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Research Paper

Artificial Intelligence Application in Membrane Processes and Prediction of Fouling for Better Resource Recovery

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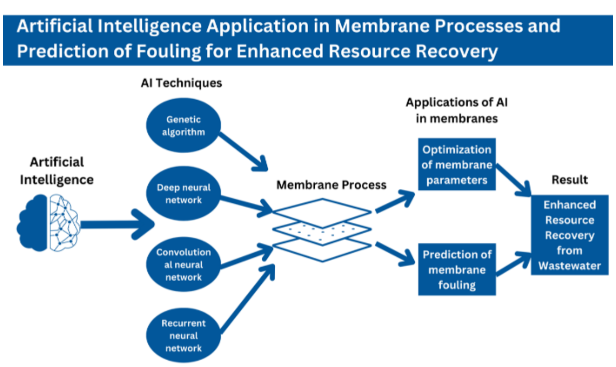
ABSTRACT

Water contamination is a global issue due to the emergence of new contaminants from solvents, personal care products, and pharmaceutical compounds. Membrane processes appear to be effective and promising in water treatment. While membrane processes can significantly reduce the levels of contaminants, problems continue to arise, such as fouling. The utilization of artificial intelligence (AI) to predict fouling and enhance the characteristics of membranes is currently receiving attention. Various artificial intelligence (AI) models can be employed to optimize the input parameters based on the output, which helps in predicting membrane performance and assessing its ability to reject contaminants effectively. The possibilities for improvement in membrane technologies and filtration processes using AI techniques are discussed in this paper. Membrane fouling causes significant issues during the operation due to the accumulation of impurities onto the membrane, which reduces the membrane's ability to function properly. AI algorithms can be used to predict permeate flux and fouling growth properties. The paper concludes that AI utilization for the prediction of membrane fouling can enhance the membrane selection for the processes, reduce costs with better fouling control system development and make the process more scalable on an industrial scale. The literature showed that there are models, such as the Neural-fuzzy interference system, that can predict forward osmosis membranes' performance with a high correlation of 0.997 and a root mean square error of 0.04. The paper also concludes that the exploration of more novel deep learning architectures like GANs would facilitate better resource recovery from wastewater and improved prediction of fouling in membrane processes.

KEYWORDS: Artificial intelligence; Emerging contaminants; Fouling; Membranes processes; Optimization.

GRAPHICAL ABSTRACT



HIGHLIGHTS

- Membrane processes are effective in the removal of emerging contaminants.
- Membrane processes pose a challenge during operation because of fouling.
- Various AI models can be employed to optimize and predict fouling.

1. Introduction

Globally, the use of contaminants in solvents, personal care, pesticides, and pharmaceuticals has emerged and has rapidly increased from 1 million to 500 million tons per year (Khan et al., 2022). These emerging contaminants (ECs) are harmful to the environment and human health, with current research addressing wastewater treatment methods to remove ECs (Qalyoubi et al., 2022). Currently, microplastics and endocrine materials for example impose a threat on human health (Abuwatfa et al., 2021, Al Sharabati et al., 2021). The Middle East has the highest volume of plastics that enter the seas per person

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compared to the other world regions (Heger et al., 2022). Furthermore, there have only been 70 publications since 2012 that have addressed the problem of ECs and wastewater treatment across 21 countries in the Middle East and North Africa region (Ouda et al., 2021). This discrepancy in levels of wastewater pollution and limited research in the Middle East and North Africa region shows the severity of the problem in the Middle East. Even though there have been recent steps and initiatives in gulf countries that have initiated and implemented systems to detect contaminants and process waterway systems (Al-Rajab et al., 2019, Ali et al., 2017, Ouda et al., 2021). Although, these systems have not been adequately developed in the Middle East and North Africa region to treat ECs (Sarkar et al., 2019). Therefore, it is crucial to investigate the different removal techniques to reduce the levels of ECs in waterway systems.

Currently, there are several main removal techniques that reduce ECs, which include photocatalytic degradation, advanced oxidation, adsorption, and membrane processes (Pham et al., 2020, Al-Bsoul et al., 2020, Shams Jalbani et al., 2021, Egea-Corbacho Lopera et al., 2019). The advantages that membrane technologies have against the other removal techniques include energy efficiency, simplicity in system design, and the ability to produce high-quality water (Tawalbeh et al., 2023, Saleh & Gupta, 2016). These advantages make membrane technologies effective techniques in wastewater treatment. Generally, filtration is a pressure-driven separation process in which particulate matter is rejected by the membrane, leaving wastewater (Gupta & Ali, 2013). The development of proper treatment methods for wastewater led to the recovery of vital resources that can be used for the development of modern societies. There have been recent efforts in using wastewater as a renewable resource where energy, nutrients, and excess water are recovered and utilized for different applications (Pikaar et al., 2022). The use of wastewater in energy recovery has been also evaluated to generate electricity (Zarei, 2020, Toczyłowska-Mamińska & Mamiński, 2022). Various amounts of nutrients, such as nitrogen, ammonium, and phosphate have been recovered from water for example, via adsorption and struvite precipitation processes, which could lead to its use as fertilizers (Ye et al., 2020). The previous examples show some possibilities for resource recovery paths based on the water-energy nexus.

There are four main types of membrane processes, which include microfiltration, ultrafiltration, nanofiltration and reverse osmosis. Figure 1 illustrates the various pore-sizes of these membranes and their applications (Zahid et al., 2018). Meanwhile, Table 1 summarizes the key findings in the literature for each membrane process and how these findings apply to the removal of contaminants, including emerging contaminants.

Meanwhile, RO membranes were able to achieve a high removal rate of ciprofloxacin, above the 90% as reported by Alonso et al. (Alonso et al., 2018). The RO membranes require pressure beyond the osmotic pressure of the feed solution to allow water to pass through and reject salt (Qasim et al., 2019). This means that the RO membranes require a high operating pressure to remove contaminants from wastewater (Qalyoubi et al., 2021). Meanwhile, membrane processes are hindered with problems, such as membrane fouling, difficulty in obtaining optimal parameters, selectivity, and permeability (Zhao et al., 2020, Tawalbeh et al., 2018). Generally, membranes have a tradeoff between selectivity and permeability, which must be considered depending on the application. Selectivity determines how far the desired molecules are separated, while permeability determines how fast molecules go through a membrane (H. B. Park et al., 2017). Another problem is that membranes have throughput, which is the volume of fluid that is filtered out from the membrane over time. Throughput is limited by the surface area of the membrane (Holdich et al., 2020). Various techniques have been developed to deal with these problems.

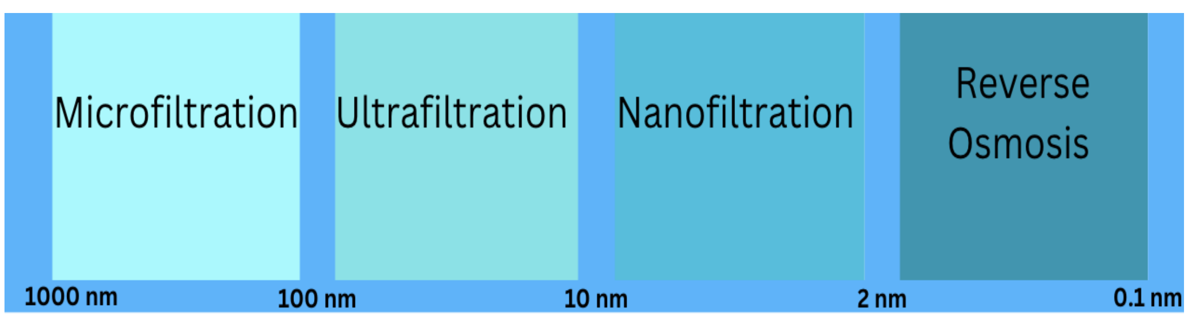

Figure 1. Figure 1. Membrane processes (Zahid et al., 2018).

Table 1
Key findings on membrane processes.

Membrane	Finding	Ref.
Microfiltration (MF)	1) The large molecular weight cut-off of MF membrane prevents the removal of some large contaminants. 2) Coating the MF membrane with titanium dioxide and silver oxide will modify the main functional properties, such as antibacterial and photocatalytic properties. 3) The relatively large pore size for microfiltration reduces its effectiveness in removing ECs from wastewater	(Cevallos-Mendoza et al., 2022, Kacprzyńska-Gołacka et al., 2020)
Ultrafiltration (UF)	1) A ceramic UF membrane had a maximum removal rate of 99% at 2.5 bar pressure. 2) High operational stability was achieved from the combination of two processes: inline coagulation and powdered activated carbon to UF membranes.	(Bhattacharya et al., 2019, Schwaller et al., 2021)
Nanofiltration (NF)	1) The larger the molecular weight, the greater rejection ratios are. 2) The NF membrane, NF90 showed the highest decrease in permeate flux.	(Wang et al., 2015, Dogan E, 2016)
Reverse osmosis (RO)	1) RO membrane (RE2521- SHF) had removal rates between 90 and 99% in the desalination plant.	(Alonso et al., 2018, Qasim et al., 2019)

Meanwhile, RO membranes were able to achieve a high removal rate of ciprofloxacin, above the 90% as reported by Alonso et al. (Alonso et al., 2018). The RO membranes require pressure beyond the osmotic pressure of the feed solution to allow water to pass through and reject salt (Qasim et al., 2019). This means that the RO membranes require a high operating pressure to remove contaminants from wastewater (Qalyoubi et al., 2021). Meanwhile, membrane processes are hindered with problems, such as membrane fouling, difficulty in obtaining optimal parameters, selectivity, and permeability (Zhao et al., 2020, Tawalbeh et al., 2018). Generally, membranes have a tradeoff between selectivity and permeability, which must be considered depending on the application. Selectivity determines how far the desired molecules are separated, while permeability determines how fast molecules go through a membrane (Park et al., 2017). Another problem is that membranes have throughput, which is the volume of fluid that is filtered out from the membrane over time. Throughput is limited by the surface area of the membrane (Holdich et al., 2020). Various techniques have been developed to deal with these problems.

Since current classical modeling techniques fail to approach the problems due to the complexity of membrane processes, current research focused on applying AI in membrane technologies (Zhao et al., 2020). A comparison between two AI models over a mathematical model in predicting water permeability of a membrane showed how far AI models surpass mathematical models in accuracy and prediction (Viet & Jang, 2023). The literature reported the coefficient and error values of the 3 models with both the neural network and the neural-fuzzy interference system surpassing the conventional intermediate mathematical blocking model in both aspects. Table 2 presents values that were adapted from the literature (Viet & Jang, 2023). The study focused on FO membranes and was presented here as an example. Table 2 demonstrates how AI-based models are better suited in membrane prediction applications.

Table 2
Table 2 Mathematical and AI models in FO membrane processes. Values from Viet et al. (Viet & Jang, 2023).

Model	Coefficient value	Root mean square error
Conventional intermediate blocking model (CIB)	0.963	0.97
Artificial neural network (NN model)	0.974	0.70
Neural-fuzzy interfence system (NFIS)	0.997	0.04

In the past two decades, the progress of AI has prompted its use in improving system performance and efficiency (Al-Othman et al., 2022). The number of papers published with application of AI in various fields has increased by a factor of 19 from 1995 to 2019 (Zhao et al., 2020). This feature allows AI to perform human tasks, such as analyzing and assessing data, but at a much faster rate. AI-based techniques surrounding the optimization and enhancement of membranes allow the problems of parameter optimization and membrane fouling to be tackled. In short, the field of AI has 6 subsets: Machine learning, deep learning, robotics, expert systems, fuzzy logic, natural language processing with machine learning, deep learning, and fuzzy logic being applied to membrane technologies in wastewater treatment (Modak et al., 2022). This occurs as AI techniques use various algorithms to extract massive data and then obtain patterns for prediction and classification. By applying these techniques to membranes, it is possible to predict membrane fouling, optimize membrane parameters, and to evaluate membrane performance. These results can reduce costs, allow more contaminants to be removed, improve water quality, and contribute to a better resource recovery of water, energy, and materials from wastewater. Even though AI techniques have been applied to deal with throughput, selectivity and permeability, the discussion will be limited to applying AI in optimizing membrane parameters and predicting membrane fouling in this context. As Table 3 indicates, the latest research in AI has been increasing and developing to very bright prospects in the application of AI in membrane processes. This is accomplished through the optimization of membrane process parameters and prediction of membrane fouling.

This paper aims at discussing the main AI techniques used in the prediction of membrane processes performance and addressing another key issue faced by membrane processes known as membrane fouling.

2. AI Applications in Membranes

In this section, the main AI algorithms used in membranes' parameter optimization are discussed.

2.1 Introduction to AI Algorithms in Parameter Optimization

The optimization of membrane filtration processes is essential to improve the quality of water and to remove contaminants. Since AI algorithms provide the most efficient way to optimize parameters, this has led numerous models to be developed to predict permeate flux by getting the optimum input constraints, such as filtration time, feed temperature, and trans-membrane pressure (Badrnezhad & Mirza, 2014). This methodology has been applied to predict water quality across varying environmental variables. Various studies have applied numerous machine learning models to predict dissolved oxygen concentration, water quality index, and biochemical oxygen demand (Badrnezhad & Mirza, 2014, Kisi et al., 2020, Nourani et al., 2021, Nur Adli Zakaria et al., 2021, Gaya et al., 2020, Arefi-Oskoui et al., 2017). Specifically, a study by Oskoui et al. (Arefi-Oskoui et al., 2017) used two AI models, artificial neural networks (ANN) and genetic algorithms (GA), to determine the most optimal input parameters for ultrafiltration membranes. The first model was an artificial neural network that has an input layer, hidden layer, and an output layer. The input parameters were the polymer and pore concentrations, which determined how these parameters affect the output. The second model applied the results from the ANN to a GA. This algorithm has an initial "input population", which is defined as the initial input parameters that is continuously evaluated by fitness levels after each iteration. Fitness levels indicate how fit each individual set of input parameters are. A fitness score is then given to each individual set and the individuals that are more fit are selected to create the population of the next generation. The process repeats for the numerous generations until a suitable fitness level is reached. In this case the initial input parameters were used to obtain the maximum values for pure water flux, protein flux, and flux recovery ratio. These optimized values had an R2 value of 0.98, showing that the developed model was accurate. This accuracy helps show the effectiveness of using AI models to optimize the input parameters and maximize the result.

2.2 Genetic Algorithm & Response Surface Methodology

Parameter optimization can be applied in the removal of ECs, which was demonstrated (Yousefi et al., 2021). The study used the genetic algorithm to enhance the removal rate of a specific contaminant, ciprofloxacin. The study used deionized water and added ciprofloxacin to the feed, which was then filtered out through a 0.22-micron pore. The initial and final ciprofloxacin concentration value was determined using an ultraviolet detector. This setup helped in understanding the removal rate of ciprofloxacin. Since the removal of ciprofloxacin depends on the pH levels, concentration of the contaminant, contact time, and the adsorbent dose, this forms the most optimal conditions required to have the highest rate of ciprofloxacin removal. The dependencies on the removal rate are expressed in Eq. 1 (Yousefi et al., 2021):

$$Y=b_0+\Sigma b_i x_i+ \Sigma b_{ii} xi^2 + \Sigma b_{ij} x_i x_j \quad (1)$$

where the output Y is the adsorption of ciprofloxacin that is optimized based on the inputs, x_i and x_j, which are the pH, dose (g/L), time (min), and ciprofloxacin concentration levels (mg/L). Meanwhile, the coefficients, b_0, b_i, b_{ii}, b_{ij}, are the constant, linear, quadratic, and interaction coefficients of the inputs, which are optimized to have the highest removal rate. The GA was applied with Figure 2 showing that after each generation, the more fit individuals are selected according to its fitness value until it reaches the best possible fitness value. In this case, the best fitness value was reached after 130 generations, which generated the most optimal input conditions. Figure 2 also shows the current best individual, which occurs after reaching the best fitness value and it displays the optimal input values that were attained. The y-axis of the current best individual graph shows the value of each input parameter. Overall, the most optimal input parameters had a pH of 4.4, dose of 0.74 g/L, time of 42 min, and ciprofloxacin concentrations of 38 mg/L, which had a removal rate of 99.1%. Meanwhile, the study also used a different machine learning algorithm, such as response surface methodology (RSM) to obtain a similar result. Overall, these machine learning algorithms demonstrate how input values can be tuned to increase the removal rate of the contaminant.

Table 3
ANN Applications in Membrane Processes Since 2017 adapted and referenced from (Niu et al., 2022).

Membrane	Inputs	Optimized parameters	Type	Performance	Ref.
RO	• Conductivity • Electrical power • Temperature	• Pressure • Flowrate	Multilayer perceptron	• Mean absolute error: • Flowrate=0.84% • 0.405%	(Cabrera et al., 2017)
RO	• Water quality • Hydraulic parameters	• Pressure • Flowrate	Multilayer perceptron	R^2 • Flowrate=0.98 • Pressure=0.87	(Roehl et al., 2018)
NF	• pH • Pressure • Recovery • Contact angle • Zeta potential • Salt rejection	• Rejection	Bootstrap aggregated neutral network	• R^2=0.9862	(Khaouane et al., 2017)
NF-RO hybrid	• Axial images of fouling layer • Corresponding x coordinate data • Initial flux values • Membrane type • Time stamps for fouling onset	• Flux • Fouling thickness	Deep neural network	R2: • Fouling thickness=0.99 • Permeate flux=0.99	(Park et al., 2019)
NF	• Concentration • Membrane • Solvent type	• Flux • Rejection	Multilayer perceptron	R^2 • Flux=0.98 • Rejection=0.91	(Hu et al., 2021)
NF	• Optical coherence tomography images • Quality-based water parameters	• Fouling thickness • Permeate flux	Recurrent neutral network	R^2 • Flux=0.9982 • Fouling thickness=0.9987	(Shim et al., 2021)
UF	• Feed water organic, five component model values and fluorescent components • pH	• fouling resistance	Multilayer perceptron	MAPE<5%	(Peleato et al., 2017)
UF	• Cumulative sampling volume • Metal to surfactant relation ratio • pH	• Permeate flux • Rejection rate	Multilayer perceptron	Coefficient of determination=0.9974	(Lin et al., 2017)

3. Prediction of Membrane Fouling

As expounded by Liu et al. (Liu et al., 2019), membrane fouling is a complex process of gradual accumulation of impurities, suspended solids, and other materials on the surface of the membrane. This accumulation reduces the performance and efficiency of the membrane over time. There are several known mechanisms for fouling that include:

1. Adsorption: The adherence of solutes or colloids onto the surface of the membrane.

2. Pore blocking: The physical obstruction of membrane pores by larger particles or suspended solids

3. Gel formation: chemical reactions or aggregation of particles causing formation of a “gel-like” layer on the membrane surface

4. Biofouling: microorganism proliferation on the membrane surface, which can produce biofilms that can block the pores and reduce the permeate flux.

Being one of the major hindrances faced by membrane processes. Niu et al. (Niu et al., 2022) conducted a comprehensive evaluation that specifically examined the use of artificial neural networks (ANN) for predicting membrane fouling in membrane-based processes over the last two decades. They have conducted the review in modeling ANN for the following membrane processes: Microfiltration (MF), ultrafiltration (UF), nanofiltration (NF), reverse osmosis (RO), and membrane bioreactors (MBR).

Amongst the many available studies in the literature, it appears that certain authors have adopted interesting approaches that are ought to be discussed. Roehl et al. (Roehl et al., 2018) studied the modeling of an ANN at a multi-effluent wastewater treatment plant that utilized a 15 staged RO system with a daily capacity of 284 megaliters. The ANNs were designed to fit only continuous monotonic functions with characterization using R2 value. They found that the fouling models were very effective at predicting effects of traditional parameters, such as turbidity, total chlorine and ammonia with total dissolved solids and electrical conductance being the most predictive. The study concluded that the guidance of ANN modeling plays a crucial role in better data collection for improvement and support of the said process. Another approach by Park et al. (S. Park et al., 2019) utilized more novel deep neural networks (DNN) for flux decline and fouling prediction. To mimic fouling, NE 90 (NF) and RE SHF (RO) membranes were fouled using 10 mg C/L humic acid and 10 mM of Ca2+ ions and the effect of the latter was measured using optical coherence tomography (OCT). To develop the model, the input scans were pre-processed using cropping of 20%, separating the fouling layer using k-means clustering algorithm, and lastly the layer image is deblurred for recovery of original state, which is then binarized to enhance the level of detail regarding the fouling visible in the image. Based on a convolutional neural network (CNN), the model rapidly identifies critical characteristics and categorizes them more efficiently than traditional methods. Specifically for the fouling layer, within the CNN, there are convolutional layers, batch normalization, concatenated rectified linear units, max-pooling layers, dropout, and fully connected layers that form its architecture. Mean square error (MSE) and root mean square error (RMSE) are used to evaluate its efficiency contingent on both simulated and observed data. The model's output was contrasted with several mathematical models, including the Faridirad model and pore blockage cake formation model, to assess its accuracy. Fig. 3 shows a visual representation of the comparison results.

The observed and predicted fouling thickness by the DNN were very close to one another. On the other hand, the mathematical models were quite apart from the observed fouling thickness especially at the initial hours. This results in the DNN model having the lowest RMSE out of the 3 models. The results are explained by the authors in terms of the necessity of optimization and requirement of optimum parameters for the mathematical models with the Faridirad model requiring 7 parameters and the pore blockage cake formation model requiring 4 parameters. DNN only required the initial fouling and initial flux information to determine the accuracy of fouling over time. However, a downside to the DNN model is the long duration needed to train the model, which takes around 4 days. Another research by Shim et al. (Shim et al., 2021) proposed another form of AI, known as long short-term memory (LSTM), which is a recurrent neural network (RNN) that leverage its ability to remember a sequence of events to predict fouling. The paper utilized natural organic matter as the foulants, namely humic acid, bovine-serum-albumin, sodium alginate, and tannic acid. They considered six inputs: Initial flux, pressure, fouling thickness, dissolved organic carbon concentration, modified fluorescence regional integration, and operation time with the relevant readings taken using OCT images. The developed LSTM model successfully predicted with very high accuracy rates permeate flux ($R^2 > 0.98$) and fouling growth ($R^2 > 0.97$) at any time. Fig. 4 illustrates the accuracy ($R^2 > 0.98$) of the LSTM given in only humic acid and mixed natural organic matter.

However, the authors mentioned one of the shortcomings and challenges of the deep learning-based approach has been the requirement for additional evaluation with further operational conditions and case studies to apply a globally viable model for more real-life applicable scenarios. However, Chew et al. (Chew et al., 2017) proposed an industrially deployable hybrid ANN model that combined Darcy's law of cake filtration through an ANN. This combination can conduct accurate predictions of crucial attributes, such as specific cake resistance and total suspended solids in feed water in an ultrafiltration pilot plant. The good results are shown in Fig. 5 for experimental and simulated results with the model ranging between 10–20 nephelometric turbidity units (NTU) at specific time intervals. In conclusion, researchers have been very keen on looking into AI for prediction of membrane fouling, with recent studies demonstrating very promising results.

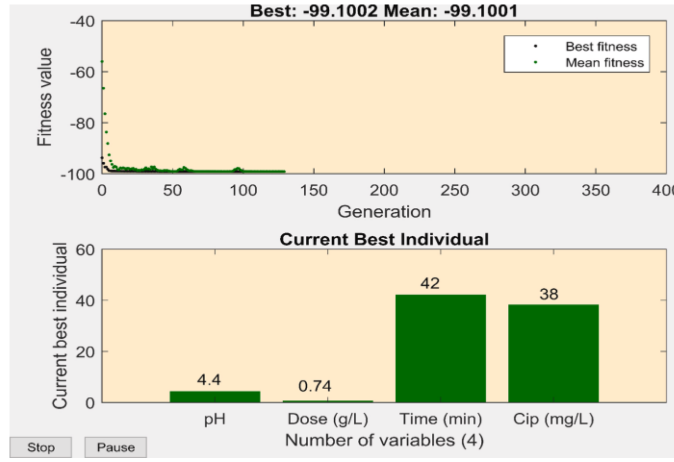

Fig. 2. Optimization of input parameters using genetic algorithm (Yousefi et al., 2021).

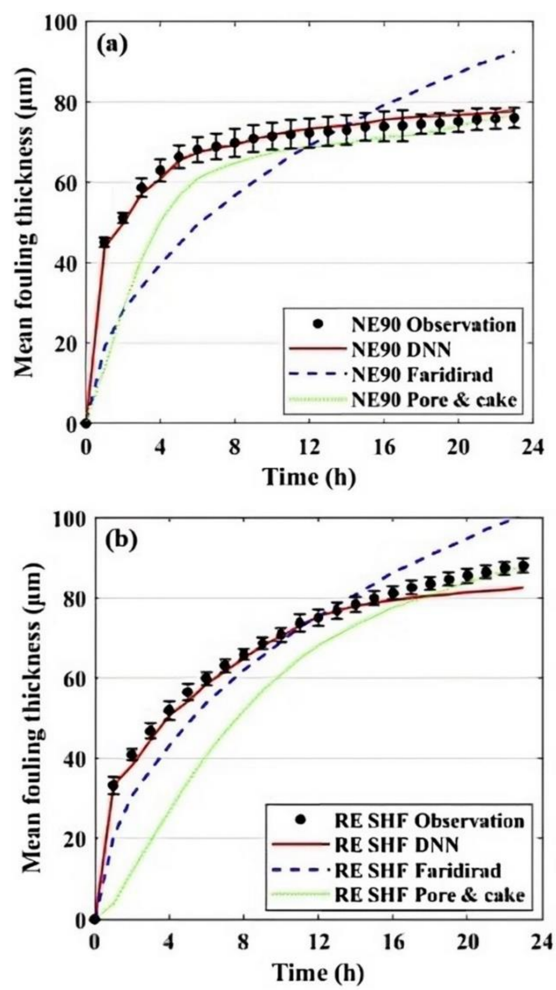

Fig. 3. NE90 vs. RE SHF comparison (S. Park et al., 2019).

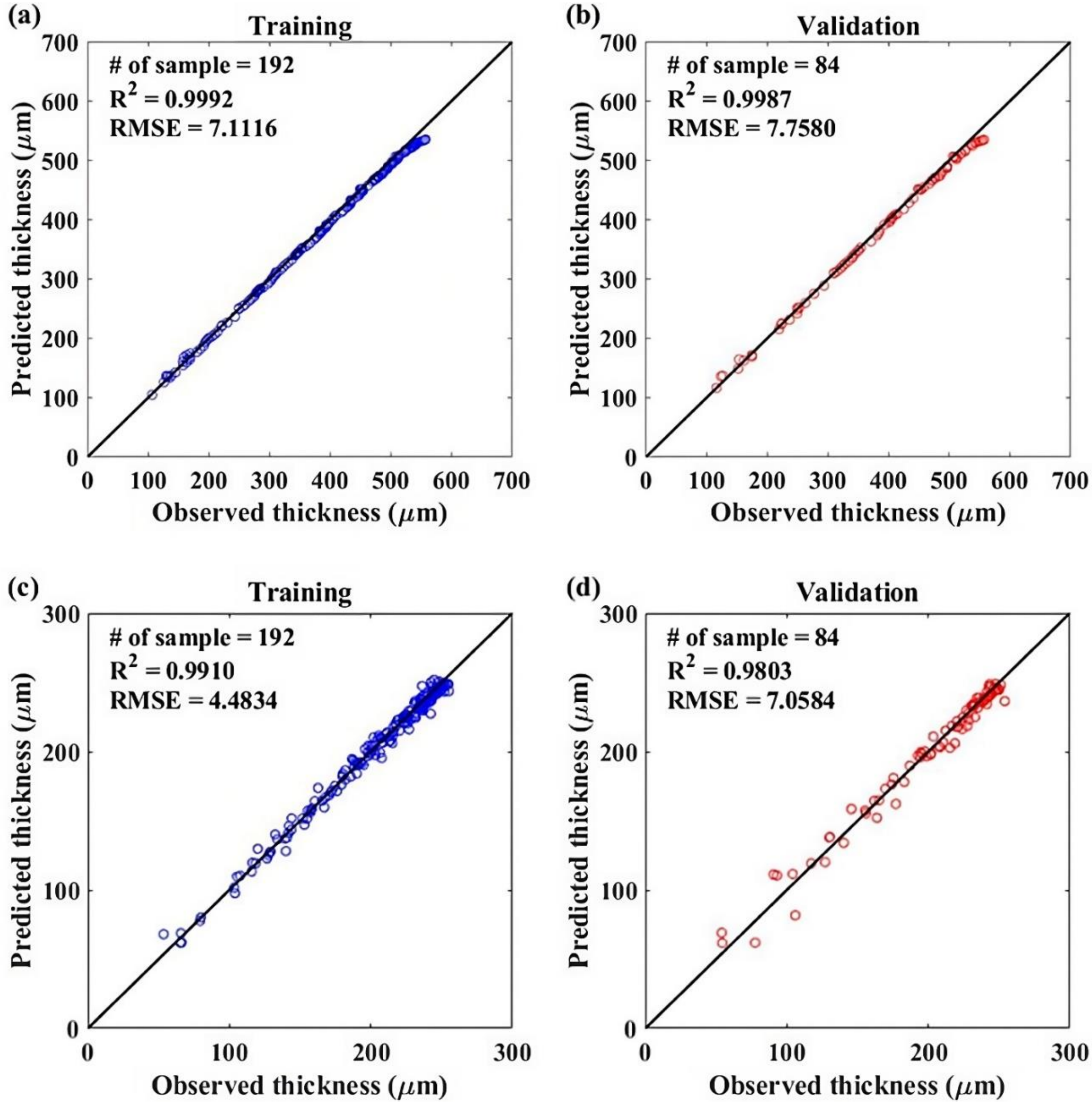

Fig. 4. Training and validation results of a single natural organic matter (a and b) and mixed natural organic matter (c and d) (Shim et al., 2021).

4. Contribution of AI techniques to Resource Recovery of Water

The resources recovery oriented (RRO) approach is adopted in research to address the water energy nexus. This allows water, and energy to be recovered from wastewater, reintroduced into the economy, augmenting their supply, and thus leading to a more circular economic model. Guest et al. (Guest et al., 2009) suggested that the traditional paradigm on wastewater treatment rooted in early 20th century is not sustainable. It stresses on what must be removed from wastewater compared to RRO, which centralizes on what can be recovered from wastewater and considers the environmental, social, and economic ramifications of the purification processes.

For example, and in the context of fresh water and nutrients recovery, Ye et al. (Ye et al., 2020) discussed the use of forward osmosis (FO) membrane process. A semipermeable membrane is used to force water from its feed side to draw side. The nutrients are rejected by the membrane and collected on the feed side. Osmotic Membrane Bioreactor was proposed by Qiu and Ting (Qiu & Ting, 2014) in which an Osmotic Membrane Reactor integrated an FO with biological processes that resulted in more than 95% of ammonia and nitrites. Qiu et al. (Qiu et al., 2015) and Holloway et. al (Holloway et al., 2015) investigated MF and UF membranes respectively to enhance the OMBR. By running them in parallel with the FO membrane, the nutrients were extracted with fewer foreign substances, thus, increases the purity. However, a significant downside to the above procedures is membrane fouling, which reduces the yield from the abovementioned processes over time. In addition, the fouling control for these systems contributes to >50% to the total cost in the form of energy (Sheng et al., 2017). In the context too, pharmaceuticals pose a significant threat by being environmentally abundant, leading to antibiotic resistance bacteria (ARB) and leading to lower efficacy of commonly prescribed antibiotics. Zarei (Zarei, 2020) highlights how nanofiltration proved to be effective in high amoxicillin recovery. However, membrane fouling, and cleaning were the main obstacles that added to the economic costs. As discussed in section 3, AI utilization for the prediction of membrane fouling can enhance membrane selection for the processes, reduce costs with better fouling control system development and make the process more scalable on an industrial scale.

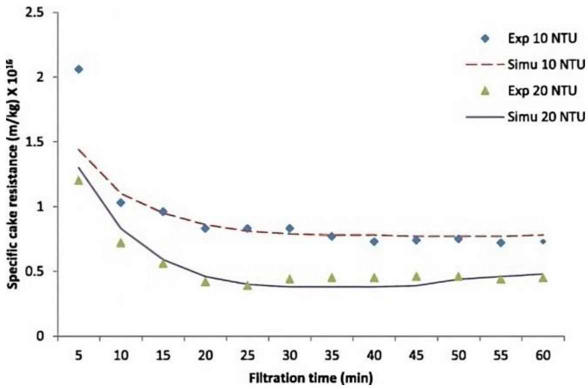

Fig. 5. Results of the hybrid model in simulation vs experimental (Chew et al., 2017).

5. Challenges and Future Directions

As discussed earlier in this context, AI techniques open many doors of possibilities for the improvement and enhancement of membrane technologies and filtration processes. There are also very particular challenges that exist, which must be addressed to create an industrially viable solution. Specifically, with ANNs, a study highlights how ANNs have poor reproducibility due to the involvement of random weights and biases (Alam et al., 2022). Moving onto more recent deep learning methods, another study pointed out the long training time required when using OCT images (S. Park et al., 2019). Apart from these issues there are more common challenges with the most crucial being the availability of data (Alam et al., 2022). The lack of large datasets from actual wastewater plants makes it very difficult to train an AI model to respond to real world issues at an industrial scale. This difficulty includes cases of unpredictability in operational conditions, affecting the AI accuracy rate. The study by Shim et al. (Shim et al., 2021) mentioned the need for more attention and progress in terms of the parameters and case studies being considered. Furthermore, not only is the sheer volume of data important, even the diversity of data is required to achieve accurate results. To achieve accurate results, the data must be sourced from different wastewater plants containing the inputs and outputs at different instances of the treatment process. However, obtaining these types of data can be difficult; thus, reducing the level of accuracy.

Meanwhile, another challenge stems from the complexity of the membrane process. The complexity of the membrane is due to the numerous variables that are involved in the process itself, some parameters can be neglected or given less weight in the prediction by the model. This issue is highlighted by Niu et al. (Niu et al., 2022) where the input parameters that are selected, such as the chemical oxygen demand neglect the inner compositions of proteins and microbes. Neglecting some parameters, may alter prediction and accuracy that can lead to decreased product quality and poor process performance. Since an AI model acts as a black box, it prevents an understanding of the trends that involve membranes and how the different variables interact with each other. Thus, there should be further research involving AI to predict fouling and to understand the fouling process itself.

It is necessary at this point to explore deep learning models further to decrease the need for frequent OCT images or applying AI techniques in machine learning that could use historical data based on parameters to predict fouling. Regarding the lack of large datasets to train the models on, an interesting approach is the utilization of Generative Adversarial Networks (GAN). The GANs are a type of deep learning model that can be used for image generation and translation. This means that GANs could potentially be used to generate synthetic OCT images that could be used as inputs to the fouling prediction model. Using GANs to generate synthetic OCT images could address the need for frequent imaging, as the model could generate images at a lower frequency than real-time measurements. Apart from that, future directions must also be centered around understanding the fouling mechanism more. Studies should focus on classifying various foulants on their properties and fouling tendencies. This would allow for exploiting AI models that could, in the future, respond in real time to immediate changes in the feed water composition based on live sensor data. This would also assist in the resource recovery from wastewater, since accurate prediction of fouling, and understanding of various input parameters would lead to better integration of various extraction processes. Ultimately, the enhancement of membrane processes through AI can be extended to creating AI enhanced membrane filtration systems and reactors. This enhancement is not only promising in eliminating contaminants but also for recovering resources that contribute to modern sustainability goals and lead to a circular economy.

6. Final Remarks

The increasing presence of antibiotics in water poses many significant health risks, specifically in the domain of antibiotic resistance and an upsurge in antibiotic resistant bacteria. This calls for advancement in existing wastewater treatment plants. Membrane processes are employed to remove ECs effectively. Membrane fouling continues to appear as a main challenge. Many researchers have attempted to predict fouling. AI techniques have received attention in this regard to further enhance the said processes within two broad domains: parameter optimization and membrane fouling prediction. Various AI models, specifically GA in isolation or in conjunction with ANNs are utilized for the prediction of the most optimal parameters to maximize the removal rate for the contaminant. Even though these models were not applied to an industrial scale, it has the potential to rapidly reduce the levels of ECs regarding membrane fouling. Researchers evaluated the more generic application of ANNs to pre-existing datasets to predict fouling. Other researchers investigated an intensive DNN based approach that requires OCT images to provide accurate results. However, both approaches had problems of their own regarding the application at the industrial scale. The former approach would require much larger datasets and the latter would be more costly in terms of constantly taking OCT images and feeding them as inputs periodically. Hence, addressing these challenges in using current AI based approaches include the need for larger datasets from various wastewater treatment plants around the world.

The dataset should contain various points of the filtration process over a period whilst also highlighting various operational parameters. The exploration of more novel deep learning architectures like GANs would facilitate better resource recovery from wastewater through better prediction of fouling and optimization of membrane processes. This paves the way for the integration of other extraction methods in conjunction with membrane processes to create membrane process systems. By addressing these challenges, AI can better provide accurate results for the performance of membranes in the removal of ECs in wastewater and in resource recovery.

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List of Abbreviations

AI: Artificial intelligence
ANN: Artificial neural network
CNN: Convolutional neural network
DNN: Deep neural network
EC: Emerging contaminant
FO: Forward osmosis
GA: Genetic algorithm
GAN: General adversarial network
LSTM: Long short-term memory
MBR: Membrane bioreactor
MF: Microfiltration
MSE: Mean squared error
NF: Nanofiltration

NTU: Nephelometric turbidity units
OCT: Optical coherence tomography
RMSE: Root mean square error
RNN: Recurrent neural network
RO: Reverse osmosis
RRO: Resource recovery orientation
RSM: Response surface methodology
UF: Ultrafiltration

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