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Challenges of industrial wastewater treatment: utilizing Membrane bioreactors (MBRs) in conjunction with artificial intelligence (AI) technology

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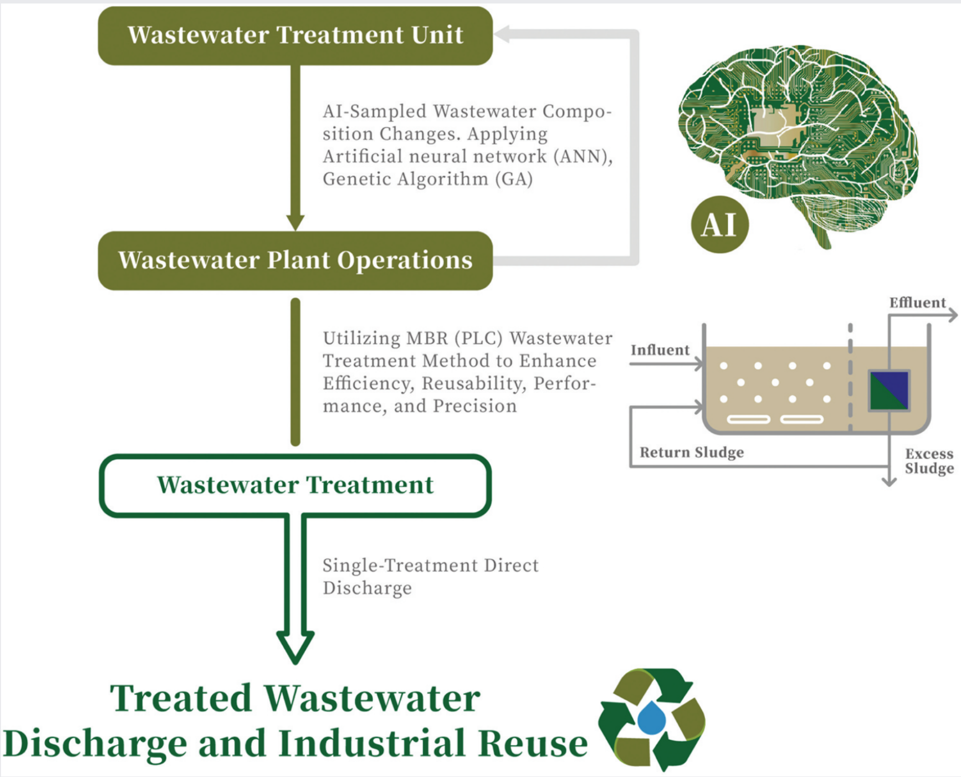
ABSTRACT

In the past, decisions on wastewater treatment methods have predominantly rested on expert opinions, utilizing the Delphi method. Yet, with an anticipated increase in diversification and customization, especially in the "small-batch and diverse" market over the next decade, addressing the formulation and execution of wastewater treatment for these non-traditional production processes will present substantial challenges. Relying solely on Delphi experts' decision-making within a short and time-constrained production planning window is expected to prove inadequate. Predominantly relies on the authors' over 15 years of industry experience in wastewater treatment, this perspective paper proposes an inventive solution that integrates Membrane Bioreactors (MBRs) with Artificial Intelligence (AI) applications. This approach signifies a more advanced method for industrial wastewater treatment compared to conventional methods, with the intention of garnering increased interest for future research endeavors.



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1. Introduction

Industrial production heavily depends on water for various purposes, presenting distinct challenges in wastewater treatment [1–3]. Currently, the focus of industrial wastewater treatment has been primarily on adhering to discharge standards, with experts employing traditional Delphi methods [4]. However, the influx of novel chemicals in industrial wastewater has diminished the accuracy of expert assessments [5–8]. For example, in the traditional synthetic process of the textile industry, Ethylene glycol and Polyethylene terephthalate are commonly used. Yet, due to lower costs and the emergence of its by-product Benzyl alcohol, Ethylene has rapidly

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supplanted Ethylene glycol in the textile industry since 2023. This shift in raw materials in the semiconductor industry has led to the evolution of next-generation and subsequent-generation materials. Notably, gallium nitride, an emerging chemical material, has exhibited superior properties – higher breakdown strength, faster switching, greater thermal conductivity, and lower on-state resistance – compared to traditional silicon wafers, thereby gradually replacing silicon-based semiconductor technology in power conversion, radio frequency, and analog applications.

While the Delphi method proves effective when raw materials are consistent and predictable, enabling the formulation of wastewater treatment strategies prior to production planning, the rise of diversification, the use of the novel chemicals, and customization in the "small-batch and diverse" market poses significant challenges. An escalating number of studies [4,5] have highlighted the concerns associated with exclusive dependence on Delphi experts within the production planning window, revealing inadequacies that become more pronounced, particularly in light of the anticipated surge in non-traditional production processes.

Predominantly relies on the authors' over 15 years of industry experience in wastewater treatment, this perspective paper advocates for a solution that combines Membrane Bioreactors (MBRs) with Artificial Intelligence (AI) applications (Artificial Neural Networks, ANN and Genetic Algorithms, GA), offering a more advanced alternative to the traditional Delphi method in industrial wastewater treatment. Framing the integration of AI and MBR as a comprehensive system aligns with Systems Theory [e.g. 7], emphasizing understanding interactions within complex systems. Implementing AI-based control strategies for MBR systems, enhancing contaminant removal and optimizing resource usage, also aligns with Process Systems Engineering theory [e.g. 8], advocating for optimization in intricate processes. Integrating ANN and GA for real-time monitoring, anomaly detection, and fault diagnosis enhances the reliability and robustness of MBR operations, in line with the view of Data-Driven Fault Detection and Diagnosis approach [9]. Wastewater treatment plants should recognize the benefits of incorporating AI, moving beyond sole reliance on expert knowledge, to improve accuracy and efficiency in water treatment.

It is worth noting that the proposed concepts and recommendations in this perspective paper are universally applicable to wastewater treatment. While wastewater treatment in industries like textiles and electronic components are likely to urgently require AI integration, other sectors, such as food processing, can also leverage AI to enhance wastewater treatment and recycling as an emerging trend.

2. Traditional wastewater treatment system

Traditional wastewater treatment systems have two main phases: "pre-facility planning" and "monitoring and operation during use." In the pre-facility planning phase, the business owner proposes an establishment model based on the scale of wastewater treatment, determined by facility planning. Experts, scholars, operational managers, and wastewater specialists determine the treatment volume and types required. This leads to a wastewater treatment facility plan designed to accommodate the expected treatment volume over the next decade and culminates in facility construction. During operation, monitoring is typically done using Supervisory Control and Data Acquisition (SCADA) systems. Production managers and experts provide production plans and pollutant wastewater quality expectations. SCADA collects data from various stages, including collection, dosing, sedimentation, and discharge, all managed manually at each plant [10].

Wastewater treatment can be categorized into primary, secondary, and tertiary treatment based on effluent quality. Primary treatment removes suspended solids, colloidal matter, and heavy metals through physical or chemical processes. Secondary treatment uses biological processes to remove aerobic substances, while tertiary treatment focuses on further pollutant removal or higher-quality effluent production. The choice of treatment process depends on effluent standards and the scale of water resource recovery centers [11]. When constructing a wastewater treatment system, the traditional Delphi method relies on the experiences of senior managers and technical experts. They consider historical data on wastewater emissions per ton, designing treatment within specified limits to meet local discharge standards.

Nonetheless, as previously highlighted, the Delphi method falls short of adequacy and accuracy due to the adoption of novel chemistry and the market shift toward small-batch customized production. Some studies [12,13] propose an enhancement to the simulation framework and models for wastewater treatment through a fuzzy Delphi approach. This approach facilitates the categorization of wastewater into classification pools, considering factors like wastewater load and pollution concentration. It enables the adjustment of additive quantities and cycles based on accurately defined, independent membership functions for measuring wastewater additives. These functions map specific pollution ranges to truth values, guiding the control of additives and supporting pre-production wastewater treatment decisions.

Despite its advantages, the fuzzy logic approach has its significant limitations. Crafting precise and comprehensive fuzzy logic rules can be intricate, demanding an in-depth understanding of the system and its variables. The complexity of rule formulation may impede practicality and ease of implementation [14]. Furthermore, fuzzy logic systems often rely on expert knowledge for rule creation and parameter tuning, posing challenges in cases where domain expertise is scarce, or knowledge transfer is difficult. Model interpretation difficulty is another challenge, as water treatment fuzzy logic models can be intricate for non-experts to comprehend, complicating the decision-making process [15]. Sensitivity to variations in input parameters is a notable drawback, potentially leading to suboptimal performance in the face of uncertainties. Moreover, fuzzy logic systems encounter limitations in handling highly dynamic or rapidly changing conditions [16].

For more complex substances, this paper suggests that fuzzy logic could be replaced using MBRs in conjunction with an AI system (applying ANN and GA) to establish a real-time AI decision-making emission system, enhancing outdated capabilities to cater to diverse and customized production trends. The proposed approach is indirectly supported by existing studies: Abuwatfa [17] delved into AI-based fouling prediction models using ANN. Their findings indicate that ANN provides an effective approach for separation with applications spanning desalination, water reuse, and wastewater treatment. Despite these advantages, membrane fouling poses a significant challenge, underscoring the need for ongoing research to develop effective mitigation strategies and enhance the performance of membrane-based processes. Alam [18] and Safeer [19] also highlighted the application of AI techniques in water treatment and desalination to optimize processes and provide practical solutions to water pollution and scarcity. Furthermore, they suggested that the use of AI is anticipated to lower operational costs in water treatment by reducing expenses and optimizing the utilization of chemicals. Sahu [20] suggested that AI and (Machine Learning serve as transformative catalysts, particularly in addressing complex challenges in wastewater treatment and microalgae-bacteria symbiosis. In the context of analyzing and managing control systems in drinking water treatment, Li [21] suggested that AI could serve as a valuable tool for enhancing the efficiency of water recycling processes.

These advanced AI technologies contribute to the development of innovative solutions, playing a crucial role in optimizing wastewater treatment processes, improving biomass yield, and enabling real-time monitoring. Although the main focus of these studies is *not* primarily on industrial wastewater treatment, they lend support to the argument and perspective of utilizing AI for predicting wastewater treatment approaches in this paper.

3. Utilizing MBRs combined with AI (ANN & GA)

The application AI to wastewater treatment and water recycling methods involves the processing of AI and vast amounts of data, particularly image recognition and natural language processing. This approach is to utilize water quality and operating parameters of water treatment systems, along with big data collection, to train AI models. These models analyze the composition of wastewater components and generate decision results, enabling intelligent control of the system. Initially, during facility establishment, aside from constructing wastewater treatment pools, monitoring systems equipped with intelligent data collection terminals within Programmable Logic Controllers (PLCs) are employed. These terminals extract real-time data on wastewater treatment water quality and equipment operations from PLCs. By upgrading on-site PLCs with wireless remote intelligent data collection terminals, real-time data on wastewater treatment water quality and equipment operations are collected from PLCs and transmitted to Web Access. These data are transformed into management dashboards through the WISE-PaaS Industrial IoT cloud platform, initiating the visualization and AI intelligent wastewater management. This includes ANN modeling, GA and the integration of MBRs production and discharge data.

3.1. MBRs

MBRs combine activated sludge with membrane separation technology, offering advantages such as high-efficiency effluent, high load capacity, and a small footprint. Currently, large (10,000 m3/d) and super-large (100,000 m3/d) MBRs sewage treatment plants have been constructed and put into operation worldwide, including in China, the United States, and Europe. The materials, reactor operating conditions, and characteristics of mixed sludge in MBRs are closely related to membrane fouling, which is influenced by various factors such as influent water quality, sludge retention time, and hydraulic retention time [22,23]. Changes in operating conditions not only directly affect membrane fouling but also alter the characteristics of mixed sludge, consequently impacting membrane fouling rates [24]. As a result, it is challenging to identify their specific roles. Thus, utilizing AI-integrated technologies, including ANN and GA with MBRs data can more accurately learn and predict membrane fouling for membrane fouling control in wastewater treatment is highly advantageous [25].

3.2. ANN

An ANN is an algorithm that mimics the behavior of animal neural networks to perform distributed and parallel information processing. ANN's information processing capabilities rely on adjusting input and output of neural nodes, neuron thresholds, and connection weight magnitudes. ANN's predictive performance can be evaluated through parameters such as

Root Mean Square Error, coefficient of determination, and relative error. While previous studies have demonstrated the superior performance of ANN in predicting MBRs membrane fouling, differences in technical equipment scale and wastewater characteristics between laboratory-scale reactors and large-scale reactors are often significant [26–28]. Therefore, promoting predictive research on MBRs membrane fouling using ANN on a pilot scale holds significant significance. For example, collecting long-term operational data from a pilot-scale submerged MBRs and constructs an ANN model between membrane flux after membrane chemical cleaning, membrane filtration time, influent water quality, and membrane permeability.

Moreover, AI technologies applicable to water treatment and water recovery methods can be categorized into massive data, image recognition, and natural language [29]. (A) Massive data applications are the most prevalent, involving the utilization of water quality and water treatment system operating parameters to train AI models for prediction and decision-making, enabling system intelligent regulation. Examples of AI applications extend to precise dosing in chemical systems for managing chemical sludge and sedimentation. In biological systems, AI contributes to intelligent regulation, particularly in conjunction with devices like the Mixed Liquor Suspended Solids sensor. This sensor, deployed in wastewater treatment plants, facilitates the measurement of suspended solids concentration in the mixed liquor of activated sludge processes. The data collected aids in optimizing processes such as sludge discharge, return sludge, and digestion liquid reflux systems. Furthermore, AI is instrumental in addressing physical system challenges, including the prediction of filter blockages, membrane system blockage prevention, and the optimization of overall system control. These AI-driven applications enhance precision, efficiency, and responsiveness in the management of complex wastewater treatment processes. (B) Image recognition employs image collection and layered image discrimination to assess system states, such as microbial species determination, biological filter height determination, and chemical coagulation size determination. (C) Although natural language application in water treatment and water recovery cases is rare, its potential applications include providing standard operating procedures and troubleshooting for water treatment facility operators [30]. For example, when system anomalies occur, how to promptly detect, process, and rectify the situation is crucial for system operators. When abnormal alarms are generated, an AI natural language system provides processing standard operating procedures and operational steps through dialogue or a one-click process in SCADA, benefiting 24-hour shift workers and understaffed sites. Rapid resolution helps water treatment and water recovery systems return to normal quickly, making natural language an important auxiliary and decision-making tool [31]. The effectiveness and opportunities of water recovery depend on the front-end water treatment water quality status and efficiency. As AIoT aids in enhancing water treatment efficiency, water quality is also improved, contributing to water recovery and application [32,33].

3.3. GA

GA can directly utilize fitness as the search information without the need for derivatives or other auxiliary information. It possesses inherent implicit parallelism and better global optimization capabilities. By employing probabilistic optimization methods, it can automatically access and guide the optimization search space, adaptively adjust search directions, and does not require fixed rules. The species conserving GA can be utilized to optimize the conditions of reverse osmosis wastewater treatment processes. By optimizing multi-stage reverse osmosis conditions, they performed permeation reprocessing and recovery degradation of N-Nitrosodimethylamine [34]. The optimal operational configuration was determined from the perspectives of inhibition rate, recovery rate, and energy consumption. Environmental quality standards such as dissolved oxygen, biochemical oxygen demand, and corresponding measures for wastewater treatment systems were used as constraint conditions or objective functions. Combining GA with water quality models, the lowest wastewater removal efficiency of wastewater treatment plants was determined and applied to the San Maria da Victoria River Basin in Brazil. The results demonstrated that this optimized model combination was an effective tool for determining the minimum wastewater removal efficiency of wastewater treatment plants, while keeping costs at a minimum by considering the river's self-purification capacity [35,36].

4. Discussions, implications and conclusions

In the past, due to lower levels of customization, factory manufacturing was primarily focused on mass production, making the use of expert-based Delphi method sufficient to meet most wastewater treatment needs. However, with the increasing variety of chemical substances and the composition of customized products, the effectiveness of the Delphi method has encountered significant bottlenecks, leading to foreseeable difficulties and challenges in wastewater treatment in the future.

With global water resources dwindling and stricter water management regulations, integrating and applying water treatment technologies with innovative intelligent approaches is essential. This paper offers solutions for industrial production wastewater treatment needs, considering changing market demands, evolving times, and stricter environmental regulations. In practical terms, this study proposes the use of AI technologies such as ANN and GA to assist in suggesting wastewater composition and recovery strategies. The resulting wastewater treatment approach can be used to enhance the filtration process of MBRs, achieving a faster response in wastewater composition analysis and meeting the customization needs of the market customers. AI facilitates advanced data collection, including anomalies, and dynamically adapts to unforeseen challenges. It optimizes resource utilization, minimizing chemical and energy wastage, thereby enhancing overall efficiency.

In terms of theoretical contribution, the perspective that this study proposed aligns with the concept of Systems Theory, Data-Driven Fault Detection and Diagnosis, and Process Systems Engineering theories. AI applications actively monitor equipment, predicting maintenance needs and reducing downtime. They ensure water consistently meets quality standards, thereby elevating production quality. Data-driven decision-making helps mitigate risks, preventing accidents and safeguarding both production processes and the environment. Tailoring its capabilities to the specific needs of small-scale customers, this initiative assumes a pivotal role in advancing circular economy principles. In addition, while some previous research has explored the application of AI in water treatment, the perspectives presented have mainly focused on transforming water components, such as desalinating seawater or converting wastewater into drinking water, fundamentally differing from the approach taken in this study. Drawing on the authors' industrial experience in the field of wastewater treatment, this study not only makes a significant theoretical contribution from the perspective of wastewater treatment in the context of factory production and market demand but also serves as a catalyst for future advancements in using AI for wastewater treatment.

As previously discussed, there is a profound link between industrial production, wastewater recycling, and factory productivity. In this context, the AI water treatment approach plays a crucial role by reducing resource waste and promoting resource recycling and reutilization for sustainability and environmental preservation. To fully leverage AI's potential, future research should expand beyond solving spatial processing challenges in industry and explore broader applications. A visionary approach could involve gradually implementing advanced RO filtration systems to convert wastewater into drinking water. This holistic approach aligns with recycling principles and has the potential to transform industrial practices, making them more sustainable and environmentally friendly. We hope that this perspective paper will inspire further wastewater treatment and AI studies in the near future alike.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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