghia, G.; Lopopolo, L.; Gikas, P.; Ranieri, F.; Gika, E.; Spagnolo, V.; Herrera, J.A.; Ranieri, A.C. Influence of Climate Change on Wastewater Treatment Plants Performances and Energy Costs in Apulia, South Italy. *Chemosphere* **2024**, *350*, 141087. [CrossRef] [PubMed]
37. Hughes, J.; Cowper-Heays, K.; Olesson, E.; Bell, R.; Stroombergen, A. Impacts and Implications of Climate Change on Wastewater Systems: A New Zealand Perspective. *Clim. Risk Manag.* **2021**, *31*, 100262. [CrossRef]
38. Yu, Y.; Zou, Z.; Wang, S. Statistical Regression Modeling for Energy Consumption in Wastewater Treatment. *J. Environ. Sci.* **2019**, *75*, 201–208. [CrossRef] [PubMed]
39. Callegari, A.; Boguniewicz-Zablocka, J.; Capodaglio, A.G. Energy Recovery and Efficiency Improvement for an Activated Sludge, Agro-Food WWTP Upgrade. *Water Pract. Technol.* **2018**, *13*, 909–921. [CrossRef]
40. Longo, S.; Hospido, A.; Lema, J.M.; Mauricio-Iglesias, M. A Systematic Methodology for the Robust Quantification of Energy Efficiency at Wastewater Treatment Plants Featuring Data Envelopment Analysis. *Water Res.* **2018**, *141*, 317–328. [CrossRef]
41. Su, X.; Chiang, P.; Pan, S.; Chen, G.; Tao, Y.; Wu, G.; Wang, F.; Cao, W. Systematic Approach to Evaluating Environmental and Ecological Technologies for Wastewater Treatment. *Chemosphere* **2019**, *218*, 778–792. [CrossRef]
42. Silva, C.; Rosa, M.J. A Comprehensive Derivation and Application of Reference Values for Benchmarking the Energy Performance of Activated Sludge Wastewater Treatment. *Water* **2022**, *14*, 1620. [CrossRef]
43. Zaborowska, E.; Czerwionka, K.; Makinia, J. Strategies for Achieving Energy Neutrality in Biological Nutrient Removal Systems—A Case Study of the Slupsk WWTP (Northern Poland). *Water Sci. Technol.* **2017**, *75*, 727–740. [CrossRef]
44. Chen, S.; Chen, B. Net Energy Production and Emissions Mitigation of Domestic Wastewater Treatment System: A Comparison of Different Biogas–Sludge Use Alternatives. *Bioresour. Technol.* **2013**, *144*, 296–303. [CrossRef] [PubMed]
45. Wang, H.; Yang, Y.; Keller, A.A.; Li, X.; Feng, S.; Dong, Y.; Li, F. Comparative Analysis of Energy Intensity and Carbon Emissions in Wastewater Treatment in USA, Germany, China and South Africa. *Appl. Energy* **2016**, *184*, 873–881. [CrossRef]
46. Corominas, L.; Foley, J.; Guest, J.S.; Hospido, A.; Larsen, H.F.; Morera, S.; Shaw, A. Life Cycle Assessment Applied to Wastewater Treatment: State of the Art. *Water Res.* **2013**, *47*, 5480–5492. [CrossRef] [PubMed]
47. Henriques, J.; Catarino, J. Sustainable Value—An Energy Efficiency Indicator in Wastewater Treatment Plants. *J. Clean. Prod.* **2017**, *142*, 323–330. [CrossRef]
48. Marner, S.T.; Schröter, D.; Jardin, N. Towards Energy Neutrality by Optimising the Activated Sludge Process of the WWTP Bochum-Ölbachtal. *Water Sci. Technol.* **2016**, *73*, 3057–3063. [CrossRef]
49. Aymerich, I.; Rieger, L.; Sobhani, R.; Rosso, D.; Corominas, L. The Difference between Energy Consumption and Energy Cost: Modelling Energy Tariff Structures for Water Resource Recovery Facilities. *Water Res.* **2015**, *81*, 113–123. [CrossRef]
50. Sarpong, G.; Gude, V.G.; Magbanua, B.S.; Truax, D.D. Evaluation of Energy Recovery Potential in Wastewater Treatment Based on Codigestion and Combined Heat and Power Schemes. *Energy Convers. Manag.* **2020**, *222*, 113147. [CrossRef]
51. Sabia, G.; Petta, L.; Avolio, F.; Caporossi, E. Energy Saving in Wastewater Treatment Plants: A Methodology Based on Common Key Performance Indicators for the Evaluation of Plant Energy Performance, Classification and Benchmarking. *Energy Convers. Manag.* **2020**, *220*, 113067. [CrossRef]
52. Di Cicco, M.; Masiello, A.; Spagnuolo, A.; Vetromile, C.; Borea, L.; Giannella, G.; Iovinella, M.; Lubritto, C. Real-Time Monitoring and Static Data Analysis to Assess Energetic and Environmental Performances in the Wastewater Sector: A Case Study. *Energies* **2021**, *14*, 6948. [CrossRef]
53. Lozano Avilés, A.B.; Del Cerro Velázquez, F.; Llorens Pascual Del Riquelme, M. Methodology for Energy Optimization in Wastewater Treatment Plants. Phase I: Control of the Best Operating Conditions. *Sustainability* **2019**, *11*, 3919. [CrossRef]
54. Bertanza, G.; Baroni, P.; Garzetti, S.; Martinelli, F. Reducing Energy Demand by the Combined Application of Advanced Control Strategies in a Full Scale WWTP. *Water Sci. Technol.* **2021**, *83*, 1813–1823. [CrossRef]
55. *ISO 50001:2018*; Energy Management Systems. International Organization for Standardization (ISO): Geneva Switzerland, 2018.
56. Salvatori, S.; Benedetti, M.; Bonfà, F.; Introna, V.; Ubertini, S. Inter-Sectorial Benchmarking of Compressed Air Generation Energy Performance: Methodology Based on Real Data Gathering in Large and Energy-Intensive Industrial Firms. *Appl. Energy* **2018**, *217*, 266–280. [CrossRef]
57. Li, M.-J.; Tao, W.-Q. Review of Methodologies and Polices for Evaluation of Energy Efficiency in High Energy-Consuming Industry. *Appl. Energy* **2017**, *187*, 203–215. [CrossRef]
58. May, G.; Barletta, I.; Stahl, B.; Taisch, M. Energy Management in Production: A Novel Method to Develop Key Performance Indicators for Improving Energy Efficiency. *Appl. Energy* **2015**, *149*, 46–61. [CrossRef]
59. Benedetti, L.; Dirckx, G.; Bixio, D.; Thoeye, C.; Vanrolleghem, P.A. Environmental and Economic Performance Assessment of the Integrated Urban Wastewater System. *J. Environ. Manag.* **2008**, *88*, 1262–1272. [CrossRef]
60. Di Fraia, S.; Massarotti, N.; Vanoli, L. A Novel Energy Assessment of Urban Wastewater Treatment Plants. *Energy Convers. Manag.* **2018**, *163*, 304–313. [CrossRef]
61. De Matos, B.; Salles, R.; Mendes, J.; Gouveia, J.R.; Baptista, A.J.; Moura, P. A Review of Energy and Sustainability KPI-Based Monitoring and Control Methodologies on WWTPs. *Mathematics* **2022**, *11*, 173. [CrossRef]
62. Lorenzo-Toja, Y.; Vázquez-Rowe, I.; Chenel, S.; Marín-Navarro, D.; Moreira, M.T.; Feijoo, G. Eco-Efficiency Analysis of Spanish WWTPs Using the LCA + DEA Method. *Water Res.* **2015**, *68*, 651–666. [CrossRef] [PubMed]
63. Hernández-Chover, V.; Bellver-Domingo, Á.; Hernández-Sancho, F. Efficiency of Wastewater Treatment Facilities: The Influence of Scale Economies. *J. Environ. Manag.* **2018**, *228*, 77–84. [CrossRef] [PubMed]

64. Guerrini, A.; Romano, G.; Indipendenza, A. Energy Efficiency Drivers in Wastewater Treatment Plants: A Double Bootstrap DEA Analysis. *Sustainability* **2017**, *9*, 1126. [CrossRef]
65. Solon, K.; Flores-Alsina, X.; Kazadi Mbamba, C.; Ikumi, D.; Volcke, E.I.P.; Vaneeckhaute, C.; Ekama, G.; Vanrolleghem, P.A.; Batstone, D.J.; Gernaey, K.V.; et al. Plant-Wide Modelling of Phosphorus Transformations in Wastewater Treatment Systems: Impacts of Control and Operational Strategies. *Water Res.* **2017**, *113*, 97–110. [CrossRef]
66. Boiocchi, R.; Bertanza, G. Evaluating the Potential Impact of Energy-Efficient Ammonia Control on the Carbon Footprint of a Full-Scale Wastewater Treatment Plant. *Water Sci. Technol.* **2022**, *85*, 1673–1687. [CrossRef]
67. Sweetapple, C.; Fu, G.; Butler, D. Multi-Objective Optimisation of Wastewater Treatment Plant Control to Reduce Greenhouse Gas Emissions. *Water Res.* **2014**, *55*, 52–62. [CrossRef]