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Literature Review

Impact of artificial intelligence in the reduction of electrical consumption in wastewater treatment plants: a review

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ABSTRACT

Wastewater Treatment Plants are energy-intensive consumers. Thus, understanding their energy consumption to achieve efficient management can provide considerable environmental and economic benefits. The complexity of the treatment systems, the non-linearity, and the uncertainty and data availability limitations require the use of energy audits, according to a truly holistic view, as well as the use of alternative analysis models and decision support, more efficient than traditional modeling techniques. The purpose of this review paper is to identify practical examples of the main lines of thought using Artificial Intelligence algorithms used to reduce the consumption of electrical energy in the wastewater sector over the last years. From the several reviewed papers, from different research platforms, it is concluded that, despite the success of AI in reducing energy consumption, in particular Artificial Neural Networks, there is room to improve energy efficiency consumption, identifying or quantifying inefficiency phenomena associated with data collection.

Keywords: Wastewater treatment plants, energy efficiency, inefficiency phenomena, electrical energy consumption reduction, artificial intelligence, decarbonization.

INTRODUCTION

Currently, climate change demands new goals of human behavior in protecting and sharing a common space, our planet. Gradually, global and unprecedented climate change is increasing the uncertainty of the water cycle through extreme weather events that risk the prediction of water availability and its quality. These events threaten sustainable development, biodiversity, and the worldwide human right to water and sanitation.

Energy expenses usually represent a significant portion of the Wastewater Treatment Plants (WWTP's) running costs. Therefore, increasing these infrastructures' energy efficiency and implementing energy management systems is crucial (Silva and Rosa, 2015). Understanding the water-energy nexus is a relevant issue for plant managers due to the significant potential in energy costs (Torregrossa et al., 2017, Molinos-Senante et al., 2014, Longo et al., 2016a). The International Energy Agency (IEA) claimed an increase of 80% in electricity consumption in this sector by 2040 (International Energy Agency, 2023). In addition, new environmental regulations, with higher standards, lead to higher energy consumption (Doherty et al., 2017).

A considerable amount of papers were found in the literature about energy efficiency concerning WWTPs (Zhao et al., 2020, Torregrossa et al., 2018, Nourani et al., 2018, Ostojin et al., 2011, Oliveira et al., 2021). The authors used different modeling and approach tools for identifying, analysing, and understanding the causes and consequences of energy inefficiency (Nieto et al., 2013, Longo et al., 2016a, Filipe et al., 2019).

Due to the physical and chemical characteristics of the influent flow, a WWTP is a highly dynamic, complex, and non-linear system, so its proper operation and control are essential to secure public and environmental welfare (Ahmadi et al., 2017). Therefore, modeling such an intricate system is quite difficult, and most of the available classical linear models are based on rough expectations, linear approximations, and assumptions, causing difficulty in decision support (Nieto et al., 2013, Gao et al., 2017, Li et al., 2017).

In this research about the impact of Artificial Intelligence (AI) on reducing energy consumption in WWTPs, two review papers (Zhao et al., 2020, Safeer et al., 2022) were identified that recognize the importance of AI in optimizing water treatment infrastructure in terms of pollutant removal, economic performance, model management, and wastewater reuse. However, according to a bibliometric analysis, only the author Zhao et al. (Zhao et al., 2020) present direct results on energy consumption in WWTPs. Considering the WWTPs non-linearity, Zhao et al. (Zhao et al., 2020) argue that AI can be an alternative approach to classical modeling techniques. Their review presents different literature approaches about AI technologies' applications to lower energy consumption in WWTPs. One of the most used models is Artificial Neural Networks (ANN). On the other hand, genetic algorithms are a robust solution with low computational costs, given their adaptability to complex and non-linear systems (Holenda et al., 2007).

Having the present review paper as the main objective of the direct reduction of electrical consumption in WWTPs, through AI methods, there are three papers (Torregrossa et al., 2016, Torregrossa et al., 2018, Long and Cudney, 2012) that stood out, that were not included in the bibliometric review of Zhao et al. (Zhao et al., 2020). Thus, the three papers cited assume special importance (i) for the solution presented to reduce the difficulty in acquiring and processing data (Torregrossa et al., 2016), (ii) for the usefulness of these techniques in energy management models (Torregrossa et al., 2018), and (iii) for the importance of a global vision in the analysis of the entire treatment system (Long and Cudney, 2012). The present paper review intends to contribute to future works in the identification of new challenges related to the identification and quantification of new phenomena of inefficiency in the study of energy efficiency in WWTPs.

This paper is structured according to the following sequence. The first step presents the approach used for selecting the reviewed literature and its content analysis. The different treatment stages of a WWTP and the respective energy consumption are presented in the second point. AI techniques will appear in the following step, according to historical evolution and individual characteristics, followed by a bibliographic review of AI applications in wastewater treatment systems. Finally, conclusions and future trends will be presented.

THE METHODOLOGY APPROACHES

The presented paper reviews the literature on the performance of applications using Artificial Intelligence (AI) algorithms to reduce energy costs during the treatment process in the Wastewater Treatment Plant (WWTP). For better qualitative and quantitative research, a period of publication between 2005 and 2022 was defined as reviewed journals, from different platforms such a IEEE, Scopus, Web of Science, and Google Scholar, among others. Institutional documents of technical support were also consulted for the efficient use of energy in water utilities, as well as current European legislation dedicated to the sector. The research focused on the combination of the following keywords: wastewater treatment plants, energy efficiency, inefficiency phenomena, reduction of electricity consumption, artificial intelligence, and decarbonization, which allowed to select, from the 104 papers reviewed, 85 citations, of which 14 were about AI applications in reducing electricity consumption in WWTPs.

ENERGY DATA AND CONSUMPTION PER TREATMENT STAGE

As previously discussed, the wastewater treatment plants' complexity, associated with the quality control requirements, needs a rigorous definition of the main indicators for the electricity assessment consumption in each treatment stage. According to the literature review (Longo et al., 2016b, ADENE, 2021), the following will present the energy Key Performance Indicators (KPIs), as well as the electrical energy consumption per treatment stage.

Parameters and Key Performances Indicators

According to the literature reviewed, to assess the WWTP performance using AI models, it is essential to identify available sources and databases containing energy data of WWTPs. Usually, the energy consumption is attached to the data related to the electrical equipment: blowers, mixers, pumps, aeration systems, and filters, according to the influent and effluent characteristics (Longo et al., 2016b), in order to control parameters such as Chemical Oxygen Demand (COD), Biochemical Oxygen Demand (BOD), Total Suspended Solids (TSS), Total Nitrogen (TN), and Total Phosphorus (TP) (Li et al., 2017, Longo et al., 2016b).

Longo et al. (Longo et al., 2016b) defined three energy KPIs referring to the volume of treated wastewater, served Population Equivalent (PE), and kg of COD removed.

$$KPI1 = \frac{eletric\ energy\ consumption}{volume\ of\ treated\ wastewater} \quad [kWh/m^3]\ (1)$$

$$KPI2 = \frac{eletric\ energy\ consumption}{served\ PE} \quad [kWh/PE\ year]\ (2)$$

$$KPI3 = \frac{eletric\ energy\ consumption}{COD\ load\ removed} \quad [kWh/kgCODremoved]\ (3)$$

As the literature review refers, commonly, energy consumption in WWTPs has indexed to the treated wastewater volume (kWh/m^3) or (kWh/PE) (Yang et al., 2010, Mizuta and Shimada, 2010, Torregrossa et al., 2016). Despite the simplicity of these approaches, which can quickly provide an estimation of energy consumption indicators, can provide incorrect values (Longo et al., 2016b). Usually, the energy consumption in WWTPs has calculated in kWh/m^3 (Longo et al., 2016b). However, in some cases where sanitation networks are connected to rainwater networks, the WWTPs often show higher energy efficiency, which is caused by the higher dilution of the polluting load in the influent (Campanelli et al., 2013, Bodik and Kubaska, 2013). Therefore, the calculation of energy efficiency based on the pollutant load (i.e., kWh/PE) provides greater accuracy. But in this case, nitrogen (N) should be favored as a basis to calculate PE load instead of BOD and COD (Benedetti et al., 2008) because N is dissolved in the form of ammonia in the influent, while BOD, in the case of low drain speed, can cause sedimentation phenomena and introduce calculation errors. On the other hand, rainwater carries inert matter that will influence the COD calculation.

Several authors (Benedetti et al., 2008, Campanelli et al., 2013, Bodik and Kubaska, 2013), present an approach to report the energy consumption of WWTPs per unit of the pollutant removed, i.e., kWh/kg TSSremoved, kWh/kg BODremoved and kWh/kg CODremoved, to quantify the removal of organic matter and nutrients are major contributors to energy consumption in WWTPs.

The influent and effluent flow characteristics of a WWTP significantly influence energy consumption during the process. Therefore, to improve the WWTP performance, there are specific parameters, i.e., BOD, COD, TSS, and TN, that have been focused on in studies using AI methods to develop efficient energy-saving strategies (Nourani et al., 2018, Li et al., 2017, Zhao et al., 2020, Torregrossa et al., 2016).

As the number of WWTPs increase and the effluent quality requirements become more demanding, the energy issue has become a crucial matter in economic and environmental terms (Molinos-Senante et al., 2015). According to EU Directive 2012/27/EU, water utilities with more than 250 employees and an annual trading volume greater than €50 million or whose annual balance sheet exceeds €43 million must perform an energy audit every four years from December 2015 (Diretiva, 2012). ISO 50001 (ISO, 2011), developed by the International Organization for Standardization, represents an international energy management standard for industrial plants' energy efficiency, based on the Plan-Do-Check-Act continuous improvement methodology, according to **Table 1**.

Table 1. ISO 50001 standard energy efficiency indicators (ISO, 2011).

ISO 50001	
Plan	Energy assessment Establishment of energy performance indicators Definition of the action plan
Do	Action plan implementation
Check	Monitoring and Measurement
Act	Management review and continuous improvement

Some AI approaches show that within the field of wastewater treatment, identifying KPIs is one of the significant challenges to reducing or optimizing electrical energy consumption (Torregrossa et al., 2016). Usually, the energy audit uses KPIs to assess the study of energy efficiency in industrial units, i.e., proper measurement and treatment of data, which is an essential approach to estimating the parameter's importance in WWTPs.

The standard definition and measure (4)–(6) of energy efficiency in the industry are evaluated based on three KPIs: Energy Intensity (EI) given by tonne of oil equivalent per euro (toe/€), Specific Energy Consumption (SEC), and Carbon Intensity (CI) (ADENE, 2021).

$$EI = \frac{energy}{productive\ activities}\ [toe/€]\ (4)$$

$$SEC = \frac{ene}{production}\ [toe/m^3]\ (5)$$

$$CI = \frac{greenhouse\ gas\ emissions}{energy}\ [tongas/toe]\ (6)$$

Energy consumption per treatment stage

Many authors consider the urban wastewater treatment sector an intensive energy consumer (Daw et al., 2012, Oliveira et al., 2021). Data reported on energy usage accounts for 7% of the electrical energy worldwide, and the water utilities' annual operating budget can represent up to 65%. (Plappally et al., 2012, Boulos et al., 2001). Nearly 4% of the electricity consumed in the U.S. corresponds to the energy consumed in the wastewater treatment sector, being the pumping systems responsible for 79%-80% of the used electrical energy consumed (Singh et al., 2012, Goldstein and Smith, 2002). For these reasons, it is essential to understand the different stages of treatment, as well as the associated electrical equipment, as a way of improving energy performance. WWTPs comprise various treatment stages: preliminary, primary, secondary, tertiary, and sludge treatment, constituted by different equipment with different energy consumption.

Preliminary treatment usually contains pumping wastewater, screening, grit removal, and comminutors. Apart from the pumping system, these different types of equipment are responsible for a tiny part of the total electric energy consumption (Longo et al., 2016b). The electrical energy consumed for influent pumping varies between 2.2×10^{-2} and 4.2×10^{-2} kWh/m^3, representing 5 to 18% of the total energy consumed, according to the size and intensity of the treatment (Longo et al., 2016b).

Primary treatment, consisting of a simple separation step in circular settling tanks equipped with mechanized scrapers, has energy consumption between 4.3×10^{-5} and 7.1×10^{-5} kWh/m^3, representing a small portion of all the total energy consumed, between 2 to 8% (Longo et al., 2016b). For one of the most complex stages of the treatment process, the secondary treatment is responsible for a considerable part of electrical energy consumption, particularly in the aeration system with consumption between 0.18 and 0.8 kWh/m^3 (Longo et al., 2016b), which varies between 45 to 75% of the energy consumed (Rosso and Stenstrom, 2006).

Tertiary treatment is responsible for increasing effluent quality as well as the total energy consumption. Depending on specific technologies used, values vary from 4.5×10^{-2} to 0.11 kWh/m^3 for Ultra-Violet (UV) disinfection or between 9.0×10^{-3} and 1.5×10^{-2} kWh/m^3 for mechanic equipment required for the dosage of chemicals, and from 7.4×10^{-3} to 2.7×10^{-3} kWh/m^3 for tertiary filtration, representing between 8 and 13% of the energy consumed. The energy consumed with the separation and sludge dewatering represents a significant portion of the global electricity balance of a WWTP, about 15% (Longo et al., 2016b), specifically during the mechanical centrifugation process, which values vary between 1.8×10^{-2} and 2.7×10^{-2} kWh/m^3 (Longo et al., 2016b).

ARTIFICIAL INTELLIGENCE TECHNIQUES IN WASTEWATER TREATMENT

The interest in using Artificial Intelligence (AI) has been growing in engineering (Fadlullah et al., 2017, Gupta et al., 2021), intending to optimize data analyses and enhance algorithm performance. The wastewater treatment sector is no exception, where the complexity of natural conditions of the influent, for instance, chemical and physical characteristics, results in uncertainties during the treatment process (Longo et al., 2016b). These ambiguities lead to variations in effluent quality, operation energy costs, and environmental dangers. There has been an attempt to apply AI technologies by researchers to reduce these issues (Torregrossa et al., 2018, Ostojin et al., 2011, Filipe et al., 2019, Asadi et al., 2017).

In 1956, a group of scientists led by John McCarthy met at Dartmouth Summer Research Project on AI, considered to be the founding event of AI as a research field. AI is a method that uses machines attempting to mimic the human brain through structured symbols to solve complex problems in real-world applications (Salehi and Burguenõ, 2018).

Another term widely used in literature to refer to a strong field of particular AI is Machine Intelligence (MI) (Fadlullah et al., 2017, Gupta et al., 2021). As a rule, there are two types of MI: Hard Computing (HC) and Soft Computing (SC) methods. As opposed to the HC, which demands a precisely stated analytical model and can produce more accurate answers, the SC is useful for handling highly nonlinear systems with ambiguous and noisy data (Chen et al., 2001, Salehi and Burguenõ, 2018).

Also known as Computational Intelligence (CI), soft computing methods are based on Fuzzy Logic (FL), Artificial Neural Networks (ANNs), Machine Learning (ML), Evolutionary Algorithms (EA), and probabilistic methods. They can solve and approximate nonlinear issues using programs that simulate human knowledge (Pedrycz, 1990, Siddique and Adeli, 2013).

Despite the same objective, there is little difference between AI and CI. According to the authors (Bezdek, 2016, McCarthy, 2007), CI is a subset of AI. Understanding the relationship between AI and other intelligent computational techniques is important. **Figure 1** presents the different intelligent techniques and their correlation. Machine Learning (ML) technique, while an AI subfield, is used to create a prediction classification learning model through the training data (Cherkassky and Mulier, 2007, Marsland, 2011). Integrated ML, Deep Learning (DL) is a tool that can learn unsupervised from unstructured data based on deep neural networks, which neural networks with more than one hidden layer (Ciresan et al., 2011). Data Mining/Science (DM/S) is a technique applied to discover information and tendencies in data sets, where the goal is the discovery of unidentified characteristics in an area with limited knowledge. The Big Data (BD) designation refers to broad or complex data sets difficult to represent using conventional processing techniques (Salehi and Burguenõ, 2018).

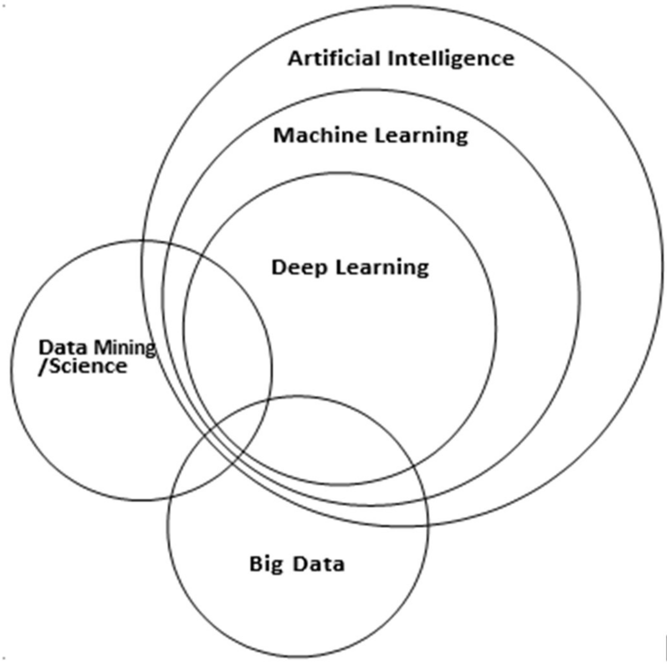

Figure 1. Computational techniques relationship

In this research field, it is possible to find as the main algorithms the ANNs, while the computing system, Random Forests (RF) learning methods and Support Vector Machines (SVM), the Genetic Algorithms (GA), and finally, also integrated into AI techniques, the Fuzzy Logic (FL) method (Zhao et al., 2020).

Framed in four currents of thought, connectionists, symbolists, analogists, and evolutionists, the algorithms can be characterized according to the process of optimization, evaluation, and representation, according to **Table 2**.

Table 2. Characteristics of the main lines of thought

	Optimization	Evaluation	Representation
Connectionists	Backpropagation	Quadratic Error	Artificial Neural Network
Symbolists	Reverse-deduction	Gain (accuracy)	Random Forest
Analogists	Optimization with constraints	Margin	Support Vector Machine
Evolutionists	Genetic propagation	Fitness	Genetic Algorithm

The result of the reviewed papers indicated, according to **Figure 2**, that it is one of the most widely used methods in WWTPs (Ramli and Hamid, 2018). Throughout this review, no papers were found, published between 2021 and 2022, according to the search criteria of the methodology approach.

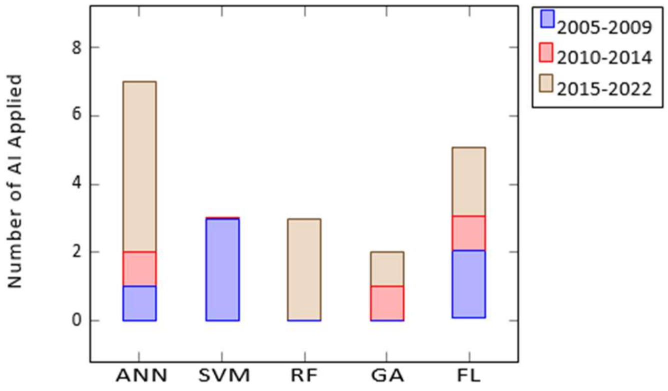

Figure 2. AI techniques applied to energy reduction trends in wastewater treatment

The first mathematical ANN model was presented in 1943 by Warren McCulloch and Walter Pitts in the published paper "A Logical Calculus of the ideas Imminent in Nervous Activity" (McCulloch and Pitts, 1943). Inspired by Alan Turing (Turing, 1936), they provided an important contribution to the construction of the first modern computational theory.

Rosenblatt, Widrow, and Hoff (1959-1960) explored for the first time the neural networks as computational structures with learning and generalization capabilities, employing a technique that distributes and stores knowledge collected through known samples (Rosenblatt, 1958, Widrow and Hoff, 1960).

ANN was developed over the years and today represents a computational model inspired by biological neural networks, containing multiple elements called neurons and connections designated by synapses (Zhang and Pan, 2014). Easily adaptable to cases with one or more variables, the model complexity can be easily altered by changing the transfer function, the training algorithm, or the network architecture (Rajaee et al., 2019). ANNs have been adopted to remove contaminants during the complex and non-linear process of WWTPs (Raduly et al., 2007, Wang and Deng, 2016, Fan et al., 2018), usually with better results than the regular regression models (Torregrossa et al., 2016, Zhang et al., 2016). One of the advantages is the ability to handle the presence of noise in the data set without affecting the prediction result. However, it requires a large amount of available data (Kuster et al., 2017).

Created in 1995 by Tin Kam Ho (Ho, 1995), RF is the most used supervised ML algorithm for classification and regression, composed of several decision trees, where the nodes are generated through input parameters, and the tree leaves dictate the classification or regression result (Breiman, 1996). The RF result is evaluated considering all the individual trees. RF algorithm has been used for studying the energy efficiency in WWTP due to the possibility of model calibration, according to the preagreed criteria (Torregrossa et al., 2018), (Zhang et al., 2016). According to the literature review, some RFs have lower generalization errors than others. To reduce the error, some authors presented different solutions. Random split selection of Dietterich (Dietterich, 1998) has better results than bagging. Breiman (Breiman, 1998) also introduced random noise into the outputs with good results. However, the forest with better results is the adaptive boosting (Adaboost) algorithm. Introduced in 1996 by Freund and Schapire (Freund et al., 1999), Adaboost is a common approach to improve the accuracy of any given learning algorithm. However, it is more sensitive to overfitting than random forest.

Developed in 1998 at AT&T Bell Laboratories by Vladimir Vapnik (Drucker et al., 1999), the SVM is one of the most robust and effective statistical ML theories used for classification, and regression (support vector regression), among other tasks. This method consists of the construction of hyperplanes in an infinite dimensional space supported by the input vectors selected through a model training process (Drucker et al., 1999). The main algorithm goal is to create an optimal hyperplane with the largest distance between the different types of samples belonging to each class (Drucker et al., 1999). The SVM method is used in various application domains, including electrical energy consumer analysis in the water and wastewater sector, to solve linear and non-linear problems (Ramli and Hamid, 2018, Zhang et al., 2012). One of the SVM advantages is the adjustment of the objective function, which allows the regularization parameter and helps to avoid overfitting the training data. Despite the difficulties, choosing a good kernel function can represent an advantage when the sample is linearly not separable. The Kernel changes the input space dimension, allows to capture non-linear relationships, and performs the regression task more efficiently (Drucker et al., 1999).

GA came from the research of John Holland, at the University of Michigan (Martin H et al., 2009), in 1975, as a way to perform a randomized search from a sample. Nonetheless, it only became popular in the 1990s. From an initial randomly generated population, according to the characteristics of the process, GA promotes the evolution of a new population with the desired characteristics (Chau, 2006, Golberg, 1989) according to Darwin's theory of natural selection, based on mutation and crossover operators. GA can work out a significant dimension of linear or non-linear problems, so GA applications have grown enormously in the wastewater treatment field (Herrera and Magdalena, 1997), such as pump scheduling to minimize pumping costs benefiting from low-cost electricity tariffs (Savic et al., 1997). GAs have as advantages the systematic random search and derivative-free optimization, but they could be challenging to tune and do not guarantee convergence to the optime (Shapiro, 2002).

Proposed in 1965 by Zadeh (Zadeh, 1965), the fuzzy method was developed for modeling complex systems, inputs variables that are partitioned into overlapping sets, and each of these sets represents a membership function that quantifies the belonging degree over the range (0,1) (Zadeh, 1965, Zadeh, 1983). Despite the difficulty of building and tuning the fuzzy membership functions and rules, the convenience of using this methodology in studying the energy efficiency of WWTP is its ability to store and process imprecise, uncertain, and resistant data for classifying (Vijayaraghavan et al., 2015).

Over the last decade, optimization processes have been used to find different solutions in the wastewater treatment field. Usually, finding the best solution involves using technologies heuristically adapted to the problem, with data availability playing a key role (Shapiro, 2002). For example, fuzzy logic is critical in approximating reasoning, nevertheless, its weak point is the lack of effective learning ability, unlike ANN. So, merging these technologies through a Fuzzy Neural Network (FNN) will allow to focus on taking advantage of their strengths and atone for weaknesses (Mingzhi et al., 2009). **Table 3** enumerates the main advantages and disadvantages

BIBLIOGRAPHIC REVIEW

This section presents several works using AI in the wastewater treatment sector according to the described methodology. **Figure 3** shows the number of published papers reviewed in this study on IA in the wastewater treatment industry. The papers' results reveal that IA is a viable alternative to classical modeling techniques.

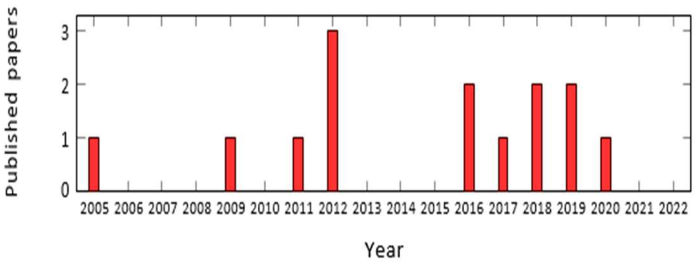

Figure 3. Number of published papers regarding AI techniques for energy reduction in the wastewater treatment industry

Fiter et al. (Fiter et al., 2005) used a fuzzy logic controller to adjust the aeration system and reduce energy consumption without interfering with the quality of the effluent. The presented results demonstrated that saving more than 10% of energy is possible.

Huang et al. (Mingzhi et al., 2009) developed a combined fuzzy neural controller to regulate an aerated submerged biofilm wastewater treatment process. To cope with the complexity of the wastewater process, the authors used a flexible neuro-fuzzy inference structure to control the environmental performance and economic goals simultaneously, with an operating cost reduction of almost 33%.

Ostojin et al. (Ostojin et al., 2011) developed a fuzzy logic controller using an AI approach to optimize the sewer pumping system. The project used a combination of the most reliable sensing technologies, data communications techniques, and analytical software in the context of the current system configuration and operating parameters. Although the results showed energy cost-saving, the fuzzy system proved robust in relation to the different flow patterns. In order to optimize the solution, the authors used a GA to adjust the parameters that define the membership functions according to the fuzzy rules. The GA system was successfully shown to be adaptable to other pumping stations with different characteristics.

Zhang et al. (Zhang et al., 2012) introduced a scheduling model pumping system to reduce energy consumption and fluid flow rate after pumping using a neural network algorithm. The scheduling model is a Mixed-Integer Non-linear Programming Problem (MINLP). The energy consumption in multiple pump system configurations can be significantly reduced, although with more complex configuration dynamics. In this case study, the results indicate that the proposed model reduces the energy consumed by the pumps, maintaining the hydraulic load, with gains in energy consumption between 7.6% and 24.3%, with a margin of error of less than 3%.

Table 3. Advantages and disadvantages of ANN, SVM, RF, GA, and FL techniques

Technique	Advantage	Disadvantage
ANN	Adaptation, learning, approximation, capability to work with incomplete information, distributed memory by entire network	Hardware dependence, slow convergencetime, "black box" data processing structure, unexplained solutions of the network
RF	The bagging algorithm and the Ensemble Learning technique reduce the overfitting problem and variance, therefore improvingthe accuracy, classification, and regression, ease of handling missing values, handles non-linear variables efficiently, less impacted by noise	Requires a lot of computing power and resources, long training time as it generates a lot of trees
SVM	Handles non-linear variables efficiently through a Kernel function, classification, regression, and stability	Memory capacity requirement, long training time for large datasets, difficult understanding and interpretation
GA	Systematic random search, derivate-free optimization, multiple optimal solutions	Difficult to tune, lacks effective learning capability, computational complexity
FL	Approximate reasoning	Difficult to tune, no convergence criterion

Wei and Kusiak (Wei and Kusiak, 2015) presented two data-driven ANN approaches to predict influent flow in WWTP: a static Multi-Layer Perceptron (MLP) and a dynamic neural network. Despite the good performance of MLP for the current time prediction, the Dynamic ANN, with an online corrector, provides a better prediction with 15% accuracy, representing an advantage regarding managing energy efficiency during treatment stages.

Zhang et al. (Zhang et al., 2016) developed a data-driven method based on an ANN to increase the performance of wastewater pumping systems, with two objectives: reducing energy consumption while maximizing wastewater flow rate. According to the results, energy consumption could be diminished by 11%, corresponding to a gain of 14%.

Asadi et al. (Asadi et al., 2017) presented a data-driven proposal applied to the aeration process of WWTP, aiming to optimize energy consumption without sacrificing water quality. Results obtained demonstrated a 31% reduction in airflow while maintaining the same water quality within the legal requirements due to the increase in noise caused by the lack of high-frequency data such as BOD and TSS. The author recommended more frequent sampling of mentioned variables to develop a reliable control system.

Han et al. (Han et al., 2018) developed an improved Multi-Objective Optimal Control (MOOC) strategy to improve operational efficiency according to the Effluent Quality (EQ) and reduce Energy Consumption (EC) in the WWTP under three weather conditions: dry, rainy, and stormy weather. They use an adaptative kernel function model of the process to describe the complex dynamics of EQ and EC dedicated to MOOC strategy, and an adaptative Fuzzy Neural Network Controller (FNNC) to achieve the tracking control of the set points. Compared with other optimal controllers, such as the Adaptative Multi-Objective Differential Evolution algorithm and PI controller (AMODE-PI), the MOOC strategy's performance of the EC's values is reduced by 1.2%, 1.15%, and 2.2%, according to the three different weather conditions.

Filipe et al. (Filipe et al., 2019) proposed a data-driven optimization framework developed specifically for operating variable-frequency pumps in the wastewater treatment sector. Using ML techniques combined with innovative predictive control, the authors presented an enhancement in the energy efficiency of 17%, in contrast to normal operations conditions.

Ramli and Hamid (Ramli and Hamid, 2018) presented a data-based modeling study to predict WWTPs energy consumption using different machine learning methodologies: Linear Regression (LR), K-Nearest Neighbor method (K-NN), SVM, and ANN. According to the results, the SVM technique has the best Amount of Cost Saving (ACS) of 158 939, but the second-highest Root Mean Square Error (RMSE) of 62 280. The method that provides the least error and maximum amount of production is the artificial neural network. Before the analysis was carried out, the Energy Performance Indicator (EnPI) was 0.44 kWh/m^3. The reduction target is 10%, which results in 0.40kWh/m^3.

Cao et al. (Cao and Yang, 2020) proposed a modified neural network with adaptive control based on an Online Sequential Extreme Learning Machine (OS-ELM) (Liang et al., 2006, Huang et al., 2004). According to the results presented, this technique of oxygen control in the aerobic and anoxic treatment tanks represents a 40% reduction in energy consumption.

Most of the cited papers in the previous paragraphs of this chapter focused on the application and comparison of AI techniques in the treatment stages of WWTPs with higher energy consumption: pumping systems and in the biological reactor. Despite the importance of having a vision of the main consumptions, we must not forget the interdependence between the different stages of treatment, as well as the importance of data collection, and the associated inefficiency phenomena in the process of modeling energy consumption. Thus, bearing in mind the complexity of wastewater treatment systems, the three papers that most stood out in the research carried out for this paper review will be presented below.

The following study by Long and Cudney (Long and Cudney, 2012) advocated integration on the same platform, establishing a relationship between energy and environmental systems in wastewater treatment plants. This model's primary goal was to optimize each treatment stage through a detailed evaluation according to each approach, allowing the WWTP operator to define strategies, schedule operations, and implement techniques to reduce consumption without neglecting the requirements imposed by environmental policies. Throughout the study, flow-based models were defined for the energy and environmental management systems (of China, 2005) based on common energy efficiency technologies, environmental occurrences, and their respective corrective measures. The factors considered an important part of the integrated management model were divided into dependent and independent variables and subjected to multivariable regression analysis. The calculation of the energy intensity according to each treatment stage made it possible to identify the most significant factors for the performance rating, according to the Energy Star reference model. Biological oxygen demand, suspended solids, flow rate, and precipitation were independent variables, and energy was considered dependent. Data was recorded over 23 months according to the independent variables. The value of the adjusted $R^2 = 0.5655$ for the three main treatment stages: clarifying, oxidation, and filtering, which demonstrates the effectiveness of the model. The authors (Long and Cudney, 2012) demonstrated the importance of a holistic view in balancing environmental and energy factors throughout the treatment process. The simultaneous analysis of the systems and the correlation between the respective performance factors enable the creation of a balanced management model that is more efficient and less energy-consuming. Long and Cudney (Long and Cudney, 2012) have also shown that auditing tools to pursue the defined objectives lack the monitoring of the cause-effect dynamics.

Table 4. Application of AI to energy reduction during wastewater treatment

Work	Treatment stage	AI technique	Performance	Energy R^2 reduction
(Fiter et al., 2005)	Aeration system	FL		10%
(Mingzhi et al., 2009)	Aerated submergedbiofilm	FL		33%
(Ostojin et al., 2011)	Pumping systems	FL, GA		
(Zhang et al., 2012)	Pumping systems	ANN	7.6%–24.3%	
(Wei and Kusiak, 2015)	Activated sludges	DM		15%
(Zhang et al., 2016)	Pumping system	ANN, RF, SVM	0.93%	10%
(Asadi et al., 2017)	Aerobic biological	ANN, DM		31%
(Han et al., 2018)	Activated sludges	FL, MOOC	1%	1.6%
(Filipe et al., 2019)	Aerobic biological	RL	2.43%	16.7%
(Ramli and Hamid, 2018)	Cost modelling of WWTP	LR, KNN, SVM, ANN		10%
(Cao and Yang, 2020)	Control of WWTP	OS-ELM		40%
(Long and Cudney, 2012)	Integration systems	MR		0.5655[a]
(Torregrossa et al., 2016)	Efficient Management WWTP	ANN, SVM, RF		0.9
(Torregrossa et al., 2018)	Cost modelling of WWTP	ML		

Note: a – Adjusted R^2

Torregrossa et al. (Torregrossa et al., 2016) introduced a methodology to perform a daily benchmark analysis under an unreliable database, applied to the Energy Online System (EOS) developed in the framework of the project INNERS (Innovative Energy Recovery Strategies in the urban water cycle). EOS calculates a set of KPIs to evaluate energy and process performances. Due to the complexity of the treatment system and the inherent data noise, the authors (Torregrossa et al., 2016) used the FL, ANN, SVR, and RF methodologies. The RF regression model was also applied to find the best results for the chemical oxygen demand analysis and has been used to solve regression problems in WWTP (Durrenmatt and Gujer, 2012). According to the results presented in this study, the author obtains different results: the validation dataset $R^2 = 0.72$, the test dataset $R^2 = 0.71$, and for the training dataset $R^2 = 0.90$.

Torregrossa et al. (Torregrossa et al., 2018), in order to understand the energy costs structure of WWTP (using conventional activated sludges technology), proposed a new methodology supported by an ML algorithm named Machine Learning Cost Modeling (MLCM), more adapted to complex and non-linear variables. Despite the importance of energy tariffs as support for decision-makers, the authors showed that the impact of the price had less importance than other parameters in modeling the global energy consumption of the WWTPs.

Table 4 summarizes the reviewed papers according to the different AI applications used to reduce energy consumption in wastewater treatment plants. The first column identifies the work. The second column indicates the stage where the method is applied. Then, the third column presents the methods used in the problem. The fourth column shows the algorithm's energy performance. The penultimate column shows the energy reduction achieved by the algorithm. Finally, the last column presents the coefficient of determination R^2.

Regarding AI algorithms, ANN and SVM are among the most used machine learning techniques, followed by RF, GA, and FL. According to this review paper, modeling techniques supported by intelligent optimization methods and data classification methods can reduce operational costs by about 30%, which will also contribute to the reduction of electricity costs. If the control is focused on the aeration stage, where energy consumption is higher (64 to 74% of total energy consumption), the reduction can reach 15%, thus demonstrating the importance of optimization and data classification methodologies based on artificial intelligence.

Some papers highlighted the importance of identifying and quantifying inefficiency phenomena that impact the calculation of indicators, especially those related to electricity consumption. It is not possible to evaluate and quantify the energy efficiency of a treatment system without knowing all the input variables and their origin.

CONCLUSIONS AND FUTURE TRENDS

Wastewater treatment systems are large electricity consumers, so it is crucial to define energy policies that allow more energy efficiency and, consequently, less greenhouse gas emissions into the atmosphere. The high-quality requirements for treated wastewater, as well as energy and environmental restraints, impose new challenges on the industry and create an opportunity for intelligent systems incorporation.

This review analyzed the contributions of AI techniques on the main energy modeling tools used in wastewater treatment systems since 2005. The methodology approach allowed a selection of papers, identifying and contextualizing the main problems and the different optimization strategies. The main conclusion of this review is the difficulty in accessing data. The variability of the physical-chemical characteristics of the influent, as well as the unpredictability of inefficiency phenomena, transform WWTPs into complex and non-linear systems. These and other factors, yet unknown, require tools that can analyze and process data in real-time, decrease response time, and improve decision support. It also demonstrated the importance of a holistic vision in defining procedures and techniques for configuring and managing treatment systems. The diversity of occurrences requires a complementarity of competencies in the management model.

The ML techniques modeling costs in WWTPs can be a suitable basis for new scientific and technological achievements to increase the energy efficiency of treatment systems. Artificial Intelligence algorithms, such as ANNs, RF, SVM, GA, and FL, may provide improved control of effluent quality and efficiency of energy consumption simultaneously. Despite the small number of published papers, it was highlighted through this review the importance of AI in reducing electrical energy consumption, which in the aerobic and anoxic treatment tanks can represent 40%. On the other hand, given the importance of different inefficiency phenomena, AI can also contribute to their identification and quantification as a way of assessing their impact on consumption and providing data to the supporting decision.

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