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The existing technology and the application of digital artificial intelligent in the wastewater treatment area: A review paper

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Abstract. Wastewater treatment using various existing technologies, including advanced oxidation processes, adsorption, and membrane separation for various pollutants removal from industrial and municipal wastewater streams, is an essential aspect of reaching environmental sustainability to keep human well-being and healthy economic growth. However, some challenging elements along with the wastewater treatment process affect pollutant removal efficiency and other resources. This condition will lead to various uncertainty in the wastewater treatment system related to the fluctuations in the quality of treated water and wastewater, operation costs, and environmental risk. Artificial intelligence can then be such a reliable solution to predict and minimize those complications and optimize the process and parameters implemented in the wastewater treatment system.

1. Introduction

These days the terms of the circular economy, waste management, and digital artificial intelligent have drawn increasing attention globally from many relevant stakeholders, including government, academics, and industrial parties. This phenomenon is derived from the need for practical ways to solve some issues related to the growing volume of industrial and municipal wastewaters, which can challenge reaching relevant goals associated with economic growth and environmental sustainability. Thus, it is necessary to manage waste with several strategies, including reducing material consumption and replacing conventional management with more modern ones.

This strategic treatment is primarily intended for industry and agriculture because of the linear economic relationship between the strategy and the existing problems [1, 2]. Polluted water and wastewater streams threaten human health, other living creatures, and environmental sustainability as a whole as they could contain oil and grease, heavy metals, dyes, phenol, or other harmful contaminant particles. These wastewaters are commonly released into the environment from various growing industrial sectors such as petroleum refinery, textiles, pulp and paper, tanneries, plastics, mining, brass and bronze manufacturing, steel production, electroplating, pharmaceuticals, galvanizing, pigments, insecticides, cosmetics, battery manufacturing, paints, and pigments [3, 4].

The increasing world population has resulted in the growing demand in many human needs, especially food and energy. The phenomenon has caused more unwanted by-products and agricultural residues, given a more significant challenge to developing the circular economy



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concept. Therefore, digital applications' involvement in predicting and optimizing the process of treating industrial and municipal wastewaters to enable the treated water reusable for further productive usage is inevitable [5].

Furthermore, artificial intelligence has been used widely in many engineering disciplines as it offers reliable solutions to solve practical problems, including wastewater treatment and machine fault analysis [6,7]. Concerning various existing technologies for water and wastewater treatment, such as the adsorption process, membrane filtration, and advanced oxidation processes [8,9], the application of artificial intelligence or machine learning is reliable and resourceful. Therefore, this review paper aims to further focus on giving information related to the available methods for water and wastewater treatment. It is also used to apply artificial intelligence as a digital transformation tool in the wastewater treatment area. The reusable components that enable less or zero waste to support a circular economy society can be manifested.

2. Existing technologies for water and wastewater treatment

2.1. Adsorption process

Adsorption could be defined as atoms or ions accumulation process from gas, liquid, or concrete to adsorbent pores or surface forming a typical layer of the adsorbate. Various pollutant particles, including oil and grease, dyes, metal ions, dissolved natural or other organic and non-organic compounds, can be part of the adsorbate typical layer [10,11]. Activated carbon, biochar, and chemically modified adsorbent are well-known adsorbent types used in various industrial wastewater treatment plants. Those adsorbent materials could be derived from synthetic, organic, and non-organic materials. Furthermore, to maintain environmental sustainability, some efforts are made to use natural materials. Some natural materials are plant-based adsorbents such as eucalyptus bark, banana peels, barley straw, watermelon peels, orange peels, and other organic materials to remove targeted pollutants [10–19].

2.2. Membrane filtration

Membrane filtration is a superior technology to remove various pollutants resulting in treated water with a high purity level, so it could be reused for different purposes, such as processing water, irrigation, and even drinking water [12]. Based on the particles' size and character, membranes can be categorized into microfiltration, ultrafiltration, nanofiltration, and reverse osmosis. Compared to other treatment methods, the membrane's filtration usage has shown outstanding work for their high efficiency, including oil, dyes, and massive metals depletion [13–15]. However, membrane materials are vulnerable to the fouling phenomenon occurring at the time of operation. Fouling is caused by deposited pollutant particles on membrane pores and surface reducing permeate flux. To lower the fouling rate, several approaches such as periodic washing, pre-treatment stage, and other optimization processes are needed [15,16].

2.3. Advanced oxidation

Advanced oxidation processes (AOPs) are characterized by radical hydroxyl production responsible for targeted organic and non-organic pollutants removal. The pollutants can be transformed into water, carbon dioxide, and other harmless products. There are various ways of performing AOPs, including Fenton ($\text{H}_2\text{O}_2/\text{Fe}^{2+}$), Fenton-like ($\text{H}_2\text{O}_2/\text{Fe}^{3+}$), electron beam irradiation, sonolysis, electrochemical oxidation, photo-assisted Fenton ($\text{H}_2\text{O}_2/\text{Fe}^{2+}/\text{Fe}^{3+}/\text{UV}$), and photo-catalytic reaction (TiO_2/O_2 , $\text{O}_3/\text{H}_2\text{O}_2$, O_3/UV , $\text{H}_2\text{O}_2/\text{UV}$) [17–20]. Literature has shown the efficacy of these methods to put targeted pollutants at bay [21,22]. Nevertheless, several shortfalls of these methods need to be concerned, such as costly chemical usage and its after-use impacts, sludge generation, and by-product formation.

2.4. Coagulation and flocculation

Coagulation and flocculation are the main methods used for treating contaminated water, primarily in the initial step to remove dissolved and suspended solid particles and other organic and non-organic pollutants through the application of flocculants and coagulants media such as aluminum and ferric chloride [12]. This process involves some influential parameters such as initial targeted pollutants concentration, coagulants and flocculants agent dosage, and pH of the solution. This process also consists of several principles like destabilization, entrapment, and aggregation or colloids binding stages to form larger and heavier flocks of pollutants particles so that they would be easily removed by subsequent settling and filtration stages. However, some concerns could be directed to avoid disadvantageous sides using this method, including costly coagulant and flocculant reagent. Also, to reduce excessively abundant sludge production for the continuous and large treatment plant and toxic sludge disposal in the environment [23].

2.5. Biological process

Various microorganisms types like abundantly available in nature, including fungi, bacteria, yeast, and algal biomass, are involved in the contaminated solution's degradation pollutant process during the biological method. Even though it has some drawbacks, including longer reaction time and wider treatment plant area, some natural approaches, including trickling filter and activated sludge, could be simple and more environmentally friendly, and cost-effective than other treatment modes. In terms of the need for oxygen, biological agents can be divided into aerobic and anaerobic types. However, combined aerobic-anaerobic microorganisms were implemented in specific conditions to get better results [24–26].

2.6. Integrated method

No wastewater treatment techniques could be used individually to obtain sufficient and efficient points with the highest standard of treated water. Several existing technologies in this area, including membrane filtration, adsorption, coagulation, and flocculation, and chemical oxidation, which have their shortcomings, should be integrated well. Some studies have proved that this integration could benefit the process and enable us to better quality wastewater with better machine and other treatment media conditions.

The hybrid of adsorption using hybrid powdered activated carbon and membrane filtration, for example, has been investigated and reported to be reliable and satisfactory by some previous studies [27,28]. Powdered activated carbon could better feed circulation even in low concentration. It can create shear stress on the membrane surface. This effect could reduce cake layer thickness, leading to a declining fouling rate and the high permeation flux and pollutant removal efficiency. Other integrated treatment methods can be derived from the same field, such as using dual membrane processes. Two different types of membrane, named ultrafiltration and reverse osmosis membrane, have been investigated for treating oily wastewater containing high initial oil and COD concentration. The study reported that this dual membrane system could yield about 7% of permeate flux decline with free suspended solid, high TOC, and cations removal efficiency in the treated wastewater [29]. However, implementing a dual membrane system could be restricted to the high cost of constructing and maintaining the system. The development of an integrated system consisting of two or more treatment methods has some advantages. They can be related to a higher quality of treated water and wastewater and safer conditions for expensive and complicated machinery used in the plants such as membrane filtration plant. A study applying advanced oxidation on wastewater as a pre-treatment stage before entering polymeric ultrafiltration membrane reported a massive fouling rate reduction leading to lesser washing cycles and longer membrane lifespan [9].

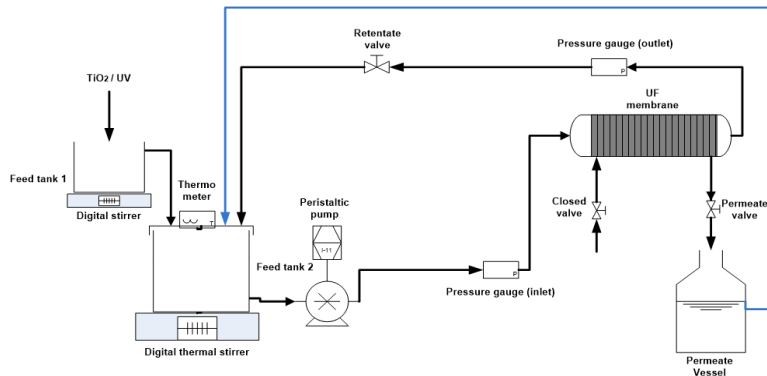


Figure 1: Integrated wastewater treatment technology that involving advanced oxidation processes and membrane filtration

3. Artificial intelligent applied in wastewater treatment technology

In the last decade, research has focused on digital application or machine learning to improve pollutants removal and benefit both economical and efficient energy levels. This artificial intelligent implementation has been implemented into various aspects, such as wastewater treatment, waste management, and resource extraction and reuse [30]. Under its specific usage, digital machine learning has been applied in the wastewater treatment field related to prediction and optimization purposes. These efforts have been developed to get more reliable real calculations that could benefit the use of chemicals in adsorption or advanced oxidation methods or the costly replacement of membrane materials due to fouling phenomena.

Most artificial intelligent techniques were modeled using experimental data to simulate, predict, confirm, and optimize targeted pollutants removal in wastewater treatment processes. In general, the experimental data set is divided into three groups, namely training data, validation data, and testing data. Or it can also be divided into two groups, namely training data, and testing data, with training data used as an initial development model. Meanwhile, the validation data is used to optimize the modeling so that the test data function can be applied to the whole data to predict the final model. In other words, the test's model performance results involve comparing the experimental data in the expected data to obtain a better correlation coefficient (R^2), performance efficiency, accuracy, and integral of the squared error [30,31].

For example, in the adsorption process, the adsorption of heavy metal named arsenic from aqueous solution using plant-based adsorbent made from *Opuntia ficus indica* biomass previously activated by pyrolysis and $ZnCl_2$ used to work with its experimental data to get the output of kinetic and isotherm pattern [32]. To set new isotherm and kinetic equations, they also developed modeling using the hybridization of the traditional adsorption equations with an artificial neural network. The artificial neural network was then used to improve the initial conventional kinetic and isotherm equations for making arsenic removal simulation at varying pH and temperature. Furthermore, the performance of models applied was examined using arsenic adsorption experimental data resulting in the outperformed model representing kinetic and isotherm adsorption equations for the better calculations of process design. Several prominent digital modeling stated in literature can be seen in Table 1.

In terms of treating wastewater using the membrane method, this digital machine learning, including artificial neural networks, could also be a competitive alternative for dynamic cross-flow

Table 1: Typical artificial intelligent applied as a machine learning tool in the wastewater treatment system

No.	AI	Treatment	Function	Ref.
1	Artificial neural network	Membrane filtration	To predict transmembrane pressure and fouling occurrence	[33]
2	Fuzzy logic	Adsorption	To predict Pb(II) removal efficiency using activated carbon nanocomposite	[34]
3	Genetic algorithm	Adsorption	To produce better adsorption bed and adsorbent porosity	[35]
4	Data mining	Activated sludge	To optimize the activated sludge process and minimize energy	[36]
5	Response surface methodology	Coagulation and flocculation	To optimize the independent parameters for better pollutant removal	[37]
6	Bayesian network	Modified sequencing batch reactor	To model and optimize wastewater treatment plant	[38]
7	Support vector machine	Adsorption	To predict drug reduction effect and improve pollutant removal	[39]
8	Linear regression	Membrane filtration	To predict the permeate rate and fouling mechanism	[16]

ultrafiltration modeling. Its application for predicting flux decline occurred during the filtration process reliable [40]. The cross-flow ceramic ultrafiltration membranes have been modeled using artificial neural networks for assessing the multilayer perceptron. For this reason, several crucial operating parameters such as transmembrane pressure, cross-flow velocity, filtration time, and dynamic fouling were used as input data to permeate flux behavior. The authors did several pre-treatments of the experimental data and the optimal selection of the neural networks' parameters to improve the fitting accuracy, compared to well-known Hermia pore blocking models considering the computational speed, high precision, and ease of the artificial neural networks. They concluded that the fitting accuracy of the artificial neural network model is comparable to that of Hermia's models adapted to the cross-flow ultrafiltration. Specifically, it was similar to those previously obtained for Hermia's intermediate blocking model in high transmembrane pressure conditions.

Another artificial intelligence that could be utilized to benefitting the wastewater treatment area is fuzzy logic application. A study used this digital type to predict and control wastewater to be recycled so that it could meet the standardized quality value of water and wastewater for further usage, including for agricultural and industrial purposes [41]. The surrogation of wastewater treatment plants could avoid simulating complex physical, chemical, and biological treatment processes that conventional methods prominently face. Each fuzzy logic model predicts water quality parameters by measuring influent water quality parameters such as biochemical oxygen demand (BOD), chemical oxygen demand (COD), pH, temperature, and total suspended solids. A supervised committee fuzzy logic (SCFL) model consisting of three fuzzy models named Takagi-Sugeno, Mamdani, and Larsen can be applied as a predictive ensemble model. This model combined with an artificial neural network to include the forecasted water quality resulted from individual fuzzy logic models. To conclude, the unique fuzzy logic models have had a mean absolute percentage error (MAPE) for BOD, COD, and TSS in the testing stage ranging from 10 to 13%. Simultaneously, the SCFL model could reduce MAPE

value to 4% in the testing step.

4. Summary

In this review article, some existing standard technologies implemented for the wastewater treatment area are explained. Because industrialization and the speed of population growth have increased from contaminated water sources that threaten the health of the population and damage the environment, an environmentally friendly waste treatment technology is needed with the least possible waste output. Another essential alternative is to reduce energy consumption, which has a very immediate impact on the environment and human life. Following that notion, optimization algorithms as digitally intelligent techniques will help optimize the significant parameters related to some aspects of wastewater treatment plants, such as predicting and reducing membrane fouling rate and optimizing adsorption capacity adsorbent in the adsorption process. To conclude, machine learning in a wastewater treatment study is a better option for gaining a circular economy society with better environmental conditions.

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