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REVIEW PAPER

Enhancing membrane fouling control in wastewater treatment processes through artificial intelligence modeling: research progress and future perspectives

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Abstract
Membrane filtration processes have demonstrated remarkable effectiveness in wastewater treatment, achieving high contaminant removal and producing high-quality effluent suitable for safe reuse. Membrane technologies play a primary role in combating water scarcity and pollution challenges. However, the need for more effective strategies to mitigate membrane fouling remains a critical concern. Artificial intelligence (AI) modeling offers a promising solution by enabling accurate predictions of membrane fouling, thus supporting advanced fouling mitigation strategies.
This review examines recent progress in the application of AI models, with a particular focus on artificial neural networks (ANNs), for simulating membrane fouling in wastewater treatment processes. It highlights the substantial potential of ANNs, particularly the widely studied multi-layer perceptron (MLP) and other emerging configurations, to accurately predict membrane fouling, thereby enhancing process optimization and fouling mitigation efforts. The review discusses both the potential benefits and current limitations of AI-based strategies, analyzing recent studies to offer valuable insights for designing ANNs capable of providing accurate fouling predictions. Specifically, it provides guidance on selecting appropriate model architectures, input/output variables, activation functions, and training algorithms. Finally, this review highlights the critical need to connect research findings with practical applications in full-scale wastewater treatment plants. Key steps crucial to address this challenge have been identified, emphasizing the potential of AI modeling to revolutionize process control and drive a paradigm shift toward more efficient and sustainable membrane-based wastewater treatment.

Keywords Digital water · Sustainable wastewater treatment · Smart wastewater management · Advanced fouling control · Data-driven modeling · Machine Learning

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Introduction

Water scarcity and pollution pose global challenges that extend without borders, also impacting regions across the Euro-Mediterranean area (Dhaouadi et al. 2021; Emmanouil et al. 2023; Frysali et al. 2023; Mendili et al. 2023; Zafeirakou et al. 2022). The scarcity of clean water poses risks to human health, disrupts ecosystem functioning, and hinders socioeconomic development (du Plessis 2022; Jones et al. 2024). Specifically, water scarcity threatens the survival of all living beings, as life cannot exist without water, while water pollution degrades natural ecosystems and facilitates the spread of infectious diseases, negatively affecting humans, animals, and plants (Bej et al. 2023; Naddeo 2021). To address these critical issues, effective water management practices must be established (Mujtaba et al. 2024). A holistic and sustainable approach is essential, involving comprehensive management of the entire urban water cycle, from freshwater extraction to the disposal of treated wastewater. This approach includes integrated planning and management of water resource use, implementation of water-saving strategies, promotion of safe water reuse, incorporation of flexible systems to adapt to varying demands and environmental conditions, and active community engagement in water conservation practices. However, practical challenges include the complexity of coordinating among different stakeholders, the significant financial investment required for infrastructure, technology, and maintenance, and the lack of technical expertise in sustainably managing the entire water cycle.

Within the urban water cycle, wastewater treatment is an essential stage that demands innovative and sustainable approaches. The discharge of raw or poorly treated wastewater introduces both conventional and emerging pollutants into the environment, making it a major contributor to pollution. These contaminants include persistent pollutants like pharmaceuticals, personal care products, endocrine disruptors, pesticides, dyes, chlorinated solvents, halogenated chemicals, and heavy metals. These substances are resistant to biodegradation and tend to bioaccumulate, posing significant toxicological risks to living organisms and negatively impacting their habitats (Bahjat Kareem et al. 2024; Li et al. 2024; Mir et al. 2023; Prihartini Aryanti et al. 2022; Sulejmanović et al. 2023a). Effective treatment technologies are, therefore, indispensable for minimizing the negative environmental impact of these contaminants and safeguarding living organisms (Ismail et al. 2024; Rodríguez-Pérez et al. 2023; Sulejmanović et al. 2023b). The urgency for sustainable and carbon–neutral wastewater treatment has driven the development of novel advanced technologies (Obaideen et al. 2022; Pervez et al. 2020; Senatore et al. 2021). Among these, membrane technologies are gaining increasing interest, offering efficient treatment of both conventional and emerging contaminants from wastewater (Abdulkarem et al. 2021; M. Ahmed et al. 2022a, b; Borea et al. 2018; Ensano et al. 2019; Millanar-Marfa et al. 2020; Naddeo et al. 2020). The benefits of membrane technologies, like high contaminant removal efficiency, reduced footprint, ease of operation, and high eco-compatibility, make them an attractive option for treating both municipal and industrial wastewater (Abdel-Fatah et al. 2021; Klimonda and Kowalska 2021; Sadr and Saroj 2015; Shehata et al. 2023). However, membrane fouling remains a persistent challenge, significantly hindering membrane filtration processes (Cairone et al. 2024e; Chang et al. 2019; Millanar-Marfa et al. 2022; Tabraiz et al. 2023; Zhang et al. 2022). Membrane fouling, resulting from the deposition and adsorption of compounds on the membrane surface or within its pores, leads to increased filtration resistance (Hasan et al. 2012; Liu et al. 2019). This results in higher energy consumption, increased cleaning frequency, and periodic membrane replacement, thereby increasing operating costs (Bagheri and Mirbagheri 2018; Buzatu et al. 2018). Additionally, membrane fouling increases energy consumption (Das et al. 2022; Liang et al. 2024), underscoring the necessity to enhance energy efficiency in wastewater treatment plants (WWTPs), which are among the major energy consumers (Lu et al. 2018; Shabbir et al. 2022; Zhang et al. 2021). Advancing fouling mitigation strategies is crucial for the continued success and viability of membrane technologies in advanced wastewater treatment (Alkhatib et al. 2021; Borea et al. 2017; Cairone et al. 2024c, 2024f; Castrogiovanni et al. 2022; Corpuz et al. 2021; Kim et al. 2024; Naddeo et al. 2015; Nair and Singh 2023; Sisay et al. 2023; Zhang and Jiang 2019).

Over the last few years, artificial intelligence (AI) has attracted global interest for its potential to revolutionize our lives. AI modeling has been explored across different fields, including environmental science and engineering, with applications, such as wastewater treatment simulation/modeling. While early studies were conducted decades ago (Boger 1992; Capodaglio et al. 1991; Krovvidy et al. 1991; Sànchez et al. 1996; Serra et al. 1994; Wen and Vassiliadis 1998), recent advancements in digital and technological development, including progress in machine learning (ML) and deep learning (DL), provide new opportunities for optimizing wastewater treatment processes. Among AI models, artificial neural networks (ANNs) have been extensively investigated to predict fouling in membrane-based wastewater treatment. AI models are instrumental in revolutionizing process control and optimization, significantly enhancing the efficiency of treatment technologies (Matheri et al. 2022; Nam et al. 2023; Ray et al. 2023; Zhao et al. 2020). By utilizing historical and real-time data, AI algorithms can identify complex data patterns and provide accurate predictions of treatment performance, supporting advanced data-driven decision-making (Al and Sin 2021; Filipe et al. 2019; Han et al. 2020; S. Zhang et al. 2023a, b). Specifically, AI models trained on historical data learn patterns and relationships among variables, while real-time data enables these models to continuously update patterns and refine their predictions based on the most current information available. This dynamic learning process helps provide timely and accurate predictions of treatment performance, allowing operators to assess system performance and implement corrective actions promptly. Additionally, advanced AI-driven control systems can automatically respond to changing conditions, enhancing system efficiency (Al Aani et al. 2019; Viet and Jang 2021). In the context of membrane-based wastewater treatment, AI modeling can optimize treatment performance and provide valuable insights for proactively mitigating fouling (Bagheri et al. 2019; Kamali et al. 2021; Niu et al. 2022; Viet et al. 2022). Specifically, predicting membrane fouling is crucial for optimizing cleaning procedures, extending membrane lifespan, and improving the economic feasibility of membrane technologies. Despite the potential benefits, implementing AI-based strategies presents challenges, such as data availability and model accuracy, that must be addressed to ensure their practical applicability in full-scale WWTPs (Bahramian et al. 2023; Y. Wang et al. 2023a, b; Yaqub and Lee 2022).

This paper investigates recent progress in modeling fouling in membrane-based wastewater treatment using ANNs. It provides a comprehensive analysis of recent studies, elucidates the current state of the art, and offers practical insights into employing ANNs for membrane fouling modeling. The review outlines the benefits and limitations of implementing cutting-edge AI-driven strategies for advanced fouling control. Additionally, future perspectives on this approach are discussed, highlighting crucial steps that must be addressed to promote its practical application.

Factors affecting membrane fouling

Membrane fouling results from the intricate physical and chemical interactions between the feed components and the membrane (AlSawaftah et al. 2021). This process involves the deposition and adsorption of solutes, colloids, and macromolecules either on the membrane surface (external fouling) or within its pores (internal fouling) (Du et al. 2020). Several factors influence these interactions, including membrane characteristics, feed properties, and operating conditions (Fig. 1).

Understanding the role of these factors in the complex interplay governing membrane fouling is essential for defining effective strategies to mitigate fouling. These strategies may include optimizing cleaning protocols, enhancing pre-treatment processes, designing novel antifouling membranes, fine-tuning operational parameters, and employing advanced real-time monitoring with adaptive control strategies. In AI modeling, identifying the factors affecting membrane fouling is a preliminary step essential for building accurate predictive models. This knowledge helps create models that can predict fouling behavior and boost the performance of membrane technologies in wastewater treatment.

Membrane properties

Membrane properties play a critical role in determining the membrane's susceptibility to fouling. Key properties include:

- Membrane material: the membrane material affects its chemical and physical interactions with foulants, leading to different behaviors depending on the feed characteristics (Miyoshi et al. 2015; Yamato et al. 2006);
- Hydrophilicity/hydrophobicity: hydrophobic membranes tend to experience more severe fouling than hydrophilic ones (Pichardo-Romero et al. 2020). This behavior can be ascribed to the hydrophobic interaction forces that, during the filtration process, cause contaminants to become entrapped within the membrane pores, leading to significant pore blocking (Kadadou et al. 2024). Conversely, hydrophilic membranes, especially those with smooth surfaces, generally exhibit a lower propensity for fouling (Díez and Rosal 2020; Fane et al. 2011);
- Pore size and molecular weight cut-off (MWCO): these properties define the size range of molecules that a membrane can reject via size exclusion mechanisms. The mutual relationship between membrane pore size and other properties (e.g., surface roughness) affects the reversibility/irreversibility of membrane fouling (Sano et al. 2022). Smaller pores retain more particles, forming a cake layer that presents higher filtration resistance, but this type of fouling can be removed more easily than the internal pore clogging observed in membranes with larger pores (Le-Clech et al. 2006);
- Surface charge: the membrane's surface charge influences its electrostatic interactions with charged foulants, which can lead to either their adsorption or rejection, thereby affecting fouling mechanisms (Cai et al. 2016; Du et al. 2020; Wu et al. 2018; Xiao et al. 2011);
- Surface roughness: rough surfaces provide additional sites for foulant adhesion, increasing the membrane's propensity to fouling (Zhang et al. 2015).

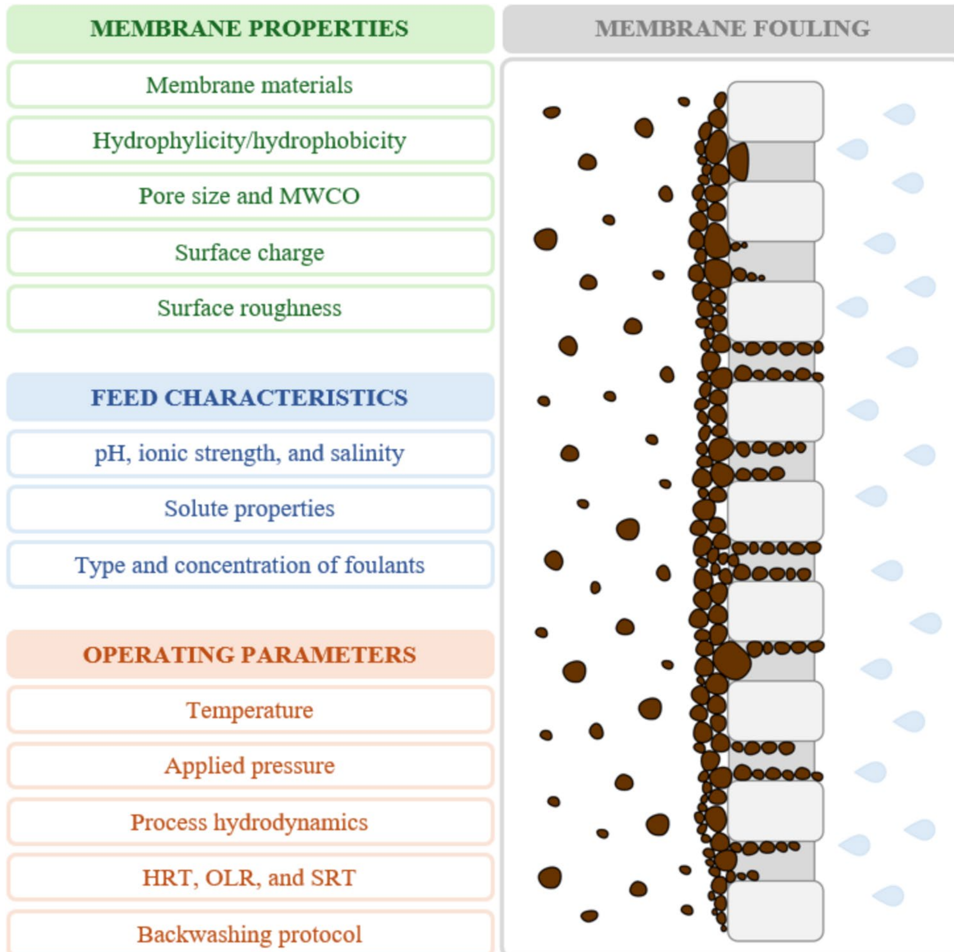

Fig. 1 Key factors affecting membrane fouling

Feed characteristics

The chemistry and composition of the feed significantly influence membrane fouling. Key feed characteristics include:

- pH, ionic strength, and salinity: these parameters affect the membrane surface charge, influencing the Donnan-exclusion mechanism and, consequently, fouling (He et al. 2008; Kucera 2019; Zacharof et al. 2016; T. Zhang et al. 2023a, b). Feed pH affects the membrane's surface charge via its zeta potential, generally increasing electrostatic interactions between membrane and solutes as pH rises (Cairone et al. 2024g, 2024d). Ionic strength affects solute rejection mechanisms and their transport/diffusion across the membrane, generally leading to membrane pore swelling, solute dehydration, and electrostatic screening effects at higher ionic strengths (Luo and Wan 2013; Roth et al. 2024). High salt concentrations in the feed can increase scaling (i.e., the accumulation of salt precipitates on the membrane), significantly decreasing permeate flux (Horseman et al. 2021);
- Solute properties: the molecular weight, size, hydrophobicity, charge, and polarity of solutes, combined with membrane properties, influence the contaminant removal mechanisms, thereby impacting membrane fouling (Kim et al. 2022; López-Muñoz et al. 2009; Mahlangu et al. 2014; Xu et al. 2020);
- Type and concentration of foulants: foulants can be classified into organic, inorganic, and biological (Ahmed et al. 2023; Lin et al. 2020). Specifically, proteins, macromolecules, colloids, emulsified oils, microorganisms, organic matter, micropollutants, minerals, and salts can act as potential foulants (S. F. Ahmed et al. 2022a, b; Ilyas and Vankelecom 2023; Miller et al. 2017). The type and amount of these foulants determine the nature of fouling. Organic fouling results from high concentrations of organic compounds, including polysaccharides, proteins, nucleic acids, humic substances, and fatty acid (Ly et al. 2019); inorganic fouling is associated with feed containing high levels of poorly soluble salts (Warsinger et al. 2015); and biofouling consists of the formation of a biofilm layer (consisting of bacteria, algae, and/or fungi) on the membrane, resulting from the interaction

of microbial colonies with the membrane itself (Díez and Rosal 2020; Lu et al. 2016; Su et al. 2023). Different fouling mechanisms correspond to each fouling type: colloidal fouling leads to pore narrowing/plugging; organic and inorganic fouling cause pore narrowing and gel/cake layer development; and biofouling primarily results in gel/cake layer formation, with a lesser impact on pore narrowing and pore plugging (Gul et al. 2021).

Initially, the scientific community considered mixed liquor-suspended solids (MLSS) as the principal cause of membrane fouling in wastewater treatment. However, attention later shifted to other compounds, particularly extracellular polymeric substances (EPS), soluble microbial products (SMP), transparent exopolymer particles (TEP), and biopolymer clusters (BPC) (Gkotsis and Zouboulis 2019; Meng et al. 2020; Wang and Li 2008). In recent years, microplastics and nanoplastics have also gained attention as emerging contaminants, with many studies focusing on exploring their role in contributing to membrane fouling (Enfrin et al. 2021, 2020; Golgoli et al. 2021; Ladeia Ramos et al. 2024; Li et al. 2021; Shen et al. 2023; Xiong et al. 2021).

Operating parameters

Operating parameters directly affect both the filtration process and the membrane's tendency to foul. Key operating parameters include:

- Temperature: temperature affects the solubility of compounds, mass transfer coefficients, and feed viscosity (Alresheedi and Basu 2020, 2019; Lee et al. 2013; Ozgun et al. 2015; Xu et al. 2024). Additionally, it also influences microbial growth and the secretion of SMP and EPS (Ma et al. 2013);
- Operating pressure: pressure impacts concentration polarization (CP), thereby impacting the filtration process (Bai et al. 2023; Nguyen et al. 2016). Specifically, higher operating pressure increases CP effects and leads to greater collisions between particles. This results in particle deposition on the membrane and rapid pore blocking, thereby leading to a faster reduction in permeate flux (Said et al. 2015). Recent research has identified the development and implementation of novel membrane geometries and spacer configurations as potential strategies to mitigate these detrimental effects of CP (Al-Amshawee and Yunus 2024; Bai et al. 2023);
- Process hydrodynamics: factors characterizing process hydrodynamics, including feed flow rate, crossflow velocity, and aeration intensity, significantly influence membrane fouling propensity (Choi et al. 2005; Fane et al. 2011; Koo et al. 2015; Le-Clech et al. 2003);
- Hydraulic retention time (HRT), organic loading rate (OLR), and sludge retention time (SRT): in membrane bioreactors (MBRs), shorter HRTs and higher OLRs promote cake layer formation and pore blocking (Deng et al. 2016), while higher SRTs are associated with increased fouling (Han et al. 2005; Szabo-Corbacho et al. 2022);
- Backwashing frequency and intensity: these parameters influence the evolution and severity of fouling (Liu et al. 2022; Yigit et al. 2009).

AI modeling of membrane fouling in wastewater treatment

The phenomenon of fouling in membrane-based wastewater treatment processes has been traditionally modeled through simplified blocking models, which describe, either independently or in combination, four primary mechanisms:

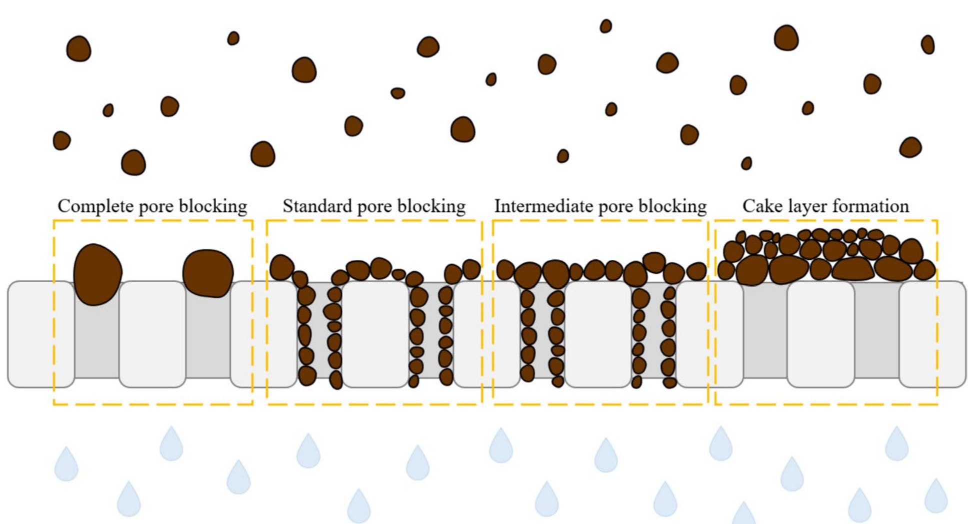

Fig. 2 Membrane fouling mechanisms

complete blocking, standard blocking, intermediate blocking, and cake layer formation (Amosa 2017; Huang et al. 2020) (Fig. 2). These models use mathematical expressions to describe these mechanisms (Iritani 2013). However, membrane fouling is also influenced by additional factors like solute adsorption, inorganic precipitation, microorganism accumulation, and concentration polarization (Guo et al. 2012).

Given the complexity and interplay of various fouling mechanisms, traditional mathematical models may not accurately describe the real evolution of membrane fouling due to their inherent simplifications and limitations, leading to reduced prediction accuracy (Wang et al. 2024). These limitations can be effectively addressed using AI modeling.

AI modeling plays a crucial role in advancing solutions toward sustainability (Luan and Cai 2023). AI models are attracting interest as tools for enhancing engineering applications in various fields, including wastewater treatment (Matheri et al. 2022; Nam et al. 2023; Ray et al. 2023; Viet and Jang 2023; Zhao et al. 2020). The potential of AI modeling in this field is particularly notable for membrane processes, where AI models can provide valuable insights to enhance treatment performance and sustainability (Kamali et al. 2021; Viet et al. 2022). Numerous research has demonstrated the effectiveness of AI modeling in predicting membrane fouling and developing proactive control strategies (Bagheri et al. 2019; Kovacs et al. 2022; Niu et al. 2022). Among these AI models, ANNs have been extensively employed. ANNs are particularly effective due to their capacity to learn complex relationships from data, making them a powerful tool for improving predictive accuracy and optimizing membrane filtration processes.

Artificial neural network (ANN)

ANNs are AI models that take inspiration from the complex functions of the human brain in processing information (Agatonovic-Kustrin and Beresford 2000). ANNs are designed to estimate output patterns using input variables (Zarei et al. 2022). An ANN typically consists of interconnected nodes, commonly referred to as neurons, which are organized into layers: the input layer, hidden layer(s), and output layer. The number of nodes in the input and output layers is equal to the number of input and output variables, respectively, while the quantity of nodes in the hidden layer(s) is a design choice (Adil et al. 2022).

The design of ANNs involves several key decisions that influence their performance:

- Topology (or architecture): the topology of an ANN refers to the number of hidden layers and the number of neurons within each layer. These choices significantly impact the ANN's capability in identifying complex relationships and patterns within the data, directly affecting prediction accuracy (Zou et al. 2009);
- Activation (or transfer) functions: the activation function is instrumental in determining the activation level of each node and connecting neurons within the network by propagating the output of nodes from one layer to the next (Liu 2021; Montesinos López et al. 2022). Selecting the proper activation function is essential for the ANN's prediction performance (Ertuğrul 2018; Khan et al. 2022). Common transfer functions are the rectified linear unit (ReLU), sigmoid, hyperbolic tangent (tanh), and hyperbolic tangent sigmoid (tansig) functions (Rasamoelina et al. 2020);
- Weights and biases: weights and biases are parameters that regulate the connections between neurons. These are fine-tuned during the training step, representing the critical control parameters for ANN training (Aljarah et al. 2018);
- Training algorithm: the training process is a key step in developing ANNs. During training, the algorithm iteratively updates weights and biases to minimize the error between actual and predicted values (Cao et al. 2018; Gülcü, 2022; Rojas et al. 2022). Selecting an appropriate training algorithm is crucial, as it influences how effectively the network learns. The error is quantified by a loss (or error) function, like mean squared error (MSE) or mean absolute error (MAE) (Abolghasemi et al. 2023).

ANNs excel at recognizing complex patterns and nonlinear relationships between inputs and outputs, providing accurate predictions (Almeida 2002; Li et al. 2019; Zhang et al. 2019). However, because ANNs are data-driven models, their performance strongly depends on the availability and quality of data. Inadequate or biased datasets may cause less accurate models (Bahramian et al. 2023; Yaqub and Lee 2022). Additionally, ANNs are described as "black-box" models, meaning they produce results without providing clear explanations or insights into their internal workings. Specifically, the relationships generated between input data and outputs in the model cannot be easily extracted or understood. This lack of transparency makes it harder to interpret how the model transforms inputs into outputs and to understand how different inputs influence the results, complicating the interpretation of outcomes (Portillo Juan et al. 2023). The "black-box" nature of ANNs presents challenges for detailed process understanding, highlighting the need for advancements in explainable/interpretable ML models (Figueroa Barraza et al. 2024; Holzinger et al. 2022; Tsang and Benoit 2023). Explainable AI allows operators to understand why a model arrived at a specific output by revealing its logical reasoning. Similarly, interpretable AI provides clarity into the models' decision-making process, helping users understand the logic behind their predictions (Vishwarupe et al. 2022).

The efficacy of ANNs in modeling fouling in membrane technologies for wastewater treatment has been evidenced in numerous research (Do and Schmitt 2020; Hazrati et al. 2017; Liu et al. 2009; Mirbagheri et al. 2015; Roehl et al. 2018; Schmitt et al. 2018; Schmitt and Do 2017). Among different ANN topologies, the multi-layer perceptron (MLP) is the most extensively applied configuration in wastewater treatment modeling (Jawad et al. 2021).

Multi-layer perceptron (MLP)

The MLP is a widely used configuration of ANNs that includes at least one hidden layers in addition to one input layer and one output layer (Fig. 3) (Kovacs et al. 2022).

MLPs have gained prominence in recent studies for their potential to accurately predict fouling in membrane-based wastewater treatment technologies (Table 1).

As discussed in Sect. “Artificial neural network (ANN)”, designing an effective ANN, including MLPs, involves critical considerations such as defining network architecture, selecting activation (or transfer) functions, choosing appropriate input and output variables, and conducting an adequate training process. The optimal architecture for an MLP varies based on the specific application and target outputs. Hosseinzadeh et al. (2020) optimized the MLP architecture for water flux modeling in an osmotic membrane bioreactor (OMBR), determining that the best configuration involved 4, 11, and 1 neurons in the input, hidden, and output layers, respectively, for thin film composite (TFC) membranes, while the optimal architecture for cellulose triacetate (CTA) membranes included 4, 8, and 1 neurons in the input, hidden, and output layers, respectively. Similarly, Viet and Jang (2021) explored MLPs for modeling OMBR performance in wastewater treatment. They observed that the optimal quantity of hidden layers and nodes varied depending on the output being modeled. For instance, they selected 2 hidden layers with 30 neurons for water flux modeling and 6 hidden layers with 5 neurons for fouling resistance modeling. They also observed that the optimal quantity of hidden layers and nodes varied for different contaminant removal efficiencies. Taheri et al. (2021) found that an MLP with 9 neurons in the hidden layer was optimal for predicting transmembrane pressure (TMP) variation in an anaerobic membrane bioreactor-sequencing batch reactor (AnMBR-SBR) system. Im et al. (2022) modeled a forward osmosis (FO) process, determining that 2 hidden layers were optimal for predicting fouling thickness, roughness, and density, while 3 hidden layers were suitable for fouling porosity and water flux. They optimized the quantity of nodes per layer, with 10 nodes found to be optimal for fouling thickness, porosity, and density, and 15 nodes for fouling roughness and water flux. These examples highlight that the optimal MLP architecture is highly context-specific, pointing out the value of customizing MLP design based on the specific application and desired outputs.

The choice of activation function is critical for MLP performance in membrane fouling simulations. The hyperbolic tangent sigmoid transfer function (“tansig”) has emerged as the preferred choice in several studies, providing the best prediction performance (Barello et al. 2014; Cifuentes-Cabezas et al. 2023; Im et al. 2022; Viet and Jang 2021). The “tansig” function introduces nonlinearity into the ANN, enabling the model to identify intricate patterns between inputs and outputs. While both the “tansig” and sigmoid functions are S-shaped and exhibit similar behaviors, they differ in their output ranges: the sigmoid function generates outputs ranging from 0 to 1, while the “tansig” function outputs values between -1 and 1. This broader range provides higher gradient values, which generally leads to more efficient weight updates during training. Additionally, the symmetry of the “tansig” function around zero contributes to faster convergence, making it a more effective choice for MLPs.

The Levenberg–Marquardt (LM) algorithm is frequently implemented for training MLPs due to its effectiveness. This algorithm combines the advantages of two numerical methods: gradient descent method and the Gauss–Newton method (X. Wang et al. 2023a, b). The LM algorithm has

Fig. 3 Schematic representation of multi-layer perceptron (MLP) topology

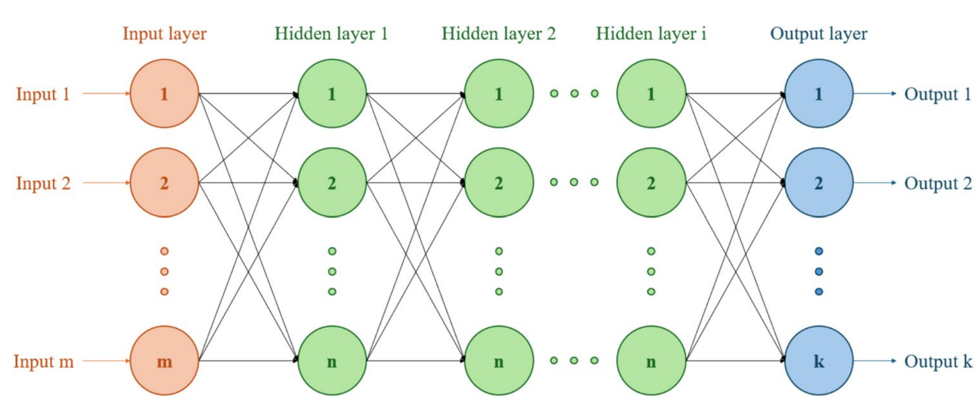

Table 1 Recent studies employing MLP for predicting fouling in membrane technologies for wastewater treatment

References	Activation function	Training algorithm [a]	Input variables [b]
(Hosseinzadeh et al. 2020)	Linear, sigmoid	LM, RBP, SCG, GDM	MLSS, conductivity, DO
(Chen et al. 2020)	Sigmoid	BP	Separation distance levels, surface properties of foulant and membrane
(Viet and Jang 2021)	Sigmoid	LM	pH, conductivity, DO, ORP, TOC, NH_4-N, TN, PO_4-P, TP
(Taheri et al. 2021)	Linear, sigmoid	LM	OLR, effluent pH, MLSS, MLVSS
(Irfan et al. 2022)	Linear, sigmoid	LM	Disk rotational speed, membrane-to-disk gap, OLR
(Waqas et al. 2022)	Linear, sigmoid	LM	Disk rotational speed, HRT, SRT
(Im et al. 2022)	Sigmoid	LM	DOC, TN, TP, Ca^{2+}, Na^{+}, Cl^{-}, proteins, polysaccharides, UV_{254}
(Kovacs et al. 2022)	Sigmoid	BFGS	Flow, permeate temperature, tank level, MLSS, cumulative flow, cycles since recovery cleaning
(Cámara et al. 2023)	n.d	BR	Filtration and backwash time, filtration and backwash flux
(Cifuentes-Cabezas et al. 2023)	Linear, sigmoid, exponential	LM	TMP, CFV
(Niu et al. 2023)	Linear, sigmoid	BP	HRT, influent COD, flux, biogas sparging rate, OLR, VSS, SMP, EPS, membrane pore size, membrane packing density
(Wang and Li 2024)	Rectified linear unit, sigmoid, hyperbolic tangent	BP	OLR, TSS, EPS, temperature, flux

[a]BFGS = Broyden-Fletcher-Goldfarb-Shanno

BP = back propagation

BR = Bayesian regularization

GDM = gradient descent with momentum

LM = Levenberg–Marquardt

RBP = resilient back-propagation

SCG = scaled conjugate gradient

[b]COD = chemical oxygen demand

CFV = cross flow velocity

DO = dissolved oxygen

DOC = dissolved organic carbon

EPS = extracellular polymeric substances

HRT = hydraulic retention time

MLSS = mixed liquid suspended solids

MLVSS = mixed liquid volatile suspended solids

NH_4-N = ammonium

OLR = organic loading rate

ORP = redox potential

PO_4-P = phosphate

SMP = soluble microbial products

SRT = sludge retention time

TMP = transmembrane pressure

TN = total nitrogen

TOC = total organic carbon

TP = total phosphorus

TSS = total suspended solids

VSS = volatile suspended solids

proven to be highly effective for training MLPs in complex prediction tasks like membrane fouling, outperforming other backpropagation training algorithms (Hosseinzadeh et al. 2020).

Selecting appropriate input and output variables is crucial for achieving accurate MLP predictions. Common output variables in membrane fouling prediction include TMP, membrane permeability, and permeate flux. Some studies have also explored more detailed fouling characteristics, including fouling thickness, porosity, roughness, and density (Im et al. 2022), and the interfacial energy between foulants and the membrane surface (Chen et al. 2020). These advanced outputs suggest that AI models can potentially provide insights similar to those conventionally obtained through sophisticated and time-consuming techniques like microscopic analysis of the fouling layer. However, more studies are necessary to assess the feasibility and potential of this application. For input variables, it is essential to align them with factors affecting membrane fouling (Sect. "Factors affecting membrane fouling"), including parameters describing membrane properties, feed characteristics, and operating conditions. Key input variables in MLP-based membrane fouling predictions include OLR, SMP, EPS, filtration/backwash cycles, pH, and conductivity (Cámara et al. 2023; Hosseinzadeh et al. 2020; Niu et al. 2023; Taheri et al. 2021; Viet and Jang 2021; Wang and Li 2024).

The performance of AI models relies on the quantity and quality of data. A sufficiently large and diverse dataset is necessary to cover various operating scenarios, ensuring that the model can generalize well. Additionally, the quality of the dataset is critical, as incomplete or biased data can significantly reduce the accuracy of AI models (Bahramian et al. 2023; Gong et al. 2023).

Different neural network models

While the MLP remains the most extensively studied model for fouling prediction in membrane-based wastewater treatment, various other configurations of ANNs have also been successfully applied. For instance, Chen et al. (2020) explored a generalized regression neural network (GRNN), a type of ANN based on radial basis functions (RBF), to forecast interfacial energy related to membrane fouling. However, they observed that the MLP model offered better predictive performance. Ren et al. (2023) proposed an innovative method built on a cascade neural network (CAS-NN) to characterize fouling in a real MBR. Their model provided accurate predictions of membrane permeability, integrity, and lifespan. Additionally, Cámara et al. (2023), Kovacs et al. (2022), and Wang and Li (2024) investigated the application of long-short term memory (LSTM) networks, a category of recurrent neural network (RNN). While Kovacs et al. (2022) and Wang and Li (2024) reported that LSTM models were less accurate than MLPs, Cámara et al. (2023) achieved accurate fouling predictions using filtration times and flux as input variables. The varying accuracy of LSTM models compared to MLPs in these studies suggests that no single model is universally preferable. The performance of a model relies on the specific characteristics of the system being modeled, the selected input and output variables, and the available dataset. Therefore, case-specific tuning and optimization are essential for selecting the most effective model and enhancing its performance.

ANN models have also shown promise in supporting image classification techniques. Im et al. (2021) proposed an innovative approach for real-time monitoring of fouling in a FO process by integrating optical coherence tomography (OCT) with a convolutional neural network (CNN), a branch of ANN specifically developed for working with grid-like data, including images. The OCT technique has emerged as a non-invasive method for monitoring membrane fouling (Fortunato et al. 2020; Huisman et al. 2024; Ranieri et al. 2024). Its integration with AI modeling, such as CNN techniques, can provide valuable insights for supporting advanced fouling control strategies.

Recent studies have also explored the implementation of an adaptive neuro-fuzzy inference system (ANFIS), a hybrid model that merges ANN with fuzzy logic, for membrane fouling modeling. These studies have shown that ANFIS can achieve better predictive performance than traditional ANNs (Hosseinzadeh et al. 2020; Taheri et al. 2021). In general, the hybrid modeling of wastewater treatment processes has shown enormous potential (Bagheri et al. 2016, 2015; Chen et al. 2022; Cheng et al. 2023; Heo et al. 2021; Schneider et al. 2022; Xie et al. 2024).

ANNs excel at capturing complex nonlinear relationships, making them highly suitable for predicting fouling in membrane-based wastewater treatment applications, as demonstrated by several studies. However, the choice between ANNs and other ML or conventional models depends on factors such as data availability, system complexity, and specific application requirements. Therefore, it is not possible to define a universally best model; instead, model evaluation and selection must be tailored to each specific application.

Benefits, limitations and future perspectives

AI modeling holds significant potential to revolutionize membrane-based wastewater treatment by enhancing real-time monitoring, predicting treatment efficiency, optimizing operating conditions, and improving fouling control. The integration of AI models, particularly ANNs, into fouling prediction for membrane-based technologies has seen considerable progress. AI models are highly suitable for simulating the complex dynamics of membrane fouling in wastewater treatment due to their proficiency in identifying non-linear dependencies and patterns in data. These predictions offer valuable insights that enable proactive fouling mitigation through advanced control strategies. Furthermore, integrating AI modeling with real-time monitoring and data analytics allows operators to make swift and informed decisions, thereby minimizing plant downtime and optimizing treatment process performance. Specifically, AI models can accurately predict the evolution of membrane fouling, enabling operators to respond quickly to emerging issues and anticipate necessary interventions before critical conditions arise, thus preventing potential system failures. This integration also facilitates predictive maintenance, optimizing overall system performance, reducing plant downtime, and lowering maintenance costs while maintaining high treatment efficiency. Accurate membrane fouling predictions contribute to optimizing maintenance procedures, tailoring cleaning protocols to specific needs, minimizing chemical usage, extending membrane lifespan, and reducing operating costs (Fig. 4). Specifically, AI models can optimize chemical usage in cleaning procedures by predicting the necessary dosages and cleaning frequencies, thereby reducing costs and minimizing negative environmental impacts. As a tool for advancing membrane fouling control, AI modeling may also improve the energy efficiency of membrane-based wastewater treatment technologies, leading to potential economic and environmental advantages. Overall, implementing AI modeling into membrane-based wastewater treatment systems is expected to deliver substantial progress in process efficiency, sustainability, and cost-effectiveness, leading to more advanced wastewater treatment solutions (Cairone et al. 2024b, 2024a).

Despite these promising benefits, several challenges remain. One significant hurdle is the need to include more representative factors affecting membrane fouling as input variables to develop more comprehensive models. Although existing models demonstrate high accuracy, their predictive power could be enhanced by incorporating a broader range of relevant variables. This inclusion would improve AI models' ability to capture additional relationships, nuances, and interactions between inputs and outputs. Few studies have employed a comprehensive set of input variables that fully consider all factors influencing membrane fouling, including membrane properties, feed characteristics, and operating parameters. For instance, few studies have included key foulants such as EPS, SMP, TEP, and BPC as input variables, despite their critical role in membrane fouling in wastewater treatment. Similarly, other crucial factors such as feed pH, operating temperature, and filtration/backwashing protocols have not been extensively considered as input variables. Incorporating these variables would allow AI models to account for a broader range of factors influencing membrane fouling, thus improving predictive performance. Future research could address this limitation, but careful consideration is necessary when selecting variables, as too many variables may require handling larger datasets and increase computational complexity. Efforts should focus on integrating parameters that are easily measurable in real WWTPs to promote practical applications.

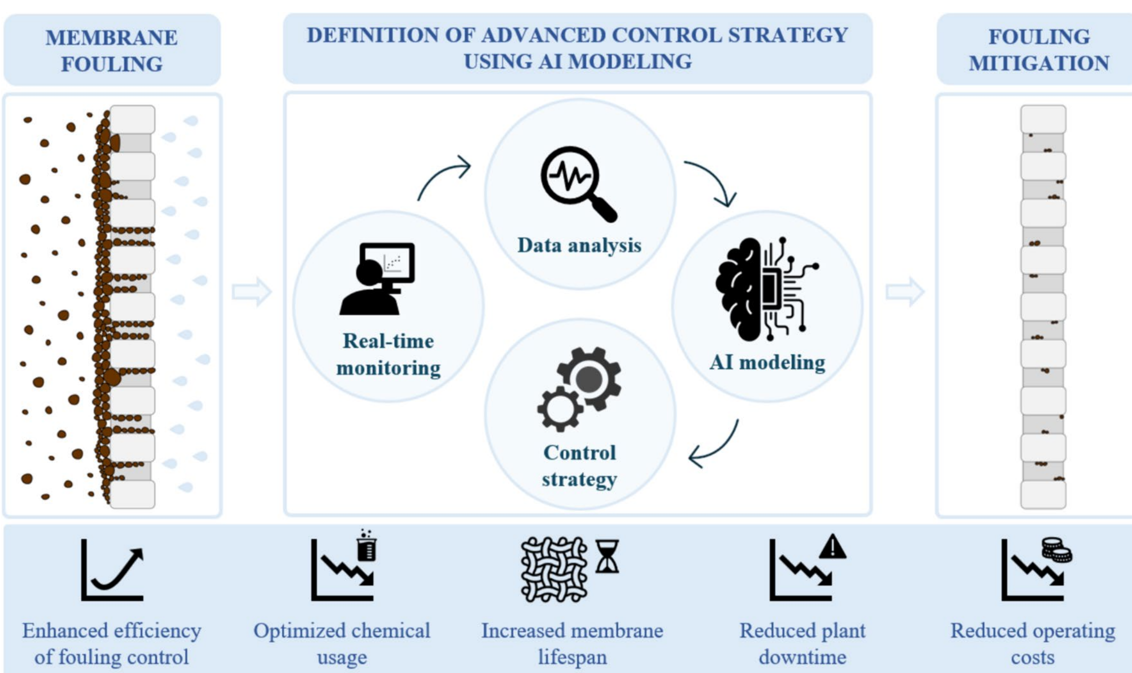

Fig. 4 Advanced AI-driven control of membrane fouling

Given that conventional ANNs function as “black box” models, providing no insights into the relationships between variables, integrating explainable AI techniques represents a promising avenue for exploration. Explainable AI involves several steps: problem definition, data processing, model training, choosing suitable explainability techniques (e.g., local interpretable model-agnostic explanations, LIME, and Shapley additive explanations, SHAP), generation and evaluation of explanations, incorporation and presentation of these explanations, and collecting feedback from users for further refinement (Barredo Arrieta et al. 2020; Hosain et al. 2024; Slack et al. 2023). This approach may enhance the explainability and interpretability of AI models, revealing how specific results are achieved and providing valuable insights into membrane fouling.

Furthermore, considering recent findings, there is a strong need for a deeper exploration of hybrid modeling. Hybrid models combine different approaches, including both AI and mathematical models, synergizing their strengths for more accurate predictions. Developing hybrid models for membrane-based wastewater treatment is highly context-dependent, influenced by factors such as data availability, system complexity, and specific application requirements. The optimal approach may vary based on these factors. Additionally, research on hybrid modeling for membrane fouling is currently in its preliminary stages, necessitating further investigation to establish best practices and refine methodologies. Additionally, as models become more accurate, it is crucial to develop software that can be easily implemented in real WWTPs to promote practical applications.

Currently, the application of AI modeling for predicting membrane fouling in full-scale WWTPs has not yet been widely explored. A search in the Scopus database utilizing the TITLE-ABS-KEY query string «(“artificial intelligence” OR “machine learning” OR “deep learning” OR “artificial neural network”) AND “membrane fouling” AND (“wastewater treatment” OR “waste water treatment”) AND (“full scale” OR “full-scale” OR “real scale” OR “real-scale” OR “real plant” OR “full plant” OR “real wastewater treatment plant” OR “real WWTP” OR “full WWTP”)» reveals only two research studies (Kovacs et al. 2022; Nam et al. 2021) implementing AI modeling for this purpose. These studies highlight the opportunities that AI modeling presents as a tool to support operators in mitigating fouling. Nam et al. (2021) implemented a dual-objective optimization process to define optimal operational conditions 24 h in advance, including aeration intensities and filtration cycle durations, based on AI model predictions. This strategy resulted in up to 12% energy savings and 26% fouling mitigation while maintaining high effluent quality. Kovacs et al. (2022) confirmed the effectiveness of AI models to accurately predict membrane fouling in real WWTPs, highlighting their potential to support decision-making for fouling mitigation. However, further studies are required to explore new approaches and assess the feasibility of implementing AI modeling in full-scale WWTPs. Addressing the limitations discussed in this section could advance the AI modeling field toward more effective and practical implementation in real membrane-based wastewater treatment applications.

Conclusions

AI modeling holds significant promise for enhancing fouling mitigation strategies in membrane-based wastewater treatment technologies. Among various AI models, ANNs are the most extensively investigated for predicting membrane fouling. ANNs can contribute to the creation of innovative control systems that can optimize treatment processes and implement advanced fouling mitigation strategies, potentially revolutionizing membrane-based wastewater treatment technologies. However, bridging the gap between theoretical advancements and practical applications remains a challenge. To facilitate practical implementation, strategies such as incorporating representative and easily measurable parameters from real WWTPs as input variables for the models, adopting hybrid models, integrating explainable AI techniques, and developing user-friendly software are essential. Viewing these ongoing challenges as opportunities for improvement can motivate the scientific community to make further strides toward achieving more effective and sustainable wastewater treatment solutions.

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Declarations

Conflict of interest The authors state that there is no conflict of interest.

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