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# Artificial Neural Networks in Membrane Bioreactors: A Comprehensive Review—Overcoming Challenges and Future Perspectives

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**Abstract:** Among different biological methods used for advanced wastewater treatment, membrane bioreactors have demonstrated superior efficiency due to their hybrid nature, combining biological and physical processes. However, their efficient operation and control remain challenging due to their complexity. This comprehensive review summarizes the potential of artificial neural networks (ANNs) to monitor, simulate, optimize, and control these systems. ANNs show a unique ability to reveal and simulate complex relationships of dynamic systems such as MBRs, allowing for process optimization and fault detection. This early warning system leads to increased reliability and performance. Integrating ANNs with advanced algorithms and implementing Internet of Things (IoT) devices and new-generation sensors has the potential to transform the advanced wastewater treatment landscape towards the development of smart, self-adaptive systems. Nevertheless, several challenges must be addressed, including the need for high-quality and large-quantity data, human resource training, and integration into existing control system facilities. Since the demand for advanced water treatment and water reuse will continue to expand, proper implementation of ANNs, combined with other AI tools, is an exciting strategy toward the development of integrated and efficient advanced water treatment schemes.

**Keywords:** membrane bioreactors (MBRs); artificial neural networks (ANNs); wastewater treatment; monitoring; modeling; optimization; control; deep learning; Internet of Things (IoT)



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## 1. Introduction

Wastewater management, treatment, and reuse have become crucial processes for the protection of the environment and public health. Rapid industrialization, along with urbanization, has consistently increased both the volume and complexity of produced wastewater [1,2]. This is because wastewater is now composed of a variety of synthetic xenobiotic substances. Therefore, there is an emerging need for the development of advanced wastewater treatment technologies that will facilitate water purification and reuse [1,2]. Among these technologies, membrane bioreactors (MBRs) present a very interesting strategy for advanced wastewater treatment, as they incorporate the “green” aspect of biological degradation with the advantages of membrane separation [3–5]. They demonstrate high performance and produce high-quality effluent suitable for various uses [4,5].

In contrast to conventional aeration systems such as activated sludge, MBRs demonstrate several advantages. These include higher efficiency and effluent quality, improved sludge retention time, lower sludge production, and higher nutrient removal. Moreover, MBRs can handle higher organic loads, increasing the possibility for use in various industrial applications in addition to the treatment of domestic wastewater [3–6].

However, the operation and maintenance of MBRs present several challenges that prevent their widespread industrial applications. These include issues related to membrane fouling, high energy consumption, and difficulties in maintaining process stability. Therefore, efficient optimization and control strategies must be developed to overcome these challenges [6–9]. Moreover, these strategies must have the capability to adapt to different operating conditions and influent fluctuations, a common phenomenon in wastewater engineering problems. Like any optimization and control problem, the efficient development of solutions requires a thorough understanding of the system, with emphasis on the interactions between the physical, chemical, and biochemical processes [8,9].

In recent decades, artificial intelligence, and in particular artificial neural networks (ANN), have demonstrated their ability to simulate, optimize, and control very complex systems in different fields, including several applications in environmental engineering and wastewater treatment [10,11]. Indeed, ANNs can understand linear or nonlinear correlations between input and output variables, and they are also capable of learning from past data [10,11]. Therefore, they are strong candidates for the development of strategies for the prediction and control of an MBR system [12,13]. The aim of this critical review is to provide a comprehensive overview of ANN applications in MBR systems, such as the optimization of efficiency and energy consumption, the prediction of membrane fouling, and the detection of faults or malfunctions. Moreover, the limitations and advantages of neural network applications in MBRs are discussed, and directions for future research are proposed.

## 2. Fundamentals of Membrane Bioreactors (MBR)

### *2.1. Basic Principles of MBR Systems and Types of Configurations*

MBRs are an integrated advanced wastewater treatment technology that combines organic matter and nutrient biodegradation with separation provided by using a membrane module. In these systems, the microorganisms are capable of degrading organic matter and nutrients similar to the conventional systems of activated sludge, while the membrane acts as a physical barrier for both substances—solids and biomass—allowing the discharge of a purified, high-quality effluent. The main MBRs components are the aeration tank, where biodegradation occurs, and the filtration unit (either microfiltration or ultrafiltration) [7].

MBR systems are divided into two different groups: (i) submerged and (ii) side stream. In submerged systems, the membrane module is immersed inside the biological aeration reactor (tank), making this type of design more compact with a reduced footprint. The strategies usually applied to prevent membrane fouling include vacuum or gravity-driven filtration, with periodic backwashing and air scouring [3,7–9]. By contrast, in the side stream configuration, the membrane module is in a different tank and the mixed liquor is continuously circulated by a high-pressure external pump. Although a side stream setup allows greater flexibility regarding membrane cleaning and maintenance, higher crossflow velocities are required to control fouling [3,7,9].

Several operational parameters affect system efficiency, including organic and nutrient loading, hydraulic retention time (HRT), solids retention time (SRT), aeration, and membrane flux. HRT and SRT are vital for the system since they represent the residence time of the wastewater and biomass in the system and, as expected, significantly affect biomass growth [7–9]. This growth is also affected by the aeration intensity, which describes the dissolution of oxygen inside the reactor. It is worth noting that in most systems, the presence of oxygen serves a dual purpose: (i) promoting the growth of biomass and (ii) preventing membrane fouling due to the scouring of the membrane's surface [3,7]. Finally, membrane flux (i.e., the volumetric flow rate per unit of membrane area) is a vital parameter that estimates the system's capacity and impacts both energy consumption and membrane fouling.

### *2.2. Challenges in MBR Operation and Maintenance*

As already stated, despite their superior efficiency, some problems still prevent the widespread implementation of MBR systems in the industrial sector. The most important problem is related to membrane fouling. Gradual membrane clogging leads to increased transmembrane pressure, reducing the flux and consequently requiring more frequent membrane cleaning or even replacement. Several factors contribute to membrane fouling, such as organic matter accumulation and organic precipitations. The latter, in addition to microbial products on the surface or within the membrane pores, can significantly decrease the flux [4–7]. Another problem, present in conventional aeration systems but more intensive due to the higher density of biomass in MBR systems, is the increased energy consumption related to aeration and the additional energy required from the use of high-pressure pumps [8,9]. In addition, like conventional wastewater treatment plants, MBRs must be controlled by efficient strategies to maintain process stability under variable influent characteristics and fluctuations to satisfy the strict legislative limits for the effluent.

## 3. Overview of Neural Networks

### *3.1. A Short Introduction to Artificial Neural Networks (ANN)*

Artificial neural networks (ANNs) represent a family of algorithms designed to emulate the functions of neurons in biological neural systems. The architecture of ANNs includes interconnected neurons (nodes) organized into distinct layers: the input layer for system input, the output layer for system output, and the hidden layer(s) [10–12]. The hidden layer, consisting of simple or extremely complex functions, serves as the heart of the system. Each node computes a weighted sum of its inputs, which is then processed through a simple or complex activation function to estimate the output. This process equips ANNs with the capability to correlate intricate relationships and interactions concerning input and output functions [11–14].

The applications of ANNs involve a learning process, wherein the system weights that represent these correlations are adjusted. This is achieved by optimizing the mean square error between the network's predictions and the actual measurements—known as targets [11–14].

### *3.2. Different Types of ANN Architectures*

Several ANN architectures have been proposed to deal with a variety of applications with special needs. Some well-known and common architectures include feedforward networks (FFN), recurrent networks (RN), radial basis function networks (RBF), and deep learning networks (DLN) (Table 1). Feedforward networks, including multilayer perceptron (MLP), are characterized by unidirectional information flow from the input layer to the output layer without implementing additional loops for feedback. By contrast, recurrent networks implement process feedback, providing them with more efficient management of temporal or sequential data [7,14–16]. Radial basis function networks are characterized by the use of radial basis functions as activation functions in the hidden layer. This type of network has the ability to provide a localized response and has demonstrated improved generalization performance in several applications [15–17]. Finally, deep learning networks, which consist of multiple hidden layers instead of just one, have become more popular in recent years due to the vast increase in computational power. They have shown superior performance in various tasks such as natural language processing and image recognition, with several applications in medical research [9–11,15,16].

In addition, in recent years, novel approaches such as implicit neural representation methods have garnered attention. In contrast to conventional NNs, these methods are continuous and differentiable, and thus are capable of handling diverse signals [18,19]. These algorithms can offer a more concise representation while enabling smoother parameter-based data manipulation [18,19]. In the realm of deep learning, new algorithms such as the transformer neural network have attracted the attention of researchers due to their ability to handle long-range dependencies [20]. These models comprise an encoder–decoder architecture based on attention layers, allowing the concentration to be focused on specific data or elements using contextual information [20–22].

**Table 1.** Artificial neural network architectures for MBRs.

| Neural Network Architecture | Implementation into MBR Systems | Strengths | Limitations | Ref. |
|---|---|---|---|---|
| Feedforward neural networks (FNNs) | Suitable for modeling static relationships between inputs and outputs | Easy implementation and training, widely used in MBR systems, good for revealing and simulating non-linear relationships | Unable to capture temporal dependencies in time series data | [11–14] |
| Recurrent neural networks (RNNs) | Capable of modeling dynamic relationships between inputs and outputs in time-series data | Can decrypt temporal dependencies, useful for the prediction of membrane fouling and aeration control | More complex than FNNs. Usually longer training time and more training data are needed | [12–14] |
| Implicit neural representation methods | Can implicitly represent complex geometries and functions, required for modeling complex structures and processes such as MBR systems | Better generalization and compact representations | Limited interpretability. Training and tuning are challenging | [18,19] |
| Transformer architectures | Able to capture long-range dependencies and patterns in sequential data and spatially distributed data | Parallelizable architecture, useful for large-scale MBR systems and the process of big data | Significant computational resources are required. May need extensive hyperparameter tuning | [20–22] |
| Convolutional neural networks (CNNs) | Can process spatially structured data, such as images or spatially distributed sensor data | Can identify/simulate local spatial dependencies, useful for fouling detection and analysis | Spatial data are rarely available. Limited applications in MBRs | [11–13] |
| Deep Learning, (deep feedforward networks, deep RNN) | Capable of modeling complex, high-dimensional relationships between input and output | Can capture higher-order interactions. Improved accuracy and performance | Large dataset needed, high computational cost, and longer training time. | [12–14] |

### *3.3. Supervised and Unsupervised Learning*

Regarding their training, ANNs can be divided into two distinct categories: (i) supervised and (ii) unsupervised algorithms. The selection is sometimes dictated by data availability combined with the specific nature of the application. Supervised learning involves the use of a set of training data consisting of input–output pairs, where the output corresponds to the desired target value for each input [10–15,17]. The optimization of the ANN refers to the iterative adjustment of network weights to minimize the observed difference between predicted and target data. Several techniques are used, such as gradient descent, backpropagation, and others [16]. In contrast, unsupervised ANNs do not use any labeled training data. The ANN attempts to uncover correlations and patterns from the input without explicit supervision. Some common unsupervised algorithms include clustering, dimensionality reduction, and techniques such as self-organizing maps and principal component analysis (PCA). Unsupervised algorithms have demonstrated their ability in different areas, including engineering, environmental science, and even finance [10–14,17].

Currently, different types of ANNs have been successfully applied to a wide range of problems in fields such as engineering, medicine, finance, and environmental science, mainly due to their ability to simulate complicated systems and generalize even from limited or restricted data while adapting to different conditions [11,12]. Environmental science, due to the complexity of the biotic and abiotic systems involved, has used ANNs to monitor and predict water quality and quantity, to forecast pollution, and to estimate ecological impact assessments [10,11]. A concise comparison of ANNs with other AI techniques is summarized in Table 2.

**Table 2.** Comparison of ANNs with other AI technologies in MBR implementation.

| AI Technique | Advantages | Disadvantages | Ref. |
|---|---|---|---|
| Neural networks | Suitable to reveal and model complex non-linear relationships; has demonstrated superior efficiency for various MBR applications (fouling prediction, control, fault detection) | A significant amount of representative data for training is required. Sensitive to noise and overfitting | [10–12] |
| Fuzzy logic | Decision-making via a more human-like approach. Can handle uncertainly and inaccurate data | Expert knowledge is required for the design of fuzzy rules. Possibly low performance for very complex systems | [10–13] |
| Genetic algorithms | Well-known and high-performance optimization. Applicability to multi-objective optimization problems. Can adapt to dynamic conditions | Usually, a large number of iterations is required, slow convergence, and high computational cost. | [11,13,14] |
| Model predictive control (MPC) | Suitable to handle multivariable systems with several constraints, and estimated optimal solutions for control. | A mathematical model of the system is required. Usually has high computational cost. Maybe not be efficient for dynamic systems. | [12–14] |

### *3.4. Applications of Neural Networks in MBR Wastewater Treatment*

(i) Neural network-based predictive modeling—Predicting membrane fouling

One of the dominant problems prohibiting MBR implementation is membrane fouling [23–25]. Therefore, it is essential to have an accurate prediction of fouling to allow proactive fouling control and, consequently, optimal operation of advanced wastewater systems [26–28]. It is not surprising, then, that several studies have investigated the use of ANNs to reveal and simulate the complex correlations among operational conditions, biomass, and fouling indicators, such as transmembrane pressure, flux, and fouling rate [23–30]. Table 3 summarizes the most important studies related to the application of ANNs for the prediction of membrane fouling.

For example, according to the work of Chen et al. [24], RBF ANNs demonstrated higher efficiency than the advanced XDLVO approach to quantify the interfacial energy of a randomly rough membrane surface in an MBR system. In another interesting study [20], the authors used a multi-layer perceptron and radial basis function artificial neural network (MLPANN and RBFANN) with weights optimized by a genetic algorithm to simulate transmembrane pressure (TMP) and membrane permeability (Perm). Both MLPANN and RBFANN models showed superior accuracy, while the GA-optimized ANN exhibited significantly improved results compared to a network used in the conventional trial and error calibration.

Hamedi et al. [28] examined the simulation of membrane fouling resistance through the application of different algorithms, including artificial neural networks (ANNs), gene expression programming (GEP), and the least square support vector machine (LSSVM), while the particle swarm optimization (PSO) algorithm was used to enhance the performance. According to the researchers, the combination of ANN–PSO demonstrated higher efficiency than the ANN–MLP approach. However, the use of LSSVM outperformed the other examined models in terms of MSE and $R^2$. In another study [29], a backpropagation feedforward network was used to estimate the COD removal and the TMP of an MBR as output, while the MLSS, hydraulic time, and time served as the inputs. The optimized network consisted of 17 hidden neurons, while according to the sensitivity analysis using the cosine amplitude method, all three inputs have an effect on both COD removal and TMP.

**Table 3.** ANN applications for the prediction of membrane fouling.

| Scope | Model Used | Input | Output | Results | Ref. |
|---|---|---|---|---|---|
| Efficient quantification of interfacial energy related to membrane fouling | Radial basis function (RBF) artificial neural network | Three probe liquid contact angles, zeta potential of sludge foulants, and separation distance | Interfacial energy | RBF ANN demonstrated high regression coefficient and accuracy with a lower computational cost that XDLVO approach | [24] |
| Prediction of membrane fouling in an anoxic–aerobic MBR | Back propagation artificial neural network | pH, alkalinity, MLSS, COD, (TN), ($NH_4$-N), ($NO_3$-N), and TP | TMP | Satisfactory performance. From all variables examined the use of $TN_{in}$–$TN_{eff}$, $TP_{in}$–$TP_{an}$, and $Nitrate_{mbr}$–$Nitrate_{eff}$ exhibited high correlation | [25] |
| Evaluation and prediction of membrane fouling in a submerged MBR | Multi-layer perceptron and radial basis function artificial neural networks (MLPANN and RBFANN) combined with genetic algorithms | Time, TSS, CODin, SRT, MLSS | TMP and membrane permeability | LPANN and RBFANN showed superior efficiency towards the simulation of TMP and permeability The GA-optimized ANN increased the ANN accuracy | [26] |
| Prediction of membrane fouling resistance in MBRs. | Artificial neural network (ANN), gene expression programming (GEP), and least square support vector machine (LSSVM) | MLSS, TMP, permeate flux, and temperature | filtration resistance (Rt) | LSSVM demonstrated higher performance. The transmembrane pressure and permeate flux were the most important inputs affecting the membrane fouling resistance. | [28] |
| Simulation of the membrane fouling under sub-critical flux conditions | Back propagation artificial neural network optimized by genetic algorithms | Q, aeration ratio A/O, concentration of EPSS, concentration of EPS, initial TMP, and operating time | TMP | ANN performance was not as stable as that of the mathematical model; however, it had better accuracy under intermittent aeration conditions | [30] |

In another study [30], the researchers compared a mathematical and ANN model for the simulation of membrane fouling under sub-critical flux conditions. According to the results, although the stability of the mathematical model was better, the ANN showed higher accuracy under intermittent aerated conditions.

Indeed, supervised ANN training with historical data allows the algorithms to predict the onset of fouling and to provide valuable insights regarding the factors that contribute to membrane fouling [25–28]. Based on these results, operators have the opportunity to (i) adjust the operating conditions and (ii) apply preventative measures or design a cleaning strategy [23–30].

(ii) Estimating Effluent Quality Parameters

Since water demand is always increasing and the reuse of wastewater has become a necessity, legislation regarding wastewater discharge has become stricter. Today, wastewater treatment plants have an obligation to monitor several parameters—water quality indicators such as chemical oxygen demand (COD), biochemical oxygen demand (BOD), total nitrogen (TN), and total phosphorus (TP), to mention a few [31–34]. The application of neural networks to simulate/predict these parameters in the effluent quality of MBR systems has shown superior efficiency based on system inputs such as influent physicochemical characteristics, operating conditions, and environmental factors [32–34].

The study of Bagheri et al. [32] applied a hybrid multilayer perceptron and radial basis function artificial neural network–genetic algorithm (MLPANN-GA and RBFANN-GA) for the prediction of BOD, COD, TN, and TP in a submerged membrane bioreactor, while influent BOD, influent COD, influent TN, or influent TP, sludge retention time (SRT), mixed liquor suspended solids, membrane permeability, and transmembrane pressure were used as the inputs. Both MLPANN-GA and RBFANN-GA models demonstrated superior accuracy between predicted and experimental values, while it was evident that the use of GA significantly improved the accuracy.

Yacub et al. [33] used different machine-learning models to predict the removal of nutrients such as ammonium (NH4), total phosphorus (TP), and total nitrogen (TN). The authors used operating conditions and influent characteristics as separate datasets and combined them for each target nutrient to assess the efficiency of the different models. The accuracy was higher for the combination of operating parameters with influent characteristics, while the extreme gradient boosting model (XGBoost) demonstrated higher performance than the other machine-learning techniques examined.

In another study [34], Abba et al. examined the efficiency of an ANN and multilinear regression analysis (MLR) model to predict the effluent COD of the Nicosia wastewater treatment plant. Inlet COD, BOD, pH, conductivity, total nitrogen (T-N), and total phosphates were used as the inputs. According to the authors, the use of an ANN resulted in significantly higher accuracy and performance compared to the MLR model.

In addition, using real-time monitoring, ANN algorithms can facilitate adaptive control strategies to maintain the operation of the system in a steady state in an efficient manner and to minimize the risk of regulatory violations [32,33].

(iii) Neural-network-based control strategies

As already discussed, aeration is one of the more vital operating factors in MBRs since it influences (i) the dissolution of oxygen inside the wastewater and (ii) the scouring of membranes [35–40]. Therefore, it significantly affects both performance in terms of pollutant removal and energy consumption and membrane fouling. From this perspective, ANNs have been applied for the development of different adaptive control strategies that use a new generation of sensors and real-time measurements of dissolved oxygen, mixed liquor suspended solids (MLSS), and membrane fouling indicators such as transmembrane pressure, to adjust and optimize aeration intensity [35–40]. Additionally, ANNs have the ability to design new strategies for membrane cleaning using different approaches such as back washing or chemical cleaning, taking into account the predicted fouling according to the network and the cleaning frequency balanced with energy consumption and membrane lifetime [30,32–34].

Preventing eutrophication of aquatic systems largely relies on the limitation of nutrient inputs; therefore, their effective removal from MBRs is a significant issue [32,33]. Some interesting ANN applications refer to the use of algorithms to model the nonlinear and dynamic systems of biological nutrient removal processes, such as nitrification, denitrification, and phosphorus uptake [33]. In this application, the algorithms can be applied to hybrid control strategies to further optimize operating parameters such as SRT, HRT, aeration, etc., towards the high removal rate of nutrients under different influent characteristics and loads [32,33]. Therefore, using these control strategies, the MBR system will be capable of maintaining high performance regarding the removal of nutrients while at the same time keeping low energy consumption and low chemical usage.

Algoufily et al. [35] designed a prediction tool in Matlab/Simulink that is able to calculate the membrane total resistance based on deterministic and stochastic models. The tool was able to predict future TMP cycles based on older TMP performance via an artificial neural network algorithm. The ANN implementation was successfully used as a controller to maintain temperature and mixed liquor suspended solids (MLSS) around their desired setpoints. Alnaizy et al. [36] used an ANN model for advanced neuro-model predictive control (NN-MPC) of an MBR system. The examined control algorithm showed excellent servo response characteristics in tracking flux changes while subjected to variable constraints (vacuum-to-backwash time ratio). The researchers concluded that NN-MPC is a feasible strategy for backwashing via NN-MPC.

Chen et al. [37] optimized the energy efficiency of the Ulu Pandan MBR plant using an ANN. The volume of membrane scouring aeration, the volume of bioprocess aeration, the volume of mixed liquor transferred into the MBR system, and the volume of treated water produced were used as inputs, while the ANN adequately predicted the energy consumption per unit permeate product water (kW-hr/$m^3$). In another study, Wahab et al. [40] used different artificial neural networks (FFNN, RBFNN, and nonlinear autoregressive exogenous neural network—NARXNN) to model TMP and flux of a submerged membrane bioreactor (SMBR) with hollow fiber. According to the results, all examined models showed satisfactory results; however, NARXNN and RBFNN demonstrated the highest accuracy (>90%), although the latter is characterized by a simpler structure. The implementation of RBFNN presented the highest closed-loop performance compared with other controllers and fast performance in the rejection of disturbances.

(iv) Neural Network-Based Fault Detection and Diagnosis

Like most advanced wastewater treatment plants, MBRs are characterized by a complex nature and are therefore subject to faults and disturbances. More analytically, they are prone to equipment failures and process upsets while the influent composition can dramatically change over time [41–44]. This variability can negatively affect system performance and stability and increase the times that the system is shut down, increasing the relative cost. With these considerations in mind, ANNs can be implemented for diagnosis and early fault detection of the equipment and operation of the system. This application involves learning the relationships that dictate the normal operation of the system and identifying deviations from this behavior as potential anomalies [42–44]. Using real-time monitoring of inputs and outputs such as flow rate, aeration intensity, and effluent quality characteristics, ANN algorithms have the ability to simulate, predict, and provide early warning signals for process disturbances or equipment malfunctions [41–44]. Early warning is vital, as it will allow operators to take action and minimize or even avoid the predicted problems [43,44].

Zhao et al. [43] implemented the Bandelet neural network, which consists of a combination of the Bandelet function, as the activation function, with neural networks for the prediction of membrane flux, and the flux recovery rate for making proper decisions regarding membrane cleaning strategies. In addition, the researchers integrated a modified Bat algorithm to enhance the optimization of the Bandelet neural network. The proposed combination exhibited higher performance than other state-of-the-art models that were examined, while according to the presented results, the appropriate cleaning period was selected from the combined algorithm.

Shi et al. [44] proposed a membrane fault diagnosis method that combines convolutional neural network (ECA-CNN) and attention mechanisms. The proposed addition of a batch normalization (BN) layer into the CNN network accelerated network convergence and improved the learning rate and diagnosis efficiency. Compared with other CNN models, the combined model improves the diagnostic accuracy and decreases overfitting issues, while the proposed strategy reduces the model complexity and improves the network's noise resistance.

Given the complexity of these systems, identifying each malfunction to design countermeasures is not an easy task, even for well-trained operators and engineers. ANNs could take on the role of fault diagnosis, knowing the patterns and behaviors of different components or conditions of the systems such as membrane fouling, aeration failure, or low nutrient concentration [45,46]. Through a comparison of the learned data with real-time measurements, ANN diagnosis algorithms can isolate the problem, providing valuable information for troubleshooting and maintenance of the system [45,46].

Figure 1 summarizes the different approaches toward the integration of ANNs into MBR systems.

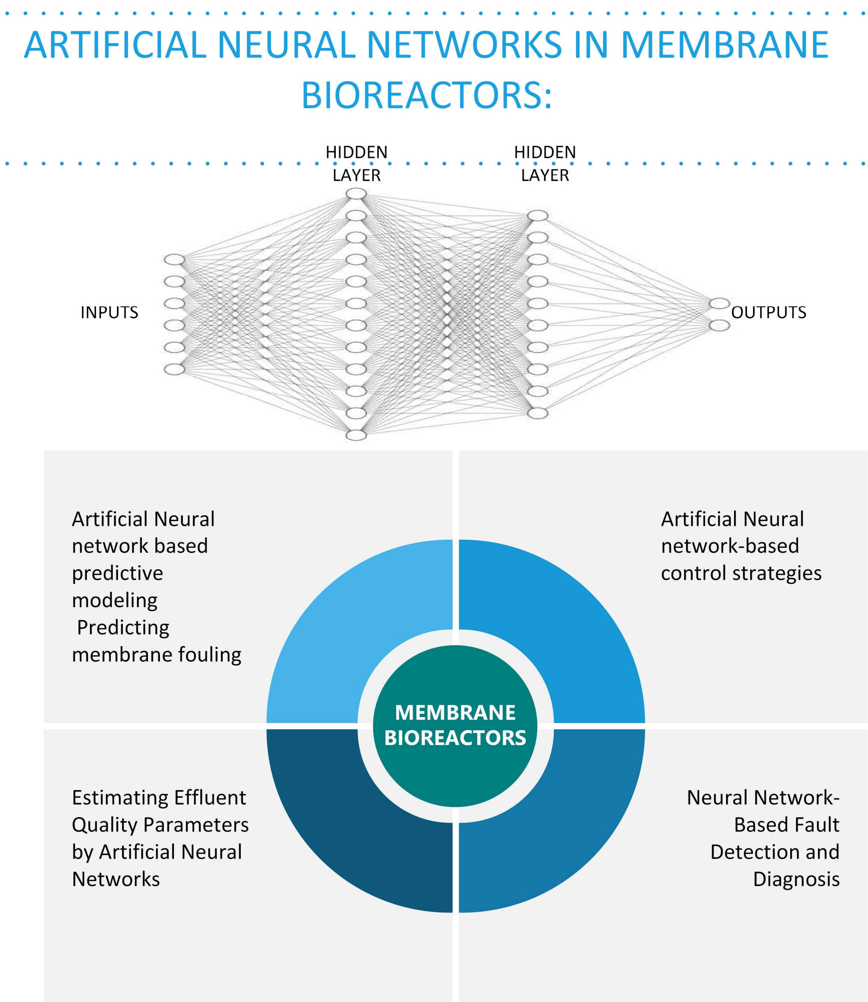


**Figure 1.** ANN implementation in MBR systems.

*3.5. Integration of Neural Networks with Other Advanced Techniques*

(i) Hybrid modeling and control approaches

One interesting strategy to enhance the accuracy and robustness of ANNs is to combine them with other well-established advanced technologies, such as genetic algorithms, fuzzy logic systems, or even model predictive control. For instance, hybrid models that integrate fuzzy logic with artificial neural networks can efficiently decipher the non-linear dynamics governing MBRs, while also incorporating expert knowledge and qualitative system information [47]. Genetic algorithms are well-established models often used for optimizing the architecture of ANNs and for tailoring control parameters in the design of effective control algorithms [26]. Integrating ANN with MPC frameworks will allow for the prediction and control of MBR systems over a longer timeframe, taking into consideration the various constraints and uncertainties characterizing the system in question [48].

(ii) Exploitation of Deep Learning

Deep learning, a field of ANN involving multiple hidden layers, has already demonstrated superior efficiency in various applications, including image recognition and natural language processing. Implementing deep-learning algorithms such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs) could enhance modeling accuracy and allow for the design of more robust control systems [43,49]. These systems have the capability to capture higher-order interactions and temporal dependencies between inputs and outputs. Future research must focus on the exploitation of deep-learning algorithms and the challenges obstructing their implementation, such as the requirement for large datasets, computational complexity, and the interpretability of algorithms and results [43,49].

### *3.6. Case Studies of Neural Network Implementation in MBR Systems*

In this section, a selection of representative case studies from the aforementioned categories is briefly discussed to better illustrate the diverse applications of ANN in MBR systems.

(i) Case study 1: Modeling of transmembrane pressure

In their compelling work, Schmitt et al. [24] developed an artificial neural network-based model for predicting membrane fouling in a pilot-scale anoxic–aerobic membrane bioreactor (AO-MBR). The model's output was the transmembrane pressure (TMP), commonly used as a membrane fouling indicator, with pH, alkalinity (Alk), MLSS, COD, total nitrogen (TN), ammoniacal nitrogen ($NH_4$-N), nitrate ($NO_3$-N), and total phosphorus (TP) serving as input parameters for the algorithm. To identify the most relevant input parameters for predicting the evolution of the transmembrane pressure, the researchers assembled several groups of these parameters and performed various training procedures under random conditions of the ANN weights. Interestingly, according to the results, some frequently used parameters such as MLSS, COD, pH, and DO exhibited a relatively low correlation ($R^2$ 0.169–0.70) with transmembrane pressure, while the use of $TN_{in}$–$TN_{eff}$, $TP_{in}$–$TP_{an}$, and $Nitrate_{mbr}$–$Nitrate_{eff}$ demonstrated a significantly higher correlation ($R^2 = 0.85$). The authors emphasized the significance of training data, proposing the gathering of data from different operating runs to prevent overfitting, and suggested that the selection of input parameters is crucial for advancing the training and optimization of the ANN architecture.

(ii) Case study 2: Nutrient Removal Optimization

In their interesting study, Giwa et al. [31] used back-propagation artificial neural networks (ANNs) to model results obtained from an electrically enhanced membrane bioreactor in which aluminum served as the anode and stainless steel functioned as the cathode. These electrodes were inserted into a submerged MBR that treated medium-strength wastewater. The removal of COD, $PO_4^{3-}$-P, and $NH_4^+$-N were chosen as output variables, with the examined system able to achieve removal rates exceeding 98%. Utilizing ANNs, the correlation of various input parameters, such as mixed liquor dissolved oxygen (DO), volatile suspended solids (MLVSS), pH, electrical conductivity, $COD_{in}$, $NH_4^+$-$N_{in}$, and $PO_4^{3-}$-$P_{in}$, was evaluated. After training and optimization, the applied ANN exhibited high correlation coefficients between experimental and predicted data ($r > 0.994$).

(iii) Case Study 3: Fault Detection and Diagnosis in an MBR System

To overcome the problem of membrane fouling and maintain efficient and steady operation in MBR systems, Wu et al. [42] proposed the implementation of a hybrid strategy. Fault identification based on different types of membrane fouling was performed using a robust deep neural network (RDNN). The authors combined the RDNN with a restricted Boltzmann machine (RBM) as a decision-making method to determine the proposed operations. The integration of these two algorithms with sensors demonstrated a strong correlation between experimental and modeled results. The authors concluded that the proposed strategy could serve as a warning method for other faults or malfunctions occurring in similar systems and that additional research is needed in this area.

## 4. Challenges and Limitations of ANN in MBR Applications

Perhaps the primary challenge hindering the application of various AI technologies, including ANNs, in advanced wastewater treatment systems like MBRs is their increased complexity. Therefore, implementing these systems requires specialized training and expertise from human resources, including operators and engineers. Additionally, all parts of the AI system—namely ANN design, training, and validation—require a deep understanding of the underlying principles and characteristics of the MBR system. Moreover, selecting the optimal network architecture, learning algorithms, and parameters is a complex task, often requiring the implementation of trial-and-error procedures or empirical tuning.

Another critical aspect is the quantity and quality of the obtained data. The accuracy of the algorithms relies greatly on this data, which should be representative and of high quality. This can be particularly challenging in real systems that often contain missing values, malfunctions, communication problems, and dynamic conditions. Moreover, for technologies such as deep learning, the quantity of data needed creates additional problems regarding data storage, processing, and management.

Since several MBR units are already in operation, integrating ANNs with existing units is of particular importance, although this can be technically challenging. This implementation requires specialized equipment (hardware) and software, in addition to modifications to the existing control infrastructure, which can be costly and time-consuming. Another important consideration is the acceptance of new technologies by the operators and engineers of the treatment plant. This acceptance may be limited due to increased system complexity, lack of human resource training, lack of transparency and interpretability of the used algorithms, and the risks associated with the implementation of these new technologies.

## 5. Future Directions

The following section summarizes perspectives derived from the current comprehensive review, as illustrated in Figure 2.

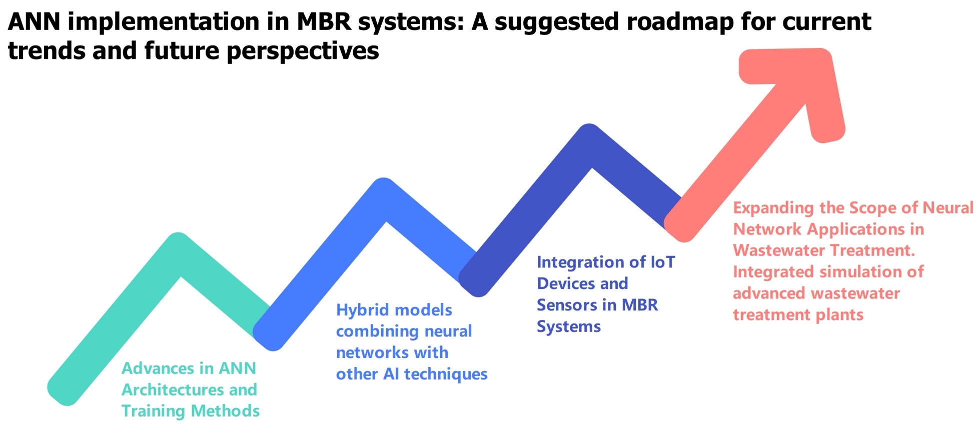


**Figure 2.** ANN implementation in MBR systems: a suggested roadmap for current trends and future perspectives.

(i) Hybrid models combining neural networks with other AI techniques

An intriguing strategy for future research involves developing hybrid models that can combine neural networks with other AI algorithms, including model predictive control, fuzzy logic, and genetic algorithms. These hybrid models have the potential to demonstrate higher accuracy, robustness, and improved interpretability than ANNs by combining the advantages of all the AI technologies used [13,42,46]. For instance, genetic algorithms can optimize the architecture of ANNs or control and operating parameters to achieve target goals such as avoiding membrane fouling or minimizing pollutants. Technologies like fuzzy logic can incorporate expert knowledge, while integration with MPC frameworks will allow MBRs to predict and control over a longer timeframe, taking into consideration different constraints and uncertainties in system dynamics.

(ii) Advances in ANN Architectures and Training Methods

As these algorithms continue to rapidly evolve, research towards the development of new architectures and training methods could potentially increase the performance of such applications. For instance, incorporating different training techniques such as adaptive learning rate algorithms, regularization methods, or unsupervised pre-training can improve generalization and ANNs convergence [10–14]. Moreover, exploiting new architectures, including deep neural networks and recurrent neural networks, will enhance the ability to reveal more complex interactions and temporal dependencies between inputs and outputs, leading to improved performance for optimization and control.

(iii) Integration of IoT Devices and Sensors in MBR Systems

Integrating Internet of Things (IoT) devices and using advanced, new-generation sensors in MBRs will enhance real-time monitoring through real data acquisition, enabling better control and allowing the full potential of ANNs or similar algorithms to be exploited. New-generation IoT devices can provide continuous, high-resolution measurements of many inputs and outputs, including flow rates, aeration, and influent and effluent quality. These parameters can be used for model training and real-time model updates.

Combining IoT with advanced algorithms such as ANNs will allow the development of innovative, smart, self-adaptive MBRs capable of autonomously controlling the process and optimizing their performance, despite the disturbances observed in advanced wastewater treatment systems.

(iv) Expanding the Scope of Neural Network Applications in Wastewater Treatment

ANNs can also be implemented in other parts of wastewater treatment plants, including activated sludge systems, sludge management, anaerobic digestion, and physicochemical processes such as advanced oxidation systems used as pre- or post-treatment polishing steps. Implementing ANNs for monitoring, modeling, and control will allow for achieving high efficiency and environmental compliance of combined systems. In fact, integrating ANNs across multiple stages of a wastewater treatment plant will lead to the development of an integrated (holistic) strategy for optimization that considers the interactions and trade-offs between different treatment stages and objectives, taking into account several operational constraints.

## 6. Conclusions

This mini review summarizes the use of ANNs as a tool for the monitoring, simulation, optimization, and control of membrane bioreactors (MBRs). ANNs represent an interesting strategy, with the capability to identify complex dynamic relationships between inputs and outputs in MBRs using different architectures such as feedforward, recurrent, radial basis function, and deep neural networks. ANNs appear to have significant potential to optimize treatment performance, reduce energy consumption, and extend membrane lifetimes. Other interesting applications of ANNs include early fault and malfunction detection, which can improve the reliability of MBRs.

For system monitoring, ANNs have already demonstrated their capability to predict key parameters such as membrane fouling, permeate flux decline, and effluent quality indicators, using both operating conditions and wastewater characteristics as inputs. Accurate monitoring can also lead to a better understanding of the fouling mechanism and proactive optimization of the operating parameters. In terms of simulation, ANNs have shown very promising results in simulating the complicated interactions governing nutrient removal, biomass growth, and membrane filtration. Additionally, hybrid ANN models with techniques like fuzzy logic have shown enhanced accuracy in modeling complex MBR systems. For process optimization, ANN algorithms allowed real-time adjustment of operating parameters such as solids retention time, hydraulic retention time, and aeration intensity, leading to lower energy consumption and membrane fouling while achieving high treatment efficiency. ANNs also facilitate the development of effective and alternative or combined strategies for membrane cleaning. Regarding system control, ANN algorithms have demonstrated interesting capabilities for system automation, adaptive aeration and permeate flux control, and membrane cleaning cycles under fluctuating conditions. ANNs have shown high potential for fault detection and diagnosis of equipment failure or process disturbances. In summary, ANNs are versatile tools that can significantly advance monitoring, simulation, optimization, and control across different aspects of MBR systems.

Therefore, incorporating ANNs into MBRs can significantly impact both the efficiency and sustainability of these systems. These benefits also have social, environmental, and economic implications in areas such as the protection of environmental quality and the achievement of sustainable development goals. Moreover, integrating neural networks with other advanced algorithms can lead to the development of more efficient and sophisticated systems. By exploiting technologies like deep learning and integrating IoT devices and sensors, the application of ANNs across different stages of complex wastewater treatment plants can push progress beyond the current state of the art and facilitate the development of new, smart, self-adaptive treatment solutions. However, despite their advantages, several limitations must be addressed. These include the requirement for high-quality and large quantities of data, the high complexity of these systems, the need for specialized training of human resources, and the challenges of integrating these technologies into existing systems, especially control systems.

As water demand continues to increase, the need for water purification and reuse will continue to expand in the coming decades. This underlines the growing importance of artificial intelligence and ANNs. Implementing these advanced tools and fostering interdisciplinary collaborations among engineers, researchers, practitioners, and policymakers is a promising start towards designing highly efficient systems for water purification and reuse with a low environmental and energy footprint.

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