CONTROL AND OPTIMIZATION OF MEMBRANE BIOLOGICAL REACTOR PROCESSES

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CONTROL AND OPTIMIZATION OF MEMBRANE BIOLOGICAL REACTOR PROCESSES

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ABSTRACT

Membrane biological reactor (MBR) is an emerging technology adopted for domestic and industrial wastewater treatment. The high selectivity of the semi permeable membrane to water results in membrane fouling. Fouling is a highly nonlinear phenomenon that affects the MBR stability, productivity, and performance. Many techniques are proposed to minimize and control fouling such as backwashing and aeration. However, such techniques may lead to high operation costs and high energy consumption rates. Therefore, optimization of MBR operating conditions is essential in order to achieve effective, stable, and economical MBR operation.

In this study, a rigorous mathematical model is developed for the MBR. The model is derived by performing a mass balance on three major parameters, the substrate concentration, the biomass concentration, and the Oxygen concentration. Then, kinetic models representing the major reactions in the MBR are stated. Four kinetic parameters namely, the maximum specific biomass growth rate, net biomass yield, Monod constant, and endogenous decay coefficient are estimated using experimental data. Further, an empirical flux model is proposed representing the flux exponential decline behavior. The flux model also requires the estimation of two constants representing the cake growth. Hence both the kinetic and flux parameters are estimated using POLYMATH nonlinear regression. Combining the mass balance equations along with the corresponding kinetic models and the estimated kinetic parameters yields to a system of first order nonlinear coupled ODEs. Hence solving
such system online is inefficient due to the large computational time and effort. Thus artificial neural networks (ANNs) are suggested for MBR modeling. The input and output variables are first selected for the ANN model. The selected input variables are the backwash pressure, vacuum pressure, and ratio of vacuum-to-backwash time, while the flux is selected as the output variable. Different ANN models are developed by training different input variables and the response of flux is observed and compared with experimental data. A better ANN predicted flux is attained when increasing the number of inputs to the ANN model. Accordingly, advanced control strategy is used to control and stabilize the MBR performance. A Model Predictive Control (MPC) is implemented with the optimum ANN model using Neuro-MPC toolbox of MATLAB/SIMULINK. The NN-MPC demonstrates the effectiveness of the proposed methodology in stabilizing the MBR and optimizing its performance. The NN-MPC performance depends on the prediction horizon and control horizon. The control prediction is performed through minimizing an objective or cost function to track a predefined set-point trajectory. Short prediction and control horizons are used for a more aggressive controller. Aggressive controller settings reduce the computational time and effort but may lead to process instabilities. Therefore, two weighting parameters are set at a large value to avoid oscillations. The NN-MPC demonstrated a good servo performance (set-point tracking) within the constrained inputs range. On the other hand, the conventional linear PID controller demonstrated unrealistic manipulated variable moves due to unconstrained manipulated variables, and the difficulty of tuning the control parameters due to lack of deterministic models.
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NOMENCLATURE

Symbols

$\mu_{\text{max}}$ – maximum specific biomass growth rate (g new biomass/g biomass·day)

$k_d$ – endogenous decay coefficient (g dead cells/g cells·day)

$K_s$ – Monod constant (g substrate/m$^3$)

$Q$ – volumetric flow rate (m$^3$/day)

$S$ – substrate concentration (g substrate/m$^3$)

$X$ – biomass concentration (g biomass/m$^3$)

$Y_{\text{bio}}$ – net biomass yield (g biomass/g substrate)

Abbreviation

AMBR – Aerobic Membrane Biological Reactor

ANN – Artificial Neural Network

BOD – Biological Oxygen Demand

bw – backwash time

CAS – Conventional Activated Sludge

COD – Chemical Oxygen Demand

DO – Dissolved Oxygen

EPS – Extracellular Polymeric Substances

F/M – Food to Microorganism ratio
HRT - Hydraulic Retention Time
LC - Level Controller
L-M - Levenberg-Marquardt
MBR - Membrane Biological Reactor
MIMO - Multi Input Multi Output
MISO - Multi Input Single Output
MLSS - Mixed Liquor Suspended Solids
MPC - Model Predictive Control
NN-MPC - Neural Network Model Predictive Controller
ORL - Organic Loading Rate
OTR - Oxygen Transfer Rate
P.G. - Pressure Gauge
PIC - Pressure Indicator Controller
PID - Proportional Integral Derivative Controller
ppm - Parts Per Million
SDNR - Specific Denitrification Rate
SISO - Single Input Single Output
SNR - Specific Nitrification Rate
SOUR - Specific Oxygen Uptake Rate
SRT - Sludge Retention Time
TMP - Trans Membrane Pressure
vac - vacuum time
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Chapter 1

INTRODUCTION

1.1 Problem Statement

Membrane Biological Reactor (MBR) is a center of attraction technology for wastewater treatment and water reclamation processes. MBR is used in municipal and industrial wastewater treatment plants due to its high efficiency in treating and producing high quality effluent. Nevertheless, the limited wide spread of MBRs is attributed to the high complexity and nonlinearity of such processes leading to instabilities and difficulties in control. The main cause of such instabilities is the tendency of the membrane to foul. Fouling is a complex phenomenon results in a sharp decline of permeate flux, an increase in trans-membrane pressure, and thus biodegrade the membrane efficiency. Different techniques are investigated to minimize and control fouling such as, operating in a fed batch mode by applying intermediate suction and thus allowing foulants to diffuse away from the membrane when filtration is stopped [1]. Replacing the dead end filtration by cross flow filtration is also an effective technique in reducing membrane fouling [2], [3]. Implementing an air diffuser below the membrane minimizes fouling by providing a shear force through the uplifting air bubbles which scours the membrane surface [1], [4]. Selecting membrane material is also investigated in terms of hydrophilicity/hydrophobicity [4] and surface roughness [5]. Preliminary treatment of the feed wastewater depending on its composition before feeding it to the MBR is proposed. Preliminary treatment using flow equalization, screening, and grid removal is found to be effective in reducing both the load on the MBR and membrane fouling [6]. Yet, several techniques are applied to regenerate and clean the membrane such as, chemical cleaning, cleaning by compressed air, and backwashing. Backwashing is the most adapted technique for cleaning and regenerating the membrane. More frequent backwashing may affect the overall permeate productivity, lead to instabilities, and rapture the membrane. On the other hand, less frequent backwashing results in severe
membrane fouling. Therefore, optimizing the frequency and duration of backwashing are the major concerns for effective fouling removal and stable operation [7]—[9]. Backwashing and aeration are the most effective techniques implemented to reduce membrane fouling. However, they increase the energy consumption, increase the operating costs, and create instability in the system. Therefore, optimization of the membrane design and operating parameters in order to minimize energy costs, minimize operating costs, control fouling, stabilize the process, and maintain a clean fresh membrane is essential. Several artificial intelligent techniques are applied on the MBR to control fouling wherein the results show satisfactory process response [8], [10].

Hence membrane fouling depends on different operating and design parameters such as: sludge retention time (SRT), hydraulic retention time (HRT), dissolved oxygen (DO), temperature, viscosity, biological activity, pH … etc. The coupling of these parameters leads to a complex nonlinear system. For example, the biomass activity depends on the SRT, DO, temperature, viscosity, and pH. High SRT leads to high biomass removal rates and hence washout condition occurs. Low dissolved oxygen concentrations inhibit the biomass activity in biodegrading of the substrate. The low DO concentration is attributed to either high sludge viscosity or low aeration rates. The high sludge viscosity may be due to low temperatures or long SRT. However, increasing the temperature to reduce the sludge viscosity may deactivate the biomass. Thus changing one operating parameter may inversely affect the other operating parameters leading to insufficient MBR performance.

1.2 Research Objectives

The objectives of this work are: To develop a rigorous dynamic model for the MBR and perform parameter estimation through model fitting of experimental data. To develop an artificial neural network model that may capture the process dynamic behavior at different operating scenarios. To perform sensitivity analysis to verify the optimum backwash scheduling ratio and to select the optimum input/output variables for the advanced control strategy. Finally, to design an artificial intelligent model predictive control system (ANN-MPC) for MBR which may enforce optimum targets for backwash scheduling that minimizes fouling (i.e. maximizes the flux).
1.3 Research Significance

The high efficiency of MBR in producing high quality disinfected effluent makes it an attractive alternative for municipal and industrial wastewater treatment. However, the presence of microorganism and the tendency of the membrane to foul contribute to the instability of such system. Stability of any dynamic system is a challenging problem due to the complexity and nonlinearity arising from both the multivariable interacting system and complexity of the biomass cells. Using conventional linear PID controllers may result in poor controller performance causing undesired washout operation. Moreover, tuning a PID controller leads to bifurcation in which the system may be stable at a certain operation point but a slight change may result in a jump to an unstable operation region. Hence advanced adaptive controllers are developed and fitted to the nonlinear complex model. Several attempts are made to control MBRs utilizing artificial intelligence techniques to control different parameters in the MBR.

Hence, the significance of this research is in optimizing MBR operating conditions in order to minimize fouling, operating costs and energy consumption. Controlling and stabilizing the MBR performance by implementing an appropriate advanced control strategy such as model predictive controller coupled with artificial intelligence techniques. Finally, optimizing the MBR intends to minimize fouling, prevent washout operation, control biodegradation, prolong constant flux operation, and maintain effective backwash frequency and duration.
1.4 Structure of the Thesis

This report is divided into six chapters. The research problem statement, objectives, and significance are discussed in chapter 1. Chapter 2 represents an overview of the MBR process and a background on the advanced control strategies including artificial intelligence techniques and model predictive control.

Chapter 3 demonstrates the derivation of a dynamic representative model for the MBR. Model solution methods and parameter estimation are performed and fitted to experimental data. Furthermore, the process methodology is revealed including the experimental set-up and process description.

Then in chapter 4, artificial neural network (ANN) techniques are utilized to model the MBR. Different ANN model scenarios are applied with different process input variables. The ANN predicted outputs are compared with experimental data. Finally sensitivity analysis is performed to study the behavior of the output variable corresponding to changes in the input variables.

Advanced control strategy is discussed in chapter 5. It utilizes model predictive control based on nonlinear artificial neural network (NN-MPC). Plant identification is first performed. The controller parameters are tuned. The process variable responses to pre-defined set-point tracking using the proposed controller are verified. Then NN-MPC performance is compared to a conventional linear PID controller. Finally, the conclusions and future work are revealed in chapter 6.
Chapter 2

LITERATURE REVIEW AND BACKGROUND

This chapter represents an overview of the membrane biological reactor (MBR) processes. The MBR is described in terms of the major advantages, drawbacks, overall reaction mechanisms, operating parameters, and industrial application. Then, the MBR control challenges and advanced control strategies along with the nonlinear intelligence techniques are demonstrated. Finally, a background on the advanced control strategy is revealed using model predictive control with neural network model (NN-MPC).

2.1 Membrane Biological Reactor

Membrane biological reactor (MBR) is an emerging technology for municipal and industrial wastewater treatment. It is a combination of activated sludge biological treatment process and membrane filtration. It performs solid/liquid separation which is traditionally accomplished by the secondary clarifier [6]. It also produces a disinfected effluent due to the high selectively of the semi-permeable membrane. Consequently, submerged MBR combines the: sludge aeration tank, secondary clarifier, and tertiary filtration for disinfection from the conventional activated sludge (CAS) process in one single unit. This allows smaller foot print as the MBR occupies half the land area of a CAS process [11]. Moreover, MBR operates under high biomass retention rates. This reduces the disinfection intensity and thus minimizes both the energy consumption and chlorine demand to attain target residual. It also produces high effluent quality with solids concentrations less than 1 ppm. The effluent water produced may be further reused in irrigation, discharged to surface water, or other uses depending on the effluent quality [12]. Additionally, the smaller foot print of MBR facilitates the operation under high mixed liquor suspended solids (MLSS) concentration, high volumetric loading rates, and long sludge retention time (SRT). The long SRT improves nitrification process [7], reduces sludge production
and hence decreases the load on the sludge handling facilities. Further, MBR enables high removal rates of biological oxygen demand (BOD), chemical oxygen demand (COD), and water reclamation [12].

Several reaction mechanisms occur in the MBR due to the coupling of the aerator and microorganism culture in a single tank. In general, the substrate (consisting of particulate or soluble organic matter) undergoes several simultaneous reactions producing water and other products. The first reaction step is the substrate oxidation reaction. The biomass utilizes the biodegradable substrate under aerobic conditions producing new biomass cells:

\[
\text{Substrate} + \text{O}_2 + \text{bacteria} \rightarrow \text{new cells} + \text{products}
\]

Then nitrification reaction occurs under aerobic condition following a two step mechanism. Each step utilizes specialized bacteria for oxidation. The first step is oxidizing Ammonia into Nitrite. Followed by the oxidation of nitrite into Nitrate as follows:

Step 1:

\[
2\text{NH}_3 + 3\text{O}_2 + \text{Nitrosomona Bacteria} \rightarrow \text{NO}_2 + 2\text{H}_2\text{O} + 2\text{H}^+ + \text{new cells} + \text{energy}
\]

Step 2:

\[
2\text{NO}_2 + \text{O}_2 + 2\text{H}^+ + \text{Nitrobacter Bacteria} \rightarrow 2\text{NO}_3 + 2\text{H}^+ + \text{new cells} + \text{energy}
\]

After that, denitrification reaction under anaerobic conditions takes place. Nitrate is biodegraded into Nitrogen gas and water is produced as follows:

\[
\text{NO}_3 + \text{Organic Source} + \text{Denitrifying Bacteria} \rightarrow \text{N}_2 + \text{water} + \text{Alkalinity}
\]

Despite the high efficiency of MBR in producing high quality effluent, membrane fouling and the high capital cost of the membrane are the main obstacles that hinder the wide spread of MBR [12]. Membrane fouling affects the MBR stability, performance, and productivity. It occurs because of the high selectivity of the semi permeable membrane in retaining foulants. It may also arise due to the excess flow quantities. Hence flow equalization is required to adjust the flow [6]. The
excessive transportation of foulants to the membrane during filtration builds-up a cake layer or fouling layer. The fouling layer blocks the membrane pores, decreases permeate flux, increases pressure drop across the membrane, reduces permeate production, and biodegrades the membrane. The severity of fouling is determined by a combination of various physical, chemical, and biological operating factors [13].

Several techniques are used to reduce membrane fouling. Backwashing and aeration are the most effective techniques in minimizing fouling. Backwashing is reversing the flow of the permeate through the membrane for a short period of time. Thus cleaning and regenerating the membrane. Aeration is provided through implementing an air diffuser under the membrane. The uplifting force of the bubbles scours the membrane surface, and hence reducing the accumulated fouling layer. However, both techniques increase the operating costs and instability of the MBR. Therefore, there is a tradeoff between both the operating costs and process stability and membrane fouling reduction. Thus optimizing MBR process parameters is crucial to control or reduce membrane fouling, obtain stable MBR system, and reduce operating costs.

2.2 Membrane Fouling

Fouling is the accumulation of foulants within the membrane pores and/or onto the membrane surface during filtration [13]. It is the phenomena responsible of the decline in permeate flow and the increase in membrane hydraulic resistance or permeability. Membrane permeability is affected by three factors: feed composition, membrane (type, geometry, material, and configuration), and operating conditions [11]. The membrane fouling phenomenon due to cake formation and pore blocking is illustrated in Fig. 2-1.
Fouling generally occurs on the external surface of the membrane. The continuous compulsive transport of foulants to the membrane surface during filtration causes the rapid formation of a dynamic fouling layer. The fouling layer results in clogging the membrane pores and building up a cake layer. The permeation drag force affects the initial attachment of feed components onto the membrane surface. Moreover, the main factors contributing in membrane fouling are the activated sludge characteristics and operating conditions. Thus controlling these two factors ensures a stable MBR operation and minimum membrane fouling rate. Sludge characteristics are directly affected by MBR operating parameters including the sludge retention time (SRT), hydraulic retention time (HRT), food to microorganism ratio (F/M), dissolved oxygen (DO), dilution rate, and organic loading rate (OLR). On the other hand, the operating conditions are characterized by the substrate concentration, temperature, aeration, backwashing, and chemical cleaning.
2.2.1 Sludge Retention Time (SRT)

Sludge retention time (SRT) is the average time the biomass spends in the MBR. It is defined as the amount of mixed liquor suspended solids (MLSS) accumulated in the MBR to the amount of sludge removed from the MBR [15]. Therefore, it is the ratio of the biomass accumulated in the MBR to the amount of biomass removed per day.

\[
SRT = \frac{XV}{\sum (XQ)_{out}} \quad (2-1)
\]

Equation (2-1) demonstrates that a long SRT indicates high MLSS concentrations and low sludge removal rates. As a result, high fouling rates are attained due to the excess production of Extracellular Polymeric Substances (EPS), the decrease in \( N_2 \) and phosphorous removal efficiencies, and the decrease in biological activity. The decline in biological activity is attributed to the low specific oxygen uptake (SOUR), the low specific nitrification rate (SNR), and the low denitrification rate (SDNR). On the other hand, a low SRT indicates high sludge removal rates leading to washout condition. Washout condition occurs when the removal rate of biomass from the MBR is greater than the rate of production of biomass. Such that the concentration of biomass declines until all biomass are washed out of the MBR resulting in severe membrane fouling. The high fouling rates is attributed to the absent of biomass in biodegrading the substrate and thus large substrate particles are transported to the membrane. To avoid washout condition, a safety factor is defined by the ratio of the desired to the minimum SRT.

\[
SF = \frac{SRT_{desired}}{SRT_{min}} \quad (2-2)
\]

Nevertheless researchers suggested operating at longer SRT. Long SRT indicates higher MLSS concentration and thus higher biomass concentration in the MBR. The high biomass concentration yields to a better treatment efficiency. Since long SRT provides sufficient time for the biomass to undergo endogenous respiration. Therefore minimizes sludge production and facilitates the growth of specialized bacteria which enhance the breakdown of macromolecules [11]. However prolong
SRT increases the MLSS viscosity. High viscosities decrease the biomass activity because it minimizes the oxygen transfer rates necessary for biomass growth. As a result severe membrane fouling is achieved [16]. In order to control fouling, more oxygen is supplied to the MBR through increasing the aeration intensity. However, excess supply of oxygen reduces the efficiency of both $N_2$ and phosphorus removal [15].

2.2.2 Hydraulic Retention Time (HRT)

Hydraulic retention time (HRT) is also referred to the residence time. It is defined as the average time a certain molecule spends in the MBR. Some researchers use the term organic loading rate (OLR) instead of HRT. OLR is defined as the reciprocal of HRT. Furthermore, HRT affects both the MBR treatment efficiency and the biomass characteristics in the suspended sludge. Short HRT (or high OLR) along with high flux rate increase the COD removal rates. However higher fouling rates are observed due to the excessive growth of filamentous bacteria [17]. The filamentous bacteria increase the sludge viscosity. The high sludge viscosity decreases the dissolved oxygen concentrations necessary for biomass growth, and thus reduces the biomass activity in biodegradation resulting in high fouling rates.
2.2.3 Dissolved Oxygen (DO)

Dissolved Oxygen is essential for biological growth and nitrification processes. DO concentration is controlled by the aeration rate or aeration intensity. High DO concentration leads to better filterability and lower fouling rate. Aidan et al. [18] reported the effect of sequential aeration on the dissolved Oxygen concentration as illustrated in Fig. 2-2:

![Figure 2-2](image)

Figure 2-2  Effects of sequential aeration on the DO concentration in an AMBR [18]

Fig. 2-2 demonstrates the increase of DO concentration to a maximum then decreases as time increases. Hence an optimum DO concentration is attained at specified operating conditions. A similar observation is found in both Hong et al. [13], Le-Clech et al. [4]. The behavior may be explained due to the biomass activity. Oxygen is required for substrate biodegradation reactions and cell respiration. However excess amounts of Oxygen may deactivate the biomass, damage the floc structure, release EPS, and reduce Denitrification process resulting in severe membrane fouling.
2.2.4 Temperature

The temperature is strongly related to the sludge viscosity. The lower the temperature is the higher the sludge viscosity and the higher the MLSS concentration. The high viscosity reduces the efficiency of aeration in scouring the membrane surface. It also reduces the oxygen transfer rate necessary for biomass growth. Furthermore, it facilitates deflocculation by reducing the floc size and releasing EPS to the solution. The smaller flocs suffer from low back transport velocity and low COD biodegradation rates. As a result, high concentrations of solute and particulate COD are achieved in the MBR causing severe fouling rates [4]. On the other hand, high temperatures deactivate or kill the biomass. The high temperatures in the MBR may be attributed to the air diffuser placed under the membrane. The air diffuser exit temperature may reach up to 85°C [19].

2.2.5 Mixed Liquor Suspended Solids (MLSS)

The higher the MLSS concentrations, the higher the fouling rate. This depends on the nature of the biological process i.e. aerobic or anaerobic. A critical MLSS concentration range is suggested in which beyond the critical point a sharp decline in permeate flux occurs. The critical MLSS concentration range is around 30,000 – 40,000 (mg/L MLSS). Beyond this range a sharp permeate flux decline is observed [20]. The sharp decrease of permeate flux at MLSS above the critical is as a result of the increase of the sludge viscosity. High sludge viscosity limits the oxygen transfer rate to the biomass which decreases the biomass activity, increases the accumulation of foulants on the membrane, decreases the permeate flux, and leads to severe membrane fouling [4].
2.2.6 Aeration Intensity

Aeration is one of the techniques used to control fouling. Implementing an air diffuser under the membrane minimizes foulants accumulation (*i.e.* minimizes fouling). The air diffuser induces shear transients and liquid flow fluctuations enhancing the back transport phenomenon. The shear transients are provided by the uplifting force of the air bubbles which scours the membrane surface and thus minimizes cake formation. Furthermore, the air diffuser supplies oxygen to the biomass in order to maintain a high biomass activity. It also provides mixing within the MBR and thus maintains the activated sludge in suspension. Nevertheless, intensive aeration leads to oversupply of O\textsubscript{2} (Increasing the DO concentration) leading to poor denitrification process, damaging the floc structure, and releasing EPS to the MBR [13], [4]. Therefore, an optimum air flow rate is imposed to be equal to 20 (L/min) for a given operating condition [13]. The rate of Oxygen required is defined by [21] as follows:

\[
Q_{\text{Air}} = \frac{(dO_2 / dt)}{4\eta m} \tag{2-3}
\]

Where:
- \( \eta \) is the specific oxygen transfer efficiency
- \( m \) is the reactor depth

Fouling control by aeration is a function of both the particle diameter and the air bubbles size. Larger particles and larger air bubbles lead to better fouling control because they enhance the back transport phenomenon [4]. However, they lead to irreversible fouling due to fine particles (*i.e.* solutes and colloids) [12]. Nevertheless, larger air bubbles induce high circulating velocity and hence reduce fouling [12]. Implementing an air diffuser in the MBR increases the operating costs. The power requirement for aeration is expressed in terms of the rate of Oxygen required [29]:

\[
P_o = 0.7Q_{\text{Air}} = 0.7 \cdot \left[ \frac{(dO_2 / dt)}{4\eta m} \right] \tag{2-4}
\]
2.2.7 Trans Membrane Pressure (TMP)

Trans membrane pressure (TMP) is one of the major factors affecting membrane fouling. Initial TMP is proven to be an important factor affecting membrane fouling as opposed to microbial concentration [20]. TMP is directly related to the permeate flux. High TMP operation increases the transport of foulants to the membrane and hence increases the permeate flow. The high permeate flow leads to an increase in fouling rates as more foulants are retained by the membrane, and thus increases the fouling layer thickness. Furthermore, the continuous transport of foulants at high TMP increases the compactness of the fouling layer due to the drag force induced by the permeate flow. The high compacted cake layer causes pore blocking resulting in severe membrane fouling. Hence, optimizing pressure is a key factor to minimize fouling. The determination of optimum pressure depends on operating conditions such as shear forces produced from air scoring.

2.2.8 Permeate Flux

Inevitably membrane filtration performance decreases with filtration time due to fouling. The permeate flux decline is a direct indication of membrane fouling phenomena. It depends on several factors such as substrate composition, membrane properties (geometry, configuration, pore size, and material of construction), and operation conditions (HRT, aeration rate, TMP ...). Moreover, the permeate flux behavior is observed as a sharp flux decline at the beginning, followed by a gradual decline due to reversible fouling and concentration polarization, and finally steady state operation is obtained due to irreversible fouling [2]. This behavior is demonstrated from Aidan et al. [8]. The flux behavior is obtained under different backwash scheduling. Backwash scheduling is switching the MBR operation between vacuum and backwash for specified operation duration. The different vacuum time durations are 10, 20, and 30 minutes, while the backwash duration is 1 and 2 minutes. Each vacuum time is tested with both backwash durations and results are demonstrated in the following figure.
Figure 2-3  Flux decline curve for various vacuum-to-backwash time [8].

Fig. 2-3 shows an exponential decline of the flux during the MBR operation at different backwash scheduling. The flux starts declining from the initial or pure water flux across the membrane (175 L/m²-days) where there is no accumulation of foulants on the membrane. Furthermore, Mallubhotla et al. [22] suggested a flux empirical model that may describe such phenomena. By defining the initial water flux as \( J_o \), the following model is suggested:

\[
J(t) = J_o \cdot e^{-f(t)}
\]  \hspace{1cm} (2-5)

The function \( f(t) \) in eq. (2-5) defines the time constants of the flux. The sharper the flux decline, the higher the order of the function \( f(t) \). Assuming the function to be a linear first order, the following flux empirical model is obtained:

\[
J(t) = J_o \cdot e^{-At + Bt^2}
\]  \hspace{1cm} (2-6)

Where:  
- A is time constant for cake growth in (Days)
- B is a constant for cake growth
The flux model in eq. (2-5) agrees with the observed flux behavior in terms of the exponential decline and the steady-state behavior. The steady state behavior may be obtained from eq. (2-6) at long operation period as follows:

\[
\text{As } t \longrightarrow \infty \text{ the flux } J(\infty) \longrightarrow J_0 \cdot e^{-\frac{t}{\bar{B}}} \quad (2-7)
\]

The flux from eq. (2-7) reflects a constant value indicating the steady state flux. It consists of two constant terms the initial flux \(J_0\) and the exponential term with respect to the cake growth constant \(B\). Nevertheless, the derived flux empirical model in eq. (2-6) is able to explain the flux behavior with respect to operation time. Hence, a more representative flux model is required to express the flux in terms of other operation parameters such as TMP and vacuum to backwash time ratio.

Furthermore, the sub-critical flux concept is introduced by Gander et al. [11]. It is defined as the initial flux in which no flux decline exists below it and fouling occurs above it. It depends on both the system specifications and operating conditions. The system specifications are categorized in terms of particle size, interactions between colloids and membrane, and suspension properties such as: pH, conductivity, viscosity, and salinity. While the system operating parameters are classified in terms of: HRT, SRT, OLR, Aeration intensity, MLSS concentration, temperature, and TMP. Conversely, operating at the critical flux is favorable because of the absence of fouling. Since at the critical flux, low trans-membrane pressure operation is attained which prevent the formation of irreversible fouling, and hence less cleaning frequency of the membrane [23].
2.2.9 Operation Modes

Despite other separation processes which depend on mass diffusion for molecular separation or transportation, MBR is a pressure driven process in which pressure gradients overcome mass diffusion limitations. It may be operated under two operation modes constant flux and constant TMP. The former is the most frequently applied since it ensures stable throughput [24].

1) Constant TMP

Also called dead-end filtration in which a rapid flux decline is observed at the start-up followed by a more gradual decrease until steady-state or pseudo-steady state flux is reached [4].

2) Constant flux

In comparison to constant TMP operation, the constant flux operation is more cost effective and avoids excessive membrane fouling. Operating below the critical flux is not economical. On the other hand, operating above the critical flux while maintaining the constant TMP operation leads to severe fouling [25]. The severe fouling under a constant TMP operation with low flux is due to the penetration of small particles into the membrane pores resulting in irreversible fouling. This limitation may be avoided by increasing the flux.

Generally, in constant flux operation irreversible fouling occurs since internal fouling by macromolecular species is dominant. This deposition acts as a pre-filter for smaller particles which may otherwise infiltrate more deeply into the membrane pores. Thus, constant flux operation consists of three stages:

1) Stage 1: conditioning fouling
2) Stage 2: slow (steady) fouling
3) Stage 3: TMP jump
The three constant flux operation stages are illustrated in the following figure:

![Figure 2-4 Schematic illustration of TMP jump occurrence [12]](image)

As the MBR is a pressure driven process. Therefore, the flux is driven by pressure gradient (TMP) instead of concentration gradient, and molecules are transported depending on the membrane permeability rather than molecular diffusion. Hence, Darcy’s law is used [11]:

\[ J = \text{permeability} \cdot \text{TMP} \quad (2-8) \]

Where: the permeability is in (L/m\(^2\)·day·Pa)

From Aidan et al. [8], experimental data of the flux at constant TMP operation is used to calculate the permeability in eq. (2-8). The following plot demonstrates the permeability decline during filtration.
Fig. 2-5 indicates that the membrane permeability undergoes a similar behavior as the permeate flux at constant TMP operation and thus validating the application of Darcy’s law. Nonetheless, membrane permeability changes during operation due to pore blocking and cake formation. Therefore, resistance-in-series flux model is suggested by Shirazi et al. [26] and is shown in Fig. 2-6.

\[
J = \frac{TMP}{\mu \cdot R_t}
\]  

(2-9)

Where: \(\mu\) is the viscosity of the permeate in (Pa·s)

And the total resistance \(R_t\) is defined as the summation of the series resistances:

\[
R_t = R_m + R_{cp} + R_c + R_p
\]

(2-10)

Where: \(R_m\) is the membrane resistance in (m\(^{-1}\))

\(R_{cp}\) is the concentration polarization resistance in (m\(^{-1}\)).

\(R_c\) is the cake resistance in (m\(^{-1}\)).

\(R_p\) is the pore blocking resistance in (m\(^{-1}\)).
2.2.10 Backwash Scheduling

Several techniques are suggested in order to clean and regenerate the membrane including intermitted filtration, chemical cleaning by commonly using nitric acid, air cleaning, and backwashing. Nevertheless, intermitted filtration is not feasible in large scale operation. It is also effective in removing only the cake layer but not fouling due to pore blocking [27]. Chemical cleaning increases the operation costs while air cleaning requires an additional wetting step. Therefore, backwashing is the most effective and standard operating strategy for cleaning and regenerating the membrane.

Backwash is reversing the permeate flow for a short period of time at filtration pressures [11]. Backwashing and regeneration of the membrane are usually preformed when the permeability is less than 10% of the initial permeability. Simultaneously,
backwashing is effective in removing reversible fouling due to pore blocking and removing the loosely attached accumulated foulants on the membrane surface (cake layer). Hence, by implementing frequent backwash and aeration, internal membrane fouling is reduced.

Optimization of frequency and duration of backwash scheduling is essential for reducing energy consumption, permeate consumption and to control membrane fouling. The importance of this optimization arises from the fact that very frequent backwashing may damage the pump and membrane, also it may affect the net volume of permeate production. On the other hand, less frequent backwashing leads to severe membrane fouling. The following table summarizes some researcher’s findings regarding the optimum filtration time/backwash time ratio:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Filter time / Backwash time</td>
<td>200 s / 15 s 400 s / 30 s 600 s / 45 s</td>
<td>No backwash for 60 min 59:45 min / 15 s 24:45 min / 15 s 09:55 min / 5 s 09:45 min / 15 s 09:40 min / 20 s 04:45 min / 15 s</td>
<td>10 min / 1 min 20 min / 1 min 30 min / 1 min 10 min / 2 min 20 min / 2 min 30 min / 2 min</td>
</tr>
<tr>
<td>Observation</td>
<td>Less frequent but longer backwash was the most efficient</td>
<td>Less frequent but longer backwash period is more effective</td>
<td>Lowest service time and longer backwash time is the more effective</td>
</tr>
<tr>
<td>Reason</td>
<td>Explained below</td>
<td>Effective fouling control only if the operating flux is lower than critical flux</td>
<td></td>
</tr>
</tbody>
</table>

Table 2-1: Optimum filtration time per backwash time ratio
Remark: Table 2-1 is not for comparing among the three findings because different operation and design conditions are utilized. However, all three studies revealed that longer backwash time is more effective for fouling control. Simultaneously, they agreed that less frequent backwash is more efficient because of the role of accumulated cake. The cake layer acts as a pre-filter preventing direct contact of fine particles (colloidal and solutes) with the membrane and hence reducing membrane pore blocking (irreversible fouling). Moreover, the optimum service to backwash ratio is provided from literature data [8]. Hence, both backwash and vacuum pressures are plotted against flux as in Figs. 2-7 and 2-8.

Figure 2-7  Backwash and vacuum pressure versus flux at 10 minutes vacuum to 1 minute backwash ratio [8].
Figure 2-8  Backwash and vacuum pressure versus flux at 10 minutes vacuum to 2 minutes backwash ratio [8].

Starting from the initial flux at 175 (L/m²-day), results show an increase in both the vacuum and backwash pressures as flux decreases. The increase in vacuum indicates a decrease in pressure across the membrane during filtration, causing the decline in flux and the presence of membrane fouling. Conversely, the increase in backwash pressure throughout the backwash period also indicates the increase in the severity of fouling and possibly the occurrence of irreversible fouling. Therefore, a higher backwash pressure will be required to clean the membrane.

By comparing Figs. 2-7 and 2-8, the later shows less fluctuation in backwash pressure through operation indicating the optimum backwash scheduling ratio. Consequently, the best vacuum to backwash ratio is with 10 minutes vacuum to 2 minutes backwash. This result agrees with the finding of [7] – [9] which are summarized in Table 2-1. The best backwash scheduling is with less frequent but longer backwash period.
2.3 Control of MBR Processes

2.3.1 Introduction

The challenge in membrane biological reactor (MBR) control arises from the high nonlinearity and complexity of such process. The main source of nonlinearity is attributed to the nonlinear interactions between the biomass, substrate, and membrane. The high nonlinear interactions facilitate membrane fouling. Fouling effects the net permeate production rate due to the rapid permeate flux decline. As mentioned earlier, backwashing is one of the techniques utilized to clean and regenerate the membrane. Except switching operation modes between vacuum and backwash leads to unstable permeate production. To maintain a stable permeate flow, the MBR is operated at the instantaneous flux. The instantaneous flux is the maximum flux attained at the process start-up when the membrane is clean and no fouling is observed. Operating at this flux requires frequent backwashing which increases the operation cost and may rupture the membrane and/or pump. Thus poor control performance may lead to unstable operation and insufficient permeate production.

Primarily, implementing a conventional linear PID controller to a nonlinear process gives unsatisfactory servo and regulatory performance responses to any change in the process operating parameters. Hence, tuning a linear PID controller with a nonlinear process at one operating condition might destabilize it at other operating conditions; such behavior is referred to as bifurcation [28]. Bifurcation in some nonlinear systems depends on a range of one parameter to be stable. If that parameter deviates from its range, the system becomes either unstable or reaches to a new equilibrium point which lies above or below the acceptable operating ranges of a plant [10]. An example on bifurcation behavior in a bioreactor is the biodegradations of dissimilar substrates due to the variation of the dilution rate [10]. Consequently considering this nonlinear multi-input-multi-output (MIMO) system, an advanced control strategy is essential to stabilize the MBR and optimize its performance. Artificial Intelligent Techniques are utilized by several researchers to control membrane fouling. Type 2-fuzzy logic controller is implemented by Galluzzo et al. [10] to stabilize the MBR. Then the MBR performance using fuzzy logic is compared with that of a conventional linear PID controller. Type 2-fuzzy logic demonstrated a
better performance but some oscillations occurred and Neural Network is recommended as an alternative.

2.3.2 Artificial Intelligence Techniques

2.3.2.1 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is used in biological processes as a modeling tool for information processing. A common example of ANN is the nervous system. ANN is a parallel mathematical computational model comprises compactly of interconnected adaptive processing units. The adaptive nature of this network makes it appropriate for learning the behavior of both static and dynamic systems. This feature makes such computational models very appealing in the application domains where there is incomplete understanding of the process to be solved while a large set of training data is available [8]. The main difference between static and dynamic ANN is that the former does not contain time delay elements or integrators and does not have any memory. Artificial Neural Network is widely used during the last decade for modeling process dynamics. ANN is also spread over diverse branches of membrane technology. Many researchers is utilizing ANN in modeling, predicting, simulating, or controlling various membrane separation/purification processes such as microfiltration (MF), ultrafiltration (UF), nanofiltration, reverse osmosis (RO), emulsion liquid membrane, membrane bioreactor, and submerged membrane bioreactor [29]. The wide spread of ANN over membrane processes is due to its ease in implementation, accuracy in understanding the process nonlinear dynamics such as fouling, and effective computing tool in membrane modeling. One major concern in the implementation of ANN is the requirement of huge data sets that accurately represent the process behavior. Once a representative data set is available, the ANN model is trained by adjusting the connection weights of the network. However, data normalization is first required in order for the data to receive equal attention and to be fitted into the limits of the transfer functions used in each layer. Then, the ANN model is tested using a different data set from the training set. Testing is performed in order to decide when to stop training, avoid over training, optimize the network architecture, and optimize the internal network parameters. Finally, the ANN model is
validated to predict the accuracy of the model also by using a different set of data from both the training and validation set.

In addition, ANN is classified according to the network architecture, neurons, and learning algorithm. The network architecture defines the interconnections of the neurons and their corresponding weights in the different layers. The neurons are the ANN processing units. And finally the learning algorithm is used to train the given data set by adjusting the connected weights through performing a prediction task.

2.3.2.2 ANN Architecture

The ANN architecture may be classified according to either the number of layers (Single or multi layer) or the way the neurons are connected (Feed forward or recurrent). In feed forward ANN, the neurons and weights are directly connected without any feedback delays. Whereas the recurrent ANN contains a feedback delay loop around each layer except for the output layer. The following figure demonstrates the different between the feed forward and recurrent ANN architecture.

![Feed forward and recurrent ANN architecture](image)

Figure 2-9   Feed forward and recurrent ANN architecture [30]
Multilayer Neural Network is used as function approximator in a continuous multivariable system with definite structure and parameters. Using a multilayer ANN enhances the computing power over the single layer ANN. Nevertheless, increasing the number of hidden layers increases the sampling time and hence increases the computation burden. Therefore, the number hidden layers selection is a key design parameter. The following figure illustrates the multilayer feed forward ANN architecture:

![3-4-2 Network](image)

Figure 2-10 Multi layer feed forward artificial neural network architecture [30]

2.3.2.3 Neuron

The neuron is the basic building block of the ANN as is demonstrated in Fig. 2-11. It consists of connecting weights, summation/multiplication operations, bias, and activation functions. The weights are adjusted by a training algorithm through minimizing the error between the predicted and target variable. The bias is used to shift the activation function allowing a better network training. The activation function is used to introduce nonlinearity into the network, and also to limit the amplitude of the neuron output. Some common activation functions are the sigmoid functions (i.e. logistic and tangential hyperbolic), and Gaussian functions.
2.3.2.4 Learning Algorithm

As mentioned earlier ANN learning is performed in three stages: training, validating, and testing. Back propagation is the most common training algorithm. Its basic network architecture consists of a two layer network with a sigmoid function in the first layer and linear function in the second. Nevertheless for faster training, different algorithms are used such as Conjugate gradient, Quasi-Newton, and Levenberg-Marquardt (L-M). L-M training algorithm is applied to small or medium size networks. Additionally, the ANN predicted output is expressed by the series parallel model in equation (2-11) obtained from Yu et al. [31]. This model predicts the process output for one step ahead.

\[
\hat{y}(t) = \hat{f}(y(t-1),...,y(t-n_y),u(t-1-k),...,u(t-n_u-k)) \quad (2-11)
\]

Where: \(y\) and \(u\) are the process output and input respectively.

\(\hat{y}\) is the predicted process output.

\(n_y\) and \(n_u\) are the maximum lags in the outputs and inputs.

\(k\) is the process dead time.

\(f(*)\) is a vector-valued non-linear function.
This follows that for a multi layer ANN the predicted jth output may be expressed as follows [39]:

$$\hat{y}_j = g_2 \left[ \sum_{i=1}^{N} w_{ji}^h g_1 \left( \sum_{i=1}^{n} w_{ji}^h \cdot u_i + b_j^h \right) + b_j^o \right]$$

(2-12)

Where:
- $w_{ji}^h$ is the connection weight from the i\textsuperscript{th} input to j\textsuperscript{th} neuron in the hidden layer
- $b_j^h$ is the bias to the j\textsuperscript{th} neuron,
- $w_{ji}^o$ is the connection weight from the j\textsuperscript{th} neuron in the hidden layer to the j\textsuperscript{th} output
- $b_j^o$ is the bias weight for the j\textsuperscript{th} output neuron
- $g_1$ & $g_2$ are non-linear activation function in the hidden and output layers

Moreover Levenberg-Marquardt (L-M) training algorithm is expressed as follows:

$$J = \sum_{t=1}^{N} (y(t) - \hat{y}(t))^T (y(t) - \hat{y}(t))$$

(2-13)

In eq. (2-13) the minimization of J function is performed through adjusting the connecting weights in the multi layer ANN. The weights adjustment is performed using the following equation obtained from Aidan et al. [8]:

$$W_N(\varphi, Z_N) = \frac{1}{2N} \left( \sum_{t=1}^{N} e_i(t, \varphi)^T e_i(t, \varphi) + \varphi^T D \varphi \right)$$

(2-14)

Where:
- $e_i(t, \varphi) = y_i(t) - \hat{y}_i(t, \varphi)$ ; error vector
  - $D = \alpha I$; $D$ is a diagonal matrix, and $\alpha$ is decay factor.

The presence of decay factor $\alpha$ in eq. (2-14) acts as an integrator for the ANN indicating a dynamic ANN structure [11]. Furthermore, ANN models suffer from two major drawbacks over fitting and under fitting. Over fitting occurs when training a complicated data set using a simple (not complex) network structure. As a result, the simple ANN model fails in detecting the signals of the complicate data set. On the other hand, under fitting occurs when a too complex ANN model is used and thus may fit the noise along with the signals. Under fitting must be avoided since it may lead to predictions far beyond the range of the training data, and hence producing wild predictions even with noise-free data. To avoid under fitting and over fitting, various
techniques are suggested including model selection, jittering, early stopping, weigh decay, Bayesian learning, and combining networks [33]. Over fitting may be also prevented by suitable network structure selection to ensure less computer processing and good performance.

2.3.3 Model Predictive Control

Model predictive control (MPC) is significantly applied to various control processes including petrochemical industries, aeronautical engineering, traffic control engineering, and biomedical industries [34]. MPC is an attractive alternative for controlling nonlinear processes due to its unique features in tracking the set-point and overcoming the plant model mismatch [31]. In general, nonlinear processes exhibit large time constants, extensive time delays, inverse responses, multi variable interactions, and constraint process variables. Therefore, implementing a conventional linear PID controller to such processes gives a sluggish response and poor control performance. Alternatively, MPC is proved to be effective in controlling such processes with unusual dynamics. It is also capable of predicting the process response over a large time horizon [35]. Moreover, it is effective in controlling highly nonlinear interacting processes with model mismatch, large time delays, and constrained input/output variables.

MPC is based on either a linear or a nonlinear model for prediction. Implementing the former to control a nonlinear plant (i.e. MBR) gives unsatisfactory closed-loop responses [34]. Instead, MPC with nonlinear models (i.e. neural network) is widely applied in most nonlinear industries. Neural network is a powerful nonlinear tool for modeling dynamic systems with industrial modeling challenges including MIMO variables, coupling effects among variables, and no representative mathematical model. The high capability of neural network in approximating and learning nonlinear functions facilitates the implementation of ANN in advanced model control strategies.

MPC control strategy is demonstrated in Fig. 2-12. The MPC calculates the control moves through manipulation of the manipulated variables based on the response of the controlled variables in the course of an explicit dynamic model. The control moves force the controlled variables to follow a predefined trajectory to track
the target or set-point. The controller moves are performed by the current measurements and future predictions [35].

The controller moves in predicting the process output response is performed through minimizing the set-point error by an open-loop optimization correlation. The optimization correlation as well as the MPC parameters will be further addressed in the later chapters.
Chapter 3

MATHEMATICAL MODELING

This chapter proposes a representative mathematical model for the MBR. An overall material balance is derived for the major parameters. Kinetic rate laws are defined to represent the major reactions taking place in the MBR. Moreover, flux empirical model is presented. Design and operation parameters are derived from the proposed mathematical models. The MBR process methodology including the experimental set-up and process description are demonstrated. Finally, parameter estimation and mathematical model solution methods are performed and validated against experimental data.

3.1 MBR Block Flow Diagram

The derived mathematical model is performed on the aerobic MBR shown in Fig. 3-1. The diagram utilizes two inputs and three outputs. The inputs consist of the influent (i.e. wastewater feed), and the air from the aerator. The outputs consist of the effluent or permeate (i.e. treated water with low biomass concentrations), the dead floating biomass removed by overflow, and the waste (i.e. accumulated sludge).
3.2 Mathematical Model

The representative mathematical model is derived by applying a material balance on three major parameters: substrate concentration (S), biomass concentration (X), and oxygen concentration (O₂) according to the following assumptions:

- Reactor volume is constant due to the overflow.
- Reactor contents are well mixed.
- No biomass in the effluent stream since the membrane is impermeable to biomass.
- No substrate in the overflow dead biomass stream.
- Biomass growth rate follows mid range concentrations kinetics.

Figure 3-1 MBR block flow diagram
3.2.1 Material Mass Balance

The general material balance takes the following form:

\[
\begin{bmatrix}
\text{rate of specie}(i) \\
\text{entering}
\end{bmatrix} = \begin{bmatrix}
\text{net rate of specie}(i) \\
\text{accumulated in the reactor}
\end{bmatrix} + \begin{bmatrix}
\text{rate of specie}(i) \\
\text{consumed/ generated}
\end{bmatrix} + \begin{bmatrix}
\text{rate of specie}(i) \\
\text{in the effluent}
\end{bmatrix} - \begin{bmatrix}
\text{rate of specie}(i) \\
\text{in dead floating biomass}
\end{bmatrix}
\]  

(3-1)

Substrate Mass Balance:

\[
Q_{in}S_{in} = \left( V \frac{dS}{dt} + r_{SU}V \right) + Q_eS_e + Q_wS_w
\]  

(3-2)

Biomass Mass Balance:

\[
Q_{in}X_{in} = \left( V \frac{dX}{dt} + r_gV \right) + Q_wX_w + Q_dX_d
\]  

(3-3)

Oxygen Consumption Mass Balance [3]:

\[
\frac{dO_2}{dt} = D_S(S_{in} - S) - \beta \frac{dX}{dt}
\]  

(3-4)

Where: \( \beta \) is the conversion factor of biomass to COD.
3.2.2 Kinetic Rate Model

The kinetics of the aerobic MBR is described in terms of the rate of substrate utilized for microorganism growth ($r_{su}$), the rate of microorganism growth ($r_g$) and consumed or dead ($r_d$), and the rate of oxygen uptake for microorganism respiration ($r_{o_2}$). This is summarized by the following reaction:

$$Substrate + O_2^{bacteria} \rightarrow New\ Cells + Products$$

Furthermore, using Monod specific biomass growth rate [36]

Rate of Substrate Utilization:

$$r_{SU} = \left( \frac{\mu_{\text{max}}}{Y_{bio}} \right) \frac{SX}{K_s + S} \quad (3-5)$$

Rate of Biomass Generated:

$$r_g = \mu_{\text{max}} \left( \frac{SX}{K_s + S} \right) - k_d X \quad (3-6)$$

Rate of Oxygen Uptake:

$$r_{o_2} = -r_{SU} - 1.42 \ r_g \quad (3-7)$$

Where: 1.42 is the COD of cell tissue (mg substrate/mg biomass)

Hence, eqs. (3-5) — (3-7) require the estimation of four kinetic parameters using experimental data which are: maximum specific biomass growth rate ($\mu_{\text{max}}$), Monod constant ($K_s$), net biomass yield ($Y_{bio}$), and endogenous decay coefficient ($k_d$).
3.2.3 Flux Model

As mentioned earlier, an empirical flux model is developed representing the flux decline as a function of time. Nevertheless, a more representative flux model is required to relate the flux to other design or operating parameters. Darcy’s law correlates the flux with both the membrane permeability and pressure gradient across the membrane. Darcy’s law is represented in the following equation:

\[ J = L_p \Delta P \]  \hspace{1cm} (3-8)

Where: \( L_p \) is the membrane permeability in \((L/m^2\cdot\text{day}\cdot\text{kPa})\).
\( \Delta P \) is the pressure gradient in \((\text{kPa})\).

Eq. (3-8) correlates the flux to two operating parameters which are the pressure gradient (or TMP) and membrane permeability. However, correlating the flux to other operating parameters such as backwash scheduling is essential in order to reduce fouling, optimize the MBR performance, and control the MBR operation. Nonetheless, Darcy’s law is not sufficient to completely describe the flux behavior in the MBR. Therefore, a more advanced nonlinear modeling technique such as artificial neural network (ANN) is required.
3.3 Design and Operation Parameters

3.3.1 Sludge Retention Time (SRT)

Solid Retention Time is defined as the ratio of biomass accumulated in the MBR to the amount of biomass removed per day. Solving eq. (3-3) at steady state by setting \( \frac{dX}{dt} \rightarrow 0 \), SRT correlation may be obtained as follows:

\[
SRT = \frac{XV}{Q_w X_w + Q_d X_d} \quad (3-9)
\]

Controlling SRT is essential in order to obtain a good MBR operation. Long SRT reduces the biomass activity while short SRT results in washout condition. The washout condition is obtained from eq. (3-9) when \( Q_w X_w + Q_d X_d \) is greater than \( XV \). Alternatively, long SRT operation indicates the biomass generation rate is greater than the biomass removal rate. As a result, high sludge viscosities are attained which minimizes the oxygen transfer rate and thus deactivates the biomass.

3.3.2 Hydraulic Retention Time (HRT)

Hydraulic Retention Time is defined as the ratio of the volume to the influent volumetric flow rate. Since the volume of reactor is constant. Then HRT is a function of the influent volumetric flow rate as expressed in the following equation:

\[
HRT = \frac{V}{Q_{in}} \quad (3-10)
\]

Moreover, HRT may be defined through the reciprocal of dilution rate as illustrated from the following equation.

\[
HRT = \frac{1}{D_{in}} \quad (3-11)
\]
HRT is also one of the process control parameters that affect membrane fouling. A short HRT or high dilution rates result in high membrane fouling rates due to the production of filamentous bacteria. On the other hand, a long HRT requires a larger MBR volume because of the high influent flow rates.

3.3.3 Food to Microorganism Ratio (F/M)

F/M is a process control number. It is defined as the ratio of COD or BOD entering the MBR to the MLSS concentration in the MBR [21].

\[
F/M = \frac{\text{total applied substrate rate}}{\text{total microbial biomass}} = \frac{Q_{in}S_{in}}{VX} \quad (3-12)
\]

Thus, F/M may be related to HRT or dilution rate by following F/M correlation:

\[
F/M = \frac{S_{in}}{(HRT)X} = \frac{DS_{in}}{X} \quad (3-13)
\]

Where: F/M is in (mg biomass /mg biomass ∙ day)

3.3.4 Organic Loading Rate (OLR)

Volumetric organic loading rate (OLR) is defined as the amount of soluble and particulate organic matter fed to the MBR per unit volume.

\[
OLR = \frac{Q_{in}S_{in}}{V} \quad (3-14)
\]

Where: OLR is the volumetric organic loading rate (kg biomass/m³ ∙ day)

Furthermore OLR affects the MBR performance. High OLR indicates membrane fouling because more foulants are fed to the MBR. Moreover, fluctuation in the OLR leads to unstable process, poor filtration performance, and severe fouling rates.
3.3.5 Oxygen Transfer Rate - OTR

Constant dissolved Oxygen concentration is required to obtain efficient operation in the MBR. Maximizing the Oxygen transfer rate between the injected air bubbles and biomass cells is essential to maintain high biomass activity [36]. The following correlation represents the OTR in the MBR:

\[
OTR = Q_{O_2}X = \left( Y_{o_2/X} \right) r_g X
\]  

(3-15)

Where: \( Y_{o_2/X} \) is the Oxygen transfer yield in (g O\(_2\)/g biomass).

\[
Y_{o_2/X} = \frac{r_{O_2}}{r_g} = \frac{\Delta O_2}{\Delta X}
\]  

(3-16)

Assuming mid range concentration kinetics

\[
OTR = \left( \frac{\Delta O_2}{\Delta X} \right) \left[ \mu_{\text{max}} \left( \frac{S}{K_s+S} \right) - k_d X \right] X
\]  

(3-17)
3.4 Methodology

Literature experimental data are obtained from Aidan et al. [8], [18], [37] utilizing a bench-scale submerged MBR under aerobic conditions (AMBR). The experimental set-up of the AMBR is demonstrated in Fig. 3-2. In this section, the AMBR process description is presented. The experiments performed from which the used experimental data are introduced. Furthermore, the experimental data is used in model fittings, parameters estimation, and artificial neural network (ANN) model.

Figure 3-2  Membrane biological reactor experimental set-up.
3.4.1 Process Description

The membrane biological reactor experimental set-up is demonstrated in Fig. 3-2. The system utilizes an air diffuser, a dissolved oxygen (DO) measuring probe, control valves, a compressor, and three pumps; piston pump P-101, vacuum pump P-102, and backwash pump P-103. The synthetic wastewater feed is prepared in tank T-101 by mixing the COD concentrations listed in Table 3-3 with distilled water. Then, Pump P-101 is used to pump the feed (stream 1) into the MBR tank T-102. Tank T-102 consists of a submerged flat sheet membrane and an air diffuser. The air (stream 5) is compressed through the compressor C-101 and is fed to the MBR through the implemented air diffuser. The treated water (stream 2) is drawn out of the membrane through the vacuum pump P-102. A split stream (stream 3) is taken from the treated water through the backwash pump P-103 and back to the membrane. Hence reversing the direction of water flow through the membrane and thus cleaning and regenerating the membrane. The remaining treated water (stream 4) is collected in tank T-103. Finally, the accumulated sludge (stream 6) is removed from the bottom of tank T-102.

Furthermore, four control schemes are utilized in Fig. 3-2. The first is the level controller (LC). An on-off level controller of a float and contactor type is used. As the desired liquid level in the MBR is attained, the LC sends a signal to switch off the feed pump P-101. The second control scheme is the dissolved oxygen control. The DO concentrations are measured through the DO probe utilizing a dissolved oxygen indicator controller (DOIC). The DO probe is submerged in the MBR tank T-102 and is continuously monitored through the PC. If the dissolved oxygen concentrations decrease, the PC sends a signal to open valve V-104 in order to increase the aeration rate. The third control scheme is the pressure control across the membrane. Two pressure gauges P.G.1 and P.G.2 are placed on streams 2 and 3, respectively. The pressure gauges give a direct indicate of membrane fouling. A decrease in vacuum pressure gauge (P.G.1) implies high filtration pressures and membrane fouling. Therefore, the pressure indicator controller (PIC) sends a signal to switch off pump P-102 and switch on pump P-103 and thus performing backwash. As the pressure gauge P.G.2 stabilizes indicating stable operation with no membrane fouling, the PIC controller sends a signal to switch on the backwash pump P-103 and switch on the vacuum pump P-102 and hence filtration is resumed. The forth control scheme is the total suspended solids controller (TSSC). The TSS concentrations represent the
accumulated sludge concentrations. As the TSS level increases the TSSC sends a signal to open valve V-105 to discharge the excess accumulated sludge. The significance of this control scheme is as an excess of sludge accumulation may block part of the membrane and hence decreases the membrane selectivity. In addition to high level of accumulated sludge may block the air diffuser and thus effects the overall MBR operation. Furthermore, both the membrane and bioreactor tank design specifications are summarized in the following tables:

Table 3-1: Membrane bioreactor tank design specifications

<table>
<thead>
<tr>
<th>Material of construction</th>
<th>Acrylic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimensions</td>
<td>22 cm x 15 cm x 22 cm</td>
</tr>
<tr>
<td>Effective volume</td>
<td>3.3 L</td>
</tr>
<tr>
<td>Water depth</td>
<td>15 cm</td>
</tr>
</tbody>
</table>

Table 3-2: Membrane design specifications

<table>
<thead>
<tr>
<th>Material of construction</th>
<th>Ceramic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Flat sheet membrane, submerged in the bioreactor</td>
</tr>
<tr>
<td>Frame dimensions</td>
<td>20 cm x 11 cm x 0.65 cm</td>
</tr>
<tr>
<td>Pore size</td>
<td>0.2 µm</td>
</tr>
<tr>
<td>Total surface area</td>
<td>0.264 m² (from all sides)</td>
</tr>
</tbody>
</table>

The MBR experiments are performed under the lab temperature. The synthesis wastewater is prepared in order to achieve the best microorganism activity inside the membrane bioreactor. The feed is prepared in a 25 L holding tank T-101 with the following conditions:
Table 3-3: Synthetic wastewater composition

<table>
<thead>
<tr>
<th>Component</th>
<th>Concentration (g/L)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acetic acid</td>
<td>31.6</td>
</tr>
<tr>
<td>NH₄Cl</td>
<td>8.8</td>
</tr>
<tr>
<td>KH₂PO₄</td>
<td>1.3</td>
</tr>
<tr>
<td>FeCl₃·6H₂O</td>
<td>0.1</td>
</tr>
<tr>
<td>CaCl₂</td>
<td>0.2</td>
</tr>
<tr>
<td>MgSO₄</td>
<td>0.2</td>
</tr>
<tr>
<td>KCl</td>
<td>0.2</td>
</tr>
<tr>
<td>NaCl</td>
<td>0.2</td>
</tr>
<tr>
<td>NaHCO₃</td>
<td>49.8</td>
</tr>
</tbody>
</table>

Table 3-3 shows a constant synthetic wastewater feed composition throughout the MBR operation and thus the feed organic loading rate is controlled. The feed temperature is also fixed at 4°C by an immersed cooling coil in the feed tank T-101. Maintaining the feed at this low temperature is necessary to inhibit any bacterial activity within the feed. Further, four liters of biomass is prepared by adding two capsules of polyseed (Bioscience Inc.) that contains a mixed culture of microorganisms into distilled water. The mixture is fed with 10 (g sugar/day). Then the biomass is incubated for 24 hours under aeration by oil free compressed air through an air diffuser. The preparation of biomass is performed separately before mixing it with the synthetic wastewater feed given in Table 3-3.
3.4.2 Modeling and Optimizing of Backwash Scheduling

Aidan et al. (2007) [8] verified the optimum backwash scheduling experimentally. The backwash scheduling was performed by applying different vacuum-to-backwash time scenarios and observing the flux decline. The optimum ratio was concluded for the scenario in which the minimum flux decline is observed. Minimum flux decline indicates steady (stable) operation and hence low fouling rates. Another approach is to observe the backwash pressure change. As a nearly constant backwash pressure operation indicates low fouling rates.

The experiment was performed utilizing two control schemes. The first scheme was a float and contactor level controller. The second was a pressure controller scheme utilizing two control valves (Castel Italy) V-102 and V-103. The pressure controller scheme was connected to Siemens LOGO computer software. The software was connected to a contactor to which the power supply of both pumps and control valves were connected. A timer was programmed within the software to specify the vacuum to backwash operation scheduling. The software was operated with 10, 20, or 30 minutes vacuum (or filtration) duration. At the end of each period, the vacuum pump P-102 was switched off and backwash pump P-103 was switched on for 1 or 2 minutes applying backwash. This procedure was repeated continuously for 90 days duration, while each 15 days a different vacuum-to-backwash time scenario was performed. Both vacuum and backwash pressures, as long as the permeate flux were recorded. Also based on the unit productivity, the permeability was calculated. The optimum vacuum-to-backwash time ratio was concluded from the scenario which resulted in the least flux decline and low backwash pressure change throughout the operation. Thus, the optimum backwash scheduling was obtained with 10 minutes vacuum and 2 minutes backwash. This indicates that less frequent but longer backwash duration is the optimum backwash scheduling. Finally, the experimental data obtained consists of the backwash pressure, vacuum pressure, permeability, and flux at different vacuum and backwash duration.
3.4.3 Phenolic Shock Loading

Aidan et al. (2009) [37] studied the effect of phenol on membrane fouling. Phenol is a major pollutant in wastewater due to its toxicity. Phenol removal from wastewater requires tertiary treatment processes such as: ion exchange, precipitation, and adsorption. However, such technologies are only applicable for low concentrations of phenol. Therefore, biological treatment is suggested such as using MBR processes.

The experiment was performed using the optimum backwash-to-vacuum time ratio obtained from the previous experiment (i.e. 10 minutes vacuum to 2 minutes backwash). Predetermined phenol concentrations of 50, 100, 400, and 800 ppm were added to the synthesis wastewater shown in Table 3-3 to study the effect of organic loading rate on the filtration performance of the MBR. Nevertheless, both the feed and phenol loading rates were maintained constant throughout the experiment. Finally, the COD and phenol concentrations in both influent and effluent were recorded and were further used in kinetic parameters estimation.
3.4.4 Particulates and Bacteria Removal by Ceramic Microfiltration, UV

Aidan et al. (2007) [18] investigated the rate of biomass removal by microfiltration systems. However, a different MBR tank and membrane design specifications were used as summarized in Tables 3-4 and 3-5.

Table 3-4: Membrane bioreactor tank design specifications for experiment 3

<table>
<thead>
<tr>
<th>Material of construction</th>
<th>Acrylic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dimensions</td>
<td>15 cm x 3 cm x 30 cm</td>
</tr>
<tr>
<td>Effective volume</td>
<td>1 L</td>
</tr>
<tr>
<td>Water depth</td>
<td>30 cm</td>
</tr>
</tbody>
</table>

Table 3-5: Membrane design specifications for experiment 3

<table>
<thead>
<tr>
<th>Material of construction</th>
<th>Ceramic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>Flat sheet membrane, submerged in the bioreactor</td>
</tr>
<tr>
<td>Frame dimensions</td>
<td>12 cm x 12 cm</td>
</tr>
<tr>
<td>Pore size</td>
<td>0.2 (\mu)m</td>
</tr>
<tr>
<td>Total surface area</td>
<td>0.048 m(^2) (from all sides)</td>
</tr>
</tbody>
</table>

The MBR was operated under intermitted aeration to allow nitrification/denitrification reactions and biological dephosphatation. The feed wastewater was a domestic sewage wastewater obtained from Bourgas Sewage Treatment Works, Bourgas, Bulgaria. The feed specifications are summarized in the following table.
Table 3-6: Domestic sewage wastewater specifications

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>BOD$_5$</td>
<td>150 ppm</td>
</tr>
<tr>
<td>COD</td>
<td>300 ppm</td>
</tr>
<tr>
<td>NH$_4$-N$_2$</td>
<td>12 ppm</td>
</tr>
<tr>
<td>TSS</td>
<td>110 – 156 ppm</td>
</tr>
<tr>
<td>Turbidity</td>
<td>4 – 5 NTU</td>
</tr>
<tr>
<td>Total coliform density</td>
<td>3 – 4 x 10$^5$ mL$^{-1}$</td>
</tr>
<tr>
<td>pH</td>
<td>6.5 – 7.3</td>
</tr>
</tbody>
</table>

The turbidity, NH$_4$-N$_2$, and DO were monitored throughout the experiment duration. The turbidity was measured through turbidimeter, NH$_4$-N$_2$ was analyzed by nesslerization, and DO concentrations were measured through a DO probe. Further, the results of biomass concentration decline during filtration period were recorded and further used in biomass mass balance solution methods.
3.5 Parameter Estimation

3.5.1 Kinetic Parameter Estimation

The developed kinetic model requires the estimation of four kinetic parameters, namely: the maximum specific biomass growth rate ($\mu_{\text{max}}$), the Monod constant ($K_s$), the net biomass yield ($Y_{\text{bio}}$), and the endogenous decay coefficient ($k_d$). The kinetic model parameters are estimated by reconciling the model output with actual plant data obtained from experiment 2. POLYMATH nonlinear regression is used to estimate the kinetic parameters by minimizing the sum of squared errors. The estimated kinetic model parameters are summarized in Table 3-7. Further, the kinetic model is fitted against literature data in Fig. 3-3.

Table 3-7: Kinetic parameters estimation

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{\text{max}}$ (g new biomass/ g biomass·day)</td>
<td>185</td>
</tr>
<tr>
<td>$Y_{\text{bio}}$ (g biomass/ g phenol)</td>
<td>0.0195</td>
</tr>
<tr>
<td>$K_s$ (g phenol/m$^3$)</td>
<td>$1.01 \times 10^5$</td>
</tr>
<tr>
<td>$k_d$ (g dead cells/g cells·day)</td>
<td>0.165</td>
</tr>
</tbody>
</table>

Figure 3-3  Kinetic model prediction versus literature data fitting
Fig. 3-3 demonstrates a good fit of the substrate kinetic model against experimental data with a regression of 0.828. Hence the assumption of middle range concentration kinetics for biomass growth is verified. Moreover, Fig. 3-3 shows the decline of substrate utilization rate with time. This is attributed to the high substrate consumption rates in biomass growth.

3.5.2 Biomass Dynamic Model

After estimating the kinetic parameters, the biomass dynamic model is solved and validated against experimental data. The data is obtained from Aidan et al. [18]. The biomass dynamic model in eq. (3-3) is solved with following assumptions:

1) \( X_d << X_w \).
2) \( X_{in} \equiv 0 \), no biomass in the feed.
3) \( K_s >> S \), which is be concluded from Table 3-7.

Solving the dynamic biomass model yields to the following correlation:

\[
X = X_o \left[ \exp \left( - \left( \frac{\mu_{max}}{K_s} \right) S - D_w + k_d \right) \right] \tag{3-18}
\]

\( D_w \) in eq. (3-18) represents the waste dilution rate. It is defined as the ratio of the waste volumetric flow rate to the MBR volume (\( D_w = Q_w / V \)). The waste dilution rate is estimated using literature experimental data obtained from Aidan et al. [18]. Moreover, POLYMATH nonlinear regression is utilized for the dilution rates estimation. The results are obtained as follows:

Influent Dilution Rate (\( D_{in} \)): 361.1238 (day\(^{-1}\))

Effluent Dilution Rate (\( D_{w} \)): 65.1438 (day\(^{-1}\))

A higher dilution rate is observed for the influent as opposed to the effluent. This indicates a higher influent flow compared to effluent flow. The lower effluent
dilution rate may be attributed to membrane fouling or pore blocking. Furthermore, the transient biomass concentration is calculated from eq. (3-19) using both the estimated waste dilution rate and the estimated kinetic parameters. It is further plotted with the corresponding experimental data as in Fig. 3-4. A good match is obtained with regression $R^2$ of 0.932.

![Figure 3-4](image)

**Figure 3-4** Model prediction versus experimental data of biomass concentration dynamics

Fig. 3-4 shows the transient biomass concentration decline with time. The transient decline of biomass concentration indicates high biomass removal rates. As more foulants are retained by the highly selective membrane, the accumulated fouling layer thickness is increased. The growing fouling layer enhances the filtration performance as it acts as a pre-filter. Furthermore, Fig. 3-4 shows a good fit of the biomass model against experimental data. This verifies both the estimated kinetic parameters and the developed biomass process model.
3.5.3 Flux Empirical Model Parameter Estimation

The flux empirical model in eq. (2-6) requires the estimation of two parameters A and B using experimental data. The experimental data is obtained Aidan et al. [8] gives the flux decline as a function of time for different backwash to vacuum time scheduling scenarios. The two parameters are estimated for each run using POLYMATH nonlinear regression. Flux parameters estimation results are summarized in Table 3-8 and are plotted in Fig. 3-5 with an average regression of 0.96.

<table>
<thead>
<tr>
<th>Ratio (min/min)</th>
<th>10 vac/1 bw</th>
<th>20 vac/1 bw</th>
<th>30 vac/1 bw</th>
<th>10 vac/2 bw</th>
<th>20 vac/2 bw</th>
<th>30 vac/2 bw</th>
</tr>
</thead>
<tbody>
<tr>
<td>A (day)</td>
<td>23.15</td>
<td>16.097</td>
<td>10.06</td>
<td>68.96</td>
<td>22.075</td>
<td>23.66</td>
</tr>
<tr>
<td>B</td>
<td>0.517</td>
<td>-0.221</td>
<td>0.00501</td>
<td>2.279</td>
<td>0.173</td>
<td>-0.769</td>
</tr>
</tbody>
</table>

Figure 3-5 Model prediction versus experimental data of flux dynamics
As illustrated in Fig. 3-5, the flux empirical model shows a good fit to experimental data at different backwash scheduling scenarios. Nevertheless, the estimated flux parameters in Table 3-8 significantly change at different operating condition (i.e. different backwash scheduling). Thus, any change in the MBR operating conditions (i.e. due to disturbance) will require re-estimation of both parameters. Consequently, the indicated empirical model is neither accurate nor representative to the flux dynamics in the MBR. Hence, a more representative dynamic flux model is to be derived. The flux model should relate the flux to different operation parameters such as: vacuum pressure, backwash pressure, and backwash scheduling. Darcy’s law describes the flux as a function of pressure gradients. However observing the flux behavior in Fig. 3-5 indicates the large effect of backwash scheduling on the flux decline. Therefore, a flux model should be developed to represent the flux in terms of backwash scheduling along with the pressure gradients. Thus, artificial intelligence techniques are suggested to model the flux in the MBR.
Chapter 4

ARTIFICIAL NEURAL NETWORK MODEL

Artificial neural network (ANN) model is used to develop an input/output model for the MBR. In this chapter, the input/output variables are first selected. Different ANN model scenarios are performed utilizing different input/output to the ANN model. Sensitivity analysis is further performed to study the effects of variation in the process inputs on the process output.

4.1 Process Variables

The selection of process variables is based on selecting the variables that may be measured experimentally and gives a direct indicate on membrane fouling. The following block diagram shows the selected input/output variables:

![MBR process variables diagram](image)

Figure 4-1  MBR process variables diagram
Fig. 4-1 demonstrates the characterization of the MBR with multi input single output (MISO) process. Four inputs are selected consisting of the backwash pressure, the vacuum pressure, the backwash time, and the vacuum time. Hence both the backwash time and vacuum time may be combined into a single input variable called the backwash-to-vacuum time ratio. It may be also referred to as backwash scheduling. A single output is selected for the MBR which is the flux. Finally, disturbances may be attributed to the operating parameters and conditions. The operating parameters include the sludge retention time (SRT), hydraulic retention time (HRT), food to microorganism ratio (F/M), dissolved oxygen (DO), dilution rate, and organic loading rate (OLR). On the other hand, the operating conditions are characterized by the substrate concentration, temperature, aeration, backwashing, and chemical cleaning.

4.2 Artificial Neural Network Model

Artificial neural network (ANN) is a powerful nonlinear computational tool. It is capable of capturing the nonlinearity of any process by providing an input/output data set. It divides the data set into three subsets: training set, validating set, and testing set. The accuracy of the ANN predicted model depends on: the size of the data set, the utilized training algorithm, and the structure of the network. The ANN structure is determined by the number of layers, number of neurons in each layer, activation functions, and connecting weights. Accordingly, modeling MBR process using ANN entails the development of an ANN model for the MISO system using the experimental data provided by Aidan et al. [8]. The selection of the ANN structure is based on the maximum regression obtained between the ANN predicted output and experimental output variable; i.e. between the ANN predicted flux and the experimental flux, respectively. The ANN model structure is illustrated in Fig. 4-2 and is summarized in Table 4-1.
Figure 4-2  ANN model structure.

Table 4-1  ANN model structure specifications

<table>
<thead>
<tr>
<th>ANN type</th>
<th>Multi layer feed forward</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of layers</td>
<td>3</td>
</tr>
<tr>
<td>(input, hidden, output)</td>
<td></td>
</tr>
<tr>
<td>Number of Neurons in:</td>
<td></td>
</tr>
<tr>
<td>1) Input layer</td>
<td>1</td>
</tr>
<tr>
<td>2) Hidden layer</td>
<td>20</td>
</tr>
<tr>
<td>3) Output layer</td>
<td>1</td>
</tr>
<tr>
<td>Activation function in:</td>
<td></td>
</tr>
<tr>
<td>1) Input layer</td>
<td>Tan sigmoid</td>
</tr>
<tr>
<td>2) Hidden layer</td>
<td>Tan sigmoid</td>
</tr>
<tr>
<td>3) Output layer</td>
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</tr>
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<td>Learning Algorithm</td>
<td>Levenberg-Marquardt</td>
</tr>
<tr>
<td>Training, validation, testing sets</td>
<td>50 % each</td>
</tr>
</tbody>
</table>
4.3 ANN Model Different Scenarios

Artificial neural network modeling is performed by different ANN modeling scenarios connecting the multi inputs to achieve the single output. The different ANN models are trained, validated, and tested. Consequently, results are compared by the regression plot between the ANN model output and experimental output variable.

4.3.1 Scenario 1

The objective is to obtain an ANN model between:

1) Ratio and backwash pressure, ANN1
2) Ratio and vacuum pressure, ANN2
3) Both backwash pressure, vacuum pressure and flux, ANN3

Figure 4-3 ANN model diagram for scenario 1

For scenario 1 each ANN model in Fig. 4-3 is trained separately. ANN1 and ANN2 are first trained; consequently the predicted outputs from both ANNs are combined and used to train ANN3. ANN1 trains the vacuum-to-backwash time ratio (input variable) to predict the backwash pressure $P_{bw}$ (output variable). The training is performed by minimizing the error between the predicted $P_{bw}$ from ANN1 and the experimental $P_{bw}$ (target variable). ANN1 training is stopped utilizing 150 epochs as is demonstrated in Fig. 4-4a with gradient equal to $4.41 \times 10^{-4}$, input mean matrix (Mu) of 0.001, and the best validation performance is 0.0239 at 144 epochs. The predicted backwash pressure from ANN1 model is validated with that obtained experimentally.
in Fig. 4-4b. Further, the overall regression between the ANN1 predicted output and target is revealed in Fig. 4-4c with training, validation, and testing regressions of 0.961, 0.955, and 0.955, respectively.

Figure 4-4a  Squared error minimization through the training epoch of ANN1 – scenario 1
Figure 4-4b  ANN predicted and experimental $P_{bw}$ of ANN1 – scenario 1

Figure 4-4c  Overall regression plot of ANN1 – scenario 1
ANN2 trains the vacuum-to-backwash time ratio (input variable) to predict the vacuum pressure $P_{\text{vac}}$ (output variable). The training is performed by minimizing the error between the predicted $P_{\text{vac}}$ from ANN2 and the experimental $P_{\text{vac}}$ (target variable). ANN2 training is stopped utilizing 692 epochs as is demonstrated in Fig. 4-5a with gradient equal to $4.08 \times 10^{-4}$, input mean matrix (Mu) of 0.01, and the best validation performance is 0.0244 at 686 epochs. The predicted vacuum pressure from ANN2 model is validated with that obtained experimentally in Fig. 4-5b. Further, the overall regression between the ANN2 predicted output and target is revealed in Fig. 4-5c with training, validation, and testing regressions of 0.961, 0.955, and 0.955, respectively.

Figure 4-5a  Squared error minimization through the training epoch of ANN2 – scenario 1
Figure 4-5b  ANN predicted and experimental $P_{\text{vac}}$ of ANN2 – scenario 1

Figure 4-5c  Overall regression plot of ANN2 – scenario 1
ANN3 trains two predicted outputs from ANN1 and ANN2 ($P_{bw}$, $P_{vac}$) to predict the flux. Therefore, ANN3 utilizes two inputs to predict a single output. The training is performed by minimizing the error between the predicted flux from ANN3 and the experimental flux (target variable). ANN3 training is stopped utilizing 54 epochs as is demonstrated in Fig. 4-6a with gradient equal to 0.114, input mean matrix ($\text{Mu}$) of 0.0001, and the best validation performance is $7.28 \times 10^{-3}$ at 48 epochs. The predicted flux from ANN3 model is validated with that obtained experimentally in Fig. 4-6b. Further, the overall regression between the ANN3 predicted output and target is revealed in Fig. 4-6c with training, validation, and testing regressions of 0.988, 0.989, and 0.989, respectively.

![Figure 4-6a](image-url)  
Figure 4-6a  Squared error minimization through the training epoch of ANN3 – scenario 1
Figure 4-6b   ANN predicted and experimental flux of ANN3 – scenario 1

Figure 4-6c   Overall regression plot of ANN3 – scenario 1
4.3.2 Scenario 2

The objective is to obtain an ANN model between:

- Ratio and flux, SISO

![Diagram](image)

**Figure 4-7** ANN model diagram for SISO system – scenario 2.

ANN trains the vacuum-to-backwash time ratio (input variable) to directly predict the flux (output variable). The training is performed by minimizing the error between the predicted flux from ANN and the experimental flux (target variable). ANN training is stopped utilizing 74 epochs as is demonstrated in Fig. 4-7a with gradient equal to $4.57 \times 10^{-4}$, input mean matrix (Mu) of 0.001, and the best validation performance is 0.0496 at 68 epochs. The predicted flux from ANN model is validated with that obtained experimentally in Fig. 4-7b. Further, the overall regression between the ANN predicted output and target is revealed in Fig. 4-7c with training, validation, and testing regressions of 0.921, 0.924, and 0.924, respectively.
Figure 4-7a  Squared error minimization through the training epoch – scenario 2

Figure 4-7b  ANN predicted and experimental flux – scenario 2
4.3.3 Scenario 3

The objective is to obtain an ANN model between all the three input variables:

- Inputs
  1) Ratio
  2) Backwash pressure, $P_{bw}$
  3) Vacuum pressure, $P_{vac}$
- Output: flux

As a result a multi-input-single-output ANN is performed

```
Ratio

$P_{bw}$

$P_{vac}$

ANN5

 Flux
```

Figure 4-8      ANN model diagram for the MISO system – scenario 3.
ANN trains all three inputs to predict the flux (output variable). The training is performed by minimizing the error between the predicted flux from ANN and the experimental flux (target variable). ANN training is stopped utilizing 40 epochs as is demonstrated in Fig. 4-8a with gradient equal to $1.88 \times 10^{-2}$, input mean matrix (Mu) of 0.001, and the best validation performance is $6.90 \times 10^{-3}$ at 40 epochs. The predicted flux from ANN model is validated with that obtained experimentally in Fig. 4-8b. Further, the overall regression between the ANN predicted output and target is revealed in Fig. 4-8c with training, validation, and testing regressions of 0.991, 0.990, and 0.990, respectively.

Figure 4-8a  Squared error minimization through the training epoch – scenario 3
Figure 4-8b  ANN predicted and experimental flux – scenario 3

Figure 4-8c  Overall regression plot – scenario 3
Results of the three alternative ANN scenarios reveal the highest regression is obtained from scenario 3. Since three input variables are trained to predict the output variable (flux). Therefore, increasing the number of variables increases the accuracy of the network. Moreover, the least network training epochs are utilized in scenario 3 indicating faster training and less computation time and effort.

4.4 Sensitivity Analysis

Sensitivity analysis is performed to determine the effects of variation in the process inputs on the process output (flux). The ANN model in scenario 3 is used to study the flux response to step changes in each process input. The sensitivity analysis is performed by changing one of the input variables while maintaining the other input variables constant. Then observing the ANN model predicted output variable response. Furthermore, the input variables step change is performed within a specific range of each input. The range is set within the upper and lower limits of the experimental data used to train the ANN model. The following diagram shows the sensitivity analysis applied on the ANN model in scenario 3.

![ANN block diagram for sensitivity analysis](image-url)
The response of flux is studied by applying a step change on the three process inputs including the backwash pressure, vacuum pressure, and vacuum-to-backwash time ratio as illustrated in Fig. 4-9. First the flux response is studied with respect to changes in the backwash pressure. The backwash pressure range is obtained from Aidan et al. [8] between 90 – 96 kPa. The vacuum pressure is maintained at 50 kPa and the ratio is maintained at 10 minutes vacuum time to 2 minutes backwash time. The following figure shows the variation of flux with respect to changes in backwash pressure at a constant vacuum pressure and vacuum-to-backwash-time ratio.

Figure 4-10  ANN predicted flux response due to backwash pressure step change
A similar procedure is followed for both the vacuum pressure and the ratio of vacuum-to-backwash time. The vacuum pressure range is set between 50.0 – 58.0 kPa. While the backwash pressure is maintained at 92.4 kPa and the ratio is maintained at 10 minutes vacuum to 2 minutes backwash. On the other hand, the ratio range is set between 4.7 – 33. While the backwash pressure is maintained at 92.4 kPa and the vacuum pressure is maintained at 50 kPa. The following figures demonstrate the flux behavior as a result of changes in the vacuum pressure and ratio, respectively.

![Graph showing ANN predicted flux response due to vacuum pressure step change](image-url)

**Figure 4-11** ANN predicted flux response due to vacuum pressure step change
Fig. 4-10 indicates as the backwash pressure increases the flux increases to an optimum point and then decreases. The optimum flux is observed at 175 (L/m²·day) corresponding to a backwash pressure of 92.4 kPa. This behavior may be explained as follows: as the backwash pressure increases a better fouling removal is attained and hence enhancing the flux behavior. However, further increase of the backwash pressure may rapture the membrane and hence inversely affects the membrane filtration performance.

Furthermore, Fig. 4-11 shows the flux behavior with vacuum pressure changes. The maximum flux is obtained at the lowest vacuum pressure. The lowest vacuum pressure indicates the highest filtration or operation pressure. The maximum flux is obtained at 175 (L/m²·day) corresponding to a vacuum pressure range between 50 – 51 kPa. Beyond this range a sharp flux decline is observed with increasing the vacuum pressure.

Figure 4-12  ANN predicted flux response due to ratio of vacuum-to-backwash time step change.
Similarly, the maximum flux is obtained at the lowest vacuum-to-backwash time ratio as demonstrated in Fig. 4-12. The low ratio indicates operating with a long but less frequent backwash time. The maximum flux is 175 (L/m²·day) corresponding to the vacuum-to-backwash time ratio range between 4.7 – 5.1. The backwash scheduling (Or vacuum-to-backwash time ratio) is further investigated using the following diagram.

![ANN block diagram for backwash scheduling flux response.](image)

The SIMULINK diagram in Fig. 4-13 investigates the flux response corresponding to step changes in vacuum time and backwash time. Each input is changed while maintaining the other input fixed. The flux behavior is demonstrated in the following figure.
Fig. 4-14 demonstrates a sharp increase in flux to a maximum value followed by a gradual decline as ratio increases. Increasing the ratio indicates longer operation or vacuum duration as opposed to less frequent backwash. The maximum flux is attained at 175 (L/m²·day) corresponding to an optimum vacuum-to-backwash time ratio of 10 minutes vacuum to 2 minutes backwash. This result is indeed consistent to that in Fig. 4-12 and hence verifies the optimum backwash scheduling. Moreover, the behavior of flux in Fig. 4-14 may be attributed to the backwash duration. The left region shows a comparable backwash to vacuum duration. While the right region shows a higher vacuum to backwash duration. For example at ratio 1, the backwash is equal to the vacuum duration. Thus unstable process operation is attained due to the frequent switching of operation between vacuum and backwash. As a result rapid flux decline is observed indicating severe membrane fouling. On the other hand, the right region represents a prolonged vacuum duration as opposed to backwash durations and hence membrane fouling represented by the gradual flux decline.
Chapter 5

NEURAL NETWORK MODEL PREDICTIVE CONTROL OF MBR

Neural network predictive control (NN-MPC) or Neuro-MPC is an advanced control strategy used to control the MBR. The NN-MPC is implemented with the MBR process model (i.e. SISO ANN model). The SISO ANN model utilizes a single input (vacuum-to-backwash time ratio) and a single output (flux). Plant identification is first performed to regenerate the SISO ANN model. Then NN-MPC parameters are tuned in order to achieve the optimum controller performance. After that, the controller performance for set-point tracking is investigated for both PID and MPC controls.

5.1 PID Controller

As a first step in controlling a membrane biological reactor (MBR) process, a conventional linear PID controller is implemented to the MBR process dynamic model. The dynamic MBR model is selected for the SISO ANN model described in scenario 2. Fig. 5-1 demonstrates the SIMULINK PID-NN control structure block diagram for the MBR. The MBR process dynamic model is indicated by the neural network model (i.e. blue block), while the set-point is provided by the signal builder block. The set-point is represented by a series of four pulse set-point changes divided equally on a sampling time of 1000 seconds. A train of positive and negative pulse changes are applied on the set-point and the output response in tracking the set-point is observed.

A conventional linear PID controller requires the tuning of three parameters: proportion gain ($K_c$), integral mode ($\tau_i$), and derivative mode ($\tau_d$). Increasing the gain leads to faster or more aggressive controller response and hence possible overshoot. Therefore, integral mode is added to eliminate off-sets and stabilize the controller response. Further, derivative mode is added to fasten the controller performance, to
eliminate oscillations, and to stabilize the controller response. Due to lack of transfer function and deterministic models for the process, PID parameters are tuned by trial and error in order to track the set-point of the controlled variable. Tuning a PID controller with a very small derivative mode ($\tau_D = 0.01$) yields unstable manipulated variable response as shown in Fig. 5-2. Hence, a proportional and integral (PI) controller with no derivative mode is selected for controlling the MBR. The PI controller parameters are listed in Table 5-1.

![Picture of Figure 5-1](image)

**Figure 5-1**  PI controller closed-loop block diagram for the SISO MBR model.

**Table 5-1**  PI controller parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportional gain, $K_c$</td>
<td>200</td>
</tr>
<tr>
<td>Integral, $\tau_I$</td>
<td>1</td>
</tr>
</tbody>
</table>

Figures 5-2 to 5-4 demonstrate the closed-loop simulations with PID and PI control schemes. Clearly, the PID controller failed to control the process within the operation constraints of the ratio.
Figure 5-2  Ratio changes to predict the output response – PID controller.

Figure 5-3  Flux response to set-point tracking – PI controller.
Figure 5-4  Ratio changes to predict the output response – PI controller.

Clearly, the major drawbacks in implementing a linear PID controller to the nonlinear MBR process are the unconstrained manipulated variables, and the difficulty of tuning the control parameters due to lack of deterministic models. Hence an advanced control strategy utilizing a nonlinear NN model is needed to control the MBR. The nonlinearity of the advanced control strategy allows future prediction of the controlled variables, consideration of constraints on the manipulated variables, which renders the control scheme to be adaptive in order to cope with the variations in operating conditions of the MBR.

5.2 Neural Network Model Predictive Control (NN-MPC)

5.2.1 Introduction

Neural Network Model Predictive Control (NN-MPC) is a subclass of model predictive controllers. It is an advanced control strategy based on a nonlinear neural network model for prediction. The neural network model is trained within the
predictive controller utilizing a given set of data. NN-MPC implementation requires a large data set and tuning several controller parameters. A large data set is essential in order to attain good controller predictions. Moreover, tuning the NN-MPC parameters is required to achieve the optimum control performance in set-point tracking and disturbance rejection. The NN-MPC block diagram is shown in Fig. 5-5.

![NN-MPC closed-loop block diagram for the SISO MBR model.](image)

The NN-MPC is represented by the blue block in Fig. 5-5. It calculates the control moves through manipulation of the manipulated variable (i.e. ratio) based on the response of the controlled variable (i.e. flux) in the course of the explicit dynamic model. The process dynamic model is derived for the SISO MBR process using the ratio and flux as the input and output variables, respectively. The control moves force the controlled variable to follow a predefined trajectory to track the set-point. The set-point in Fig. 5-5 is represented by the signal-builder. Moreover, the controller moves are performed by the current measurements and future predictions [35]. The flux current measurements are obtained through a feedback signal from the MBR process. On the other hand, the flux future predictions are determined from the embedded NN in the MPC. Moreover, the controller moves in predicting the process output response is performed through minimizing the set-point error by an open-loop optimization correlation. The optimization correlation is defined in terms of the predicted error, $E$ and input control moves, $\Delta u$. This is expressed in the general optimization form in eq.
(5-1) or quadratic cost function as in eq. (5-2). Moreover, the minimization of the cost function (J) in (5-2) is performed by solving the optimization problem using sequential quadratic programming and producing a solution constrained within the process input operating ranges [38]:

$$\min_{\Delta u} \left[ \sum_{i=1}^{N} (\text{Prediction} - \text{setpoint})^2 + \sum_{j=1}^{M} (\text{Controleffort})^2 \right] \quad (5-1)$$

Or

$$\min_{\Delta u} J = \sum_{i=1}^{N} \left( E_i^T Q E_i + \Delta u_i^T R \Delta u_i \right) \quad (5-2)$$

Where: M is the control horizon.
N is the model horizon.
P is the prediction horizon.
Q is the weighting matrix for predicted errors (Q > 0).
R is the weighting matrix for control moves (R > 0).

The first term in eq. (5-2) represents the set-point tracking through minimizing the error (E) between the set-point and process output, while the second term is designed to smooth the control signal [38]. Moreover, the above equations require the estimation of six design parameters for MPC tuning. The parameter selection guidelines are followed from [35] as follows:

1) Model Horizon and sampling time, N and Δt:

The model horizon and sampling period (If not specified) are selected according to the following correlation:

$$N \Delta t \geq \text{open-loop settling time} \quad (2-15)$$

Typically the model horizon is selected between: 30 ≤ N ≤ 120.
2) Control Horizon, M:

The control horizon defines the number the controller predicting moves. Increasing M results in more aggressive controller moves and hence increases the computational effort required to solve the optimization problem. A typical range of the control horizon is set between $3 \leq M \leq 20$. However, the MPC implements the first control move out of the M calculated moves.

3) Prediction Horizon, P:

The prediction horizon is designed to be greater than the process output time delay, in order to provide enough time for future output prediction and smoother control [38]. Moreover, a sufficient large prediction horizon is selected to minimize the aggressiveness of the controller action. In other words, increasing P results in less aggressive controller action. As a result, the prediction horizon is set to be equal to: $N + M$.

4) Weighting matrices, Q and R:

Diagonal matrices with largest elements correspond to most important variables. More emphasis is placed on the outputs by further increasing the diagonal elements. It follows from eq. (2-14), if minimizing the error or the output scaling is more important; then larger Q diagonal elements are selected. On the other hand, if input scaling is more important; then larger R diagonal elements are selected. In addition, if the variables in the cost functions are in the same range, then the weighting matrixes are set to be equal to the identity matrix [38].

Prior to simulating the NN-MPC, plant identification is performed and the controller parameters are tuned. Plant identification is achieved by identifying the structure of the nonlinear neural network, the plant model, and the input/output data set. The input/output data set may be either imported if a huge data set is available or generated through the predefined plant model. After accepting the data, the neural
network is trained, validated, and tested according to the selected learning algorithm. Subsequently, the best NN training performance is chosen based on the regression plots.

5.2.2 MPC Model Identification

Plant identification requires identifying the plant or process model. The model is further used in generating data for training the ANN model. The process model is selected for the single-input-single-output system with the ratio and flux being the input and output, respectively. Moreover, the ANN model is modified through the addition of two discrete time delays. The time delays are necessary to allow sufficient time for the controller prediction. Furthermore, the ANN structure consists of three layers: input, output, and one hidden layer. Both the input and output layers consist of one neuron; while the hidden layer consists of three neurons. Levensberg-Marquardt (L-M) training algorithm is used to train the network with the following activation functions: tan-sigmoid activation function in the first two layers, and pure line activation function in the output layer. The pure line function allows unbounded output predictions. The neural network model is generated using MATLAB in which the network is trained using experimental data from Aidan et al. [8] (i.e. experiment 1). The following diagram shows the ANN model.

Figure 5-6 NN-MPC model, ANN model with two discrete time delays
Training the ANN model in Fig. 5-6 is stopped utilizing 24 epochs as shown in Fig. 5-7 with gradient equal to $4.87 \times 10^{-3}$, input mean matrix (Mu) of 0.01, and the best validation performance is 0.184 at 18 epochs. The predicted flux from ANN model is validated with the experimental flux in Fig. 5-8. Further, the overall regression between the ANN predicted output and target is revealed in Fig. 5-9 with training, validation, and testing regressions of 0.958, 0.705, and 0.709, respectively. Although a better regression (or ANN performance) may be obtained by increasing the number of neurons in each layer, this ANN structure is selected to decrease the predictive controller computational time and effort. Since a larger ANN structure requires more prediction computations and hence a slower/less aggressive controller response. Therefore, there is a trade-off between model accuracy and controller robustness.

Figure 5-7  Squared error minimization through the training epoch for NN-MPC model
Figure 5-8  ANN predicted and experimental flux for NN-MPC model

Figure 5-9  Overall regression plot for NN-MPC model
Simulating the optimum feed forward ANN model in Fig. 5-5 yields the following plots representing the flux response in both the feed forward and feedback loops.

![Flux response from SIMULINK for NN-MPC model](image)

*Figure 5-10  Flux response from SIMULINK for NN-MPC model*
ANN predicted flux response is further investigated according to an impulse, step, and random signals. The impulse response is applied through signal builder. The pulse is applied at sampling time of 4 for sampling time duration of 120 seconds. The ratio is pulsed from 20 – 4.7 and back to 20. While the flux step response is applied at sampling time of 10 seconds for sampling time duration of 40 seconds. The ratio is stepped from 20 to 4.7. The random signal is performed within the ratio range of 4.7 to 33. Finally, the flux response with respect to the three signals is illustrated in Figs. 5-12 to 5-14, respectively.
Figure 5-12  ANN predicted flux response to ratio impulse change for NN-MPC model

Figure 5-13  ANN predicted flux response to ratio step change for NN-MPC model
5.2.3 NN-MPC Simulation

A large data set is required to simulate the NN-MPC. Since, a relatively small experimental data set is obtained from Aidan et al. [8]. Consequently a new set of data is generated using the ANN in Fig. 5-6. The generated data is trained using Levenberg-Marquardt learning algorithm with 200 epochs. A summary of the ANN model architecture and data set is given in Tables 5-2 and 5-3, respectively.
Table 5-2  ANN-MPC model structure

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size of Hidden Layers</td>
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<tr>
<td>Sampling interval (sec)</td>
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</tr>
<tr>
<td>No. Delayed Plant Inputs</td>
<td>2</td>
</tr>
<tr>
<td>No. Delayed Plant Outputs</td>
<td>2</td>
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</table>

Table 5-3  Training data set

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<tr>
<td>Maximum Plant Input</td>
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</tr>
<tr>
<td>Minimum Plant Input</td>
<td>4.5</td>
</tr>
<tr>
<td>Maximum Interval Value (sec)</td>
<td>200</td>
</tr>
<tr>
<td>Minimum Interval Value (sec)</td>
<td>50</td>
</tr>
</tbody>
</table>

Note from Table 5-3, the plant input (manipulated variable) which is the ratio is constrained between the minimum and maximum value obtained from the experimental data; corresponding to the minimum ratio at 10 minutes vacuum to 2 minutes backwash and the maximum at 30 minutes vacuum to 1 minute backwash. The generated data set from plant identification is shown in Fig. 5-15. Training and validating the neural network using the generated data set are illustrated in Figs. 5-16 and 5-17. The ANN training is stopped utilizing 23 epochs with gradient equal to 6.81, input mean matrix (Mu) of 0.001, and the best validation performance is $2.48 \times 10^{-3}$ at 21 epochs. Further, the overall regression between the NN predicted output and target (from the generated data set) is revealed in Fig. 5-18 with training, and validation regressions of 0.999, and 0.989.
Figure 5-15  NN-MPC generated data set.
Figure 5-16  Training the NN within the NN-MPC
Figure 5-17   Validating the NN within the NN-MPC

Figure 5-18   Overall regression plot between the NN predicted output and target.
Once the neural network is trained; plant identification is completed. Hence the next step is to tune the controller parameters. Selecting the NN-MPC parameters defines the aggressiveness of the controller. A more aggressive controller performance is a trade-off between stability and computational speed. As such, a more stable controller performance is attained at longer horizons. However, this requires more computational time and hence slower controller response (i.e. less aggressive controller). Tuning the controller parameters is performed following the previously mentioned guidelines. Then the NN-MPC parameters are further adjusted through running several simulations to attain the optimum set-point tracking. The optimum NN-MPC parameters are summarized in Table 5-4.

Table 5-4  NNPC parameters

<table>
<thead>
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<th>Parameter</th>
<th>Value</th>
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<tbody>
<tr>
<td>Cost Horizon, N2</td>
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<tr>
<td>Control Horizon, Nu</td>
<td>4</td>
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<tr>
<td>Control weighting factor, $\rho$</td>
<td>0.1</td>
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<tr>
<td>Search factor, $\alpha$</td>
<td>0.1</td>
</tr>
</tbody>
</table>

The NN-MPC parameters listed in Table 5-4 reveals an aggressive controller performance with no oscillations. The prediction horizon is selected to be greater than the output time delays in order to provide sufficient time for future output prediction. Therefore, the prediction horizon is set to be 8 indicating a short prediction horizon and hence more aggressive controller. Besides, a short control horizon is selected indicating less controller moves in prediction signifying less computational time and effort. Further, the weighting and search factors are selected to be large; given that the typical values are within the range of: 0.01 – 0.03 indicating no observed oscillations. The NN-MPC is further simulated with the tuned parameters in Table 5-4. The set-point is provided by the signal builder block in Fig. 5-5. The signal range is set between: 50 – 120 (L/m$^2$·days) with pulse duration of 200 sampling time. The controlled variable (i.e. flux) response in tracking the set-point is illustrated in Fig. 5-19. The manipulated variable (i.e. ratio) changes within the constrained range are also shown in Fig. 5-20.
Figure 5-19  Flux response to set-point tracking – NN-MPC

Figure 5-20  Ratio changes to predict the output response – NN-MPC
The results shown in Figs. 5-19 and 5-20 illustrate that a good controller performance is achieved in terms of set-point tracking with no oscillations. The controller is able to drive the process variable to track the set-point pulse changes in both directions (increasing/decreasing). Furthermore, a fast process variable response in tracking the set-point is observed. Yet, a slower response is observed at the highest flux (i.e. 120 L/m²-days) but ultimately the set-point is achieved with no overshoot. Nevertheless, the maximum flux (i.e. 175 L/m²-day) is not achieved due to the NN-MPC constraints. As illustrated in Fig. 5-20, the input reaches saturation range while the corresponding flux is 120 (L/m²-day).

By contrast, the NN-MPC demonstrates a satisfactory performance due to the high ability of the neural network in capturing the nonlinearity of the MBR model. NN-MPC overcomes the major drawbacks in the linear PID controller. It demonstrates a good servo response with respect to large pulse set-point changes within the constrained manipulated variable range. Moreover, the adaptive feature of the NN-MPC enhances its implementation to the highly nonlinear MBR process.
Chapter 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

In this thesis, a rigorous nonlinear model is developed for the MBR. The derived model represents a system of first order nonlinear coupled ODEs. Solving the derived model online requires a huge computational time and effort. Therefore, artificial neural networks (ANNs) are used to model the MBR process. ANN high capability in capturing the nonlinearity of the MBR process provides accurate prediction of the process output in less computational time and effort (i.e. faster modeling).

The high nonlinearity and complexity of the MBR process requires an advanced nonlinear control strategy. Neural Network Model Predictive Control (NN-MPC) or Neuro-MPC is implemented to the nonlinear MBR process represented by the SISO ANN model. NN-MPC parameters are tuned for an aggressive controller performance with no oscillations. A short prediction horizon is used to obtain an aggressive controller performance in set-point tracking. Also a short control horizon is selected indicating less controller moves in prediction and hence less computational time and effort are attained. Furthermore, large weighting and search factors are selected since no oscillations are observed in the process. The NN-MPC shows a good servo (set-point tracking) performance with minimum overshoot and no oscillations at the specified controller parameters. NN-MPC satisfactory performance is due to the high ability of the neural network in capturing the nonlinearity of the MBR model. On the other hand, implementing a linear PID controller demonstrates an unrealistic manipulated variable moves because of the unconstrained input variables. Also PID control parameters tuning is difficult due to lack of deterministic models. Therefore, the nonlinear adaptive nature of the proposed NN-MPC proved the selection of this control strategy for controlling the MBR process. However, real time implementation
of NN-MPC is only feasible if the computational load is manageable without sacrificing the stability and performance of the system.

6.2 Future Work

Based on the high performance of NN-MPC in controlling the MBR process, NN-MPC may be implemented in a real time system. Furthermore, other advanced control strategies may be implemented to the MBR. Then the performance of the applied strategies is compared to that of the NN-MPC.
REFERENCES


VITA

Noor Abachi was born on January 4, 1987, in Sharjah, UAE. She was educated in local public schools and graduated in 2005. Further she was educated in the American University of Sharjah in Sharjah, UAE, from which she graduated in 2009. Her degree was a Bachelor of Science in Chemical Engineering.

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