ARTIFICIAL NEURAL NETWORK BASED MODELING OF THE FOULING PHENOMENA IN MEMBRANE BASED BIOREACTORS

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By

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CANDIDATE'S DECLARATION

We, Pranav Tyagi (2k22/MSCCHE/25) and Srishti Duber (2k22/MSCCHE/41) hereby certify that the work which is being presented in the Dissertation entitled "Artificial neural network based modeling of the fouling phenomena in membrane based bioreactors by using relaxation and backwashing method" in partial fulfillment of the requirements for the award of the Degree of Master of Science in Chemistry, submitted in the Department of Applied Chemistry, Delhi Technological University is an authentic record of my own work carried out during the period from June 2023 to May 2024 under the supervision of Dr. Manish Jain.

The matter presented in the dissertation has not been submitted by me for the award of any other degree of this or any other Institute.

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ARTIFICIAL NEURAL NETWORK BASED MODELING OF THE FOULING PHENOMENA IN MEMBRANE BASED BIOREACTORS

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ABSTRACT

Membrane-based bioreactors represent a pivotal technology in various biological processes, offering unique advantages such as selective product removal and continuous nutrient replenishment, which are conducive to optimizing reaction efficiency and sustainability. However, the pervasive issue of membrane fouling presents a significant obstacle to the efficacy of these systems. Fouling, characterized by the accumulation of particulates and microorganisms that obstruct membrane pores, leads to decreased flux rates and increased operational costs. Traditional approaches to modeling membrane fouling in bioreactors often fall short due to the complex and nonlinear nature of the phenomenon. In response to this challenge, this study employs an Artificial Neural Network (ANN) approach, leveraging its ability to capture intricate relationships and nonlinearities within the fouling process. ANNs offer a data-driven framework that can learn and adapt from experimental data, making them well-suited for modeling the dynamic behavior of fouling in membrane-based bioreactors. The ANN model developed in this study is trained and validated using experimental data sourced from literature, ensuring its accuracy and reliability in capturing the underlying fouling mechanisms. Through meticulous optimization of the ANN architecture, including the determination of an optimal number of neurons in the hidden layer, the model achieves minimal error and demonstrates robust performance in predicting experimental outcomes. Optimization reveals that an ANN with seven neurons in the hidden layer yields the minimum error, with validation demonstrating relative errors of less than 10% between theoretical and experimental results for all data points. Subsequently, the trained ANN serves as a powerful tool for exploring the effects of various operational parameters, such as flux, backwashing duration, and interval of relaxation, on membrane fouling dynamics. These findings offer valuable insights into optimizing membrane-based bioreactor performance and suggest avenues for future research in this field. Specifically, there is a need for the development of more sophisticated modeling techniques and the exploration of novel membrane recovery strategies to further enhance the efficacy and sustainability of membrane-based bioreactors across diverse biological applications.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOL, ABBREVIATION AND NOMENCLATURE

hr – hour

L- litre

h- Planck constanat

TMP- Trans-membrane pressure

mbar- Millibar

ANNs- Artificial Neural Network

MBR- Membrane based bioreactors

CHAPTER 1

INTRODUCTION

1.1 MEMBRANE-BASED BIOREACTORS

Membrane-based bioreactors (MBRs) have revolutionized wastewater treatment by integrating biological processes with membrane filtration. These systems efficiently remove contaminants from wastewater while producing high-quality effluent.

MBRs combine suspended growth bioreactors with membrane filtration units, enabling simultaneous treatment and solid-liquid separation. Unlike conventional activated sludge processes, where settling is used for biomass separation, MBRs employ membranes with precise pore sizes to retain suspended solids and microorganisms while allowing permeate to pass through.

By integrating biological treatment and membrane separation into a single compact unit, MBRs offer numerous advantages, including enhanced treatment efficiency, reduced footprint, and greater flexibility in system design and operation[1].

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In our research project, we address the challenges of membrane fouling in MBRs and aim to develop predictive models using artificial neural networks (ANNs) to optimize system performance and mitigate fouling.

1.2 SIGNIFICANCE OF MEMBRANE FOULING

Membrane fouling remains a formidable challenge in the operation of membrane-based bioreactors (MBRs), posing significant obstacles to their efficiency and sustainability. Fouling occurs due to the accumulation of organic and inorganic substances on the surfaces of membranes, resulting in the obstruction of water flow and decreased permeate flux. This phenomenon leads to increased energy consumption and operational costs, making fouling mitigation a critical aspect of MBR operation.

Our research endeavors to address the complexities of membrane fouling by exploring innovative techniques and methodologies, particularly focusing on the utilization of artificial neural networks (ANNs) for predictive modeling and fouling mitigation. The mechanisms of fouling are complex and multifaceted, influenced by factors such as membrane material, pore size distribution, feedwater quality, and hydrodynamic conditions[2].

1.3 STUDY OBJECTIVE

 Evaluate the effectiveness of ANN models in predicting the dynamics of membrane fouling based on various operational parameters and environmental factors.

 Investigate the influence of key variables such as flux rates, backwashing intervals, and relaxation methods on membrane fouling.

 Develop and propose optimized approaches for managing and controlling fouling in MBR systems, with the goal of enhancing overall performance and extending membrane lifespan.

CHAPTER 2

THEORY

2.1 MEMBRANE FOULING IN BIOREACTOR

The accumulation of various substances such as organic matter, colloids, microorganisms, and other particulate materials on the surface of membranes presents a significant challenge in the operation of membrane-based bioreactors (MBRs). This phenomenon, known as membrane fouling, results in the formation of a fouling layer, leading to decreased permeate flux and increased energy consumption. The integration of these two processes offers several advantages, including higher effluent quality, reduced footprint, and improved process control[3].

The fouling layer acts as a barrier, impeding the transport of water molecules across the membrane, and thus reducing the permeate flux. As a result, the operational performance of MBRs is compromised, leading to decreased treatment efficiency and increased energy consumption. Moreover, membrane fouling necessitates frequent cleaning and maintenance activities, which incur additional operational costs and downtime.

Understanding the mechanisms and factors contributing to fouling is essential for developing effective fouling mitigation strategies in MBRs. By elucidating the underlying causes of fouling, researchers can identify potential intervention points and design targeted approaches to minimize fouling and maximize membrane performance[4].

2.1.1 TYPES OF FOULING

Fouling in membrane bioreactors (MBRs) presents itself in diverse forms, each with unique traits and root causes. Grasping the nuances of these various fouling types is pivotal for devising efficient strategies to mitigate fouling and enhance the performance of MBR systems[2].

Particulate Fouling:

This type of fouling arises when suspended solids within the incoming water accumulate on the membrane surface, creating a physical barrier that hinders water flow. It is frequently observed in MBRs treating wastewater with elevated levels of suspended solids or colloidal particles.

Cake Fouling:

Cake fouling occurs when organic substances and microbial biomass gather on the membrane surface, forming a gel-like layer termed a cake. This cake layer acts as an additional barrier, further obstructing water flow and raising hydraulic resistance. Cake fouling is common in MBRs treating wastewater streams rich in organic matter, as often found in industries such as food processing or pharmaceuticals.

Biofouling:

Biofouling emerges when microorganisms adhere to the membrane surface and develop a biofilm, which can modify membrane properties and encourage additional fouling. Biofouling poses a significant challenge in MBRs operating under aerobic conditions, where microbial proliferation is favored.

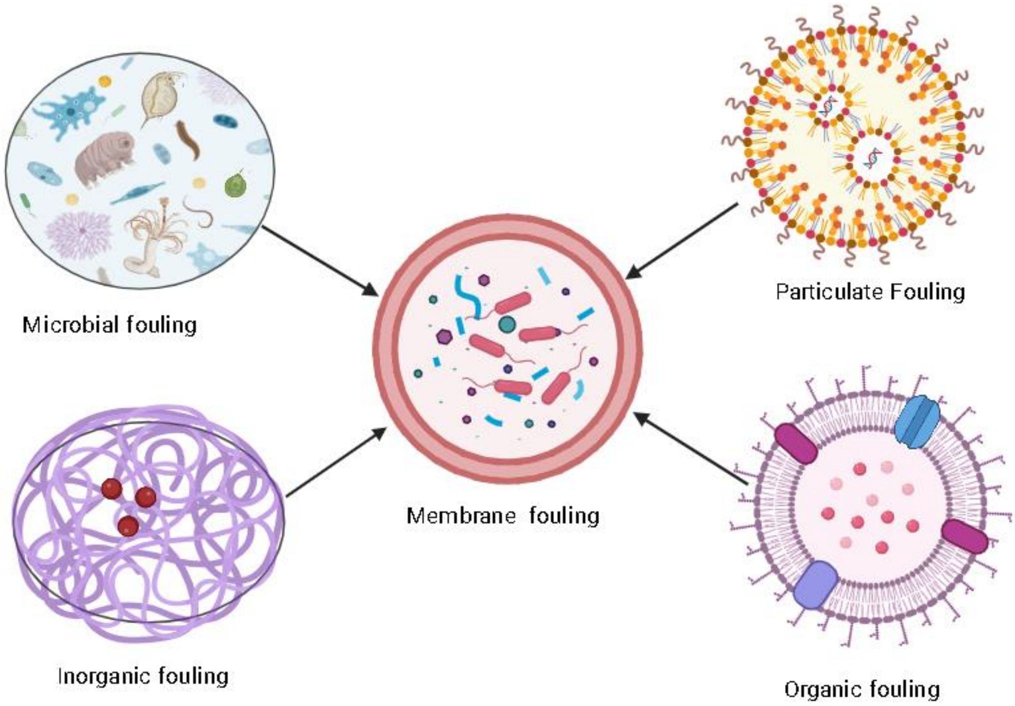

Fig 2.1: Types of membrane fouling

2.1.2 MECHANISM OF FOULING

The complicated processes of fouling in membrane bioreactors are impacted by a number of variables, such as feedwater qualities, membrane properties, and operating conditions. The following mechanisms have been shown to be involved in fouling phenomena in MBRs.

Cake Formation:

A cake is a dense layer that progressively builds up on the membrane surface as a result of suspended particles or organic matter accumulating there. By physically preventing water from passing through and decreasing membrane permeability.

Pore Blockage:

Pore blockage occurs when particles or foulants are deposited within the membrane pores, obstructing water flow and reducing filtration efficiency. Pore blockage is particularly problematic in membranes with smaller pore sizes, where even small particles can cause significant flux decline.

Biofilm Development:

The development of a biofouling by microorganisms adhering to the membrane surface causes biofouling, which can alter the membrane's characteristics and promote further fouling. In MBRs working in aerobic circumstances, where microbial multiplication is encouraged, biofouling presents a serious problem[5].

2.2 FOULING CONTROL METHODS

Techniques for controlling fouling are essential to preserving the longevity and effectiveness of membrane bioreactors (MBRs). This section examines several methods used to reduce fouling and enhance MBR efficiency.

2.2.1 PHYSICAL CLEANING METHOD

In physical cleaning techniques, foulants are removed from the membrane surface by applying mechanical or hydraulic forces. These techniques are necessary for the regular upkeep and recovery of membrane flux.
Typical methods for physical cleaning consist of:

2.2.1.1 BACKWASHING TECHNIQUE IN MBRs:

In backwashing, the membrane module is filled with clean water or permeate in the opposite direction of the filtration flow. By dislodging and flushing away accumulated foulants, this hydraulic activity restores the permeability of the membrane.

Efficiency and impact on fouling:

The efficacy of the backwashing technique in reducing fouling and regaining membrane permeability in MBRs is well known. Backwashing contributes to stable flow rates and increases membrane longevity by dislodging and clearing accumulated foulants from the membrane surface. A number of variables, such as membrane characteristics and operating conditions, backwash frequency, duration, and intensity, can affect how effective backwashing is[6].

2.2.1.2 RELAXATION TECHNIQUE IN MBRs:

The filtration process is periodically stopped in the relaxation technique, often referred to as idle or no-filtration operation, to allow the foulants that have accumulated on the membrane surface to separate and disperse.

The transmembrane pressure (TMP) progressively drops and the influent flow is halted during relaxation periods, which makes it easier for foulants to escape the membrane surface[7]. Operating needs, membrane type, and fouling severity can all influence the length and frequency of relaxation cycles.

Productivity and Effect on Fouling:

By lessening the buildup of foulants on the membrane surface, the relaxation approach has been demonstrated to successfully minimize fouling in membrane bioreactors[6], [8]. This method contributes to stable flow rates and increases membrane longevity by enabling foulants to separate and scatter during relaxation periods. However, the efficiency of the relaxation technique may vary depending on factors such as membrane material, operating conditions, and wastewater characteristics[8].

2.2.1.3 AIR SCOURING METHOD IN MBRs:

By injecting compressed air or gas bubbles into the membrane module, a physical cleaning method known as "air scouring" is employed in membrane bioreactors (MBRs) to eliminate foulants from the membrane surface. Bubbles are created that rise through the membrane sheets or fibers as a result of the air being distributed through porous membranes or nozzles placed at the bottom of the membrane tank. Foulants are dislodged and suspended from the membrane surface by the turbulence and shear forces created by this ascending bubble. The bioreactor's circulating flow then removes the entrained foulants, stopping them from adhering to the membrane.

2.2.2 CHEMICAL CLEANING METHOD:

Chemical cleaning methods entail utilizing cleaning agents or solutions to dissolve, disperse, or neutralize foulants adhering to the membrane surface. These approaches become necessary when physical cleaning alone proves insufficient or when fouling primarily stems from organic or biological sources. Typical chemical cleaning methods encompass:

Citric Acid Cleaning:

This method relies on citric acid, a widely utilized cleaning agent prized for its efficacy in dissolving inorganic scale and mineral deposits present on the membrane surface.

Sodium Hypochlorite Disinfection:

Sodium hypochlorite serves dual roles as both a disinfectant and a cleaning agent, employed to combat biofouling and curb microbial proliferation. Its action effectively deactivates and eliminates bacteria, algae, and other microorganisms adhering to the membrane.

2.3 MODLING OF MEMBRANE FOULING

The complicated phenomena of membrane fouling are influenced by a number of variables, including the properties of the membrane, the feedwater, and the working environment. To comprehend fouling mechanisms, forecast fouling behavior, and maximize MBR performance, modeling techniques are crucial[9].

2.3.1 TRADITIONAL MODELING APPROACHES

Traditional modeling approaches for membrane fouling typically involve empirical correlations or mathematical equations based on experimental data. These models aim to describe fouling kinetics, fouling mechanisms, and the impact of operational parameters on fouling behavior[10]. While traditional models provide valuable insights, they often have limitations in capturing the complex and nonlinear nature of fouling processes observed in MBRs.

2.3.2 ARTIFICIAL NEURAL NETWORK (ANNs) IN MODELING

Artificial Neural Networks (ANNs) have risen as potent computational instruments to model intricate and nonlinear systems, rendering them especially adept at comprehending and forecasting membrane fouling within membrane bioreactors (MBRs). ANNs present numerous benefits compared to conventional modeling methods, notably their capacity to discern intricate associations and patterns within fouling data sans dependence on explicit mathematical formulations.

2.3.2.1Overview:

The design and operation of artificial neural networks, or ANNs, are based on the principles of biological neural networks found in the human brain. An artificial neural network (ANN) is made up of interconnected nodes or neurons layered in input, hidden, and output layers. ANNs learn from data by modifying the connection weights between neurons to reduce prediction errors through a procedure called training. Because of their capacity for adaptive learning, ANNs are able to identify complex patterns and correlations in fouling datasets that would be difficult to identify with more conventional modeling techniques[11][10].

An Artificial Neural Network (ANN) is structured into three primary layers: the input layer, hidden layer(s), and output layer.

1. **Input Layer:**

   This initial layer acts as the conduit for external data, transferring it into the network. Each node within the input layer signifies a distinct feature or attribute of the input data. Its function is to serve as the gateway for data entry without engaging in computational processes.

2. **Hidden Layer(s):**

   The hidden layer(s) undertake the task of processing the data relayed from the input layer. Comprising neurons, these layers conduct computations on the input data through weighted connections. Every neuron in the hidden layer receives inputs from the preceding layer, applies a transformation function (such as the sigmoid or rectified linear unit function), and transmits the outcome to the subsequent layer.

3. **Output Layer:**

   Positioned at the final stage, the output layer generates the conclusive result or prediction of the network. Each node within the output layer represents a feasible outcome or classification. By leveraging the processed information from the hidden layer(s), the output layer executes computations to deliver the ultimate output of the network.

2.3.2.2ANN Process:

 Training:

- During the training phase, the ANN learns from a dataset containing input-output pairs.
- It adjusts the connection weights between neurons to minimize errors in predicting outputs.
- Optimization algorithms like gradient descent or the Levenberg-Marquardt algorithm are commonly used for this purpose.
- The primary objective of training is to fine-tune the network parameters to accurately forecast outputs based on given inputs[9].

 Validation:

- Following training, the ANN's performance is assessed using a distinct validation dataset.
- This dataset comprises data that the network hasn't encountered during training.
- By comparing the network's predictions with actual outputs on the validation dataset, metrics like accuracy, precision, and recall are calculated[12].
- Validation aids in evaluating the network's ability to generalize to new data and identifies potential issues like overfitting.

 Simulation:

- Once trained and validated, the ANN is ready for practical use in making predictions or classifications on new, unseen data.
- The input data is fed into the trained network, which processes it through its layers to generate an output[13], [14]
- Depending on the application, such as predicting fouling behavior in membrane bioreactors or categorizing data, the output is interpreted accordingly.
- By simulating real-world scenarios, the ANN can effectively address problems and make informed decisions based on learned patterns from the training data.

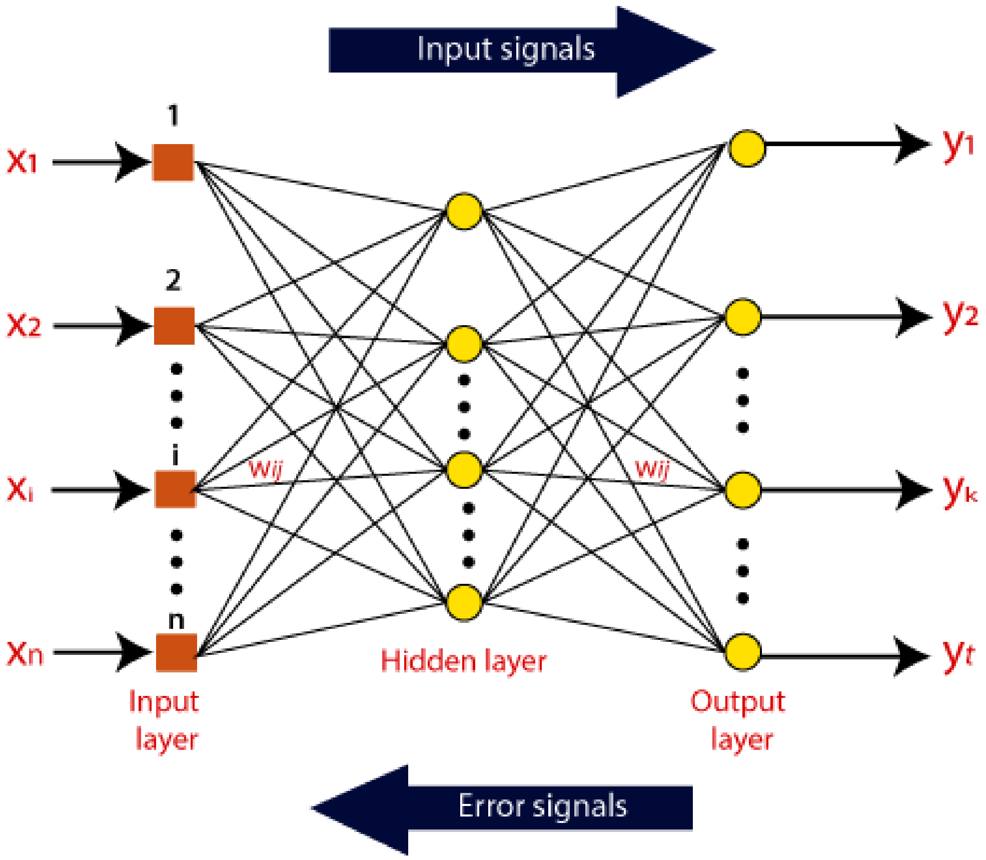

Fig 2.2- Schematic diagram of artificial neural network (ANN) architecture

2.3.3 APPLICATIONS IN MEMBRANE FOULING

- **Prediction of Fouling:** ANNs are trained to forecast fouling occurrences based on various input parameters like feedwater properties, membrane characteristics, and operational settings. By scrutinizing historical fouling data, ANNs discern patterns and trends to accurately predict future fouling incidents.

- **Identification of Fouling Mechanisms:** ANNs contribute to understanding the fundamental mechanisms underlying fouling in MBRs. Through analyzing correlations between fouling parameters and experimental observations, ANNs deduce the primary fouling mechanisms and their respective impacts on overall fouling dynamics.

- **Optimization of Fouling Control Strategies:** ANNs play a pivotal role in refining strategies to mitigate fouling and enhance MBR efficiency. By simulating diverse operational scenarios and assessing their influence on fouling behavior, ANNs facilitate the selection of optimal operational conditions and cleaning protocols.

2.3.4 LEVNBERG-MARQUARDT ALGORITHM

The Levenberg-Marquardt algorithm is a popular method for training ANNs, particularly in regression and optimization tasks. It combines the advantages of gradient descent and Gauss-Newton methods, offering fast convergence and robust performance[15]

.

2.3.4.1 Introduction to Levenberg-Marquardt Algorithm

The Levenberg-Marquardt algorithm adjusts the connection weights between neurons in an ANN by iteratively minimizing the sum of squared errors between predicted and actual outputs. It incorporates a damping parameter that controls the step size during weight updates, allowing for efficient convergence even in ill-conditioned optimization problems[16].

2.3.4.2 Use in ANN Training

In membrane fouling modeling, the Levenberg-Marquardt algorithm holds significant importance in training Artificial Neural Networks (ANNs) to forecast fouling behavior[17]. This algorithm is instrumental in optimizing network parameters, thereby facilitating accurate predictions regarding fouling based on input factors like feedwater characteristics, membrane attributes, and operational parameters. By leveraging the Levenberg-Marquardt algorithm[18], ANNs can provide reliable insights crucial for informed decision-making in the operation and maintenance of Membrane Bioreactors (MBRs).

2.4 IDENTIFICATION OF RESEARCH GAP

Despite significant advancements in membrane fouling modeling through the utilization of Artificial Neural Networks (ANNs) and other computational methodologies, several research voids remain, necessitating further exploration.

One such gap pertains to the adequacy of datasets utilized in modeling endeavors. Existing datasets often lack diversity in terms of encompassing a wide array of operational circumstances and membrane configurations[19]. Consequently, the predictive capabilities of fouling models developed with ANNs may be constrained. Broadening the scope of data collection initiatives to encompass a more expansive range of scenarios could bolster the reliability and applicability of fouling prediction models[20].

Additionally, there is a discernible need for heightened transparency and reproducibility in the formulation and validation of fouling models. Many studies utilizing ANNs in fouling prediction neglect to furnish detailed insights into network architecture, training methodologies, and validation protocols[20], impeding efforts for result replication and validation by peers. Standardizing protocols and reporting guidelines for the creation and assessment of fouling prediction models using ANNs could bridge this gap[1], [19], [20].

Through concerted efforts to amass comprehensive datasets, devise transparent modeling frameworks, integrate real-time monitoring technologies, and assess long-term model performance, researchers can advance the frontier of membrane fouling modeling using Artificial Neural Networks, fostering sustainable MBR operation.

CHAPTER 3

PROBLEM STATEMENT AND PROCEDURE

3.1 PROBLEM STATEMENT

Membrane bioreactors, or MBRs, are an essential wastewater treatment technology that provide benefits including compact footprint and good effluent quality. However, the ongoing problem of membrane fouling, which raises operating costs and decreases system efficiency, prevents MBRs from being widely used. Because fouling phenomena are complicated and nonlinear, traditional fouling models frequently fail to capture their essence[21]. Thus, there is an urgent need for sophisticated modeling techniques that can both help optimize operating measures to minimize fouling and properly forecast fouling behavior[22].

3.2 RESEARCH OBJECTIVES

This study aims to develop an Artificial Neural Network (ANN) model to effectively predict membrane fouling behavior in MBRs based on key operational parameters. **By accurately modeling the relationships between inputs such as run duration, instantaneous flux, and time, and the output variable, transmembrane pressure (TMP), the ANN can provide valuable insights into fouling dynamics**. The objective further includes optimizing the ANN model to achieve minimal prediction error, thereby serving as a reliable tool for guiding MBR operation and maintenance.

3.3 DATA COLLECTION

The data utilized for this study were sourced from a comprehensive review of relevant literature on MBR operations incorporating relaxation and backwashing methods. Key operational parameters and corresponding TMP values were extracted from these studies[23]. **The dataset includes variables such as run duration, instantaneous flux, and time, which are essential for training the ANN model**. The extracted data were preprocessed to ensure consistency and accuracy, forming a robust basis for model development.

3.4 ARTIFICIAL NEURAL NETWORK APPROACH (PROCEDURE)

3.4.1 ANN ARCHITCTURE

The ANN model developed for this study consists of an input layer, hidden layers, and an output layer. The input layer has three neurons, each representing one of the input parameters: run duration, instantaneous flux, and time. The output layer contains a single neuron corresponding to TMP. One or more hidden layers with varying numbers of neurons are used to capture the complex relationships between the inputs and the output[24]. The optimal architecture, including the number of hidden layers and neurons, is determined through experimentation and validation[21].

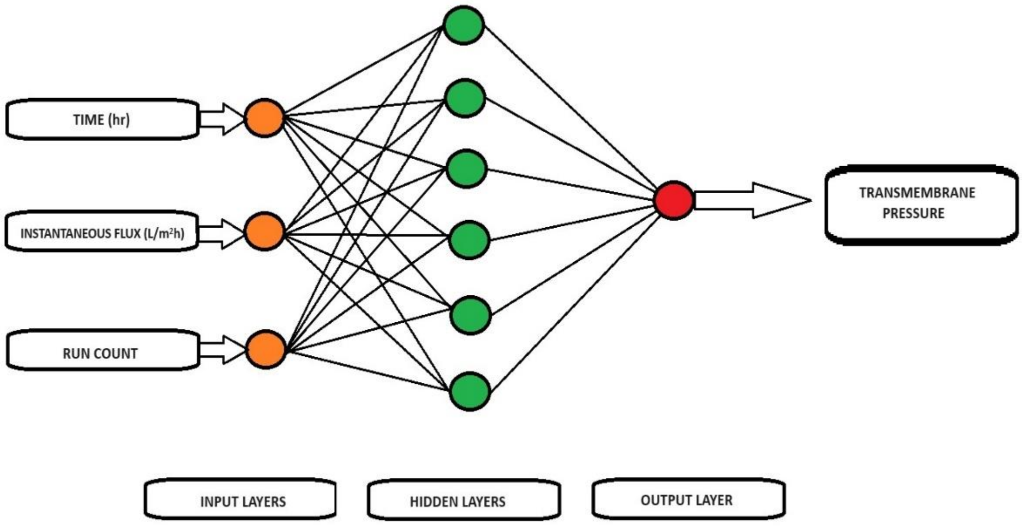

Fig 3.1 Architecture of ANN model

In the present investigation, the ANN was trained using the relaxation and backwashing data. Table 4,5 presents an analysis of the experimental data from the reference work [6] and the ANN assumptions. The ANN model made use of MATLAB's neural network fitting toolkit, which makes use of a multi-layer network. In order to determine the minimum MSE for the set of 40 experimental data points for each technique—which had been randomly divided into 3 sets to train, test, and simulate an artificial neural network—neurons in the hidden layer were optimized to layer size 7 for the relaxation technique and size 12 for the backwashing technique.

3.4.2 TRAINING AND VALIDATION

Training the ANN involves feeding input data into the network and adjusting the weights to minimize prediction error. The Levenberg-Marquardt algorithm is employed for this purpose due to its efficiency in handling nonlinear optimization problems[25].

The dataset is split into training and validation sets, with the former used for training the model and the latter for performance assessment[26]. The model's accuracy is evaluated using metrics such as Mean Squared Error (MSE) and R-squared (R^2) value19.

Table 1 reports the functioning parameter's higher and lower values. The data was simulated using the feedforward technique and the algorithm developed by Levenberg-Marquardt within the same range. By running simulations with two input parameters varied within the range as shown in Table 1, a surface graph was produced. Plotting the surface graphs requires modifying another input parameter, one of which is regarded as run time. This made it possible to examine how these parameters affected TMP and the overall fouling behavior that is observed and examined, as well as how these two parameters' fluctuations interacted with one another.

Table 1: Input Parameters used for training the ANN model

INPUT PARAMETERS	RANGE OF PARAMETERS
Run Duration (hr)	1-24
Instantaneous flux (L^2/mh)	24.5-34
Run Count	1-5

3.5 EXPERIMENTAL SETUP

3.5.1 DESCRIPTION OF LAB SCALE MBR

The experimental setup features a lab-scale MBR designed to replicate real-world conditions. The MBR includes a membrane module, aeration system, and control unit to regulate operational parameters. Feedwater characteristics, including suspended solids and organic content, are monitored to ensure they reflect typical wastewater treatment scenarios[27].

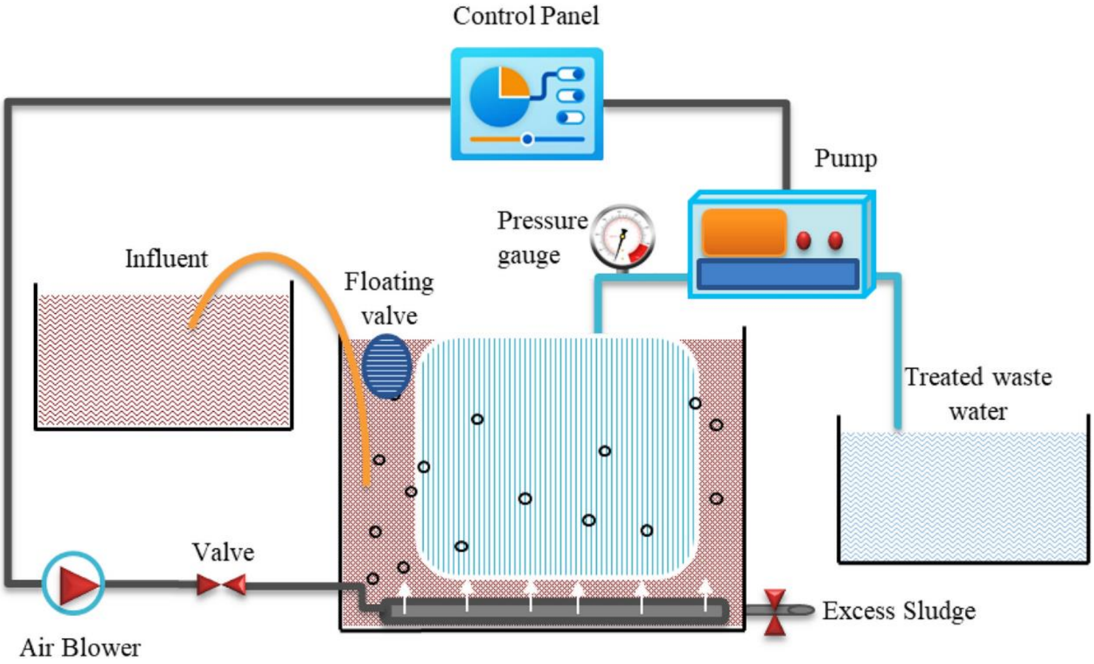

Fig 3.2-Schematic diagram of lab scale MBR treatment system.

3.5.2 OPERATIONAL PARAMETERS

Operational parameters such as **instantaneous flux, backwashing and relaxation duration, and run count** are systematically varied to create a comprehensive dataset. The impact of these parameters on TMP and overall fouling behavior is recorded and analyzed. This data is essential for training and validating the ANN model.

3.6 OPTIMIZATION TECHNIQUES

3.6.1 SELCTION OF HIDDEN NEURONS

Selecting the optimal number of hidden neurons is crucial for the ANN's performance. Too few neurons can lead to underfitting, while too many can cause overfitting[28]. A systematic approach involving cross-validation and performance evaluation is used to determine the ideal number of hidden neurons. This process ensures that the model generalizes well to unseen data[29].

3.6.2 PERFORMANCE METRICS

Mean Squared Error (M.S.E.) is the function we define to quantify the difference between generated and experimental outcomes.
The network's prediction performance is assessed using the mean squared error (MSE) function. For a given input data collection, it calculates the average squared difference between the expected and actual output[27]. The prediction is more accurate when the MSE value is smaller, indicating that.

$$\textbf{Mean square error} = 1/n \sum_{i=1}^{n} (Y_{exp} - Y_{model})^2$$

where n is the data point's number. The variables $y$exp and $y$model denote the model predictions and the experimental results, respectively

CHAPTER 4

RESULT AND DISCUSSION

4.1 ANN TRAINING AND VALIDATION RESULT

Upon training, testing, and validating some percent of the data from the experimental findings of [6] were randomly selected, with fifteen percent going toward testing, fifteen percent toward validation, and seventy percent toward training. The training dataset is a labeled dataset that the model uses to learn from during training. Using an optimization approach, the model optimizes its internal parameters in order to reduce the variation between the expected outputs and the actual labels[30]. In order to allow the model to update its parameters by computing gradients and propagating them through the network, the training dataset is usually segmented into batches or mini-batches[31].

4.1.1 FOR RELAXATION METHOD

The relaxing technique produced the lowest Mean Squared Error (MSE) when the ideal number of neurons in the hidden layer was found to be 7. Table 2 displays the MSE and correlation coefficients (R) between the model predictions for the trained data and the experimental findings. The regression plot, which shows the relationship between the experimental and projected data, is shown in Figure 4.1. A correlation factor more than 0.91, which denotes good prediction accuracy, in this figure validates the ANN model's capacity to predict data.

When comparing the experimental and predicted outcomes for the relaxation condition, we determined a maximum relative error of 4.7% and 8.6% is the absolute error, as seen in Table 4.

Table 2: MSE and R value in training, validation and testing (Layer size 7)

Process	No. of data points	MSE	Correlation coefficient between experimental and model prediction (R)
Training	50	507.8973	0.9393
Validation	11	554.3361	0.9173
Testing	11	465.2070	0.9158

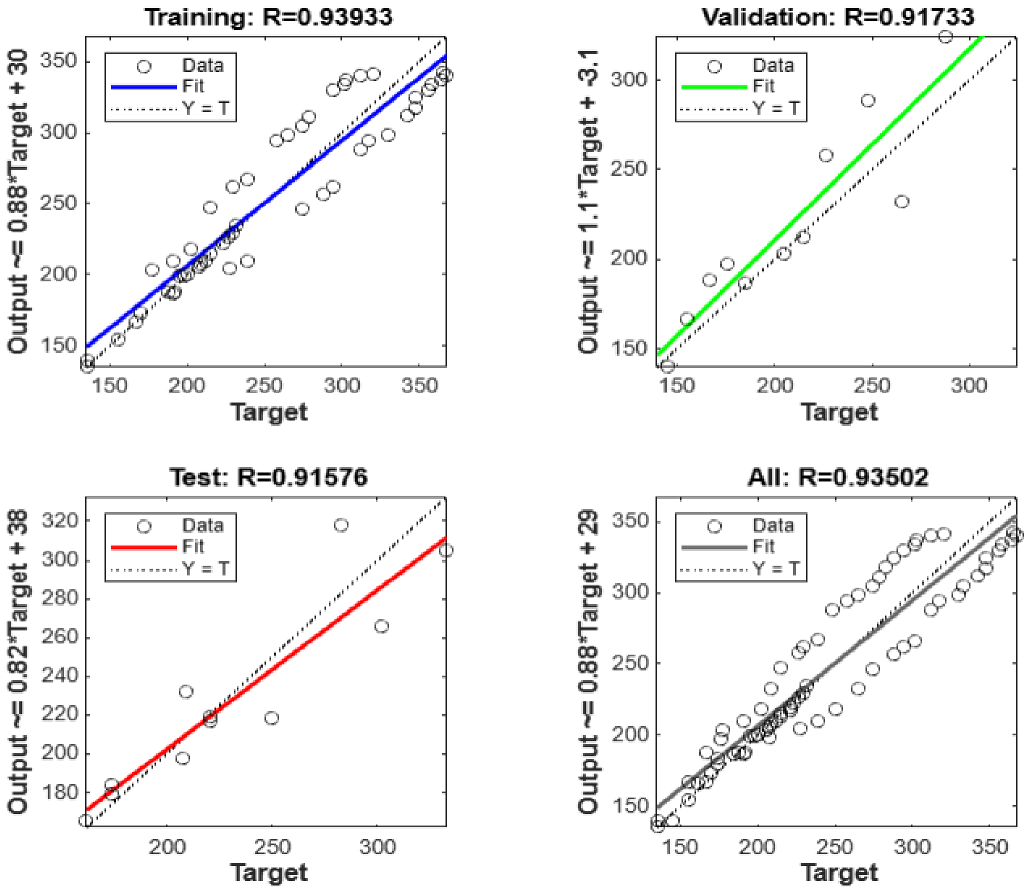

Fig 4.1 Regression Plots of Experimental and Model predicted results

4.1.2 FOR BACKWASHING METHOD

The hidden layer was optimized to include 12 neurons, the lowest Mean Squared Error (MSE) was obtained. Table 3 provides a detailed breakdown of the MSE and correlation coefficients (R) between results from the experiment and model predictions. High predictive accuracy is confirmed by a correlation factor greater than 0.98 in the regression plot of Figure 4.2, which shows the link between experimental and anticipated data. This shows the ANN model's predictive accuracy.

After comparing the experimental and expected outcomes for the backwashing procedure, we discovered a maximum relative error of 14.3% and an absolute error of 21.4%, which are shown in Table 4.

Table 3: MSE and R values of training, validation, and testing (Layer size 12)

Process	No. of data points	MSE	Correlation coefficient between experimental and model prediction (R)
Training	84	265.9982	0.9808
Validation	18	187.3680	0.9861
Testing	18	219.9259	0.9722

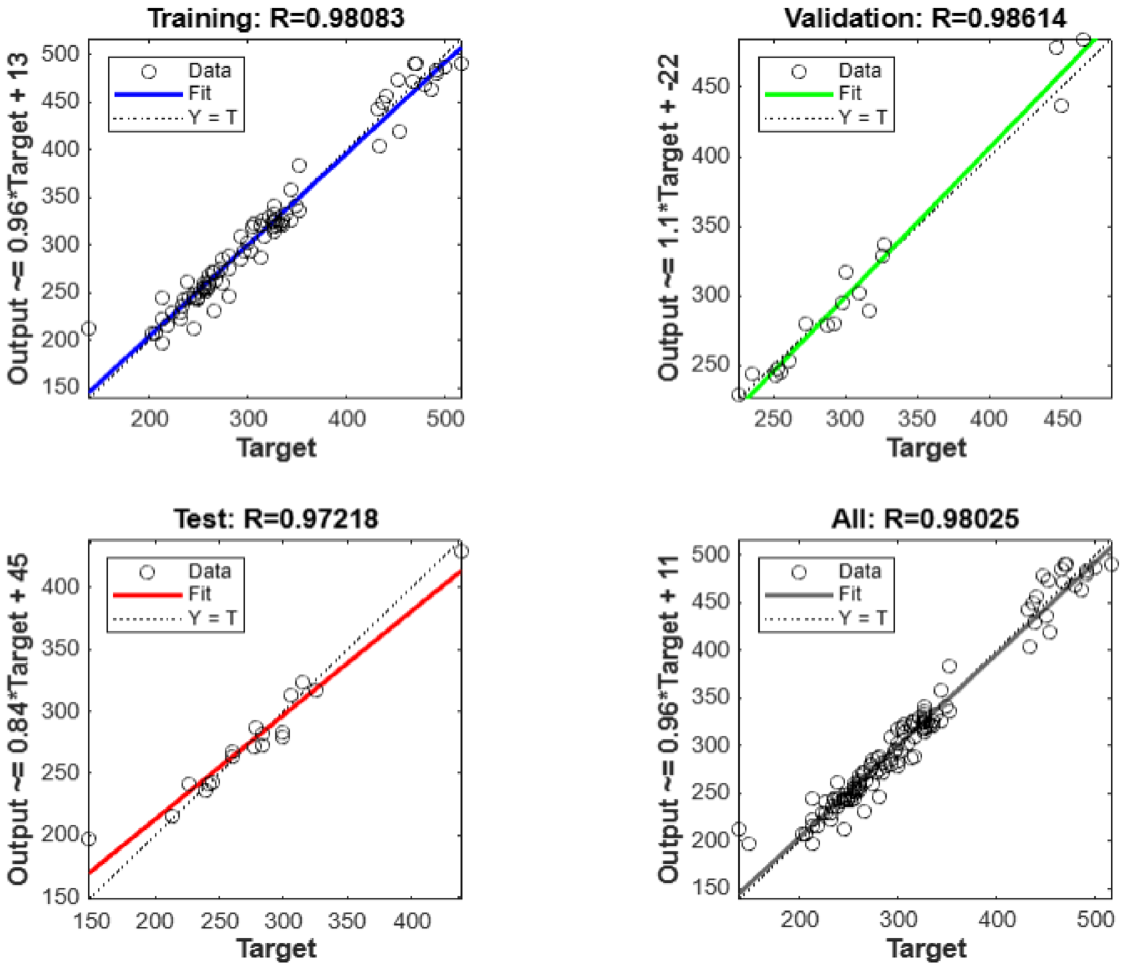

Fig 4.2 Regression Plots of Experimental and Model predicted results

4.2 SURFACE PLOTS FOR RELAXATION AND BACKWASHING

4.2.1 EFFECT OF INSTANTANEOUS FLUX:

For relaxation:

Effect of instantaneous flux- The influence of run duration and instantaneous flux on trans-membrane pressure for the relaxation strategy employed to prevent membrane fouling is shown in Fig. 4.3. Trans-membrane pressure (TMP) increased as run time and flux increased. An increase in TMP with rising instantaneous flux and run time intensifies membrane fouling.

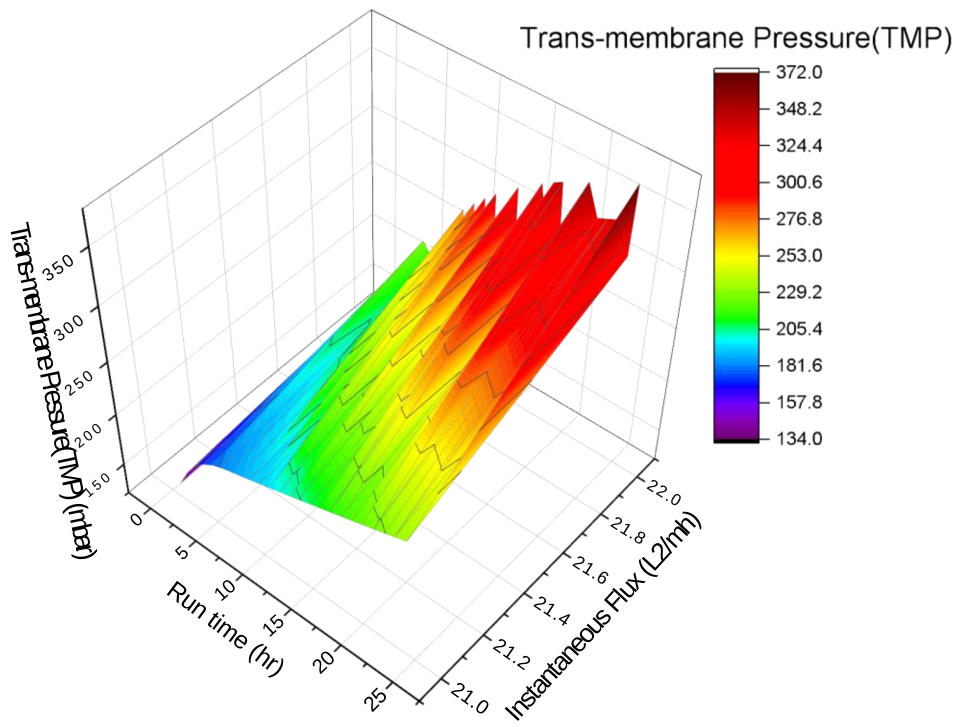

Fig 4.3 Effect of Instantaneous flux and run time on TMP

Effect of Run count and run time on TMP-

Fig 4.4 depicts that TMP increases with both run time and run count, indicating progressive membrane fouling as operational duration and cycles extend the increase in TMP shows that fouling resistance builds up over time. Implementing relaxation techniques (periodic cessation of flow) can help alleviate fouling.

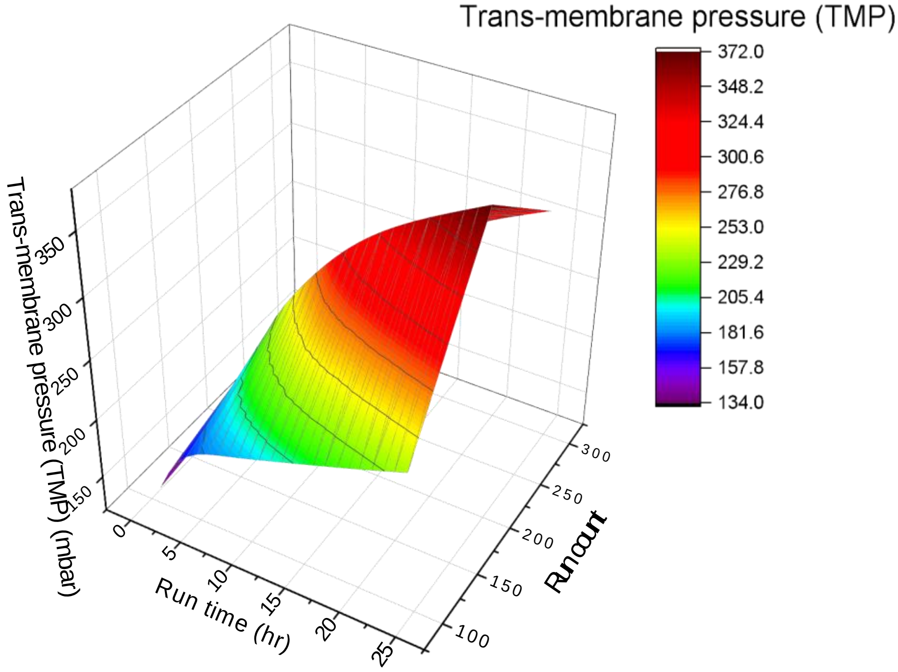

Fig 4.4 Effect of run count and run time on TMP.

For Backwashing: □

Effect of Flux - Fig 4.5 depicts that as both the instantaneous flux and run time increase, TMP also rises.

Impact on Membrane Fouling: Higher flux rates lead to more particles depositing on the membrane, increasing fouling. Similarly, longer run times allow more fouling agents to accumulate, further raising the TMP. Effective fouling control measures like periodic cleaning or backwashing are crucial to maintain membrane performance and longevity.

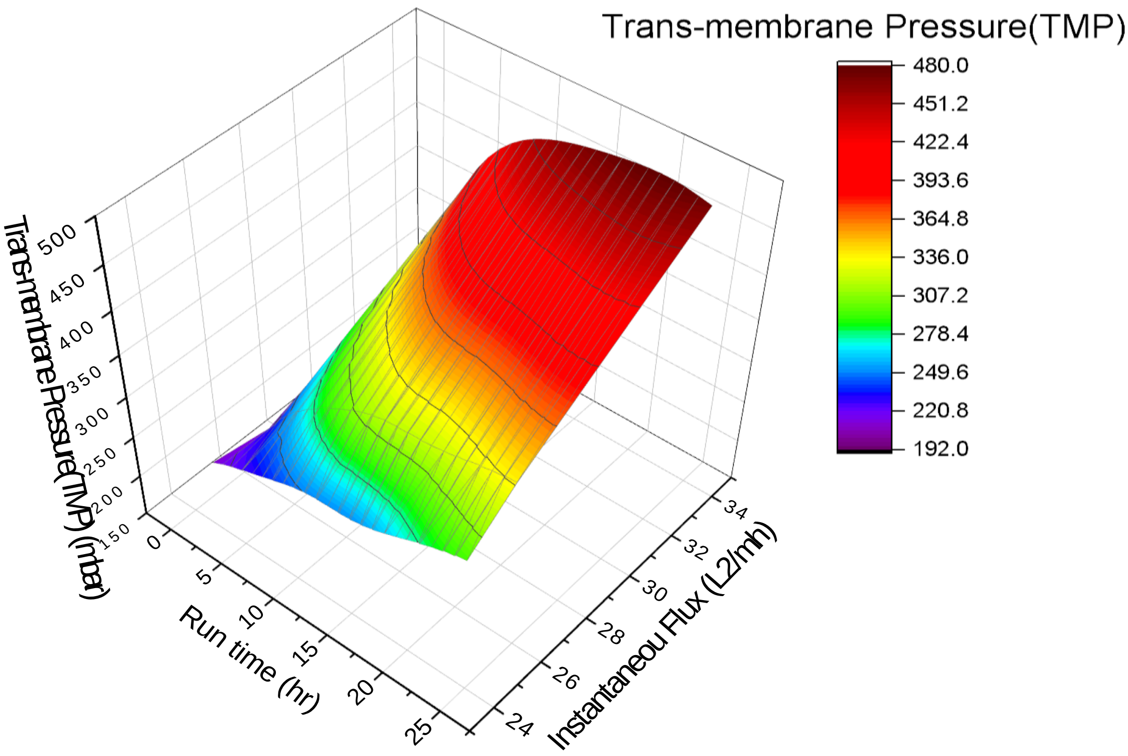

Fig 4.5 Effect of Instantaneous Flux and run time on TMP.

Effect of run count and duration- As the run time increases, the TMP tends to increase across all run counts as shown in Fig 4.6. For each run count, there is a clear trend of rising TMP with increasing run time, indicating a buildup of fouling over time. Optimize backwashing frequency, duration, pressure, and chemical cleaning to reduce TMP and control membrane fouling.

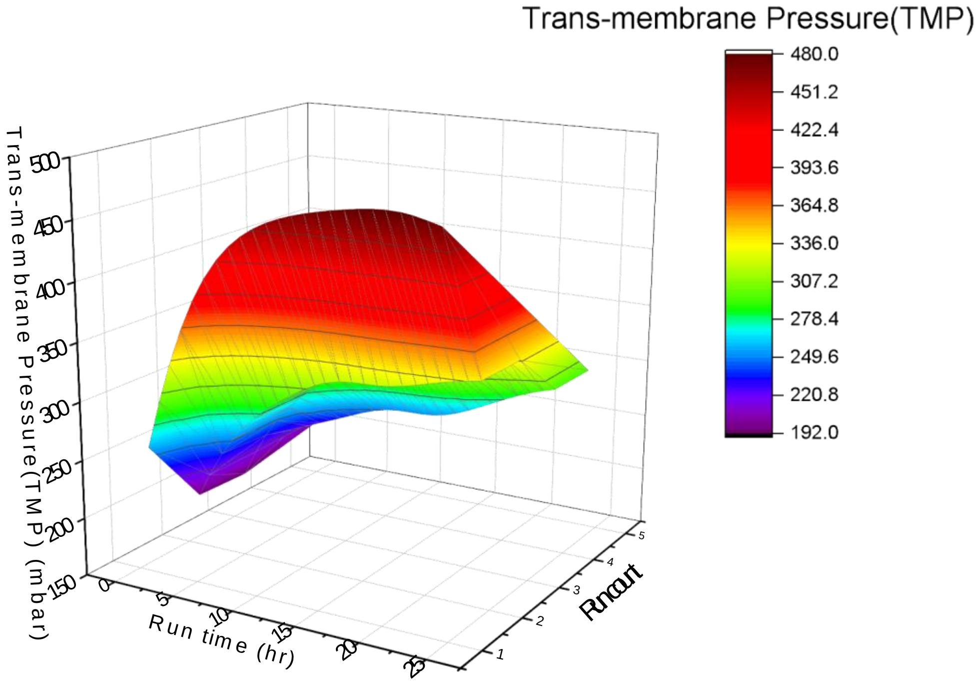

Fig 4.6 Effect of Run time and count on TMP in case of backwashing.

CHAPTER 5

CONCLUSION

Based on the findings of this study, the application of artificial neural networks demonstrated effectiveness in modeling fouling phenomena within membrane-based bioreactors. The model exhibited its most favorable performance with seven nodes in the hidden layer, achieving a correlation factor of 0.91 using the relaxation technique data points, and with twelve nodes, yielding a correlation factor of 0.98 using the backwashing technique data points. Notably, prolonged operational durations correlated with heightened trans-membrane pressure in tandem with instantaneous flux. Conversely, shorter operational durations characterized by lower instantaneous flux and minimal run counts corresponded to reduced fouling occurrences. Consequently, optimal conditions for minimizing fouling in membrane-based bioreactors, as extrapolated from relaxation and backwashing data, were identified as operational durations ranging from (1.02 to 12 hours), a flux value of (21 L^2/mh), and a minimized number of run counts.

APPENDICES 1

Table 4: Correlation of model prediction and experimental findings for backwashing technique and relaxation technique (Experimental data sourced from [6]).

Type of Process	Run	Instantaneous flux (L/m^{2}h)	Time (hour)	Experimental Result TMP (mbar)	Theoretical Result (TMP (mbar))	Absolute Error	Relative Error in %
1	1	34	1.05	259.68	258.3367731	-1.343226947	0.519951895
1	1	34	2.1	298.39	299.6534567	1.263456661	0.421639275
1	1	34	3.04	343.55	332.3391129	-11.21088708	3.373327616
1	1	34	4.08	343.55	363.2349056	19.6849056	5.419332035
1	1	34	5.13	351.61	388.8462162	37.23621622	9.576077808
1	1	34	6.08	433.87	407.5695099	-26.30049013	6.453007278
1	1	34	7.12	453.23	423.8581268	-29.37187316	6.92964728
1	1	34	8.11	438.71	435.9532089	-2.756791144	0.632359411
1	1	34	9.1	450	445.3704935	-4.629506475	1.0394731
1	1	34	10.08	432.26	452.6168213	20.35682132	4.497583909
1	1	34	11.12	437.1	458.5777236	21.47772356	4.683551436
1	1	34	12.11	440.32	463.0158306	22.69583063	4.901739666
1	1	34	13.11	485.48	466.6094087	-18.87059129	4.044194339
1	1	34	14.09	467.74	469.5140905	1.774090549	0.377856721
1	1	34	15.07	446.77	471.9927105	25.22271045	5.343877118
1	1	34	16.06	464.52	474.1885398	9.668539782	2.0389653
1	1	34	17.12	516.13	476.2586057	-39.87139425	8.371795023
1	1	34	18.15	470.97	477.9570585	6.987058517	1.46185905
1	1	34	19.19	469.35	479.2077028	9.857702766	2.057083538
1	1	34	20.13	498.39	479.7204175	-18.66958255	3.891763175
1	1	34	21.23	490.32	479.264516	-11.05548402	2.30676039
1	1	34	22.04	490.32	478.0702953	-12.24970471	2.562322911

1	1	34	23.13	451.61	475.4284777	23.81847765	5.009897129
1	1	34	24.18	479.03	472.373775	-6.656224992	1.409101297
1	2	26.4	1.04	212.9	194.8965705	-18.00342955	9.237427577
1	2	26.4	1.97	245.16	215.2485677	-29.91143227	13.89622824
1	2	26.4	3.14	266.13	236.7837439	-29.34625615	12.39369547
1	2	26.4	4.07	280.65	250.8983504	-29.75164956	11.85804909
1	2	26.4	4.99	274.19	262.6546488	-11.53535117	4.391832097
1	2	26.4	6.04	283.87	273.9674006	-9.902599393	3.61451741
1	2	26.4	7.09	291.94	283.6479328	-8.292067159	2.923365975
1	2	26.4	8.01	291.94	291.1860953	-0.753904674	0.258908199
1	2	26.4	9.06	296.77	298.9654934	2.195493422	0.734363487
1	2	26.4	10.1	300	305.8081745	5.808174525	1.899286876
1	2	26.4	11.09	291.94	311.295512	19.35551199	6.217729212
1	2	26.4	11.96	306.45	315.02975	8.579750008	2.723472944
1	2	26.4	13.12	300	318.173739	18.17373904	5.711891591
1	2	26.4	14.11	304.84	319.368879	14.52887901	4.549246958
1	2	26.4	15.1	312.9	319.8065958	6.906595751	2.159616419
1	2	26.4	16.14	312.9	320.3103097	7.410309741	2.313478373
1	2	26.4	17.07	306.45	321.361682	14.91168204	4.640155585
1	2	26.4	18.11	314.52	323.4142156	8.894215557	2.750100376
1	2	26.4	19.16	325.81	326.2198688	0.409868849	0.125641902
1	2	26.4	20.08	314.52	328.9550019	14.43500186	4.388138736
1	2	26.4	21.07	320.97	331.8579658	10.88796576	3.280911379
1	2	26.4	22.06	325.81	334.4841655	8.67416546	2.593296292
1	2	26.4	23.1	327.42	336.8079118	9.387911847	2.787319275
1	2	26.4	24.09	325.81	338.5720032	12.7620032	3.769361637
1	3	26.4	1.02	148.39	192.8544183	44.46441825	23.05595
1	3	26.4	2.06	138.71	215.569733	76.85973298	35.65423212

1	3	26.4	3.01	222.58	233.1891888	10.60918878	4.549605765
1	3	26.4	3.99	212.9	248.4383254	35.53832544	14.30468724
1	3	26.4	5.04	238.71	261.980474	23.27047403	8.8825223
1	3	26.4	6.04	264.52	272.7828048	8.262804772	3.02907831
1	3	26.4	7.08	272.58	282.4528753	9.872875305	3.495406196
1	3	26.4	8.13	279.03	291.0851888	12.0551888	4.14146417
1	3	26.4	9.06	303.23	298.0030343	-5.226965744	1.753997491
1	3	26.4	10.05	309.68	304.614778	-5.065222034	1.662828727
1	3	26.4	11.09	316.13	310.4866513	-5.643348677	1.817581739
1	3	26.4	12.02	325.81	314.4998429	-11.31015706	3.596236157
1	3	26.4	13.13	325.81	317.5080904	-8.301909629	2.61470806
1	3	26.4	14.17	325.81	318.7591466	-7.050853364	2.211968955
1	3	26.4	15.04	329.03	319.1447282	-9.885271805	3.097426005
1	3	26.4	16.15	335.48	319.6608391	-15.81916088	4.948732828
1	3	26.4	17.07	333.87	320.6771205	-13.19287949	4.114069464
1	3	26.4	18.11	324.19	322.690721	-1.499278952	0.464617931
1	3	26.4	19.1	325.81	325.2858004	-0.524199648	0.161150486
1	3	26.4	20.03	335.48	328.0129983	-7.467001685	2.276434691
1	3	26.4	21.13	325.81	331.2061179	5.396117924	1.629232563
1	3	26.4	22.06	338.71	333.6463136	-5.063686437	1.517680919
1	3	26.4	23.05	351.61	335.8578001	-15.75219994	4.690139676
1	3	26.4	24.04	348.39	337.6378973	-10.75210271	3.184507069
1	4	24.5	1.03	206	210.3366716	4.33667161	2.061776283
1	4	24.5	2.08	219	217.153426	-1.846573961	0.850354514
1	4	24.5	3.01	232	221.9514733	-10.04852668	4.527352995
1	4	24.5	4.06	232	226.6553522	-5.344647818	2.358050567
1	4	24.5	5.04	239	230.8591185	-8.140881537	3.526341776
1	4	24.5	6.03	242	235.1996473	-6.800352744	2.891310775

1	4	24.5	6.96	245	239.3749031	-5.625096936	2.349910899
1	4	24.5	8	248	243.8934846	-4.106515442	1.683733147
1	4	24.5	8.99	245	247.5873552	2.58735521	1.045027202
1	4	24.5	10	252	250.256181	-1.743819008	0.696813562
1	4	24.5	11	255	251.6024466	-3.397553366	1.35036579
1	4	24.5	12.1	253	251.9729606	-1.027039374	0.407599042
1	4	24.5	13	258	252.1049779	-5.895022061	2.338320373
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1	4	24.5	16	261	258.3070248	-2.692975171	1.042548174
1	4	24.5	17.1	268	263.263679	-4.736321014	1.799078791
1	4	24.5	18.1	261	268.4290102	7.429010166	2.767588407
1	4	24.5	19	266	273.2487607	7.248760697	2.652806431
1	4	24.5	20	281	278.480141	-2.519859029	0.904861302
1	4	24.5	21.1	287	283.8107615	-3.189238537	1.123720087
1	4	24.5	22.1	300	288.1160632	-11.88393681	4.124704703
1	4	24.5	23.1	313	291.8356641	-21.1643359	7.252141702
1	4	24.5	24	316	294.6694389	-21.3305611	7.238810099
1	5	24.5	1.03	203	209.7635299	6.763529896	3.224359306
1	5	24.5	2.08	213	216.6062576	3.606257587	1.664890769
1	5	24.5	3.01	213	221.4193275	8.419327519	3.802435683
1	5	24.5	4	226	225.8759044	-0.124095623	0.054939735
1	5	24.5	5.04	234	230.3511397	-3.648860282	1.584042643
1	5	24.5	6.03	227	234.707517	7.707517021	3.283881624
1	5	24.5	7.07	235	239.3979152	4.39791517	1.837073296
1	5	24.5	8	240	243.4489431	3.448943102	1.416700791
1	5	24.5	9.05	235	247.3649115	12.36491151	4.998652169
1	5	24.5	10.1	248	250.0535811	2.053581137	0.821256439

1	5	24.5	11.1	248	251.2840296	3.284029559	1.306899433
1	5	24.5	12.1	245	251.569394	6.569394025	2.61136457
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1	5	24.5	14.1	255	252.5518616	-2.44813836	0.969360647
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1	5	24.5	16.1	256	258.1012993	2.101299274	0.814137426
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1	5	24.5	18.1	260	267.7104786	7.710478632	2.880155708
1	5	24.5	19	277	272.4898175	-4.510182532	1.655174705
1	5	24.5	20.1	273	278.1849912	5.184991196	1.863864464
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1	5	24.5	23	274	290.6038902	16.6038902	5.713581531
1	5	24.5	24	281	293.7593023	12.75930228	4.343454721
2	100	21	1.02	136	134.102594	-1.897405964	1.41489132
2	100	21	2.03	155	151.8004557	-3.199544261	2.10773034
2	100	21	3.05	162	164.963964	2.963964028	1.796734242
2	100	21	3.95	170	172.8812944	2.881294403	1.666631669
2	100	21	5.02	174	178.937519	4.937519009	2.759353676
2	100	21	5.98	174	182.515674	8.515673964	4.665722006
2	100	21	6.94	185	185.3011076	0.30110764	0.162496406
2	100	21	8.01	188	188.1309537	0.13095373	0.069607753
2	100	21	8.97	192	190.6802056	-1.319794429	0.692150727
2	100	21	10	195	193.4965501	-1.503449927	0.77699056
2	100	21	11	198	196.2993452	-1.700654798	0.866357856
2	100	21	12.1	200	199.4277481	-0.572251897	0.286946978
2	100	21	13.1	205	202.2918144	-2.708185619	1.338751955
2	100	21	14	208	204.8784296	-3.121570387	1.523620809

2	100	21	15.1	209	208.0508575	-0.949142517	0.456206972
2	100	21	16	212	210.6587655	-1.341234476	0.636685814
2	100	21	17	215	213.5745515	-1.42544851	0.667424325
2	100	21	18.1	215	216.810292	1.810291994	0.834965894
2	100	21	19.1	221	219.7828948	-1.217105202	0.553776127
2	100	21	20	221	222.4868255	1.486825468	0.668275735
2	100	21	21.1	223	225.8317061	2.831706079	1.253901026
2	100	21	22.1	226	228.9131836	2.913183646	1.272615059
2	100	21	23	230	231.7212192	1.721219211	0.742797408
2	100	21	24.1	232	235.199684	3.199683996	1.36041169
2	200	22	0.96	145	144.9194497	-0.080550301	0.055582809
2	200	22	1.97	167	167.5620968	0.562096776	0.335455803
2	200	22	2.99	191	189.801378	-1.198622014	0.631513863
2	200	22	4.01	208	209.820948	1.820947984	0.867858048
2	200	22	5.02	227	226.8203553	-0.179644705	0.079201316
2	200	22	5.98	239	240.6541031	1.65410308	0.68733633
2	200	22	7	250	253.6160139	3.616013878	1.425782948
2	200	22	8.01	265	265.358007	0.358007025	0.134914725
2	200	22	8.97	274	275.8276458	1.827645761	0.662604271
2	200	22	10	288	286.3737505	-1.626249497	0.567876593
2	200	22	11	294	295.8741439	1.874143913	0.633426054
2	200	22	12	302	304.5919714	2.591971373	0.8509651
2	200	22	13	312	312.5265662	0.526566178	0.168486854
2	200	22	14	317	319.7315911	2.731591059	0.854338807
2	200	22	15	330	326.2959582	-3.704041759	1.13517856
2	200	22	16.1	333	332.9003278	-0.09967217	0.029940544
2	200	22	17.1	342	338.4550354	-3.544964553	1.047396015
2	200	22	17.9	348	342.6555228	-5.344477227	1.559723066

2	200	22	19.1	348	348.6460601	0.646060088	0.185305432
2	200	22	20.1	356	353.4258395	-2.574160541	0.728345314
2	200	22	21.1	358	358.068767	0.068767016	0.019204975
2	200	22	22	364	362.1646247	-1.835375291	0.506779284
2	200	22	23.1	368	367.0999958	-0.900004163	0.245165942
2	200	22	24.2	365	371.9895317	6.989531683	1.878959241
2	300	22	0.96	135	135.6870753	0.68707531	0.506367544
2	300	22	1.97	155	152.4144274	-2.585572602	1.696409353
2	300	22	3.11	167	167.4564053	0.456405299	0.272551712
2	300	22	3.95	176	175.7774334	-0.222566649	0.126618443
2	300	22	4.96	177	183.5134465	6.513446451	3.549302014
2	300	22	5.98	191	190.3169807	-0.683019345	0.358885131
2	300	22	7	202	197.5620308	-4.437969193	2.24636747
2	300	22	8.01	209	205.8848515	-3.11514852	1.513053776
2	300	22	9.03	215	215.3805885	0.380588545	0.176705128
2	300	22	10.1	226	225.9327979	-0.067202054	0.029744267
2	300	22	11.1	230	235.7197348	5.719734817	2.42649807
2	300	22	12.1	239	244.9828022	5.982802169	2.442131495
2	300	22	13	248	252.6700938	4.670093799	1.848297014
2	300	22	14.1	258	261.1481241	3.148124129	1.205493679
2	300	22	15	265	267.3649938	2.364993778	0.884556256
2	300	22	16	274	273.6030393	-0.396960679	0.145086356
2	300	22	17	279	279.2503056	0.250305643	0.089634868
2	300	22	18.1	283	284.9203242	1.920324234	0.673986399
2	300	22	19.1	288	289.6966235	1.696623525	0.585655264
2	300	22	20	294	293.763592	-0.236407997	0.080475594
2	300	22	21.1	302	298.5158377	-3.48416235	1.167161641
2	300	22	22	303	302.2757066	-0.724293369	0.23961349

2	300	22	23.1	312	306.7661728	-5.233827171	1.706129174
2	300	22	24	320	310.3855703	-9.614429679	3.09757624

CHAPTER 6

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