PREDICTION OF BIOLOGICAL WASTEWATER TREATMENT PERFORMANCE USING ARTIFICIAL NEURAL NETWORKS

by

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Declaration

I, Winile Sindane declare that the contents of this thesis represent my own unaided work, and that the thesis has not been previously submitted for academic examination towards any qualification. Furthermore, it represents my own opinions and not those of Cape Peninsula University of Technology.

Signature ………………..............

Date 17 February 2023 …………………………….

Abstract

Process control and monitoring of wastewater treatment plants are essential, but have proven to be slow, expensive and dearth. It is currently achieved by examining effluent wastewater quality and adjusting the treatment process. This justifies the need to develop robust mathematical modelling tools known for high accuracy to predict the performance of wastewater treatment plants for future purposes.

A comparative study on the prediction of biological wastewater treatment performance of industrial wastewater, biodiesel- (BDWW), textile- (TTWW), polymer- (PWW), as well as pulp and paper wastewater (PPWW) using artificial neural networks (ANN), was carried out based on historical data from previous studies. Industrial wastewater was characterised by high levels of pollutants represented by the chemical oxygen demand (COD) since it is one of the important parameters used to evaluate the performance of wastewater treatment systems. Three ANN-based models, namely, nonlinear autoregressive neural network model with exogenous inputs (NARX), feedforward backpropagation (FFB) and cascade feedforward backpropagation (CFBP), were developed to predict the COD of the effluent using the Levenberg-Marquardt (LM) backpropagation algorithm. The ANN models were developed using a three-layered ANN architecture, including the input, hidden and output layer. The best ANN architecture from the three models was chosen after several steps of training, testing and validation using a trial-and-error method altering the number of neurons ranging from 2 to 11 in the hidden layer.

Based on all three model performances and prediction capabilities, the most appropriate ANN model was found to be the NARX for all four industrial wastewater and treatment methods with a mean square error (MSE) of 0.0239, 0.303, 0.0719, 0.343 and an overall model correlation coefficient (R) for training, validation, and testing of 0.988, 0.838, 0.964, 0.809 for the BDWW, TTWW, PWW and PPWW, respectively. According to the MSE and R values obtained, it was concluded that the NARX performed better and could accurately predict COD effluent concentration, which proves that ANN-NARX can be employed successfully to estimate COD effluent concentration from biological wastewater treatment systems. The CFBP model also showed better prediction results compared to the FFB model with overall R values of 0.947 for BDWW, 0.736 for TTWW, 0.837 for PWW and 0.739 for PPWW. However, the model showed poor performance with an MSE values of 0.1024, 0.444, 0.297 and 0.457, respectively, which could result in poor generalisation when presented with new data sets.

Based on the results obtained from all the ANN methods, it can be concluded that ANNs are reliable modelling tools for successfully predicting biological wastewater treatment systems performance focused on the effluent COD. Proper selection of ANN input parameters resulted

in good prediction and network performance of the ANNs. The quality and quantity of the historical data had a significant influence on the network performance, poor quality and fewer data resulted in poor prediction and ANN performance.

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Dedication

This thesis is dedicated to my beloved sister, Martha Sindane and brother, Augustine Sindane, thank you for your unconditional love, continuous support, encouragement, and for believing in me, if it were not for you, I would not have been where I am today.

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List of Abbreviations

Abbreviation	Definition
ABR	Anaerobic Baffled Reactor
AD	Anaerobic Digestion
AF	Anaerobic Filter
AFBR	Anaerobic Fluidised Bed Reactor
AHR	Anaerobic Hybrid Reactor
AI	Artificial Intelligence
AnMBR	Anaerobic Membrane Bioreactor
ANN	Artificial Neural Networks
AS	Activated Sludge
ASTM	American Society Testing and Materials
BDF	Biodiesel Fuel
BDWW	Biodiesel Wastewater
BOD	Biological Oxygen Demand
BR	Bayesian Regulation
CPUT	Cape Peninsula University of Technology
CFBP	Cascade Feedforward Backpropagation
CN	Total Cyanides
CNN	Convolutional Neural Networks
Cl	Chloride
CO_2	Carbon Dioxide
CoCT	City of Cape Town
COD	Chemical Oxygen Demand
CSTB	Continuous Stirred Tank Bioreactor
Cu	Total Copper
Cr	Total Chromium
EABR	Electrolysis Anaerobic Baffled Rector
EC	Electrical Conductivity
EGSB	Expanded Granular Sludge Bed Reactor
FBB	Fluidised Bed Bioreactor
FBNN	Feed Backward Neural Networks
Fe	Total Iron
FFA	Free Fatty Acids
FFB	Feedforward Backpropagation
FFNN	Feedforward Neural Networks
FOG	Fats, Oil and Grease

GAC	Granular Activated Carbon
H_2	Hydrogen Gas
Hg	Total Mercury
HRT	Hydraulic Retention Time
LM	Levenberg-Marquardt
MAPE	Mean Absolute Percentage Error
MBR	Membrane Bioreactor
MLP	Multilayer Perceptron
MNN	Modular Neural Network
MSE	Mean Square Error
Mt	Metric Tonnes
Na	Sodium
NARX	Autoregression Neural Network with Exogenous input
NEMA	National Environmental Management Act
OED	Orthogonal Experimental Design
O&G	Oil and Grease
OLR	Organic Loading Rate
Pb	Total Lead
PPWW	Pulp and Paper Wastewater
PWW	Polymer Wastewater
R	Correlation Coefficient
R^2	Coefficient of Determination
RBFNN	Radial Basis Function Neural Network
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RSM	Response Surface Methodology
SA	Sensitivity Analysis
Std. Dev	Standard Deviation
SBR	Sequencing Batch Reactor
S	Total Sulphides
SS	Suspended Solids
SCG	Scaled Conjugate Gradient
SO_4	Total Sulphates
SVM	Support Vector Machine
TAG	Triacylglycerols
TCOD	Total Chemical Oxygen Demand

TD	Time Delay
TDS	Total Dissolved Solids
TN	Total Nitrogen
TOC	Total Organic Carbon
TP	Total Phosphorus
TPH	Total Petroleum Hydrocarbons
TSS	Total Suspended Solids
TTWW	Textile Wastewater
UASB	Up-flow Anaerobic Sludge Blanket
UD	Uniform Design
USEPA	United States Environmental Protection Agency
VFA	Volatile Fatty Acids
WWTP	Wastewater Treatment Plants
WHO	World Health Organisation
Zn	Total Zinc

List of Symbols

Symbols	Definition
b_i^k	Bias Vector
$f(x)$	Activation Function
i	Input Data
n	Total Number of Runs
n_u and n_y	Input and Output Order
OC_{feed}	Organic Matter Concentration (kg COD/m^3)
OLR	Organic Loading Rate (kg COD/m^3.day
Q_{feed}	Feed Flowrate (L/m^3)
R	Correlation Coefficient
t	Time
td	Target Data
$u(t)$	Output Data for NARX
V_w	Reactor Volume (m^3)
$X_i^k w_{ij}^k$	Input and Weight Vector
Y_j^{k+1}	Output Vector
$y(t)$	Input Data for NARX
$\mathcal{Z}i$	Algorithm Estimated Value
$\hat{\mathcal{Z}}\imath$	Experimental Value
$\mathcal{Z}m$	Average Experimental Value
Σ	Sum of the Input, Weights, and Bias

Glossary

Terms	Definition
Anaerobic Baffled Reactor (ABR)	A reactor with up-flow reactors connected by means of baffles in series (Barber & Stuckey, 1999).
Anaerobic Digestion (AD)	The process during which organic matter is converted to methane in the absence of oxygen (Xu *et al*., 2018).
Artificial Neural Networks (ANN)	Mathematical modelling tool that works the same way as a human brain by learning, processing and storing information (Gupta & Raza, 2020).
Correlation coefficient (R)	The statistical relationship between two variables (Zhou *et al.*, 2016).
Chemical Oxygen Demand (COD)	The amount of oxygen consumed during the chemical oxidation of organic compounds (Hassan *et al.*, 2018).
Expanded Granular Sludge Bed Reactor (EGSB)	A combination of an up-flow and fluidised reactor (Cruz-Salomón *et al*., 2019).
Extrapolation	The estimation of data based on the sequence of data beyond the existing training data (Bartley *et al*., 2019).
Generalisation	The ability to work and handle unseen data (Mitchell *et al*., 1986).
Hidden Layer	The layer between the input and output layer where a set of weighted inputs generate output layers through an activation function (Di Franco & Santurro, 2021).
Hydraulic Retention Time (HRT)	The average time soluble particles remain in a reactor (Karaosmanoglu Gorgec & Karapinar, 2019).
Mean Square Error (MSE)	The difference between target and experimental output values (Yogitha & Mathivanan, 2018).
MATLAB®	A mathematical programming platform used to analyse and design systems developed by MathWorks (Maros & Juniar, 2016).
"Noisy" Data	Corrupted data (i.e. meaningless) not used/read by mathematical programs (García *et al*., 2013).
Normalisation	A technique used to prepare data in machine learning (Ahsan *et al*., 2021).
Overfitting	Poor generalisation of artificial neural network models due to noisy data and insufficient training data sets (Ying, 2019).
Organic Loading Rate (OLR)	The rate at which organic matter enters an anaerobic digestion system (Musa *et al*., 2018).

Outliers	Data point measurements that are not representative of the general trend of the data, in the sense that they are numerically distant from the majority of data (Khamis *et al*., 2005).

Chapter 1: INTRODUCTION

1.1 Background

The necessity to treat wastewater is rapidly influenced by environmental concerns and water scarcity worldwide. This calls for the implementation and development of cost-effective methods to treat and manage wastewater (Aziz *et al*., 2019). This study is focused on the mathematical modelling of industrial biological wastewater treatment of biodiesel-, textile-, polymer- and pulp and paper wastewater.

During the production and purification of biodiesel, large volumes of biodiesel wastewater (BDWW) with high concentrations of chemical oxygen demand (COD) (60 000 – 545 000 mg/l) oil and grease (O&G) (7 000 – 44 300mg/l), alcohol, soap, glycerol and low or high pH (8.5 – 10) is generated. BDWW is difficult to bioremediate due to the low nitrogen and phosphorus concentrations, high pH and high levels of hexane-extracted oil (Daud *et al*., 2015a). Veljković *et al*. (2014) estimated that approximately 28 million m^3 of BDWW was generated worldwide in 2011. In 2016, Brazil alone had an estimated 11.4 million m^3 of BDWW generated (Ferreira *et al*., 2019).

BDWW is generated from the washing process, this process is done to purify biodiesel fuel in order for its quality to meet the American Society Testing and Materials (ASTM) standard requirements. The washing process can be done using three different methods that include dry washing, wet washing and membrane extraction (Leung *et al*., 2010). In wet washing, residues such as soap, alcohol and sodium salts are removed from the biodiesel fuel using distilled water. This process is repeated (2 to 5 times) until clear colourless water is obtained (Veljković *et al*., 2014). Wet washing is more convenient although it may be time consuming and requires more energy (Chozhavendhan *et al*., 2020).

In the dry washing technique, adsorbents and ion-exchange resins are used instead of water for the removal of impurities (Chozhavendhan *et al*., 2020). Therefore, in this process wastewater is not generated, although the end product never meets the European standard limits (Berrios & Skelton, 2008). The reduction of large volumes of excess water from biodiesel fuel brought about a new method, namely membrane extraction, to reduce the oil in the wastewater produced. The membrane extraction process is done to eliminate the emulsification process that could lead to less biodiesel fuel yield. Membrane extraction reduces the amount of water used in the production of BDWW (Leung *et al*., 2010).

In the treatment process of biodiesel wastewater, anaerobic baffled reactors (ABR) produces less sludge (Kim *et al*., 2007). Phukingngam *et al.* (2011) reported on the performance of an ABR for treating biodiesel wastewater with organic waste removal efficiency of COD (100%), glycerol (100%), O&G (100%) and methanol (100%) which justifies excellent performance of the ABR system.

The manufacturing of wool, cotton and flax from textile industries produces large volumes of chemically contaminated wastewater, containing high concentrations of chemical oxygen demand (COD), biological oxygen demand (BOD), nitrogen, colour, surfactants total dissolved solids (TDS), pH, colour, turbidity, but is mostly contaminated by dyes (Al-Mamun *et al*., 2019; Lafi *et al*., 2018). The textile industry focuses either on dry or wet fabric with operations such as desi zing, scouring, bleaching dyeing, printing, mercerisation, and finishing (Holkar *et al*., 2016). According to Sarayu & Sandhya (2012), about 50% of wastewater is generated from the desizing process in the textile finishing industry.

Large consumption of water is widely used during the wet process in the dye house, which results in the production of wastewater (Paździor *et al*., 2019). Al-Mamun *et al*. (2019) and Syam Babu *et al*. (2020) reported that the world bank estimated about 17-20% of industrial wastewater from the textile industries, are generated from dyeing and finishing treatment processes (Holkar *et al*., 2016). Textile wastewater (TTWW) is harmful to human health and aquatic life as part of the food chain in the ecosystem (Al-Mamun *et al*., 2019), the discharged textile water inhibits direct sunlight in water streams which affect oxygen content resulting in the extinction of marine life (Lafi *et al*., 2018).

The textile industry is one of the largest industries contributing to the economic growth of South Africa, however, the textile industry is in the top 80% of water users in the manufacturing stage. It was reported that about 36% of water used from the eThekwini municipality and 29% of water used in the City of Cape Town in textile manufacturing processes corresponds to the wastewater generated depending on the production process used in the textile industry (Le Roes-Hill *et al*., 2017).

Polymers are natural and synthetic substances containing macromolecules used in municipal, industrial and agricultural industries. The metal coating and battery manufacturing industrial sector contributes to a large generation of polymer wastewater (PWW) (Nath *et al*., 2021).

The large demand of paper has led to the growing of pulp and paper industries (Ping *et al*., 2019; Krishna *et al*., 2014). According to Liang *et al*. (2021) in 2015, it was estimated that the production of paper was over 390 metric tonnes (Mt). Toczyłowska-Mamińska (2017) reported that the pulp and paper industries use about 5 to 100 m^3 of water per 1 tonne of paper produced. The production of paper generates large volumes of pulp and paper wastewater (PPWW), globally contributing about 42% of three billion tonnes of industrial wastewater (Toczyłowska-Mamińska, 2017). PPWW is highly polluted with COD of about 10 000 mg/l or more and can be successfully treated using anaerobic treatment methods (Ravichandran & Balaji, 2020) with a removal efficiency of 60 to 97% of COD using an expanded granular sludge bed (ESGB) (Ping *et al*., 2019).

Pulp and paper industries consumes large volumes of water in the preparation of wood chips, cooking, pulp washing, screening, bleaching and dilution (Ravichandran & Balaji, 2020) which then generates wastewater (Vashi *et al*., 2018) depending on the on the type of production process used (Barapatre & Harit, 2016). The use of fresh water amounts to about 250 to 300 m^3 per tonne to paper produced (Nikjoo, 2018).

To manage the quality of water, wastewater treatment methods are crucial. Due to environmental issues arising from wastewater discharged to municipal sewers, proper optimum operation and control of wastewater treatments plants is important (Hamed *et al*., 2004). The current study focused on the prediction of biological wastewater treatment systems using anaerobic digestion (AD) for the treatment of biodiesel-, textile-, polymer- and pulp and paper wastewater. AD processes are known to be complex and nonlinear, as a result, mathematical modelling tools for the prediction of organic waste removal via biological treatment prior to discharge is preferred (Jain *et al*., 2015). Predicting organic waste removal such as COD is important because it determines whether the wastewater effluent can be discharged, thus predicting the downstream wastewater treatment plants (WWTP) performance. Prediction of organic waste effluent can be obtained from data driven modelling tools such as artificial neural networks (ANN) (Krivec *et al*., 2021). According to Elbisy *et al*. (2014), ANNs are excellent in prediction purposes for the water and wastewater treatment industry due to their nonlinearity, generalisation and adaptability.

ANN modelling tools have been used over the past years because of their capability to identify, classify and solve real world problems. ANN are computer systems with process elements such as units and neurons or nodes (Ahmad *et al*., 2021). Three different types of ANN models, the feedforward backpropagation (FFB), the nonlinear autoregressive neural network model with exogenous inputs (NARX), and the cascade forward backpropagation neural network (CFBP) were developed to predict the biological wastewater treatment performance focusing on the chemical oxygen demand (COD) of the effluent. According to Ahmad *et al*. (2021); Gramatikov (2017) and Çoruh *et al*. (2014) FFB neural networks are the simplest and most commonly used ANN types. The FFB, NARX, and CFBP were employed to predict COD output from an ABR and EGSB reactor system using historical data obtained from previous biological biodiesel, polymer, pulp and paper and textile wastewater studies for the organic loading rate (OLR), and COD in the ANN as input parameters.

1.2 Problem statement

Many biodiesel, paper, polymer, and clothes-producing industries tend to dispose the untreated hazardous and chemically contaminated wastewater generated from purification processes into municipal drainage systems. This has a negative impact on the environment due to the high levels of COD, BOD, fats, oil and grease (FOG), suspended solids (SS), alcohol, and other impurities present in industrial wastewater, which also has a potential of polluting surface and ground water. There has been water scarcity in the Western Cape, South Africa, since 2015. Individuals have been advised to reduce the amount of water used per day. Therefore, water-intensive industries such as biodiesel, textile, polymer and pulp and paper industries need to investigate methods that can be used to treat the wastewater generated to be reused for production or purification processes and to meet the City of Cape Town (CoCT) industrial effluent discharge limits. However, for acceptable wastewater quality prior to the discarding process, these industries need to predict the organic and inorganic waste removal efficiency and/or effluent concentration from the wastewater treatment approaches using mathematical modelling tools, which will determine treatment system performance and whether the wastewater can be discharged in future.

1.3 Aim and objectives

The main intent of this project was to evaluate the feasibility of ANNs to identify correlated patterns between data sets and corresponding target values of COD from biological wastewater treatment systems.

The objectives of the project are to:

a. Identify a suitable artificial neural network (ANN) model for biological wastewater treatment systems
b. Investigate the impact of wastewater type on the ANN model development
c. Investigate the impact the type of biological treatment system has on the ANN model development.

1.4 Research questions

The following research questions were answered by this study:

a. How accurately can artificial neural networks (ANNs) predict the performance of biological wastewater treatment systems?
b. How does the type of wastewater by treated influence the ANN model's performance?
c. Does the type of biological wastewater treatment influence the ANN model's performance?

1.5 Delineation

During the prediction of biological wastewater treatment performance, the following were not covered:

a. Investigating the impact of reactor size.
b. Biogas analysis.
c. Manual selection of *dividerand* data sets in MATLAB®.
d. Manual adjustments of ANN weights.
e. Use of software(s) for data pre-processing.
f. Adjustments of number of ANN layers.
g. Investigating the effect of organic loading rate variation in ANNs.

1.6 Significance of study

This study outlines the importance of industrial wastewater treatment in biodiesel, textile, polymer and pulp and paper producing industries prior to discharging to municipal drains. Biological wastewater treatment methods were used to treat biodiesel-, textile-, polymer- and pulp and paper wastewater. This method is beneficial in accordance with the industrial effluent discharge standard limits in Cape Town (South Africa (Western Cape), 2013), as it has proven to be more efficient in organic and inorganic waste removal. The main purpose of this study was to develop mathematical modelling tools to successfully predict biological wastewater treatment performance. The study highlights a convenient and cost-effective method to predict COD effluent concentration from biological wastewater systems while introducing knowledge on the use of ANNs for analysis and prediction purposes. ANNs can determine whether the biological wastewater treatment plants will result in treated industrial wastewater acceptable for discharge.

This study will benefit industrial wastewater treatment industries considering the implementation of mathematical modelling tools and provide clear information for future researchers interested in artificial intelligent (AI) models for wastewater treatment plant performance system prediction.

Chapter 2: LITERATURE REVIEW

2.1 Introduction

This chapter outlines important aspects with regards to industrial wastewater treatment of biodiesel (BDWW), textile (TTWW), polymer (PWW) and pulp and paper wastewater (PPWW) using biological wastewater treatment systems mainly focussing on anaerobic digestion (AD). Biological treatment methods have been proven to achieve high removal efficiencies with low chemical and energy consumption compared to chemical treatment techniques (Liu *et al.*, 2019a). It examines the necessity for proper operation and improved wastewater treatment methods and the use of cost effective empirical mathematical prediction modelling tools such as artificial neural networks (ANNs) published in literature over the last 10 years, which justifies the need for this research study. ANN is an artificial intelligence (AI) tool that works the same way as a human brain by processing and storing information to solve real problems (Hassen & Asmare, 2019). ANNs have been employed in modelling wastewater treatment methods due to their high accuracy and ability to solve nonlinear problems (Saleh, 2021).

2.2 South Africa's water crisis

Water is a limited natural resource in South Africa, being a semi-arid country. In 1998, it was forecast that South Africa would experience extreme drought disasters by the 2025 with less than 1000 m^3 per capita available for supply per year (Otieno & Ochieng, 1998). It was later predicted by Harding *et al*. (2017) that this would happen by 2040. According to Falizi *et al*. (2018) about 50% of the world population will be located in water stressed areas by 2025. The water demand has been anticipated to escalate by 32% due to population growth and industrial development by the year 2030 (Webster & Ras, 2016). Furthermore, there has been insufficient rainfall at about 500 mm per annum occurring in South Africa. The stress on water as a resource is further exacerbated by economic and population growth, migration of citizens from rural to urban areas and climate change (Wanjiru & Xia, 2018).

Water scarcity poses an extreme threat to agriculture and the global economy (Alam, 2015). In 2015 is was reported that South Africa, particularly the Western Cape has been experiencing a water crisis since 1904 (Booysen *et al*., 2019). Households in the Western Cape were advised to reduce their use of water from 540 to 280 L per day to avoid the approach of dry tabs, day zero (Booysen *et al*., 2019). Drought as a natural disaster does not only affect the citizens, but agriculture as well (Alam, 2015).

Bwapwa (2018) investigated the causes of the polluted water resources and demonstrated that power generation, urbanisation, mining and industries are the main causes of water pollution (Bwapwa, 2018). Bwapwa (2018) also observed that the pollution of water has a negative environmental impact in South Africa and poses a threat to the agricultural sectors, marine life and human health (Bwapwa, 2018).

South African citizens rely on sources of water such as lakes and dams. However, these sites are conventionally used for industrial and domestic wastewater discharge resulting in water pollution affecting most developing countries such as South Africa (Figure 2.1) (Rodríguez *et al*., 2017). The focus of this study was on the biological treatment of industrial wastewater, mainly biodiesel-, textile-, polymer- and pulp and paper wastewater.

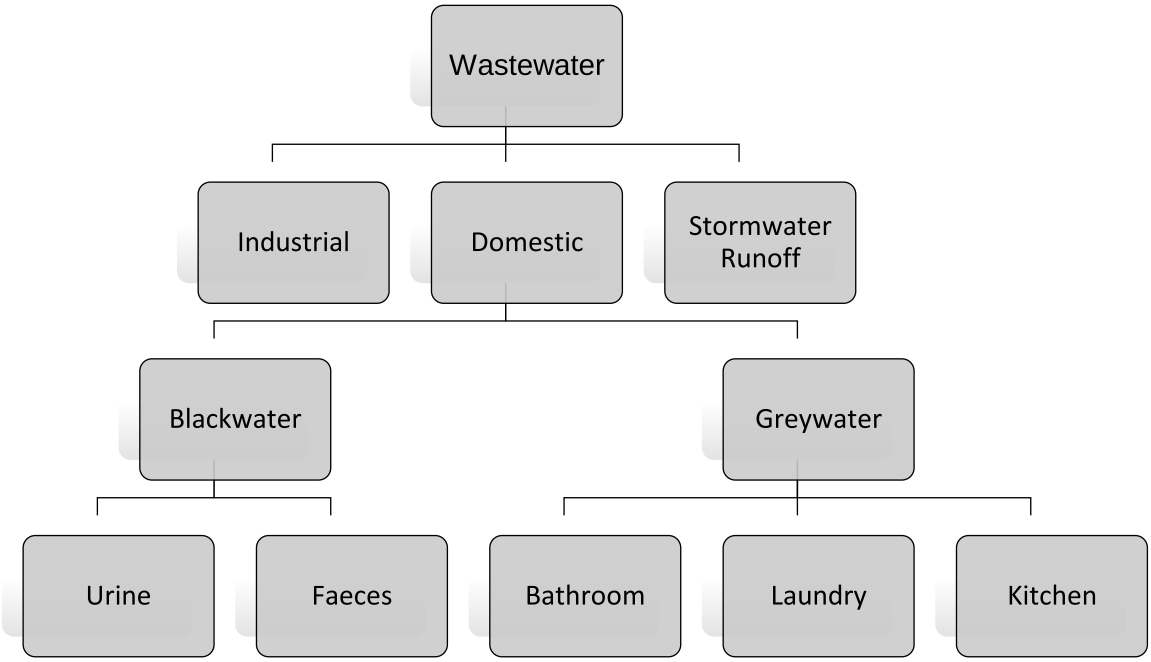

Figure 2.1: Types of wastewater, adapted from Rodríguez *et al*. (2017)

Types of industrial wastewater include the following (Yuliasni *et al*., 2023):

- Brewery
- Petrochemicals and refineries
- Mining
- Cane sugar
- Pharmaceutical
- Dairy

2.3 Overview of industrial wastewater

Biodiesel wastewater (BDWW) is a liquid with an opaque white colour (Jaruwat *et al*., 2010), which is produced from the purification step of the biodiesel fuel production process. The purification process is repeated several times to ensure the fuel is impurity free, about 20-120 L of wastewater is generated per 100 L of biodiesel produced (Daud *et al*., 2015a). In

Thailand, the production of about 350 000 L/day of biodiesel was reported to be associated with more than 70 000 L of BDWW per day. This BDWW was shown to be composed of among other components alcohol like methanol and soap which causes high chemical oxygen demand (COD) and oil and grease (O&G) (Ngamlerdpokin *et al*., 2011). Table 2.1 shows the quantities of BDWW produced as reported in literature

Table 2.1: Volume of biodiesel produced daily and the corresponding biodiesel wastewater produced

Production (L/day)	**Wastewater (L/day)**	**References**
1	0.2-3	Veljković *et al*., 2014
100	20-120	Daud *et al*., 2015
350 000	70 000	Jaruwat *et al*., 2010
6000 000	1200 000	Pitakpoolsil *et al*., 2014

The production of pulp and paper and textile products as growing industries, consumes large volumes of clean water, which then generates large volumes of wastewater containing products of lignin, carbohydrates and extractives from wood preparation, pulping, pulp washing, coating and bleaching (Hubbe *et al*., 2016); and high concentrations of chemical oxygen demand (COD), biological oxygen demand (BOD), nitrogen, colour, surfactants total dissolved solids (TDS), pH, colour, turbidity, but is mostly contaminated by dyes (Al-Mamun *et al*., 2019; Lafi *et al*., 2018) from desizing, scouring, bleaching dyeing, printing, mercerisation, and finishing (Holkar *et al*., 2016), respectively. These industries tend to reuse a small ratio of water for the production process (Toczyłowska-Mamińska, 2017). It was estimated that the textile industry consumes roughly 21 to 377 m^3 of water per 1 tonne of textile product (Asghar *et al*., 2015). In Pakistan, it was estimated that textile wastewater contributes about 288 326 million gallons of industrial wastewater out of the 926 335 million gallons of wastewater produced (Fazal *et al*., 2018). According to a review paper by Hubbe *et al*. (2016) pulp and paper production process use about 70% clean water.

2.3.1 Characteristics of industrial wastewater

a) Chemical Oxygen Demand (COD)

The chemical oxygen demand (COD) is used to characterise wastewater and is of significance in controlling wastewater treatment plants (Zheng *et al*., 2008). COD is measured chemically by analysing the organic matter present in wastewater (Abdalla & Hammam, 2014). High levels of COD in BDWW are caused by the presence of glycerol, soap, methanol, residual oil and methyl esters (Ngamlerdpokin *et al*., 2011). BDWW especially in oil industries has high levels of COD which results in environmental concerns (Yu *et al*., 2021). If untreated BDWW with high levels of COD is discharged to public/municipal drains, it will have a negative impact to marine life and subsequently the environment (Lee *et al*., 2021). According to Hossain *et al*. (2018) textile wastewater has high COD and biological oxygen demand (BOD) concentrations from the sizing and desizing stages. Table 2.2 shows the quantities of COD present in different types of industrial wastewater as reported in literature.

Table 2.2: Chemical oxygen demand quantities for different types of wastewater

Feedstock	Chemical Oxygen demand (COD) mg/L	References
Palm oil	5900	Daud *et al*., 2015
Vegetable oil	312-588	Ngamlerdpokin *et al*., 2011
Waste cooking oil	428 000	Siles *et al*., 2010
Vegetable oil	19-37	Daud *et al*., 2014
Industrial waste	34.980	Cheirsilp *et at*., 2011
Textile	150-10000	Asghar *et al.*, 2015
Textile	250-8000	Fazal *et al*., 2018
Textile	315-2607	Cinperi *et al*., 2019
Textile	728-1033	De Jager *et al*., 2014
Textile	1835-3828	Syam Babu *et al*., 2020
Wood	500-115000	Toczyłowska-Mamińska, 2017
Wood	5540	Bakraoui *et al.*, 2019

b) Oil and grease (O&G)

Oil and grease (O&G) concentration in BDWW is dependent on the type of oils used as feedstock to produce biodiesel fuel (Table 2.3). O&G contains free fatty acids (FFA) such as triacylglycerols (TAG), phospholipids, sterols and esters depending on the source generating the oils. FFA content depends on the type of O&G, such that yellow grease contains less than 15% FFA while brown grease contains more than 15% FFA (Abomohra *et al*., 2020). Owning to this, the disposal of BDWW into public sewers causes clogging of pipes, making it hard for water to flow through. The oil in the wastewater has toxic substances, these include phenols, petroleum hydrocarbons and polyaromatic hydrocarbons which may cause plants not to grow (Alade *et al*., 2011). Oily water is harmful to marine life, which means humans are also at risk as they form part of the food chain in the ecosystem (Alade *et al*., 2011). Table 2.3 shows the quantities of O&G present in different industrial wastewaters.

Table 2.3: Oil and grease in industrial wastewater

Feedstock	Oil and grease (O&G) mg/L	References
Palm oil	2680	Daud *et al*., 2015
Crude palm oil	6020	Chavalparit *et al*., 2009
Vegetable oil (plant in Thailand)	18-22	Jaruwat *et al*., 2010
Palm oil	4000-6000	Alade *et al*., 2011
Canola oil	25252	Tanattı *et al*., 2018
Textile	17	Rakkan *et al*., 2021

c) Suspended solids (SS)

Suspended solids (SS) are the mass and concentration of organic and inorganic matter present in water, lakes, reservoirs or rivers causing it not to move, be stationary or be in an unsteady motion. SS in wastewater causes ecological degradation of marine life and the treatment of water with high levels of SS is expensive. This characteristic of wastewater contains high organic content, which consumes all the oxygen present in water leading to the destruction of aquatic life (Bilotta & Brazier, 2008). Table 2.4 illustrates the quantities of SS in industrial wastewater as reported in literature.

Table 2.4: Suspended solids in industrial wastewater

Feedstock	Suspended solids (SS) mg/L	References
Palm oil	348	Daud *et al*., 2015
Vegetable oil	233-405	Daud *et al*., 2014
Canola oil	12800	Tanattı *et al*., 2018
Vegetable oil	1,500-28,790	Rattanapan *et al*., 2011
Textile	100-700	Fazal *et al*., 2018
Textile	325	Rakkan *et al*., 2021

d) pH

The pH level is used to determine the success of biological treatment systems such as an anaerobic baffled reactor (ABR) used for anaerobic digestion (AD). Optimum pH levels for biological processes range from 6.8 – 7.7 (Al Smadi *et al*., 2019).

2.4 Different treatment techniques of industrial wastewater

Types of wastewater treatment techniques include physical, chemical and biological treatment processes. Wastewater can be treated using one or a combination of two or more treatment techniques. Physical treatment includes sedimentation and screening and is normally used as a primary treatment method to remove solid particles and immiscible liquids prior to the implementation of biological treatment. Chemical treatment methods include oxidation reactions to treat industrial wastewater. Biological treatment methods use microorganisms (i.e. bacteria) to break down organic compounds in wastewater. During this process, the bacteria multiplies as it feeds on nutrients present in the wastewater and the waste is then converted to CO_2 and CH_4 (Aljuboury *et al*., 2017). Table 2.5 illustrates the different types of wastewater treatment methods.

2.4.1 Biological treatment of industrial wastewater

Biological treatment methods can be categorised by suspended growth such as the activated sludge process, adding powdered activated carbon process for treated water of high quality, sequencing batch reactor (SBR), continuous stirred tank bioreactor (CSTB), membrane bioreactor (MBR) and fluidised bed bioreactors (FBB) (Jafarinejad *et al*., 2017). Biological treatment can be classified as anaerobic and aerobic biological treatment methods, these methods are affected and influenced by nutrients and oxygen supply, hydraulic retention time (HRT), pH and the physicochemical properties of the wastewater. The nutrients are essential to stabilise bacterial growth, while oxygen supply is dependent on the type of biological treatment method used (Shi *et al*., 2016).

The pH and HRT are two of the most important controlling parameters in biological treatment. Unfavourable pH causes biomass washout in ABR systems. The acidic or alkaline pH has an effect on the microbial population, adaptability, sustainability and growth in biological systems (Shi *et al*., 2016). High HRT has a slow reaction outcome, which has a positive effect on the biomass capacity and also results in fast bacterial growth (Daud *et al*., 2015). Chen *et al*. (2020) reported on the treatment of glutamate-rich wastewater investigating the effect of HRT using an up-flow anaerobic sludge blanket (UASB) reactor and observed that the COD removal efficiency increased to 95% as the HRT increased from 4.5 to 6 hours. Shi *et al*. (2016) investigated the effect of pH and HRT in anaerobic baffled reactor (ABR) start up and discovered the HRT has an influence on the pH, short HRT causes sludge washout which results in loss of methanogens bacteria and fluctuating pH (Alepu, Odey *et al*., 2016).

This study was focused on the anaerobic biological treatment process. Compared to aerobic biological treatment, anaerobic treatment has high organic removal efficiencies at a lower cost. Liang *et al*. (2021) reported that anaerobic treatment processes are capable of removing about 70% of pollutants in pulp and paper wastewater with maximum COD of 7000 mg/l. Different types of reactors have been used for the treatment of industrial wastewater including the UASB reactor and 82% COD removal efficiency was obtained from the treatment of petroleum wastewater using an up-flow UASB reactor (Aljuboury *et al*., 2017).

Table 2.5: Different wastewater treatment methods

Treatment method	Brief description	References
Coagulation	This treatment process is when a coagulant is added for the separation of particles which then flocculate into large particles in a solution. The large particles (i.e. flocs) reduce COD, SS, and colour. Coagulation is also capable of removing metals present in the wastewater and removing toxic waste. This treatment method is very expensive and the` wastewater produced requires further treatment because of its low quality.	Daud *et al*., 2014; Ngamlerdpokin *et al.*, 2011
Electrocoagulation	Electrocoagulation is a treatment method that utilises electrical current in the process of treating impurities present in wastewater. This method uses fewer chemical coagulants. Wastewater with phenols is one of the wastes treated using electrocoagulation. It produces less sludge; the waste requires less treatment time and operates in a simple equipment set-up.	Daud *et al*., 2014; Butler *et al*., 2011
Biological treatment	Biological treatment uses microorganisms to breakdown organic matter These methods are mostly used for the treatment of BDWW, although not much research has been done on it.	Daud *et al*., 2014; Chowdhury *et al*., 2010
Adsorption	This treatment method is mostly used in separating chemical compounds from BDWW. It does not produce sludge and the pH of the wastewater does not have to be adjusted.	Daud *et al*., 2014

2.4.2 Biological wastewater treatment advantages

The following advantages guarantees water purification through biological wastewater treatment processes (Khataee & Kasiri, 2011):

a) Operation at ambient temperature.
b) High energy recovery.
c) Reduction in aquatic toxicity.
d) Effective operational and capital costs.
e) Oxidation of organic compounds in aerobic processes.
f) Purification of wastewater by removing contaminants such as ammonia via denitrification.

Table 2.6 shows organic waste removal efficiencies using biological treatment processes adapted from (Daud *et al*., 2015).

Table 2.6: Removal efficiency of biodiesel wastewater contaminants (Daud *et al*., 2015)

Treatment method	**Microorganism**	**Wastewater**	**Wastewater characteristics**	**Parameters**	
				COD	**Other**
Algae plate	*Rhodotorula mucilagiinosa*	Raw BDWW; artificial wastewater	Raw biodiesel fuel (BDF) wastewater; pH: 11; Oil: 15.1 g/L; Solids: 2.67 g/L	-	Oil: 98.0%
Rotating biological contactor	*Bacillus cepacia*	Diesel – rich wastewater	pH: 7.5; total COD (TCOD): 4512 mg/L; total petroleum hydrocarbons (TPH): 4961 mg/L	97.0%	TPH: 98.4%
Batch reactor	Textile wastewater treatment inoculums	Palm oil biodiesel wastewater	pH: 11.1; COD: 3681mg/L; total organic carbon (TOC): 1700 mg/L; O&G: 387 mg/L	90.0%	TOC: 21%

2.5 The City of Cape Town (CoCT) wastewater and industrial effluent by-law (2013)

It is stated in the Constitution of the Republic of South Africa Section 24 situated in 1996 that: “everyone has the right to an environment that is not harmful to their health and well-being and the right to have the environment protected through legislative and other measures that prevent pollution and ecological degradation”. The environmental legislation on industrial wastewater discharge is related to the National Environment Management Act (NEMA) 62 of 2008 which was introduced and effective from 2009 in support of this right. The NEMA Act

107 of 1998 was implemented to ensure that every organisation obtains environmental authorisation before commencing any activities listed in the NEMA terms. Tables 2.7 and 2.8 outlines the standard limit of wastewater discharge in Cape Town and several other countries including organisations such as the World Health Organisation (WHO) and United States Environmental Protection Agency (USEPA).

Radelyuk *et al*. (2019) reported that WHO is regarded as the main international organisation for public health and water quality. WHO provides scientific national regulations to governments. According the WHO guidelines, treated wastewater must be within the standard limits before discharging to public drainage (Javadinejad *et al*., 2020; Vojtěchovská Šrámková *et al*., 2018).

Table 2.7: Industrial wastewater discharge standard limits (City of Cape Town, 2013)

Parameters	**Maximum standard discharge limit**
Suspended solids (SS)	$1000\ mg/L$
Total dissolved solids (TDS)	$4000\ mg/L$
Chemical oxygen demand (COD)	$5000\ mg/L$
Fats, Oil, and grease (FOG)	$400\ mg/L$
pH	12.0
Electricity Conductivity (EC)	$500\ mS/m$
Sodium (Na)	$1000\ mg/s$
Total sulphides (S)	$50\ mg/L$
Chloride (Cl)	$1500\ mg/L$
Total sulphates (SO_4)	$1500\ mg/L$
Total phosphates (P)	$25\ mg/L$
Total cyanides (CN)	$20\ mg/L$
Total lead (Pb)	$5\ mg/L$
Total zinc (Zn)	$30\ mg/L$
Total iron (Fe)	$50\ mg/L$
Total copper (Cu)	$20\ mg/L$
Total chromium (Cr)	$10\ mg/L$
Total mercury (Hg)	$5\ mg/L$

Table 2.8: Industrial wastewater discharge limits worldwide

Organisation / Country	FOG (mg/l)	COD (mg/l)	pH	BOD (mg/l)	TDS (mg/l)	SS (mg/l)	References
European Countries*	50	200	-	40	-	50	Hessel *et al*., 2007
USEPA	-	25-45	6-9	125	-	30-45	Mavinic *et al*., 2018
China	-	100-1000	6.9	20-600	-	70-800	Hao *et al*., 2019
United Kingdom	<100	-	6-10	-	-	<400	Helmer & Hespanhol, 1997
Canada	-	25	6-9	25	-	25	Mavinic *et al*., 2018
India	-	250	5.5-9	30	150	2100	Islam & Mostafa, 2019

*European Countries: France, Germany and Poland

2.6 Anaerobic baffled reactor (ABR) and expanded granular sludge bed (EGSB) for wastewater treatment

Anaerobic baffled reactors (ABR) produce less sludge and can separate different phases of anaerobic catabolism (Kim *et al*., 2007). An ABR first was developed by McCarty in 1981 with advantages based on the way it was constructed, biomass and chambers that enhance the digestion process and organic matter removal (Shi *et al*., 2016). The most important advantage of ABRs is that it can keep the processes of acidogenesis and methanogenesis separate making the reactor a two-phase system and therefore cost effective (Barber & Stuckey, 1999). The expanded granular sludge bed (EGSB) reactor was developed from an UASB reactor (Miao *et al*., 2018). An ESGB was designed to allow sufficient mixing of the wastewater and anaerobic granular sludge due to its recirculation features that promotes sustainability and better reactor performance (Cruz-Salomón *et al*., 2020; Williams *et al*., 2019). Li *et al*. (2019) mentioned that EGSBs are considered to be among the best anaerobic reactors due to highly efficient organic waste elimination and according to Yang *et al*. (2018) anaerobic sludge granulation has been receiving much attention for wastewater treatment compared to anaerobic sludge processes due to the high removal efficiency of contaminants and biogas production.

Both the ABR and EGSB reactors have long start up periods ranging from 30 days up to 60 days. However, for the EGSB reactor, the long start up period can be reduced by adding metal ions and granular activated carbon (GAC) (Yang *et al*., 2018). According to Phukingngam *et al*. (2011), the start up time for ABRs takes approximately two months for the microorganisms to stabilise in an ABR system. This is because of the slow growth of the methanogen microbes in the anaerobic reactor. During the start up period, ABRs have to be operated at low organic loading rates which guarantees high biogas production (Ramandeep, 2016).

2.6.1 The concept of an ABR and EGSB wastewater treatment design

ABR uses baffles for the wastewater to flow vertically from the influent to effluent (Bachmann *et al*., 1985). Table 2.9 illustrates ABR organic waste removal efficiencies for the treatment of various types of wastewater, while Table 2.10 lists the advantages and disadvantages of the different anaerobic methods used to treat wastewater as reported in literature. Most biodiesel producing industries that use the alkali-catalysis transesterification process produce large volumes of wastewater containing oils and alcohols which would be suitable to be treated using an ABR (Phukingngam *et al*., 2011). Figure 2.2 illustrates an example of an ABR system.

Table 2.9: Treatment efficiencies of various anaerobic reactors

Type of wastewater	Type of reactor	Organic loading rate (kg/m^3/day)	COD $_{inlet}$ (g/L)	COD removal (%)	HRT (hours)	References
Slaughterhouse	ABR	0.2 - 0.825	-	29 - 92	42	Al Smadi *et al.*, 2019b
Brewery	UASB	12	-	89.1	4	Dutta *et al*., 2018
Dairy	Anaerobic filter (AF)	17	30	80	38.4	Karadag *et al.*, 2015
Dairy	Anaerobic fluidised bed reactor (AFBR)	15.6	0.2-0.5	94.4	1.992-7	Karadag *et al.*, 2015
Synthetic	ESGB	1.80	426.6	62-82.3	6	Yang *et al*., 2018
Slaughterhouse	EGSB	2	-	93	115.2	Williams *et al*., 2019

Table 2.10: Anaerobic treatment technologies (Shende & Pophali, 2021)

Anaerobic treatment technology	Advantages of anaerobic treatment technology	Disadvantages of anaerobic treatment technology	Precautions
ABR	Two-phase system separating acidogenesis and methanogenesis.	Long start up time resulting in the accumulation of VFA in the reactor	OLR must be low to promote microbial growth, the recommended OLR is 1.2 COD/m^3d.
UASB	High settleability forming the sludge blanket at the bottom while retaining the sludge.	Long start up time.	Always maintain a high up-flow velocity of 0.6 to 0.9 m/hr in order to form granules and to wash out non-flocculent sludge.
AF	Easily and locally available media.	Clogging of the reactor resulting in faulty connection of power lines/wires.	Media balance between specific surface area and porosity.
Anaerobic hybrid reactor (AHR)	Cost effective media.	High organic loading rate (OLR).	Carefully place media on top of the reactor to avoid falling at the bottom.
Anaerobic membrane bioreactor (AnMBR)	Complete retention of biomass.	Expensive.	Reduce membrane fouling by gas sparging.

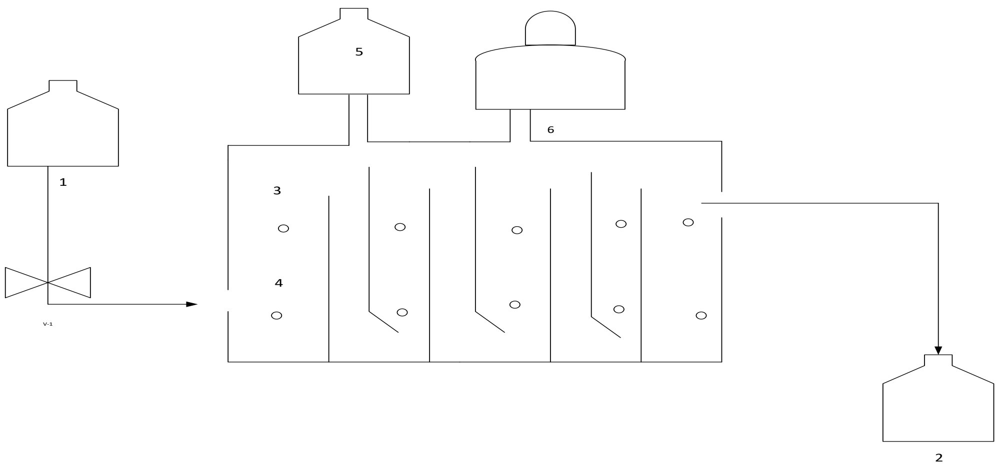

Figure 2.2: Schematic diagram of an experimental ABR system:1 – wastewater feed tank, 2 – effluent collection tank, 3 – liquid sampling ports, 4 – sludge sampling ports, 5 – gas/water displacement system, 6 – gas sampling port, adapted from Phukingngam *et al*. (2011)

2.6.2 Advantages of anaerobic baffled reactor (ABR) and expanded granular sludge bioreactor (EGSB)

According to Yang *et al*. (2018), Mortezaei *et al*. (2018) and Barber & Stuckey (1999) the following advantages apply to ABR and EGSB reactor systems:

- Low sludge yield.
- High solid retention time.
- Low capital and operating costs.
- Low hydraulic retention time (HRT).
- Stable to organic shock.
- ABRs can separate acidogenesis and methanogenesis in the reactor thereby behaving as a two-phase system.
- Low energy requirements.
- Simple and easy to design.
- Easy to operate.
- High removal efficiency of contaminants.
- High removal efficiency of soluble pollutants.

2.6.3 Disadvantages of anaerobic baffled reactors (ABR) and expanded granular sludge bed (EGSB) reactors

ABRs being simple to design is an advantage, but also a disadvantage at the same time. For an even feed distribution of the liquid and gas velocities, a shallow reactor design must be used (Barber & Stuckey, 1999). Without a design expert, this could result in a delay in the start up of the reactor and bacteria washout (Liu *et al*., 2010). A disadvantage of the EGSB reactor includes failure to meet standard effluent discharge limits and the ineffective removal of suspended solids (Mortezaei *et al*., 2018).

2.6.4 Anaerobic digestion (AD)

Anaerobic digestion (AD) is the conversion of organic matter to biogas in the absence of oxygen (Zhang *et al*., 2016). AD is alternatively called bio-gasification and serves as an important technology in most industries for industrial and municipal wastewater treatment and energy production (McAteer *et al*., 2020). Wastewater treatment processes tend to produce large amounts of sludge which is an expensive problem to solve. However the use of an anaerobic digester tends to reduce the volume of sludge production (Madsen *et al*., 2011). The main use of an AD process is to produce water and gas that can be reused in the absence of negative health implications to human beings and the environment (Kleerebezem *et al*., 2015).

In the AD reaction, the biogas produced contains 60-70% methane gas (Li *et al*., 2011). Organic and inorganic matter requires the following processes for the AD reaction to be complete, namely hydrolysis, acidogenesis, acetogenesis and methanogenesis. Figure 2.3 shows the processes that occur during AD of organic material.

The first reaction to take place during the AD process (Figure 2.3) is the hydrolysis reaction where complex organic polymers are broken down to simple soluble molecules by extracellular enzymes and proteins, while carbohydrate polymers are hydrolysed to amino acids, long-chain fatty acids and sugar. This reaction determines the conversion effectiveness of the biomass (Li *et al*., 2011). The compounds which were reduced are then fermented by bacteria to short chain volatile fatty acids, carbohydrates, hydrogen and acetic acid, this phase is called the acidogenesis. The bacteria present in the acidogenesis phase is responsible for the degradation of the simple organic compounds from the hydrolysis phase to volatile acids (i.e. propionic acid), carbon dioxide and alcohols (Li *et al*., 2011).

The volatile acids are then broken down to hydrogen gas by acetogenic microorganisms present in the acetogenesis phase. The final reaction which is methanogenesis is where methane is produced (Gude, 2016). This is where the methanogenetic bacteria consumes acetate, carbon dioxide and hydrogen to produce methane containing biogas as the final product and main focus of the AD process (Kleerebezem *et al*., 2015; Li *et al*., 2011)

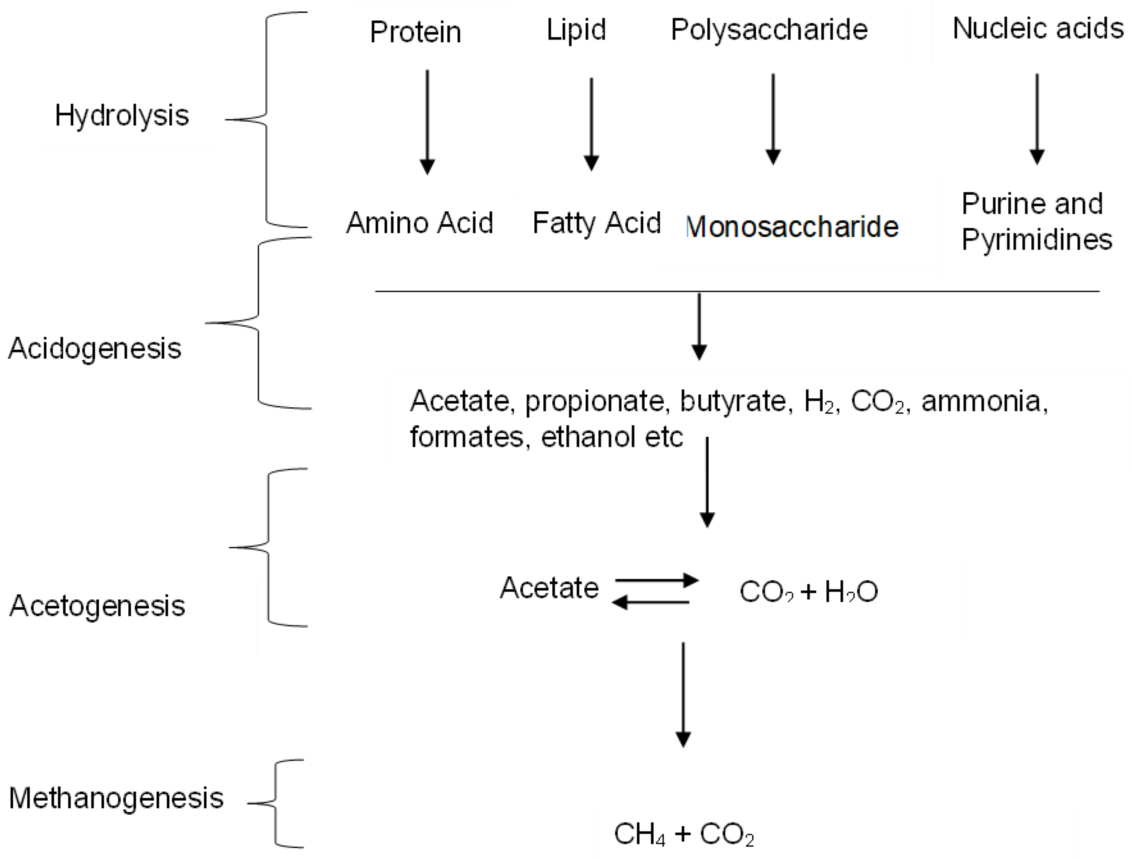

Figure 2.3: Organic material through anaerobic digestion, adapted from Aziz *et al*. (2019)

2.6.5 Activated sludge (AS)

The activated sludge (AS) process for wastewater treatment, with the aim to remove organic compounds, was developed 100 years ago (Korzeniewska & Harnisz, 2018). According to Gao *et al*. (2016), the AS process is best used for the treatment of domestic and industrial wastewater because it contains various active microorganisms. AS has aerobic and anaerobic microorganisms including bacteria, *Archaea*, fungi and protists used for breaking down organic pollutants present in domestic and industrial wastewater (Shchegolkova *et al*., 2016).

2.7 Anaerobic baffled reactor (ABR) and expanded granular sludge bed (EGSB) reactor operational parameters

The following are conditions or parameters required by anaerobic bioreactors to operate in a desired manner, and includes the pH, temperature, hydraulic retention time (HRT) and organic loading rate (OLR).

2.7.1 The effect of pH on ABR and EGSB reactor systems

pH is one of the most important factors in the AD process, by providing a suitable environment for the microorganisms present in the anaerobic digester. Microorganisms prefer a neutral pH of 7 to function well. In the acidogenesis phase the pH value can range from 4.0 to 8.5 as the microorganisms are not too sensitive to the pH during this phase. However, for biogas production the pH value is required to range from 6.8 to 7.2 during the methanogenesis phase, (Hagos *et al*., 2017).

In the early 2000s, Du (2007) discovered that the bacteria in anaerobic digestors can be used to generate both electricity and break down organic matter. ABRs consist of compartments with the pH to decrease from the first to the last compartment depending on the number of compartments. To prevent system failure the pH can be adjusted using either sodium hydroxide (i.e. NaOH) or sodium hydrogen carbonate (i.e. $NaHCO_3$) (Ramandeep, 2016).

Liu *et al*. (2019b) reported the effect of pH on hydrolytic acidification performance and bacterial community in an EGSB reactor and observed a stable average COD removal rate of 40% at a pH of 8, which decreased to 30.3% at a pH of 6 and 30.8% at a pH of 4. An Illumina MiSeq sequencing was used for microbial community and the best microbial community was observed at pH 6.

2.7.2 Temperature

According to Liao *et al*. (2018) temperature is a major parameter in bioreactors. The ABR treatment efficiency depends on temperature variation. However, previous studies (Khalekuzzaman *et al*., 2018) have observed that there is little to no effect on the ABR treatment efficiency when the influent temperature is at 25℃ to 35℃. In 2019, Al Smadi *et al*. conducted a study on the treatment of slaughterhouse wastewater using an ABR operating at temperatures ranging from 15℃ to 23℃ and later increased the temperature to 40℃, which resulted in an increase in COD and total suspended solid (TSS) removal efficiencies from 70% and 33% to 90% and 44%, respectively. Ramandeep (2016) also stated that, bacteria in ABRs require temperatures ranging from 25℃ to 35℃ for maximum growth, while a temperature of less than 25℃ prevents maximum organic removal efficiency (Yao et al., 2018, Xu *et al*., 2018).

2.7.3 The effect of organic loading rate (OLR) on COD removal efficiency

COD is a parameter used to measure organic waste in anaerobic systems (Cruz-Salomón *et al*., 2020). OLR controls the performance of ABRs. High OLRs result in better ABR performance with respect to COD removal and biogas production. A study on the treatment of municipal wastewater using a modified ABR operating at three OLRs of 0.258, 0.787, 2.471 kg COD/m^3/d showed an increase in COD removal from 95% to 99% as the OLR increased (Chelliapan *et al*., 2017). A slight decrease in COD removal was observed at an OLR of 0.787 kg COD/m^3/d, this was due to a sudden increase in OLR. The methanogenic bacteria responsible for the breakdown of organic matter experienced organic shock. This can be prevented by feeding the ABR with methane precursors, acetate, an acetate formate mixture or by adjusting the pH with either NaOH or phosphoric acid (i.e. H_3PO_4) in the first compartment of the ABR before increasing the OLR (Barber & Stuckey, 1999). Zhu *et al*. (2015) concluded that in order to achieve greater organic removal efficiency when treating low concentrated wastewater, the HRT should be low with a high OLR. However, when treating high concentrated wastewater, a low OLR is preferred to guarantee complete biodegradation of the organic matter.

In ABRs, the OLR can be set at different levels for the removal of COD, O&G, glycerol and methanol. Phukingngam *et al*. (2011) studied the performance of an ABR treating BDWW and discovered that 82% of O&G was removed from the BDWW at an OLR of 0.5 to 1.5 kg COD/m^3/d, but decreased to 43% when the OLR was increased (Phukingngam *et al*., 2011). According to Cruz-Salomón *et al*. (2020) EGSBs operate at high OLRs of up to 40 kg COD/m^3/d. Maleki *et al*. (2018) used a submerged membrane bioreactor to investigate the effect of OLR and observed an increase in OLR ranging from 1.36 to 3.18 kg COD/m^3/d resulted in a decrease in COD removal efficiency from 94.1 to 90.2%.

Li *et al*. (2019) used an EGSB to treat cephalosporin wastewater at an OLR ranging from 5.70 to 9.96 kg COD/m^3/d. A high COD removal efficiency of 72% was achieved at an OLR of 9.96 kg COD/m^3/d.

The organic loading rate (OLR) is the rate at which organic matter is introduced into a reactor and can be determined using Equation 1.

$$OLR = \frac{OC_{feed}}{HRT} \qquad 1)$$

Where, OLR is the organic loading rate (kg COD/m^3/d); OC_{feed} is the organic matter concentration of the feed substrate (kg COD/m^3) and HRT is the hydraulic retention time in days (Sukkasem *et al*., 2011).

2.7.4 The effect of hydraulic retention time (HRT) on the removal of chemical oxygen demand (COD) in ABRs and EGSBs

ABRs and EGSB reactors are controlled by HRT which has a great influence on hydrogen transfer and the AD process (Cruz-Salomón *et al*., 2018). Thanwised *et al*. (2012) discovered that the COD removal increased when the HRT was decreased from 24 to 18 hours and 12 to 6 hours. It was observed that COD was removed through the formation of gases (i.e. CO_2 and H_2) while the rest of the COD was converted to liquid intermediates (e.g. ethanol) where the acidogenesis phase was quite dominant (Thanwised *et al*., 2012). Thanwised *et al*. (2012) concluded that COD removal efficiency during acidogenesis was less than during methanogenesis.

Li *et al*. (2019) treated wastewater using an EGSB and observed the effect of HRT on COD removal efficiency. When the EGSB operated at an OLR of 3.6 kg COD/m^3/d with an HRT of 24 hours the resulting COD removal efficiency was greater than 60% and suddenly decreased to 40% when OLR was increased to 4.32 kg COD/m^3/d. An increase in the HRT to 25 hours resulted in the COD removal efficiency increasing back up to 60%. According to Cruz-Salomón *et al*. (2020) to obtain better COD removal efficiency in an EGSB, low strength wastewater must be treated at HRTs ranging from 0 to 2 days and high strength wastewater must be treated at HRT of up to 10 days.

HRT is best defined as the average time that particles remain in the reactor and can be determined using Equation 2.

$$HRT = \frac{V_w}{Q_{feed}} \qquad 2)$$

Where, HRT is the hydraulic retention time in days; V_w is the reactor volume in litres and Q_{feed} is the feed flowrate in litres per day (Sukkasem *et al*., 2011).

2.8 Artificial neural networks (ANN)

An artificial neural network (ANN) is a type of computer system that works the same way as a human brain, by processing and storing information in the system (Wajeeh *et al*., 2018; Göçken *et al*., 2016; Deo & Mehmet, 2015; Platon *et al*., 2015; Lek & Gue, 1999);). ANNs are of interest and applied in a wide range of problems in finance, medicine, engineering, geology, physics and biology (Ramchoun *et al*., 2017; Deo & Mehmet, 2015). These networks can predict patterns with corresponding target values and classify problems. ANNs consist of nonlinear data and can be used as a modelling tool when data is unknown. It is important that the networks are first trained to predict the commensurate outcome of an independent input data. ANN processes are suitable for complex data that are not precise (Jha, 2004).

Classification of ANNs include; pattern, sequence recognition, identification of new or unknown data and decision making (Prieto *et al*., 2016). ANNs consist of input layers, one or more hidden layers and output layers which are interconnected as neurons (Gonzalez-Fernandez *et al*., 2018). Learning techniques used in neural networks are classified as deep and shallow learning. Shallow leaning is used on two or three layers whilst deep learning is used on complex layers. Both these learning techniques are from input data. A trial-and-error procedure as explained by Patki *et al*. (2021) is used to determine the number of neurons which will give better ANN performance according to how complex the problem is. Neurons and hidden layers have a great impact on ANN training, less or more neurons may be considered best or bad. A higher number of neurons results in great synthesising, but poor generalisation of ANNs; while less neurons may not fit the data which will result in the network not learning (Elshamy *et al*., 2021). Depending on how complex the problem is, one hidden layer is sufficient to evaluate and solve problems (Saleh, 2021). Alwosheel *et al*. (2018) stated that, ANNs require large numbers of data sets for network training. Theoretically ANNs consisting of a lot of parameters require large amounts of training data (Alwosheel *et al*., 2018).

Compared to other optimisation software model tools, such as response surface methodology (RSM), orthogonal experimental design (OED), support vector machine (SVM), and uniform design (UD), artificial neural networks (ANN) and SVM have proven to be the best modelling tools as they showed high model accuracy. Zhang *et al*. (2020) used ANNs to optimise and model microbial lipid fermentation from ethanol wastewater. It was observed that the mean square error (MSE) and correlation coefficients (R) for the training and test data were 0.0043 and 0.0105, and 0.9899 and 0.9758, respectively. Vinoth Arul Raj *et al*. (2021) used ANNs to optimise biodiesel production parameters to improve the yield. The ANN model tool was found to be a good fit as the R value and root mean square error (RMSE) were 0.957 and 0.44, respectively. Figure 2.4 shows the steps required when developing an ANN model.

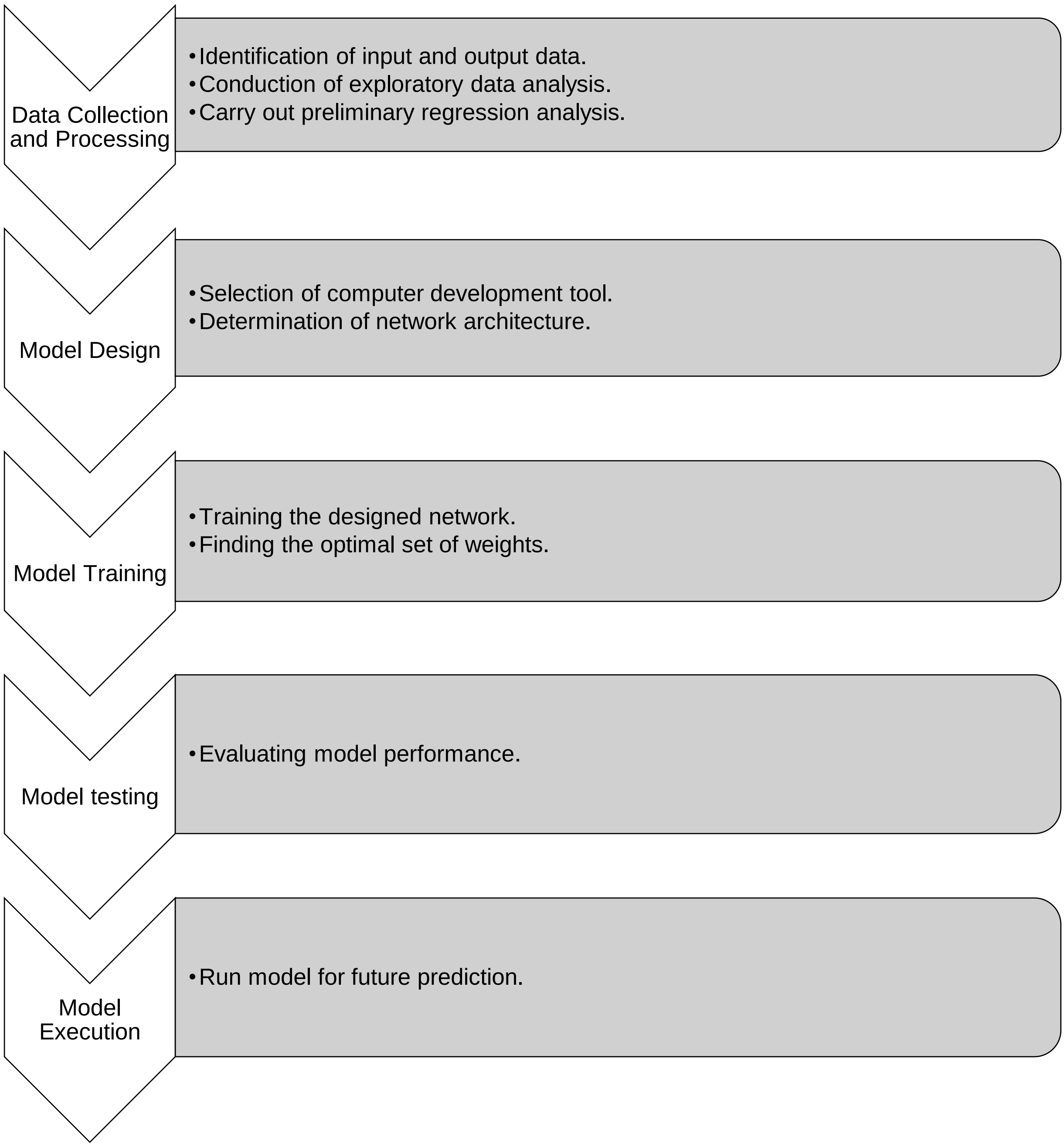

Figure 2.4: The ANN model development process, adapted from Ã *et al*. (2004)

2.9 Different types of artificial neural networks

ANNs can be classified as feedforward neural networks (FFNN) and feed backward neural networks (FBNN) or backpropagation. FFNNs is an algorithm with layers which are the same as human neuron processing, these layers are interconnected in relation to their units. The connection of the layers with their units is not equal due to the individuality of each connection such as the difference in weight and strength. The weight determines the potential knowledge of the neural network. FFNN sends information from input nodes to hidden nodes then to output nodes, hence it is called a feedforward neural network, information moves in one direction (Abiodun *et al*., 2018). Advantages of using FFNNs include that they are less complex, fast and highly responsive. Other types of neural networks are as follows, as reported by Sewsynker-Sukai *et al*. (2017):

a) **Convolutional neural networks (CNN):** These networks can be applied in image processing, speech recognition and machine translation. CNNs are used for deep learning and highly valuable in the presence of less parameters.

b) **Radial basis function neural networks (RBFNN):** These can be classified as multilayered feedforward error-backpropagation networks consisting of three layers overall. Basher & Hajmeer (2000) classified RBFNNs as "special" because they are cable of being trained by various numbers of learning algorithms.

c) **Recurrent neural networks (RNN):** These networks are used in text processing, sentiment analysis and text to speech processing. For these networks to be more precise, they can be used together with convolution layers. RNNs can send information in both backward and forward directions.

d) **Modular neural networks (MNN):** These networks can be applied in stock market prediction analysis and can be useful for high level input data. MNN's are efficient and can be trained independently.

e) **Hopfield neural networks:** These are nonlinear interconnected recurrent networks which are more convenient when optimising problems (Basheer & Hajmeer, 2000).

f) **Kohonen neural networks:** The type of networks which are unsupervised and used to recognise patterns from maps as the input and target data points are close together.

2.10 Artificial neural network topology

The selection of the input and output quantity parameters is the most crucial part of ANN topology (Elbisy *et al*., 2014). According to Vaferi *et al*. (2014) the most used topology in neural network development is the multilayer perceptron architecture (MLP). To obtain a superior ANN architecture the ANN model has to undergo training, validation and testing (Nagarajan *et al*., 2019). MLP neural networks are mostly applied in solving engineering problems (Stoffel *et al*., 2020) and are known to minimise errors while adjusting the neural network parameters (Badalians Gholikandi *et al*., 2014). Advantages of using MLP neural networks include the ability to learn, stability of the network performance after adding more data "noise", nonlinearity, generalisation, the correspondence of data (Faris *et al*., 2016) and the production of accurate results (Shoaib *et al*., 2018). MLPs have effective generalisation abilities with the learning process highly dependent on the constraints of the architecture and learning algorithm

(Shi *et al*., 2021; Bansal *et al*., 2019). ANN topology has an impact on network performance (Kaviani & Sohn, 2021; Kaviani & Sohn, 2020).

2.11 Selection of neural network type

This study will focus on the development of three diverse types of ANNs to evaluate which network model is best suited for the prediction of COD output data from biological treatment systems.

2.11.1 Feedforward backpropagation (FFB)

Feedforward backpropagation (FFB) neural networks often referred to as an MLP employing a supervised learning process (Sewsynker-Sukai *et al*., 2017) are static and the most used network type (Basheer & Hajmeer, 2000). These networks are characterised by three layers: 1.) an input layer with nodes constituting the input process variables; 2.) an output layer consisting of the predicted variables depending on the intent of the ANN model; and 3.) one or more hidden layers (Basheer & Hajmeer, 2000). The hidden layer is used to determine the correlation between the input and output data (Elbisy *et al*., 2014). FFBs are designed to send errors back from the output data to the hidden layer and then the input layer (Sewsynker-Sukai *et al*., 2017). FFB network topology can be expressed by Equation 3:

$$Y_j^{k+1} = f\left(\sum_{i=1}^{N} X_i^k w_{ij}^k + b_i^k\right) \qquad 3)$$

Where, Y_j^{k+1} represents the output vector; $X_i^k w_{ij}^k$ is the input and weight vector and b_i^k represents the bias vector of ANN models (Moreno-Pérez *et al*., 2018).

Türkmenler & Pala (2017) conducted a study on the prediction of biological wastewater treatment using a FFB ANN and concluded that ANN models can successfully predict BOD effluent concentration for biological systems with training and testing correlation coefficient values of 0.9413 and 0.9318, respectively. The model was also evaluated with a mean absolute percentage error (MAPE) for the training and testing values of 23.801 and 24.327, respectively. Hassen & Asmare (2018) utilised an FFB ANN to predict wastewater treatment plant performance and concluded the model was able to predict COD effluent concentration with an R value of 0.969. Proving that an FFB ANN model can accurately predict effluent COD concentration when presented with new data sets. Gopi Kiran *et al*. (2021) used an FFB ANN model to accurately predict the effluent COD concentration for a rotating biological contactor treating heavily contaminated wastewater with R^2 values ranging from 0.91 to 0.98 and 0.92 to 0.98 for the training and testing data, respectively. A study by Antwi *et al*. (2018) used an FFB model to predict the performance of a UASB treating industrial starch processing wastewater and observed that the network model was able to predict COD removal efficiency with training, testing and validation R values 0.86, 0.98 and 0.83, respectively, indicating the FFB ANN model performed well.

2.11.2 Nonlinear autoregressive model with exogenous input (NARX)

Nonlinear autoregressive model with exogenous input (NARX) neural networks is a type of dynamic recurrent ANN mostly used to solve nonlinear and complex problems such as wastewater treatment for prediction purposes. These networks are known to have strong memory (Yang *et al*., 2021). Unlike FFB networks, NARX networks are also known for being able to generalise better and for fast convergence. The NARX model can be expressed by Equation 4:

$$y(t) = f(u(t - n_u), \ldots . u(t-1), u(t), y(t - n_y), \ldots y(t-1) \qquad 4)$$

Where, f represents the nonlinear system function from ANNs; $y(t)$ and $u(t)$ represents the input and output data at time t; and n_u and n_y are the input and output order (Çoruh *et al*., 2014).

NARX networks are designed to regress output data sets on the actual target data during the training of the network and then feed back to the network to guarantee better learning and training of the network. Thus working the same way as the feedforward neural network but with time delay (TD) units (Çoruh *et al*., 2014). NARX neural networks are also best at minimising errors and weights to generalise a better network model. NARX ANNs have been used in a variety of problems and have shown great performance in monitoring, controlling, optimisation and simulation of wastewater treatment process plants (Sanayei *et al*., 2014). Yang *et al*. (2021) used NARX network modelling to predict wastewater effluent quality and achieved R values ranging from 0.84 to 0.87 for COD effluent prediction for several TD values with the best results obtained with a TD value of 2. Studies conducted by Yang *et al*. (2019) and Wunsch *et al*. (2018) proved that a long TD resulted in poor prediction performance and overfitting of the network. According to Lee & Sheridan (2018) a TD from 2 to 4 presents the best modelling performance for NARX networks.

2.11.3 Cascade forward backpropagation (CFBP)

Cascade feedforward backpropagation (CFBP) neural networks are similar to the FFB network, but differ in the weights function (Moreno-Pérez *et al*., 2018). Weights are connected from the input layer to all the layers. CFBP ANNs are best at learning since the network has a link from the input layer to all the layers of the networks. The CFBP neural network is a general network with three layers, meaning the first layer (i.e. input layer) has a link with the second layer (i.e. hidden layer) and the second layer has a link with the third layer (i.e. output layer). Layer one also has a link with the third layer (Elshamy *et al*., 2021; Devi *et al*., 2016).

CFBP neural networks are used to solve nonlinear periodic pattern problems. This network topology performance in highly influenced by the relationship between the selected input and output variables. Compared to an FFB neural network with a direct relationship between the input and output layers, a CFBP neural network uses both the direct connection from the FFB neural network and the indirect relationship between input and output layer. CFBP neural networks can represented by Equation 5 (Warsito *et al*., 2018):

$$y = \sum_{i=1}^{n} f^i w_i^i x_i + f^o(\sum_{j=1}^{k} w_j^o f_j^h(\sum_{i=1}^{n} w_{ji}^h x_i)) \qquad 5)$$

Where, f represents the activation function and w_i^i represents the weights. The addition of bias (w^b) would result in Equation 6:

$$y = \sum_{i=1}^{n} f^i w_i^i x_i + f^o(w^b \sum_{j=1}^{k} w_j^o f_j^h(\sum_{i=1}^{n} w_{ji}^h x_i)) \qquad 6)$$

2.12 Artificial neural network training function algorithm

Yogitha & Mathivanan (2018) reported on three types of training algorithms used in ANNs, namely the descent algorithm also known as *TRAINGD*, the conjugate gradient also known as *TRAINSCG*, and the quasi-Newton algorithm known as *TRAINLM*. *TRAINLM* is the most used and preferred training algorithm in ANNs, because it administrates better convergence results.

2.13 Artificial neural transfer function

Choosing the best transfer function is important in ANN models. The transfer function also known as the activation function is used to determine the firing intensity of a neuron (Basheer & Hajmeer, 2000). The three types of training functions mostly used in ANNs are PURELIN, TANSIG and LOGSIG (Prasad *et al*., 2012). PURELIN transfer functions are used in solving problems which are linear in the output layer, because of the slight difference from the hidden layer (Prasad *et al*., 2012). PURELIN transfer functions can be represented by Equation 7:

$$F(x) = x \qquad 7)$$

TANSIG transfer functions are used to solve nonlinear problems in the hidden layer of ANNs (Yogitha & Mathivanan, 2018). Mirarabi *et al*. (2019) stated that tan sigmoid transfer functions effectively escalates ANN model performance in nonlinear approximation. These transfer functions are classified as hyperbolic tangent sigmoid transfer functions and can be represented by Equation 8:

$$Tanh(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \qquad 8)$$

LOGSIG transfer functions are also known as logistic sigmoid transfer functions and are used to solve nonlinear problems in both the output and hidden layers of ANNs. According to Yogitha & Mathivanan. (2018), LOGSIG transfer functions are preferably used in feedforward backpropagation neural networks. LOGSIG transfer functions can be represented by Equation 9:

$$Logsig(x) = F(x) = \frac{1}{1+e^{-x}} \qquad 9)$$

2.14 Artificial neural training function

ANN performance is influenced by the learning algorithm used during the training process. Training guarantees the best weight connectivity of the processing elements of the network (Faris *et al*., 2016). Network training is done to guarantee a close or equal prediction of target values by minimising the errors computed by the output values. Hamed *et al*. (2004) stated that the Levenberg-Marquardt (LM) algorithm is the most used and preferred training function for optimisation, simulation and prediction purposes. During the training process, the ANN model must undergo the learning process depending on the interconnection between neurons. These ANN learning paradigms can be classified as either supervised or unsupervised learning (Hamed *et al*., 2004).

2.14.1 Supervised learning

Supervised learning is a machine learning technique used in ANNs to learn and gain knowledge from given historical input and output data to predict target data. This type of training process is best used in the gradient-based method known as FFB or MLP network models and the most preferred learning technique (Faris *et al*., 2016). Error signals play an important role in the adjustment of the interconnected weights in supervised learning (Sathya & Abraham, 2013). According to Dongare *et al*. (2012) supervised learning learns with both the input and output data represented in vector data (Mishra & Gupta, 2017). The supervised learning process has four steps that need to be considered: 1.) determining the training examples (Prasad *et al*., 2012); 2.) obtaining data sets that describe the problem that needs to be solved; 3.) expressing the training data to the preferred ANN model; and lastly 4.) learning and testing the ANN performance using the validation data sets (Zakaria *et al*., 2014).

2.14.2 Unsupervised learning

Unsupervised learning is a machine learning technique also known as self-organisation learning (Hamed *et al*., 2004). This is the opposite of supervised learning as it does not require error signals to solve the problem at hand. This type of learning learns by using information computed from the neurons in the ANN model (Sathya & Abraham, 2013). Mishra & Gupta (2017) reported on literature that unsupervised learning learns with input data only. The input process variables train with the aim of achieving a cluster of pattern responses. The ANN model development process has its own representation of input stimuli, hence the patterns do not need to be classified into categories (Dongare *et al*., 2012). According to Zakaria *et al*. (2014) unsupervised learning is best suitable in estimating statistical modelling, separation and clustering problems with respect to how the given data is organised.

2.15 Overfitting and overtraining of data of neural networks

Bilbao & Bilbao (2018) and Alkinani *et al*. (2020) stated that ANN models are considered overfit when the model tends to accurately fit almost all the data; thus resulting in zero error and an almost perfect fit which indicates that the model has noisy data. A learning model with high training prediction can learn complex data, but result in network overfit which may tend to the network memorising non predictive features of training data. Overfitting is when the model shows high training accuracy with less error, but simultaneously shows low validation and testing accuracy with high errors between the predicted and target data (Hagan *et al*., 1997). According to Saleh (2021) this means the network was able to descriptively learn, but would show poor generalisation when presented with new data. Network overfit is caused by the network size, high network variance due to the presence of outliers, the use of complex algorithms, the use of large amounts of data during network training and a large number of neurons in the hidden layer (Zhang & Friedrich, 2003).

2.16 Artificial neural network data preparation

It is crucial to prepare data prior to developing an ANN model. This is due to the fact that input data influences the data analysis results. Prepared data guarantees data quality, great ANN performance and data analysis efficiency; while unprepared data results in poor data analysis and it is therefore almost impossible to result in good ANN performance (Yu *et al*., 2007). According to Nguyen *et al*. (2020) ANNs perform better, with high prediction accuracy when created with a significant number of parameters compared to when the network was developed with only one or two input parameters.

ANNs are data driven models and can be classified in three categories of data sets including training, validation and testing data sets. In MATLAB® the "*dividerand*" function is used to divide the data sets (Jain *et al*., 2015). MATLAB® data division functions include the *divideblock*, *divideint* and *divideind* (Hassen & Asmare, 2018). In this study the *dividerand* function will be used in MATLAB® as it is set to divide the data by default. Meaning 70% of the data is randomly selected and used for training, 15% is used for validation and lastly, 15% is used for testing the network to make up 100% of the available data (Gramatikov, 2017). The training data sets are used to find the correlation between the input and output data and adjusting the network weights in relation to the errors The testing data sets are used to determine and assess the optimal generation of the developed neural network (Saleh, 2021; Zounemat-Kermani *et al*., 2019). The validation data set is used to generalise the network and ensures network training. Iteration stops when generalisation of the network stops and the performance decreases (Pasini, 2015). When the neural network being developed overfits the data the validation set error increases, although the training error will most likely decrease when the training is initiated (Gramatikov, 2017).

2.17 Data normalisation

It is important to normalise the data before introducing it to the MATLAB® toolbar, this is to prevent the overriding of larger numbers to small numbers and the premature saturation of the hidden nodes (Basheer & Hajmeer, 2000). The selected data must be normalised using the *mapminmax* function in the MATLAB® toolbar. The mapping can be represented by Equations 10 - 12 (Zhang *et al*., 2020):

$$\mathrm{f: x \rightarrow y = \frac{x - x_{min}}{xmin_{max}}} \qquad 10)$$

$$\mathrm{[y,;ps];=;mapminmax(x,:ymin.;ymax)} \qquad 11)$$

$$\mathrm{Y = \frac{(ymax;-ymin)\times(x;-xmin)}{xmax\backslash;-xmin} + ymin} \qquad 12)$$

Where, x is the original data before normalisation; $ymin$ and $ymax$ represents the range parameters of the mapping with default values of -1 and 1; y represents the normalised data and ps is the structure holding the normalised mapping (Zhang *et al*., 2020).

The performance of ANNs is evaluated by the root mean square error (RMSE), which can predominately be the mean square error (MSE). The MSE is the measurement of the mean squared errors from the trained neural network. The error is the difference between the target and experimental output values (Yogitha & Mathivanan, 2018). MSE and RMSE can be expressed by Equations 13 and 14, respectively:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\widehat{Z\imath} - Zi)^2 \qquad 13)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{Z\imath} - Zi)^2} \qquad 14)$$

Where, $\widehat{Z\imath}$ is the experimental value; $\mathcal{Z}i$ is the algorithm estimated value and n is the total number of runs (Hamada *et al*., 2018; Yogitha & Mathivanan, 2018). The coefficient of determination for regression (R^2) (i.e. correlation coefficient) can be evaluated using Equation 15:

$$R^2 = 1 - \sum_{i=1}^{n}(\mathcal{Z}i - \widehat{\mathcal{Z}\imath})/(\mathcal{Z}i - \mathcal{Z}m) \qquad 15)$$

Where, $\mathcal{Z}m$ represents the average experimental value (Vinoth Arul Raj *et al*., 2021; Miraboutalebi *et al*., 2016).

2.18 Types of software for artificial neural network (ANN)

2.18.1 Freeware software (e.g. NNIGnets)

Freeware software is a computer system used in the research, teaching or business applications in ANNs (Iliadis & Jayne, 2011). NNIGnets was constructed specially for engineering problems, it was tested with different skill frameworks and proved to be easy to use in ANNs (Fontes *et al*., 2011).

2.18.2 Commercial software (e.g. MATLAB®, neural network toolbar)

In this study, the commercial software MATLAB® was used to predict the target values. MATLAB® is a mathematical tool used to analyse data, the data analysed is accessible in terms of interpolation, statistical analysis, equation solvers and optimisation. With this toolbar, the ANNs can be tested and trained. ANN networks can easily provide outputs corresponding to the inputs and provide proof that they are correct, they are also capable of drawing training error functions (Taylor, 2006).

ANNs were invented by Dr Robert Hecht-Nielsen and require a large number of runs to determine the best solution, Table 2.11 shows the advantages and disadvantages of using ANNs.

Table 2.11: Advantages and disadvantages of ANNs, adapted from Mustafa *et al.* (2021)

Advantages	Disadvantages
The ability to solve nonlinear and complex structures.	ANNs can overfit data.
ANNs easily predict interactions between input and output data.	Extrapolation of data.
The final output is not affected by the training which may contain errors.	ANNS require sufficient training data.
ANNs can train for an exceedingly long time depending on the main factor such as the number of weights present in the network, training examples and setting of various learning algorithm parameters.	Training data must be closely related to the predicting parameters.
High prediction accuracy.	ANNs require large amounts of data.

The major components of artificial neurons are nodes, weights, bias, input and output patterns. Input layers transmit signals to the neurons in the hidden layers, which then extracts significant patterns from the signal received and directs them to the output layer which is the final result of the model production (Hatem *et al*., 2011). ANNs are arranged in layers with interconnected nodes containing activation functions, these networks contain a learning rule that is responsible for moderating the weights of the connections according to the input patterns. Diverse types of learning rules are used by ANNs, including the delta rule where the learning rule is supervised in every cycle (Ellacott, 1990). Figure 2.5 is an illustration of an ANN design adapted from Shenfield *et al*. (2018).

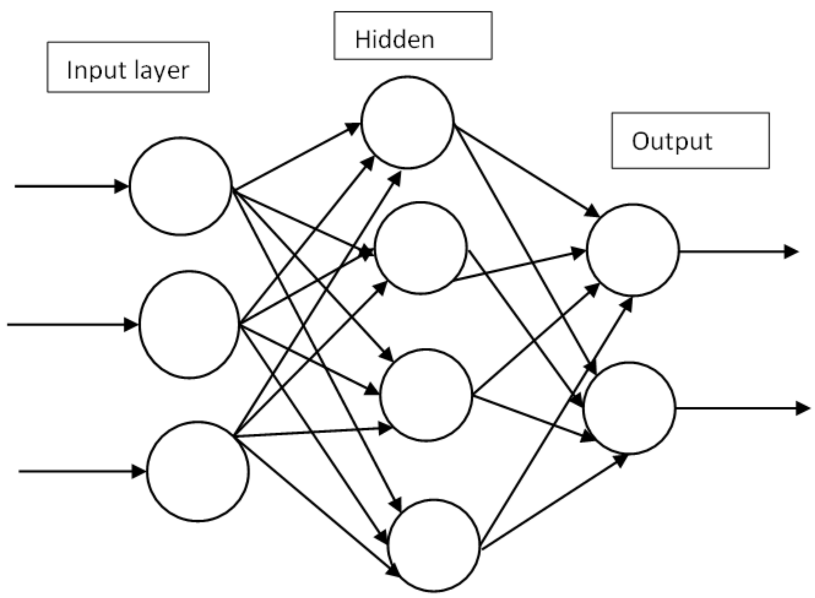

Figure 2.5: General MLP artificial neural network design, adapted from Shenfield *et al*. (2018)

Figure 2.6 illustrates an example of a basic artificial neuron, where X_1, X_2, and X_3 represents the input nodes; W_1, W_2 and W_3 represent the weights; Σ represents the sum of the input, weights and bias; and $f(x)$ represents the activation function of the neural network model (Zhang *et al*., 2019).

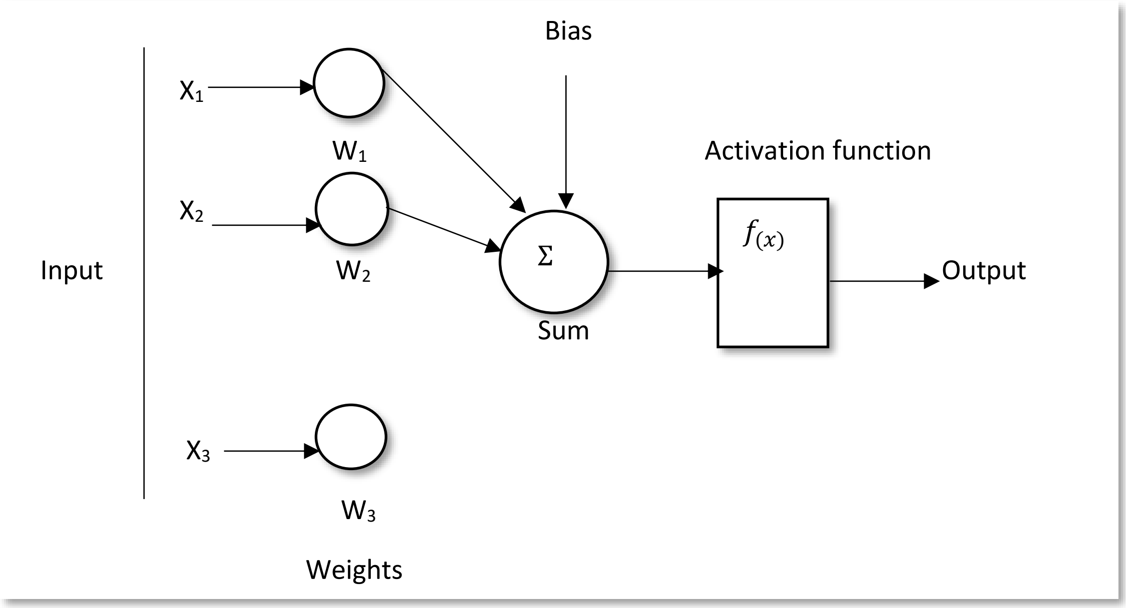

Figure 2.6: Basic artificial neuron

The product of input data points with their corresponding weights is added and applied to a transfer function to predict the output, summarised by Equation 16:

$$Z = f(\sum_{i-1}^{n} w_i x_i + d) \quad 16)$$

Where, Z is the output; x_i represents the input values with the corresponding weights (w_i,); d is the bias value and f is the transfer function (Elbisy *et al*., 2014).

2.19 Artificial neural networks for biological wastewater treatment

Wastewater treatment plants (WWTP) require proper operation, controlling and monitoring for better performance (Hamed *et al*., 2004). According to Yang *et al*. (2021) ANN mathematical modelling tools have been developed for wastewater treatment purpose to predict organic waste removal efficiency, effluent concentration and bioreactor performance (Nadiri *et al*., 2018), because of their high prediction and accuracy capabilities compared to other modelling tools.

Hassen & Asmare (2018) used ANNs to predict the effluent water quality of Habesha brewery's WWTP and concluded that ANNs can successfully predict WWTP performance (i.e. water quality parameters) when an R value of up to 0.969 was obtained between the target and predicted effluent COD concentration. Gheytaspour & Bigdarvish (2018) also used ANNs to predict WWTP performance and obtained an R value of 0.920 for the COD concentration of the effluent.

Zeinolabedini & Najafzadeh (2019) used two types of neural networks (i.e. FFB and RBFNN) to determine which performed best in predicting the quantity of sewage sludge produced in a WWTP. It was observed that both neural network models provided high accuracy results with an R value of 0.99 for the FFB neural network and 0.90 for the RBFNN. Table 2.12 shows the correlation coefficients (R) of biological wastewater treatment systems using ANN models.

Table 2.12: Application of artificial neural networks (ANN) in wastewater treatment

Type of wastewater	Type of ANN architecture used	Treatment methods	Input	Output	*R*	References
Brewery wastewater	Feedforward, backpropagation (FFB)	Up-flow anaerobic sludge blanket (UASB) and an aerobic reactor	COD, pH, total nitrogen (TN)	Prediction of the Habesha brewery wastewater plant performance	0.969	Hassen & Asmare, 2018
Municipal wastewater	Feedforward, backpropagation (FFB)	Membrane bioreactor technology (MBR)	NH_4^+-N, COD, pH, PO_4^{3-}-P	Prediction of NH_4^+-N, COD, and PO_4^{3-}-P effluent concentrations	NH_4^+-N – 0.9995; COD - 0.9942 and PO_4^{3-}-P – 0.9998	Giwa *et al*., 2016
-	Feedforward, backpropagation (FFB)	Konya wastewater treatment plant	COD, pH, temperature, BOD, flow rate and TSS	TSS, Konya wastewater treatment plant performance prediction	0.99	Paquin *et al*., 2015
Synthetic wastewater	Multilayered perceptron neural network	Anaerobic baffled rector employing electrolysis system (EABR)	COD, pH, HRT, voltage,	Optimisation of EABR performance	0.99	Gholikandi & Amouamouha, 2018
Municipal wastewater	Feedforward, backpropagation (FFB)	Anaerobic baffled reactor (ABR)	COD, BOD, TSS, TDS, total phosphorous (TP), pH, VFA, temperature	Optimising ABR design, configuration and performance	0.974	Badalians Gholikandi *et al*., 2014

Chapter 3: METHODOLOGY

3. Introduction

To meet the objectives of this research study, data was obtained and pre-processed from four previous biological wastewater treatment studies treating biodiesel- (Grobbelaar, 2019), textile-, polymer- and pulp and paper (Sheldon *et al*., 2012) wastewater. The biodiesel- and textile wastewater were individually treated using a six-compartment anaerobic baffled reactor (ABR) designed in a manner similar to that of Phukingngam *et al*. (2011). The ABR was operated for 7 and a half months and 3 months for the treatment of the biodiesel- and textile wastewater, respectively. The polymer- and pulp and paper wastewaters were both individually treated using an expanded granular sludge bed (EGSB) reactor with the column design based on Zang *et al.* (2008). For both the polymer- and pulp and paper wastewater treatment, the EGSB was operated for 6 months, respectively.

3.1 Artificial neural network (ANN) analysis and procedure

Neural networks, used to study the behaviour of a system, are sets of processing elements (i.e. nodes, neurons, units) that determines output values from the input values, connectivity, activation functions and training algorithms (Rodríguez *et al*., 2019). When using neural networks, there are essential steps that need to be considered: 1.) the behaviour of the process and predicted output values with respect to the constructed neural network model, and 2.) the control variables need to be modified to control and optimise the output values (Kalogirou *et al*., 2014).

The input values are the measurements of the variables specific to the equipment, measurement of the dimensions and controlled variables modified by the operator (Ibrić *et al*., 2012). Training data (i.e. available data) for the identification of variables are important for the performance of neural networks and checking errors from the data. In order to verify if the variables reflect the known information, graphs have to be drawn (Kalogirou *et al*., 2014).

For artificial neural network (ANN) problems to be solved, the selection of a suitable learning rate, momentum, the number of neurons from each of the hidden layers and the activation function is crucial (Montesinos López *et al*., 2022). Therefore, the collected data must be prepared in a Microsoft Excel spreadsheet format with input and output columns. A training file is then created with samples of the whole problem domain to select the required parameters. Three data sets are used: a training data set, test data set and validation data set. When the training process takes place, the neural network will be tested against the testing data to determine accuracy, and training will be stopped when the mean average error remains the same for a period of time (Alwosheel *et al*., 2018b). This is done in order to avoid overtraining, in which case, the network learns the training patterns perfectly but is unable to make predictions when an unknown training set is presented (Kalogirou *et al*., 2014). Figure 2.4 in chapter 2, section 2.8 shows the steps used to develop three ANN models.

3.2 Artificial neural networks (ANNs): Selection of input and output process variables

The main intent of this research study was to evaluate the feasibility of three ANNs in the identification of correlated patterns between data sets and corresponding target values for biological wastewater treatment systems using an ABR for the treatment of BDWW and TTWW; as well as an EGSB reactor treating PWW and PPWW, respectively. The impact of all the anaerobic process parameters including COD, OLR, HRT, volatile fatty acids (VFA), total suspended solids (TSS), FOG, nitrogen and pH for an ABR and EGSB system were studied before the selection of the appropriate process variables for the implementation of the ANN models. The ANN models were developed to predict the COD output (i.e. effluent COD) from BDWW, TTWW, PWW and PPWW, given the feed COD (i.e. influent COD) as input and effluent COD concentration data from the published and unpublished previous studies as the target COD (refer to Appendix E). The selected input variables were the COD as the operational parameter determining the level of water purification, and OLR.

3.3 Description of the artificial neural network (ANN) method

Three network algorithms were employed in the development of the ANN model using MATLAB® (2021a) software under the Department of Chemical Engineering's licence at Cape Peninsula University of Technology (CPUT) and was also used for the modelling and simulation of the artificial neural networks. MATLAB® (2021a) software was chosen due to its high interactive performance in scientific and engineering computations. The network algorithms were selected to evaluate which model performed best in the prediction of effluent COD. Historical data sets for the prediction of COD removal efficiency were obtained from previous published (Grobbelaar, 2019; Sheldon *et al*., 2012) and unpublished studies based on the biological treatment of industrial wastewater using bioreactors including an ABR and EGSB system. After carefully investigating and pre-processing the obtained data, variables such as the HRT and the number of compartments from the ABR were eliminated, because the HRT and number of compartments remained constant throughout the experimentation period for the biodiesel and textile wastewater treatment in the ABR. Since the focus of this study was the COD of the effluent, further variables such as the TSS, oil and grease (O&G), pH and TDS were eliminated as these variables have little to no effect on COD prediction (Ruben *et al*., 2017; Talib & Amat, 2012). The remaining variables (i.e. COD and OLR) were then normalised using Equation 12 in Chapter 2. After data preparation, the selected input (i.e. influent COD and OLR) and target data (i.e. effluent COD) were loaded from the Microsoft

Excel spreadsheet to the MATLAB® (2021a) software workspace (i.e. transposed) as *input_data* (i) and *target_data* (td). Before the training of the neural network, the original input and target data, mean, and standard deviation (Std. Dev.) were determined prior to the network simulation.

For ANN simulation, the three selected ANN types, namely nonlinear autoregressive neural network model with exogenous inputs (NARX), feedforward back propagation (FFB) and cascade feedforward backpropagation (CFBP) were trained, validated, and tested using the previously obtained published (Grobbelaar, 2019; Sheldon *et al*., 2012) and unpublished data. In the MATLAB® (2021a) software command window, *nntool* was typed in order to import the input and target data values in the Data Manager tab from MATLAB® (2021a) workspace. *Input_data (i)* and *target_data (td)* were imported under the input and target workspaces, respectively. To create the neural network architecture, three different network types were chosen. FFB also known as the multilayer perceptron (MLP) neural network architecture, was selected for the ANN model, because of its ability to learn, minimise errors, generalise well and maintain the stability of the network after adding more data (Faris *et al*., 2016). As previously mentioned in Chapter 2, Hassen & Asmare (2018) utilised the FFB ANN to predict wastewater treatment plant performance and concluded that the model was able to predict COD effluent concentration with correlation coefficient (R) of 0.969 which proved that the FFB model can accurately predict COD effluent concentration when presented with new data sets. Gopi Kiran *et al*. (2021) conducted a study to determine effluent COD concentration from a rotating biological contactor treating heavily contaminated wastewater using an FFB ANN and observed that the model accurately predicted the COD concentration of the effluent with the R^2 value ranging from 0.91 to 0.98 and 0.92 to 0.98 for the training and testing data, respectively. NARX and CFBP then followed due to the selection of the training function, learning function (i.e. supervised learning), performance function, *TRAINLM*, *LEARNGDM* and mean square error (MSE), respectively. To train the networks, a trial-and-error method (Patki *et al*., 2021) was used to achieve the best network performance and regression graphs, this was done by randomly choosing and adjusting the number of neurons in the hidden layer to randomly range from 2 to 11. Tables 3.1, 3.2, 3.4, 3.5, 3.7, 3.10 and 3.11 illustrates the statistical raw data from the different industrial wastewater biological treatment systems obtained from previous published (Grobbelaar, 2019; Sheldon *et al*., 2012) and unpublished studies. Tables 3.3, 3.6, 3.9 and 3.12 illustrates the statistical values of the normalised data.

Table 3.1: Raw operational data of the biodiesel wastewater influent

Variable	Units	Min	Max	Mean	Std. Dev.
COD	mg/L	5373	33450	14129.38	8847.464
ORL	kg COD/m^3.days	0.58	3.46	1.23023	1.043071
Time	Days	6	225	-	-

Table 3.2: Raw operational data of the treated biodiesel wastewater effluent

Variable	Units	Min	Max	Mean	Std. Dev.
COD	mg/L	1745	11158	5868.299	3177.904
Time	Days	6	225	-	-

Table 3.3: Normalised biodiesel wastewater operational data

Variable	Units	Min	Max	Mean	Std. Dev.
COD_{in}	mg/L	-0.9897	2.18375	-7.1463E-17	1
COD_{out}	mg/L	-1.2974	1.66452	7.40149E-17	1
OLR	kg COD/m^3.days	-0.6234	2.13769	1.50072E-15	1

Table 3.4: Raw operational data of the textile wastewater influent

Variable	Units	Min	Max	Mean	Std. Dev.
COD	mg/L	100	5910	830.7258	1049.1969
ORL	kg COD/m^3.days	0.184606	0.544587	0.299538	0.119824
Time	Days	9	84	-	-

Table 3.5: Raw operational data of the treated textile wastewater effluent

Variable	Units	Min	Max	Mean	Std. Dev.
COD	mg/L	100	2600	1067.0967	652.51376
Time	Days	9	84	-	-

Table 3.6: Normalised textile wastewater operational data

Variable	Units	Min	Max	Mean	Std. Dev.
COD_{in}	mg/L	-0.47725	0.49731	-3.2232E-17	1
COD_{out}	mg/L	-0.03386	-0.01087	1.43926E-16	1
OLR	kg COD/m^3.days	-0.95918	2.04507	4.58415E-16	1

Table 3.7: Raw operational data of the polymer wastewater influent

Variable	Units	Min	Max	Mean	Std. Dev.
COD	mg/L	1460	46325	15527.73	6028.349
ORL	kg COD/m^3.days	0.58	24.09	9.26	4.04
Time	Days	3	122	-	-

Table 3.8: Raw operational data of the treated polymer wastewater effluent

Variable	Units	Min	Max	Mean	Std. Dev.
COD	mg/L	226	22600	7774.718	4663.313
Time	Days	3	122	-	-

Table 3.9: Normalised polymer wastewater operational data

Variable	Units	Min	Max	Mean	Std. Dev.
COD_{in}	mg/L	-2.15195	0.42255	6.8572E-17	1
COD_{out}	mg/L	-1.47796	-0.38700	7.4450E-17	1
OLR	kg COD/m^3.days	-2.04510	2.13769	-1.2016E-16	1

Table 3.10: Raw operational data of the pulp and paper influent wastewater

Variable	Units	Min	Max	Mean	Std. Dev.
COD	mg/L	180	3427.5	1780.43	573.40
ORL	kg COD/m^3.days	2.97	5.52	3.66	0.68
Time	Days	0	175	-	-

Table 3.11: Raw operational data of the treated pulp and paper wastewater effluent

Variable	Units	Min	Max	Mean	Std. Dev.
COD	mg/L	10	1210	696.69	393.66
Time	Days	0	175	-	-

Table 3.12: Normalised pulp and paper wastewater operational data

Variable	Units	Min	Max	Mean	Std. Dev.
COD_{in}	mg/L	-0.45418	1.11539	3.58908E-17	1
COD_{out}	mg/L	-0.30276	1.30395	1.16286E-16	1
OLR	kg COD/m^3.days	-1.00741	2.72783	2.70665E-15	1

3.4 Model evaluation

To determine which of the three network types, FFB, NARX or CFBP performed best, the MSE between the predicted and target effluent COD output data sets for training, validation and testing (Saleh, 2021) (refer to Equation 13 in Chapter 2) and the correlation coefficient (R) (refer to Equation 12 in Chapter 2) were used to evaluate the performance of each network. A low to zero MSE value is preferred and the overall goal for this study, because a zero to low error value between the target and predicted effluent COD data indicates the network that performed best (Abba & Elkiran, 2017). An (R) value of 1 between the target and predicted effluent COD data was the main goal for this study, as a value of 1 shows a close correlation between the predicted and target effluent COD data and indicates the network has a high prediction accuracy (Ruben *et al.*, 2017).

Chapter 4: RESULTS AND DISCUSSION

4.1 Introduction

The complicated operation, which leads to poor quality effluent from biological wastewater treatment systems, due to the variety of wastewater strengths, physical and chemical composition has led to the implementation of robust computer based mathematical models to optimise, simulate and predict wastewater treatment plant (WWTP) performance (Nasr *et al*., 2012). Three ANNs, FFB, NARX and CFBP (refer to section 2.11 in Chapter 2 and section 3.3 in Chapter 3) were developed to predict biological wastewater treatment performance, the main aim of this study was to evaluate the feasibility of ANNs to identify correlated patterns between data sets and corresponding target values of effluent COD from biological wastewater treatment systems.

According to Mirarabi *et al*. (2019), ANNs are data driven. Historical data was obtained from previous published (Grobbelaar, 2019; Sheldon *et al*., 2012) and unpublished studies on industrial biological wastewater treatment systems. The pre-processed raw data of influent and effluent from biological treatment systems for biodiesel wastewater (BDWW), textile wastewater (TTWW), polymer wastewater (PWW) and pulp and paper wastewater (PPWW) brought about the development of three types of ANN models for the evaluation of biological wastewater treatment performance and the prediction of the COD of the wastewater effluent from historical data. The performance of the three ANN models, namely FFB, NARX with a time delay(TD) value of 2 and CFBP were assessed by adjusting the number of neurons in one hidden layer to range from 2 to 11 in the same manner as explained by Patki *et al*. (2021) in order to determine which network architecture would be able to accurately predict the COD of the wastewater effluent when presented with new training data sets after learning, training and using the Levenberg-Marquardt (LM) algorithm set by default on MATLAB® (2021a). All model architecture consisted of three layers namely input, hidden and output. According to Valente *et al*. (2014), one hidden layer is enough for solving engineering problems with ANNs. Additional hidden layers can lead to network over training and thus the tendency to memorise the training pattern which then results in poor network performance. Linear and tan sigmoid transfer functions were selected by default by MATLAB® (2021a) for the output and hidden layers, respectively. According to Yogitha and Mathivanan. (2018), tan sigmoid functions are most preferred in ANNs for solving nonlinear engineering problems. Examples of FFB, NARX and CFBP architectures are presented in Figures A.1, A.5 and A.8 of Appendix A, respectively.

4.2 Network 1: Feedforward backpropagation (FFB)

4.2.1 Anaerobic baffled reactor (ABR) treating biodiesel wastewater (BDWW)

The feedforward backpropagation (FFB) algorithm was created as the first network type to train, validate and test data sets for the prediction of wastewater effluent COD as an output variable from historical data sets (Grobbelaar, 2019). Before developing the FFB network model using MATLAB® (2021a) software the correlation between the initial raw data of the wastewater influent COD (i.e. feed) and wastewater effluent COD (i.e. product and target) after biological treatment was determined. Looking at Figure 4.1 it is evident that the COD removal efficiency is on average 79.84% and that as the feed COD increases, so does the product COD, although the COD of the product keeps fluctuating throughout the treatment period and is not a constant value. This is due to the organic loading rate (OLR) changing which resulted in the anaerobic baffled reactor (ABR) system experiencing organic shock. According to Barber and Stuckey (1999), organic shock could have been avoided by adjusting the pH in the first compartment of the ABR system by feeding the reactor with either sodium hydroxide (NaOH) or phosphoric acid (H_3PO_4) before introducing wastewater influent with an increased COD concentration. Figure 4.1 shows the relationship between the feed and product COD raw data. The calculated correlation coefficient (R) is 0.903 which is a positive correlation although the considered R^2 value of this study was 1, since an R value of 1 indicates close correlation between input and output data and thus a high prediction accuracy of the ANN models (Ruben *et al*., 2017).

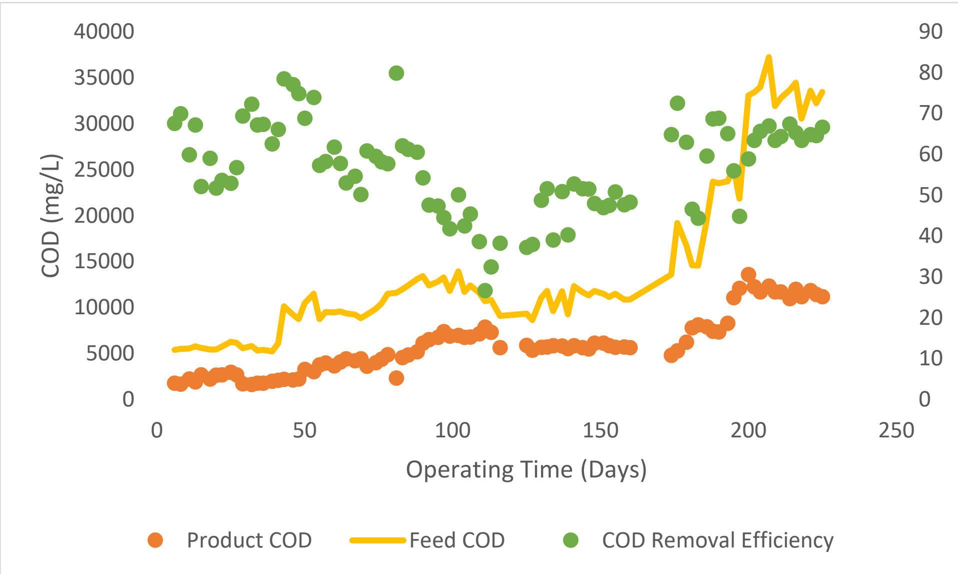

Figure 4.1: Wastewater influent COD and wastewater effluent COD following biological treatment

Figure 4.2 illustrates the comparison between the feed and target COD effluent from the FFB ANN model developed using MATLAB® (2021a). Before developing the ANN model for the

ABR system treating biodiesel wastewater (BDWW), the raw data sets were normalised using Equation 12 from Chapter 2 in order to fit the range of 0 to unity to ensure equality of the data sets and to promote accuracy in ANN models (Zounemat-Kermani *et al*., 2019). Figure 4.2 shows the COD data set predicted by the FFB ANN model corresponding closely to the wastewater effluent (i.e. product and target) COD data set. There appears to be some errors when predicting some data points, this is due to the fluctuating COD and according to Gopi Kiran *et al*. (2021) ANNs cannot elucidate microbial activity. A trial-and-error method (Patki *et al*., 2021) was implemented in the development of the best ANN model topology mainly through changing the number of neurons in the hidden layer for training, validating, and testing the data sets to determine which number of neurons would give maximum correlation and better performance of the FFB network. Figure A.3 in Appendix A shows the effect of the number of neurons on the MSE. Starting from 2 neurons there was less of an error between the target and predicted COD data sets. However, as the number of neurons increased, so did the MSE peaking at 6 neurons and then decreasing as the number of neurons increased.

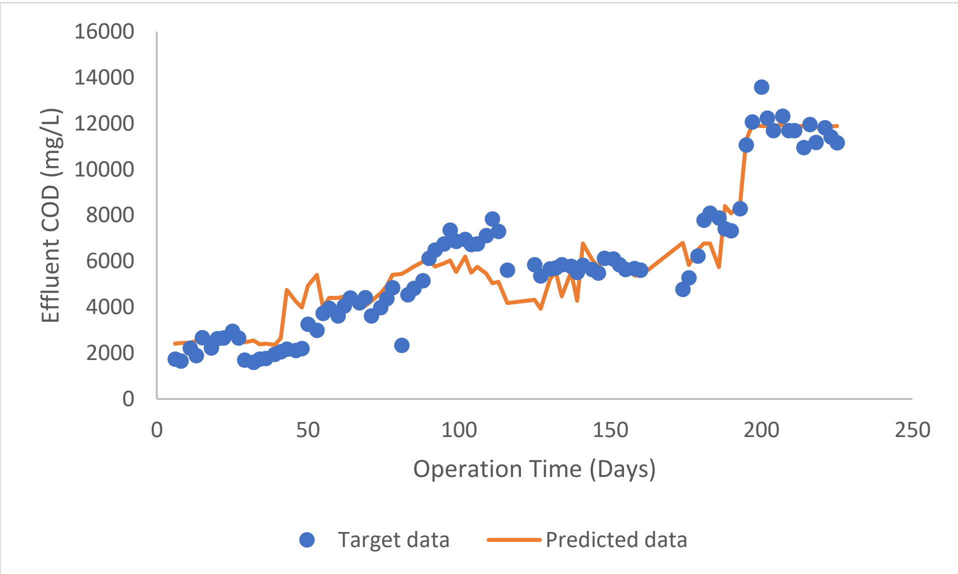

Figure 4.2: Comparison between the target and predicted effluent COD data (FFB ANN model for BDWW)

Table 4.1 shows the statistical performance of the FFB network for the different number of neurons. According to Table 4.1, the FFB network architecture with 8 neurons performed better with a high prediction accuracy for training, testing and validation (i.e. 0.937, 0.910 and 0.975, respectively). From the results in Table 4.1 the highest number of neurons resulted in the lowest MSE of 0.109 and an overall R of 0.943. The preferred R value is 1, which indicates a perfect relationship between the target and predicted COD data sets (Ruben *et al*., 2017). Table 2.12 in Chapter 2, literature review, shows FFB regressions results with high prediction accuracy from different types of wastewater and treatment methods ranging from 0.974 to

0.999, this is due to the difference in input parameters, impact of input parameters on the target variables, number of input parameters, quality and quantity of data sets.

Table 4.1: Performance statistics of effluent COD prediction (FFB ANN model for BDWW)

Number of neurons	MSE	Training R	Testing R	Validation R	All R
2	0.11794	0.920	0.936	0.986	0.939
4	0.12356	0.931	0.942	0.972	0.936
6	0.14519	0.946	0.951	0.928	0.941
8	0.10964	0.937	0.910	0.975	0.943

Figure A.2 in Appendix A shows the COD regression results for the correlation between the target and predicted COD data sets. The validation regression data set shows accurate and an acceptable correlation between the target and predicted COD data with an R value of 0.9754 which is a good fit compared to the testing R value of 0.919 and training data R value of 0.937 with an overall R coefficient of 0.943. These results mean the FFB network would be able to accurately predict COD wastewater effluent values when presented with a new set of data from training, validating, and testing neural networks.

4.2.2 Anaerobic baffled reactor (ABR) treating textile wastewater (TTWW)

Figure 4.3 represents the relationship between the feed and product COD data from a previous biological wastewater treatment study of textile wastewater using an ABR system. Figure 4.3 shows the product COD fluctuating constantly and increasing when compared to the COD of the feed, which means the textile wastewater needed to be further treated to decrease the COD of the effluent. As a result, the poor quality of data had a robust effect on the ANN model's performance and prediction capabilities.

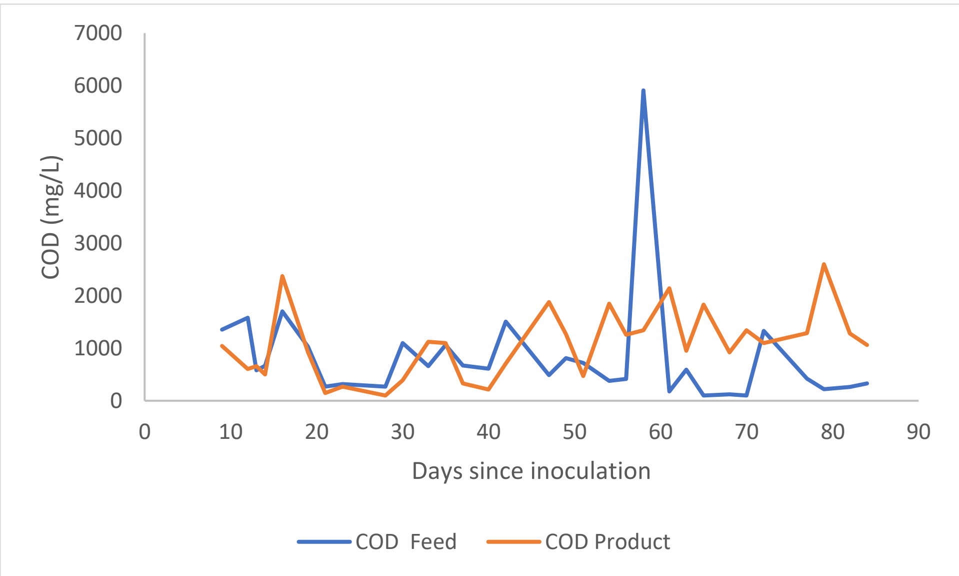

Figure 4.3: Comparison between the feed and product COD of the TTWW treated with an ABR

The comparison of the predicted and target COD data for the biological treatment of textile wastewater using an ABR is illustrated in Figure 4.4. Based on Figure 4.4, the FFB neural network did not perform well in predicting the COD of the effluent, this is because the network was presented with poor historical data quality and quantity with only a total of 31 data sets including training, validation, and testing data. According to literature, ANNs require large amounts of data over 100 for training in order to show maximum prediction accuracy, to have weak extrapolation and perform best (Platon *et al*., 2015; Abdalrahman & Abdalrahman, 2021). Table 4.2 shows the statistical performance of the FFB network. The trial-and-error method (Patki *et al*., 2021) of increasing the number of neurons in the hidden layer did not improve the network performance and COD prediction. The network performed slightly better with the lowest MSE value of 0.505 and overall R value of 0.714 when trained with 8 neurons in the hidden layer. The poor testing, training and validation results could have been improved by the provision of more data for training and validation (Du & Swamy, 2006). Figure B.1 in Appendix B shows the regression graph which has too many outliers because the data points fall outside the linear graph area.

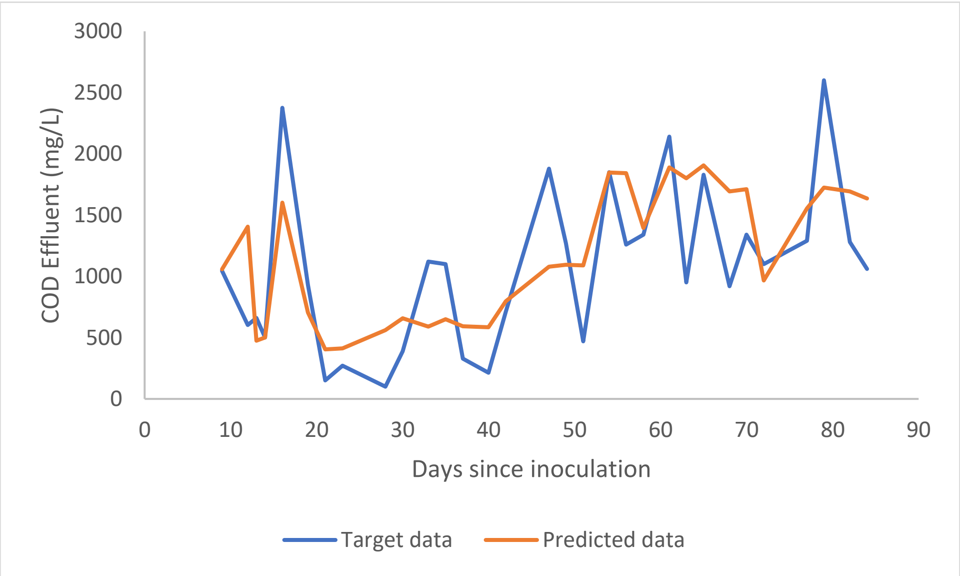

Figure 4.4: Comparison between the target and predicted effluent COD data (FFB ANN model for TTWW)

Table 4.2: Performance statistics of effluent COD prediction (FFB ANN model for TTWW)

Number of neurons	**MSE**	**Training** R	**Testing** R	**Validation** R	**All** R
2	0.58786	0.741	0.359	0.732	0.640
4	3.16439	0.126	0	0	0.077
6	0.65716	0.627	0.921	0.865	0.696
8	0.50547	0.752	0.690	0.881	0.713

4.2.3 Expanded granular sludge bed (EGSB) reactor treating polymer wastewater (PWW)

The comparison of feed and product COD of PWW treated with an EGSB reactor is illustrated in Figure 4.5. Based on Figure 4.5, the data quality appears to be superior as the COD of the effluent decreased following treatment, which justifies the benefits of treating industrial wastewater with biological systems like the EGSB. However, there are some data points visible in the product COD that are high and continuously fluctuating due to the different OLRs used when operating the EGSB reactor. Good quality data has been proven to result in the best network performance and high accuracy (Chen *et al*., 2021). However, based on the results in Table 4.3, the network shows poor training sets with the R value ranging from 0.7823 to 0.7964 when using different numbers of neurons (a range of 2 to 8 neurons) in the hidden layer. Poor training means the network was unable to learn. Figure C.1 in Appendix C shows the relationship between target and predicted COD data, where the training, testing and validation regression graphs have too many outliers.

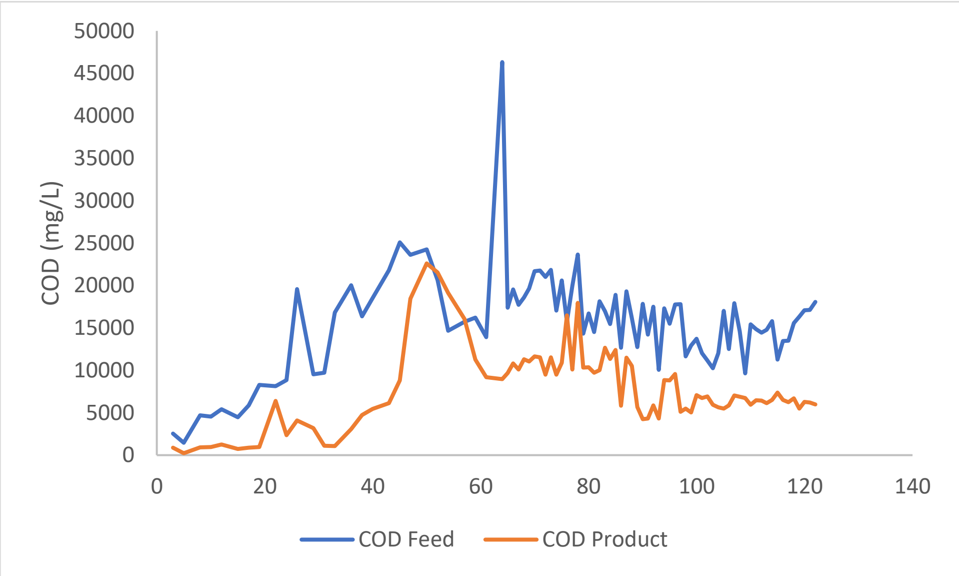

Figure 4.5: Comparison between the feed and product COD of PWW treated with an EGSB

Table 4.3: Performance statistics of effluent COD prediction (FFB ANN model for PWW)

Number of neurons	MSE	Training R	Testing R	Validation R	All R
2	0.41754	0.782	0.775	0.841	0.767
4	0.39656	0.748	0.832	0.885	0.774
6	0.39647	0.756	0.919	0.749	0.776
8	0.37542	0.796	0.811	0.911	0.816

Table 4.3 shows the statistical performance of the FFB network for predicting the COD of the effluent from biologically (i.e. EGSB) treated PWW. The historical data for the development of

the FFB network had a total of 85 data points after data pre-processing. Based on the statistical performance in Table 4.3, the lowest MSE of 0.375 and highest overall R value of 0.816 was obtained for 8 neurons in the hidden layer. These MSE and R values indicate that the network performed poorly, which means the network did not generalise the date well and would not be able to make an accurate prediction when presented with new data even though the MSE and R values decreased and increased, respectively as the number of neurons increased. Poor performance of the FFB network occurred due to missing data, on some days the COD effluent or influent COD values were not recorded which resulted in the elimination of data in these rows. According to Emmanuel *et al*. (2021) missing data has a negative impact on ANN development as it may result in biased outcome, network performance degradation and analysis issues. Figure 4.6 illustrates the comparison between the target and predicted COD of the PWW. The linear regression and MSE plot for the FFB network for PWW is presented in Figures C.1 and C.2 in Appendix C.

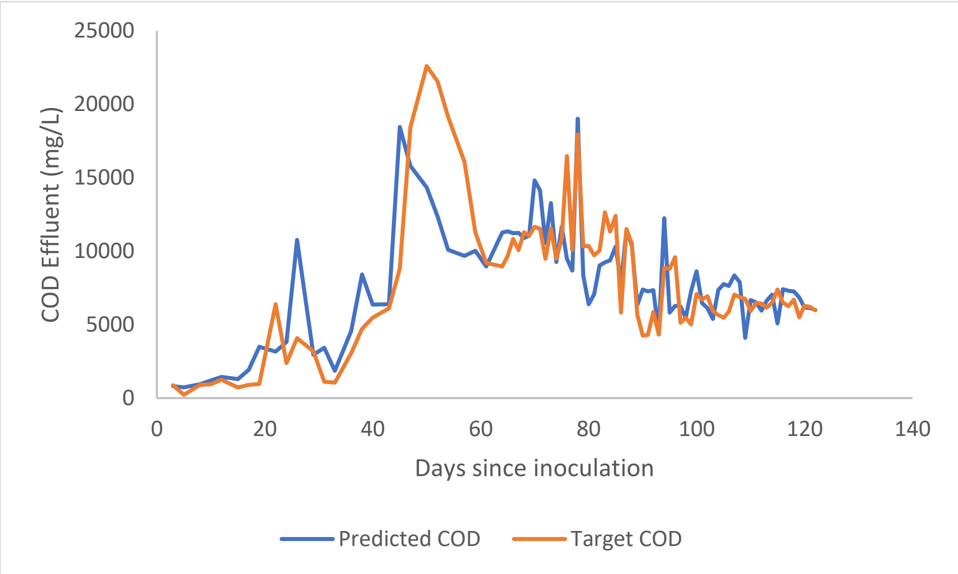

Figure 4.6: Comparison of the target and predicted effluent COD data (FFB ANN model for PWW)

4.2.4 Expanded granular sludge bed (EGSB) reactor treating pulp and paper wastewater (PPWW)

Figure 4.7 illustrates the relationship between feed and product COD of PPWW biological treated with an EGSB reactor. As can be observed in Figure 4.7 the EGSB reactor successfully treated the PPWW with the product COD (i.e. average 500 mg/L) being lower than the feed COD (i.e. average 1500 mg/L).

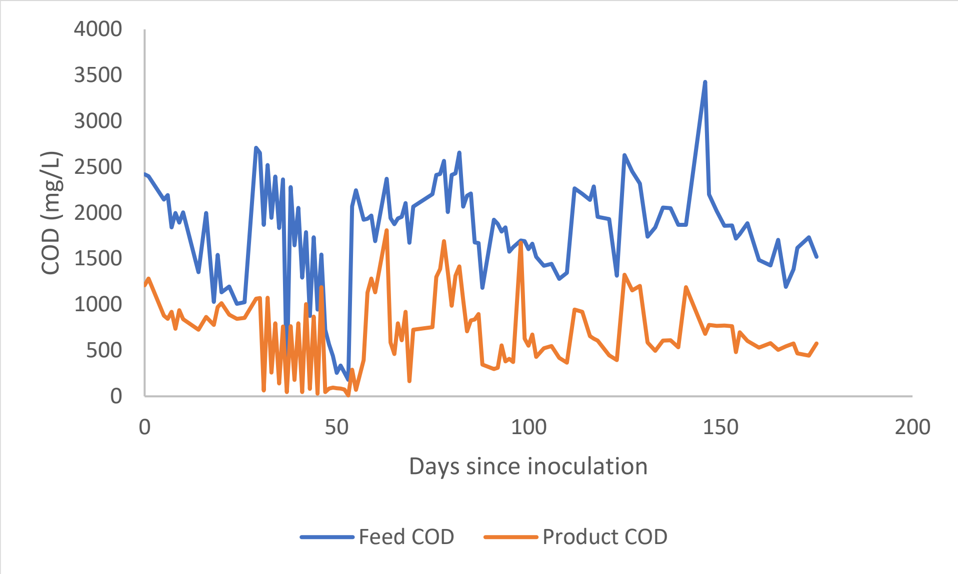

Figure 4.7: Comparison of the feed and product COD of PPWW treated with an EGSB

A FFB network model was developed using the trial-and-error method (Patki *et al*., 2021) of changing the number of neurons in the hidden layer to determine the best network architecture for the prediction of the effluent COD. Table 4.4 presents the statistical performance results of the FFB network model. Based on Table 4.4, the FFB network model generalised with an MSE of 0.472 and R coefficient of 0.725, this means a network architecture consisting of 3 layers, namely an input, hidden and output layer with 8 neurons would result in poor accuracy and generalisation when presented with a new set of data for the prediction of effluent COD. The historical data obtained from a previous published study (Sheldon *et al*., 2012) for the PPWW treated with an EGSB had some missing data points for the feed (i.e. influent) and product (i.e. effluent) COD which led to the elimination of data rows which justifies the poor network performance and correlation depression of the learning algorithm stage (Gill *et al*., 2007). Figure 4.8 presents the comparison between the target and predicted effluent COD.

Table 4.4: Performance statistics of effluent COD prediction (FFB ANN model for PPWW)

Number of neurons	$\mathbf{MSE}$	**Training** $\boldsymbol{R}$	**Testing** $\boldsymbol{R}$	**Validation** $\boldsymbol{R}$	**All** $\boldsymbol{R}$
2	0.56839	0.694	0.665	0.825	0.660
4	0.53903	0.646	0.803	0.767	0.677
6	0.54584	0.639	0.772	0.717	0.671
8	0.47215	0.729	0.821	0.702	0.725

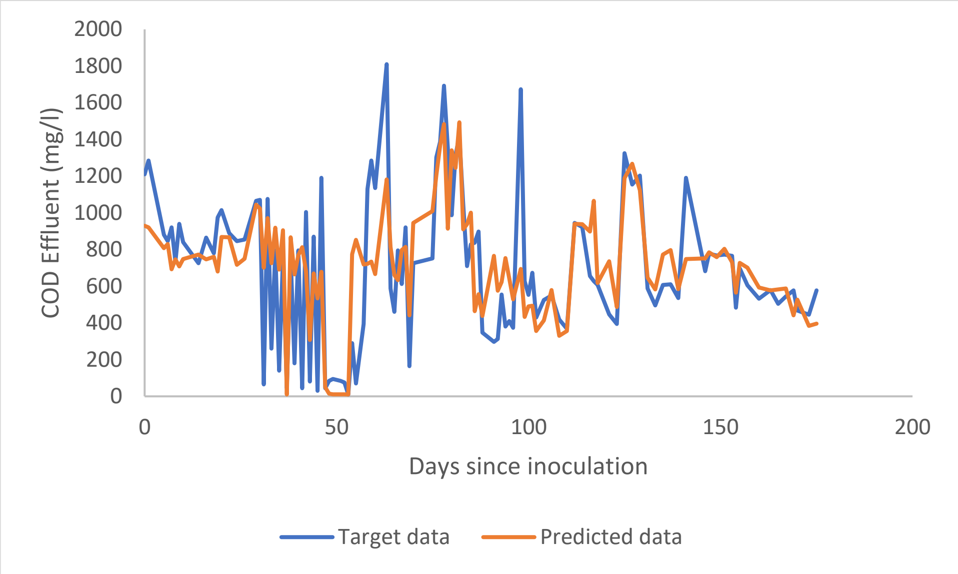

Figure 4.8: Comparison between the target and predicted effluent COD data (FFB ANN model for PPWW)

4.3 Network 2: Nonlinear autoregressive neural network model with exogenous inputs (NARX)

4.3.1 Anaerobic baffled reactor (ABR) treating biodiesel wastewater (BDWW)

The nonlinear autoregressive neural network with exogenous inputs (NARX) known for accurate prediction was developed as the second ANN model for the prediction of effluent COD concentration from historical BDWW treatment data sets (Grobbelaar, 2019). The training function, learning function (i.e. supervised learning) and performance function were selected by default to be *TRAINLM*, *LEARNGDM* and MSE respectively on the MATLAB® (2021a) software. The trial-and-error method (Patki *et al*., 2021) was used to determine the number of neurons that would represent an optimum network architecture and give maximum accuracy between the predicted and target COD concentration data, as well as better network performance. The performance statistics of the target and predicted effluent COD concentration in Table 4.5 shows that high accuracy and better network performance was achieved when the NARX network was trained with 5 neurons in the hidden layer. The overall correlation coefficient (R) after training, validating, and testing the NARX network was found to be 0.988 with an MSE of 0.02396. Increasing the number of neurons did not affect the prediction accuracy of the network as it remained high, although the MSE kept increasing NARX still showed superior network performance. Increasing the neurons in the hidden layer results in great synthesising, but could result in poor generalisation of ANNs (Elshamy *et al*., 2021).

Table 4.5: Performance statistics of effluent COD prediction (NARX ANN model for BDWW)

Number of neurons	MSE	Training R	Testing R	Validation R	All R
3	0.02900	0.980	0.989	0.991	0.985
5	0.02396	0.988	0.961	0.992	0.987
7	0.02509	0.987	0.989	0.986	0.987
9	0.02862	0.985	0.995	0.982	0.985

Figure 4.9 shows the predicted COD data corresponds to the target COD data although it can be observed there is a significant difference in data on day 81 of operation with a target COD of 2833 mg/L and the predicted COD concentration to be 4255 mg/L, according to Grobbelaar (2019) this was due to the change in organic loading rate.

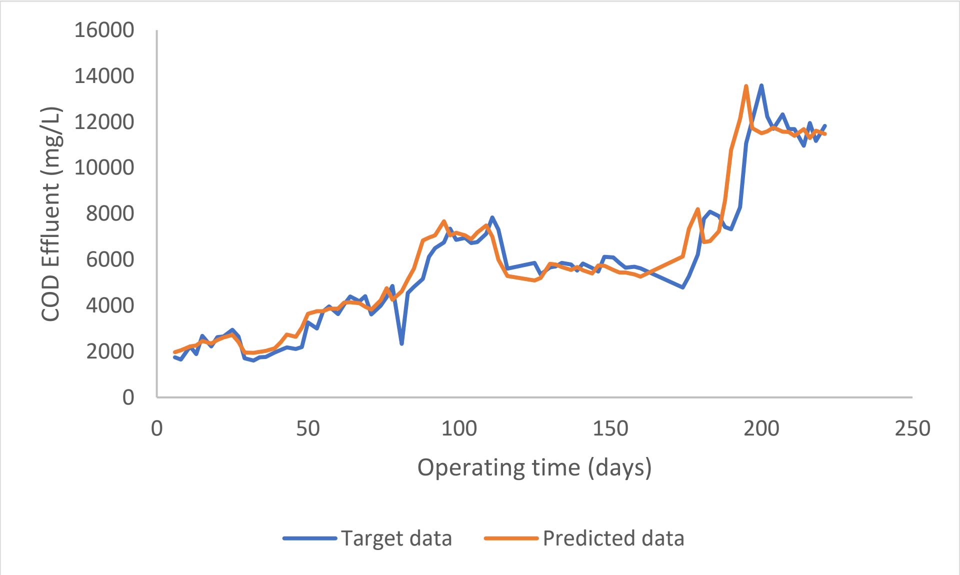

Figure 4.9: Comparison between the target and predicted effluent COD concentration (NARX ANN model for BDWW)

The regression graph in Figure A.7 in Appendix A shows accurate correspondence between the target and predicted COD concentration of the effluent with a perfect fit although some data points do not fall in the linear regression graph, these data points are called outliers, located far from other training data points with small variation (Khamis *et al* (2005). As the data sets were divided into training, validation and training subsets, it is evident from Figure A.7 that the regression analysis of the training and validation subsets show a good fit with R values of 0.989 and 0.992, respectively, while the testing subsets show slightly low regression results compared to the training and validation subsets with an R value of 0.961. This could be the result of network overfitting, Alkinani *et al*. (2020) and Bilbao & Bilbao (2018) mention that, overfitting may be caused by a large number of neurons and hidden layers or network overtraining. However, this was not the case in this study because the network had a minimum number of neurons (i.e. 5) and hidden layers (i.e. 1). It can be concluded that the COD regression results are acceptable since the R value (i.e. 0.988) is close to 1.

4.3.2 Anaerobic baffled reactor (ABR) treating textile wastewater (TTWW)

NARX known for high accuracy in prediction purposes showed poor performance in the prediction of the effluent COD concentration of textile wastewater biologically treated with an EGSB reactor. This is evident in Table 4.6 which shows the statistical performance of NARX. The network could only predict the effluent COD concentration with an overall R value of 0.838 and a network architecture consisting of 3 layers (i.e. input, hidden and output layers) with 3 neurons in the hidden layer. The network having a low number of neurons could not differentiate complex patterns which then resulted in a linear estimate of the trend (Göçken *et al*., 2016). The network performed poorly with an MSE of 0.303 which means it did not generalise well and will not be able to accurately predict effluent COD concentration when provided with a new data set for training, validation and testing (Willemink *et al*., 2020). The negative R coefficient of the testing data set indicates the network extrapolated. This could be solved by providing more data for training and validation (Jiang *et al*., 2019; Hagan *et al*., 1997).

Table 4.6: Performance statistics of effluent COD prediction (NARX ANN model for TTWW)

Number of neurons	$\mathbf{MSE}$	Training $\boldsymbol{R}$	Testing $\boldsymbol{R}$	Validation $\boldsymbol{R}$	All $\boldsymbol{R}$
3	0.30298	0.849	0.954	0.749	0.838
5	0.47617	0.934	-0.747	0.936	0.756
7	0.79691	0.999	-0.514	0.944	0.586
9	0.57534	0.936	-0.813	0.843	0.677

Figure 4.10 represents the relationship between target and predicted effluent COD concentration data. As mentioned before the data quality obtained from a previous unpublished study of the biological treatment of TTWW with an EGSB was poor which resulted in poor network performance.

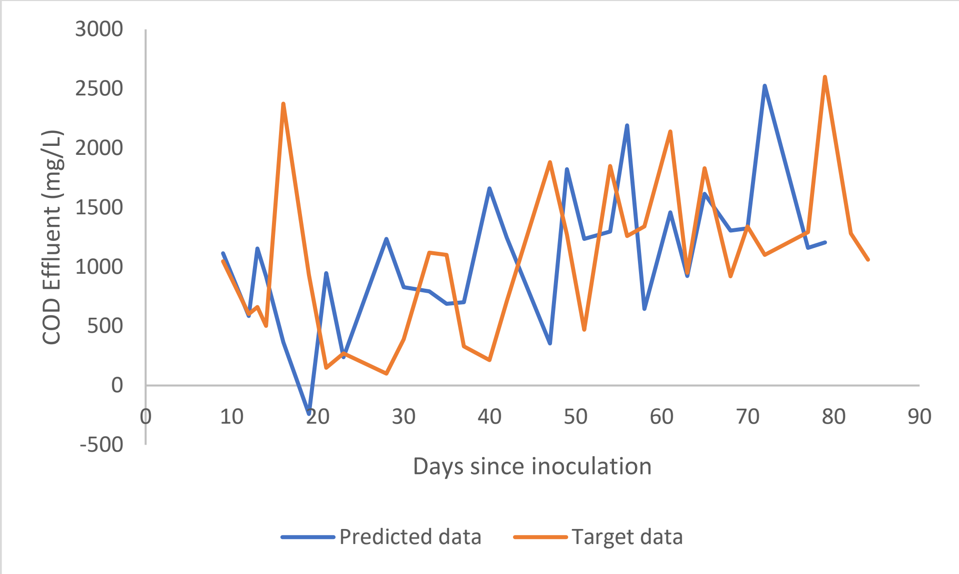

Figure 4.10: Comparison between the target and predicted effluent COD concentration (NARX ANN model for TTWW)

4.3.3 Expanded granular sludge bed (EGSB) reactor treating polymer wastewater (PWW)

Figure 4.11 represents the relationship between the target and predicted effluent COD concentration from the NARX neural network model. Figure 4.11 shows an accurate prediction of the effluent COD when compared to the target effluent COD concentration obtained from a previous unpublished study, this is supported by the statistical performance analysis of NARX in Table 4.7.

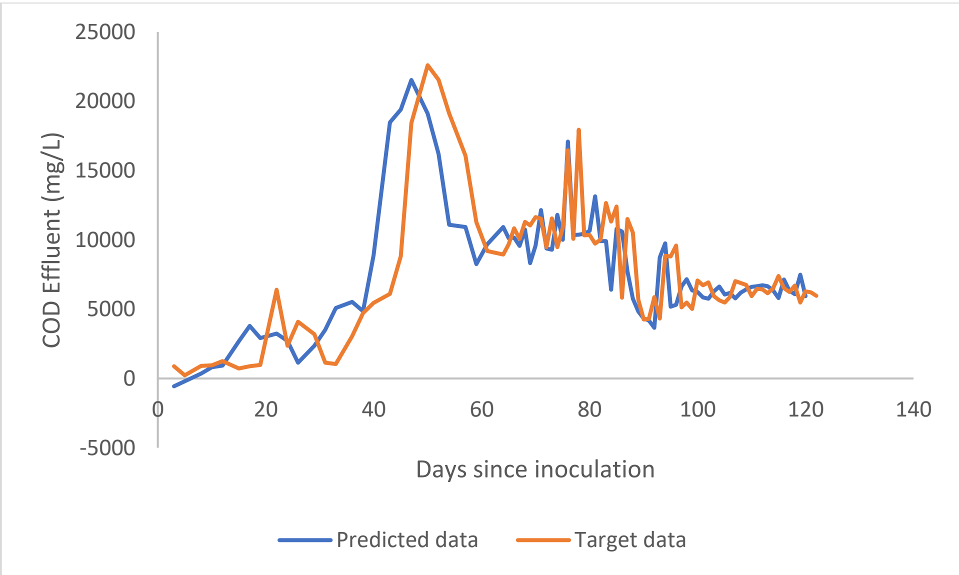

Figure 4.11: Comparison between the target and predicted effluent COD for PWW (NARX ANN model for PWW)

The trial-and-error method (Patki *et al*., 2021) by changing the number of neurons in the hidden layer to range from 3 to 9 neurons was applied in order to determine which network architecture would give optimum network performance and the highest accuracy in predicting the COD concentration of the PWW effluent. The best performance was recorded with 9 neurons in the hidden layer with an R value of 0.964 and an MSE of 0.0719 (refer to Table 4.7). Based on the statistical performance in Table 4.7, the training and testing subsets could accurately predict the COD concentration of the PWW effluent with the R value ranging from 0.942 to 0.982 and 0.924 to 0.946, respectively, for training and testing of the NARX network. An increase in the number of neurons in the hidden layer resulted in the optimum prediction and best network performance although it may cause overfitting of the network. The data set also shows good validation with R values ranging from 0.9 to 0.932. It may therefore be concluded that the NARX network will show high accuracy when presented with new sets of data. This indicates superior network performance. Based on Figure C.4 in Appendix C, the regression graph shows sufficient results, with almost all the data points falling within the regression line.

Table 4.7: Performance statistics of effluent COD concentration prediction (NARX ANN model-for PWW)

Number of neurons	MSE	Training R	Testing R	Validation R	All R
3	0.13014	0.941	0.923	0.900	0.930
5	0.14246	0.940	0.909	0.902	0.924
7	0.14729	0.922	0.916	0.942	0.923
9	0.07187	0.981	0.946	0.931	0.963

4.3.4 Expanded granular sludge bed (EGSB) reactor treating pulp and paper wastewater (PPWW)

Comparison between the target (Sheldon *et al*., 2012) and predicted COD concentration of the effluent data for the biological treatment of PPWW with an EGSB is presented in Figure 4.12.

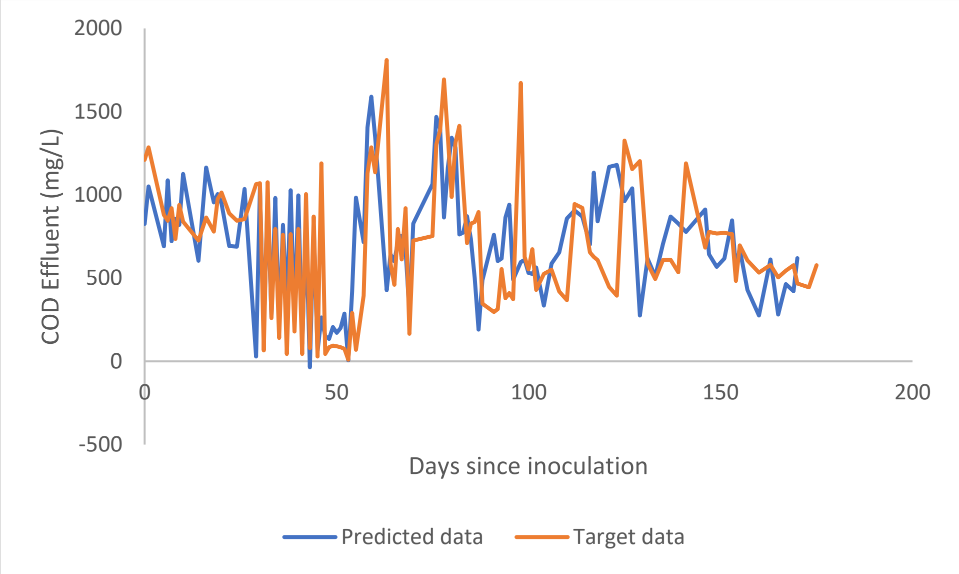

Figure 4.12: Comparison between the target and predicted effluent COD concentration for PPWW (NARX ANN model for PPWW)

Table 4.8 shows the statistical performance (i.e. prediction accuracy and network performance) of the NARX network for predicting the COD concentration of effluent produced from the treatment of PPWW with an EGSB. After the trial-and-error method (Patki *et al*., 2021) was used to determine the optimum network architecture for network performance and COD prediction, it is evident from Table 4.8 that the NARX network performed better with 5 neurons as indicated by an MSE of 0.343 and R value of 0.809. The training data set shows high accuracy with the correlation coefficient ranging from 0.801 to 0.928 but shows poor testing with the correlation coefficient ranging from 0.173 to 0.663 for the different number of neurons in the hidden layer. This is due to too many data points not falling within the regression line as presented in Figure D.1 in Appendix D. According to Saleh (2021) network overfitting occurred and therefore good generalisation will not occur when presented with new data sets. Based on Table 4.8, the NARX network also seems to have extrapolated, because it shows good training and validation (i.e. the correlation coefficient ranges from 0.334 to 0.833) results but poor testing data results with regard to the coefficient of determination R^2.

Table 4.8: Performance statistics of effluent COD prediction (NARX ANN model for PPWW)

Number of neurons	MSE	Training R	Testing R	Validation R	All R
3	0.48363	0.800	0.172	0.832	0.719
5	0.34288	0.839	0.651	0.876	0.809
7	0.37011	0.836	0.662	0.830	0.799
9	0.54379	0.927	0.284	0.334	0.683

4.4 Network 3: Cascade feedforward backpropagation (CFBP)

4.4.1 Anaerobic baffled reactor (ABR) treating biodiesel wastewater (BDWW)

The cascade forward backpropagation (CFBP) network model architecture was developed as the third ANN model for the prediction of the COD concentration of effluent from historical biological wastewater treatment data sets (Grobbelaar, 2019). The training function, learning function (i.e. supervised learning) and performance function were selected to be *TRAINLM*, *LEARNGDM* and MSE, respectively. Figure 4.13 represents the relationship between the target and predicted COD concentration of the effluent and shows good correspondence between the predicted and target data sets.

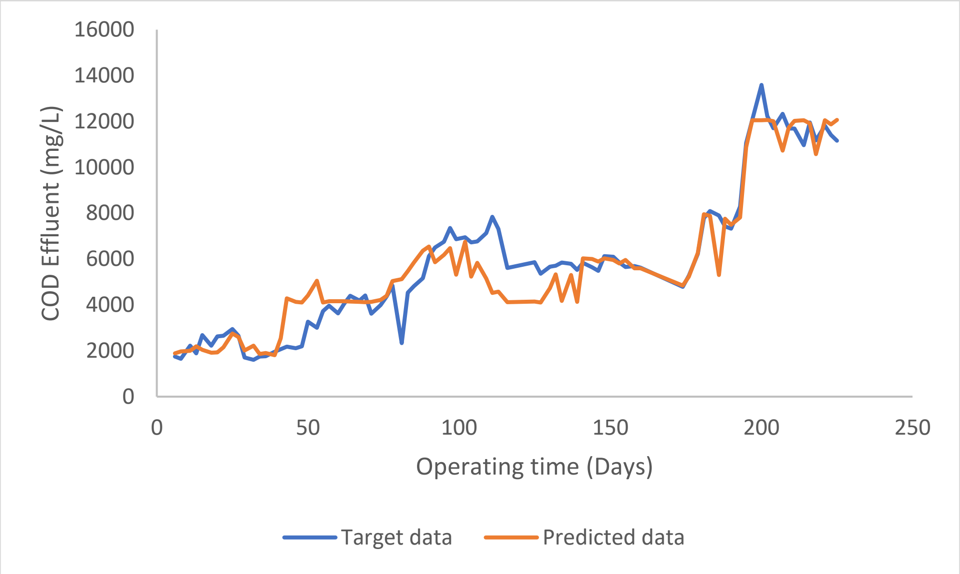

Figure 4.13: Comparison between the target and predicted effluent COD concentration for BDWW treated with an ABR (CFBP ANN model)

Table 4.9 shows the statistical performance of the CFBP network trained using different numbers of neurons in the hidden layer. The network shows a fluctuating or rather deficient performance as the number of neurons increases. An acceptable network performance was achieved when the network was trained, validated and tested with 11 neurons in the hidden layer with an MSE of 0.1024. The R value was found to be 0.947 as recorded in Table 4.9 which indicates high accuracy and a good overall fit. This is supported by the regression graph in Figure A.9 of Appendix A which shows a sufficient number of data points falling within the linear regression line with minimal outliers.

Table 4.9: Performance statistics of effluent COD prediction (CFBP ANN model for BDWW)

Number of neurons	$\mathbf{MSE}$	Training $\boldsymbol{R}$	Testing $\boldsymbol{R}$	Validation $\boldsymbol{R}$	All $\boldsymbol{R}$
3	0.11270	0.934	0.952	0.965	0.941
5	0.10634	0.935	0.962	0.981	0.945
7	0.1226	0.933	0.942	0.947	0.936
9	0.15428	0.936	0.946	0.957	0.938
11	0.10237	0.958	0.922	0.941	0.947

Figure A.9 in Appendix A represents the regression graphs for the three subsets, namely training, validation and testing. The difference in R values between the subsets means network overfitting or extrapolation. The training regression with the correlation coefficient (R) ranging from 0.934 to 0.958 shows accurate prediction with minimum variation as few data points are outliers. The validation and testing regression graphs with R values ranging from 0.941 to 0.982 and 0.922 to 0.963, respectively show a high correspondence between the target and predicted effluent COD concentration data. The CFBP network showed high accuracy, but poor network performance with an MSE ranging from 0.1024 to 0.1543. It can therefore be concluded that the CFBP network would result in acceptable generalisation when presented with new feed (i.e. wastewater influent) COD data sets.

4.4.2 Anaerobic baffled reactor (ABR) treating textile wastewater (TTWW)

The quality and quantity of the historical data used in ANNs has a huge effect on successful network model development (Platon *et al*., 2015). The poor quality of the TTWW historical data available for developing the CFBP network resulted in poor model accuracy and network performance. Figure 4.14 illustrates the poor correspondence between the target and predicted effluent COD data supporting the statement by Platon *et al*. (2015).

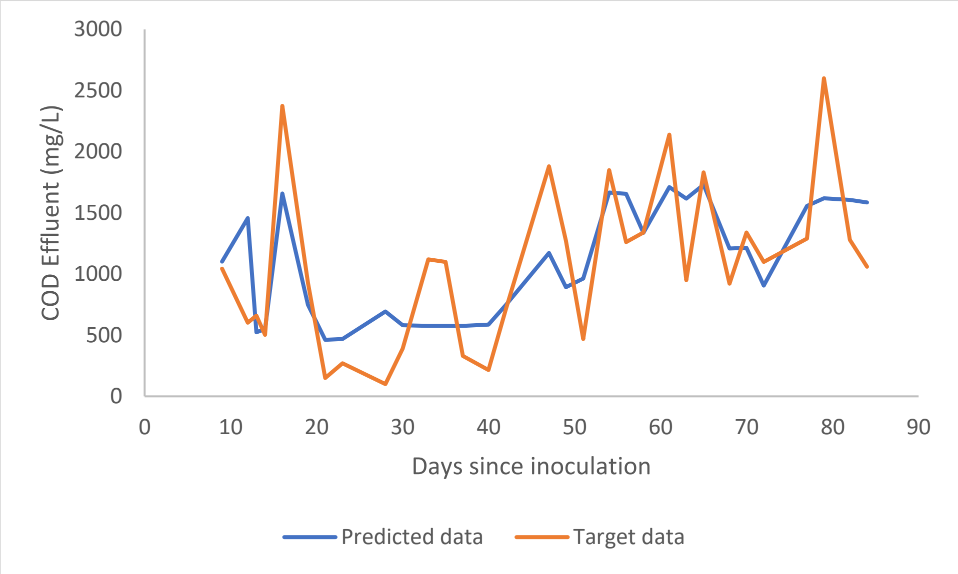

Figure 4.14: Comparison between the target and predicted effluent COD for TTWW treated with an ABR (CFBP ANN model for TTWW)

After the trial-and-error method (Patki *et al*., 2021) to identify which CFBP network architecture would result in optimum model accuracy, the statistical performance of CFBP model in Table 4.10 indicates that the CFBP network would predict best when the network architecture consists of 5 neurons with an MSE of 0.444 and R value of 0.736. All the results recorded for training, testing and validation are poor with correlation coefficient values ranging from 0.663 to 0.814, 0.532 to 0.849 and 0.290 to 0.989, respectively. As seen in Figure B.6 of Appendix B showing the regression graphs for testing, training and validation, too many data points fall outside the linear graph and are regarded as outliers.

Table 4.10: Performance statistics of effluent COD prediction (CFBP ANN model for TTWW)

Number of neurons	MSE	Training R	Testing R	Validation R	All R
3	0.65272	0.663	0.531	0.639	0.627
5	0.44396	0.746	0.385	0.988	0.736
7	0.50376	0.747	0.620	0.816	0.713
9	0.45113	0.814	0.848	0.290	0.751
11	0.44555	0.758	0.741	0.703	0.747

4.4.3 Expanded granular sludge bed (EGSB) reactor treating polymer wastewater (PWW)

Figure 4.15 shows the relationship between the target and predicted effluent COD for PWW treated with an ABR. With good quality data, the network was able to relate the predicted effluent COD data to the target effluent COD data.

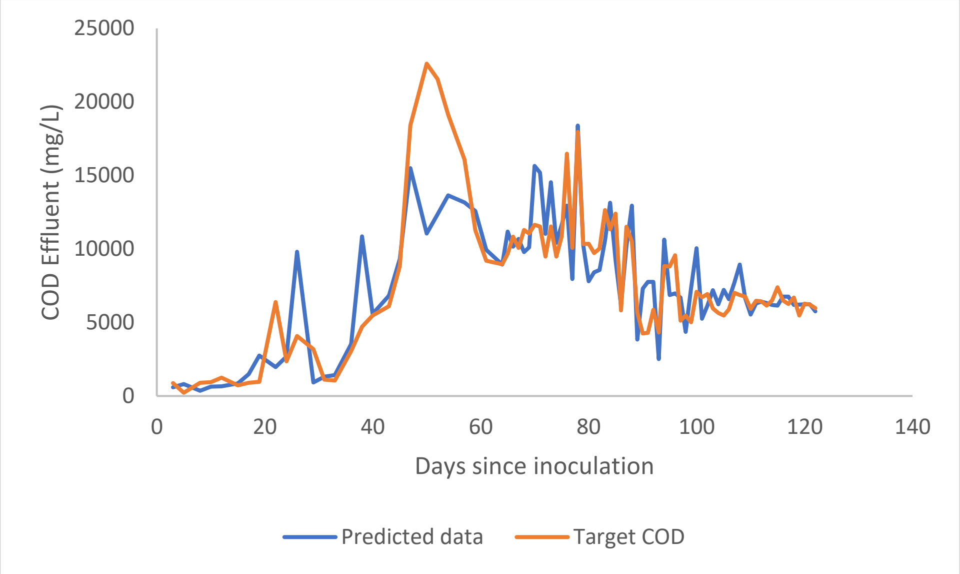

Figure 4.15: Comparison between the target and predicted effluent COD for PWW treated with an ABR (CFBP ANN model for PWW)

Based on Table 4.11, showing the statistical performance analysis of CFBP network, the network was able to accurately predict the COD concentration of the PWW effluent. After the trial-and-error method (Patki *et al*., 2021) was used to determine the appropriate number of neurons in the hidden layer, a CFBP network architecture consisting of 9 neurons in the hidden layer was identified. Table 4.11 shows the training, validation and testing R values ranging from 0.737 to 0.827, 0.799 to 0.917 and 0.740 to 0.962, respectively. Increasing of the number of neurons in the hidden layer resulted in high network prediction with a correlation coefficient of 0.837 and an MSE of 0.297 between the target and predicted effluent COD data. The CFBP network shows poor generalisation for untrained data due to too neurons in the hidden layer (Göçken *et al*., 2016). Based on Figure C.7 in Appendix C, the CFBP network accurately predicted the COD concentration of the PWW effluent, but due to the poor performance represented by the MSE ranging from 0.297 to 0.364 in Table 4.11, the network did not generalise well and will continue to perform poorly when presented with new wastewater data sets.

Table 4.11: Performance statistics of effluent COD prediction (CFBP ANN model for PWW)

Number of neurons	**MSE**	**Training R**	**Testing R**	**Validation R**	**All R**
3	0.35956	0.737	0.961	0.798	0.797
5	0.36400	0.781	0.740	0.947	0.796
7	0.31611	0.826	0.830	0.864	0.828
9	0.29693	0.827	0.903	0.819	0.837
11	0.32650	0.815	0.850	0.917	0.821

4.4.4 Expanded granular sludge bed (EGSB) reactor treating pulp and paper wastewater (PPWW)

As observed in Figure 4.16 representing the relationship between the target (Sheldon *et al*., 2012) and predicted COD effluent concentration data of the treatment of PPWW with an EGSB reactor, the CFBP network did not perform well and shows poor effluent COD prediction.

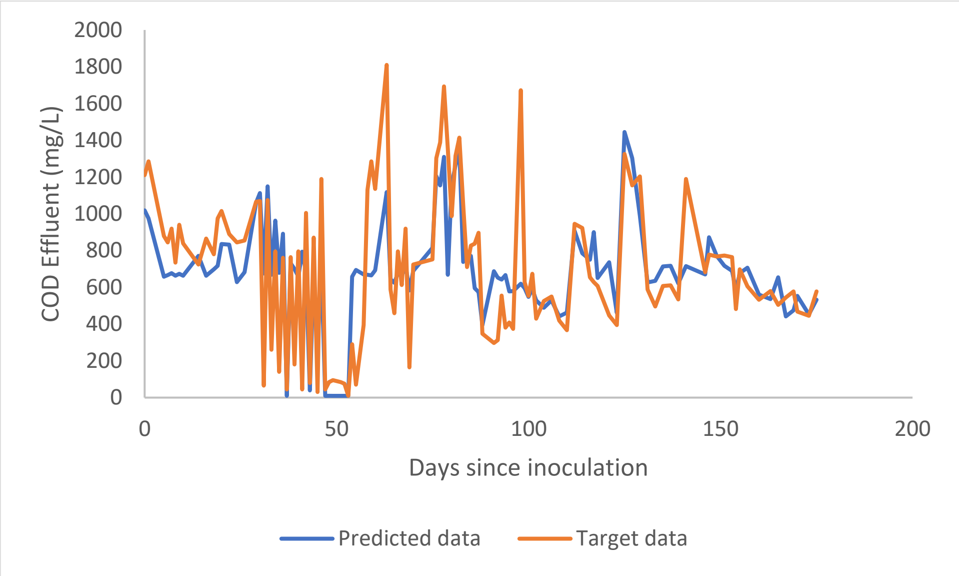

Figure 4.16: Comparison between the target and predicted effluent COD concentration of PPWW treated with an EGSB reactor (CFBP ANN model)

Increasing the number of neurons in the hidden layer did not affect the CFBP network performance, although better network performance is observed when the CFBP network was developed with 5 neurons in the hidden layer as shown in Table 4.12. The MSE was found to be 0.453 with an overall correlation coefficient (R) of 0.739, a training R value of 0.723, validation R value of 0714 and testing R value of 0.893. All results which include the training, validation and testing data sets show poor network accuracy, this may be due to the smaller number of hidden layers as changing the number of neurons in the hidden layer showed almost no effect on the MSE and R values. As seen in Figure D.7 of Appendix D the regression graphs for testing, training and validation have too many data points falling outside the linear graph and are therefore regarded as outliers.

Table 4.12: Performance statistics of effluent COD prediction (CFBP ANN model for PPWW)

Number of neurons	MSE	Training R	Testing R	Validation R	All R
3	0.50450	0.737	0.702	0.710	0.702
5	0.45267	0.722	0.893	0.714	0.739
7	0.50425	0.729	0.694	0.674	0.702
9	0.45393	0.788	0.530	0.722	0.736
11	0.45666	0.708	0.777	0.876	0.734

4.5 Summary

4.5.1 Anaerobic baffled reactor (ABR) treating biodiesel wastewater (BDWW)

When comparing the predicted COD concentration of the effluent from the FFB, NARX and CFBP artificial neural network models Figure 4.17 shows that all the network models were able to accurately predict the COD concentration of the effluent as the output data points lie close to that of the COD concentration of the target data. It was observed that the NARX network model performed better for BDWW biological treatment when compared to the FFB and CFBP network models for BDWW treatment with an ABR system. Figure 4.17 shows the NARX network model's predicted COD output data points are located close to the effluent COD target (i.e. product COD) data points obtained from a previous published study (Grobbelaar, 2019).

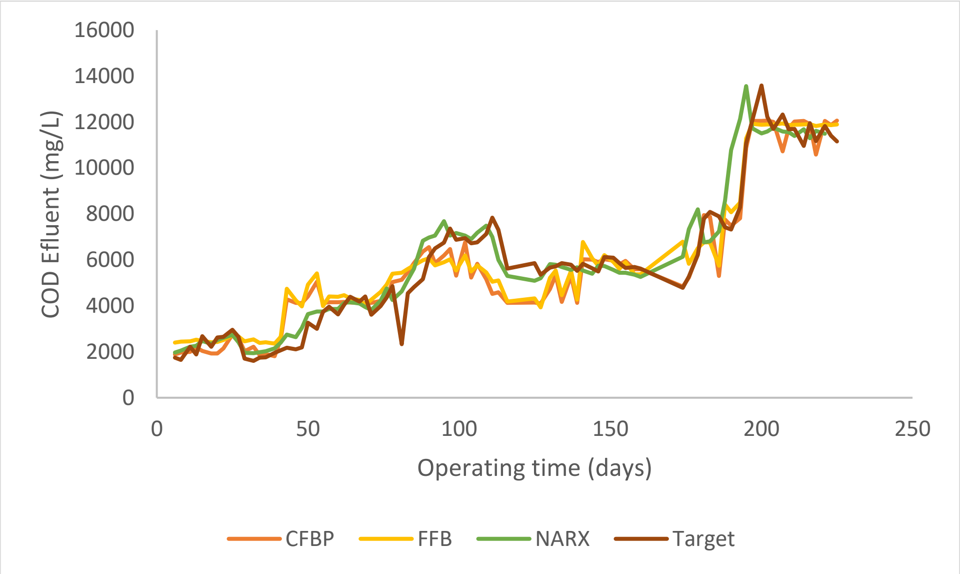

Figure 4.17: Target effluent COD data and predicted effluent COD data associated with the cascade feedforward backpropagation (CFBP), feedforward backpropagation (FFB) and nonlinear autoregressive neural network with exogenous inputs (NARX) network models for BDWW treatment with an ABR system

Table 4.13 shows a summary of the statistical performance of the FFB, NARX and CFBP network models. All three network models show an acceptable network performance in relation to the accurate prediction of effluent COD output, although there is a difference observed in network performance with regards to the error between target and predicted effluent COD data. Comparing the three networks, NARX performed better at predicting the effluent COD output with an R value of 0.988 and MSE of 0.0239. The NARX network model is most likely to generalise well when presented with new input data (i.e. influent wastewater).

Table 4.13: Performance comparison between the feedforward backpropagation (FFB), nonlinear autoregressive neural network with exogenous inputs (NARX) and cascade feedforward backpropagation (CFBP) network models for the prediction of BDWW effluent COD concentration

Model performance	**FFB**	**NARX**	**CFBP**
MSE	0.10964	0.02396	0.10237
R	0.943	0.987	0.947

4.5.2 Anaerobic baffled reactor (ABR) treating textile wastewater (TTWW)

Figure 4.18 illustrates the comparison between the target effluent COD concentration of TTWW treated by an ABR system and the effluent COD concentration data as predicted by the FFB, NARX and CFBP neural networks. Poor prediction and network performance, is observed in Figure 4.18 although, based on the statistical performance in Table 4.14, the NARX network seems to have been able to mimic the behaviour/trend of the target COD effluent concentration data. The NARX network performed and predicted the COD concentration of the TTWW effluent better when compared to the FFB and CFBP networks with an R value of 0.838 and an MSE of 0.303. As mentioned before, the poor network performances were attributed to the poor quality and quantity of the historical data used to train the networks which led to poor network generalisation.

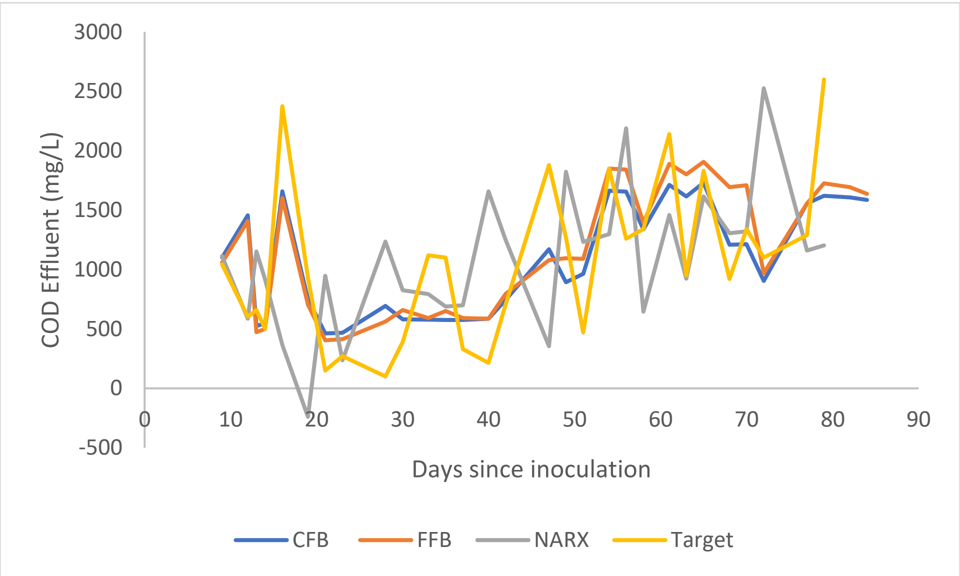

Figure 4.18: Target effluent COD data and predicted effluent COD data associated with FFB, NARX and CFBP for TTWW treated with an ABR system

Table 4.14: Performance comparison between the FFB, NARX and CFBP network models for predicting the COD concentration of TTWW effluent

Model performance	FFB	NARX	CFBP
MSE	0.50547	0.30298	0.44396
R	0.713	0.838	0.736

4.5.3 Expanded granular sludge bed (EGSB) reactor treating polymer wastewater (PWW)

Figure 4.19 represents the graphs comparing the target effluent COD concentration for PWW treated with an EGSB reactor to the predicted effluent COD concentration by the FFB, NARX and CFBP neural networks. Based on the statistical performance of the FFB, NARX and CFBP neural networks shown in Table 4.14, the NARX neural network performed better when compared to the FFB and CFBP neural networks with an MSE of 0.0719 and an R value of 0.964. Thus, indicating the NARX neural network is most likely to accurately predict the COD concentration of the PWW effluent when presented with a new set of data.

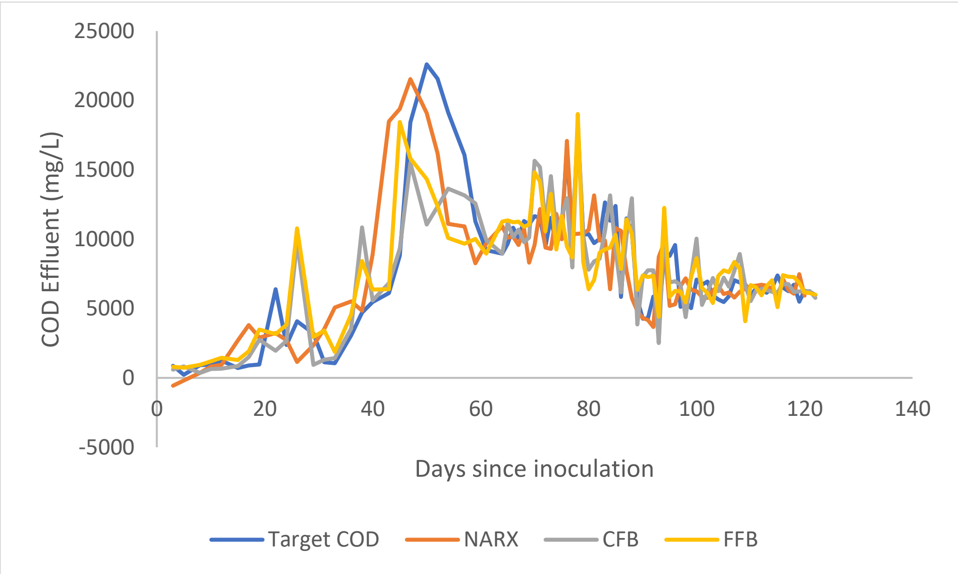

Figure 4.19: Target effluent COD data and predicted effluent COD data associated with the FFB, NARX and CFBP neural network models for PWW treated with an EGSB

Table 4.15: Performance comparison between the FFB, NARX and CFBP neural network models for predicting the effluent COD concentration of PWW

Model performance	FFB	NARX	CFBP
MSE	0.37542	0.07187	0.29693
R	0.816	0.963	0.837

4.5.4 Expanded granular sludge bed (EGSB) reactor treating pulp and paper wastewater (PPWW)

Figure 4.20 shows the FFB, NARX and CFBP neural network model prediction of the effluent COD concentration for PPWW treated using an EGSB reactor, as well as the target effluent COD concentration data set.

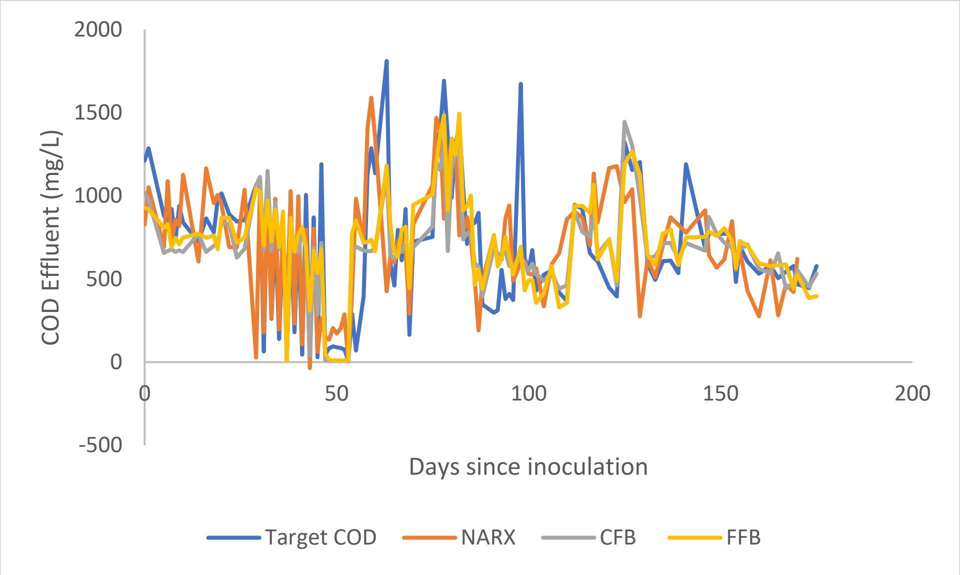

Figure.4.20: Target effluent COD data and predicted effluent COD data associated the FFB, NARX and CFBP neural network models for PPWW treated with an EGSB reactor

From Table 4.16 it may be concluded that the. NARX neural network model performed better compared to FFB and CFB neural network models with an MSE of 0.343 and with an R value of 0.809 has a higher prediction accuracy when compared to the other neural network models. Although the NARX neural network model may have accurately predicted the COD concentration of the PPWW effluent, is shows deficient performance which means it will most likely poorly predict effluent COD when presented with a new set of data.

Table 4.16: Performance comparison between feedforward backpropagation (FFB), cascade feedforward backpropagation (CFBP) and nonlinear autoregressive neural network with exogenous inputs (NARX) network models for the COD concentration of the PPWW effluent

Model performance	**FFBP**	**NARX**	**CFBP**
MSE	0.47215	0.34288	0.45267
R	0.725	0.809	0.739

Chapter 5: CONCLUSION AND RECOMMENDATION

5.1 Conclusions

Based on the results obtained in Chapter 4, artificial neural networks (ANNs) are a reliable modelling tool for successfully predicting the performance of biological wastewater treatment systems, as well as predicting the COD of the effluent. The prediction and network performance obtained was due to the correct selection of ANN input parameters COD and OLR since COD effluent is dependent on the organic loading rate (OLR). The results demonstrate that the quality and quantity of data strongly influence prediction and ANN performance. The quality of the training data constraints ANN model quality. The textile wastewater treatment data had fewer data points (i.e. poor), which resulted from missing data and the elimination of unpaired data points. This resulted in the inaccurate prediction of the effluent COD concentration and, therefore, poor network performance. Out of all three ANN models developed (i.e. FFB, NARX and CPFB), NARX showed high prediction accuracy for biological wastewater treatment systems. The COD treatment efficiency or output concentrations from all wastewater treatment types and systems had a significant influence in the three model performances, higher COD removal efficiency or output concentration resulted in high ANN model prediction and performance, vice versa. The type of wastewater and biological treatment did not have an impact on ANN model development.

5.1.1 How accurately can artificial neural networks (ANN) predict the performances of biological wastewater treatment systems?

Based on the statistical performance of the three ANNs developed; namely the autoregression neural network with exogenous input (NARX) ANN, the cascade feedforward backpropagation (CFBP) ANN and the feedforward backpropagation (FFB) ANN, for predicting the effluent COD of biodiesel- (BDWW), textile- (TTWW), polymer- (PWW) and pulp and paper wastewater (PPWW) following biological treatment, NARX predicted the effluent COD more accurately and performed better when compared to CFBP and FFB with Pearson correlation coefficient (R) values of 0.988, 0.838, 0.964 and 0.809, respectively and a mean square error (MSE) of 0.0239, 0.303, 0.0719 and 0.343, respectively. This means the network was able to generalise well with high predictive performance. Therefore, when presented with a new set of data NARX is most likely to generalise well, showing high prediction accuracy.

5.1.2 Does the type of wastewater biological treatment system impact the artificial neural network (ANN) model development?

When comparing both the four types of wastewater (i.e. BDWW, TTWW, PWW and PPWW) and the different biological treatment systems (i.e. anaerobic baffled reactor (ABR) and expanded granular sludge bed reactor (EGSB)), based on the ANN simulation results, correlation coefficient and MSE, it can be concluded that the ANN models were not influenced by the type of wastewater or the biological wastewater treatment technique. It was observed that the model performances and accuracy is mainly influenced by the quality and quantity of the data sets available for each biological wastewater treatment system. In conclusion ANNs can successfully predict biological wastewater treatment performance as long as the correct input parameters are selected, and the quality and quantity of the data sets are sufficient for the development of a model with high prediction accuracy. According to Nguyen *et al*. (2020) ANNs perform better, with a high prediction accuracy when created with a significant number of parameters compared to when the network was developed with only one or two input parameters.

Wastewater management is a crucial challenge in industries, these leads to (e.g. water and air contamination and soil erosion). The results obtained from the three ANN model performances shows accurate and cost-effective industrial wastewater management methods prior to discharge.

5.2 Recommendations

To improve and achieve high prediction accuracy and better ANN model performance, the following recommendations are suggested for further studies:

- Use large amounts of data sets for ANN model development preferably over 100 points to ensure better model performance.
- Use data pre-processing software such as Minitab statistical analysis to investigate missing data, outliers and the completeness of the raw data (Hassen & Asmare, 2018).
- For missing data, do not leave the cell blank rather:
    a) Replace the missing value with zero.
    b) Replace the missing value with the mean value obtained from the raw data set.
    c) Use multiple imputation procedures to estimate and predict the missing data value.
- Investigate the impact of the different training algorithms on ANNs for biological wastewater treatment systems such as the:

a) Bayesian regularisation (BR), and
b) The scaled conjugate gradient (SCG).

- Minimise network overfitting by using large training data points.
- Improve network generalisation by restricting the number of weights and neurons in the hidden layer.
- Stop the training in order to restrict the magnitude of the weights (i.e. early stopping).
- Use more input parameters that influence the effluent COD (Hamed *et al*., 2004).
- Use sensitivity analysis (SA) to investigate the relationship of each input parameter to the effluent and identify insignificant variables (Mrzygłód *et al*., 2020; Guinter *et al*., 2016).
- Identify and handle "noisy" data to improve model accuracy for future predictions (Gupta & Gupta, 2019).

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APPENDICES

Appendix A: ANN MATLAB® Figures

Biodiesel wastewater

A.1 FFB

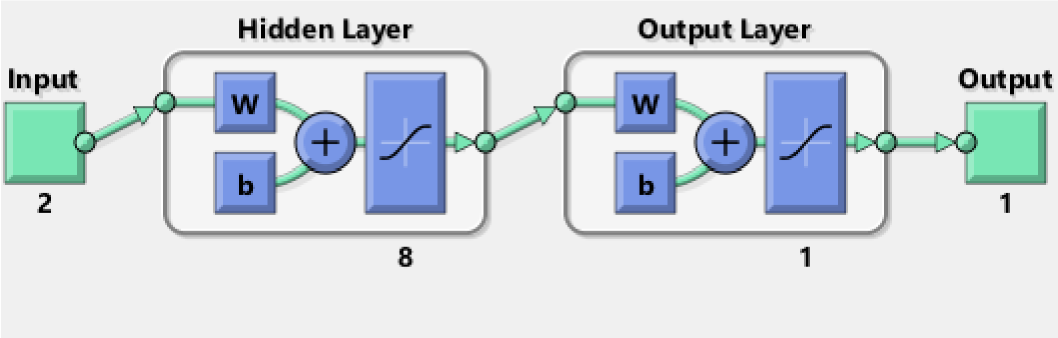

Figure A.1: FFB network architecture

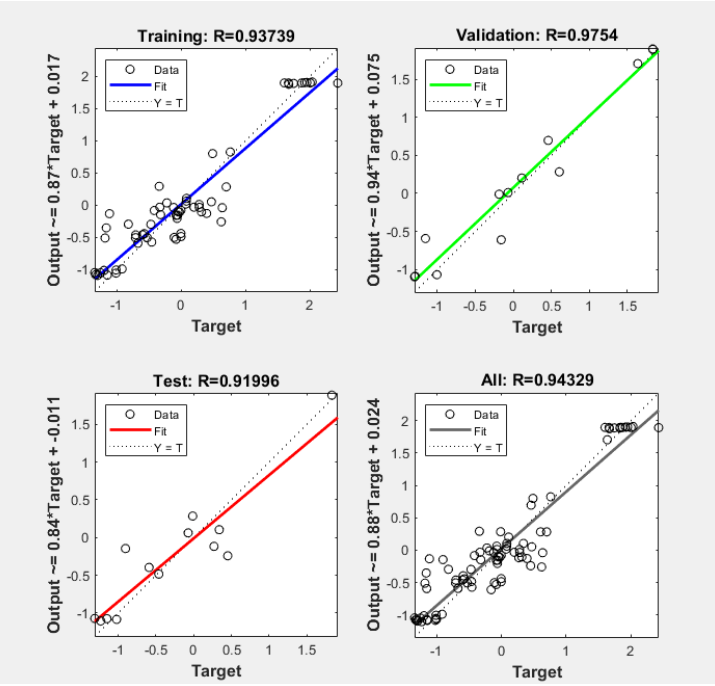

Figure A.2: Regression graph (BDWW)

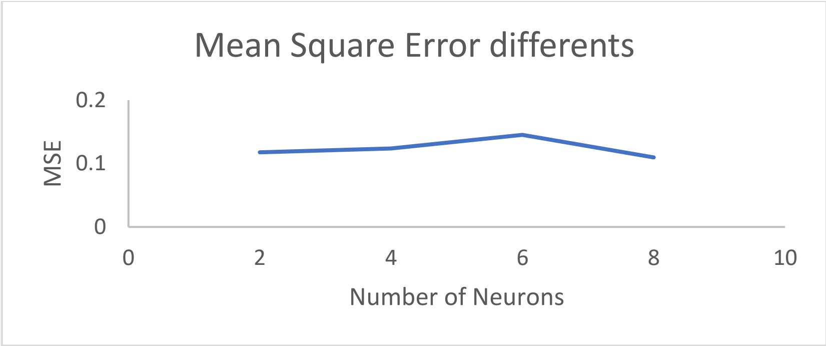

Figure A.3: Mean square error: FFB-BDWW

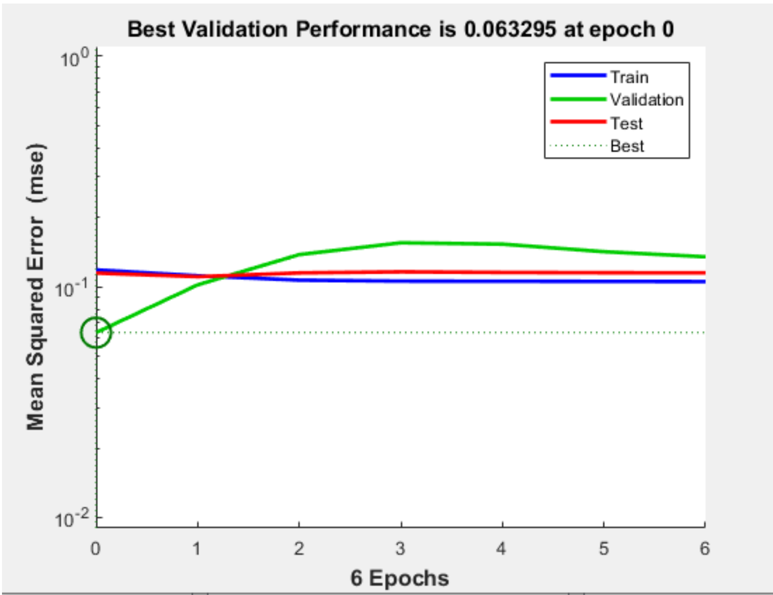

Figure A.4: Network performance (BDWW)

A.2 NARX

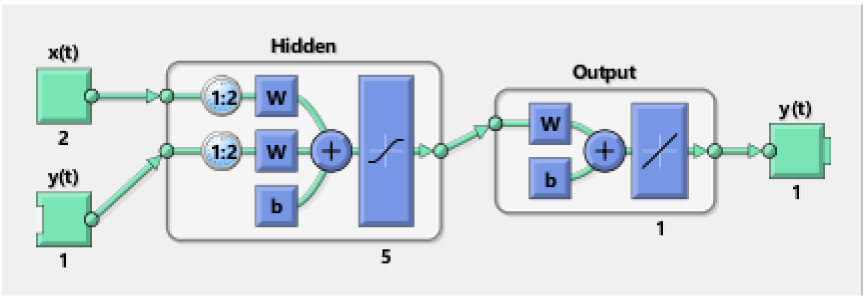

Figure A.5: NARX Network architecture

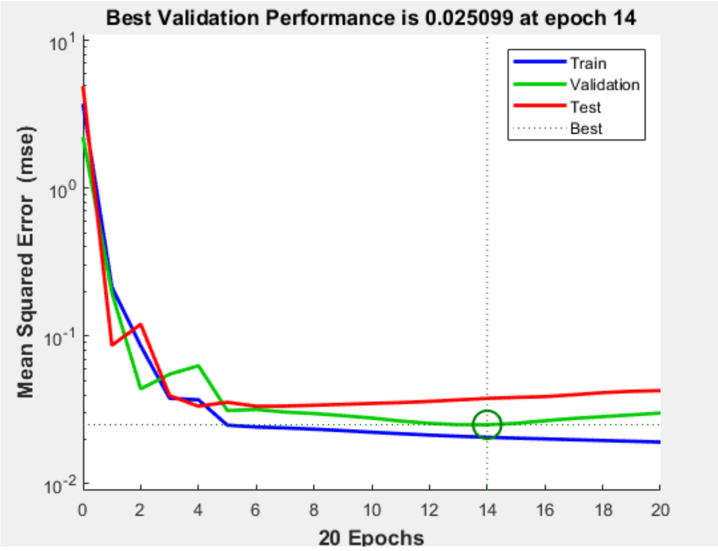

Figure A.6: Network performance (BBDW)

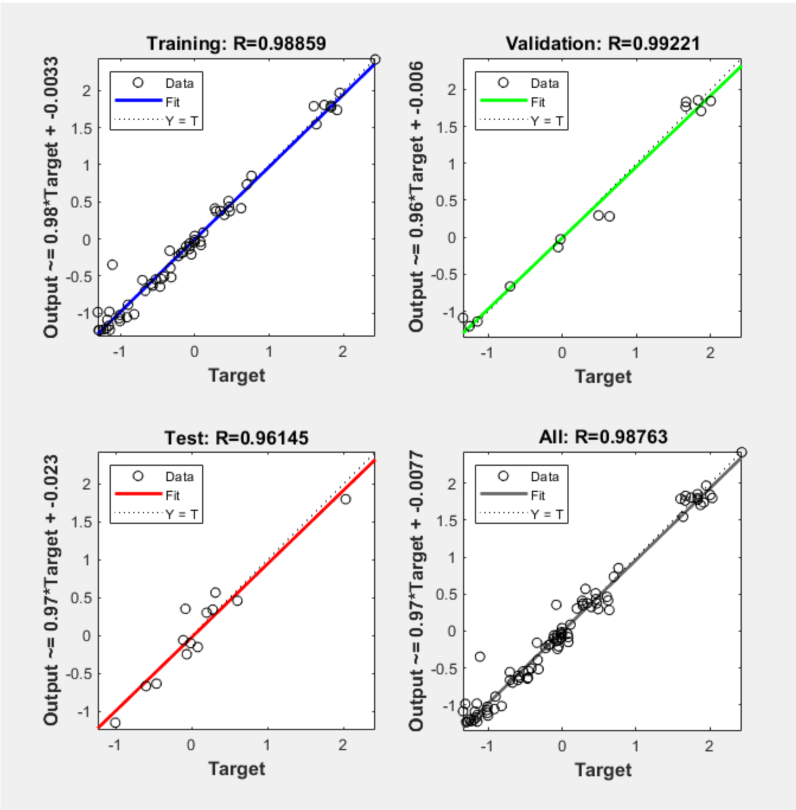

Figure A.7: Linear Regression graph (BDWW)

A.3 CFBP

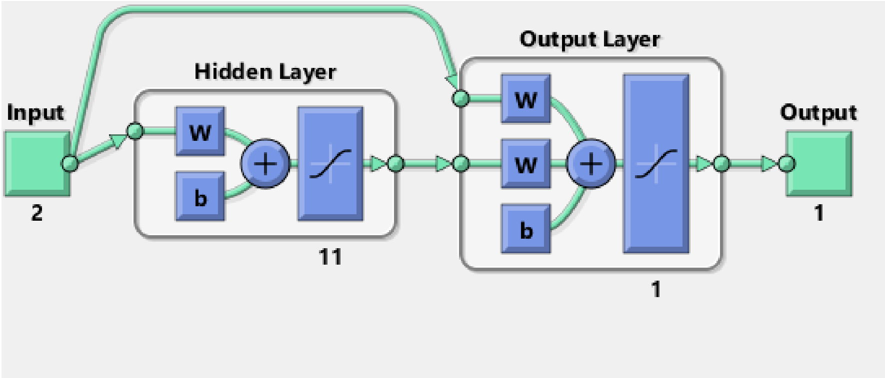

Figure A.8: CFBP Network architecture

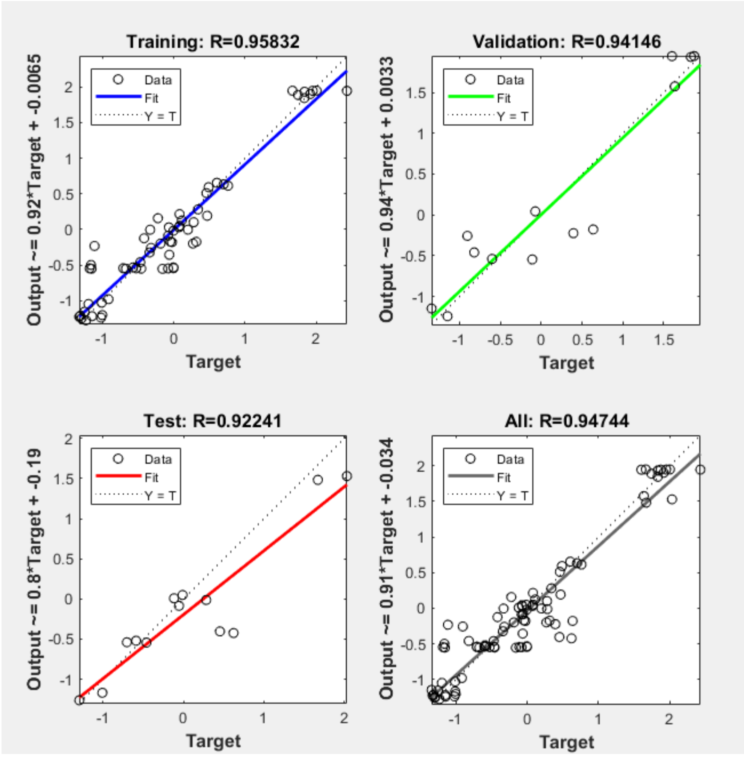

Figure A.9: Regression graph (BDWW)

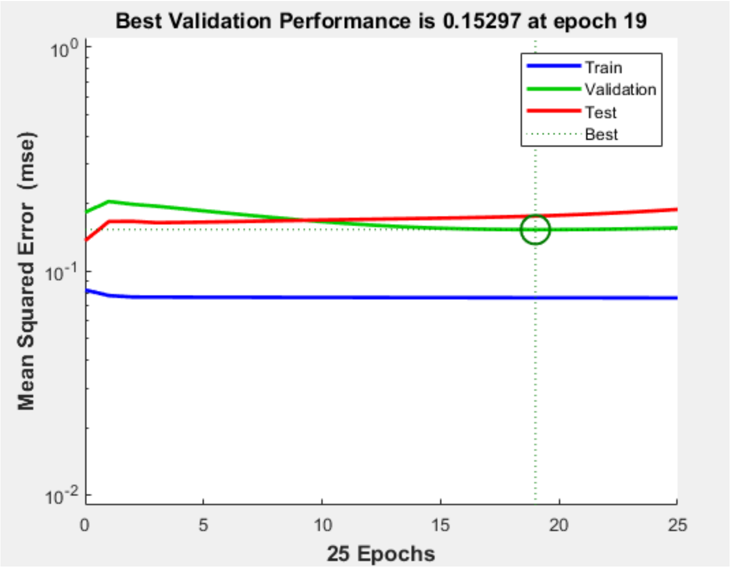

Figure A.10: Network performance (BDWW)

Appendix B: ANN MATLAB® Figures

Textile Wastewater

B.1 FFB

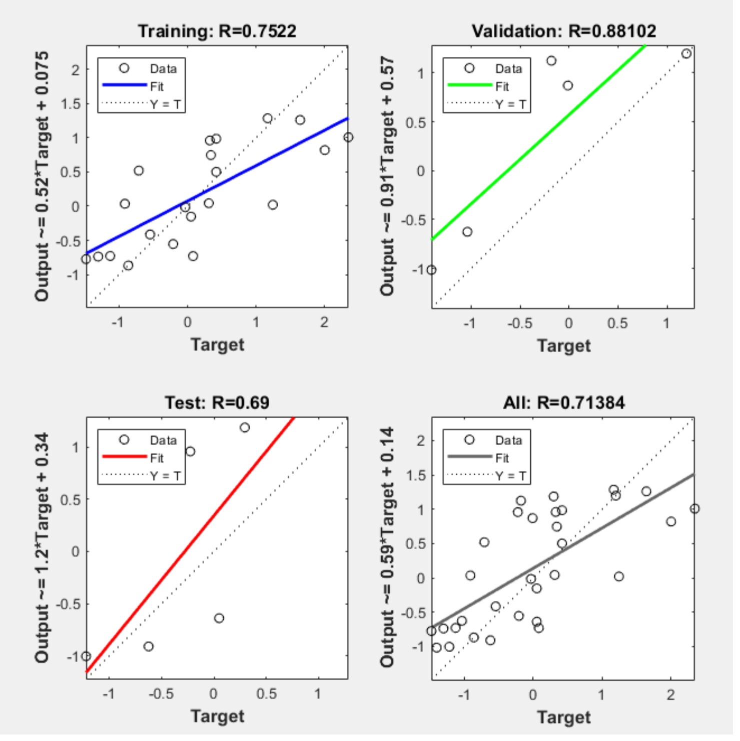

Figure B.1: Regression graph (Textile: FFB)

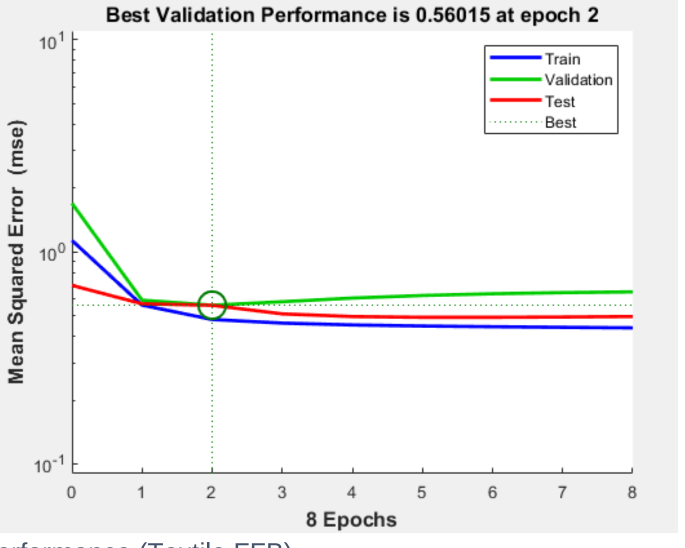

Figure B.2: Network Performance (Textile FFB)

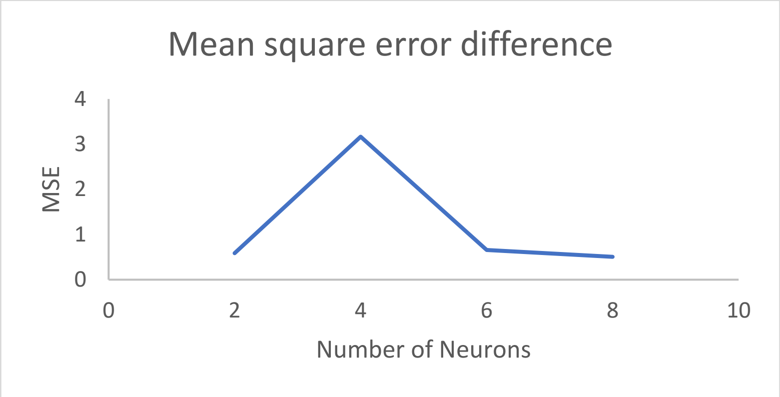

Figure B.3: Mean square error (FFBP ANN model-Textile WW)

B.2 NARX

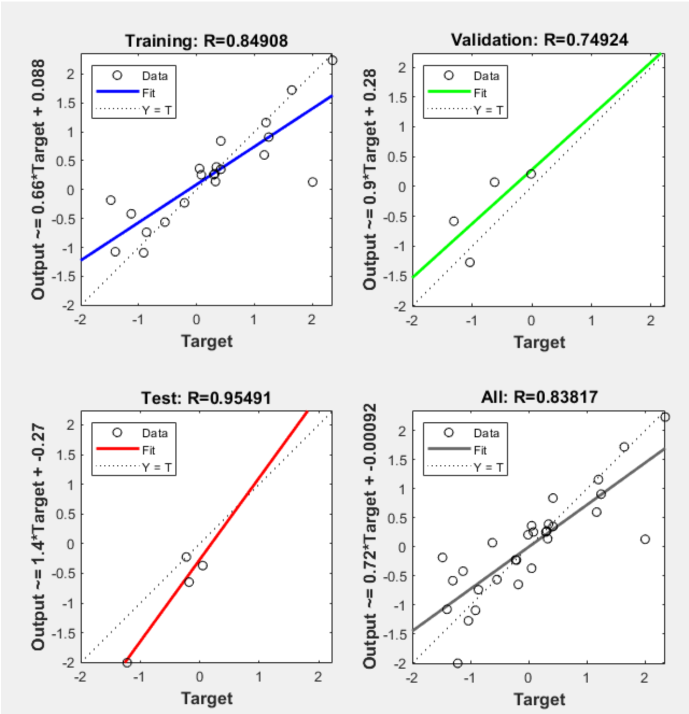

Figure B.4: Regression graph (Textile: NARX)

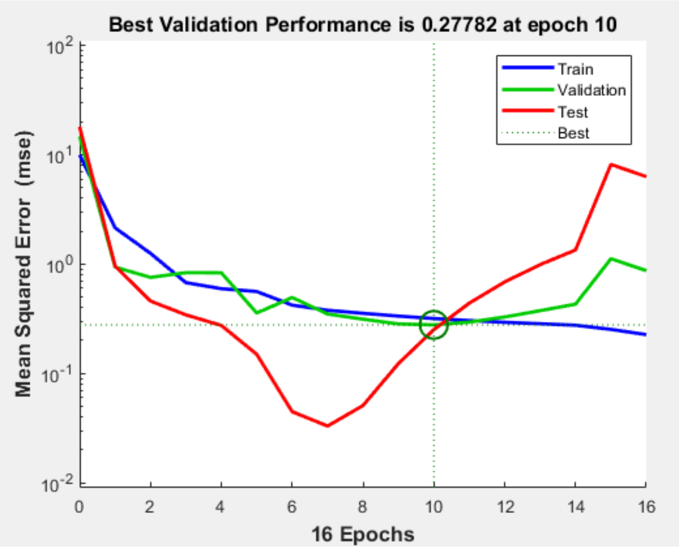

Figure B.5: Network Performance (Textile- NARX)

B.3 CFBP

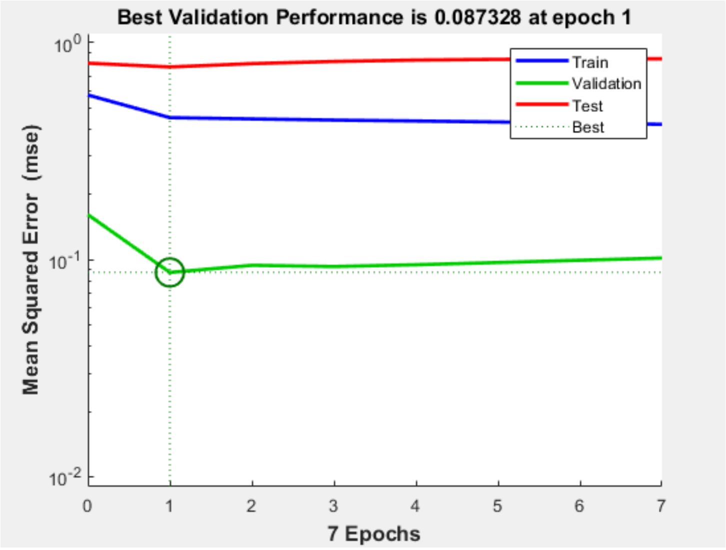

Figure B.6: Network Performance (Textile: CFBP ANN)

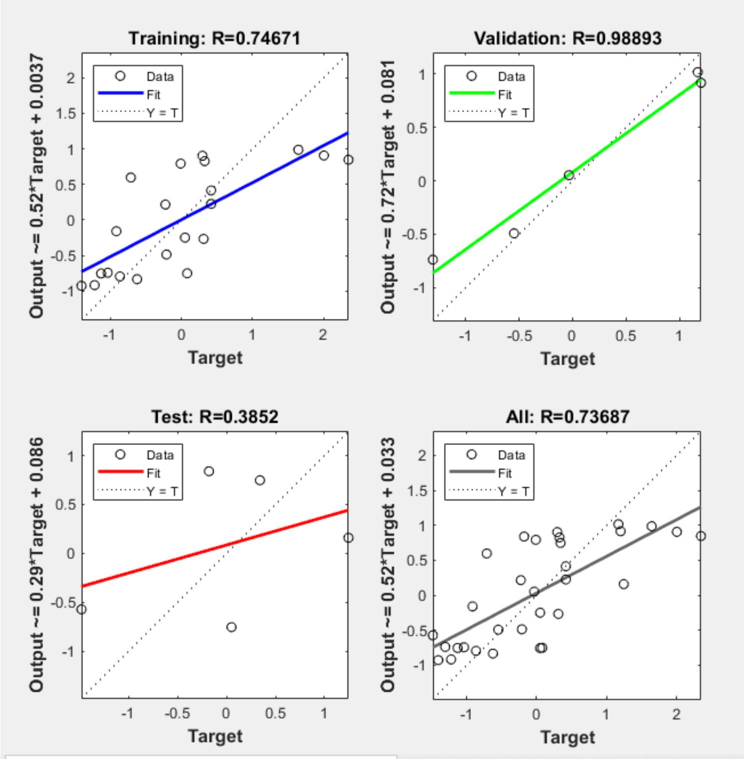

Figure B.7: Regression graph (Textile: CFBP ANN)

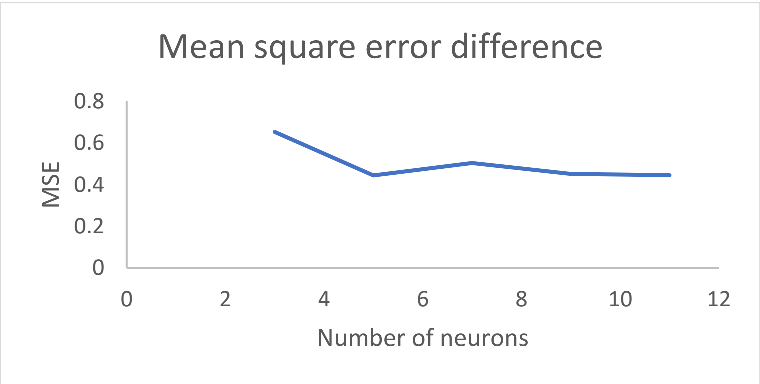

Figure B.8: Mean square error (CFBP ANN model-Textile)

Appendix C: ANN MATLAB® Figures

Polymer wastewater

C.1 Feedforward backpropagation

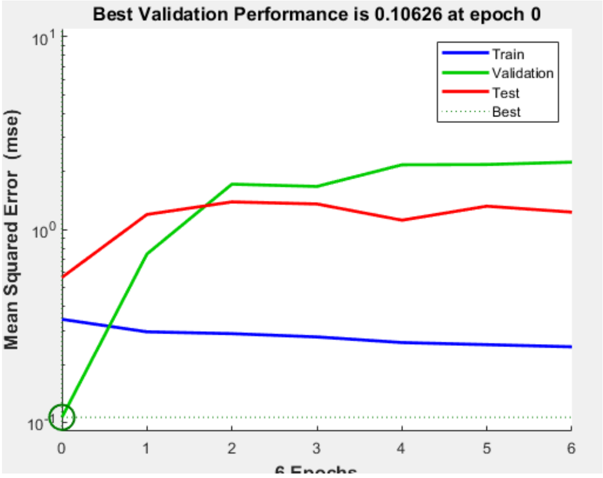

Figure C.1: Network Performance (Polymer: FFB ANN)

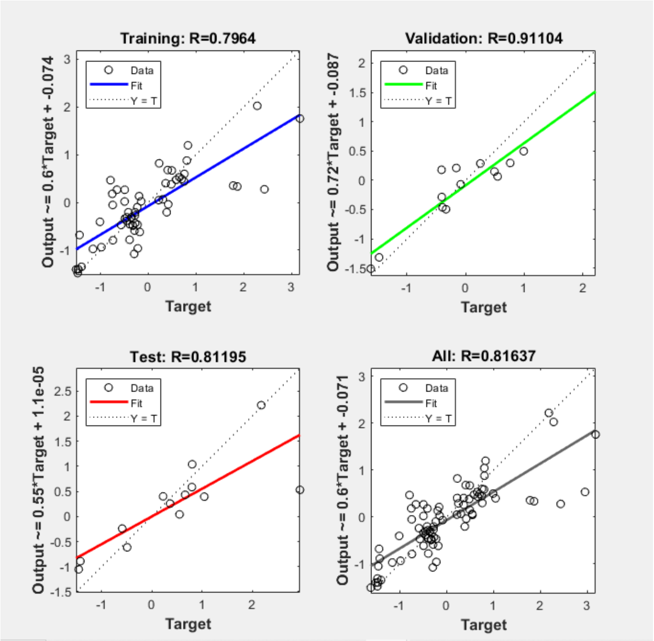

Figure C.2: Regression graph (Polymer: FFB ANN)

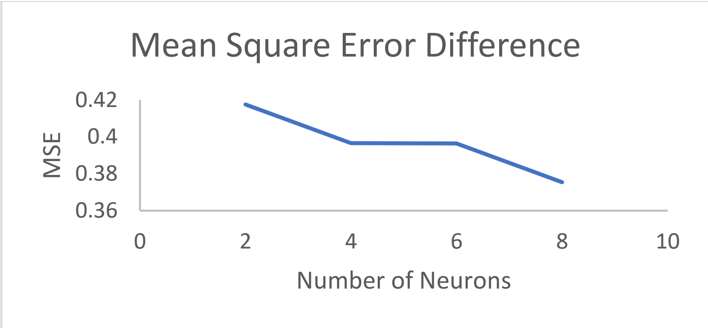

Figure C.3: Mean square error (FFBP ANN model-Polymer WW)

C.2 NARX

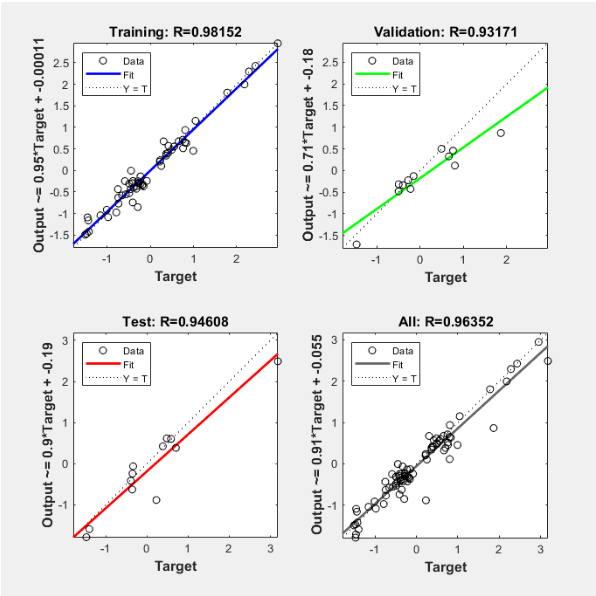

Figure C.4: Regression graph (Polymer: NARX ANN)

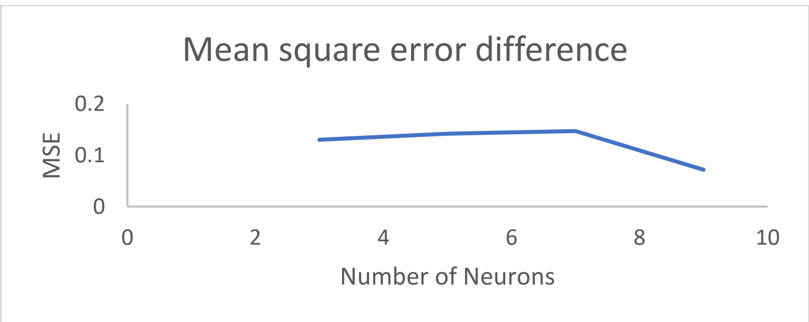

Figure C.5: Mean square error (NARX ANN model-Polymer WW)

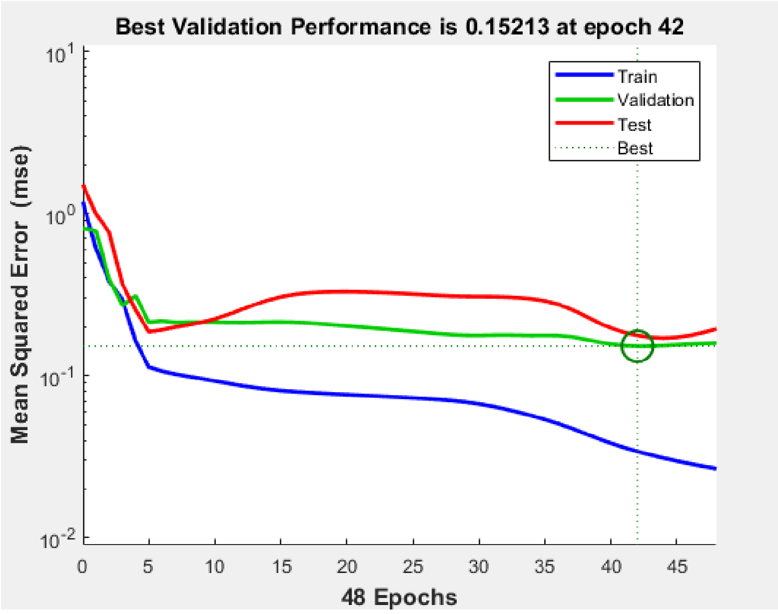

Figure C.6: Network Performance (Polymer WW: NARX ANN)

C.3 CFB

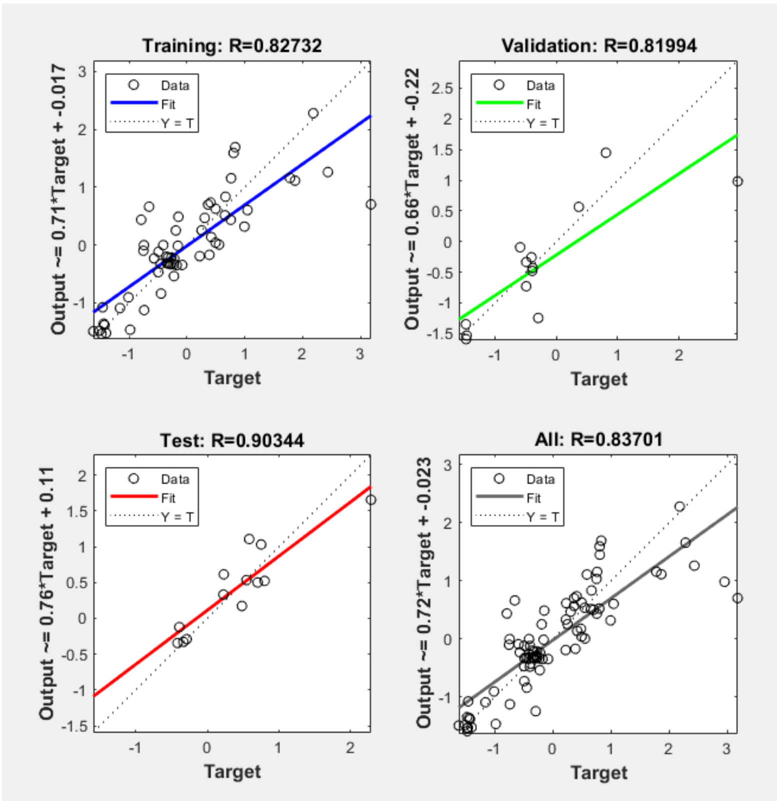

Figure C.7: Regression graph (Polymer WW: CFBP ANN)

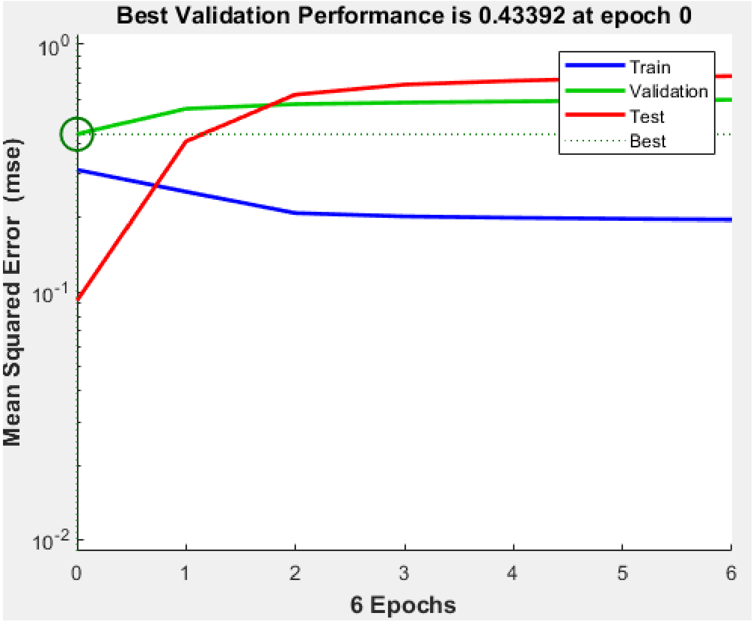

Figure C.8: Network Performance (Polymer: CFBP ANN)

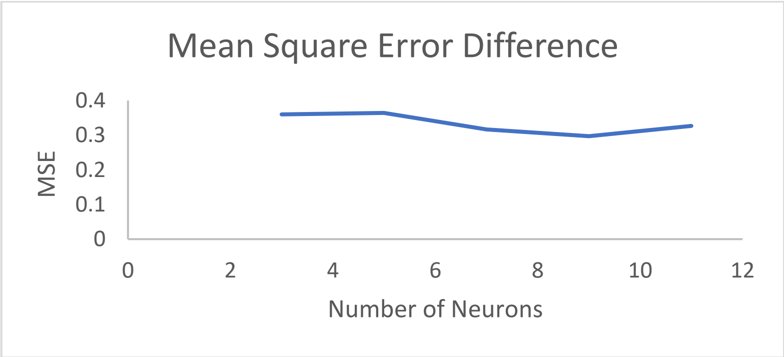

Figure C.9: Mean square error (CFBP ANN model-Polymer WW)

Appendix D: ANN MATLAB® Figures

Pulp and paper wastewater

D.1 Feedforward backpropagation

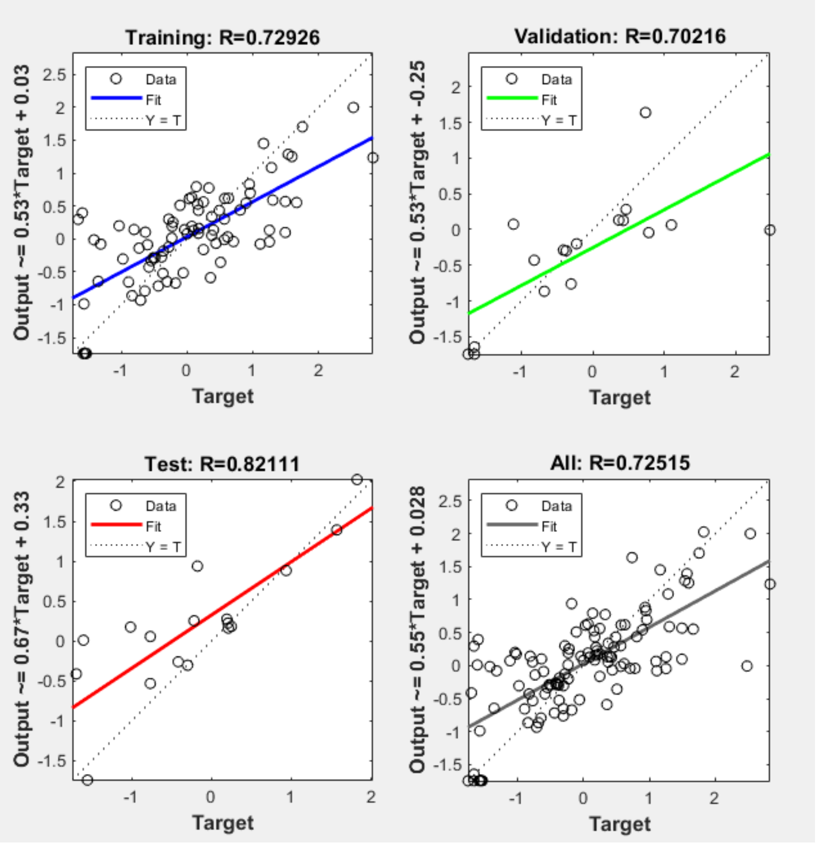

Figure D.1: Regression graph (Pulp and paper: FFB ANN)

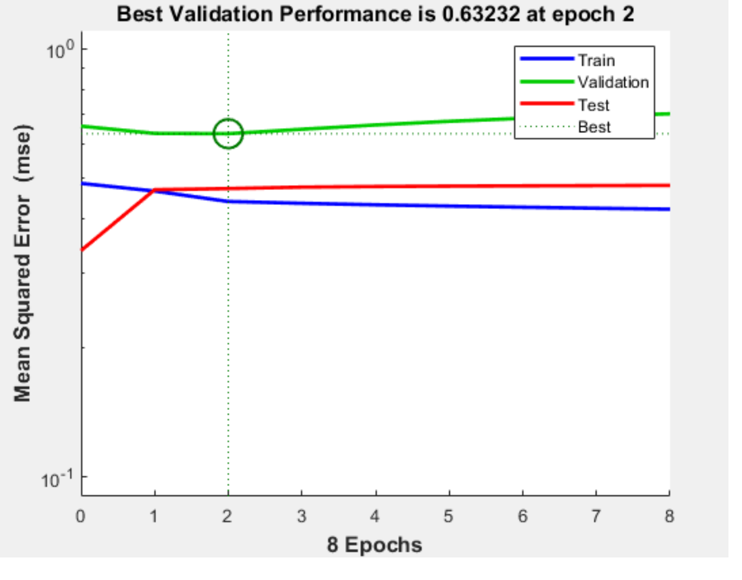

Figure D.2: Network Performance (Pulp and paper: FFB ANN)

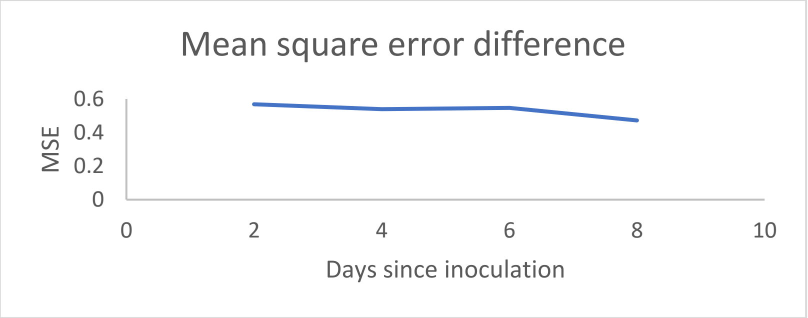

Figure D.3: Mean square error (FFB ANN model-Pulp and paper)

D.2 NARX

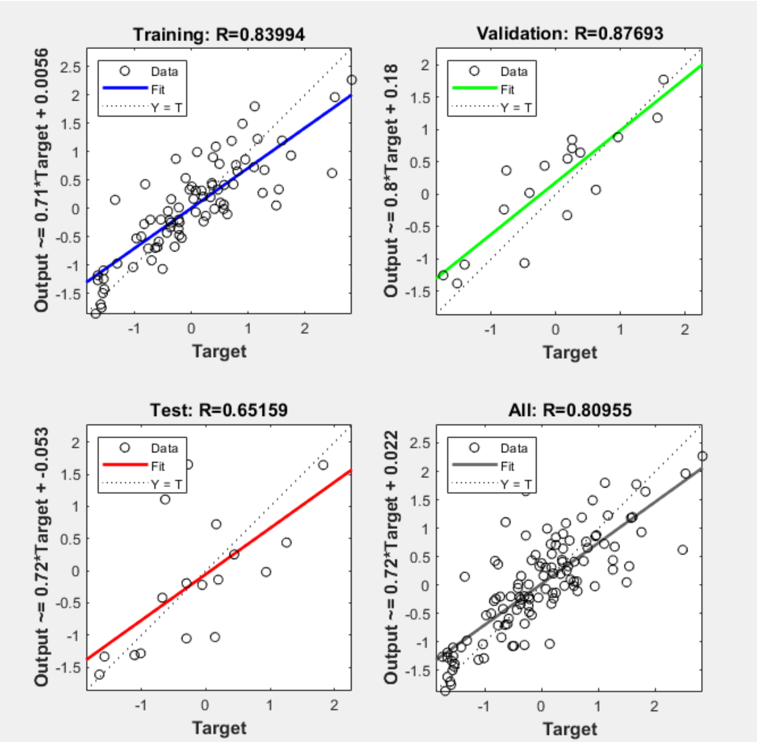

Figure D.4: Regression graph (Pulp and paper WW: NARX ANN)

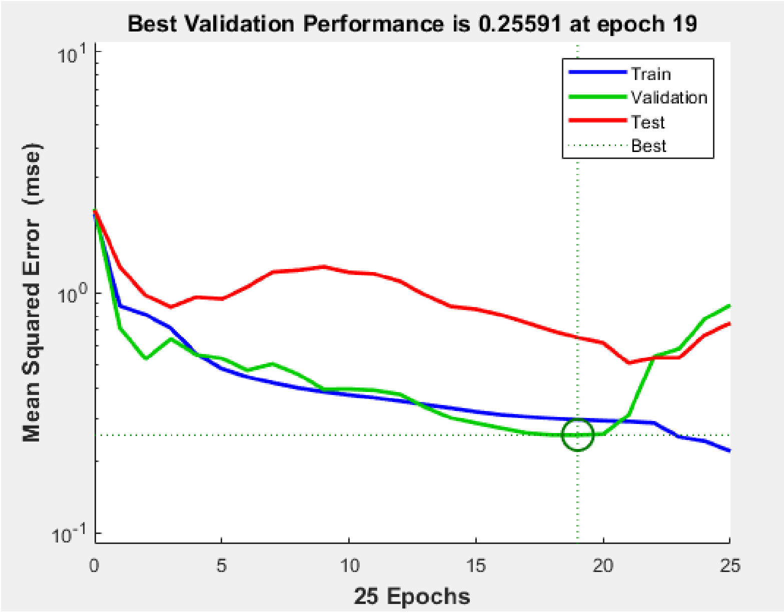

Figure D.5: Network Performance (Pulp and paper: NARX ANN)

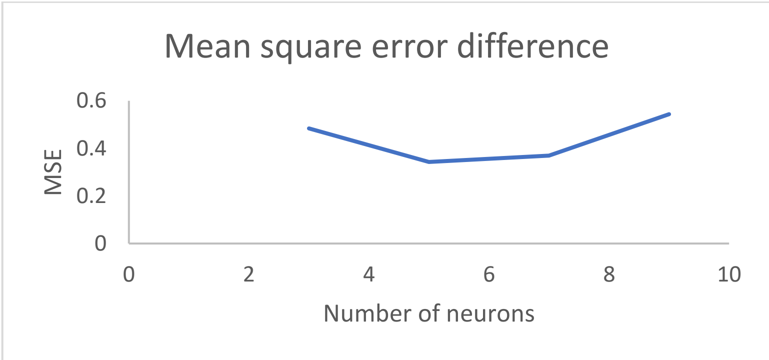

Figure D.6: Mean square error (NARX ANN model-Pulp and paper)

D.3 CFBP

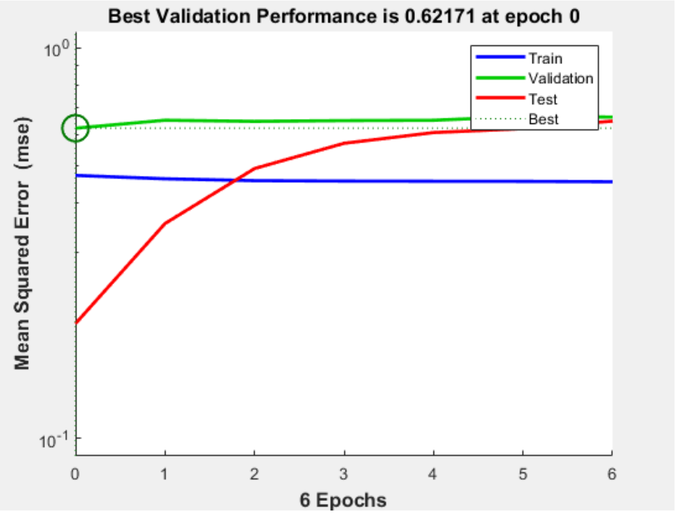

Figure D.7: Network Performance (Pulp and paper: CFBP ANN)

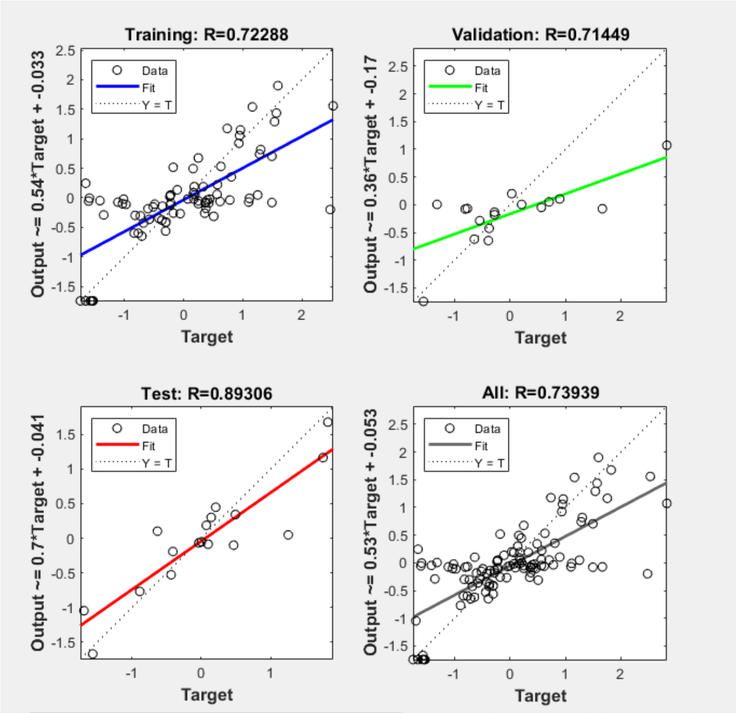

Figure D.8: Regression graph (Pulp and paper WW: CFBP ANN)

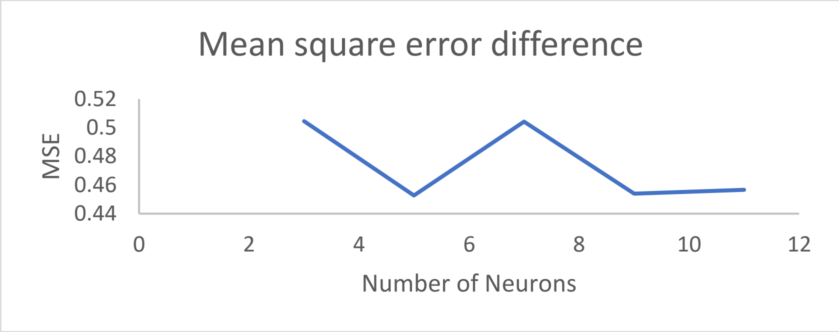

Figure D.9: Mean square error (CFBP ANN model-Pulp and paper)

Appendix E: Historical Raw data

E.1 Biodiesel wastewater treatment raw data

Table E.1: BDWW Raw Data

Days since inoculation	OLR (kg COD/m^3/d)	COD Influent (mg/L)	COD Effluent (mg/L)
6	0.58	5373	1745
8	0.58	5493	1653
11	0.58	5525	2218
13	0.58	5760	1890
15	0.58	5588	2678
18	0.58	5423	2225
20	0.58	5433	2625
22	0.58	5720	2655
25	0.58	6265	2953
27	0.58	6133	2655
29	0.58	5558	1703
32	0.58	5793	1605
34	0.58	5315	1745
36	0.58	5390	1763
39	0.58	5213	1953
41	0.58	6083	2065
43	0.58	10110	2175
46	0.58	9200	2113
48	0.58	8735	2198
50	0.58	10458	3263
53	0.58	11478	2998
55	0.58	8743	3735
57	0.58	9478	3960
60	0.58	9473	3625
62	0.58	9580	4048
64	0.58	9350	4400
67	0.58	9225	4190
69	0.58	8850	4415
71	0.58	9228	3618
74	0.58	9853	3990
76	0.58	10448	4373
78	0.58	11465	4850
81	0.58	11570	2333
83	0.58	11965	4543
85	0.58	12400	4815
88	0.58	13068	5160
90	0.58	13383	6125
92	0.58	12403	6500

95	0.58	12816	6755
97	0.58	13248	7358
99	0.58	11788	6870
102	0.58	13920	6948
104	0.58	11695	6725
106	0.58	12373	6763
109	0.58	11603	7123
111	0.58	10693	7843
113	0.58	10808	7305
116	0.58	9090	5615
125	0.58	9328	5858
127	0.58	8640	5363
130	0.58	11050	5668
132	0.58	11800	5713
134	0.58	9600	5853
137	0.58	11770	5785
139	0.58	9250	5523
141	1.15	12330	5828
144	1.15	11645	5638
146	1.15	11313	5490
148	1.15	11783	6130
151	1.15	11495	6098
153	1.15	11150	5853
155	1.15	11473	5648
158	1.15	10868	5688
160	1.15	10861	5620
174	1.98	13590	4785
176	1.98	19190	5275
179	1.98	16790	6223
181	1.98	14580	7790
183	1.98	14535	8090
186	1.98	19530	7893
188	1.98	23665	7418
190	1.98	23490	7325
193	1.98	23705	8288
195	1.98	25140	11068
197	3.46	21845	12063
200	3.46	33053	13590
202	3.46	33405	12233
204	3.46	33968	11698
207	3.46	37230	12325
209	3.46	31920	11690
211	3.46	32783	11693
214	3.46	33645	10958
216	3.46	34440	11955
218	3.46	30563	11175

221	3.46	33593	11820
223	3.46	32228	11410
225	3.46	33450	11158

E.2 Polymer wastewater treatment raw data

Table E.2: PWW raw data

Days since inoculation	OLR (kg COD/m^3/d)	COD Influent (mg/L)	COD Effluent (mg/L)
3	1.000622556	2555	882.5
5	0.579027719	1460	226
8	1.849454729	4707.5	907.5
10	2.046694417	4542.5	950
12	2.488283002	5422.5	1250
15	2.156994934	4452.5	720
17	3.071686078	5854.5	892.5
19	4.300880892	8290	975
22	4.084670739	8132.5	6397.5
24	4.491275351	8842.5	2370
26	10.06488869	19575	4082.5
29	4.418811038	9525	3192.5
31	4.588920616	9700	1125
33	7.771889471	16825	1055
36	9.735910076	20025	3055
38	8.157813396	16375	4715
40	9.087669326	18525	5465
43	10.73757079	21800	6110
45	12.49880198	25075	8820
47	11.89632235	23625	18425
50	12.00357974	24250	22600
52	10.76792	20625	21550
54	7.618531201	14650	19125
57	7.982836613	15700	16075
59	8.275197526	16225	11275
61	7.121123677	13900	9200
64	24.08729945	46325	8950
65	9.054975723	17375	9675
66	10.10813411	19525	10825
67	9.206241943	17725	10075
68	9.577823537	18575	11300
69	10.14341385	19650	11050
70	11.41612407	21700	11650
71	11.32136355	21750	11525
72	10.68745143	21000	9475
73	11.24396181	21850	11540
74	8.584724653	17050	9475

75	10.64875219	20600	10875
76	7.967182189	15725	16475
77	10.02409972	19950	10075
78	12.21666334	23650	17950
79	7.195379124	14325	10325
80	8.137585532	16700	10350
81	7.11876616	14500	9725
82	9.124914669	18150	10025
83	8.532087438	16950	12650
84	7.826267029	15445	11325
85	9.661239597	18900	12400
86	6.493001231	12670	5830
87	10.03613992	19300	11500
88	8.292511519	16150	10500
89	6.260575803	12740	5680
90	8.811625053	17840	4260
91	7.003921588	14200	4300
92	8.621692483	17480	5860
93	4.946267914	10060	4320
94	9.510565093	17320	8840
95	10.14025021	15480	8800
96	11.3166611	17760	9580
97	11.77447039	17800	5120
98	7.734769423	11640	5480
99	8.215862981	12920	5020
100	8.434175643	13700	7080
101	7.678636257	12000	6720
102	6.969770809	11150	6940
103	6.306753657	10260	5950
104	7.358919263	12032.5	5645
105	10.54665904	17015	5475
106	7.728339342	12500	5880
107	10.89431712	17890	7032.5
108	9.226147619	14580	6875
109	6.376550305	9650	6750
110	11.88333782	15425	5932.5
111	14.69100209	14840	6470
112	14.31014739	14435	6430
113	14.57859626	14770	6140
114	15.71783931	15810	6495
115	11.06570931	11245	7385
116	13.3155528	13470	6507.5
117	13.33986361	13495	6250
118	15.37744072	15550	6702.5
119	16.28885065	16325	5485
120	17.23647876	17075	6275

121	17.30226674	17125	6215
122	18.29220035	18075	5970

E.3 Pulp and paper wastewater treatment raw data

Table E.3: PPWW raw data

Days since inoculation	OLR (kg COD/m³/d)	COD Influent (mg/L)	COD Effluent (mg/L)	Feed Flow rate (L/d)
0	4.033333	2420	1210	40
1	4	2400	1285	40
5	3.575	2145	880	40
6	3.658333	2195	845	40
7	3.066667	1840	920	40
8	3.333333	2000	735	40
9	3.158333	1895	940	40
10	3.341667	2005	840	40
14	2.258333	1355	725	40
16	3.333333	2000	865	40
18	1.716667	1030	780	40
19	2.566667	1540	975	40
20	1.891667	1135	1015	40
22	1.991667	1195	890	40
24	1.683333	1010	845	40
26	1.708333	1025	855	40
29	4.516667	2710	1065	40
30	4.425	2655	1070	40
31	3.116667	1870	65	40
32	4.2	2520	1075	40
33	3.241667	1945	260	40
34	3.991667	2395	795	40
35	3.058333	1835	140	40
36	3.941667	2365	760	40
37	0.3	180	45	40
38	3.8	2280	765	40
39	2.741667	1645	180	40
40	3.425	2055	795	40
41	2.158333	1295	45	40
42	2.983333	1790	1005	40
43	1.458333	875	80	40
44	2.891667	1735	870	40
45	1.575	945	30	40
46	2.575	1545	1190	40
47	1.208333	725	45	40
48	0.941667	565	84	40
49	0.733333	440	95	40
50	0.425	255	90	40

51	0.558333	335	85	40
52	0.433333	260	76	40
53	0.3	180	10	40
54	3.45	2070	290	40
55	3.741667	2245	70	40
57	3.208333	1925	395	40
58	3.225	1935	1130	40
59	3.283333	1970	1285	40
60	2.816667	1690	1135	40
63	5.53	2370	1810	56
64	3.943093	1942.5	587.5	48.71774618
65	3.753156	1875	460	48.04039972
66	4.316872	1937.5	795	53.47351296
67	4.139785	1957.5	612.5	50.75598727
68	4.631842	2105	920	52.80959655
69	3.620222	1675	165	51.87184233
70	4.369344	2069.5	725	50.67129889
75	5.215475	2202.5	752.5	56.83150464
76	5.449794	2412.5	1302.5	54.21556562
77	4.932998	2425	1387.5	48.82142643
78	5.222876	2567.5	1692.5	48.82142643
79	4.182292	2007.5	1352.5	50
80	5.126563	2412.5	987.5	51
81	5.632229	2430	1315	55.62695163
82	5.787925	2657.5	1415	52.27100894
83	4.838034	2067.5	1050	56.16098005
84	4.939524	2187.5	710	54.19363376
85	4.79546	2212.5	827.5	52.0185477
86	3.774629	1677.5	837.5	54.00364054
87	3.48495	1670	897.5	50.08310685
88	2.412035	1182.5	347	48.95461581
91	4.450449	1925	297.5	55.48612059
92	4.116175	1880	313	52.54691711
93	4.110171	1795	555	54.95492969
94	4.326249	1842.5	380	56.35277191
95	3.833293	1577.5	409.5	58.31951696
96	3.725947	1625	374	55.02937527
98	4.047978	1697.5	1673	57.23209329
99	3.748657	1692.5	628	53.15673381
100	3.235519	1605	552.5	48.38159376
101	3.773158	1663	674	54.45327372
102	3.305215	1522.5	430	52.10190835
104	2.859095	1422.5	525	48.23780405
106	3.591613	1445	550	59.65307993
108	2.880769	1280	419	54.01442479
110	2.870565	1347.5	367.5	51.12694652

112	5.506127	2265	945	58.34307132
114	4.927927	2207.5	922.5	53.57655239
116	4.854414	2140	655	54.44202252
117	5.190013	2287.5	627.5	54.45259593
118	3.32825	1957.5	607.5	40.80613222
121	5.047726	1932.5	447.5	62.68845002
123	3.062279	1315	395	55.8894978
125	6.387615	2627.5	1325	58.34548658
127	5.66413	2452.5	1155	55.42879247
129	5.44561	2317.5	1202.5	56.39466447
131	4.033826	1740	587.5	55.63897617
133	3.964255	1840	495	51.70767434
135	4.616855	2057.5	607.5	53.85396349
137	4.643605	2049	611	54.39068859
139	3.70721	1870	535	47.57916693
141	4.915856	1870	1190	63.09120152
146	9.218415	3427.5	682.5	64.54907383
147	5.900033	2201	778	64.33475253
149	5.3278	2020	767.5	63.30059323
151	5.006649	1860	772.5	64.60192711
153	4.568032	1862.5	765	58.86323119
154	3.467348	1720	482.5	48.38159376
155	4.650977	1767.5	697.5	63.1532905
157	4.733263	1886	605.5	60.23240272
160	3.914357	1485	532.5	63.26233064
163	3.785874	1425	579	63.76209268
165	4.954026	1705	505	69.73408394
167	3.515182	1191.5	544	70.8051697
169	2.817403	1385	577.5	48.82142643
170	3.295446	1620	468.5	48.82142643
173	5.587951	1735	444.5	77.29730885
175	4.714338	1520	577.5	74.43692101

E.4 Textile treatment raw data

Table E.4: TTWW raw data

Days since inoculation	OLR (kg COD/m³/d)	COD Influent (mg/L)	COD Effluent (mg/L)	HRT (days)
9	0.300556	1352.5	1045	4.5
12	0.351111	1580	602.5	4.5
13	0.129444	582.5	660	4.5
14	0.147222	662.5	502.5	4.5
16	0.377778	1700	2375	4.5
19	0.228889	1030	930	4.5
21	0.06	270	150	4.5
23	0.071111	320	270	4.5
28	0.075	270	100	3.6
30	0.305556	1100	390	3.6
33	0.183333	660	1120	3.6
35	0.294444	1060	1100	3.6
37	0.186111	670	330	3.6
40	0.169444	610	215	3.6
42	0.419444	1510	710	3.6
47	0.152444	490	1880	3.214285714
49	0.252	810	1270	3.214285714
51	0.224	720	470	3.214285714
54	0.152	380	1850	2.5
56	0.166	415	1260	2.5
58	2.364	5910	1340	2.5
61	0.072	180	2140	2.5
63	0.236	590	950	2.5
65	0.04	100	1830	2.5
68	0.06	120	920	2
70	0.05	100	1340	2
72	0.665	1330	1100	2
77	0.275333	420	1290	1.525423729
79	0.144222	220	2600	1.525423729
82	0.170444	260	1280	1.525423729
84	0.216333	330	1060	1.525423729

Appendix F: Historical Normalised data

F.1 Biodiesel wastewater treatment normalised data

Table F.1: BDWW normalised data

OLR (kg COD/m^3/d)	COD Influent (mg/L)	COD Effluent (mg/L)
-0.623380127	-0.989705004	-1.29749008
-0.623380127	-0.976141795	-1.32643998
-0.623380127	-0.972524939	-1.14864983
-0.623380127	-0.945963655	-1.25186252
-0.623380127	-0.965404255	-1.00390034
-0.623380127	-0.984053667	-1.14644712
-0.623380127	-0.982923399	-1.020578
-0.623380127	-0.950484725	-1.01113781
-0.623380127	-0.888885152	-0.91736531
-0.623380127	-0.903804682	-1.01113781
-0.623380127	-0.968795057	-1.31070634
-0.623380127	-0.942233773	-1.34154427
-0.623380127	-0.996260555	-1.29749008
-0.623380127	-0.987783549	-1.29182597
-0.623380127	-1.007789282	-1.23203813
-0.623380127	-0.909456019	-1.19679478
-0.623380127	-0.454297338	-1.16218077
-0.623380127	-0.557151671	-1.18169048
-0.623380127	-0.609709105	-1.15494329
-0.623380127	-0.414964033	-0.81981674
-0.623380127	-0.299676759	-0.90320503
-0.623380127	-0.608804891	-0.67129117
-0.623380127	-0.525730238	-0.60048978
-0.623380127	-0.526295372	-0.70590518
-0.623380127	-0.51420151	-0.57279857
-0.623380127	-0.54019766	-0.46203374
-0.623380127	-0.554326003	-0.52811503
-0.623380127	-0.59671103	-0.45731365
-0.623380127	-0.553986923	-0.70810789
-0.623380127	-0.483345211	-0.5910496
-0.623380127	-0.4160943	-0.47052991
-0.623380127	-0.301146106	-0.32043097
-0.623380127	-0.289278299	-1.11246246
-0.623380127	-0.244632737	-0.41703553
-0.623380127	-0.195466105	-0.33144452
-0.623380127	-0.119964243	-0.2228824
-0.623380127	-0.08436082	0.080776875
-0.623380127	-0.195127025	0.198779182
-0.623380127	-0.148446981	0.279020752

-0.623380127	-0.09961943	0.468768462
-0.623380127	-0.264638469	0.315208126
-0.623380127	-0.023665461	0.339752606
-0.623380127	-0.275149956	0.269580567
-0.623380127	-0.198517827	0.281538134
-0.623380127	-0.285548416	0.394820349
-0.623380127	-0.388402749	0.62138478
-0.623380127	-0.375404674	0.452090803
-0.623380127	-0.569584613	-0.07970626
-0.623380127	-0.542684249	-0.00324077
-0.623380127	-0.620446646	-0.15900381
-0.623380127	-0.348052203	-0.0630286
-0.623380127	-0.263282149	-0.04886833
-0.623380127	-0.511940976	-0.00481413
-0.623380127	-0.266672951	-0.02621188
-0.623380127	-0.551500334	-0.10865616
-0.076916975	-0.203377977	-0.01268095
-0.076916975	-0.280801293	-0.07246879
-0.076916975	-0.318326171	-0.11904037
-0.076916975	-0.265203603	0.082350239
-0.076916975	-0.297755304	0.072280709
-0.076916975	-0.336749529	-0.00481413
-0.076916975	-0.300241892	-0.06932206
-0.076916975	-0.36862307	-0.05673515
-0.076916975	-0.369414257	-0.0781329
0.718810071	-0.060964285	-0.3408847
0.718810071	0.571985457	-0.18669502
0.718810071	0.300721282	0.111614811
0.718810071	0.050932187	0.604707121
0.718810071	0.045845984	0.699108967
0.718810071	0.610414548	0.637118421
0.718810071	1.077780116	0.487648831
0.718810071	1.058000437	0.458384259
0.718810071	1.082301186	0.761414185
0.718810071	1.244494557	1.636204626
2.137696851	0.87207145	1.949304082
2.137696851	2.138875147	2.429809479
2.137696851	2.178660559	2.002798462
2.137696851	2.242294614	1.834448503
2.137696851	2.610987838	2.031748361
2.137696851	2.010815851	1.83193112
2.137696851	2.108357927	1.832875139
2.137696851	2.205786977	1.601590616
2.137696851	2.295643235	1.915319418
2.137696851	1.857438565	1.669874618
2.137696851	2.199909586	1.872838587

2.137696851	2.045628087	1.74382273
2.137696851	2.183746763	1.66452518

F.2 Polymer wastewater treatment normalised data

Table F.2: TTWW normalised data

OLR (kg COD/m^3/d)	COD Influent (mg/L)	COD Effluent (mg/L)
-2.04511	-2.15195389	-1.47797
-2.14955	-2.333595658	-1.61875
-1.83482	-1.794890962	-1.4726
-1.78596	-1.822261639	-1.46349
-1.67657	-1.676284693	-1.39916
-1.75864	-1.8371911	-1.51281
-1.53204	-1.604623283	-1.47582
-1.22753	-1.200615496	-1.45813
-1.28109	-1.226742052	-0.29533
-1.18037	-1.108965198	-1.15899
0.200387	0.671372956	-0.79176
-1.19832	-0.995750123	-0.98261
-1.15618	-0.966720617	-1.42596
-0.36766	0.215194999	-1.44097
0.118889	0.746020258	-1.0121
-0.27205	0.140547697	-0.65613
-0.0417	0.497195917	-0.4953
0.367031	1.040462393	-0.35698
0.803341	1.583728869	0.22415
0.654088	1.343198674	2.283845
0.680659	1.446875482	3.179131
0.374549	0.845549994	2.953969
-0.40565	-0.145600294	2.433952
-0.3154	0.028576744	1.779911
-0.24297	0.115665263	0.7506
-0.52887	-0.270012464	0.305637
3.674161	5.108740354	0.252027
-0.0498	0.30643059	0.407496
0.2111	0.663078811	0.654102
-0.01233	0.364489603	0.493272
0.079726	0.505490062	0.755961
0.21984	0.683814173	0.702351
0.535129	1.023874104	0.831015
0.511654	1.032168249	0.80421
0.354615	0.907756079	0.364608
0.492479	1.048756538	0.807426
-0.16629	0.25251865	0.364608
0.345028	0.841402921	0.664824

-0.31928	0.032723816	1.865687
0.190282	0.733579041	0.493272
0.733446	1.347345746	2.181986
-0.51048	-0.199512235	0.546882
-0.27706	0.194459637	0.552243
-0.52946	-0.170482728	0.418218
-0.03247	0.434989832	0.48255
-0.17933	0.23593036	1.045455
-0.35419	-0.013723394	0.761322
0.100391	0.559402002	0.991845
-0.68448	-0.474048423	-0.41702
0.193265	0.62575516	0.798849
-0.23868	0.103224046	0.584409
-0.74206	-0.462436621	-0.44919
-0.11008	0.383566135	-0.7537
-0.55791	-0.220247596	-0.74512
-0.15714	0.323848294	-0.41059
-1.06765	-0.907002775	-0.74083
0.063064	0.297307031	0.228439
0.219056	-0.007917493	0.219861
0.510489	0.370295504	0.387124
0.623902	0.37693082	-0.56928
-0.37685	-0.644907804	-0.49208
-0.25767	-0.4325777	-0.59072
-0.20359	-0.303189043	-0.14898
-0.39076	-0.585189962	-0.22617
-0.56637	-0.726190421	-0.179
-0.73062	-0.873826196	-0.39129
-0.46996	-0.579798768	-0.4567
0.319736	0.246712748	-0.49315
-0.37845	-0.502248515	-0.4063
0.405861	0.39186028	-0.15916
-0.00739	-0.157212097	-0.19294
-0.71333	-0.975014761	-0.21974
0.650872	-0.017041052	-0.39504
1.346415	-0.114082545	-0.27978
1.252066	-0.181265117	-0.28836
1.318568	-0.125694347	-0.35055
1.600793	0.046823862	-0.27442
0.44832	-0.710431546	-0.08357
1.005675	-0.341342109	-0.27174
1.011697	-0.337195036	-0.32696
1.516466	0.00369431	-0.22993
1.74225	0.132253552	-0.49101
1.977006	0.256665722	-0.3216
1.993304	0.264959867	-0.33447

2.23854	0.422548615	-0.387

F.3 Pulp and paper wastewater treatment normalised data

Table F.3: PPWW normalised data

OLR (kg COD/m^3/d)	COD Influent (mg/L)	COD Effluent (mg/L)
0.231459	1.115396778	1.303958877
0.207968	1.080517138	1.494479281
-0.09155	0.635801722	0.465669097
-0.03282	0.723000823	0.376759575
-0.44979	0.103887205	0.567279979
-0.26186	0.382924329	0.097329648
-0.38519	0.199806216	0.618085421
-0.25598	0.391644239	0.364058214
-1.01945	-0.741944076	0.071926927
-0.26186	0.382924329	0.427565016
-1.40118	-1.308738234	0.211641891
-0.80216	-0.419307402	0.706994943
-1.27785	-1.125620121	0.808605825
-1.20738	-1.0209812	0.491071817
-1.42467	-1.343617874	0.376759575
-1.40706	-1.317458144	0.402162295
0.572083	1.621151565	0.935619428
0.507482	1.525232554	0.948320788
-0.41455	0.156206666	-1.60465263
0.348916	1.289794981	0.961022149
-0.32646	0.287005317	-1.10929958
0.202095	1.071797228	0.249745972
-0.45566	0.095167295	-1.41413223
0.166858	1.019477767	0.16083645
-2.39956	-2.791122953	-1.65545807
0.067021	0.871239295	0.17353781
-0.67883	-0.236189289	-1.31252135
-0.19726	0.47884334	0.249745972
-1.08992	-0.846582997	-1.65545807
-0.50852	0.016688104	0.783203104
-1.58324	-1.579055447	-1.56654855
-0.57312	-0.079230907	0.440266376
-1.50102	-1.456976705	-1.69356215
-0.79628	-0.410587492	1.253153436
-1.75943	-1.84065275	-1.65545807
-1.94736	-2.119689874	-1.55638746
-2.09418	-2.337687627	-1.52844447
-2.31147	-2.660324301	-1.54114583
-2.2175	-2.520805739	-1.55384719

-2.3056	-2.651604391	-1.57670964
-2.39956	-2.791122953	-1.7443676
-0.17964	0.50500307	-1.03309142
0.025911	0.810199924	-1.59195127
-0.34995	0.252125677	-0.76636285
-0.3382	0.269565497	1.100737112
-0.29709	0.330604868	1.494479281
-0.62597	-0.157710098	1.113438472
1.286217	1.028197677	2.828122113
0.167863	0.282645362	-0.27736048
0.034008	0.164926576	-0.60124517
0.43128	0.273925452	0.249745972
0.30648	0.308805093	-0.21385368
0.653251	0.566042441	0.567279979
-0.05968	-0.183869829	-1.35062543
0.468259	0.504131079	0.071926927
1.064559	0.736080688	0.141784409
1.229693	1.102316913	1.538934043
0.865487	1.124116688	1.754857168
1.069775	1.372634127	2.529640146
0.336436	0.396004194	1.665947646
1.001899	1.102316913	0.738748343
1.358262	1.132836598	1.570687443
1.467987	1.529592509	1.824714649
0.798563	0.500643115	0.897515347
0.870086	0.709920958	0.033822847
0.768559	0.753520508	0.332304814
0.049141	-0.179509874	0.357707534
-0.15501	-0.192589739	0.510123858
-0.91113	-1.042780975	-0.88829591
0.525417	0.252125677	-1.01403938
0.289841	0.173646486	-0.97466516
0.28561	0.025408014	-0.35991932
0.437888	0.10824716	-0.80446693
0.090484	-0.353908076	-0.72952891
0.014833	-0.27106893	-0.81970857
0.24178	-0.144630233	2.480104841
0.030837	-0.153350143	-0.17447946
-0.33079	-0.30594857	-0.36627
0.048104	-0.204797613	-0.05762695
-0.28167	-0.449827087	-0.67745333
-0.59607	-0.62422529	-0.43612748
-0.07984	-0.584985694	-0.37262068
-0.5808	-0.872742728	-0.70539632
-0.58799	-0.755023941	-0.83622033
1.269393	0.845079565	0.630786781

0.861913	0.744800598	0.573630659
0.810106	0.627081812	-0.10589212
1.046615	0.88431916	-0.1757496
-0.26544	0.308805093	-0.22655504
0.94634	0.265205542	-0.63299857
-0.45288	-0.811703357	-0.76636285
1.890611	1.477273048	1.596090164
1.380743	1.172076194	1.164243914
1.226744	0.936638621	1.284906836
0.231806	-0.070510997	-0.27736048
0.182777	0.103887205	-0.51233565
0.642689	0.483203295	-0.22655504
0.661541	0.468379448	-0.21766409
0.001628	0.156206666	-0.41072476
0.853407	0.156206666	1.253153436
3.885582	2.872458666	-0.03603464
1.546993	0.733464715	0.206561347
1.143719	0.417803969	0.17988849
0.917392	0.138766845	0.19258985
0.608282	0.1431268	0.17353781
-0.16741	-0.105390638	-0.54408905
0.666736	-0.022551492	0.002069446
0.724726	0.184110378	-0.23163558
0.147612	-0.515226413	-0.41707544
0.057066	-0.619865334	-0.29895279
0.880306	-0.131550368	-0.48693293
-0.1337	-1.027085137	-0.38786232
-0.62545	-0.689624615	-0.3027632
-0.28856	-0.27978884	-0.57965286
1.327057	-0.079230907	-0.64061939
0.711389	-0.454187042	-0.3027632

F.4 Textile wastewater treatment normalised data

Table F.4: TTWW normalised data

OLR (kg COD/m^3/d)	COD Influent (mg/L)	COD Effluent (mg/L)
0.061342	0.497308148	-0.033864074
0.184912	0.714140649	-0.712010693
-0.35689	-0.23658647	-0.623889946
-0.31344	-0.16033768	-0.865264166
0.250092	0.828513837	2.004407119
-0.11383	0.189930206	-0.210105568
-0.52663	-0.53443332	-1.405482659
-0.49947	-0.48677782	-1.221578491
-0.48997	-0.53443332	-1.482109395
0.073564	0.256647899	-1.037674323
-0.22518	-0.16272046	0.081076031
0.046405	0.218523503	0.050425336
-0.21839	-0.15318936	-1.129626407
-0.25912	-0.21037595	-1.305867901
0.351935	0.647422956	-0.547263209
-0.30068	-0.32474914	1.245802427
-0.05734	-0.01975397	0.310956241
-0.12578	-0.10553386	-0.915071545
-0.30176	-0.42959123	1.199826385
-0.26754	-0.39623238	0.295630893
5.104885	4.841106502	0.418233672
-0.4973	-0.62021321	1.644261457
-0.09645	-0.22943815	-0.179454873
-0.57552	-0.696462	1.16917569
-0.52663	-0.6773998	-0.225430915
-0.55107	-0.696462	0.418233672
0.95213	0.475863175	0.050425336
-0.00031	-0.39146683	0.341606935
-0.32077	-0.58208881	2.349227434
-0.25668	-0.54396441	0.326281588
-0.14452	-0.47724672	-0.010876053

Appendix G: Sample calculations

G.1 Determination of organic loading rate (OLR)

To determine the organic loading rate using Equation 1 in Chapter 2:

$$OLR = \frac{OC_{feed}}{HRT}$$

$$= \frac{OC_{feed} \times Q}{V_{reactor}}$$

$$= \frac{1780.43 \times 40}{24}$$

$$= 2.967 \frac{kg\ COD}{m^3}.day$$

G.2 Data normalisation

First find the mean and standard deviation for all the data.

$$Mean = \frac{COD_{sum}}{Number\ of\ data\ points}$$

$$= \frac{5373 + 5493}{2}$$

$$= 5433$$

$$Standard\ deviation = \sigma = \sqrt{\frac{\sum(x_i - \mu)^2}{N}}$$

$$= 84.85$$

G.2.1 COD data normalisation

Using Equation 12 in Chapter 2:

$$\mathrm{Y} = \frac{(\mathrm{ymax;}\ \ -\mathrm{ymin}) \times (\mathrm{x;} -\mathrm{xmin})}{\mathrm{xmax\backslash;} -\mathrm{xmin}} + \mathrm{ymin}$$

$$= \frac{5373 - 5433}{84.85}$$

$$= -0.7071$$