Application of Data Mining Techniques to predict the performance of matured Vertical-Flow Constructed Wetlands Systems treating urban wastewater

by

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Declaration

I UMAR ILIYASU, at this moment declare that this work presented in this thesis was carried out by me. Any ideas, thoughts or quotations from other work found in the literature, published or otherwise, are fully acknowledged in accordance with the standard reference practices of the University of Salford, Manchester.

Sign Date

Abstract

The rapid urbanisation and industrialisation, due to technological advancement, led to severe environmental pollution. The environmental pollution in the last few decades resulted in an adverse impact on the environment causing massive accumulation of wastewater. Wastewater is one of the closest sources of environmental problems, at the same time water scarcity is becoming alarming due to its high demand as the global population is increasing. Hence, the application for managing available water resources becomes crucial. The ever-increasing demand for water brings the need for wastewater treatment as an alternative source of water. Constructed Wetlands (CW) have gained broader research attention due to their environmental and safety benefits for wastewater treatment. In this study, over three years of monitoring performance data from 03rd December 2014 to 28th March 2018 (thirty-nine months) of the vertical flow vertical wetlands system, receiving and treating domestic wastewater, were collected and utilised to assess and investigate the treatment performance efficiency of the Vertical Flow Constructed Wetland Systems (VFCWs) for removing pollutants from wastewater. Different laboratory-scale vertical-flow constructed wetlands filters filled with gravel and planted with common reed were built to remove removal from wastewater. The overall evaluation of the system treatment performance was calculated using percentage removal efficiency. The results were recorded it was observed that all vertical flow constructed wetland filters had recorded high removal performance for the water quality parameters, irrespective of filter set-up and operation. The system was discovered to be very useful in pollutants removal (water quality parameters) with significant efficiency.

However, the high cost of analysis laboratory tests, time-consuming parameters couple with uncertainties associated with an analysis of water quality variables, lead to the development of two data mining technique models Multiple Linear Regressions (MLR) and Multilayer Perceptron (MLP). To predict the wastewater treatment performance of CW by predicting selected output water quality parameters these include Chemical Oxygen Demand (COD), Biological Oxygen Demand (BOD), orthophosphate phosphorous (PO4-P), ammonium nitrogen (NH4-N) and suspended solids (SS) with respect to other known input parameters that will provide comfortable, reliable and cost-effective methods. Correlation analysis was conducted to select the most highly correlated input parameters to be used for the model

development (prediction of output parameter). The monitoring dataset of all the parameters used was divided into training dataset to build prediction models (MLR and MLP) and testing dataset to validate the models constructed. In this current work, 70% of the whole data was used as a training dataset while the remaining 30% of the data set was used as a testing dataset. The prediction models built were evaluated and compared using two model evaluation criteria: graphical model evaluation (scatter plot and hydrograph) and numerical model error evaluation criteria using five model evaluation criteria, these include: Root Mean Square Error (RMSE), regression coefficient (r), Relative Absolute Error (RAE), mean absolute error (MAE) and root relative squared error (RRSE). The results obtained indicated that the predicted values of output parameters were in good agreement and relationship with their respective measured parameters. Thus, this showed that the two models built yielded satisfactory predictions and both models had performed reasonably well in predicting output variables concentrations accurately given the value of input dependent variable.

Furthermore, the comparison between the model's outcomes showed that MLP model prediction performance was discovered to be better than the MLR model in a majority of water quality parameters. Both models built could be effectively used as a tool for predicting removal of water quality parameters efficiency of vertical flow constructed wetlands treating domestic wastewater and in predicting constructed wetland performance in wastewater treatment process in term of pollutants removal. The results demonstrated the potentiality of vertical flow constructed wetlands to treat domestic wastewater and remove pollutants for future reuse.

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Table of Contents

List of Figure

List of Tables

List of Publications

Conferences

1. Iliyasu U, Al-isawi, RH Scholz M (2017). Application of Data Mining Techniques to Assess and Predict the Removal Efficiency Performance of COD in Wastewater Treatment Treating Domestic Wastewater. 7th MMU conference
2. Iliyasu and Scholz M. (2017) Evaluation of regression model in the prediction of water quality parameters removal in constructed wetlands treating domestic wastewater University of Salford SPARC conference
3. Iliyasu U, and Scholz M. (2018) Application of a multiple linear regression models (MLR) to predict nutrient removal in vertical-flow constructed wetlands the *University of Salford SPARC conference 2018 4th and 5th July 2018 Salford, Manchester UK*
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List of Nomenclature

Names	Notations
Al	Aluminium
APHA	American Public Health Association
BOD	Biochemical Oxygen Demand
C	Carbon
cm	Centimetre
COD	Chemical Oxygen Demand
Cr	Chromium
Cu	Copper
CW	Constructed Wetland
DM	Data Mining
DO	Dissolve Oxygen
DW	Distilled Water
EC	Electrical Conductivity
Fe	Iron
HF	Horizontal Flow
HFCW	Horizontal Flow Constructed Wetland
Hg	Mercury
HLR	Hydraulic Loading Rate
HRT	Hydraulic Retention Time

ITRC	Interstate Technology and Regulatory Council Wetlands Team
IWA	International Water Association
MAE	Mean Absolute Error
MLP	Multilayer Perceptron
MLR	Multiple Linear Regression
mm	millimetre
Mn	Manganese
MS	Microsoft
mV	Millivolts
N	Nitrogen
N/A	Not Applicable
N2	Nitrogen gas
NH4-N	Ammonia-Nitrogen
Ni	Nickel
NO3-N	Nitrate nitrogen
NTU	Nephelometric Turbidity Unit
OP	Organic Phosphorus
ORP	Oxidation Reduction Potential
P	Phosphorus
Pe	Person equivalent
pH	Potential of Hydrogen

PO_4-P	Orthophosphate phosphorous
r	Regression Coefficient
RAE	Relative Absolute Error
RMSE	Root Mean Squared Error
RRSE	Root relative squared error
SD	Standard Deviation
SE	Standard Error
SF	Surface Flow
SPSS	Statistical Package for Social Science
SS	Suspended Solids (mg/l)
SSF	Subsurface Flow
T	Temperature
TBD	Turbidity
TDS	Total Dissolve Solids
TKN	Total Kjeldhal Nitrogen
TN	Total Nitrogen
TOC	Total Organic Carbon
TSS	Total Suspended Solids

TWW	Tap Water and Waste water
U.S.D.A	United State Department of Agriculture
UK	United Kingdom
USA	United States of America
USEPA	United States Environmental Protection Agency
VF	Vertical Flow
VFCW	Vertical-flow Constructed Wetland
WEKA	Waikato Environment for Knowledge analysis
WHO	World Health Organization
WRc	Water Research Council
Zn	Zinc

Chapter 1: Introduction

1.1 Overview

This section provides an overview of the chapter. Section 1.2 explained the background of the study, section 1.3 highlight the research motivation, while the problem of this research was described in section 1.4. The research questions were defined in section 1.5 while section 1.6 explained the justification, aim and objectives, and lastly, the research outline has been described in section 1.7.

1.2 Background of the study

An increase in the global population has led to rapid growth of urbanisations and industries. As a result, water has been increasing in other hand water supplying is decreasing due to water scarcity (Almuktar & Scholz, 2016). The three main natural sources of water globally are rainfall; groundwater and surface water but the main ground and surface water are dependent on rainfall and appear to be virtually unlimited for their access.

The access to clean, tidy and safe water is becoming critical challenges globally; as a result the contemporary society confronting growing imbalance between freshwater availability and consumption (Zhang et al., 2014). One of the most persistent problems affecting human health in developing countries is insufficient access to tidy and hygienic water. Research revealed that water problems are expected to keep deteriorating in many years to come (Zhang et al., 2014)

The on-going current scarcity of water worldwide as a result of drought and the need of water in large cities and in the rural areas for agricultural uses and other requirements have made wastewater treatment and recycling an essential element of source of water in the sustainable management of water resources (Rousseau, et al, 2008). Advances in the constructed wetlands created an enabling environment to collect and record huge volumes of data from analysis and optimisation of water treatment processes, with implication for a wide range of research fields, such as irrigation, animal rearing, husbandry and human consumptions (Greenway, 2004). This data has become an essential part of decisions making in the area of re-use of treated wastewater and their environmental implications.

Wastewater treatment and reusing have been continuously practised worldwide for many reasons which include: To increase the availability of water, battling drought and shortages of water, and aid in environmental and public health protection (Fountoulakis, et al., 2016).

The needs for re-use of wastewater in some countries more especially the arid lands are due to an increase of human population and food consumptions, couple with environmental concern in more industrialised countries (Zhang et al., 2014). Therefore, according to (Al-Isawi, et al., 2015), application of constructed wetlands (CWs) in wastewater treatment is important due to their very low energy usage, easily accessible, simplicity and low cost of operation. CWs are used widely as an alternative means of water pollution control.

Constructed wetlands are based on applications of natural processes involving greenery, soils, and microbial organism to treat wastewater (Ouyang, et al,. 2011). They are engineered systems to mimic the natural wetland used globally to treat wastewater emanated from various sources (Gikas & Tsihrintzis, 2014, Vymazal, 2014). There are two major classes of Constructed Wetlands namely: Surface Flow Constructed Wetlands (SFCWs) and Sub-Surface Flow Constructed Wetlands (SSFCW) (Kadlec & Wallace, 2008; Scholz, 2006; Vymazal, 2014b; Vymazal & Kröpfelová, 2011; Wu et al., 2015).

The SFCW have been used for wastewater treatment for many decades, where water flows above a gravel medium and planted with macrophytes and has an exposed water surface which is different from subsurface flow constructed wetland (SSFCW) that has no clear water surface. As a result of water movement direction in the treatment systems (Vymazal, 2002b; Vymazal & Kröpfelová, 2011; Wu et al., 2014). In SSFCWs wastewater flows horizontally or vertically through the substrate which supports the growth of plants, and based on the flow direction, it can be subdivided into Horizontal Flow Constructed Wetland Systems (HFCWs) and Vertical Flow Constructed Wetland Systems (VFWs). Generally, the substrate in HFCWs is flooded with water, unlike the substrate in VFCWs that is holding back and drained the water as water intermittently feed into the systems (Stefanakis, et al, 2014; Vymazal, 2014b) which supports the growth of different plants.

VFCWs has been used for wastewater treatment (Kumar, et al, 2018). In comparison with horizontal-flow and demonstrated to be successful in removing pollutants from wastewater pressure removal efficiency specifically for Nitrogen, the flow of water through the gravel and the plant root downward to the bottom of the system (Rawaa 2016; Chen et al., 2008; Cooper, 1999; Gikas & Tsihrintzis, 2012)

Various research studies revealed that vertical flow constructed wetland systems are capable in attaining a high pollutant removal through of oxygen transfer (Fan, et al, 2013; Li, et al, 2015; Prochaska, et al, 2007). In vertical-flow constructed wetland systems wastewater poured into them and then permeates through the wetland body by gravity as reported by many study researches like Kumar et al., (2018); Miklas Scholz (2016); Paing & Voisin, (2005); Aboulroos, & Kamel, (2016). As wastewater get into the gravel and pass through, air enters the gravel holes (Sani & Scholz, 2013; Stefanakis et al., 2014). Eventually, the substrate may become so clogged that lead untreated wastewater to pass through the system (Babatunde, 2010; Hua et al., 2014).

However, there are associated problems in dealing with wastewater treatment data due to large volumes of data involved. These problems may include measurement errors, missing values, false correlation, scalability, and storage bottleneck. Various researchers have employed and presented several data analysis techniques and models of constructed wetlands including data mining techniques.

1.3 Data Mining

For many decades, data mining has been used as one of the instruments for the data analysis and management knowledge, as many parts have been adjusted of data mining approach to resolving their problems (Mohamed et al, 2016). It has recently created awareness in the research industry and society in general, due to enormous obtainability of big data and the necessity for transforming such data into useful knowledge and information (Kaur, et al, 2015). Data mining, sometimes referred to as Knowledge Discovery in Databases (KDD), especially is the area of determining new and potentially valuable information from enormous databases using one or more data software (Kaur et al., 2015; Arockiam et al., 2010). Data mining techniques become generally used in everyday activities to discover knowledge and have been applied and used for numerous research areas, applications and various purposes worldwide such as in healthcare industry (Gomathi & Priyaa, 2017), in education areas (Mohamed, et al, 2015; Thakar, 2015), in a crime and fraud detection (Bhowmik, 2008; Muslim & Herowati, 2018). Data mining is also applicable to advertising and marketing (B, G, & K.M, 2013; Saini, et al, 2014), in loan assessment (Scholar, 2015; Surve et al., 2016), in weather forecasting , in hydrology (Liang & Liang, 2001; Spate, et al, 2006) and in predicting constructed wetland systems performance (Lee & Scholz, 2006). In a research study of Weiss & Indurkhya, (1998), they described data mining as a tool that permits exploration for significant and valued information by data miners, in huge amount of data from different perspectives, to detect patterns and create relationships, and to resolve problems using data analysis and summarizing it into useful information, for the purpose of future trends description and prediction. In simple words, data mining refers to a process that is used to remove usable data from a broader set of raw data. It implies analysing data patterns in large batches of data using one or more software which is collected and accumulated in usual places, like databases and data warehouses, for effective data analysis. Data mining algorithms, enabling research studies and other information requirements for determining and making knowledge usable in the proper prediction of future events based on the understanding of past events. It can also be regarded as one of the statistical method (Paramasivam et al, 2014), and consider as information technology that developed and branches into sub-processes comprising of data collection, database creation and management, data analysis and lastly data interpretation (Han, et al, 2011).

The primary aims of data mining are to detect valid, original, and understandable correlations and patterns in datasets (Chung & Gray, 1999). Data mining is a process of analysing data from different views and summarising it into valuable knowledge, it also performs a significant part in prediction and helps in data cleaning (Periasamy, 2017). Data mining process comprises of six main phases: data selection, unwanted data filtration, assessing filtered data, programming, data mining and final report formation (Lei-da Chen & Frolick, 2000). Collection of monitoring data from the experiment and laboratory analysis is conducted and selected; it is filtered to remove outlier or inappropriate data. The second phase an essential element of the process is normalisation of data to reduce idleness and to generate a reliable dataset. The third phase is the additional information possessions that can be combined into the present data. The fourth phase comprises programming where the transformation of data occurs into arrangements appropriate for data mining. The fifth phase is the actual discovery stage. It is the primary process of applying intelligent approaches to detect and determine patterns in data. The six and last phase is appropriate reports generation. The knowledge that was mined is offered through visualisation techniques, and knowledge demonstration techniques with the goal of conclusions generation or attempt in prediction as contained in Figure 1.1 symbolise data mining process.

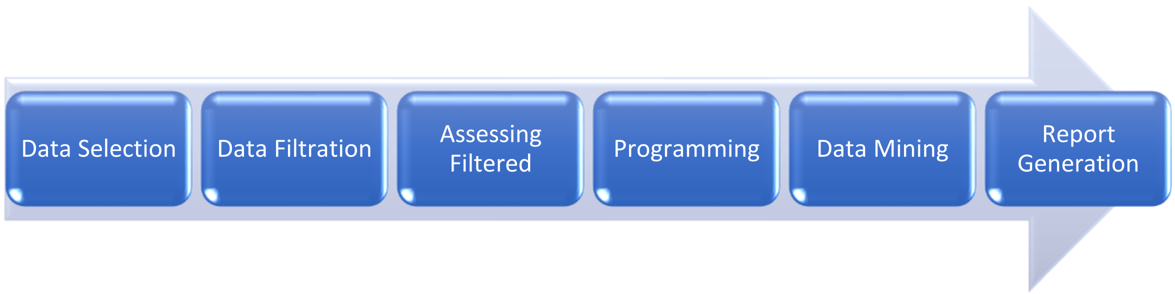

Figure 1.1: Data mining process

In a constructed wetland, data mining techniques can be used and apply to predict its performance in treating wastewater by predicting water quality parameters removal. All data mining techniques can be applied to discover, monitor and extract valuable knowledge from large unstructured dataset and turn it into a particular benefit for future use. Data mining techniques can easily be used with monitoring data from the experiment for evaluating and predicting water quality variables to help in upgrading treatment performance efficiency of the constructed wetland system and to enhancing system design and operation. Data mining techniques include the following: clustering, association mining, and classification (Periasamy, 2017).

Over the last twenty years, numerical models were established to mimic differing purposes occurring in constructed wetlands with differing goals ranging from biochemical and geochemical processes, clogging, and hydraulic behaviour. Many researchers have studied and work on different data mining techniques that have been used to assess and predict the quality of waters due to their accuracy in the predictive performance of various areas like in hydrology (Xu Liang & Yao Liang, 2001). Also in the constructed wetland (Gikas, et al, 2011; Li et al., 2018) and water resource management (Bertholdo, da Silva, et al, 2014; Mohan & Ramsundram, 2013). Numerical models are also used in the prediction of water quality parameters (Singh, 2017).

Data mining techniques are also applied in the hospital (Aghajani & Kargari, 2016; Hachesu, et al, 2013; Paramasivam et al., 2014; Srinivas, et al, 2010), in agriculture requirement (Khan et al., 2012; Fetanat, Mortazavifar, & Zarshenas, 2015; Jaganathan, Vinothini, & Backialakshmi, 2014; Majumdar, Naraseeyappa, & Ankalaki, 2017). There are also reported cases of data mining application in computing, in predicting student record and performance (Shaleena & Paul, 2015; Yassein, et al., 2017), also in the building (Alencar, Carvalho, Koenders, et al, 2017). Another area in which data mining was applied is business performance prediction (Huang & Lin, 2014; Linoff & Berry, 2011) which lead to appropriate decisions. Many data mining techniques like Clustering, Regression analysis, Classification, Artificial Neural Networks, Association Rules, Decision Trees, Fuzzy logic, K-Nearest Neighbour method etc., are applied and used for discovering useful information from databases.

Multi-Layer Perceptron Artificial Neural Network (MLP-ANN) is one of the popular and approach of data mining techniques. An Artificial Neural network (ANN) involves many connected processing elements, comprising several input nodes and a weighted sum of interconnections. The structure of Multi-Layer Perceptron (MLP) includes nodes which are in an input layer, a hidden layer(s), and one output layer. To represent the human brain's ability to process in parallel, the notion was stimulated biologically and learn from experience, and to be highly connective and modifiable. The brain also functions through supervised learning, or the capability to train itself presently and learn from past experiences. The mind is capable to both of feeding connections forward, near sensory input, and feed relationships backwards near sensory input. In the study research of Tomenko, Ahmed, & Popov, (2007), they confirmed that ANN could be applied as alternative methods when the constructed wetland systems parameters cannot be adequately defined in terms of direct and clear mathematical models.

MLP are widely used to predict pollutants removal performance in vertical flow constructed wetland. Some successful and practical applications of artificial neural network technique in constructed wetland include in pollutant removal prediction (Schmid & Koskiaho, 2006; Li et al., 2015; Ozengin et al., 2016; Lyu et al., 2018) and in water quality parameters prediction (Emamgholizadeh et al, 2014; Zare Abyaneh, 2014; Maier & Dandy, 1996).

Another widely used data mining techniques in constructed wetland is Multiple Linear Regressions (MLR). MLR models are used to design an optimal equation for predicting the value of an output dependent parameter from two or more input independent parameters (Tomenko et al., 2007). Some practical applications of multiple linear regressions in constructed wetland include prediction of water quality parameters (Emamgholizadeh et al., 2014; Zare Abyaneh, 2014) and evaluation and prediction of removal performance of different pollutants (Nalcaci etal., 2011; Zou et al., 2012; W.-B. Chen & Liu, 2015). MLR models are used in this research to predict the wastewater treatment performance of constructed wetland by determining the relationship between one output parameter given many inputs parameters that influence the outcome of the output parameter.

However, it has been reported that MLR has been applied to help in detecting fraud (Gopal, 1999; Perantalu & Bhargavkiran, 2017), it also use in solving health care system delivery related problem (Chao et al., 2008; Cruz et al, 2008; Kumar et al., 2014; Scholar, 2017). MLR models are also applied in science and engineering (Akan, et al., 2015; Madden, Wilson, Dong et al, 2004; Salleh et al, 2017), in predicting banking performance (Bakar & Tahir, 2009; Jilkova & Stranska, 2017), in predicting population growth (Jain & Mishra, 2015; Qu et al., 2011), in agricultural products estimation (Garcia-Paredes et al., 2000;

Sellam & Poovammal, 2016). It also used in predicting student academic performance (Oyerinde & Chia, 2017; Yang et al., 2018).

In this study, different laboratory-scale vertical-flow constructed wetlands filled with gravel and planted with common reed were built and operated, to assess wastewater treatment performances and their relationship. Data mining techniques were also applied to evaluate and predict wastewater treatment performance effectively of vertical-flow constructed wetland systems. These include the prediction of the wastewater treatment performance by estimating various water quality parameters using data mining techniques Multilayer perceptron (MLP) and Multiple linear regression (MLR), these parameters are used as criteria for assessing and predicting the treatment performance of the system.

1.4 The Motivation of the Research

In an effort to solve water scarcity associated problems, Constructed Wetlands technology are employed to treat wastewater. These Wetland systems restored and maintain the chemical, physical, and biological integrity of the water for human, animal and plant re-use. However, these Constructed wetland systems involve dealing with large volume of data acquired over a long period, therefore dealing with large size of data come with some challenges of inconsistency and missing values, which can lead to misleading treatment evaluation of the constructed wetland system performance. Hence the need for modelling and most of the previously concerted attempt of modelling vertical-flow constructed wetlands processes regarding the prediction of wastewater treatment performance shows a greater success. However, the reported literatures are lacking in the area of quality data of complete matured constructed wetland treatment systems and prediction model of long-term treatment performance. thus, the need for the research.

In this present investigation, both experimental and data mining techniques are utilised, and new methodological framework is proposed to predict wastewater treatment performance of a range of long-term experimental monitoring dataset of constructed wetland system by predicting water quality parameters. The data mining techniques used in this study research are MLR and MLP designed using R-Language and WEKA respectively.

1.5 Research problem

Urbanisation and industrialisation due to population growth led to an increase in water consumption for human and agricultural use. Also in arid areas and another part of the world hit by drought, the source of clean water is limited. These associated water problems have made wastewater treatment and recycling a significant source of clean water, for irrigation and other agricultural and human needs. Natural and Constructed Wetland system have been used for wastewater treatment (Ouyang et al., 2011). Though there has been reported literature on the treatment performance of the Vertival-Flow Constructed Wetland systems (VFCWs), still there are needs to have long-term data so as to evaluate treatment performance effectively. Despite the several articles published on wetlands in the past, there is an essential gap in the literature concerning research on the long-term treatment performance and prediction of the constructed wetland systems using data mining techniques. However, because of the complexity or heterogeneity of wastewaters and the lack of quality data of complete constructed wetland treatment systems, many designs of constructed wetland fail to deliver accurate long-term wastewater treatment performance and prediction by constructed wetland systems.

1.6 Justifications, Aim and Objectives

1.6.1 Justification

Most of the previous works on wastewater treatment efficiency performance of the constructed wetland focussed on evaluating the general performance of the short-term monitoring data (Bojcevska, 2004; Kantawanichkul & Wannasri, 2013; Kurniadie, 2011; Mavioso & Galvão, 2013; Mustafa, 2013; Mwangi, et al, 2012; Raude et al., 2018; Sehar et al., 2016; Toromanovic et al., 2017; Zidan et al., 2015). And also some evaluate treatment performance of the constructed wetland in a long-term period of data (Kayranli et al., 2010a; Jan Vymazal, 2010a, 2014b).

Majority of previous study research works have made an intensive effort to explore the use of modelling data mining technique to predict short-term wastewater treatment performance of constructed wetland by predicting missing incomplete water quality parameter in question as output parameter given other water quality parameters as input parameters (Bustillo-Lecompte et al., 2016; Galvão et al., 2010; Gholizadeh et al., 2015; Manu & Thalla, 2017; Raude et al., 2018; Ribeiro & Matos, 2007; Wietlisbach et al., 2016). However only a few focus on long-term treatment performance of constructed wetland (Akratos et al., 2008a; Dzakpasu, Scholz et al., 2016; Hamada et al., 2018; W. Li et al., 2014).

This present work particularly provides the modelling community with statistically validated long-term data interpretation for the wastewater treatment. This long-term data will allow accurate modelling for prediction of the individual water quality parameters, and wetland managers with insight into long-term and seasonal performance of the system, allowing them to revise wetland management plans accordingly. The thesis highlights the gaps in the knowledge for the current state of the art for simulating wetland pollutant dynamics and suggests mechanisms for increasing the scope of such modelling approaches in the proper design and operation of the CW systems. The research gap is lack of appropriate information (data) on long-term wastewater treatment performance. The investigation into wastewater treatment performance by the constructed wetland systems, which was discovered to be very effective in removing pollutants, which could be used to evaluate wastewater treatment performance for possible future re-use. Prediction models are designed to increase the understanding and addressing the governing biological and chemical degradation processes happening in the “black box” constructed a wetland and can provide insight in which wastewater is treated and therefore increase the system operational understanding and the existing design criteria.

A comprehensive and multi-disciplinary approach was used to understand and differentiate the proposed framework and prediction model of treatment performance of vertical-flow constructed wetlands for the removal of pollutants effectively.

1.6.2 Aim

This work is aimsed to investigate the performance of vertical flow constructed wetland in treating urban wastewater. And to design and apply data mining techniques using Multi-layer perceptron (MLP) and Multiple linear regressions (MLR) to predicts wastewater treatment performance of vertical-flow constructed wetlands.

1.6.3 objectives

The following objectives are designed, to achieve the set aims. These includes:

i. To analyse different water quality parameters, present in the wastewater inflow and treated water outflow of the vertical-flow constructed wetlands systems;
ii. To evaluate the wastewater pollutants removal performance for different filters of the system.

iii. To determine missing and hidden information from data and deal with it without affecting the consistency and accuracy of the data.

iv. To design a model with the existing data using data mining techniques that will predict the treatment performance of wastewater by vertical flow constructed wetland system using:

- ✓ Multi Linear regression (MLR); and
- ✓ Multilayer Perceptron (MLP)

1.7 Research Contribution

The study research employed the use of data mining techniques to match identify missing values identified during performance monitoring of vertical flow constructed wetland system. The system contributed in monitoring, investigating and evaluating performance 10 different experimental vertical flow constructed wetlands filters for the treatment of urban wastewater in different season of the year for more than three (3) years (thirty-nine months). The research also contributed in predicting wastewater treatment performance of the constructed wetland systems Also, these experimental data for the VFCWs were used to develop a model applying data mining techniques. The model developed predict the performance (by predicting water quality parameters removal) of vertical flow constructed wetland systems given other readily available water quality parameters (input parameters) using data mining techniques models.

1.8 The Scope of the Research

The study of the vertical flow constructed wetland system was conducted in operation for all the seasons of the year, from December 2014 to March 2018. The boundary condition, upon which the experiment was conducted includes climatic conditions, wastewater composition, porous filter material, and plant species (Guenter Langergraber, 2011). Because of the irregularity of natural systems, the outcomes and recommendations of the vertical flow constructed wetland system study concern only to similar conditions.

1.9 Research Outline

This research reviewed the existing information on wetlands and constructed wetlands applied for treatment of urban wastewater. The study investigated treatment performances of different filters of the experimental vertical-flow constructed wetlands for pollutants removal from wastewater. The thesis is structured into different chapters as follows:

a. Chapter 1 describes the background, justification, aims and objectives of the research work.
b. Chapter 2 discussed the literature review on treatment performance of different types of pollutants in different constructed wetland systems from earlier conducted researches. With much emphasis on constructed wetlands, specify the role of primary wetlands. This chapter also discussed literature on prediction modelling for VFCW performance in contaminants removal.
c. Chapter 3: The chapter discussed the materials and method used, the experimental set-up and operation methods applied for the study. The chapter explains the design of the experimental filter, and aggregate compositions as well as their physical arrangement. It also includes the sampling in the greenhouse; water quality parameters analysed in the laboratory. Furthermore, the chapter describes the framework used in designing the prediction model on how to predict particular water parameters given other parameters.
d. Chapter 4: The chapter discusses discusses the seasonal variations in the performance efficiency of the wetland systems of different filters. Furthermore, general evaluation of the wastewater treatment performance of the constructed wetland systems on water quality is also described.

e. Chapter 5 discussed the prediction model built, evaluate their accuracy in predicting water quality parameters removal and the compared the prediction performance between the two models built.
f. Chapter seven discussed the conclusion of the research study and the recommendation for further research

Chapter 2: Literature Review

2.1 Overview

The chapter, discusses extensively, various relevant literature related to the constructed wetlands, showing the hydrology, components, types and removal mechanisms of pollutants. It also describes the historical development of wetlands, the mechanisms of wetlands, design and operational control of constructed wetlands on performance in wetlands experimental and modelling of different configurations of a constructed wetland. Applications of data mining techniques in predicting the wastewater treatment performance of experimental vertical flow constructed wetland ware also reviewed and discussed.

2.2 Natural Wetlands

As the name suggests, wetlands are flooded water-rich areas which are either permanently or seasonally with water. Natural wetlands are one of the vital natural resources in the world, which enhance the quality of water through natural processes. These natural processes include sedimentation, nutrient conversions, microbial and plant uptake of a large number of nutrients and range of different toxic materials (Knox, et al., 2008).

Wetland is an ecosystem where the surface of the land area can be fully or partially covered and saturated with water, either seasonally or permanently, such that it takes on the characteristics of a distinct ecosystem (Zhang, et al., 2010). It can also be described as land areas fronts of swamp, fenland, peatland or water which could be characterises as natural or man-made, permanent or temporary, with water that is straming or static, fresh, brackish or salt, including zones of marine water, the deepness of which at low tide does not surpass six (6) meters (Nwankwoala, 2012). Wetland covers 10% size of the world entire total land mass area and has economic value to the living community (Pan et al., 2011., Economic, 2004). Historically, natural wetlands have been used as convenient sewage and wastewater disposal sites. This led to many wetlands, such as marshes, being saturated with nutrients and experiencing severe environmental degradation. It occurs naturally on every continent except Antarctica, examples of wetland are salt, fresh or somewhere in between consisting of marshes or swamps; saturated land, Marshes develop along the edges of rivers, ocean and lakes, the delta at the mouth of a river, low-lying areas that frequently flood. The source of its water is mainly from point sources of water and in some cases and nonpoint sources of water pollution, including stormwater runoff, domestic wastewater, agricultural wastewater, and mine drainage (Zhang et al., 2010). Natural Wetlands improve physical, chemical, and biological procedures of water quality (Gopal, 1999), it performs a significant part in the control of flood and erosion and enhances water quality thereby decreasing the soluble pollutants levels in runoff and overflow water.

Natural wetlands are commonly known as biological filters and biologically diverse ecosystem that protects water resources such as estuaries, lakes and groundwater (Brzezinska & Kalwasin, 2012). Wetland has been in existence for many decades in some parts of the world, including Europe and USA, which helps in expediting, the removal of water quality parameters, as well as in the treatment of wastewater. However, the processes were not understood by the researchers of the wetland system in the early 1960s (Rustum, et al., 2008a). Natural Wetlands are one of the vital natural resources in the world generally a wetland is an ecosystem where water is at or covering the surface of the ground for all or part of the year. Wetland is water saturated landscapes that include an area roughly about 8.6×10^6 km^2 which equivalent to 6.4 per cent for the world's land surface (Gorham, 1996).

2.2.1 Main functions of wetlands

In general, wetland has value as attested to be of great use to human and animal (Greeson, et al., 1979). The main function of natural wetlands can be outlined to the following: water quality, water supply and storage, flood control, erosion control, wildlife support, recreation, culture, and commercial benefits. Other includes windbreak, wastewater treatment, food and energy resource, recreation and tourism, scientific research and education.

Wetlands are among the most productive ecosystems in the world, comparable to rain forests and coral reefs; Wetlands play an integral role in the ecology of the watershed, Scientists now know that atmospheric maintenance may be an additional wetlands function. They also provide surprising environmental services. Wetland provides habitat for important species, significant links in the cycling nutrients and the global storage of carbon, buffering against contaminants and other packages.

2.3 Constructed Wetland systems (CWs)

2.3.1 History of CWs

The German scientist, Kathe Seidel conducted the first experiments on the possibility of wastewater treatment with wetland plants in 1952 at the Max Planck Institute in Germany

(S C Reed, 1991). A significant increase in the number of CWs took place in the 1990s as the application expanded to treat different kinds of wastewater such as industrial wastewater and stormwater. Constructed Wetland in contrast to natural wetlands is systems that are engineered or man-made wetland designed, built and operated to provide wastewater treatment and to mimic and utilise the function of natural wetlands process involving wetland vegetation, soil and any other microbial grouping to help in treating wastewater for human desired and needs. With progressively attaining acceptance globally, Constructed Wetland is nowadays used for treatments of many types of wastewater; these include industrial and agricultural wastewater, stormwater runoff and landfill leachate (Jan Vymazal, 2005). CWs is created mainly for wastewater treatment for contaminants removal. The use of constructed wetlands for wastewater treatment is becoming more and more popular in many parts of the world and is an environmentally friendly means of treating wastewater. Today subsurface flow CWs are quite common in many developed countries such as Germany, UK, France, Denmark, Austria, Poland and Italy. Constructed wetlands are appropriate for developing countries, but are still regarded as new technology (Sayadi, Kargar, Doosti, & Salehi, 2012). Constructed wetlands (CWs) have been proven a cost-effective wastewater treatment system, which uses the interactions of new plants and microorganisms in the pollutants removal (Mimis & Gaganis, 2007).

For over two decades the use of constructed wetlands has become acceptable which are specifically designed for the treatments of wastewater in urban, industrial, agricultural and municipal (Greenway, 2004). This has further attracted its usage, considering the need for low-cost water treatment systems and its simplicity in construction.

Constructed wetlands (CWs) produce a natural way for easy, simple, low-cost, and reliable wastewater treatment. Understanding the general operation of CW is hard, due to a large number of physical, chemical, and biological procedures happen in parallel and affect each other. As a result, CWs have seen as "black boxes" where wastewater enters and treated water leaves the CW system, this is due to lack of proper understanding of internal operation taking place (Gao, et al., 2014).

Constructed wetlands (CWs) are used globally, as an alternative and efficient means of water and environmental pollution control and economical choice for the treatment of contaminated wastewaters (Campbell, 2008). Its application ranges from treatment and recycling of different type of water streams including treated wastewater for irrigation (Greenway, 2004). These needs arose due to the scarcity of water in arid countries (Scholz

& Lee, 2005). The Method of Constructed wetlands was also applied for assessing water quality and performance of wastewater treatment operations (Sundaravadivel & Vigneswaran, 2001). According to Al-Isawi et al., (2015) constructed wetland provide a collection of physical, biological and chemical processes to facilitate the removal, recycling, transformation or immobilisation of sediment and nutrients (Rousseau et al., 2008). Petroleum producing countries use constructed wetlands to restore the water streams that have been contaminated with oil and harmful contaminant (Wu et al., 2011). They are made of different configuration. Therefore, constructed wetlands are employed due to their low energy condition, accessibility, environmentally friendly, mechanical simplicity and low cost of operation. They are also recently applied successfully to treat domestic wastewater (Zhang et al., 2014). Constructed wetland models are currently recognised as a useful management tool, which increases the understanding of simultaneous chemical, biological and physical processes involved in the wastewater treatment (Al-Isawi et al., 2015) and improves the wetland design. Even though there are several reported experimental data and system modelling for performance prediction, there are fewer on data mining techniques applied for the prediction of treatment performance in wastewater, hence the needs for the research.

Constructed wetlands (CWs) are ‘‘engineered systems, designed artificial and constructed to imitate the natural wetland vegetation's natural functions, aggregates and their microbial populations in order to treat pollutants in surface water, groundwater or waste streams" (Scholz & Lee, 2005) by taking the advantage of physical, chemical and biological processes which are all similar to processes occurring in natural treatment wetlands (Miklas Scholz, 2016). Constructed wetlands (CWs) are the system to provide a natural technique for inexpensive, simple, and long-lasting wastewater treatment and to improve the quality of water polluted. Most constructed wetlands around the world have now become primary sources that are used to treat municipal and domestic wastewater. In addition to that, treatment of many types of agricultural and industrial wastewater, landfill leachate, storm water runoffs are also common. In spite of the doubt of the many civil engineers and water authority, constructed wetlands have become an appropriate solution for wastewater treatment and have been accepted all over the world (Choudhary et al., 2011).

Nowadays, the used of constructed wetlands as an alternative to treat domestic wastewater is been studied and is prevalent worldwide which help in reducing pollution and contribute to the improvement of water quality (Vymazal, 2011, J. Vymazal, 2013, Chang, et al., 2012, Sharma et al., 2014, Idzwana & Idris, 2015). The problem associated with constructed wetlands has been studied (Bird et al, 2002, Obarska-pempkowiak, et al., 2013). Moreover, It has been projected that if proper measures are not taken, some developing countries will face a severe water shortage by the year 2050, constructed wetlands as an alternative of source water were not common in developing countries, due to lack of knowledge of their essential part in control of environmental contaminations. Though a little study researches have been published recently in Nigeria (Alagbe, 2016, Oginni & Isiorho, 2014) and Morocco (Bouchaib et al., 2012). South Africa (Ms et al, 2013). However, no practical knowledge for proceeding the research technology on a geographical basis (Scholz, 2007). Consequently, the understanding of the potential for the use of the constructed wetland technology with regard to water contaminants control and environmental protection necessitate to be spread and fully understood for proper treatment performance (Chang et al., 2012, Dzakpasu et al, 2010, Choudhary et al., 2011). Constructed wetland technology and application in wastewater treatment has been into full operation since the late 1960s, and the exploration of its research keeps increasing in other developing countries such as Brazil (Kleiber et al, 2008) and Malaysia (Asmaliza et al., 2011, Idzwana & Idris, 2015).

Constructed wetland systems were reported to have a a considerable ability for the treatment of wastewater under a wide range of conditions (Knight et al., 2000, United States EPA, 2000, Vymazal, 2002). Many constructed wetlands show high removal efficiencies (i.e. >80%) for biochemical oxygen demand (BOD) and suspended solids (SS) (e.g. Newman et al., 2000, United States EPA, 2000, Cerezo et al., 2001, Vymazal, 2002), but removal efficiency of nitrogen (N) and phosphorus (P) has been inconsistent and is often low (United States EPA, 2000). The US EPAs design manual (United States EPA, 2000) stresses that constructed wetlands cannot remove significant quantities of Nitrogen or Phosphorous, and bases its design procedure on BOD and SS.

2.3.2 Classification of constructed wetlands

Constructed wetlands are classified based on the characteristics of the plants used in the system and the flow pattern. Based on macrophyte plants in the system, which are aquatic plants that grow in or near water. There are

1. Floating macrophyte-based system (i.e. Lemna app, Eichornia crassipes)
2. Rooted emergent macrophyte-based system (i.ephragmites australis, Tipha spp)

They are emergent, submerged or floating in water, example common reed plant (Phragmites australis) used in this study research.

Constructed wetlands are classified according to the water flow regime and water level on the bed which is one of the two free water surface flow (FWSF CWs) or subsurface flow (SSF CWs) and according to the type of macrophyte plant as well as flow of water direction in the constructed wetlands (Vymazal, 2014b, Vymazal, 2008, Khalil, 2017). Subsurface flow CWs are designed to keep the water level totally below the surface of the filter bed (Abdelhakeem et al., 2016).

However, based on the direction of the flow of inflow water, constructed wetlands are also classified as vertical and horizontal constructed wetland system. Vertical and horizontal constructed wetlands may be combined as a single entity with each other to form hybrid systems to achieve higher pollutants removal efficiency (Vymazal, 2014b). In a related studied it was discovered that constructed wetland are categorised according to their aim and objective as constructed wetlands for wastewater treatment, for habitat creation and the environment and flood control (J. Vymazal, 2014b, Khalil, 2017, Beef & Ad, 2017). They are emergent, submerged or floating in water, example common reed plant (Phragmites australis) used in the present study. Figure 2.1 shows the classification of the constructed wetland systems.

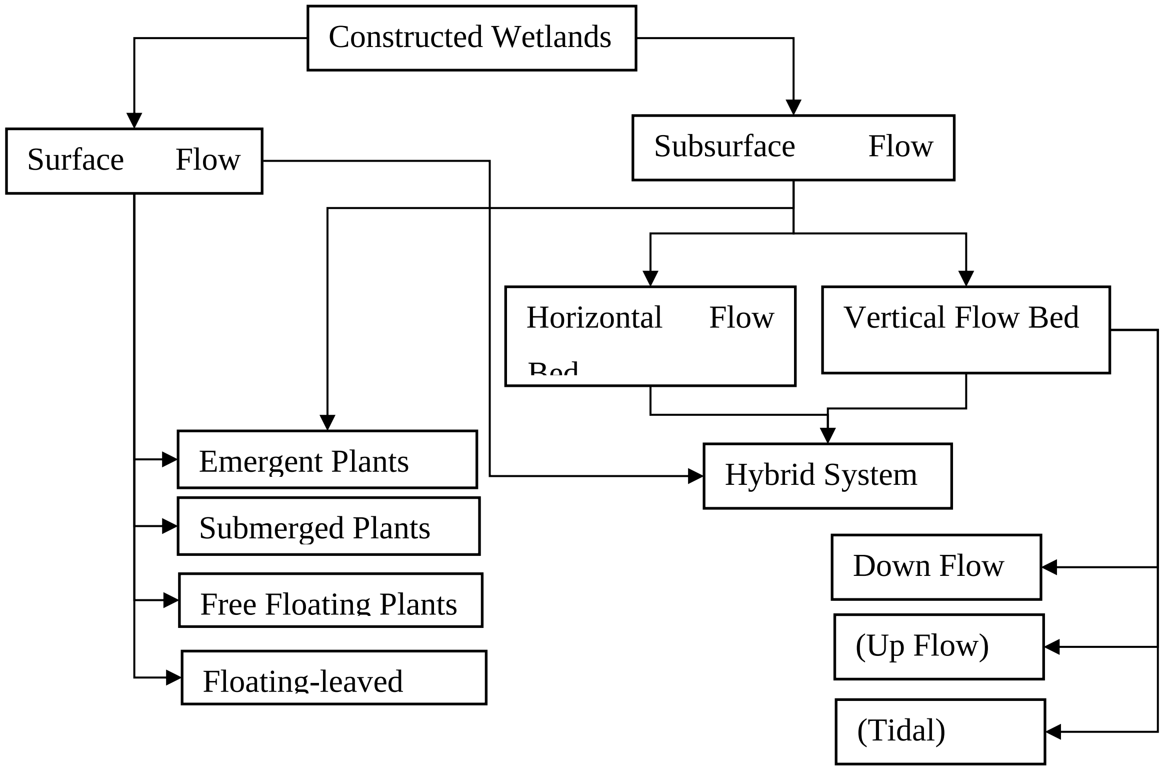

Figure 2.1: Classification of Constructed Wetlands: (Vymazal & Kröpfelová, 2011)

The gravel or coarse sand used in subsurface flow CWs contributes to the treatment processes by providing a surface for microbial growth and by supporting adsorption and filtration processes (Hoffman et al., 2011). This results in lower area demand and higher treatment performance per area for subsurface flow CWs, compared to FWS CWs. Subsurface flow CWs are the predominant wetland type in Europe.

2.3.2.1 Free water surface-flow constructed wetlands (FWSF-CWs)

FWSF-CWs function in a similar way like a natural wetland (Vymazal, 2014b, Rousseau et al., 2008, Wu et al, 2014). The constructed wetland pond is shallow and closed to prevent wastewater from leaking to the sinkhole. The substrate of the wetland is soil that covers up its thickness to 40 cm height thereby permitting the creation of wetland plants (Wang et al., 2017). The constructed wetland systems are submerged by water from the top down and flow horizontally on to the top of the porous wetland media, growing a depth of water column of around 20 to 40 cm or up to 80 cm (Jan Vymazal, 2014b). The wastewater penetrates through the porous media or evaporated to the atmosphere due to high temperature as shown in Figure 2.2.

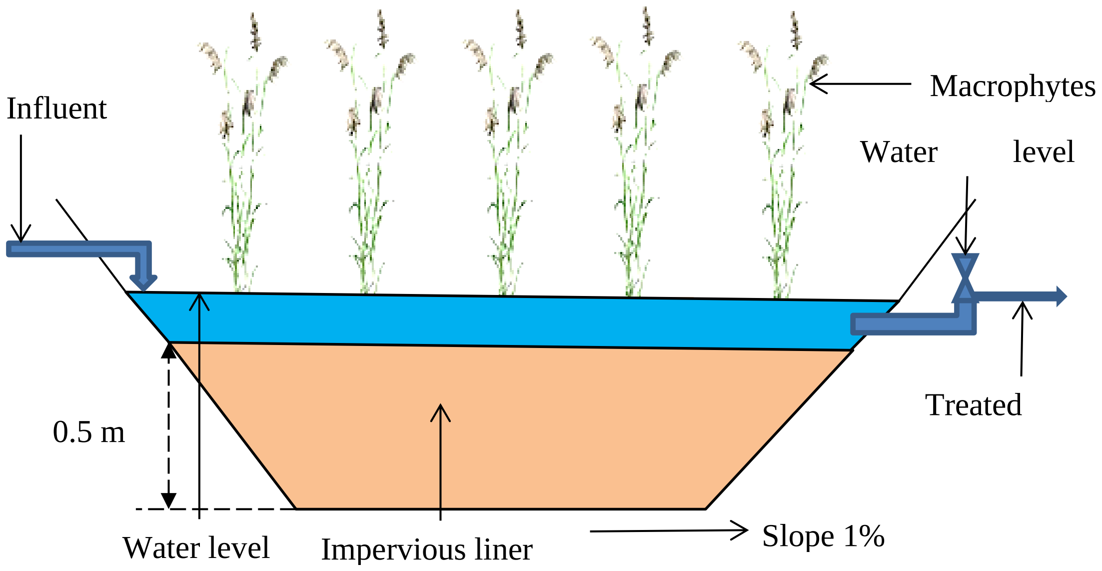

Figure 2.2: Schematic illustration of free water surface-flow constructed wetlands (FWSF CWs) with emergent macrophytes

The inflow wastewater in FWSF-CWs flows directly through the wetland bed going down to get contact with the soil, gravel and wetland plants, then directing removal of biological, chemical and physical water quality parameters processes to take place. These processes cause the reduction of many wastewater pollutants (Khalil, 2017, Wang et al., 2017, Li & Zheng, 2018).

Regarding wastewater treatment, FWSF CWs ware discovered to be very good for Suspended solid removal, nitrogen, biochemical oxygen demand (BOD5), phosphorous, and other pollutants such as heavy metals (Li & Zheng, 2018). The use and application of FWSF-CWs have been described to be prevalent in North America (Kadlec & Wallace, 2008) and applied entirely for treatment of domestic wastewater. Different types of macrophytes can be planted in the systems such as emergent, free-floating, floating-leaved, bottom rooted or submersed macrophytes. Moreover, despite their advantages as cost-effective and simple to operate, the FWS-CWs require a large area of land and the water is possibly open to human contact (International Water Association [IWA] Specialist Group, 2000). Moreover, their nearly standing water strengthens the possibility of mosquito breeding.

2.3.2.2 Subsurface-Flow Constructed Wetlands (SSFCW)

As Subsurface Flow Constructed Wetland Systems (SSFCW) is a comparatively new technology, the operational conditions that affect the performance of constructed wetland are poorly defined presently (Abdelhakeem et al., 2016). Subsurface flow constructed wetland systems are dependable treatment system with very high treatment efficiencies for the organic matter, pathogens and nutrient removal. In SSFCW, wastewater surface is commonly below the surface of media matrix. Media material is an important factor to ensure a sufficient hydraulic conductivity (Sayadi et al., 2012). Subsurface flow CWs is divided further into vertical flow constructed wetland systems and horizontal flow constructed wetland system and divided depending on the direction of water flow through the porous medium (sand or gravel).

SSFCWs are known with other names as vegetated gravel-bed, planted soil filters, vegetated submerged beds, gravel bed hydroponic filters and red bed treatment system. Subsurface flow constructed wetland systems is a sink that is filled with filter material (substrate) mostly sand or gravel and planted with vegetation that withstands flooded condition. Wastewater is poured into the system sink and courses through gravel or sand and is released out of the sink through construction that controls the deepness of the wastewater in the constructed wetland. The substrate used in subsurface flow constructed wetland systems help in the treatment processes by giving a surface microbial growth and supporting wetland plant the absorption and filtration processes. This effect in lower area demand and higher treatment per area for SSFCWs, in comparison with FWSCWs. SSFCWs are more appropriate in a warm climate due to biological decomposition rates decrease with decreasing temperature; they also freeze in a cold climate. Furthermore, the oxygen transfer from the atmosphere decreases as soon as ice covers open water surface, thereby decreasing the oxygen-dependent treatment process (US EPA 2000).

The performance of constructed wetland is usually assessed base on the removal efficiency and the rate of pollutant removal. Removal of pollutants in SSFCWS is a complex process that depends on a variety of mechanism which includes physical, biological and chemical processes (Vymazal, 2014b, Abdelhakeem et al., 2016). Many features involved in the options select between FWSFCWs and SSFCW, these include size, cost, functionality, another option include strength, health and nuisance matters and additional benefits (Kadlec, 2009). The advantages and disadvantages of FWSFCWs and SSFCW are presented in Table 2.1.

Table 2.1: Advantages and Disadvantages of Free water surface-flow constructed wetlands (FWSFCWs) and subsurface flow constructed wetland systems (SSFCW)

	FWSFCWs	SSFCW

Advantages	Lower installation and operating costs	Greater assimilation rate, less land required
	Good integration into the landscape	No visible surface flow
	More secondary benefits (such as wildlife habitat), but contamination exposure concern	More cold tolerant
	Shorter development period to reach full performance	Reduction in odour and insect problems
Disadvantages	Less cold tolerant Moreland required	Not attractive to wildlife, more isolated from humans

2.3.2.2.1 Type of subsurface flow constructed wetlands (SSFCW)

There are three (3) types of subsurface flow constructed wetland (SSFCW) viz.:

i. Vertical-flow Constructed wetland (VFCW)
ii. Horizontal-flow Constructed Wetland (HFCW)
iii. Hybrid Constructed Wetland (HCW)
iv. the downflow (intermittent loading) systems

2.3.2.2.1.1 Vertical flow constructed wetlands (VFCW)

Vertical flow constructed wetlands for wastewater treatment represent a relatively new and still growing technology. They were initially established by Seidel in 1965 as a middle stage after an aerobic and anaerobic septic tank before HFCW (Vymazal et al., 2006). At an early stage of the Constructed Wetland systems (CW) technology, the focus was only given on the other CW types, since VFCWs usually keep the higher cost of operation. Typically, the media in VFCW experiences immersion and desaturation cycles as the water is being nourished intermittently into the systems, and flow vertically down to the bottom (Choudhary et al., 2011; Tsihrintzis, 2017), which makes the systems powerful and effective in accomplishing a high rate of oxygen transfer (Abdelhakeem et al., 2016). The wastewater is applied and surges the wetland surface at first and after that permeates through the wetland body by gravity (Scholz & Lee, 2005). As the wastewater percolates, air enters the substrate pores (Al-Isawi et al., 2015) enhancing the aeration and the microbial activity. VF systems perform well in organic matter (BOD5 and COD), suspended solids and limited Phosphorus removal (Brix & Arias, 2005; Prochaska et al., 2007), because of the inadequate contact time between the wastewater and the substrate. In addition to that, they can achieve a satisfactory level of nitrification (Sheet, 2003). The vertical-flow constructed wetland system designed and described in the guiding principle will fulfil the treatment phases which require 95% removal of BOD5 and 90% nitrification, but will not remove sufficient phosphorus to fulfil the demand of 90% removal of Phosphorous based on the past research (Brix & Arias, 2005). Vertical flow constructed wetlands are effective in the high reducing percentage of water quality parameter as long as the inflow of the parameter exceeds the natural level at which the VFCW operates (Scholz & Lee, 2005). Vertical flow Constructed Wetlands have been used in a wide range of situations recently, as a sustainable and economical substitute for the treatment of polluted wastewaters (Abdelhakeem et al., 2016). The significant difference between a vertical and horizontal constructed wetland is not only the water flow direction but also the aerobic conditions.

A vertical flow constructed wetland (VFCW) is a planted bed column used as a treatment facility for secondary or tertiary wastewater (municipal or industrial wastewater, greywater) treatment to produce an inflow of high quality that drains vertically down through the filter layer and collected at drainage pipe located at the bottom of the filter. The pre-treated wastewater is put onto the top surface of the VFCW filter using mechanical dosing system until it reaches the drainage system connected to an outlet manhole (Sharma et al., 2014, Al-isawi et al., 2015). The wastewater treatment involves a combination of the physical, chemical and biological process. These include filtration, adsorption precipitation, nitrification, decomposition etc. The treated water by the well-constructed functioning system vertical flow constructed wetland can be reused for irrigation, groundwater discharge and agriculture. Vertical flow constructed wetland are particularly efficient in the removal of suspended solid, organic material and for nitrification while it is less capable in de-nitrification (Al-isawi et al., 2015, Chang et al., 2012, Gikas, et al., 2007). It has been proved to be capable of removing a variety of pollutant present in wastewater, namely, organic matter (BOD5 and chemical oxygen demand - COD), suspended solids, nitrogen, phosphorus, heavy metals, pathogenic microorganisms, and micro-organic compounds. Figure 2.3 shows the vertical flow constructed wetland.

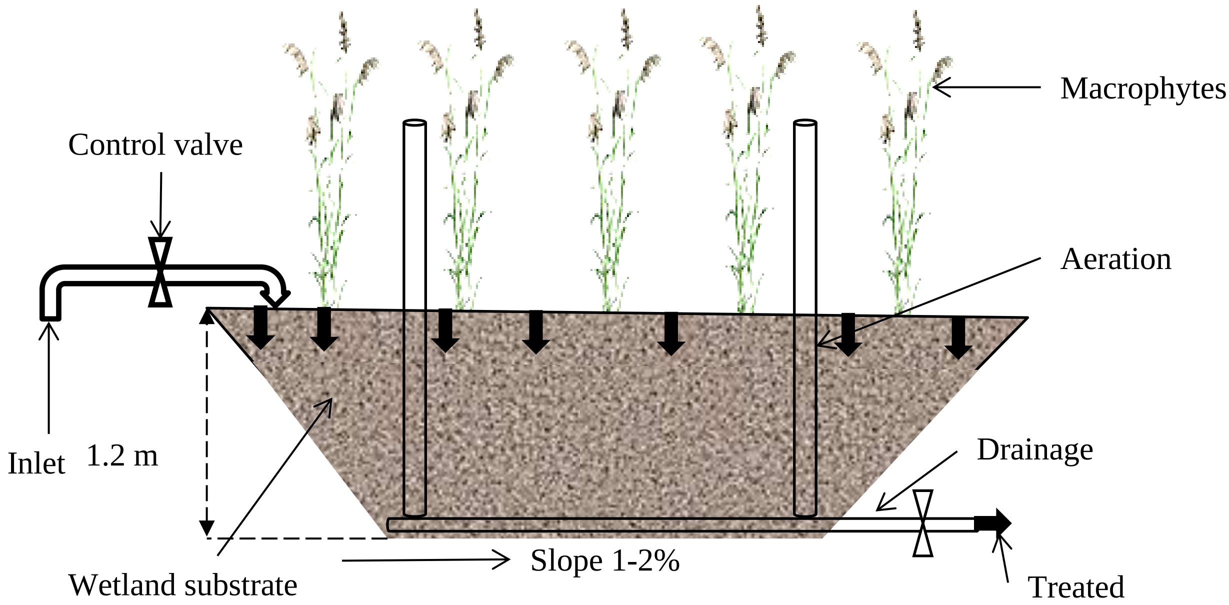

Figure 2.3: Typical illustration of vertical-flow constructed wetlands

Seidel in 1965 established the vertical flow constructed wetland systems, in Germany when they have implanted in-between HSF-CWs and a septic tank (Jan Vymazal et al., 2006; Jan Vymazal & Kröpfelová, 2011). The application of the HSF-CWs became relevant gradually when people acknowledged the non-fulfilment of HSF systems to oxidise ammonia-nitrogen effectively from wastewater inflow because of limited oxygen in their substrate bed (Stefanakis et al., 2014; Vymazal, 2005, 2014a). Usually, when inflow wastewater is being fed intermittently into the systems it pass through porous media underfilling and draining cycles and drain at the valve (Nivala et al., 2013; Stefanakis et al., 2014; Vymazal & Kröpfelová, 2008a) which makes the systems capable in attaining a high rate of oxygen transfer (Paul Cooper, 1999; Huang et al., 2015; Morris et al., 2011; Nivala et al., 2013; Stefanakis et al., 2014; Vymazal & Kröpfelová, 2011). According to Frazer-Williams, (2010), Huang et al., (2015), in their respective research they reassured that wastewater is poured and floods the surface of the wetland firstly and then permeates through the wetland body by gravity (Figure 2.3). As the wastewater enters through the wetland filters, air penetrates the gravel (Fan, et al., 2013; Song et al., 2015; Vymazal et al., 2006), thereby improving the aeration and the microbial activity. VFCW systems, are discovered to be very effective in wastewater treatment as conducted and indicated by many studies research. In the research study of Prochaska et al., (2007), Lu et al., (2016) and Wu et al., (2015), they demonstrated that VFCW systems perform considerably well in the treatment of biochemical oxygen demand, chemical oxygen demand, dissolved oxygen, suspended solids and little phosphorus due to insufficient associations of the wastewater and the filter media. Moreover, in the research of Tietz et al, (2007) Vymazal et al., (2006), Gikas & Tsihrintzis, (2012) they all demonstrated that the VFCW systems could also attain an acceptable level of nitrification. However, some study researches stated them as poor denitrifies (Scholz & Hedmark, 2010; Vymazal, 2005; Vymazal & Kröpfelová, 2011). Many studies revealed that VFCW systems with intermittent loading schemes with some modifications could denitrify perfectly (Carlos et al., 2005; Fan, et al., 2013; Gross et al, 2007; Weedon, 2003, 2010). VFCWs are wastewater treatment system with macrophytes rooted in gravel (substrate); it also differs considerably from the horizontal-flow constructed wetland in term of feeding method. Water flow directly, and filling media (Figure 2.3) inflow wastewater is usually applied discontinuously on the surface through several mechanisms, infiltrates and percolate with ideal plug-flow over the support plant root. The new batch of sewage is poured to the filters only all the water percolate and bed free of water and leave to rest for stipulated time (resting time). This enables the diffusion of oxygen from the air into the bed

Vertical flow constructed wetland (VFCWs) are mainly applied to the treatment of urban and domestic wastewater due to their evolution in nitrification ability, treatment of other kinds of sewage is also applicable, commonly those with high concentration of ammonium nitrogen, such as leachate, landfill, dairy wastewater, and food processing wastewater to mention but few (Robert H Kadlec & Wallace, 2008). VFCWs are mostly used in the United Kingdom and other Europe countries like Denmark, Australia France and Germany, it is also used in the United States. The continuing increase in VFCWs application was due to the comprehension that HFCWs constitutes relatively low oxygen transfer capacity (OTC) for the secondary treatment demand, which respectively reduces ammonium nitrogen (NH4-N) oxidising capacity (Cooper, 1999).

Reviews made in the journals and publications disclose that the use of vertical flow constructed wetland study treating domestic water will be helpful for monitoring the water quality in the environment predicting the treatment performance of constructed wetland. These discoveries were the critical guide behind this thesis. The literature review found that CWs have the potential to be valued for wastewater treatment in the UK and many EU countries

2.3.3 The advantage of Constructed Wetland for wastewater treatment

The advantages of constructed wetland in wastewater treatment include the following:

1. It is in the expensive way of treating wastewater, which uses the local resources available, that the system that encourages, its biological treatment system is more environmentally friendly.
2. The system can be created at a lower cost than other treatment options, with a low-technology method where no new or complex technological tools are needed.
3. The system can tolerate both more significant and small volumes of water and varying contaminated levels; these include municipal and domestic wastewater urban storm runoff agricultural wastewater, industrial effluent and polluted surface water in rivers and lakes.
4. The constructed wetland system could be used to clean polluted rivers and any other bodies of water.
5. The primary purpose constructed a wetland to treat various kind of wastewater (municipal, industrials and stormwater).
6. It can serve as a wildlife sanctuary and provide a habitat for wetland animals, and it can also be pleasing and serves as an alternative destination for tourist and local urban dwellers. Can also as use public attraction sanctuary for visitors to explore its environmental and educational possibilities.
7. The system also offers research, training ground and nature studies for the young scientist in this new research and education setting.
8. Constructed wetlands are used to improve the quality of water polluted from the point and nonpoint sources of water pollution, including stormwater runoff, domestic wastewater, agricultural wastewater, and mine drainage
9. Constructed wetlands are also being used to treat petroleum refinery wastes, compost and landfill leachates
10. It is a treatment option that provides ecological benefits
11. They are constructed using local materials with minimum ‘external costs’ and are sustainable over a long lifetime (>50 years).
12. They reduce odours produced, due to factors such as shallow surface flow and dense plant cover
13. The captured nutrients can be recycled for land management, and the treated water can be reused.

2.3.4 The disadvantage of Constructed wetland for waste water treatment

1. Not clear maintenance knowledge
2. Risk of the existence of insects (particularly in those of the surface flow) or rodents

3. If the removal of suspended solids in the primary pre-treatment is not active, clogging may arise (particularly in horizontal surface flow constructed wetland)
4. The design surface area is more significant than in conventional system (especially free flow), (typically 1-2% of farm area) although lower than in the case of the pond (especially those of surface flow).
5. Few control factors during operation
6. The construction and establishment of vegetation may be weather dependent
7. If deep areas of water are included, there is a potential water hazard
8. If inadequately designed, constructed or managed, they may pose a threat to surface and ground waters
9. Their performance is not consistent throughout the year
10. They required competent skills for design, site analysis and characterisation, and construction, planning permission and discharge licences
11. Its establishment need a large area of land
12. It can effect by highly toxic materials on its action
13. Pre-treatment is essential for medium and high concentrated contaminants. Regular cleaning is also necessary.

2.3.5 Application of Constructed wetlands

Constructed wetlands are used for the treatment of domestic and municipal wastewater of both secondary and tertiary phases. Although CW is generally used for wastewater treatment, the application of CW has expanded considerably to another form of sewage these include industrial wastewater, wastewater from agricultural activities, runoff, abattoir, refinery (Wu et al., 2015)

CWs are designed to remove contaminants from wastewater like suspended solids, BOD, COD DO, EC, nutrients and pH. Other pollutants that are also removed but that are not commonly targeted when designing municipal wastewater treatment systems are heavy metals, surfactants, pharmaceuticals and personal care products (PPCPs) as well as other emerging pollutants.

2.4 Basic design, operation and Maintenance of VFCWs

To design a Vertical Flow Constructed Wetland (VFCW) system, The most common composition of VFCWs setup involves permeable substrate bed of either rock (gravel) or sand with size increment with depth (Jan Vymazal & Kröpfelová, 2011). The bed arrangement is from top to bottom with depth between 45 cm and 120 cm, and the incline of the base of the bed of 1–2% that encourages natural movement, drainage, and collection of the treated water effluent drainage. The bottom of the system is covered by a geomembrane or made of reinforced concrete. Common reed (*Phragmites australis*) are most commonly used plant and are planted at the top of the bed. After designing the system before starting the operation, seeking knowledge and advice from experts is recommended.

Vertical flow constructed wetlands have been reported to treat a variety of wastewaters effectively with high-performance (Scholz et al., 2010; Dzakpasu et al., 2010; Kayranli et al., 2010). The vertical flow constructed wetland is designed and constructed as a shallow excavation or as above ground. The design and size of the wetland are dependent on hydraulic and organic loads. Each filter has an impermeable liner and an outflow collection system. Structurally, there is a layer of gravel for drainage (10 mm and 20mm), Phragmites australis (reed), Typha sp. (cattails) is a common plant option. As a result of good oxygen transfer, vertical flow wetlands can nitrify, but denitrification is low. Bohórquez, Paredes, & Arias, (2017) in their study research they examined and evaluated the effect of different design and operational parameters to find the optimum of vertical-flow constructed wetlands treating domestic wastewater under tropical conditions. Ten filters arrangements units were investigated to compare between the substrate used (small and large gravel).

The different loading rate applied, did not display any essential statistical differences in the removal of the tested pollutants. Initial results were discovered in the elimination of the pathogen, where the fine sand as the substrate is suitable. Frazer-Williams, (2010) also evaluate the effect of wetland design criteria area sizing, and operation parameters (hydraulic and inflow loading) for the removal of pollutant (organics, solids, nutrients and coliforms) in both subsurface and surface flow systems. Results showed that even though high removal performance of contaminants was attained for most wetlands, residual concentrations for BOD are regularly higher than those forecast based on the 95 percentile first-order Kickuth design equation. Also, correlation results indicate that hydraulic and pollutant loading impacted strongly wetland performance for organic matter (BOD, COD) removal. In all cases, removal of pollutants decreases typically as the hydraulic loading rate also increases. Correlation between Hydraulic loading and nutrient removal was not discovered. Overall, it can be resolved that organic removal can be modelled better compared to a nutrient in constructed wetlands. Since the critical design parameters do not primarily influence the removal of solids and coliforms, it is expected that they will fit into any design model developed

Some study researches like Stefanakis & Tsihrintzis, (2012b) and Zhi & Ji, (2014) indicated that during the experimental setting-up phase of the constructed wetlands, outflow water quality parameters like chemical oxygen demand (COD) are discovered to be relatively unstable when the wetland is maturing.

Furthermore, an extended hydraulic retention time impacts in higher removal performance efficiencies for ammonia-nitrogen, irrespective of plant maturity. Long resting times generally certifies biodegradation and nitrification. However, Stefanakis et al., (2014) reported that the biodegradation of organic matter in VFCWs depends on the inside of the organic matter and the retention time applied during treatment of wastewater by the system. Therefore, they summarised that readily biodegradable organics are oxidised quickly, due to high oxygenation in the wetland media bed while the disorderly ones are partially degraded caused by inadequate contact time. Moreover, the organic matter decomposition was mostly happening in the top 10– 20 cm due to the accessibility of high oxygen and microbe population density in the upper wetland gravel bed (Kadlec & Wallace, 2008; Stefanakis & Tsihrintzis, 2012b; Tietz et al., 2007).

In the work of Stefanakis & Tsihrintzis, (2012a) they studied and investigated the removal performance of organic matter pollutants (BOD_5 and COD) and recorded to be above 78% removal and that of nitrogen (TKN and NH_4- N) was recorded to be 58% removal and 37% for phosphorus removal (total phosphorus [TP] and orthophosphate phosphorus (PO4-P). The research also recognised the system performance due to the enhanced aeration in the porous media bed.

Kayranli et al., (2010) and Rousseau et al., (2008) indicated that pollutants removal performance by constructed wetlands is linked to the hydraulic loading rate and contact time; i.e. if the hydraulic loading rate is high and contact time is low, highly contaminated wastewater leaves the wetland quickly, which results in a corresponding relative decrease of the treatment efficiency due to inadequate time for biodegradation processes. (G D; Gikas & Tsihrintzis, 2014) Pointed out that water quality outflow parameters such as chemical oxygen demand (COD) are relatively unstable during the experimental setting-up phase when the wetland matures. Furthermore, a long contact time results in higher removal efficiencies for ammonia-nitrogen, regardless of plant maturity. Nitrification and biodegradation, in general, can be promoted by relatively long resting times (artificially induced drying and aeration times).

Constructing VFCW system is relatively cheap where land is inexpensive, the system can also be conducted and maintained by unskilled labour. VFCWs are generally considered as a systems that simple to construct and operate, though accurate and accepted CW facility design is not simple as expected, as it is comparatively new and emerging technology, As a result there no recognised setup that is universally accepted by the researchers. Individual experience by the researchers and scientist is typically a key factor. Moreover, there are common key design consideration and regulations and that are applied during the process like metrological topographical and operational parameter (A. Stefanakis et al., 2014). These include the following:

1. Information Topographic to select installation site which is the most suitable
2. Climate condition of the area where the system will be fixed
3. Availability of the necessary land
4. Current and future wastewater flow and volume
5. Any legal limit that applies in the area of the effluent quality desired treatment performance
6. Total cost
7. Possibility and need for outflow reuse choice
8. A close by water body outflow receiver

During the first growing season, it is important to remove weeds that can compete with the planted wetland vegetation. Collection pipes should be removed and cleaned twice a year, to eliminate sludge and biofilm that may block the passages. Clogging is a common problem of VFCWs, Gradually; the gravel will become clogged by solids and bacterial film accumulation. Resting time interval may restore the hydraulic conductivity of the filters. If this does not help, the accumulated solids have to be eliminated, and clogged portions of the filter solid changed. Maintenance activities should concentrate to make sure that primary treatment is active at decreasing the solids concentration in the wastewater before it pours into the wetland filters. Maintenance should also make sure that trees and weeds do not germinate in the area as their roots can damage the liner.

2.4.1 Horizontal flow constructed wetland

Horizontal subsurface flow constructed wetlands (SSF CWs) are treatment systems in which wastewater is feed in at the inlet and flows slowly across the porous medium under the surface of the bed, roots and rhizomes of the emergent planted vegetation in a more or less horizontal path until it reaches the outlet zone (Figure 2.4). During the passage, the wastewater will enter into the contact network of aerobic, anoxic and anaerobic zones. The aerobic zones are found nearby the root and rhizomes that leak oxygen into the surface (Shuib et al, 2011, Vymazal, 2008). Figure 2.4 shows the horizantal subsurface-flow constructed wetland systems.

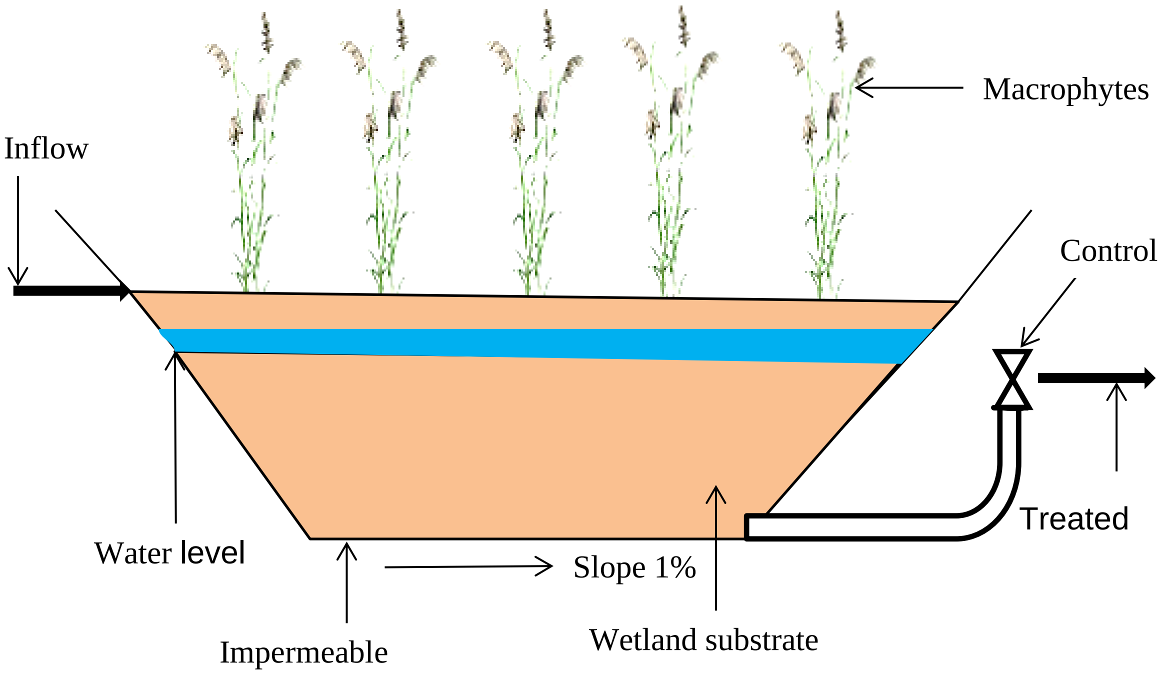

Figure 2.4: Schematic illustration of horizontal subsurface-flow constructed wetlands

The reactor is mostly anaerobic, with the physical, chemical and biological mechanism, bacterial reduction and oxidation, filtration, settling and chemical settling. Inflow wastewater flows underground with ideal plug-flow where it is collected before leaving, through a level control arrangement at the outlet (Shuib et al., 2011). Passing through porous media support, (Normally, the media in HFCWs is permanently flooded with water) and contacting the biofilm formed over the support and plant roots hydraulic retention times (HRT) differ from a few several days, depending on the objectives and management. The removal of contaminants occurs because of complex physical, chemical and microbial interactions (Zidan et al., 2015). Through this passage, the wastewater will meet a network of aerobic, anoxic and anaerobic zones. The aerobic zones normally occur around roots and rhizomes that leak oxygen into the substrate (Zidan et al., 2015). HFCWs consists of an inlet pipe, an outlet pipe with water level control, a clay synthetic (HDPE or PVC) linear, filter media, emergent vegetation: the most common macrophytes are Phragmites australis (common reeds), but Typa spp (cattail) and Scirpus spp (bulrush) are also used.

The sizing of the HFCWs systems depends on many parameters that should be examined during the preliminary feasibility evaluation. After defining the treatment goal and the most appropriate treatment scheme, the sizing procedure may be performed using the well-known and scientifically approved method. Area requirement and determine based on design equation such as the various commonly used first-order kinetic equation (Lijuan Cui et al., 2016) for the removal of pollutants and the Darcy law for the hydraulic aspects (Ghimire et al, 2012).

2.4.2 Hybrid constructed wetland

Hybrid constructed wetland combined both vertical and horizontal flow constructed a wetland to achieve higher treatment effect (higher removal efficiency) especially for nitrogen removal and to treat complex agricultural and industrial wastewaters treated in the constructed wetland (Jan Vymazal, 2013). In these systems, VFCW and HFCW are combined to enhance each other for proper wastewater treatment. It is also called a mixed system (Sheet, 2003). Hybrid constructed wetlands are the different types of CWs that combined on various arrangements to form a combined system to get adequate treatment performance of wastewater. Hybrid CWs are used to achieve higher efficiency wastewater treatment rather than single CW, particularly in the removal of nutrients components (Sayadi et al., 2012). Some of the water quality parameters (Total nitrogen) cannot attain high removal by single stage CWs (vertical or horizontal), due to their incapability to produce aerobic and anaerobic condition. In this regard, Combination of various types of CWs may be combined to control the advantages of single stage systems. A German, called Dr Käthe Seidel first introduced hybrid constructed wetlands in the early1960s due to high demand of eliminating ammonia nitrogen and any other nitrogen-related compound from wastewater, as such is was discovered that Hybrid was able to provide such requirement (Vymazal, 2013, Vymazal & Kröpfelová, 2011, Vymazal, 2011).

Presently, hybrid constructed wetlands are applied and used worldwide due to their capability of ammonia, nitrate and total nitrogen removal from various types of wastewaters (Bouchaib et al., 2012; Sayadi et al., 2012; Jan Vymazal, 2013; Kadlec et al., 2017).

Moreover, they are also applied to treat a different type of wastewaters including wine producer wastewaters (Varga, Ruiz, & Soto, 2013) they are also applied to treat pharmaceuticals and personal care products (PPCPs) (Reyes-contreras, Matamoros, Ruiz, Soto, & Bayona, 2011). Hybrid constructed wetlands are also applied and used to treat oil field produced water (Alley et al., 2013), hybrid constructed wetlands are also applied to treat grey water under adjustable and stress conditions (Comino et al, 2013), and hybrid constructed wetlands are also used to treat industrial effluents (Jan Vymazal, 2014b). In the research of Jan Vymazal, (2013), hybrid constructed wetlands are classified into: VF-HF systems, multistage VF-HF systems, VF hybrid systems, and hybrid-constructed wetlands with FWSFCW systems. Nevertheless, in his research, he discovered that VF-HF hybrid systems are slightly more active in the treatment of Ammonia than other types of hybrid constructed systems. Figure 2.5 represents diagram of the hybrid constructed wetland systems.

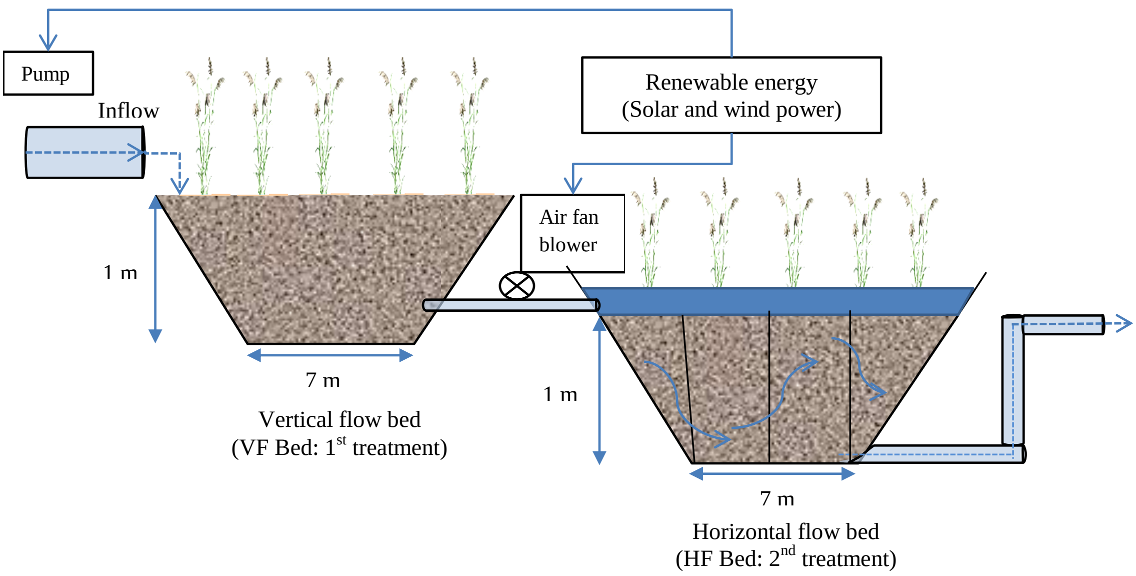

Figure 2.5: Schematic illustration of hybrid constructed wetlands

2.4.3 The advantage of Vertical flow constructed Wetland over others

1. High rate removal of carbonaceous oxygen demand, suspended solids, nutrients coliform bacteria and pathogens, thus better outflow quality
2. It has good oxygen transfer capacity (aeration) which result in good nitrification
3. It restricts clogging to very minimal in comparison with a horizontal subsurface flow Constructed Wetland because it was built with a porous material and wastewater circulate.

4. It requires less total space area than a Horizontal Flow Constructed Wetland.
5. It has very low construction, maintenance, and operation costs.
6. It does not require specialised personnel for the operation as it is straightforward to operate.
7. It does not have the problem of a mosquito of the Free-Water Surface Constructed Wetland.
8. It offers better treatment performance of wastewater.
9. It is a dependable treatment system of wastewater

2.4.4 The disadvantage of Vertical flow constructed Wetland

1. Needs more regular maintenance than another type of constructed wetland
2. Some of parts and materials may not be available locally
3. Needs design and construction by an expert, mostly, the feeding system
4. It requires long start-up time to work at the complete capability
5. A constant source of electricity may be required

2.5 Component of Constructed Wetland

To understand the treatment processes, it is essential to know about the parts of the constructed wetland system because all the processes occur within each or several components of the system. Constructed wetlands have three different of major components: a fixed component, a water component and an atmospheric component (Breen, 1990; Qasaimeh et al, 2015). The fixed component includes the wetland substrate, wetland vegetation, water component comprises the wastewater inflow, treated outflow, wetland filters, and the related pollutants. The atmospheric constituent regulates the gases movement in and out of the wetland filters (Wallace & Knight, 2006).

2.5.1 Macrophytes

In the wetland ecosystems and aquatic, Microphytes (wetland vegetation) are critical and major components of constructed wetland systems (Scholz et al., 2007; Scholz & Hedmark, 2010; Vymazal, 2013 Rejmankova, 2016; Kadlec et al., 2017) including constructed systems and, undoubtedly due to its presence, the systems are referred to as green technology (Abou-Elela, 2017). They are sometimes called a hydrophytes plant (Cronk & Fennessy, 2016). A macrophyte is an aquatic plant that always grows in or near water and is emergent, sub-mergent, or floating, which includes helophytes. Although these emergent plants are one of the main components of the wetland environment, cleaning or treatment of wastewater is directed by the unification of many processes, which include chemical, physical and biological processes between the macrophytes, substrate and the association of wetland microorganisms. Normally, Macrophytes are used as a plant species in the treatment of the constructed wetlands (Brix, 2014; Cronk & Fennessy, 2016; Abou-Elela, 2017). Their classifications include: cattail (Typha spp), common reed (Phragmites spp), rush (Juncus spp) and bulrush (Scirpus spp). Besides, the macrophytes utilise their tissue to ingest toxins and supply the microorganisms with an ideal developing or growing condition and environment (Vymazal, 2002a).

The roots of the macrophyte dissolve organic matter, strengthen the surface of the beds in the constructed wetland. They also, provide a good condition for physical filtration, and prevent vertical flow system from clogging by forming openings for the water to permeate within the substrate. It also shields against frost in the course of water growth, generates appropriate possibility for bacteria growth, absorbs nutrients and provides oxygen to the water (B. Lee & Scholz, 2006). The growth of macrophyte does not affect the increase in hydraulic conductivity of the substrate in soil based surface flow constructed wetland (Brix, 2014). Figure 2.6 shows a picture of common reeds (Phragmites australis) plants cluster.

Figure 2.6: Cluster of common reed plants (Phragmites australis)

Globally Phragmites australis (Cav.) Trin. Ex Steud. (Figure 2.6) has been accepted as wetland plant species as indicted by previous studies (Miklas Scholz, 2006; J. A. N. Vymazal, 2011; Jan Vymazal, 2014b; IWA Specialist Group, 2000; Scholz, 2006; Vymazal, 2011c, 2014). While they are widely used throughout Europe and Northern America as part of the treatment wetlands, the function of macrophytes plus the influence of many types of wetland plant on the treatment wetland is still not understood (Miklas Scholz, 2006).

Past investigations revealed a substantial contribution of macrophytes to pollutants removal. For instance, the percentage decrease of about 89% in BOD and COD was reported to be more prominent in plant than control systems that have a percentage reduction of about 85% (Akratos & Tsihrintzis, 2006). It was also discovered that that macrophyte, e.g. common reed plants (Phragmites australis) are capable of removing large quantities of organic and inorganic substances from polluted water (R. H K Al-Isawi et al., 2015; Chu, Wong, & Zhang, 2006). The percentage reduction of BOD and TSS to be greatly minor in control systems (46%) and (63%) than in open systems (88–90%) and (70–75%) respectively for SSF wetlands (Karathanasis, Potter, & Coyne, 2003). Removal of polycyclic aromatic hydrocarbons (PAHs) and linear alkylbenzene sulfonates (LASs) from domestic wastewater in pilot constructed wetlands and a gravel filter in Greece were also examined (Antonopoulos, Papamichail, & Mitsiou, 2001; Mimis & Gaganis, 2007). The authors discovered that the vegetated filter listed 79.2% and 55.5% removal efficiency of PAHs and LASs respectively in comparison with 73.3% and 40.9% for the gravel filter (Fountoulakis, Terzakis, Kalogerakis, & Manios, 2009). Recently, in their review, high removal efficiency has been detected in planted wetlands treating pharmaceuticals including caffeine, naproxen, diclofenac and ibuprofen compared unplanted ones (Paola Verlicchi & Zambello, 2014).

Moreover, in a research conducted by Hijosa-valsero et al., (2011) to evaluate the antibiotics removal from urban wastewater by constructed wetland optimisation. They stated that their improved SF systems revealed higher removal of clarithromycin and trimethoprim in comparison with vegetated ones. However, in various studies, it was shown that there was no significant contribution of macrophytes about pollutants reduction in planted and unplanted wetland systems. In the research of Miklas Scholz, (2006), he discovered that (BOD) removal efficiency of constructed wetlands essentially the same regardless of developing periods of the wetland plants, in related research Donze, (2014) observed irrelevant removal efficiencies in their systems planted with duckweed, reed and algae.

2.5.2 Substrate

The substrate is the porous media used in constructed wetland building. The media is also called aggregates or wetland media. These wetland media include rock or gravel, organic materials (such as compost), soil and sand. Several studies (Wang & Zhang, 2012; Dordio & Carvalho, 2013; Meng et al., 2014) exposed that soil is the major components of the wetlands that support the growth of macrophytes and microorganisms biofilm in constructed wetlands. Likewise, the hydraulic mechanism of the wetland system depends on the type and origin of the soil. In addition to pollutants adsorption by substrate media in constructed wetlands, the substrate displays an essential part in giving an atmosphere favourable for wetland plants growth and microbial activity on wastewater contaminants (Dordio & Carvalho, 2013; Ge, Wang, & Zheng, 2015). Nevertheless, the porous media size should not be considerable because, big size media does not provide enough surface area for the formation of biofilm (Meng et al., 2014). Brix, (2014) also discovered that media that is small-sized-grain, like organic soil, give a surface area for the growth of biofilm whereas narrow pore diameters media lead to media pore blockage. The depth of a substrate in constructed wetlands (CWs) has a significant effect on the construction investment and the purification performance of CWs. The substrate cannot only provide carriers for the growth of plants and microbes, but it also removes pollutants directly by its sedimentation, filtration, and adsorption.

Selection of the porous filter media has been proposed by Meng et al., (2014) due to its importance regarding hydraulic loading rate in SSFCWs. The reason behind the selection methods of the media was to avoid clogging of the media pores, which may cause a problem and can affect the overall performance of the system. The clogging associated problem of the system results from in appropriate media porosity selection for the organic loading application equivalent. The filtration media used for constructed wetlands depend upon the objectives that should be achieved. Constructed wetlands have been planned and built with substrates extending from fine surface soil to fieldstone.

A coarse-grained material with high water hydraulic conductivity will stop the filter from getting clogged, and close-grained material will be more effective in decreasing suspended solids and turbidity (Table 2.2). Substrate media in wetlands are considered as hydric while they are saturated or inundated with water. For saturated conditions, the water displaces the air in the substrate pore spaces, and the microbes use the dissolved oxygen. The oxygen used by microbes in the wetlands media is bigger than what will be reverted over diffusion. Hence the wetland media become anoxic. Furthermore, the substrate media became anaerobic in flooded conditions (Scholz, 2006) and mixture of sand and gravel is suggested to enhance hydraulic conditions and pollutants removal (Kadlec et al., 2017).

Nevertheless, previous studies recommended that biofilm growth were supported by smaller-sized media as such is better than large-sized porous media, which did not support proper growth of the biofilm. Hence, the ability to achieved higher biodegradation by microbes (Dordio & Carvalho, 2013; Meng et al., 2014), while substrates with fine pores lead to clogging of the porous media (Brix & Arias, 2005; Wallace & Knight, 2006). Aggregates gravel in the wetland systems make SS settling easy and give a surface area for the biofilms to grow and decompose dissoluble pollutants. Multiple layers of gravel are prepared with a corresponding increase in size of the gravel from top most layer to the bottom layer. Straight arrangement of aggregates is a major factors for clogging formation in the system (Langergraber et al, 2003). Therefore, Sun, Zhao, & Allen, (2007) proposed an anti-sized reed bed system, that was extra functional than a conventional mono-sized reed bed concerning the removal of numerous critical contaminants from a high strength piggery wastewater.

Recently study research was carried out by Song et al., (2015) which clarified that clogging can be reduced employing an increasing sized packing of the media strategy and high COD, ammonia and nitrogen removal obtained in their evaluated vertical-flow constructed wetland systems. Various studies were also carried out to assess the possibility of increasing the capacity of adsorption by different substrates of filter media. For instance, many publications assured that substrates like rice husk and organic mulch had enhanced removal of total nitrogen due to the content of organic carbon (Tee et al, 2012; Saeed & Sun, 2013) this also as revised by Meng et al., (2014). Table 2.2 is the media classification and properties of substrate

Table 2.2: Media classification and properties for the substrate

Media type	Effective gravel size	Porosity	Hydraulic Conductivity

	(mm)	(η)	(k_s, ms^{-1})
Coarse sand	2	0.32	1.2 X 10^{-2}
Gravelly sand	8	0.35	5.8 X 10^{-2}
Fine gravel	16	0.38	8.7 X 10^{-2}
Medium gravel	32	0.40	11.6 X 10^{-2}
Coarse rock	128	0.45	115.7 X 10^{-2}

Nevertheless, there have been conflicting opinions concerning the task of expensive filter media in the constructed wetlands treatment process. In the study research of Miklas Scholz, (2002) they observed that the use of expensive adsorption media, like granular activated carbon, to improve filtration of constructed wetlands performance did not increase adsorption capacity of the media. Additionally, in joint research of Stefanakis & Tsihrintzis, (2012), they did not find any significant improvement in the performance evaluation of their systems, when zeolite and bauxite substrates were used and in their study of a constructed wetland.

2.5.3 Microorganisms

It was uncovered by the past investigation that communities of several microbial happen in both oxygen consuming and anaerobic zones of wetlands, comprising the different structure of different microorganisms (Stottmeister et al., 2003; Faulwetter et al., 2009). The organic pollutants removal in wetlands results from the interaction of biological, physical and chemical processes occurring in the system and also the transformation of nitrogen and phosphorus in wastewater. The microbial community in the wetlands are responsible for the contaminants reduction. The microbial activity in constructed wetlands performs a vital role in the wastewater treatment as a result of the microscopic size of the microorganisms which allows them to meet and feed the contaminants using their enzymes directly (Truu et al., 2009). Moreover, micro-organisms that recover succeed and have the ability to have metabolic activity in wetland systems partake in the removal of pollutants. The capability of constructed wetlands to eliminate contaminants depend on the activity of the microorganisms, nature of the wetland media and the plant species in the wetland system.

Micro-organisms attain disintegration and decomposition of organic matter during wastwater treatment under aerobic and anaerobic conditions. Kadlec & Wallace, (2008) and Meng et al., (2014) in their respective studies, stated that, organic matter bio-degradation is commonly associated to certain classification of bacteria, specifically protozoa and fungi including basidiomycetes and yeasts. The microorganisms can also embrace to transformations in the wastewater brought to them and grow rapidly in favourable presence environment and sufficient nutrients. However, Truu et al., (2009) in their effort observed that many microorganisms become dormant for their growth and survival in wetlands when the favourable condition is not sustainable. Furthermore, they can stay dormant for numerous years providing the favourable conditions are not sustainable.

Conversion of various organic and inorganic compound or materials that are unsafe to any application specifically agricultural and human use, were converted to be used safely by the activities of microorganisms in the wetlands system. They influences the physical, chemical and biological processes by changing oxidation/reduction reactions of the wetland media which help in the nutrients recovering (Truu et al., 2009; Ji et al., 2013; Wang et al., 2015). Moreover, the chemicals biodegradation complexity varies mostly, subject to the microbes involved (Meng et al., 2014). For example, β-Proteobacteria and γ-Proteobacteria involved actively in nitrogen removal (Faulwetter et al., 2009) for oxidation of ammonia. These, β-Proteobacteria and γ-Proteobacteria are some classes of bacterial groups. Moreover, other bacterial groups such as Enterobacter and Micrococcus are denitrification agents (Meng et al., 2014), and planctomycete-like bacteria Candidatus Brocadia anammoxidans are agents for oxidation of anaerobic ammonium.

Microorganisms that reside in water naturally, roots or substrate, of wetland macrophytes ingest organic substances or nutrients thus decreasing, breaking down or completely eradicating a wide range of pollutants in the wastewater. Roles of wetlands are considerably managed by microbes and their metabolism (Faulwetter et al., 2009; Truu et al., 2009; Meng et al., 2014). The alliance of microbes in constructed wetlands involves internal and external microorganisms (Truu et al., 2009). Internal micro-organisms are categorised by some qualities as follows: metabolic activity capability, grow and live in wetland systems and involve in pollutants treatment. While external micro-organisms such as pathogens in the inflowing wastewater have no critical part to partake in the wetland environment, as the foreign micro-organism does not survive because the wetland environment is opposed to non-indigenous micro-organisms (Jan Vymazal, 2005). Figure 2.7 below shows the constituents that affect micro-organic relationships and functions in constructed wetlands.

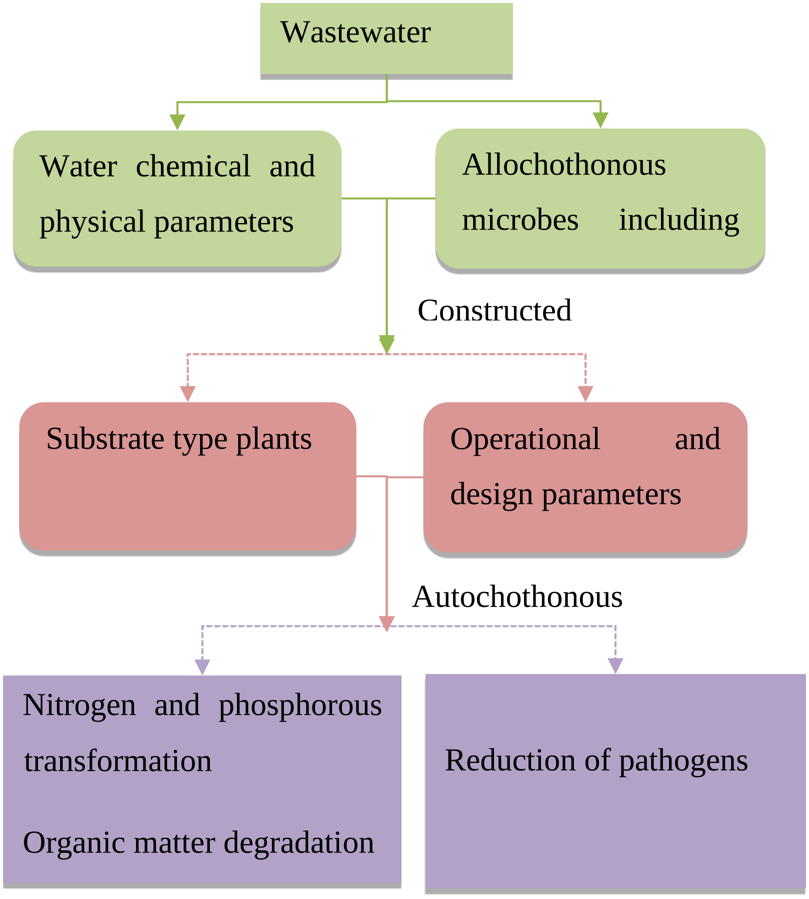

Figure 2.7: Constituents that affect micro-organisms relationships and functions in constructed wetlands. Adopted from (Truu et al., 2009)

2.5.4 Hydrology

Hydrology is the most significant and essential for the formation and persistence of wetlands with the occurrence, characteristics and movement of wetland's inflow and outflow. It helps to the anaerobic condition. Hydrology in the wetland dealt with the intermittent saturation of a substrate media and serves as the approach and area where general biogeochemical operations occur (Morandeira & Kandus, 2015; Scholz, 2010). The hydraulic retention time (HRT) in wastewater treatment plant is a measure at an average length of time holding the wastewater in a filter for treatment before discharging. It is also known as hydraulic residence time. The operations help the growth of typical wetland media that provides a suitable environment for a predominant macrophyte society appropriate to the current in saturated media (Mitsch & Gosselink, 2000; Mueller et al., 2003).

Therefore, hydrology is defined by two variables in wetlands namely, hydro period and depth of flooding (Cole et al., 1997). The hydro period is the time at which the soil is flooded or saturated, expressed in percentage, and is influenced by many natural factors like geology, groundwater, topography, subsurface soil features, and weather conditions. In a natural wetland, the depth of flooding differs between +2 m and –1 m corresponds to the ground surface, with an average of approximately +1 m. These two variables highly affect the characteristics (oxygen concentration, pH, nutrients, plants, etc.) and stability of the wetlands (Scholz, 2006, 2010; Scholz & Lee, 2005).

Hydraulic retention time (HRT), refers to the average period of time wastewater stays in the wetland. It is an essential variable in designing and evaluating treatment performance of wetland treatment systems (Ghosh & Gopal, 2010; Kadlec, 2016). More so, it is required in determining the performance efficiency of settling solids, biochemical processes, and plant uptake (Ghosh & Gopal, 2010; Kadlec & Knight, 1996b; Stefanakis et al., 2014). Subsurface flow constructed wetland systems (SSFCW). The wetland hydrology is critical in wastewater treatment processes because it determines the duration of water-biota interactions, and the transport of waterborne substances to the sites of biological and physical activity (Kadlec & Wallace, 2008). The more water stays in the wetland filters, the better is the possibility of sedimentation, adsorption, biotic processing and retention of nutrients (Johnson et al., 2016).

2.6 Constructed wetlands on treatment performance: Design and operational impact

The pollutant treatment performance efficiency by constructed wetlands is a function of the Hydraulic Loading Rate (HLR) and Hydraulic Retention Time (HRT), specifically when the hydraulic loading rate is high and the retention time is low. It was discovered that very polluted wastewater rapidly passes through the wetland, which results in a corresponding relative decrease of the treatment efficiency by the constructed wetland because of inadequate time for biodegradation processes to take place.

The different loading rate applied, did not display any important statistical differences in the removal of the tested pollutants. Initial results were discovered in the removal of the pathogen, where the find sand as the substrate is good. Frazer-Williams, (2010) also evaluate the effect of wetland design criteria area sizing, and operation parameters (hydraulic and inflow loading) for the removal of pollutant (organics, solids, nutrients and coliforms) in both subsurface and surface flow systems. Results showed that even though high removal performance of pollutants was attained for most wetlands, residual concentrations for BOD are frequently higher than those predicted based on the 95 percentile first-order Kickuth design equation. Also, correlation results indicate that hydraulic and pollutant loading impacted strongly wetland performance for organic matter (BOD, COD) removal. In all cases, removal of pollutants decreases normally as hydraulic loading rate also increases. Correlation between Hydraulic loading and nutrient removal was not discovered. Overall, it can be resolved that organic removal can be modelled better compared to a nutrient in constructed wetlands. Since the removal of solids and coliforms are not primarily influenced by the key design parameters, it is expected that they will fit into any design model developed.

Some study researches like Stefanakis & Tsihrintzis, (2012b) and Zhi & Ji, (2014) indicated that during the experimental setting-up phase of the constructed wetlands, outflow water quality parameters like COD are discovered to be relatively unstable when the wetland is maturing. Furthermore, an extended hydraulic retention time effects on performance efficiencies for ammonia-nitrogen removal, regardless of plant maturity. Long resting times generally certifies biodegradation and nitrification. However, Stefanakis et al., (2014) reported organic matter biodegradation in VFCWs depends on the internal of the organic matter and contact time used during treatment of wastewater by the system. Therefore, their researche summarised that readily biodegradable organics are quickly oxidised due to high oxygenation in the wetland media bed while the disorderly ones are partially degraded caused by inadequate contact time. Moreover, the organic matter decomposition was mostly happening in the top 10– 20 cm due to the accessibility of high oxygen and microbe population density in the upper wetland gravel bed (Kadlec & Wallace, 2008; Stefanakis & Tsihrintzis, 2012b; Tietz et al., 2007).

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2.7 Wastewater

Wastewater is a combination of water and a huge number of chemicals (organic and inorganic chemical) and heavy metal that can be formed from domestic, industrial and commercial activities (Rezania et al., 2015). Wastewater is water that has been previously used and polluted, that contains waste products. Furthermore, it also comprises of stormwater, groundwater and surface water (Dixit, Dixit, & Goswami, 2011). Because of the chemical access into the wastewater, it must be treated before the final disposal into the environment. Several processes of physical-chemical and biological were established for wastewater treatment, among the processes biological process was discovered to be more compelling for the treatment of wastewater, phytoremediation is part of the branches of biological process for the treatment of wastewater (Roongtanakiat et al., 2007). Wastewater is approximately 99% water; only 1% is a mixture of suspended and dissolved organic solids, detergent, and cleaning chemicals.

In the study research of Avelin et al, (2014), they reiterated that wastewater as a compound combination of organic and inorganic materials also known as sewage, which can be divided into domestic, industrial, and municipal wastewater, The plant in which wastewater is treated view for the main part of the energy-demanding methods associated with water. The energy that is consumed in the aeration processes is of a significant amount, where oxygen is provided for a biological system such as an activated sludge treatment. Wastewaters from the household, hospital, and industries (organic, chemicals, industry and refining industry) consist of practice water, water to cool the machines when heated, surface water runoff, and hygienic sewage water (Speight, 2005; Speight & Arjoon, 2012).

Wastewaters consist of water in which solids exist as settle particles at the bottom, spread as a mixture, which is materials that do not settle freely, dissolved state nature of solid. The wastewater mixture will comprise huge numbers of microscopic organisms, usually bacteria capable of ingesting the organic component (carbohydrates, fats and proteins) of the mixture and bringing about fast changes in the wastewater. As the origin of wastewater as well as the inputs are greatly variable and since there is also an active microbial component, the configuration of all wastewaters is regularly varying. Before entering a wastewater treatment plant, it is called raw sewage (Krishna et al, 2017).

Water pollutants represent one of the considerable environmental problems. This makes it essential to take necessary actions for water resources management. Water bodies have many uses such as municipal use, agricultural use, industrial use, fisheries and recreational use. The term quality must be considered relative to the intended use. To set a standard for desire quality of a water body, it is essential to identify the uses of water of that particular water body. Water quality standards are the basic of water quality control programme, directed by certain authorize agency. A water quality standard is the one that protects and maintain the water quality of water necessary to meet its requirement such as swimming, recreation, public water supply and aquatic lives if present. Water quality standard consist of four basic elements:

a. Designated use of the water body
b. To protect designated used by limiting chemical constituents that may be present in the water body
c. An anti-degradation policy to maintain and protect existing uses and high-quality waters
d. General policy addressing implementation issues

Water quality criteria are statement broadly defining the safety margin for the physical, chemical and biological characteristics and constituents of water. Water standard are prescribed by authorize agency considering the type of use, quality of criteria and other features such as practical attainability, causes, local condition, public needs, etc. Water quality standard is prepared to base on criteria like health all unknown sample data is compared to such substandard. Drinking water has to have a high standard, whereas water for use by the animal can have a lower standard. Every country has their water standard relevant to that region. World Health Organisation (WHO) has mapped out globally suitable health base quality standard. UK Government has set up water quality control standard and designed suitable restoration programme for the various water body.

Wastewater is contaminated water that can no longer be used or re-used by people or manufacturing process (Brix & Arias, 2005). It refers to any water that has been adversely affected in quality by anthropogenic influence (Choudhary et al., 2011). Wastewater formed by the combination of industrial, domestic, commercial or agricultural activities, surface runoff or stormwater, and from sewer inflow or infiltration (Sheet, 2003). However, according to Miklas Scholz & Lee, (2005), they described wastewater as the one that consists of pollutants which are normally structured in an environmental pattern. Wastewater is treated to remove substances which pollution when discharges to rivers, lake and sea and this lead to course. Wastewater is passed through a series of sequential faces these are called pre-treatment where the pollutant is removed from the wastewater treatment. The qualities and quantities of wastewater are analysed and determined by many features.

2.7.1 Problem of wastewater

Water Pollution of sources can cause diseases to increase, such as e-coli, diarrhoea and hepatitis. It also affects people's immediate environments and leads to water-related illnesses. To minimise wastewater and pollutant emissions, a constructive method is underlined to design wastewater recycling so that the treated water can be reused for irrigation, agricultural, park and golf course and to a maximum extent in the same plant (Sayadi et al., 2012). Domestic wastewater is known as one of the major sources of COD, TDS, TSS, BOD_5, metals, salts, indicator organisms like e-coli, diarrhoea, hepatitis colour, nutrients (Sayadi et al., 2012)..

2.7.2 Wastewater treatment

Wastewater treatment is associated with the standards set for the treated outflow quality, which consists of processes such as a combination of biological, chemical and physical treatment processes (Su et al., 2015). Wastewater treatment processes are planned to attain enhancement in the quality of the wastewater. Raw wastewater is a combination of solid and liquid, to treat wastewater, this consists of two main steps: primary wastewater treatment and secondary wastewater treatment (Tansel, 2008). In the primary treatment phase, mechanical process of treatment in considered which involve larger contaminant, solids are removed from wastewater by allowing it to settle while in Secondary treatment further treat the wastewater through extra procedures that involve a big biological procedure for supplementary removal of the remaining suspended and dissolved solids. Secondary treatment removes up to 85% of the remaining organic material through a biological process of cultivating and adding sewage microorganisms to the wastewater and through bio filtration, aeration, oxidation ponds and the interaction of waste.Treatment of wastewater is the process of eliminating pollutants from wastewater. This includes physical, chemical, and biological procedures to eradicate organic, inorganic and biological contaminants. The key purpose of wastewater treatment is to make water appropriate for the end-users need (Potgieter, 2010). The chief aim of wastewater treatment is to eradicate as much as of the suspended solids and other organic matters as possible before the remaining water called effluent and returned to the to the water cycle with minimum impact on the environment (Aguilar, Tadiosa, & Tondo, 2014). The usual configuration of wastewater (after pre-treatment) which are treated in CWs comprises suspended solids, organic matter (BOD and COD), and nutrients (especially nitrogen and phosphorus) and some trace heavy metals, as shown in Table 2.3.

Suitable wastewater treatment and removal are critical for public health protection. The wastewater treatment procedures help to attain water quality objectives and to reduce water pollution control. When purified the treated water will be suitable for future reuse (Siracusa & La Rosa, 2006) The development of advanced wastewater treatment technologies is essential to meeting the regulatory requirements for water quality

Table 2.3: Concentration pollutants in the normal untreated domestic wastewater

Parameter	**Unit**	**Concentration**		
		Weak	Medium	Strong
BOD	mg/l	110	220	400
COD	mg/l	250	500	1,000
TP	mg/l	4	80	15
TN	mg/l	20	40	85
TDS	mg/l	250	500	850

TSS	mg/l	100	220	350
TS	mg/l	350	750	1,200
Total Coliform	No/100mL	106 ~ 10^6	107 ~10^8	107 ~10^9

Abbreviations: TS, total solid; TDS, total dissolved solids; TSS, total suspended solids; BOD, biochemical oxygen demands; COD, chemical oxygen demands; TN, total nitrogen; TP, total phosphorous.

2.8 Water Quality Parameters

Water Quality variables, parameters or indicators refer to the parameters used for the analysis by the scientist to specify the presence of harmful pollutants. Water quality is a term used to describe the situation of water; this includes chemical, physical, and biological features of the water. Is good to ascertain the quality of water before use for various intended purposes, such as potable water, agricultural, industrial, etc. generally regarding suitability for a particular or designated use, there many expect of water pollution and their many variables that determine water quality for a given used. The quality of water is defined regarding its physical, chemical, and biological parameters (Al-Rekabi & Al-Ghanimy, 2015). Water features, such as dissolved oxygen, pH, nutrients, and temperature, are known as parameters or indicators. Parameters can be physical, chemical or biological. Water quality has the greatest contribution to temporal variation in the source of water such as sea, river, lake, and ocean as well as wastewater. The term quality must be considered relative to the internal use; there are many expect of water pollution and properties that determine water quality for a given use. Example water for domestic use should free from all type of suspended and dissolve impurities and microorganism. Water quality is an issue that relates to the chemical composition of water for particular use and societal needs and treated waste water samples were analysed using contaminant indicating parameters (Kushwah et al, 2011). Modelling water quality parameters is a very important characteristic in the analysis of any water systems management. Prediction of water quality parameters is essential for proper management of the wastewater so that sufficient measure can be taken to keep contaminants within accepted limits used to identify cost-effective pollution control strategies

The three important properties that control the quality of water include physical, biological and chemical properties; they have a varied impact across different uses of water in different sectors. Any physical, chemical or biological properties that affect the quality of water is said to be a water quality variable or parameter. Table 2.4 represents the properties of water quality parameters.

Table 2.4: Properties of water quality parameters

<table>
<tr><th>Physical Properties</th><th>Biological Properties</th><th>Chemical</th></tr>
<tr><td>Dissolve and suspended solid in the water bodies</td><td>Micro-organism, cellular and microscopic bacteria</td><td rowspan="2">These include solubility, chemical reactivity and temperature etc. and all those that play a role in the chemical quality of water</td></tr>
<tr><td>Plants, leaves and degraded organic material become part of the suspended matter</td><td rowspan="2">They contaminate both ground and surface water and cause various water-borne diseases like diarrhoea, cholera, typhoid etc.</td></tr>
<tr><td>Ions like nitrate, hydroxides, chlorides that are completely soluble in water and dissolve solid</td><td>A High level of acidity or toxic alkalinity elements and carcinogens etc.</td></tr>
</table>

Physical properties of water quality include temperature and turbidity, Chemical characteristics involve parameters such as pH and dissolved oxygen. Biological indicators of water quality include algae and Biochemical demand. Researchers and analysts determine water quality by testing for specific chemicals. Most often, the type of water being tested determines what parameters are important to a particular situation. Water quality testing is an important part of environmental monitoring. When water quality is poor, it affects not only aquatic life but the entire ecosystem surrounding will be affected as well (Wu et al., 2015). Water quality is measured by using some combination of water quality parameters. As there are many different uses of water, it is not likely to come up with a particular definition of water quality (Uality et al., 2000) Wastewater quality parameters are laboratory test procedures to assess the appropriateness of wastewater for re-use or disposal. Tests selected, and desired test results differ with the intended use or discharge position. Tests conducted and measured are physical, chemical, and biological features of the wastewater (Sanchez, Weiland, & Travieso, 1994). Whenever the quality of water is studied, water quality parameters will look into. Therefore, water quality standard is assigned according to the goals of the aquatic system by assigning its uses managing to protect those uses and creating requirement such as anti-degradation policies to protect them from various pollutants. Set by each state water quality standards regulate how clean a water body should be, state designates water bodies for specific uses base on their goal and expectations for their waters typically designated use include the following:

1. Protection and propagation of fish, shellfish and wildlife
2. Recreation purpose
3. Public water supply
4. Agricultural, Industrial, Navigational and other purposes

2.8.1 Biological Oxygen Demand

The Biological Oxygen Demand ($BOD_{5)}$ according to Kotti, Sylaios, & Tsihrintzis (2013) is the amount of oxygen consumed by bacteria in the decomposition of organic material and removal of organic matter measured as BOD_5 is always required to a level 90 or 95% is the regulation treatment class of BOD_5. BOD is a prime indicator for quality of both waste and surface glasses of water it also includes the oxygen required for the oxidation of various chemical in the water, such as sulphides, ferrous iron and ammonia (Kotti et al., 2013a)**.** BOD is a measure of organic pollution to both waste and surface water. Biological oxygen demand is said to be an indicator of the quantum of pollution load, BOD5 is a measure of how much-dissolved oxygen is consumed a greater amount of dissolve oxygen shall consumed, similarly in low value of BOD indicates relatively pure water. It is estimated that for drinking water the BOD should be in the range of 0.75 to 1.5 ppm. High BOD_5 is an indication of poor water quality. For this tree plantation project, any discharge of waste into the waterways would affect the water quality and thus users downstream (Uality et al., 2000). It was documented that vertical flow beds are very effective in removing BOD_5. and they do nitrify at high loading rates even during cold winters. Biochemical oxygen demand (BOD_5) is one of the main factors for checking organic pollution present in water and evaluating the bio treatability of wastewater (Kushwah et al., 2011). Furthermore, BOD_5 is also used for treatment plant of wastewater discharge consents and other purposes of water pollution control, however, the traditional bioassay process for estimating the BOD_5 comprises for 5 days for the incubation period of the wastewater sample. (Rustum et al., 2008a). This is to say the standard BOD analysis usually takes 5 days minimum (BOD_5), but alternatives are sometime used. The conventional method of testing BOD_5 was stated by the American Public Health

Association Standard Methods Committee, it includes the 5-day biochemical oxygen demand (BOD5) test, this method has been commonly used as the normal method for long period to determining the concentration of biodegradable organics present in wastewater (Karia & Christian, 2013). However, this method is said to be time-consuming (5 days of incubation period) which needs skill and experience to achieve reproducible and accurate results. As a result of its time consuming, researchers embarking to conducted and developed alternative approaches for real-time or on-line BOD monitoring (Seop et al., 2004).

It is the extensive measure of the strength of the organic matter in wastewater. BOD measure biodegradable organic matter and is the standard test for testing the oxygen-demanding strength of wastewater, however, it a measure of the amount of amount of oxygen that bacteria will consume while decomposing organic matter under aerobic conditions in 5 days at 20^{o} C. The higher the amount of the organic matter in wastewater the higher the BOD value. Although there exist various methods for BOD measurement, the principle is the same for all of them. A volume of water sample in a recipient where the changes in the oxygen contents are measured before and after incubation at 20^{o}C for a certain time which indicates BOD5 is a measure of how much-dissolved oxygen is consumed by aerobic bacteria in 5 days at 20^{o}C temperature. If the sample is expected to have a low content of microorganism, an inoculum should be added.

Moreover, an extra nutrient solution may be added to ensure that the growth of the microorganism is not limited. BOD values are increases over time as the organic matter is progressively biodegraded. However, after five days the majority of the organic matter contained in the sample has already been degraded. For that, reason BOD_5, which measured after 5 days of incubation is the most widely used method. High BOD means that there is a little amount of oxygen to support life that indicates organic pollution and poor water quality (Kushwah et al., 2011).

The equation below describes the biochemical process behind the BOD test

$$\text{Organic matter} + \text{microorg} + O_2 + \text{nutrientes} \rightarrow CO_2 + H_2O + \text{microorg} \quad 2.1$$

BOD is expressed milligram per litre (mg/l)

Contamination of water by any specific chemical cannot be measured by BOD; it is a measure of contamination caused by the totality of those compounds which can oxidise in the presence of the microorganism. A large number of the organic and inorganic compound are resistant to microbial oxidation. These, therefore, do not add to the BOD because they are not fit for drinking purposes. The usual value of BOD_5 present in domestic wastewater ranges from 100 to 300 mg/L (Abdalla & Hammam, 2014).

2.8.2 pH

pH is a parameter used in the measurement of a solution's acidity or alkalinity; it is a measure of how much acidic and base a waste substance is, and it is a measure of the balance between positive hydrogen ion (H^+) and negative hydroxide ion (OH^-). These ions are either missing electron as in the case of hydrogen ion, or they have an extra electron as in the case of hydroxide ion. In water, small numbers of water molecules (H_2O) will break apart or disassociate into hydrogen ions (H^+) and hydroxide ions (OH^-). pH is a measure of how acidic or alkaline the water is, the term pH comes from the French: "puissance d'Hydrogène" that means strength of the hydrogen in the water. It is defined as the negative log of the hydrogen ion concentration. pH is a determined value based on a defined scale, similar to temperature. pH of water is not a physical parameter that can be measured as a concentration or in quantity and is on a standard scale for pH from 0 to 14. Both domestic and industrial wastewater treatment bacteria operate efficiently at a pH range of 6.8 to 7.2, but when the range of pH drops below 6.0 or rises above 8.5, activity drops off dramatically. The pH scale is arranged and written in the logarithmic form and goes from 0 to 14. For each whole number increase (i.e. 1 to 2) the hydrogen ion concentration decreases tenfold, and the water becomes less acidic (i.e. pH 2 is ten times increase more acidic than pH 3). The value of pH depends on many stages of water treatment and water supply these include acid-base, neutralization, coagulation, sedimentation, corrosion control (Sarda & Sadgir, 2015). When the value pH decreases, water tends to become more acidic but when water becomes more basic, the pH increases as well. pH meter is calibrated potentiometrically with electrode system using standard buffers having assigned values. pH may be measured accurately using a pH meter and electrodes. If the pH of water is equal to seven, the water is in its natural form. If the pH of water is less than 7 the water has acidic properties, and the pH of water is greater than 7 the water has base properties (Collins & Gillies, 2014).

$$pH = -\log([H^+]) \qquad 2.2$$

The pH meter was calibrated before use and checked after each sampling event

2.8.3 Nitrate Nitrogen

Nitrate Nitrogen (NO_3- N) is formed in contaminated water when dissolved bacteria use oxygen to oxidise ammonium. Nitrate is said to be mobile and can leak into lakes, streams, and estuaries from groundwater enriched by an animal or human wastes or commercial fertilisers. When the amount of dissolved nitrate in water increases, this cause water quality problem. Dissolve Nitrate in water is important for plant to grow but excess nitrates can cause too much growth of algae and aquatic plants, which can reduce the amount of doing available in the water, nitrates are caused by bacteria, animal and human wastes, too much content of nitrates will cause phytoplankton (algae) and macrophyte (aquatic plant) happening (Kushwah et al., 2011). This is mostly due to the usage of fertilisers. Nitrogen (N_2) is naturally abundant on earth; it consists of 80% of air (Heidtke & Sonzogni, 1986). Most plants cannot use this as this form. However, blue-green algae and legumes can convert N_2 gas into nitrate (NO_3) ammonia found in soil being turned into nitrates (NO3-), which are inorganic forms of nitrogen that plants can use. Nitrogen can be used by plants because plants and animals (all living organisms) need nitrogen which is a chemical element used in forming proteins, proteins construct the structure of organisms and produce life-sustaining functions, comprising reproduction, development and growth. Plants use nitrate so as to form protein, and animals that eat plants also use organic nitrogen to build protein (Ouyang et al., 2011). It was documented that vertical flow beds are very effective in nitrification at high loading rates even during cold winters (Brix & Arias, 2005).

Order of decreasing oxidation state:

$$\text{Nitrate-Nitrite} \rightarrow \text{Ammonia} \rightarrow \text{Organic Nitrogen} \qquad 2.3$$

2.8.4 Phosphorous

Phosphorus in small quantities is essential for plant growth and metabolic reactions in animals and plants, but phosphate in large quantity can cause too much algae blooms. It is the nutrient in shortest supply in some of the fresh waters, with even small amounts causing significant plant growth and having a large effect on the aquatic ecosystem. Phosphorus is an essential requirement for biological growth. An excess of phosphorus can have secondary effects by triggering eutrophication within a wetland and leading to algal blooms and other water quality problems. Phosphorus removal in wetlands is based on the phosphorous cycle and can involve some processes (Hafner & Jewell, 2006a).

Phosphorus is commonly known as the limiting nutrient for plant growth, which means it is in a relatively small supply relative to nitrogen (Schreiber, 1988). Phosphorus usually occurs in nature as phosphate, which is a phosphorous atom combined with four oxygen atoms, or PO4-3. Phosphate that is bound to plant or animal tissue is known as organic phosphate Phosphate that is not associated with organic material is known as inorganic phosphate. Both forms (organic and inorganic) are found and present in aquatic systems and may be dissolved form in suspended or water. Inorganic phosphate is also referred to as orthophosphate (PO_4) or reactive phosphorous. It is the form most readily available to plants, and thus may be the most useful indicator of immediate potential problems with excessive algae growth and aquatic plant. Total phosphorus (TP) is a measure of phosphorus in all its form.

Phosphates are found in detergents, fertilisers, rocks and soil. Phosphate can rise temperature, decrease DO, decrease the amount of sunlight getting through the water and indicate pollution. An ideal measurement of phosphates is 0.01 mg/L. Phosphates do not pretence health or human risk unless when it is concentrations is very high (The Environmental & Protection Agency, 2001). PO4-P is used to determine the quantity of phosphorus is a sample and is considers the phosphorus in the compound only

PO_4-P is generally used in the wastewater treatment plant reporting unit while in Boiler water analysis as PO_4–3 is indicated to be used because trisodium phosphate (TSP) is fed in boiler and orthophosphate value is essential here. Total phosphorus (TP) is a measure of phosphorus in all its form. Total phosphorous is the measure used in most regulatory guidelines

2.8.5 Forms of Phosphorus

In water or wastewater, the overall forms of phosphorus (TP) is determined by analytical means made around whether Phosphorous is in dissolved or particulate form for whether or not the P is molybdate (Mo) reactive (J. Murphy & Riley, 1962).

Conversely base on the research study of Murphy, (2007), it was discovered that phosphorus in natural waters is usually found in the form of phosphates ($P0_4^{-3}$). Phosphates can be in the form of inorganic (including orthophosphates and polyphosphates) or a form of organic (originally- bound phosphates). Animals can utilise any of organic or inorganic phosphate

2.8.5.1 Organic Phosphate

This is the phosphate that is certain to plant or animal tissue and is formed mainly by the biological process; it involves a phosphate molecule related with a carbon-based molecule (Paraskova, 2014). They donate to sewage body waste and food residue and may be formed orthophosphates in biological treatment processes by getting waste biota. Organic phosphate may take place because of the breakdown of the inorganic pesticides that encompass phosphates, and they may be occurring in solution as a loose fragment or aquatic organism bodies. Phosphate that is not associated with organic material is inorganic.

2.8.5.2 Inorganic Phosphate

Inorganic phosphate is phosphate that is not related to the organic material. Orthophosphate and polyphosphates are the types of inorganic phosphates. In the research study of Murphy, (2007), it was discovered that orthophosphate is denoted to as "reactive phosphorus" and it is the most steady kind of phosphates that plant required. Orthophosphate is said to yield by natural process and is discovered in sewage; it is also called metaphosphates or condensed phosphates, they are a robust condensing agent for some metal ions. Polyphosphates are used for treating boiler waters and in detergent. In water, polyphosphates are unstable and will finally convert to orthophosphates. Orthophosphate plus phosphorous can easily turn to orthophosphate upon oxidative digestion. For constructed wetland treating wastewater, the key input of phosphorus is found from wastewater itself.

2.8.6 Chemical Oxygen Demand (COD)

The chemical oxygen demand known as COD is the amount of total quantity of oxygen required to oxidise the organic matter (chemical substances via chemical processes) in water or wastewater under a specific condition of an oxidising agent, temperature and time, in other words, to oxidise all organic material into carbon dioxide and water. COD use to monitor wastewater in various places from inflow to outflow of the treatment plant to measure in a safe and controlled manner (Kolb et al., 2017). It is used as a quantity of the oxygen equivalent of the organic matter content of sample water that is susceptible to oxidation by a strong chemical oxidant. For samples from a specific source, COD can be related empirically to BOD, organic carbon, or organic matter. The test is useful for monitoring and control after correlation has been established (Choudhary et al., 2011). COD is also an indicator of organics in the water, usually used in conjunction with BOD (Talib & Amat, 2012). High organic inputs activate deoxygenation. If excess organics are introduced to the system, there is potential for complete depletion of dissolved oxygen. Without dissolved oxygen (DO), the entire aquatic community is threatened. The only organisms present will be air-breathing insects and anaerobic bacteria (Brix & Arias, 2005). COD unit is expressed in milligram per litre (mg/l) which indicates the mass oxygen consumed per liter solution. COD value is about 2.5-time BOD value. COD measures the amount of oxygen consumed for oxidation of total organic matter, it is the empiric laboratory essay, which measures the amount organic matter (biodegradable and non-biodegradable), contained in a water sample. Thus, it is measured in milligram of oxygen per litre (mg/l) or (mgo_2/l). COD does not differentiate between biologically available and inert organic matter. However, it is a measure of total quantity required to oxidise all organic material into carbon dioxide and water, in this way. The COD values of a water sample can be typically related to its BOD values, in a more less constant ratio COD values are always greater than BOD values. However, COD measurements can be made in a few hours while BOD measurements take at least five days since the COD test can be performed rapidly. It's often used as a rough approximation of the water's BOD, even though the COD test measures some additional organic matter such as additional organic matter such as cellulose which is not normally oxidised by biological action (Abba & Elkiran, 2017). There exist different methods to measure COD. In all of them, a fixed volume with the known excess amount of oxidants is added to the water sample being analyzed. The basis for the COD test nearly all organic compounds can be fully oxidized to carbon dioxide with a strong oxidizing agent under a condition at high temperature. After a digestion step, the concentration of the organic digestion substances in the sample is calculated from the titrimetric spectrophotometric determination of the remaining oxidant. COD values are usually higher than BOD5 values, and the ratio between them will differ depending on the type and wastewater features of the.

2.8.7 Why is COD important?

Chemical Oxygen Demand is one of the vital water quality parameters; it offers help to assess the effect of discharged wastewater will have on the receiving environment and ecosystem (Sanchez et al., 1994). If COD levels are high, it means there is a higher amount of oxidizable organic material present in the sample, which will reduce dissolved oxygen (DO) levels. A reduction in DO can lead to anaerobic conditions, which is deleterious to higher aquatic life forms. The COD test is often used as an alternate to BOD due to the shorter length of testing time (Sanchez et al., 1994).

2.8.8 Turbidity

The measurement of turbidity is one of the key tests of water quality. Turbidity is a measure of the cloudiness of sample water. Cloudiness is formed by suspended solids (mostly soil particles present in water sample) and plankton (microscopic plants and animals) that are suspended in the water column (Uality et al., 2000). Turbidity may be due to organic and inorganic ingredients. Organic particulates may harbour microorganisms. Thus, turbid conditions may increase the possibility for waterborne disease.

Nonetheless, inorganic constituents have no notable health effects (Brix & Arias, 2005). Suspended sediment, Algae and organic matter particles can haze the water that makes it more turbid. Water with high turbidity has high temperature and provides shelter and food for the pathogen. Turbidity is a measure of how clear the water is. A good measurement is between 0 and 15 JTU (Jackson turbidity units) the common unit of turbidity is NTU (Nephelometric Turbidity Unit) which is then used in this research NTU or JTU these units are interchangeable in practice, and the two units are roughly equal. It is suggested that, for water to be disinfected, the turbidity should be constantly less than 5 NTU or JTU. Less than 5 NTU value of turbidity indicates Clarity of sample can indicate contamination which is the acceptable limit. Lack of clarity in a water sample usually shows that bacteria may be present (The Environmental & Protection Agency, 2001). Regardless of whether readings are in NTU, FNU or any other SI units, it is vital to remind that a turbid meter's optical design will affect turbidity readings.

Turbidity can be measured using either an electronic turbidity meter or a turbidity tube. Turbidity can be caused by:

- Chemical precipitates
- Bacteria and other germs;
- Silt, sand and mud;

2.8.9 Temperature

Temperature is a measure of kinetic energy of an object (how fast its particles are moving). Water temperature is one of the serious parameters that is used to assess our river/stream for aquatic environment health. Many organisms in water, mostly fish, are sensitive to temperature changes in the river water (Uality et al., 2000). Temperature is a widely fluctuating abiotic factor that can vary both diurnally and seasonally. Temperature exerts a strong influence on the rate of chemical and biological processes in wetlands, including BOD decomposition, nitrification and denitrification (Brix & Arias, 2005). Water with high temperature will always have a low amount of Dissolve oxygen, but the higher the temperature, the less DO because gas particles escape from the surface of the water. High temperature can increase wetland plant growth, which is good, but when there is too much plant growth, it causes a decrease in DO when plant die. There are numbers of factors that affect the temperature of water, the colour of water impact the temperature because darker colour water will absorb more heat, how deep the water typically has an impact because deeper water is often colder it takes more heat to warm up these deep water. The time of year also has an impact on the temperature of water because naturally, the water tends to be warmer in the summer months and colder in the winter months. The amount of water also has an impact on the temperature because more water takes longer to heat up and to cool down. Another factor that impact temperature is the temperature of water inputs known as effluents which are liquid waste that is dumped into the water system some example of the effluent that can increase the temperature of the water includes waste water from factories or even runoff water from the building. The temperature of water influences different stages of animal life in different ways, as it is one of the most important aspects of aquatic life survival (Sarda & Sadgir, 2015). Understanding temperature requires understanding energy as well. The temperature of a substance will change depending upon the rates of energy gain and energy loss.

2.8.10 Suspended Solid

These are particles floating in the water, with low wetland water velocities and appropriate composition of influent solids, suspended solids will settle from the water column within the wetland. Sediment suspension not only releases pollutants from the sediments, but it also increases the turbidity and reduces light penetration (Uality et al., 2000). The physical processes responsible for removing suspended solids include sedimentation, filtration, adsorption onto Biofilm and flocculation/precipitation. Wetland plants increase the area of substrate available for development of the Biofilm. The surface area of the plant stems also traps fine materials within its rough structure. It was documented that vertical flow beds are very effective in removing suspended solids (Brix & Arias, 2005). Suspended solid can also raise water temperature, which reduces the DO. The traditional standard for SS removal from secondary wastewater is 30 mg/l Water with a low amount of suspended solids is important to many waters uses. Although the amount of total suspended solid is important for recreational uses, the degree of importance depends on the activity. A total suspended solid is measured as the dry weight of particulates. Both organic and inorganic materials contribute to total suspended solids (Uality et al., 2000).

2.8.11 Ammonium Nitrogen

Ammonia is existed naturally both in surface and in wastewater. Its concentration is generally low in ground waters because it adsorbs in soil particles and clays and is not leached readily from soils. Ammonia nitrogen (NH_3-N) is one of the most poisonous and usual classes of nitrogen, and It was discovered recently that pollution of ammonia nitrogen in waterways had become one of the main tasks of the environment (Azreen et al., 2017). NH_3-N establishes normally in industrial and domestic wastewater or decomposed from organic nitrogen compounds in the wastewater. When Ammonia levels exceed the recommended boundaries, will result in depletion of dissolved oxygen, eutrophication and may harm aquatic life (Uğurlu & Karaoğlu, 2011). Although the ammonia molecule is a nutrient required for life, excess ammonia may accumulate in the organism and cause alteration of metabolism or increases in body pH. It is an indicator of pollution from the excessive usage of ammonia-rich (Uality et al., 2000). Ammonia concentration in water varies from less than 10µg in some natural surface and ground waters to more than 30 mg/L in some wastewaters. The wastewater that has high ammonia nitrogen contents would deter the natural nitrification process, make water hypoxia, result in poisoning of fish, ability to reduce water purification, and lastly pollute water environment (Luo et al., 2015).

2.8.12 Dissolve Oxygen (DO)

Dissolve oxygen (DO) is the amount of volume dissolve oxygen present in the wastewater and is part of the indicator to determine and evaluate the efficiency of the treatment process and indicate whether the water meets the standard (Uality et al., 2000). This is an important water quality indicator as it's one of the best indicators that determine the water of quality. It is used to determine ecological status, productivity and health of any given water (Sarda & Sadgir, 2015). Dissolve oxygen is oxygen that is dissolved in water and is great indicator of how healthy a body of the water system is. It is invisible to our naked eye and is what makes aquatic life possible (Haider & Ali, 2016). Dissolved oxygen can get into the water two ways, through atmospheric oxygen mixing into a stream in turbulent areas through diffusion into the air, or a waste product by the release of oxygen from aquatic plants during photosynthesis and through aeration of tumbling water. All microorganisms and aquatic animals need to dissolve oxygen to survive which makes aquatic life possible. According to Imfeld et al., (2009). Oxygen can be transported to wetlands together with the inflow water, from the atmosphere and via plant tissues into the water filter. Dissolve oxygen (DO) concentration is one of the main parameters that determine the performance of constructed wetland in wastewater treatment, it is a significant since most of the degradation processes (carbon degradation, nitrification) need aerobic condition and therefore adequate supply of oxygen is of great importance. Actual air supply significantly increases the treatment performance of constructed wetland particularly the removal of nitrogen (Kimwaga, 2015).

It is an important parameter in assessing water quality because of its influence on the organisms living within a body of water. Most aquatic organisms need oxygen to survive and grow. The amount of dissolve oxygen in a body of water indicates the quality of water and is controlled by temperature because Dissolve oxygen is greatly affected by temperature of the water. Cold water contains more dissolved oxygen than warm water, as organism die and decompose; the bacteria use up the DO in the water. Water must have an adequate amount of dissolve oxygen to support life; clean water condition should have dissolved oxygen concentration at a range of 7.4 to 9.0 ppm (parts-per-million) depending on the temperature. It has been discovered that DO can go through water in three (3) ways

1. Through the process called diffusion at the surface of the water
2. Though aeration (Manmade or because of water movement)
3. In photosynthesis as a waste product

Need for Dissolve Oxygen

1. To evaluate raw water quality
2. Biological changes determination by aerobic or anaerobic organisms
3. To investigate pollution
4. D.O. is the basis of the BOD test to assess any possible contamination of wastes
5. A significant factor in corrosion
6. All aerobic biological treatment processes of wastewater

Each type of aquatic animal requires a different amount of dissolved oxygen, as the temperature of the water increases the amount of dissolved oxygen that the water can hold physically decreases. As the temperature of the water increases, it can physically hold less and less dissolved oxygen, while as the temperature of the water decreases, it can keep more and more dissolved oxygen as shown in Figure 2.8.

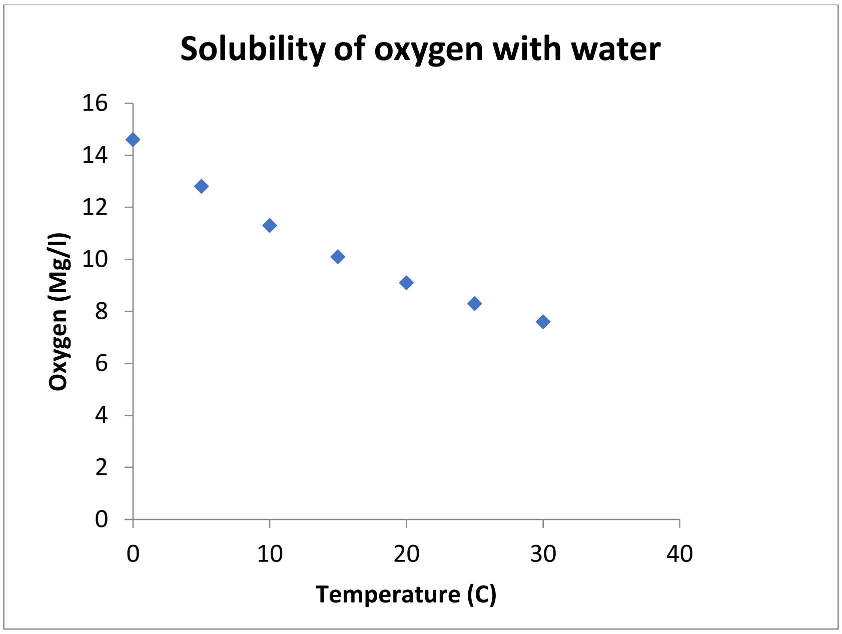


Figure 2.8: oxygen solubility of water at various temperatures

The oxygen dissolves by diffusion from the surrounding air; aeration of water that has collapsed over falls and rapids; and as a waste product of photosynthesis. A formula is presented below.

Photosynthesis (in the presence of light and chlorophyll)

Carbon dioxide	+	**Water** $\longrightarrow$	**Oxygen**	+	**Carbon-rich food**
CO_2		**H_2O**	**O_2**		**$C_6H_{12}O_{12}$**

The amount of dissolved oxygen is controlled by water when the amount of dissolved oxygen reduces in the water the eutrophication starts. Sufficient Dissolve oxygen is a total necessity for good water quality and is crucial for aquatic life. Department of Natural Resources (DNR) who is environmentalist have set up a minimum value of 5 mg/l as a minimum for dissolved oxygen concentration (Kusiak et al, 2010).The measurement of Dissolved Oxygen (DO) content is also ascertaining to be one of the essentials in water management. At levels around 5 mg/l of dissolved oxygen, irrigation water is typically considered marginally acceptable for plant health. Most greenhouse crops, however, will perform better with higher levels. Levels of 8 mg/l or higher are generally considered to be good for greenhouse production and much higher levels, as high as 30 mg/l or more, are achievable and can be beneficial. If DO levels are below 4 mg/l, the water is hypoxic and becomes very detrimental, possibly fatal, to plants and animals. If there's a severe lack of

DO, below around 0.5 mg/l, the water is anoxic. No plants or animals can survive in anoxic conditions. Usually, a less dissolve oxygen concentration is an indication of high biological activity in the water (being bad for hygiene).

2.8.13 Electrical conductivity (EC)

EC is the ability of a material to conduct an electrical current, measured in micro Siemens per centimeter (mS/cm) or Millisiemens/meter (mS/m). It is an indirect measure of the presence of inorganic dissolved solids. Measurements electrical conductivity are commonly used to discover the amount of salinity in a clean and waste waters (Vepraskas, 2002). Conductivity depends on the presence of ions (Cations and anions) in water such as chloride, nitrate, potassium, sulphate, iron, phosphate, magnesium, calcium, aluminium and sodium that gives water its ability to conduct electricity (Tiwari, 2015). Salinity and total dissolved solids (TDS) are used to calculate the EC contents in water, which helps to indicate the water's purity, the purer the water, the lower the electrical conductivities. EC meter is the name of the device for measuring the electrical conductivity of the water. Conductivity often is used to estimate the amount of total dissolved solids (TDS) rather than measuring each dissolved constituent separately (Uality et al., 2000). Solids were initiated in a dissolved form naturally. Salts that dissolve in water disintegrate into charged ions positive ions and negative ions. When the value of electrical conductivity is high, it is due to the existence of dissolved salts of cations such as calcium, magnesium and sulphate in higher concentration in the rains (Sarda & Sadgir, 2015). Conductivity refers to the ability of water to conduct electrical current, and the dissolved ions in the water are called conductors.

Conductivity will vary with water source: groundwater, water removes from agricultural fields, municipal wastewater, and rainfall. Therefore, conductivity can indicate groundwater seepage or a sewage leak. High quality deionised, pure, dechlorinate water is not a good conductor of electricity. Usual drinking water has conductivity in the range of about 5–50 mS/m at 25 °C. The electrical conductivity of the water can be measured rapidly and cheaply, using portable meters. Micro Siemens/centimetre (µS/cm) or Milli Siemens/mete (mS/m).

2.8.13.1 Factors affecting the electrical conductivity of water

The electrical conductivity of the water solidly depends on the temperature of water: the higher the temperature, the higher the electrical conductivity in any given water sample.

The electrical conductivity of water increases by 2-3% for an increase of 1 degree Celsius of water temperature. Many EC meters nowadays automatically standardise the readings to 25^{o}C temperature.

2.8.14 Oxidation/reduction potential (ORP)

ORP stands for oxidation-reduction potential is usually measured to discover the oxidising or reducing potential of a water sample. ORP determines the degree of the cleanliness of the water & its ability to break down contaminants". It has a range of –2,000 to + 2,000 and units are in "mV" (millivolts). (Vepraskas, 2002). It indicates possible contamination, especially by water and industrial wastewater (Goncharuk et al, 2010). Redox potential is an electrical measurement that indicates the inclination of a soil solution to transfer electrons to or from a reference electrode. From this measurement, it can be concluded if the soil is aerobic, anaerobic and whether chemical compounds such as Fe oxides or nitrate have been chemically dropped or are existing in their oxidised forms. In well-oxidised water, if oxygen concentrations remain above 1 mg/l, the ORP value will be highly positive (above 300–500 mV). In lowered environments, like in the deep water of stratified lakes or the sediment of eutrophic lakes, the ORP value will be little (below 100 mV or even negative). Microbial-mediated redox processes can reduce the value of OPR to a low negative level of −300 mV. It was reported in the research study of Inniss, (2003), that The ORP could be used to categorise the condition of water; aerobic, anoxic, or anaerobic responsible on the concentration range of ORP values. Redox potential is a voltage differential is commonly between a platinum electrode and a saturated calomel electrode as a reference both are in contact with the soil solution**.** The redox potential is used to describe an overall reducing or oxidising capacity in the water. ORP is measured in volts (V), or millivolts (mV), relative to a standard hydrogen electrode

The value of ORP in determining the content of environmental water is critically improved if the scientist has some information or history of the site. ORP data can typically become more useful if used as an indicator over time and with other common parameters to help develop a complete picture of the water quality parameters being tested.

Many significant biochemical processes are oxidation or reduction reactions the oxidation of ammonia to nitrate is executed when the ORP concentration occurs between the ranges +100 to +350 mV, while the reduction of nitrate to nitrogen happens during the ORP ranges

+10 to – 50 mV (e.g. ammonia > nitrite > nitrate > nitrogen) (Al-Samawi & Al-Hussaini, 2016).

ORP is very significant in several drinking glasses of water and wastewater procedures and applications. Measurements of ORP are used to regulate disinfection with chlorine or chlorine dioxide in swimming pools, cooling towers, portable water supplies and other water applications analysis.

2.9 Contaminants in Wastewater

Using of Unprocessed or inappropriately treated wastewater effluent sample can lead to negative impacts and affect environmental and human health. Effects of wastewater pollution include oxygen depletion, the impairment to fish and wildlife communities, and contamination to drinking water sources. Wastewater can contain a wide range of contaminants, including a variety of pharmaceuticals and hormones, pesticides, toxic trace elements and metals, total suspended solids (TSS), microorganisms, organic matter, and excess nutrients. Wastewater contains contaminants, depending on what it used for. It often contains contaminants

2.10 Treated wastewater for future re-use

The treated outflow of urban wastewater was confirmed to be reused for limited or unlimited irrigation of crops (e.g. willow, chilly), a subject on the quality of the treated water (Reed, 1991). Other applications are watering of gardens, playgrounds, toilet flushing, golf courses, public parks (Bouwer et al., 1993). Outflow water can be reused for flushing toilets, for cleaning purposes (roads) as cooling water (cars) and as a source of water supply for natural wetlands (common reeds) or nature reserve areas (game reserve).

2.11 Pollutant removal mechanism in constructed wetland

The two major mechanisms at work in most constructed wetlands system are liquid and solid separations and component degradations and transformations. The reason for constructed wetlands is to eradicate pollutants from wastewater. These pollutants if are not treated properly, pose health threats to a wider public, aquatic organisms, and the environment in general. Different type of pollutants were treated and removed by wetland systems, these include BOD5, COD suspended solids, turbidity, electrical conductivity, redox potential, dissolve oxygen, pathogens, nitrogen, pesticides, heavy metals, phosphorus, oestrogenic compounds, in varying quantities (Chen et al., 2008; Saeed & Sun, 2012;

Sheoran & Sheoran, 2006; Tang & Huang, 2007; Verma & Suthar, 2018; Vymazal, 2002b). There are inclusive displays of physical, chemical and biological mechanisms that modify and allocate contaminants in the various abiotic and biotic components of wetland systems. When wastewater passes through the wetland, this enables the velocity of wastewater to drastically reduced because of the porous media, thereby higher percentage of suspended solids in wastewater sediment and settle, as numerous different procedures take place simultaneously in the constructed wetland system to decrease the level of pollutants of wastewater (Sudarsan et al., 2017; Sudarsan et al., 2017). Nutrients increase plant biomass production whilst the growth, dieback and decomposition of plant biomass create internal storage compartments. Removal of pollutants occurs through different processes such as sedimentation, filtration, microbial degradation, plant uptake, and adsorption (Kadlec et al., 2017; Norton, 2003; Sudarsan et al., 2017; Yeh et al., 2006).

2.11.1 Physical removal processes

Physical pollutants removal processes of constructed wetlands are regularly used in primary treatment of traditional wastewater treatment systems (Norton, 2003). Physical processes performed an important role in the decrease of both dissolved and solid pollutants. Water that flows down in wetlands filters passes gradually due to resistance from plant matter and a uniform sheet flow of water. The plants in the wetland help catch sediment but less than sediment that settles from lower velocity (Norton, 2014). This low flow allows particles to settle out and this is also helped by bedded movements in most wetlands (DeBusk, 1999). The key physical pollutant removal processes from constructed wetland systems are diffusion, gravitational settling, and volatilisation. Gravitational settling is an important process that is responsible for suspended solids removal (Sudarsan et al., 2017). The diffusion process enables oxygen transfer from the atmosphere into the wetland filter resulting in a thin layer of nearly-saturated Dissolve Oxygen at the top of each constructed wetland filter. Volatilisation take place when compounds with important vapour pressures change to the gaseous state and leave the wetland filter (Wallace & Knight, 2006). The processes are no different from in wetlands.

2.11.2 Chemical removal processes

Chemical removal processes performed an important role in the removal (absorption) and desorption of phosphorus and dissolved metals from sediment particles (Reddy & D'angelo, 1997). The major chemical removal mechanisms are adsorption, ultraviolet (UV) radiation and chemical precipitation. The gather plant detritus is the substrate of wetland and during adsorption, the pollutant is adsorbed by porous media (substrate). If the absorption material (gravel) for organic compounds can be microbial degraded, then the absorption sites can be enhanced. If the material cannot be microbially degraded, like phosphorus then the absorption sites will finally become saturated and removed across this apparatus will terminate functioning (Norton, 2014). The radiation of the Ultra violet that pass through the wetland filter from sunlight, affects the molecules chemically. For instance, the viability of pathogens is affected. The process of chemical precipitation takes place when reactions within the wetland filters result in the formation of insoluble compounds such as Calcium carbonate, copper (I) chloride, and lead sulphide. Metals like iron, zinc, lead and copper are removed by hydroxide or sulphide precipitation within the constructed wetland system (Wallace & Knight, 2006).

2.11.3 Biological removal processes

One of the most significant tools for pollutant removal in wetlands is done by biological means. The main and most popular method this is done is by plant uptake (DeBusk, 1999). Wetlands house a wide variety of microorganisms such as bacteria, fungi and algae. These organisms are responsible for the breakdown and consumption of different pollutants in particular organic matter and nutrients.

There are six major biological reactions involved in the performance of constructed wetlands, including photosynthesis, respiration, fermentation, nitrification, denitrification and microbial phosphorus removal. Photosynthesis is performed by wetland plants and algae, with the process adding carbon and oxygen to the wetland. Both carbon and oxygen help in nitrification process. Oxygen is transferred to plants through direct uptake to their roots, where it permits to the root zones (rhizosphere), thereby removing inorganic nutrients and heavy metals. Respiration is the oxidation of organic carbon, and all living organisms accomplished it for their survival, heading to the carbon dioxide and water formation. In the constructed wetland, the usual microorganisms found are bacteria, fungi, algae and protozoa. The maintenance of optimal conditions in the system is required for the proper functioning of wetland organisms (Garcia et al., 2010). Fermentation occurred in the absence of oxygen to decompose of organic carbon, producing energy-rich compounds (e.g. alcohol, volatile fatty acids, and methane). This process is regularly assumed by microbial activity. Removing of Nitrogen by nitrification/denitrification is the processes intervene by microorganisms. For Nitrogen removal, the use of physical process of volatilization is very important. Plants take up the dissolved nutrients and other pollutants from the water, using them to yield additional plant biomass. The nutrients and pollutants then travel through the plant body to underground storage organs when the plants senesce, being deposited in the bottom sediments through litter and peat accretion when the plants die (Ávila et al., 2014; Wallace & Knight, 2006).

Wetlands microorganisms, including algae, fungi and bacteria, eliminate soluble organic matter, clot colloidal material, stabilize organic matter, and convert organic matter into various gases and new cell tissue (Garcia et al., 2010). Many of the microorganisms are the same as those occurring in conventional wastewater treatment systems. Different types of organisms, however, have specific tolerances and requirements for dissolved oxygen, temperature ranges and nutrients.

2.12 Mechanisms of suspended solids removal

Most of the suspended solids present in the inflow wastewater are eliminated by free-surface constructed wetlands through settling, sedimentation, adsorption, microbial degradation and filtration in constructed wetland systems, as plants and gravel block the flow of the inflow and reduces flow velocities (Norton, 2014). Wastewater inflow that applied to constructed wetlands comprises suspended solids particles; they may be organic or inorganic of different compositions and sizes. Wetlands have the mechanically capability to remove suspended solids from wastewater. In a constructed wetland, several study research affirm the removal of suspended solids and particles matter are highly achieved with accuracy (Garcia et al., 2010; Greenway, 2004; Hua, et al, 2014; Robert et al., 2017). Moreover, the primary removal means in eliminating pollutant physically, involve settling and sedimentation. These processes attain effective suspended solids and particulate matter removal (Abou-elela, Golinielli, Abou-taleb, & Hellal, 2013; R H Kadlec & Knight, 1996b; Robert H Kadlec & Wallace, 2008).

To eradicate suspended solids in surface flow constructed wetlands, the major mechanical means have been discovered Kadlec, 2009; Kadlec & Wallace, 2008) for flocculation/sedimentation and filtration. The sedimentation of suspended solid depends on discontinuation flow of inflow that afterwards results in settling down of the solids part by use of force of gravity. Additionally, in the study research of Sundaravadivel & Vigneswaran, (2001), they discovered that suspended solid integrate and follow many pollutants in the wastewater such as pathogens, organic matter, nutrients and heavy metals, this aids in removing suspended solids. Commonly, wastewater treatment by constructed wetlands was described to reduce total suspended solids efficiently by about 80 to 90 percent (Parena, 2000; Van Nieuwenhuijzen & Van der Graaf, 2011). Moreover, many research studies recently have shown higher percentage removal performance rate recorded to be greater than 90% in their constructed wetland systems (Abou-elela et al., 2013; Georgios D Gikas & Tsihrintzis, 2012; Song et al., 2015; Wallace & Knight, 2006). However, In collective research of Manios, Stentiford, & Millner, (2003) sated that the decrease of suspended solid in vertical-flow wetlands relies on structures of the filter media, and hydraulic load rate, microorganisms. Vertical-flow constructed wetlands are very effective for the removal of suspended solid Gikas & Tsihrintzis, 2012; Sharma et al., 2014; X. Song et al., 2015). Because of the large surface area porous media, the gravity drives the settlement of suspended solids, constrict, and follow to media and macrophyte surfaces. Moreover, it was reported by Manios et al., (2003) that the key problem related to the sedimentation and filtration of suspended solids of the inflow wastewater is the possibility of blockage by pores media as the wastewater infiltrates through thereby generating clogging with comparable low hydraulic conductivity, causing loss of water at the inlet of the constructed wetland.

2.13 Mechanisms of organic matter removal

Removing of organic matter in CW happens by physicochemical and biological procedures. Sedimentation, filtration and sorption are the main physicochemical processes while microbial metabolism mimic to the biological one. Removal of organic matter (BOD and COD) in constructed wetlands was achieved rapidly through expansion and gravity settling of coarse organic matter in the pore openings of the substrate media as noted by Sherwood C Reed, (1993) while BOD removal in constructed wetlands was mostly either through aerobic or aerobic microbial degradation and sedimentation or filtration processes. The upper reaches of the wetland filter, aerobic conditions tend to prevail while anaerobic conditions will occur in the plant or detritus layer at the base of wetland filter. However, some studies specified that organic matter removal in constructed wetlands is primarily through aerobic, anaerobic, filtration, adsorption, and microbial metabolism (Z. Song et al., 2006; A. Stefanakis et al., 2014) which can be evaluated by COD and BOD change in concentrations in the constructed wetlands. Aa result, organic carbon is degraded to carbon dioxide by aerobic respiration (Equation 2) or by fermentation Kadlec, 2000; Randerson, 2006). During the most predominant anaerobic conditions, the fermentative bacteria generate as main product fatty acids, such as acetic acid (Garcia et al., 2010).

$$(CH_2O) + O_2 \qquad CO_2 + H_2O \qquad 2.4$$

In addition, the removal of soluble organic substances is achieved by the growth of microorganisms on the porous media, observed on the rhizomes and roots of the macrophytes (Z. Song et al., 2006). The constructed wetlands function is mainly dependent on organic matter growth, dissipation and cycling. In constructed wetlands, organic matter growth supplies energy to microorganisms for denitrification by giving a source of long-term carbon and bearable source of nutrients. However, the accumulated organic matter may lead to media clogging by obstructing wastewater penetration through the pores media (substrate) thus, reducing the hydraulic retention time of the wastewater and nutrient removal capacity (Nguyen, 2000). Generally, Constructed wetlands deliver a high removal BOD and COD (Abou-elela et al., 2013;Gikas & Tsihrintzis, 2012; Paing & Voisin, 2005; Scholz, 2010). According to Noyes & Stiles, (2001) in their research titled “Nature and transformation of dissolve organic matter in treatment wetland” they reported that biochemical transformations are essential mechanisms in the degradation of organic matter in wetlands, thereby improving quality of water. The transformation could responsible for organic substances removal because of mineralization or gasification and the formation of organic matter via synthesis of fresh biomass. However, it was observed by DeBusk, (1999) that the carbon content in the organic matter (45 to 50%), serves as a source of energy to various microorganisms. This organic carbon is transformed into carbon dioxide in the root zone by the macrophysics that provides the oxygen essentially for the conversion. Moreover, organic matter can also be removed through adsorption/absorption processes. Additionally, Parena, (2000) stated that the ratio and strength of adsorption by constructed wetland depend on the surface porous media, macrophytes, litter and organic matter properties.

2.14 Mechanisms of nutrients removal

Nutrients removal in CW is similar to organic matter, it is done by a mixture of biological and physicochemical processes, such as microbial decomposition, volatilization, adsorption, chemical precipitation and plant uptake. Nitrogen and phosphorus elimination from any form of wastewater has been evolving and become an concern globally concern because these compounds cause eutrophication in natural water (Yamashita & Yamamoto-ikemoto, 2014). Treating and removing them is very vital issues due to their health effects in the environment. Receiving water courses become eutrophic when they receive large amounts of nitrogen and phosphorus nutrients subsequently promoting enormous plant growth that leads to the depletion of oxygen in the water environment. Primarily composed of a combination of nitrification and aerobic denitrification is usually considered to accomplish nitrogen treatment. Nitrogen is removed by growth of large wetland plants but, since most freshwater macrophytes have their roots in the soil or gravel, they remove little nitrogen from surface water. The main drawback with an uptake-for-growth system is the need to remove and dispose of the very large amount of biomass that will fill up the marsh or, worse, recycle organic nitrogen and ammonium back into the system when decomposition occurs in winter.

2.15 Nitrogen removal by constructed wetlands

Nitrogen is a serious concern in wastewater because of its role in eutrophication and toxicity to water aquatic life. Many biological and physiochemical processes in wetlands are mainly important in the changes of nitrogen into varying useful biologically forms. Moreover, plants that need nitrogen for their growth play an active role in removing it from the wastewater by plant uptake. CW systems have a number of ways to remove nutrients and have been used for wastewater and groundwater nutrients treatment in many applications (R H Kadlec & Knight, 1996b; Jan Vymazal, 2007). The economic and best way of removing total nitrogen in constructed wetlands is usually found to be bigger than 50% and is mainly by microbial aerobic nitrification and aerobic denitrification (Brix, 2014; C. Lee & Fletcher, 2009). The appropriate levels of nitrogen forms in constructed wetlands as contain in research reported by R H Kadlec & Knight, (1996) are observed to be as follows nitrate-nitrogen is approximately zero, ammonium nitrogen is approximately zero in summer, while is non-zero in winter, and organic nitrogen is approximately 1.5 mg/l. Nitrite is not chemically stable in most wetlands and is commonly discover to be very low in concentrations. (Table 2.3 and Figure 2.8). The potential mechanisms for removal of nitrogen in wetland systems are plant uptake, volatilization of ammonia, and denitrification (C. Lee & Fletcher, 2009). Ammonia is oxidized to nitrate during nitrification process. This oxidation of ammonia to nitrate, reduces nitrate to gaseous nitrogen by the denitrification process. Nitrogen removal is inadequate without adequate active aeration, for aerobic biological degradation which is due to lack of available oxygen used, in some of the constructed wetland systems (Fan et al., 2013; Scholz, 2010; Song et al., 2015; Vymazal, 2014b). However, some research studies reported when removing nitrogen from the wastewater in constructed wetlands there are processes to be conducted comprised these include nitrification, fixation, , ammonia nitrate ammonification, ammonia volatilization ammonification, denitrification, organic nitrogen burial, anaerobic ammonium oxidation (anammox), plant and microbial uptake and ammonia (Choudhary et al., 2011; Vymazal, 2007). These are the main nitrogen tools some of which happen in different types of constructed wetlands. The following will go into more detail on these mechanisms and in which types of wetlands the mechanisms are present (Vymazal, 2007). Change of organic nitrogen to ammonia in wetlands, for instance, leads to an increase in the quantity of the ammonia as a result of the ammonification process (Itokawa, Hanaki, & Matsuo, 2001). Furthermore, it was observed in the study research of Vymazal, (2007), that nitrogen removal processes generally depend on the type of constructed wetlands, for instance removal of total nitrogen was recorded to be in small quantities in a single stage constructed wetland except in a wide treatment surface area. As a result, combined type of constructed wetland systems like hybrid constructed wetlands should be an alternative for complete total nitrogen removal (Cervantes, David, & Gómez, 2001; Jan Vymazal, 2013; Jan Vymazal & Kröpfelová, 2011). However, in many constructed wetlands, the main nitrogen removal process is the combination of nitrification and denitrification (Scholz, 2010). Nitrogen removal in constructed wetland takes place by the processes called nitrification and denitrification, which occurs in nitrogen removal in N2 gas form (Khanijo, 2002).

The denitrification/nitrification mechanisms require both aerobic and anaerobic environments. However, water quality variables like dissolved oxygen, temperature and pH, affect nitrifying bacteria performance (IWA Specialist Group, 2000). On the other hand, the enzyme needed for denitrification may be blocked in the presence of dissolved oxygen. Nitrification/denitrification can therefore happen concurrently only both aerobic and anaerobic soil zones (Paul Cooper, 1999). It was reported by (Neralla, Weaver, Lesikar, & Persyn, 2000; Vymazal, 2007) that nitrification rate to be higher in vertical–flow constructed wetlands than the horizontal–flow constructed wetlands system due to the good aeration of the soil through regular bed draining, in which is naturally anoxic. It was reported by many study researches (Cervantes et al., 2001; Itokawa et al., 2001; Vymazal, 2005, 2013; Vymazal & Kröpfelová, 2011), intermittent loading that was planned is a possible preference to guarantee long flowing distance and supply the organic substances necessary for denitrification to achieve high removal of nitrogen.

The required oxygen for nitrification is removed directly from the atmosphere through the water or sediment surface, or by leakage from plant roots. Oxygenation is commonly the limiting stage for the removal of nitrogen, and hence removal of nitrogen can be influenced by the wetland design and the type and wastewater composition (Brix, 1994) In the collaborative research of study of Wittgren & Tobiason, (1995), they demonstrated that deficiency of oxygen was uncertain to limit nitrification in a free-surface wetland. Instead, they maintain that suboptimal hydraulic loading conditions, a lack of suitable surfaces for ion exchange of $NH4^+$ and for the attachment of nitrifies, and phosphorus deficiency were considered potentially important factors in limiting nitrification.

2.16 Phosphorus removal by constructed wetlands

The ability of wetland systems to remove phosphorus has been conducted in many study researches globally, like in the United States (Kadlec & Knight, 1996b; Kadlec, 2016), the United Kingdom (Heal et al., 2001; Kadlec, 2005), Australia (Mann & Bavor, 1993; Shan et al, 2011), Denmark (C A Arias, Del Bubba, & Brix, 2001; Brix, Arias, & Del Bubba, 2001). Others include Norway (Robert H Kadlec, 2005; Zhu, Jenssen, Maehlum, & Krogstad, 1997), the Czech Republic (Vymazal, 2001; Vymazal, 2004), Sweden (Hamisi, 2017) and the Netherlands (Schreijer et al, 1997). Also in African countries like Uganda (Kyamb, 2005) and in Nigeria (Sudarsan et al., 2015) there are reported cases of the ability of wetland system to remove phosphorous. Moreover, constructed wetlands were discovered to be unable to eliminate phosphorus effectively from wastewater in the long-term (Gao et al., 2014; Kadlec & Knight, 1996b; Mann & Bavor, 1993). According to Drizo et al, (1999) in their research finding, they discovered to remove phosphorus there is for full capacity needed is likely to be about 2-5 years.

Phosphorus originates as phosphate in both organic and inorganic forms in treating different wastewaters in constructed wetlands (Choudhary et al., 2011; Vymazal, 2007). However, due to its bioavailability, macrophytes and algae utilize orthophosphate phosphorus straightforward. Additionally, Jan Vymazal, (2007) reported that phosphorous may serve as a medium between the two forms of phosphorus cycling in wetlands. Therefore, phosphorus removal in wetlands system is by sediment retention, adsorption, desorption, fragmentation, plant or microbial uptake, mineralization and leaching (Vymazal, 2007). However, Gikas & Tsihrintzis (2012) argue that the porous media adsorption and microbial ingestion were used mainly to remove phosphorous.

To determine the point at which Phosphorus be stored or removed by any type of constructed wetland. For instance, in the study research of (Vymazal, 2001), it was stated that soil media in vertical-flow constructed wetlands adsorbs phosphorus, but the capacity of the absorption depends on the media type. While in natural wetlands, the adsorption is by the emergent floating macrophytes, but dead macrophytes was harvested and returned back to the wetland, these resulted in the phosphorus removal to be maximised in the wetland. Phosphorus removal in VFCW occur through the processes as follows: sorption to porous media, absorption of biofilm and digestion of macrophyte (Lantzke et al., 1999). and the removal quantity by the processes as follows: media larger than wetland vegetation, larger than macrophytes, larger than biofilm, while macrophyte (70%) bigger than media, (20%) greater than biofilm, having (10%). Additionally, in the research study of Lantzke et al., (1999) it was stated that harvesting of wetland plant removed additional phosphorus ranging 10–20%.

2.17 Heavy metals removal mechanisms in constructed wetlands

Some metals that are essential in very small quantities for growth of plant and animal. These include selenium, copper, and zinc. When they are in higher concentrations, they are found to be toxic. However, at low concentrations, some metals can be toxic, these include lead cadmium, and mercury that are normally found in industrial wastewater (Norton, 2014). The contact of heavy metals into the environment is greatest concern because of their severe consequences on food, animal and human health. Heavy metals removal in constructed wetlands is achieved generally by plant uptake and by plant direct adsorption. Removal of heavy metals in constructed wetlands occur through several processes, these include physical, chemical, and biological processes. All processes are dependent on each other, making it to be a complex one.

It was discovered that little quantities of heavy metal may be detected in urban and municipal wastewaters (Vymazal, 2005). In the study research of Thullen, Sartoris, & Nelson, (2005), they reported that the key heavy metals related with wastewater which was formed by mines and industries include mercury, chromium, iron, cadmium, zinc, copper and lead. These heavy metals are eliminated from constructed wetland system by different methods including: filtration, adsorption and sedimentation, cation and anion exchange, and co precipitation, and metal sulphides, photo degradation, phyto accumulation, biodegradation, microbial activity uptake into plant material and precipitation by geochemical processes (Stottmeister, Wießner, Kuschk, Kappelmeyer, Kästner, et al., 2003; P Verlicchi, Galletti, Al Aukidy, & Ranieri, 2010; Núñez et al, 2011) demonstrated that heavy metals removal rates by constructed wetland have been recorded to be close to 100 %. It was reported by Sheoran & Sheoran, (2006) that demonstrated other heavy metal removal rates by a CW, to be the range between 75-99 % cadmium, 76 %, 67 % for zinc, silver and 26 % lead, while BOD, COD, and TSS were eliminated at a rate range 75 and 80 %. Metals were confirmed to collect in the shoots, rhizomes, leaves, with roots and lateral roots having the maximum content, while the minimum concentrations were establish within the shoots (Zachritz et al, 1996).

Furthermore, the metals are possibility to meet at the top-most layer (litter and sediment) or near the valve depending on the constructed wetlands system configurations (vertical or horizontal flow) irrespective of the removal means (Cheng et al., 2002; Scholz & Xu, 2002). However, in the study research report of Sheoran & Sheoran, (2006) and Guittonny-Philippe et al., (2014), they both confirmed that the entire heavy metal removal process rely on each other making the process very compound. Several heavy metals in constructed wetlands were removed from the wastewater through porous media interaction, after which the macrophytes work as an enhancing system Heavy metals are dangerous mechanisms in different type of wastewater including agricultural and industrial wastewaters.

Metals removal in constructed wetlands happens by plant uptake, soil adsorption, and precipitation. The ability of plants to uptake metals depends on the type of plant and type of metal. There are some types of plants which are capable of storing large amounts of metals in plant biomass and in its roots (DeBusk, 1999). However, in slow water, metal particles heavier than water will settle down. Moreover, it was found that the physical sedimentation process is the major pathway of removal of heavy metal in both natural and constructed wetlands.

In the constructed wetland system, removal of heavy metal is mostly by chemical precipitation, ion exchange and absorption by plants etc. According to some researchers, they believed that, zinc rate removal can reach up to 96% and the removal of iron, chromium and magnesium is also high when the hydraulic retention time is between 22-34h in the surface flow wetland (Qin & Chen, 2016).

2.18 Mechanisms of other contaminants removal

The usual water quality pollutants that were commonly used to analyse quality of wastewater treated in constructed wetlands, includes COD, BOD, SS, turbidity, dissolve oxygen, nitrogen compounds, petroleum hydrocarbons, and heavy metals. Others were trace elements, personal care products, pharmaceuticals, pesticides, herbicides, phenols, endocrine disruptive chemicals (EDCs) or linear alkylbenzensulfonates (LASs), and polychlorinated biphenyls (PCBs). All these were also treated by different types of constructed wetlands (Olujimi et al., 2010; Tijani et al., 2013; Yao et al., 2014). In constructed wetland systems, trapping of sediments refers to a physical removal mechanism of solids and organic particles in the wastewater. When the wastewater permeates through the wetland gravel media, the particles settle on the media bed or plant roots because of the slow water movement affected by the gravels and broadsheet flow enhancing the sedimentation process afterward (DeBusk, 1999; Gikas & Tsihrintzis, 2012; Paing et al., 2015). In the research of Imfeld et al., (2009) and Leppich et al., (1999), they reported that one of the removal pathway for chlorobenzenes and fuel in wastewater is sedimentation process. Removal of pollutants include two groups of persistent organic pollutants: polycyclic aromatic hydrocarbons (PAHs) and polychlorinated biphenyls (PCBs) in landfill leachate (LL) treated in three constructed wetland systems (CWs) (Wojciechowska, 2013). Removal of persistent organic pollutants from landfill leachates treated in three constructed wetland systems. PCBs (Campanella et al, 2002), effectiveness of the CW in pesticides removal (Budd, O'Geen, Goh, Bondarenko, & Gan, 2009). Removal of inorganic pollutants derived from motor way suspended on solids have also been treated with constructed wetlands through sedimentation and filtration as removal mechanisms among other processes.(Hares & Ward, 2004) However, there are some pollutants that requires to be treated by other mechanisms after treating with constructed wetlands. For instance, in the collaborative research of Türker, Vymazal, & Türe, (2014), they described that sedimentation enhances plant uptake to eliminate boron in constructed wetlands under suitable environmental conditions. Also, in a research studies of Türker et al., (2013) and Türker et al., (2014) they achieved 40% and 32% and removal efficiency of boron in their wetland systems through plant uptake and sedimentation procedures respectively.

Organic pollutants like herbicides and phenols were described to be treated in wetlands through the adsorption process as a chemical removal pathway (Zhang et al., 2014). Equally, Vymazal & Kröpfelová, (2008) conducted 28 months study research in Czech Republic to investigate removal of inorganic pollutants in horizontal flow wetlands, It was discovered that 34 trace elements were mostly removed through the adsorption process. In a collaborative research effort of García et al., (2005), they discovered that pharmaceuticals such as carbamazepine are treated through sorption of the particles to the gravel media from the water phase and therefore gather in the sediments of the constructed wetlands. Moreover, in study research of (García et al., 2005), a pilot vertical subsurface-flow constructed wetland (VFCW) were used to evaluate removal performance of 13 pharmaceuticals and personal care products (PPCPs) together with BOD5, TSS, and ammonium and compared with those got by a sand filter. On the origin of the observed removals, the studied were grouped in connection to PPCPs elimination performance into first: those that are very efficiently removed greater than 95% removal rate was recorded in one of the systems like caffeine, salicylic acid, methyl dihydrojasmonate, CA-ibuprofen, hydrocinnamic acid, oxybenzone, ibuprofen, OH-ibuprofen; secondly: those that are moderately removed, with removal rate between 70 - 90% in the two systems like naproxen, diclofenac, galaxolide, and tonalide; and lastly: those that are removed poorly, with elimination rates of less than 30% like carbamazepine.

In the study research of Stein et al., (2005) and Polprasert et al., (1996) they evaluated constructed wetlands treated in treating acetone and phenol removal and attributed the high removal because they were treated through volatilization and phytovolatilization respectively. Furthermore, lower chlorinated benzenes (Keefe et al., 2004) and chlorinated ethenes (Bankston et al., 2003) were reported to be treated through the volatilization and phytovolatilization elimination processes in constructed wetland systems.

During treatment of wastewater, the important mechanisms involves in removing biological pollutants in constructed wetlands system includes plant uptake, phytodegradation, and phytoaccumulation. Chu et al., (2006) evaluated the accumulation, distribution, and transformation of DDT (dichlorodiphenyltrichloroethane) and PCBs by Phragmites australis and Oryza sativa L plants and found that plant uptake and accumulation were the main removal pathways for the removal of pollutants. Additionally, treatment of nutrients of agricultural significance, however unsafe to plants when in excess, with constructed wetlands has been reported (Gross et al., 2007; Kröpfelová et al., 2009; Lizama et al., 2011) and has accomplished significant removal. For example, Türker et al. (2013a) measured the capacity of macrophytes for boron elimination from wastewater in their wetland systems in Turkey and concluded that Typha latifolia and Phragmites australis consumed a lot of boron in their roots which later transferred to leaves and stems of the wetland plants (Rees et al., 2011). It was concluded that phytoaccumulation was the key removal mechanism. Pathogen performance removal efficiencies have been reported by many authors to performed up to about 99.99% removal rate employing a number of different constructed wetland designs

(Weber & Legge, 2008). Nevertheless, by virtue of nearer inspection it can be observed that the reported efficiencies of individual wetland systems may differ, when comparing CWs of a similar design. Constructed wetland design tends to be based largely on rule of thumb sizing, as the specific mechanisms and essential variables involved in pathogen removal are only unsure comprehended.

Overall, all type of constructed wetlands, have been confirmed to treat different types of pollutants in wastewater in different parts of the world with high efficiency (Vymazal, 2014b)

Figure 2.9 shows the removing process occurring in a wetland.

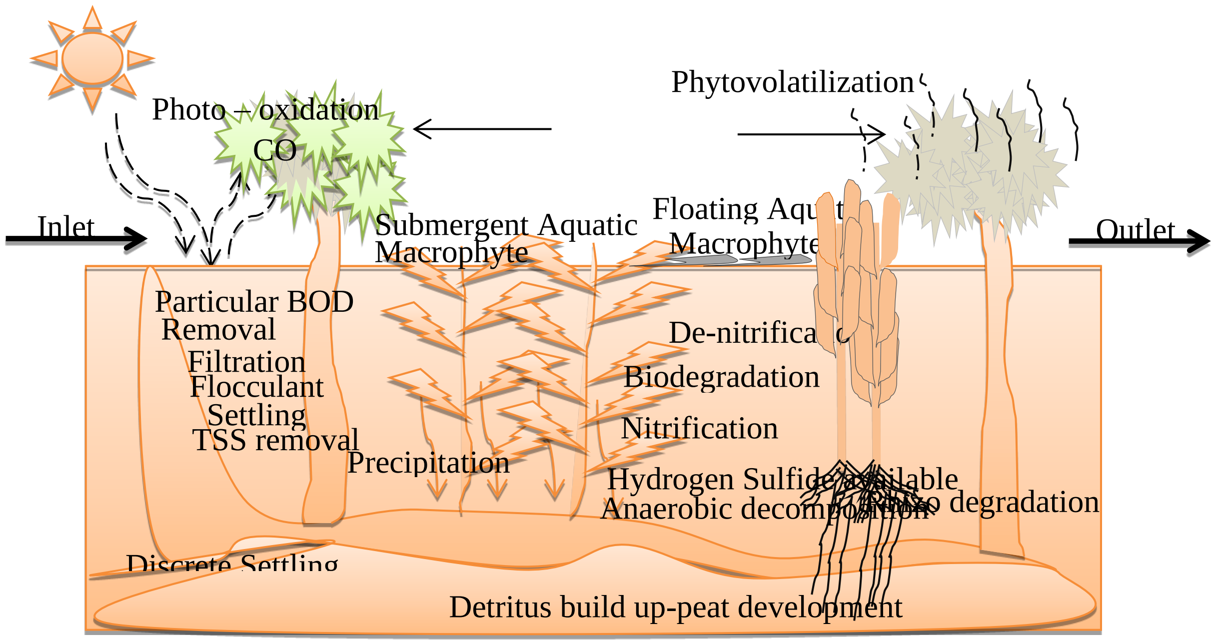


Figure 2.9: Removal processes occurring in a wetland. Source: ITRC (2003)

2.19 Important values of natural and constructed wetlands

Natural wetlands are very important basis for sustainable development, besides the biodiversity and landscape functions, they can be widely used for the treatment of wastewater and energy or production of material (Greeson et al., 1979; Wohlgemuth & Hershner, 1993).

Wetlands are important features in the landscape that provide numerous beneficial services for people and for fish and wildlife. Some of these services, or functions, include protecting and improving water quality, providing fish and wildlife habitats, storing floodwaters and maintaining surface water flow during dry periods. These valuable functions are the result of the unique natural characteristics of wetlands. Many research studies have evaluated the good of natural and constructed wetlands, in terms of their capability to treat wastewater for the improvement of water quality or additional services (Ghermandi et al., 2010).

Natural wetlands, have been in existence since the history of human beginning time, constructed wetlands ecological engineering emerged from mimicking the natural wetlands (Council, 1996). The natural wetland values are many and play a key role in the history of humanity including the prime civilizations like Egypt and Mesopotamia who used to live near the wetland territories that provided them with numerous economic opportunities and essential resources. However, despite all these several benefits and the historical impact of these wetlands, it was during the last 5 decades, that humans recognised their various positive influences (A. Stefanakis et al., 2014; Jan Vymazal, 2014a). Wetlands as a water body fuse assortment of creatures and plant species. Besides, they offer help to the lives of these plants and creatures living in the environment and supply numerous indispensable biological system benefits that aid human improvement, for example, arrangement of fuel, sustenance, water, wood, surge control direction, water quality and supply, living space like biodiversity, and social administrations, for example, amusement and tasteful enhancement (Sukhdev, 2008). Other values include reduction of carbon dioxide in the atmosphere, with subsequent effects on global warming, supporting the food chain indirectly by fish production and other related edible water animals (Stefanakis et al., 2014), reduction of flood, regulation of small and large-climatic changes, pollutants degradation and control of erosion (Ming, et al, 2007). Due to wetlands good qualities, such as control of water pollution, some wetland scientists have called them “Earth’s kidneys” as they provide similar functions with kidney, absorbing waste such as nitrogen and phosphorous. They also sieve and recollect the pollutants passing through them before they reach the receiving water courses (Cui et al.,2012; Palma et al., 2004; Scholz & Lee, 2005). Furthermore, they are also referred to as biological supermarkets (Chen & Lu, 2003; Mitsch & Gosselink, 2000) because they give large quantities of food, this draw many animal species, and they are also among the natural environments with high natural production on Earth.

Classification of Wetland comprises the grouping of wetlands by specified characteristics. For over two decades, combined efforts were made by wetland scientists to understand, wetlands and wetland values and to classify and summarize values of wetlands. For instance, in the research of Cui et al., (2012), they classified the values of wetlands ecosystems as follows:

- Hydrological and hydraulic values which comprise control of flood and erosion, recharge of ground water aquifers, and flood plain hydrodynamics and bank stabilization
- The nature conservation values of wetlands is very high
- Effects of climatic including protecting global warming, carbon fixation and CO_2 balance, and micro-climatic effects;
- Aquaculture development and integrated systems, fishing and rice cultivation; and
- Many living organism depend on natural wetlands for their survival (human being and wildlife.
- Meeting sustainable water management objectives cost effectively
- The functions of biodiversity may include wild life enhancement, breeding ground for water fowl, and vegetation and animal conservation among others.
- Wetlands provide multiple benefits to cities and rural communities and Mining activities.

In the study research of Millennium Ecosystem Assessment MEA, (2005), Ghermandi et al., (2010), Cui et al., (2012). They describe the values of the wetlands as groundwater aquifers enhancement, control and management of flood incidents, retaining of sediments and other materials, carbon dioxide reduction, storage and heat release, solar radiation reduction and relevant support to food chains. However, in the research study of A. Stefanakis et al., (2014), they noted that the wetlands values can be classified as ecological, sociocultural, and economical as contained in Figure 2.10. Additionally, they recommended that the overall general wetlands values would be based on the combination of these. Values of wetland have been shortlisted as follows: ecological, socio-cultural and economical ones, which include biodiversity, irrigation, fishery, livestock, water supply, water quality reclamation and flood reduction. Others are culture, climate improvement, recreation, scientific value, CO_2 emission protection, prey value, and educational value. Other values as mentioned include timber provision, source of hydroelectric power supply, salt provision, provision of sand, ant corrosiveness, warm restoration and transportation (MEA, 2005; Schuyt & BRander, 2004).

There have been an intensive reported investigation to evaluate the values of wetlands on economic scale or bases. For example, Costanza et al., (1997) assed the value of the world's wetland in term of economic parameters and predicated that their aggregate valuation utilizing American dollars came up to an aggregate sum of US$ 14.9 trillion. Also, Schuyt

& BRander, (2004) reported in terms of economic and monetary value of the global wetlands to be US$ 70 billion yearly based on the estimated Ramsar Convention wetland region of 12.8 million km^2 including qualities, for example, biodiversity, logical, natural, sociocultural, and other imperative ones. The creators likewise figured the financial esteem given by US beach front wetlands in securing storm occasions in fiscal terms to be US$ 23.2 billion every year and a decrease from US$ 3– 8 billion to US$ 1.5 billion if another wastewater treatment plant were to be built to supply the equivalent measure of free water supply given by the characteristic wetland existing repositories.

Human society recognised that the estimated values of wetlands, including flood management and control and wastewater treatment capacity, has made them become increasingly recognized (Stefanakis et al., 2014; Vymazal, 2014b). Today, wetlands are recognized capable of removing various types of contaminants these include inorganics, organics, trace elements metals, etc. This acknowledgment encouraged the research on artificial constructed wetlands to discover different technological applications of wetland potentials. The major idea behind these constructions wetlands is to replace the various wetland processes in a more advantageous way to people and wildlife under controlled environmental such as flood prevention and water quality improvement.

Concerning constructed wetlands, some scientist researchers also tried to assess their values as previously done for natural wetlands (Knight et al., 2001). in their assessment of subsurface-flow constructed wetlands as a habitat for humans and wild life, they discovered that the wetland systems (constructed and natural) provide habitat for wildlife and diversity, provide recreational activities, such as birdwatching, water storage, and aesthetic enhancement in urban or rural environments. Whereas many research studies revealed that both natural and constructed wetlands have similar ecological values (Campbell, Cole, & Brooks, 2002). In the study research of Ghermandi et al, (2010), in their effort, they stated that constructed wetlands have more values than the natural wetland. Figure 10 is the categories of Important values of wetlands.

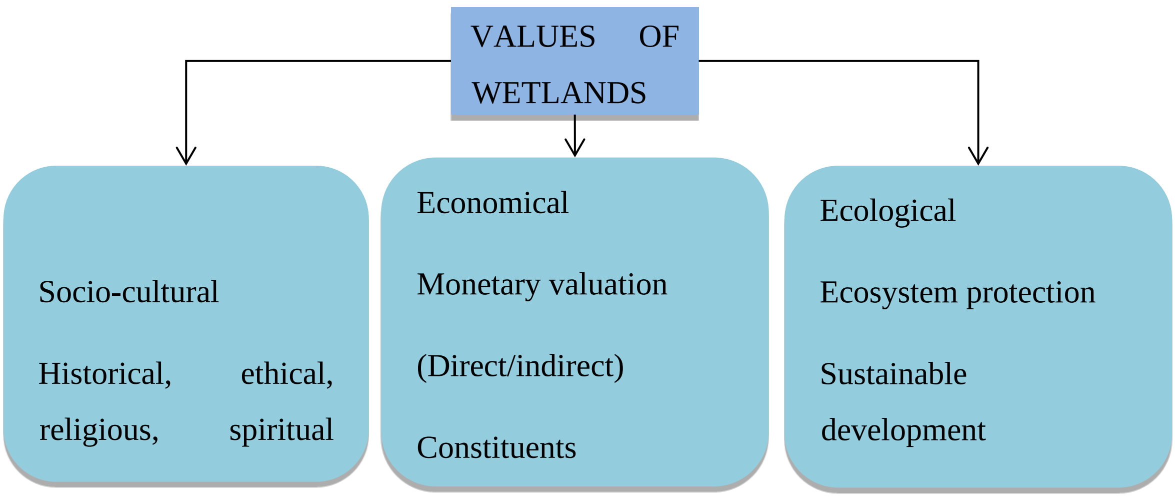


Figure 2.10 : Important values of wetlands which was adapted from (Stefanakis et al., 2014)

2.20 Selection of vertical-flow over horizontal-flow constructed wetland

The used of Vertical-flow and horizontal-flow constructed wetlands as an alternative means of wastewater treatment from different sources is increasingly gaining momentum worldwide (Abou-Elela, 2017; Abou-elela et al., 2013; Jan Vymazal, 2014b; S. Wu et al., 2015; Yalcuk & Ugurlu, 2009a). This is due to their low cost of operation, treatment enhancement, easy maintenance and their simplicity to operate (Schulz, 2006, 2010). Moreover, some study research has projected that vertical flow constructed wetlands performed better than horizontal flow constructed wetlands in removing some water quality parameters. For example, some study researches explained that, draining of the substrate bed in VFCWs affirms BOD reduction and ammonia nitrogen removal efficiently and gives excellent conditions for nitrification unlike in horizontal flow constructed wetland systems (G D; Gikas & Tsihrintzis, 2014; J Vymazal, 2008; Jan Vymazal, 2005, 2014a; Paing et al., 2015). According to study researches of Brix & Arias, (2005) and Prochaska, Zouboulis, & Eskridge, (2007), they specified that vertical-flow constructed wetlands systems perform reasonably for the particle removal in wastewater, and for the removal chemical and biochemical oxygen demand (COD and BOD). However, some researchers itemised them as poor nitrite and nitrate remover (Vymazal, 2005), recently many research studies revealed that VFCW systems with irregular loading rate can remove nitrate or nitrite with some modification. For example, Brix & Arias, (2005) and Gross, Shmueli, Ronen, & Raveh, (2007) described percentage removal performance efficiency between the ranges of 50% and 69% for total nitrogen (TN) and more than 90% for COD and BOD5 after outflow recirculation. Moreover, Weedon, (2003) in their effort to access two years treatment performance of vertical flow constructed wetlands, they discovered that their systems successfully denitrified and treated and removed higher percentage of SS, BOD5, and NH4-N from pre-settled urban wastewater up to 90% of after 10 years of operation in the UK after recirculation at usual loading rates. The writer of the research reiterate that the system was improved using sand as the major filter media, wastewater was intermittently fed and the aeration time used was the interval between the wastewater application regimes, indicating that the systems capability of attaining high treatment performance (Stefanakis et al., 2014). Furthermore, wetland systems were assessed in China as reported in a study research by (Shen et al., 2015) to improve nitrate removal using starch blends as solid carbon source, the system recorded high percentage of denitrification with 98% removal efficiency of nitrate. However, in the study research of C. Li, Wu, & Dong, (2015), percentage removal of organic matter and ammonia-nitrogen by constructed wetland were recorded to be 95% without any alteration. The treatment performance efficiency in VFCWs can be impacted by many operational features, of which inflow COD/N ratios always play a vital part (Li et al., 2015).

Vertical flow constructed wetland systems (VFCWs) are the state of the art technologies used for the control pollutants in wastewater, and interest in them is increasing rapidly worldwide, probably due to the lower area demand advantage compared to Horizontal-flow constructed wetland systems HFCWs (Abou-elela et al., 2013; Paing et al., 2015; Stefanakis et al., 2014; Wu, et al., 2015). Clearly, there is huge variety in the design characteristics of vertical flow constructed wetlands particularly regarding the quality of wastewater which need be treated per square meter, it directly affect the surface area demand, as it decreases pollutant load. VFCWs need 1 to 2 square metres per person equivalent (m^2/pe) because values lower than 3 m^2/pe decreases the system's surface area in contrast horizontal flow that needs about 5 to 10 m^2/pe. Several countries, including UK are investigating with (1-2) m^2/pe, for the VF reed bed system VFCWs systems and use this equivalent of unit area per person (P Cooper, 2005; Weedon, 2010). Other countries include Belgium with 3.8 m^2/pe France with 2.0 2.5 m^2/pe (Molle et al., 2006; Paing & Voisin, 2005) Germany with 1.6 m^2/pe (Olsson, 2011), Greece with 1–1.5 m^2/pe (Stefanakis & Tsihrintzis, 2012b) and also Greece with 3 m^2/pe (Gikas & Tsihrintzis, 2012), and Spain with 1.0 – 3.2 m^2/pe (Puigagut et al., 2007) Denmark with 3.2 m^2/pe (Brix & Arias, 2005) all these were reported in a study reported by Stefanakis et al., (2014). In comparisons to HFCWs, VFCWs shows a better removal efficiency of other water pollutants including organic and inorganic other than traditional ones like BOD, COD, SS, etc. In study research of Verma & Suthar, (2018) the conducted a comparative study to evaluate treatment performance between horizontal and vertical surface flow constructed wetland system in removing heavy metals (Fe, Cr and Ni) and other water quality parameters from dairy wastewater using multivariate principal component analysis. It was discovered that VFCWs performed better in removing heavy metal and other water quality parameters than HFCWs.

In another study of Yalcuk & Ugurlu, (2009b) VFCWs and HFCWs were compared in treating landfill leachate in Turkey, in term of their removal efficiency. They found that vertical-flow systems performed better in heavy metals removal including Cr, Cu, Zn, Pb, and Ni present in the leachate as compared to horizontal flow systems. Moreover, in the study of Konnerup, Trang, & Brix, (2011) to evaluate the potentiality of HFCW and VFCW systems in enhancing the water quality of the degraded river in Vietnam, a tropical country due to pollution from aquaculture practices which lead to the eutrophication of the receiving water courses. It was concluded the by the researchers that the vertical-flow constructed wetland systems have a higher possibility to repair the fishpond outflow with minimal negative impact in environmental than horizontal-flow wetland systems. Similarly, in a collective research studies of Canga et al, (2011) to investigate and compare nitrogen removal rates of different constructed wetlands system in Boku University, Vienna after operation of 4 years. They reported that VFCWs systems were better in removing nitrogen than the HFCWs.

Recently, some publications on municipal wastewater treatment studies also suggested that vertical-flow constructed wetland systems should be preferred regarding water quality improvement over horizontal-flow constructed wetland systems. For example, Pandey et al., (2013) compared the performance of the two systems in municipal wastewater treatment in Nepal, to evaluate their treatment performance efficiency. They indicated that vertical-flow systems performed better when compared with horizontal-flow ones after a 7-month of operational study. Moreover, in 3 years long-term study research of (Abou-elela et al., 2013), in their collective research they observed that vertical flow constructed wetland systems were the preferred option in comparison with horizontal-flow constructed wetland systems because, in the research, VFCWs were proved to be more successful in wastewater contaminants removing treated in the municipal sewage than the latter.

2.21 Modelling of Wetland Data

Accordingly, multiple efforts have been dedicated to the modelling of CW processes, ranging from simple rule of thumb and regression equations to the well-known first-order k-C* models, KSOM models (Rustum, Adeloye, & Scholz, 2008b), Fuzzy logic models (Kotti et al., 2013b), Artificial Neural Networks models (Latif K, 2010). In the research study of Rustum et al., (2008a), they presented a methodology which when examined, focused and designed the used on KSOM model for the prediction of the concentration of BOD_5 in domestic wastewater, which they got at three-wastewater treatment plant Scotland. The model built, after testing and validation work perfectly in predicting the BOD_5. However, other parameters are still required to be modeled.

Numerical models describe the biochemical transformation and degradation processes taking place in CWs, hey are promising tools to better understand CW functioning. Modelling technique in wetland systems is a prediction tool, used to manage, improve and properly predict treatment performance of constructed wetlands alongside saving cost, time and to produce better water quality results. Prediction of wetland performance using different modelling techniques to mine and get the needed information in any given dataset and filter out the noise and unwanted data is currently gaining attraction in the field of water quality improvement by constructed wetlands (L Kalin & Isik, 2010) as a result of increase in the growing interest in the use of constructed wetlands for wastewater treatment coupled with meeting the strict water quality standards, which are costly and time consuming, but necessitated by regulatory bodies (Dzakpasu et al, 2015).

Numerical models are designed to describe the most common processes taking place within CWs, and to use the model to make it clear on the internal operation in the systems in the long period. (Langergraber, 2011). Numerical modelling of constructed wetlands (CWs) is increasingly gaining interest recently. Purposely because of the need to increase understanding in the dynamics and operation of the complexity in CW system by using mechanistic or process-based models that describe transformation and degradation processes in detail. As these mechanistic models are complex and therefore rather difficult to use, on the other hand, simplified models for CW design is needed (Langergraber et al., 2009). Predictive model can act as an efficient platform to test these new configurations, and to compare them with the traditional ones, thus, reducing the required efforts for experimental studies and evaluations. In the past, only simple models were developed, ranging from regressions (black box stochastic models) to deterministic models based on first-order or Monod-type equations (Diederik et al, 2004). Simple models aim to offer basic tools for the design of CWs, but they provide only a limited understanding of the system: optimisation of the facility and insight into the treatment process are not main objectives for this class of models. The mechanistic approach for modelling CWs has been adopted only recently since it requires a significant effort for numerical implementation.

For decades, constructed wetland (CW) models have been considered a promising tool to increase understanding of the simultaneous physicochemical and biological processes involved in the treatment of wastewater with this technology.

Most of the concerted efforts on the previous modelling work on the wetlands performance focused on wetland processes varying from simple models to complex ones (Meyer et al., 2015; Diederik P.L. Rousseau et al., 2004). Numerical modelling is also used to predict wetland complex processes by applying Artificial Neural Network (ANNs) (Chen et al., 2008; Meyer et al., 2015), and recently employing Adaptive Neuro-fuzzy Inference Systems (ANFIS) (Dzakpasu et al., 2015).

Recently, research has shown that the field of data mining had developed significantly, and currently continues to receive rising academic observation because of the massive developments in the technology of hardware and software (Allahyari et al., 2017). Nowadays, data mining is considered applicable to major human needs, and to play a major role in our daily activities. Such activities include retail, fraud detection, marketing, banking and finance, shopping, telecommunication, manufacturing, health care, weather forecast and aerospace. Government agencies utilise data mining tools and techniques to take out information concerning historical data. Because of these technological needs and their relevance in society, the ability to generate, gather, collect manage data for proper use has rapidly increased (Han et al., 2011).

2.21.1 Data

Data are said to be the backbone of knowledge discovery and data mining; it is a set of standards of qualitative or quantitative variables; restated, pieces of data are individual pieces of information. Data refers to representation unstructured facts of an input and output information collected from observations or recordings about events, objects or people by a detecting device or organ that includes both useful and irrelevant or redundant information and must be processed to be meaningful. Data is measured, collected, reported, and analysed for a specific purpose, to create information suitable for making decisions as a result of which data can be pictured with the used of graphs or images codes. However, there are certain restriction encounters when handling a large set of data. Thus, it is important to understand some of the key problem related with the dataset. The problems include measured error, standard error and missing values etc. (Han et al., 2013)

The data for this study were collected from the monitoring water samples (inflow wastewater and outflow treated water) the vertical flow constructed experimental wetland analysis in the laboratory. In overall, the dataset included 11 water quality parameters that were used for over three years. Figure 2.11 below shows the presentation of a processed data

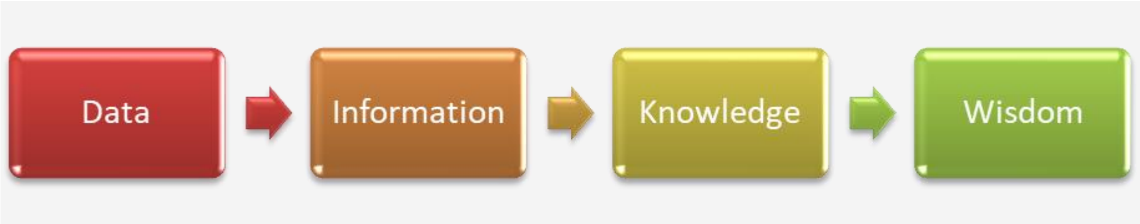


Figure 2.11: Diagramatical presentation of a processed data

2.21.2 The standard error of measurement

The standard error of measurement is associated with test reliability which indicates the dispersion of the measurement errors when trying to estimate the true value of experimental measurement from their observed values (Brown, 1999). The standard error of measurement can be calculated from the relationship in equation 2.1 below.

$$\mathrm{SEM} = \mathrm{S}\sqrt{1 - \mathrm{r}_{\mathrm{xx}}} \qquad 2.1$$

Where: SEM is the standard error of measurement, S is the standard deviation of the test, r_{xx} is the reliability of the test.

2.21.3 Missing value, Outliers and Errors

To ensure proper modelling, the dataset is filtered for errors, outliers, and invalid data entries to ensure the accuracy of the dataset. Various industrial, practical, survey and research dataset, nowadays in existence, contain missing values. There are numerous reasons for missing values in a given datasets, ranging from miss entry during manual data entry procedures, equipment errors and incorrect measurements (Kaiser, 2014). The missing value commonly appears as empty cells within a table or spreadsheet or as NULL values in a database while other flat-file formats use a different symbol to represent the missing value. Missing values is an inevitable and common problem in a given large set of data (Steinberg, 2012) and are predicted in most of the informational sources used.

However, missing values problem in data found in almost all the surveys, practical and designed experiments. Analyzing dataset by evading or disregarding cases of missing values may lead to appropriate results (Kaiser, 2014). The efficiency in data loss, as well as complications in handling and analyzing data and bias due to differences between missing and complete data, are major problems associated with missing values.

2.22 Data Mining

People nowadays make use of data mining in order to gain knowledge, not just prediction alone but to gained knowledge from the prepared data which sound like a proper idea if one can fight to do it (Witten et al, 2011). Data Mining is a process of analytic designed to ascertain data (usually large amounts of data) in search of consistent patterns and systematic relationships between variables, and then to confirm the findings by applying the detected patterns to new subsets of data. Data Mining (DM) refers to the software and computational process of discovering patterns in large datasets involving methods at the intersection of artificial intelligence, machine learning, statistics, Predictive analytics, and database systems.

Data mining according to (Abbas) 2015 refers to the extraction of hidden predictive information (data) from any large databases. Data mining is particularly concerned with extraction of data to make it useful information. The experimental dataset is thoroughly prepared either by humans or by collecting some data in a semi-automated way. It also helps in extracting a very valuable knowledge from data, based on which decision can be made in order to improve performance, sell, accuracy of medical diagnosis, processing and analysis of information etc. Data Mining is said to be a sustainable techniques viable to extract very essential knowledge from the data and is all about explaining the past and predicting the future by means of data analysis (Witten et al., 2011). This is about taking the raw data and transformed it into more useful and meaningful information to use the intelligent method to mine patterns or knowledge (Witten et al., 2011). The software and computational process are needed for the discovering patterns in large datasets involving methods at the intersection of artificial intelligence, machine learning, statistics, Predictive analytics, and database systems (Folorunso & Ogunde, 2004). There is no magic in data mining but rather a massive collection of different means of techniques to be used and straightforward machine-learning algorithm. There is no single universal best method; data mining is experimental science there is need to find out what works best in any given problem. Many data mining techniques make mining work very easy by using a different method with huge amount of data. Care must be taken when using data mining techniques for the good of the work in analysing data, in order to get an accurate result and perfect prediction. Data mining can examine any type of data and information flow (Weiping & Wang, 2013).

2.22.1 Data Mining Techniques

In recent years, the application of data mining for the prediction in hydrology and in constructed wetland and in wastewater management have gained growing attention (Spate et al., 2002; Sudarsan et al, 2018; Wang et al., 2013; Liang & Liang, 2001). Generally, the most used data mining techniques include association rule mining, sequential pattern mining, clustering, correlation analysis, genetic algorithm, decision tree analysis, logistic regression, rough set approach, Bayesian networks, statistical analysis and neural networking. In this study research, the literature review focuses on selected data mining techniques that are used in the report.

Statistical analysis is the accurate technique of data mining design according to statistics and probability theory. For instance, regression analysis and factor analysis, through the modelling of objects, find a conclusion. Usually divided into the following phases: analytical data description to nature, researching group of data relationship, model building, data and relationship summary of basis group, model validity explanation, and finally prediction for the future development. Multiple linear regressions used in this study research is also part of the data mining technique.

2.22.2 Data mining techniques used in the research

The following are the data mining techniques used in this research to predict the performance of vertical-flow constructed wetland treating domestic wastewater.

1. Artificial neural network (ANN)
2. Multiple linear regression (MLR)

2.22.2.1 Artificial neural network (ANN)

Over the past decade, Artificial Neural Network (ANN) research has found its way into the areas of hydrology, ecology, medical and other biological fields. The American Society of Civil Engineers wrote a report to investigate the usage of ANNs in hydrologic applications, and found it being used for such purposes as rainfall-runoff modelling, stream flow forecasting, groundwater modelling, precipitation prediction, and water quality issues. Neural network models are attractive to decision makers because of their established methodology, long history of application, availability of software and deep-rooted acceptance among practitioners and academicians alike. Models of ANN are very strong ones that use the non-linear activation function, where the weights of the parameters are emphasized but not the weights function themselves. Nevertheless, large datasets are also needed. Discovering both approaches can affirm main findings and based on application yield an appropriate model. Many researchers showed that the ANN model gives better performance compared to the other model in forecasting water quality. Applications of ANN in the areas of water engineering, ecological sciences, and environmental sciences have been reported since the beginning of the 1990s. A computing system invented of a highly interconnected set of simple information processing nodes, similar to the enormous network of neurons, called units. The neuron collects inputs from both a single and multiple sources and produces output from the output layer in accordance with a programmed non-linear function (Sarkar & Pandey, 2015). Artificial neural networks (ANNs) have shown the ability to learn the history of the model data and apprehend non-linear static or dynamic behaviour among many input variables to determine one or more output variables based on a given dataset (Rene & Saidutta, 2008). The applications of neural networks have increased rapidly in the field of water quality management (Wen & Lee, 1998).

The advantages of ANN are as follows: easy to use, rapid prototyping, high accuracy performance, little assumptions, it need of expert knowledge is reduced, non-linearity, multi-dimensionality and simple interpretation (Iovine, 1998; Werner & Obach, 2001)

2.22.2.2 Types of Artificial Neural Network

The following are types of artificial neural network, these include:

1. Feed forward artificial neural network
2. Radial basis function neural network
3. Kohenem self-organising neural network
4. Recurrent neural network (RNN)

5. Convolutional neural network
6. Modular neural network

Feed forward Artificial Neural Network This neural network is one of the simplest forms of ANN, where the data or the input travels in one direction. The data passes through the input nodes and exit on the output node. Feed-forward neural networks are the typically come across the type of artificial neural networks that used to several diverse areas (Sazli, 2006) Feed-forward neural networks fall into two classes depending on the number of the layer. The term feed forward describes how this neural network processes input. A perceptron is always feed forward, each layer except output one contains arcs or connections to the next layer, all the arrows are going in the direction of the output not backwards. The table 2.5 shows the classes of feed forward Neural Networks.

Table 2.5: Classes of Feedforward Neural Networks

Parameter	**Types**	**Description**
Based on the number of hidden layers	Single layer, Multi-Layer	Single-Layer - Having one hidden layer. E.g. , Single Perceptron Multi-layer – Having more than one hidden layers. Eg. Multilayer Perceptron

2.23 Data mining in Water Quality Parameters

Application of data-mining techniques to develop models for the prediction water quality parameters has been an on-going area of research for more than a decade and is still growing technology. The water quality variables selected for this research include dissolved oxygen, salinity, temperature and chlorophyll-a. This study recommends using the trained neural network in conducting data mining for different locations (Palani et al., 2009).

In the study research of Liao et al., (2015), they reiterate the use of two-stage data mining technique is employed in discovering chemical components of plants. Findings from this research indicate the possibility of utilising data mining in discovering new chemical compounds that may be present in water. Although the water quality parameters that are relevant to the irrigation purpose have been documented in the literature, however, such technique could lead to new findings especially in the seasonal area interruption where experimental data could not be gathered.

Kotti et al., (2013) in their joint research, they successfully applied CBR to predict BOD5 and SS in accessing treatment performance efficiency of wastewater by the constructed wetland. The result of the study revealed better treatment performance for constructed wetlands, and they suggested for a room of improvement by applying optimisation techniques to control the variance of the input variable.

It was reported in the research study of Kotti et al., (2013a) in their effort, the proposed a methodology to assess and model the prediction of the organic matter (BOD5) removal performance in free water surface (FWS) constructed wetland, the model was developed based on fuzzy-logic model which was validated using 2 year period experimental data in five different CW filters. Model predictions showed good agreement with experimental data and are a satisfactory tool for studying FWs CWs. The models are said to have been expanded to integrate newer datasets to continuously improving their efficiency performance to predict adequately CW organic matter (BOD5) removal.

In their study Liao et al., (2015), they reiterate the use of two-stage data mining technique is employed in discovering chemical components of plants. Findings from this research indicate the possibility of utilising data mining in discovering new chemical compounds that may be present in water. Although the water quality parameters that are relevant to the irrigation purpose have been documented in the literature, however, such technology could lead to new findings especially in the seasonal area interruption where experimental data could not be gathered.

Reviews made in the journals and publications disclose that the use of data mining techniques are applicable in modelling and predicting the treatment performance of constructed wetland by predicting water quality parameters using other input water quality parameters. These discoveries were the key guide behind this thesis.

2.24 Previous studies on MLP-ANN predicting treatment performance of CW

According to Muttil & Chau, (2006) the continuous need in utilising computing in solving complex problems has provided the use of numerical models, mathematical and statistical models down to techniques based on Artificial intelligent in solving flow and water quality in coastal areas can be applied to effectively predict the system’s future outputs from the known given values of input. However, emphasis on the accuracy has been highly dependent on the algorithmic procedures. This study reviewed the current state of the art in the utilisation of Artificial Intelligence (IA) including artificial neural network, genetic algorithm, knowledge-based systems and fussy inference system.

Findings from this research indicate the potential of integrating the IA methods with the numerical simulation in order to relieve the burden of uncertainty while relying on the algorithm especially in water quality parameters application.

Similarly, Lee et al., (2015) in their research when dealing with uncertain data, during mining has been explored from a single-item to a more complex databases, although traditional mining techniques could not generate important of each of the single item recovered from the real situation, this study employs the use of importance of the single items recovered base on its weight rating. Evidence from this study experiment indicates the efficiency and scalability of the state-of-the-art models. The benefits that could be shared from this study include classifying the water quality parameters based on their priority and then assign such priority to the variables including finding its value base on the relevance in water quality assessment (Liao et al., 2015).

In the research study of City, (2009) they researched utilised the suitability of artificial neural network (ANN) in conducting Dissolved Oxygen(DO) and Biochemical Oxygen Demand (BOD) along with Indian coastal areas. Moreover, in an attempt to ensure proper environmental conservation through monitoring of water quality parameters remotely and using data mining, an integrated algorithm (Doña et al., 2015).

(Hafner & Jewell, 2006b) In their effort to improve on the model designed to predict the removal efficiency of Nitrogen (N) and Phosphorous (P), modelled a system that will predict N and P removal by detritus in a constructed wetland. The nutrient retention time, mass of organic material remaining, decomposers parameter in both aerobic and anaerobic waste treatment system are the model parameters. The results obtained for N and P removal with the net productivity of the model over the period shows a linear relation

According to Rustum et al., (2008a), in their effort to develop a methodology using a kohenem self-organising map (KSOM) based software for the rapid prediction of BOD5 concentration in wastewater using data obtained at three wastewater treatment plant in

Scotland which previously designed by some researchers recorded to be a partial success, they tried to solve the problem BOD_5 unavailability for real-time decision making and process control by developing more rapid biosensors. The method plays a significant role for timely intervention and cost saving during problem diagnosis in wastewater treatment process and when tested the model showed that it is adequately comprehensive to predict the BOD5 (Rustum et al., 2008a).

In the study research of Island et al., (1993), they demonstrated that most of the water and environmental regulatory bodies rely upon the use of computer simulation to effectively and efficiently understand, formulate and utilises data source from water quality for regulatory and decision making. There are several factors that are overlooked, among which is model uncertainty. V et al., (1993) in their collective research they employed Monte Carlo simulation techniques and predicted error associated with models designed in different dimensions, which includes spatial, temporal and mechanistic. However, there is little or no more literature in the use of data mining technique to predict the removal efficiency of water quality parameters using constructed vertical wetland system

Kotti et al., (2013) predicted water quality parameters in an ungauged basin, using an Artificial Neural Networks Model. They found that availability of data from several watersheds in an area with relatively similar physiographic properties determined the prediction impact of the input parameters (LULC percentage, temperature and flow discharge) on the water quality parameters. This shows that having data of water quality parameters of many different system, predictions can have made for a new or old system having the same configurations and operating conditions with the existing data sources. It is, therefore, intended to apply the data mining techniques to predict the existing constructed vertical wetland system (Kalin & Isik, 2010). The study was also conducted by Areerachakul, (2013) using Artificial Neural Network (ANN) which aimed to model and estimate chemical oxygen demand (COD) on data from 11 sampling sites. The data were obtained from the Department of Drainage and Sewerage, Bangkok Metropolitan Administration, during 2007-2011. The twelve other parameters of water quality ware used as the input of the models to predict COD. These water quality indices affect the COD. The experimental results indicate that the ANN model provides a high correlation coefficient, recorded as (R=0.89) and root mean square error recorded as (RMSE= 15.16).

In the research study of Tomenko et al., (2007), they make comparison between multiple regression analysis (MRA) and two artificial neural network (ANNs): multi-layer perceptron (MLP) and radial basis function network (RBFN), in term of their accuracy and efficiency when applied to predict BOD concentration at the effluent and intermediate point of SSF wetland. The data used in this research study were acquired from many hydraulic and BOD loading of pilot units located in India which involving 91 pattern tool in predicting constructed wetland performance. MLP and RBFN are found to be the most accurate in predicting the result indicating strong potential modelling of wastewater treatment processes

Civelekoglu et al., (2007) in their research study conducted, they developed three independent ANFIS models for the prediction of CODeff,$NH4^{+}$–Neff, and TNefffor. A full-scale wastewater treatment plant (WWTP) treating process waste, in their effort they showed the overall results which indicated that the simulated effluent COD,NH4+–N and TN concentrations well fit measured concentrations, which was also supported by the relatively low RMSE and APE and very high R values. Such very good prediction performances of ANFIS models for all the three effluent parameters are particularly important considering the high level of complexity in biological processes, the large quantity of variable information spread in the dataset and the wide concentration ranges. Thus, the ANFIS modelling approach may provide an alternative generic framework for the modelling of various biological or other treatment processes. Furthermore, the ANFIS modelling approach may have application potential for performance prediction and control of treatment processes in treatment plants.

In a research study of Hamed et al, (2004) Artificial neural networks (ANN) models were developed to predict the performance of a wastewater treatment plant (WWTP) based on past information. The data used in this work were obtained from a major conventional treatment plant in the Greater Cairo district, Egypt. 10 months data from the plant laboratory of daily records of biochemical oxygen demand (BOD) and suspended solids (SS) concentrations through various stages of the treatment process over were obtained. Two ANN-based models for prediction of BOD and SS concentrations in plant effluent are presented. The appropriate architecture of the neural network models was determined through several steps of training and testing of the models. The ANN-based models were discovered to deliver an effective and vigorous tool in predicting WWTP performance.

It was discovered in a collaborative work of Mjalli et al., (2007), they highlighted that a dependable model for any wastewater treatment plant is essential in order to provide a tool for predicting its performance and to form a basis for controlling the operation of the process. In their work, an artificial neural network (ANN) black-box modelling approach was used to obtain the information data, based on a real wastewater plant and then used the data as a process model. The study indicates that the ANNs are capable of capturing the plant operation features accurately. A computer model is developed that incorporates the trained ANN plant model. The developed program is implemented and validated using plan scale data obtained from the Doha West wastewater treatment plant (WWTP). It is used as a tool for valuable performance assessment for plant operators and decision makers. The ANN model provided accurate predictions of the effluent stream of biological oxygen demand (BOD), chemical oxygen demand (COD) and total suspended solids (TSS) when using COD as an input in the crude supply stream. It was discovered that the ANN predictions based on three crude supply inputs together, namely BOD, COD and TSS, resulted in better ANN predictions when using only one crude supply input.

2.25 Previous studies on MLR on predicting water quality parameters

Multilayer perceptron artificial neural networks (MLP-ANNs) are flexible and data mining tools from neuro-informatics that have achieved well in some hydrologic applications to date and constructed wetlands. They are very active when they are applied to complex processes that their details of are not fully understood (Schmid & Koskiaho, 2006).

Obaid et al., (2015), used MLR analysis methods to model BOD and TSS parameters of municipal wastewater during the festival and rainy days for 34 year period. Their results indicated that TSS concentration was increased by 26-46 mg/l while BOD concentration was improved by 9-19 mg/l for an increase of rainfall by 1 mm during festival periods. The result also demonstrated that BOD concentration increases by 4-17 mg/l for individual rise for a population of 10, 0000.

In a research study of Gikas et al., (2011), they developed a simple model based on stepwise multiple linear regression (SMLR) analysis to predict the performance of 32-month wastewater treatment of VFCW by predicting water quality parameters. The results of the model indicated that the predictions and measured values were highly correlated with each other which symbolise the accuracy of the model built.

Multiple linear regression models as empirical techniques were used to model urban stormwater quality which analysed 5 different constituents such as chemical oxygen demand, lead, suspended solids, total nitrogen, and total phosphorus as influenced by many interrelated processes. MLR were compared with artificial neural networks model. The result indicated that multiple linear regression models were more accurate for predicting urban stormwater quality than ANN models (May & Sivakumar, 2008).

A detailed technique of multiple linear regressions (MLR) was prepared as an advance tool for surface water modelling and forecasting in an attempt to assess and determine the contributions of sources affecting the water quality. Using collective dataset of more than five years (2003 to 2007) in Klang River, Selangor. Nine principle components were found responsible for the data structure provisionally named as soil erosion, anthropogenic input, surface runoff, fecal waste, detergent, urban domestic waste, industrial effluent, fertilizer waste and residential waste clarifies 72% of the total variance for all the datasets. The result showed that the use of principal component analysis PCA as inputs improved the MLR model prediction by reducing their complexity and eliminating data collinearity where R^2 value in this study is 0.75 and the model indicates that 75% variability of WQI explained by the five independent variables used in the model. It will be used to improve the water quality and then aids to decrease the time of sampling and cost for reagent used before analyses (Eregno, 2013).

Regression Models is developed to determining and predict the fate of BOD5 during a biological treatment method in Polluted Rivers that has been acknowledged as the best and technologically effective technology to treat contaminated urban rivers and streams. The results indicate high R^2 relationships between measured and predicted values. The accuracy of the Prediction models was also evaluated and disclosed errors in the range of ± 26% ~ ± 37%. These errors seem acceptable according to former work on measurements of BOD5 and predicting. The results also indicate credible application for prediction and management of biological treatment projects and reproduce for wastewater treatment systems (Kabo-Bath et al., 2012).

In the research study of Schmid & Koskiaho, (2006), various different networks of the MLP-ANNs were developed to test their accuracy in predicting near-bottom concentrations of dissolved oxygen regime in Finnish free water surface constructed wetland ponds at Hovi, Finland, which discovered to be a complex process, governed by a considerable number of hydrologic, hydrodynamic, and ecological controls which operate at a wide range of spatiotemporal scales. The study reports on the results from a study conducted found the application proved to be successful, and in particular, it was observed that MLPs were able to “learn” the mechanism of convective oxygen transport quite well. The MLR

ANN was also used to determine the relative influence of flow rate and wind shear on near bottom oxygen saturation.

In need to study the water quality of the River Krishna in detail, in order to estimate the level of pollution present in the river and also main sources of pollution. Zheng et al., (2014), multiple regression models were to predict dissolved solids (DO) concentration of River Krishna, and its tributaries drain three important states of South India, using land use data of the basin, which is accounted for significant variation in concentrations for the majority of (DO). Before model development, Correlation studies conducted to explain the relationships, between dissolved solids (DO) concentration and land use of the basins, which are used to develop the model. It was discovered in the result that the predicted concentrations of DO by the model are in good agreement with the measured DO value. This symbolised multiple regression models predicted DO concentration with high accuracy

In the study research of Zheng et al., (2014), they employed two type of models (first order plug flow and multiple regression) to predict system performance, The result indicated that multiple regression models were found to provide slightly better predictions of outflow nitrogenous pollutant in the tertiary stage treated wastewater concentration than first-order plug flow models. However, they further concluded that the performance of CWs could hardly be accurately predicted by using simple models because the conversion of pollutants in CWs was complex and a lot of other issues may directly or indirectly distress the process

It was reported in the research study of (Babatunde et al., 2011), that multiple linear regression models (MLR) had been effectively used to evaluate and predict the performance of final outflow concentrations of a pilot field-scale constructed wetlands system (CWs) treating animal farm wastewater. The outflow water quality parameters to be predicted include BOD5, COD, NH3-N, and TP. The author discovered that multiple regression analyses (MRA) predicted results more accurate than the k-C* model acceptable; however, some errors were encountered as both models were unable to predict the final outflow of NO_3-N.

Seven years of performance data from a free surface flow constructed wetland system receiving agricultural runoff were used to determine treatment performance and to develop regression and wetland design models. Removal rates by the wetland were 21–43.6% for 5-day biochemical oxygen demand (BOD5), 49.0–58.1% for total phosphorus (TP), 24.1–

46.0% for total nitrogen (TN), and 57.6–77.8% for total suspended solids (TSS). First-order area-based rate constant (k 20) values for BOD5 were 15.48 m/year in the early stage of observation and decreased to 12.00 m/year for the stable period. Similar results were found for TP, for which k 20 values were 18.72 m/year in the early stage and 14.92 m/year for the stable period. For TN, k 20 values in the early stage (21.32 m/year) were slightly lower than those for the stable period (38.02 m/year). Finally, TSS had values of 132.4 and 172.6 m/year in the early and stable periods, respectively. The low k 20 for BOD5 was not crucial for nonpoint source pollution control in the constructed wetland because these kinds of wetlands mainly focus on nitrogen and phosphorus retention. The wetland area and outlet concentration could be approximately predicted using the first-order kinetic model, but the maturity and hydraulic loading rate should be considered for more accurate prediction.

A methodology for characterising groundwater quality of watersheds using hydrochemical data that mingle multiple linear regression and structural equation modelling is presented. This work aims to analyse hydro-chemical data in order to explore the compositional of phreatic aquifer groundwater samples and the origin of water mineralization, using mathematical method and modelling, in Maknassy Basin, central Tunisia. The principal component analysis is used to determine the sources of variation between parameters. These components show that the variations within the dataset are related to variation in sulphuric acid and bicarbonate, sodium and chloride, calcium and magnesium which are derived from the water-rock interaction. Thus, an equation is explored for the sampled ground water. Using Amos software, the structural equation modelling allows, to test in the simultaneous analysis the entire system of variables (sodium, magnesium, sulphate, bicarbonate, chloride, calcium), in order to determine the extent to which it is consistent with the data. For this purpose, it should investigate simultaneously the interactions between the different components of ground water and their relationship with total dissolved solids. The integrated result provides a method to characterise groundwater quality using statistical analyses and modelling of hydrochemical data in Maknassy basin to explain the groundwater chemistry origin.

2.26 Previous studies on integrated approach predicting treatment performance of CW

Many authors have carried out comparison studies between Multi linear regression (MLR) and Multi-layer perceptron artificial neural networks MLP ANNs. It has been reported in the literature that multiple linear regression and neural network models have become competing for wastewater treatment performance prediction model building procedures (Smith & Mason, 1997).

In the research study of Zare Abyaneh, (2014), the efficiency of multivariate linear regression (MLR) and artificial neural network (ANN) models were examined in the effort to predict two major water quality parameters (COD and BOD) in a wastewater treatment plant. Performance of the ANN models was assessed using two criteria: coefficient of correlation (r), root mean square error (RMSE) and bias values. The predicted values of BOD and COD by the model were in close agreement with their respective observed values. Results indicated that the ANN performance model was better than the MLR model. They also discovered that the ANN model could be engaged successfully in estimating the BOD and COD in the inlet of wastewater biochemical treatment plants. Moreover, their sensitivity analysis results showed that pH parameter has more influence on BOD and COD predicting to another parameter. In addition, both designed models (MLR and ANN) have predicted BOD and COD better, but BOD prediction is better than that of COD.

In the research study of Tomenko et al., (2007) they make comparison between Multiple regression analysis (MRA) and two artificial neural networks (ANN) – multilayer perceptron (MLP) and radial basis function network (RBF) in terms of their accuracy and efficiency in predicting biochemical oxygen demand (BOD) concentration at effluent and intermediate points of subsurface flow constructed treatment wetlands (CTW). The data used in this study research were obtained from many hydraulic and BOD loading units situated in India which encompass 91 patterns. MRA and ANN models were found to provide an efficient and robust tool in predicting the performance of constructed wetland. MLP and RBF generated the most accurate results signifying strong possibility for modelling for treatment processes of wastewater.

In the research study of Akratos et al, (2008b), they offered a model, used in the design of horizontal subsurface flow HSF constructed wetlands. This model was developed from experimental data of five pilot-scale CW units, used in combination with artificial neural networks (ANN). The CWs were operated for a two-year period under four different hydraulic residence times (HRT). To select parameters entering the neural network properly, a principal component analysis (PCA) was performed first. From the PCA and model results, the main parameters affecting BOD elimination are discovered to be porous media porosity, wastewater, temperature and hydraulic retention time (contact time), meteorological ones are set of other parameters that were included. Two artificial neural networks (ANNs) were examined: the first included only the three main parameters selected from the PCA, and the second included, and meteorological parameters too. BOD removal was predicted by the first ANN which was satisfactory and the second one inspected recorded better predictions. From the predictions of the ANNs, a hyperbolic design equation was produced to predict removal BOD, which sums zero and first order kinetics. The ANNs results and of the design equation model were compared to available data from the literature, and recorded satisfactory correlation. COD removal was discovered to be correlated strongly to BOD removal. An equation for COD removal prediction was also generated.

It was reported in study research of Yalcuk, (2013) that artificial neural network was developed to represent phenol removal in vertical and horizontal constructed wetland. The aim was to design a pilot scale horizontal-flow (planted and unplanted) and three vertical-flow (planted and unplanted) rector structured with PVC. In this reactor system two wetland plants were used, this include Typhalatifolia and Cyperusalternatifolius and different porous media bed (sand, zeolite, thin zeolite, and pebble). A feedforward network was used and fed with two subsets of operational data. The training procedure for effluent phenol concentration from different wetland was recorded to be successful: measured and calculated concentration was found to be of perfect match.

The collective research of Akratos et al, (2009), they investigated that if nitrogen removal can be predicted using artificial neural networks (ANNs) in horizontal flow constructed wetlands (HFCWs). Development of ANN was based on experimental data from five pilot-scale CW units. The proper selection of the components entering the ANN was achieved using principal component analysis (PCA), which identified the main factors affecting total nitrogen removal, i.e., gravel porosity, wastewater temperature and contact time. Two neural networks were investigated: the first included only the three factors selected from the PCA, and the second involved also meteorological parameters (i.e., barometric pressure, wind speed, rainfall, humidity, solar radiation). The first model could predict TN removal rather satisfactorily ($R^2 = 0.53$), and the second model recorded better prediction with $R^2 = 0.69$. From the application of the ANNs, a design equation was obtained for the prediction removal of TN, resulting in predictions comparable to those of the ANNs ($R^2 = 0.47$).

Artificial neural networks model is designed as an equation to predict phosphorus removal in horizontal subsurface flow constructed wetland (CWs). Experimental data from five pilot-scale CWs was analysed, which had many set-ups base on size and origin of the gravel media and vegetation type, and functioned repetitively for the period of more than 2 years under four different hydraulic retention times (HRTs) for 6, 8, 14 and 20 days and many temperature choices. To select components entering the neural network properly, a principal component analysis (PCA) was executed first, which discovered the main factors affecting phosphorus removal this include porous media porosity, HRT and wastewater temperature. Two neural networks were examined: the first included only those above three main factors; the second included, also, the month, substrate aluminium content and meteorological parameters (barometric pressure, rainfall, wind speed, solar radiation and humidity). The first model recorded success on for the removal prediction and the second recorded even better removal predictions. According to the predictions of the neural networks model, a hyperbolic design equation was developed to predict phosphorus removal. Modelling results were validated against available data from the literature and indicated an acceptable correlation (Akratos et al, 2009a).

Abba et al, (2017) In there study, they developed multilinear regression (MLR), artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) techniques to predict the Dissolve oxygen concentration at downstream of Agra city, using monthly monitoring input data which are dissolve oxygen (DO), pH, biological oxygen demand (BOD) and water temperature (WT) at three different places viz,. The performance of the three models was evaluated using determination coefficient (DC), and root mean square error (RMSE), the result of the output DO indicate that both ANN and ANFIS can be used in modelling DO concentration in Agra city, it was also discovered that, ANN model is slightly better than ANFIS and also indicates a substantial supremacy to MLR.

Many previous study research studies in the literature have revealed and confirmed the use of MLR and MLP approaches have been used to design suitable as an important tool and model have successfully predicted many water quality parameters of domestic wastewater from different areas, and they depen d on different other input water quality parameters for the model prediction. They can also apply to wastewater from different sectors. It was also revealed from the previous literature reviews that water quality parameters study would be helpful for monitoring and prediction of the treatment performance of constructed wetland.

But there is a research gap in predicting the treatment performance of matured constructed wetland in treating urban wastewater, to understand the internal processes that contribute to the reduction of pollutants. This study tried to fill the gap of predicting the performance of vertical flow constructed in treating urban wastewater of long monitoring data using Multilayer perceptron artificial neural network and multiple linear regression models. In the present study, MLP-ANN and MLR were used to evaluate the relative effects of various pollution sources on some selected water quality parameters. This will help the researchers to find the site-specific model approach. Table 2.6 is the summary of some literature reviewed sighted in the work.

Table 2.6: Summary of some of the literature cited

Author & Year	System/Parameter	Finding	Limitation
Abba & Elkiran (2017)	MLR, ANN and ANFIS/DO, pH, BOD and WT	Performance criteria were determined and ANFIS was of higher accuracy than the other prediction methods	Restricted to DO, pH, BOD and WT
Sudarsan et al., (2018)	CWs and Fuzzy Inference System (FIS)/BOD and COD	Typha sp contained wetland cell showed greater efficiency in removal of parameters such as COD and BOD than Phragmites sp. wetland cell	Petrochemical wastewater
W. Li et al., (2018)	TF-CWs and BP artificial neural network/TN, TP, NH_4^+-N, and NO_3^--N	Predicted and actual values were in good agreement	BP artificial neural network and limited water quality parameters
Kurniadie (2011)	CWs Using Phragmites Karka/COD, BOD5, NO3-N, NO2-N, NH4-N, total-N, PO4-P, total coliform bacteria, pH, O2 and settle able solids	The overall results show that all the effluent concentration from constructed wetlands except BOD5 were still low and fall considerably short of Indonesian effluent standards for irrigation water.	Farm house wastewater
Sudarsan et al., (2017)	CWs using Typha latifolia and Phragmites australis/BOD and COD	Typha latifolia was more effective than Phragmites australis for BOD removal	BOD and COD removal comparism

		while interms of COD they have the same efficiency.	between the two plants

Table 2.6: Cont.

Ozengin, N., Elmaci, A., Yonar (2016)	**SSFCW (Phragmites australis (Cav.) Trin. Ex. Steudel), LECA (light expanded clay aggregate) and artificial neural network (ANN)/All the parameters**	**The investigations shows that the adopted Levenberg–Marquardt back-propagation algorithm yields satisfactory estimates with acceptably low MSE values.** **The constructed wetland planted with P. australis and with LECA as a support matrix may be a good option to encourage and promote the prevention of environmental pollution.**	**SSFCW**
Al-isawi et al., (2015)	TF_VFCWs/All the WQ parameters	The wetlands system shows a good performance regarding total petroleum hydrocarbon (TPH) removal.	One-off spill of diesel
Sani & Scholz (2013)	VFCWs/COD	Small aggregate diameter, a short contact time, a long resting time and a low COD inflow concentration	Compares the performance efficiency based on design and

		were most beneficial in reducing SS accumulation within the wetland filters.	operational parameter

Table 2.6: Cont.

Kotti et al., (2013a)	**FWS CWs and Fuzzy Inference System (FIS)/Organic matter removal**	**The removal performance prediction model, based on fuzzy logic showed good agreement with the experimental data. The BOD removal predictions correlated well with independent experimental observations, leading to the conclusion that the proposed models are satisfactory tools for studying FWS CWs.**	**FWS CWs and restricted to BOD only**
Chang et al., (2012)	Integrated vertical-flow constructed wetlands (IVCWs)	Mean removal efficiencies of 61.4% and 51.6% for COD and TP, respectively, were achieved at a loading rate of 250 mm/d.	

		DO was a dependence factor for the eliminations of organic matter and NH4 + N, and it could be employed to predict removal rates of COD and TN. Nitrification was the limited step for TN removal due to the insufficient DO concentration.	

2.27 Software used in the research

The following software was used in the course of the research and findings, namely: -

1. Weka
2. R language Software

WEKA stand for Waikato Environment for Knowledge Analysis which is a common collection of machine learning software written in Java, developed at the University of Waikato, New Zealand. It came about via the understand need for a unified workbench that would allow researchers, educationist, scientists, data miners and Project managers simple entry to state-of-the-art techniques in machine learning. It is a free software that that is easily accessible and written in Java (GNU Public License), it can also be run on any application platform like Windows, Linux and Mac.

Weka is free software available under the GNU General Public License. The Weka workbench contains a collection of visualisation tools and algorithms for data analysis and predictive modelling, together with graphical user interfaces for easy access to this functionality. Weka tool contains many packages which include Filters, Classifiers, Clusters, Associations, and Attribute Selection. The Visualization tool in WEKA allows datasets and the predictions of Classifiers in a pictorial form. WEKA is a collection of machine learning algorithms for solving real-world data mining problems. It is written in Java and runs on almost any platform. The algorithms can either be applied directly to a dataset or called from own Java code. In Weka, datasets should be formatted to the ARFF format. Two-thirds of the data are allocated to the training set, and the remaining one third is allocated to the test set. The training set help in building the model, and it is used for classification. For estimating classifier accuracy, k-fold cross-validation is used. Training and testing are performed k-times. The accuracy estimate is the overall number of correct classifications from the k iterations divided by the total number of samples in the initial data.

The supported data formats in WEKA software are ARFF, CSV, C4.5 and binary. Alternatively, you could also import from URL or an SQL database. After loading the data, pre-processing filters could be used for adding/removing, attributes, discretisation, Sampling, randomising etc.

2.27.1 WEKA

weka workbench is a collection of state-of-the-art machine learning algorithms and pre-processing data tools. It was designed so that existing methods can try out quickly on new datasets in flexible ways. It provides extensive support for the whole process of experimental data mining, including preparing the input data, evaluating learning schemes statistically, and visualizing the input data and the result of learning

One way of using Weka is to apply a learning method to a dataset and analyse its output to learn more about the data. Another is to use learned models to generate predictions on new instances. A third is to apply several different learners and compare their performance in order to choose one for prediction. (Witten et al., 2016).

2.27.2 R language

R language is a system for statistical calculation and visuals. It offers a programming language, high-level graphics, boundaries to other languages and debugging services (Team, 2000). R is a programming language and free software environment for powerful statistical computation analysis and graphical visualization sustained by the R Foundation for Statistical Calculating. The R language is generally used among data scientists business leaders and data miners and statisticians for design statistical software and analysis data (Field et al., 2012).

R is a programming language and interactive environment for the analysis of data and statistical calculating. The development of R was directed by the principles of exploratory data analysis, with the driving goal to make it easy to ask and answer questions of data. It was discovered that R language has an estimated two million user's world wide

R language is commonly used as a complete programming language that offers a situation in which statistical analysis can be performed and produce graphical representation. It (Dalgaard, 2002). R can be regarded as a programming language that has a large pre-defined purposes library that can be used to accomplish many tasks. Statistical data analysis is the main basis of these pre-defined purposes, as such these regarded R to be used simply as a standard statistical technique toolbox. R acts as an alternative to usual statistical packages like SPSS, SAS, and Stata, it is also a compatible, open-source language and computing environment for Windows, Macintosh, UNIX, and Linux computers. R is renowned for its capabilities to visualize data. Officially, R version 1.0.0 was released on February 29, 2000 but the project began 7 years it was officially made available to the public. R is a statistical analysis made available free to the public through the Internet under the General Public License (GPL) (Verzani, 2014). It has three main supports. First, it is accessible and available free online for all the operating systems, including Windows, Macintosh, and Linux. Second, it self-consciously implements a ''best practices'' approach to the analysis of data, and third, it has powerful graphics abilities that allow for instrumental data and model visual representations (Healy, 2005). Multiple linear regression used in this study research was developed using R language

2.28 Chapter Summary

The chapter describes and explains the natural wetlands and modern progress of constructed wetland systems and their type and presents the early concepts of the wetland's technology in treating domestic wastewater. It also explains the discussion on wetland composition, removal mechanisms and numerical modelling. Furthermore, the chapter clarifies the significant of wetlands to human beings, animal and the environment in general, vertical-flow constructed wetland systems preference over horizontal-flow constructed wetland systems were highlighted.

More so, the chapter discussed data mining techniques used in this study to predict treatment performance the performance of the wetlands system as well as the prediction of key water quality parameters as regards to the performance. Specific methods for water quality and wetland hydrology monitoring and analysis were emphasised. And finally, the tools used for the evaluation and prediction of treatment performance of vertical flow constructed wetland in this study have been introduced.

Chapter 3: Methodology

3.1 Over view

This chapter describes the research design and the theoretical framework of the research, which includes the methodological approaches, experimental and numerical modelling used for the present research study. This research was divided into three stages as depicted in Figure 2.12. The first stage (STAGE I) section provides the descriptions of the equipment, materials and procedures for vertical flow constructed wetland systems. The experiment was conducted in two phase viz a viz: The first phase of the investigation was the laboratory analysis (G19, Cockroft Building) of the wastewater for water quality parameters and treatment of the wastewater sample using 10 different filters of VFCWs in the greenhouse (242, Newton Building). While the second phase was the collection of the treated wastewater sample and laboratory analysis of the 11 different water quality parameters of the treated water sample involved, the second stage (STAGE II) consists of the treatment performance assessment and evaluation for the VFCWs system. The final stage (STAGE III) consists of the prediction model which was designed and employed to predict the performance. The research stages run from 3rd December 2014 to 28th February 2018.

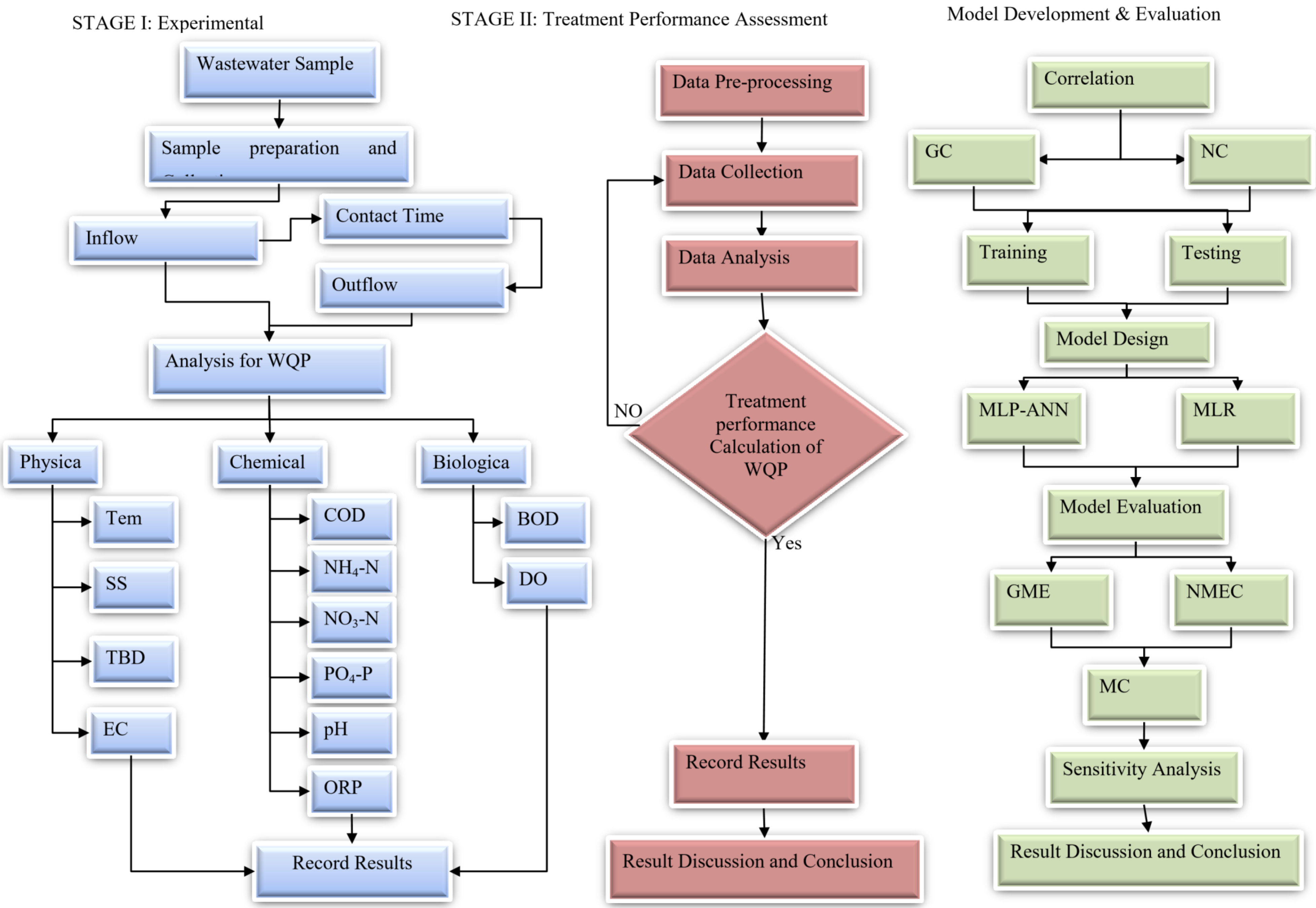

STAGE I: Experimental
Wastewater Sample
Sample preparation and
Inflow
Contact Time
Outflow
Analysis for WQP
Physica
Chemical
Biologica
Tem
SS
TBD
EC
COD
NH4-N
NO3-N
PO4-P
pH
ORP
BOD
DO
Record Results
STAGE II: Treatment Performance Assessment
Data Pre-processing
Data Collection
Data Analysis
NO
Treatment performance Calculation of WQP
Yes
Record Results
Result Discussion and Conclusion
Model Development & Evaluation
Correlation
GC
NC
Training
Testing
Model Design
MLP-ANN
MLR
Model Evaluation
GME
NMEC
MC
Sensitivity Analysis
Result Discussion and Conclusion

Figure 3.1: Schematic representation of the methodological approach in this work

3.2 STAGE I: Experimental

3.2.1 Experimental set-up for VFCWs

The vertical-flow constructed wetland system (VFCWs) is located in a greenhouse, second floor, Newton Building of The University of Salford, Greater Manchester, UK. Ten (10) different laboratory-scale vertical-flow constructed wetlands filters were designed and built from Pyrex tubes 19.5 cm wide (an inner diameter of the Filter) and length of 120 cm (height of the Filter). Each filter was filled with pea gravel (porous media) up to 60 cm depth (Filter 1 and 2 were filled with 10 mm size gravel while the remaining filters were filled with 20 mm size gravel). Moreover, each filter was engrained with Phragmites australis (Cav.) Trin. ex Steud. (Common Reed) as a substrate. Aqua Medic Titan chillers machine (Aquacadabra, Barnehurst Road, Bexleyheath, UK) were used to maintain the temperature of the system to natural below-ground part, of the natural wetland systems at about 12°C. This temperature mimics the upper earth layer temperature where the root system of the wetland plants of a real treatment system would be. Figure 3.2 shows the components parts of the VFCWs.

The experimental set-up comprises two filters (Filter 5 and 6) that serve as controls receiving only clean dechlorinated water. The system was constructed to investigate and evaluate the performance of different filters of the constructed wetland system in treating domestic wastewater for the removal of pollutants, regarding aggregate size, hydraulic and contaminant loading rate, contact time, resting time and the nature of wastewater. The wastewater fed to the constructed wetland was a pre-treated mixture of urban and agricultural runoff one**.** Dead macrophyte plant materials were harvested in each winter and returned to the tallying wetland filters when they were completely dried by depositing it on top of the litter zone, thereby serve as organic matter or manure when they decompose in the filters. The main outlet valve was located at the bottom of each constructed wetland system. The experimental setup for the VFCWs has been in operation since 26th June 2011 to date. The different gravel sizes used for the constructed are shown in Figure 2.14, while, Table 3.1 indicates an overview of the statistical experimental setup used to test the impact of four variables**.**

Figure 3.2: Laboratory Set-up of the Vertical-flow Constructed Wetland
Note: that the above set up includes two filters in the middle (filter 5 and 6) that are not in operation. They serve as controls receiving clean de-chlorinated water.

(a) (b)

Figure 3.3: Gravels used for the construction of the VFCWs systems: (a) 10mm pea gravel used for filters 3 to 10 and (b) 20 mm pea gravels used for filters 1and 2

3.2.2 Experimental procedures of VFCWs

Vertical-flow constructed wetlands are a potentially valuable tool for removing pollutants from wastewater. The pre-treated urban wastewater (free from large particles) used for the inflow water was acquired from the Davyhulme Sewage works, a treatment plant located in Manchester, operated by the United Utilities water company. Fresh wastewater was collected regularly and was stored and aerated by standard aquarium air pumps in a cold room (Peel building, University of Salford) before use. The quality of wastewater was highly variable, which constitutes domestic wastewater and a small volume of industrial wastewater and small volume from surface water runoff.

When the wastewater influent sample is ready after the settlement, the concentration of the water quality parameters in the inflow was measured, before pouring (feeding or loading) the sample into the different filters of the constructed wetland system. The inflow wastewater sample loading is intermittent. This intermittent loading pattern is perhaps the most usual operational mode used, especially in Europe like the UK (Sani, Scholz, & Bouillon, 2013a). The water flows vertically down by gravity through the porous media (gravel) until it reaches the drainage system on the bottom connected to an outlet manhole (where it is collected in a drainage pipe). As the treated water was draining from constructed wetland filter, air from the atmosphere pass in the wetland system and fill the vacuum space of the gravel replacing the drain water. Thereby enhancing aeration through the gravel and stimulated microbial actions (Miklas Scholz, 2006). When the treated water is completely drained, resting time is introduced to completely re-established aerobic condition in the gravel. The treatment process is a biological and physical process combined and is characterised by intermittent loading intervals (72 hours and 48 hours) depending on the filters, after which the inflow samples will then remove from different filters (harvest) for water quality analysis in the laboratory. Figure 3.4 shows diagram representation and the process flow of the constructed vertical wetland, which includes the downflow, litter zone, pea gravel positions and the control valves from the influent to effluent.

Chemical Oxygen Demand (COD) was used as the benchmark to differentiate between low and high loads (Table 3.1). An inflow target for the COD is about 283 mg/L (usually between 122 and 620 mg/L) was set for wetlands with a high loading rate as in filters 7 and 8 because they received a full dose of wastewater (6.5 litres). The remaining Filters 1, 2, 3, 4, 9 and 10 received wastewater diluted with de-chlorinated tap water (50% wastewater and 50% tap water). The target inflow COD for these filters is approximately 139 mg/L (usually between 43 and 350 mg/L) (Al-Isawi et al., 2015).

All wetland filters received 6.5 L of inflow during the feeding mode, which was different between several filters. The designed and operational variables of the ten (10) filters used (Vertical flow constructed wetlands) is described in Table 3.1 below 6.5 litres of inflow (influent) of pre-treated wastewater was feed into the filters, and there was the difference in concentration of the feeds among the filters.

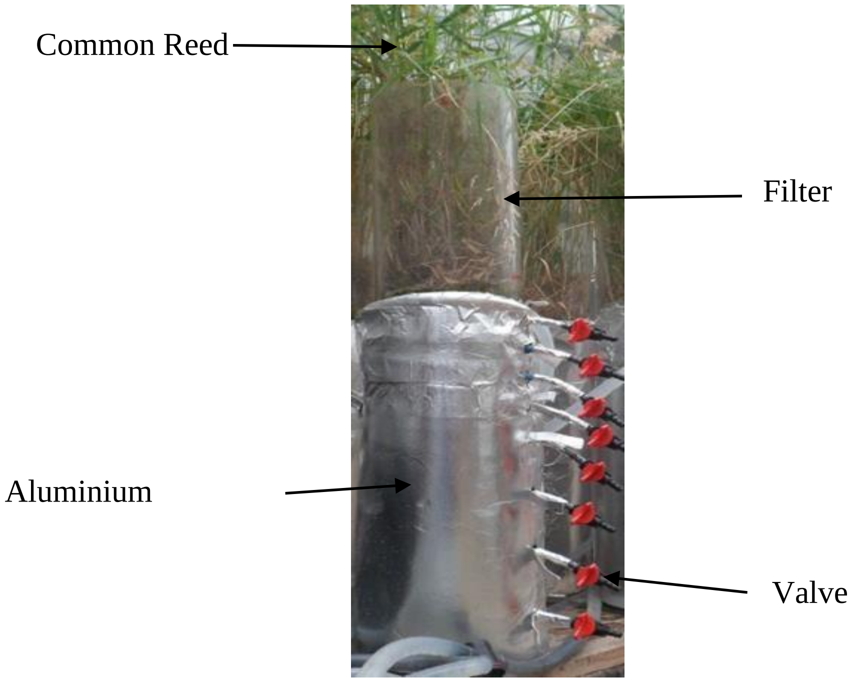


Figure 3.4: Constructed wetland filter in the greenhouse

Table 3.1 indicates an overview of the experimental set-up used in the current study to test the impact of variables. Filters 1 and 2 compared to Filters 3 and 4 test the influence of a larger aggregate diameter. Filters 7 and 8 compare to Filters 3 and 4, which examine the impact rate of a higher loading between them. However, to test the impact of lower contact time, filter 9 is compared with Filters 3 and 4. Finally, to examine the impact of lower resting time filter 9 compared with filter 10. Undiluted wastewater (full dose) was introduced to wetlands with a high loading rate (Filters 7 and 8). The remaining Filters 1 to 4 and Filters 9 and 10 received wastewater diluted with de-chlorinated tap water. All wetland filters received 6.5 l, of inflow wastewater during the feeding mode (Table 3.1). Furthermore, all filters except 9 and 10 have a replica (R. H K Al-Isawi et al., 2015).

Table 3.1: Experimental set-up used in the study

Design and operational variable	Unit	Filters					
		1 and 2	3 and 4	5 and 6	7 and 8	9	10
Aggregate Diameter	mm	20	10	10	10	10	10
Contact Time	h	72	72	72	72	36	36
Resting time	h	48	48	48	48	48	24
Chemical Oxygen Demand	mg/l	145.6	145.6	2.1	292.1	145.6	145.6

Note: The yearly treatment volumes of wastewater: Filters 1 to 8, 470 l/ an (except 5 and 6, which receive tap water); Filter 9, 624 l/a; Filter 8, 858 l/a. Filters 2, 4 and 8 are replicated for the most common operational scenarios. Likewise, COD was used as the criterion to differentiate between low and high loads (Table 3.1). An inflow target COD of about 273 mg/l (usually between 122 and 620 mg/l) was set for wetlands with a high loading rate (Filters 7 and 8). The remaining Filters 1, 2, 3, 4, 9 and 10 received wastewater diluted with de-chlorinated tap water. The target inflow COD for these filters was approximately 139 mg/l (usually between 43 and 350 mg/L).

3.2.3 Design, Mode of operation and maintenance of VFCWs

The mode of operation of VFCW systems was first designed and developed in the early 1950s by Käthe Seidel in Germany, for wastewater treatment. The CWs experiments were conducted and applied successively for the treatment of wastewater in the late 1960s to early 1970s (G D; Gikas & Tsihrintzis, 2014; Jan Vymazal, 2014a; Jan Vymazal & Kröpfelová, 2011; H. Wu, Zhang, Hao, et al., 2015). High removal performance in VFCW system, depends on a number of measures for the design and operation, which include variables like selection of plant and substrate (gravel), feeding of inflow wastewater or hydraulic loading rate (HLR), contact time or hydraulic retention time (HRT), and dosing mode (feeding). These variables are vital in VFCW system to achieve the long-lasting treatment performance by the system (Trang, Konnerup, Schierup, Chiem, & Brix, 2010; Tsihrintzis, 2017). Phragmites australis (common reed) used in this study research is one of the most common plant options used in constructed wetland especially in Europe.

Amount of wastewater-fed depend on the design and size of the constructed wetland. The pre-treatment phase has been demonstrated to be a critical and essential component in the design of a VFCW system. Therefore, inflow wastewater should be well settled in a primary stage before feeding into constructed wetland filters, aimed at reducing the concentration of solids, organic matter and large particles in the wastewater. As a result, the threat of gravel clogging by solids accumulation is minimised. The wastewater used in this research is pretreated (secondary wastewater) and free from sludge, which was gotten from Manchester treatment plant. However, removal of pollutants in wastewater by constructed wetland is always achieved by operating the system's feeding conditions and by selecting the suitable type of wetland plant (Robert H Kadlec & Wallace, 2008; Jan Vymazal, 2007).

The wastewater was load into the system (VFCWs) manually after the preparation and measurement of the desired amount (6.5 litres) into each different filter irrespective of the ratio content of inflow. Raw wastewater (full dose) and diluted (half dose) with tap water were used to feed the system depending on the wetland filter as presented in Table 3.1. The application of the inflow water is intermittent, as a batch through the surface of the filter. The inflow flows from the top of the constructed wetland systems (see Figure 3.3) and then gradually, percolates vertically downward through the gravel layers. It then distributed over the surface of the CW filter and stay in the system for treatment (Figure 3.4) and drained to the bottom of the system. The treated wastewater was then collected in a drainage pipe network (Figure 3.4) after attaining the contact time. The contact and resting time is different among the filters and is described in Table 3.1. After the full drainage of the water, a resting period was then allowed for the system to restore applied. The resting time was to allows air to refill the wetland systems, leading to improvements in more circulation of air (aeration) within the bed, and oxidation of the accumulated organic solids, to prevent clogging of the bed (Robert

H Kadlec & Wallace, 2008; Jan Vymazal, 2007; Jan Vymazal et al., 2006). Which will help in increasing the lifecycle cost of CW and achieving higher performance of pollutants removal, the bed aeration will be improved, and the microbial activities reproduced (Paul Cooper, 1999; Jan Vymazal, 2007). The treatment technology generally relies on processes similar to those used extensively in gravel ―filter beds‖, enhanced by the extensive rhizomatous root system of the common reed plants (Phragmites australis) which can transfer limited quantities of oxygen into the surrounding media, to make bacterial communities more active.

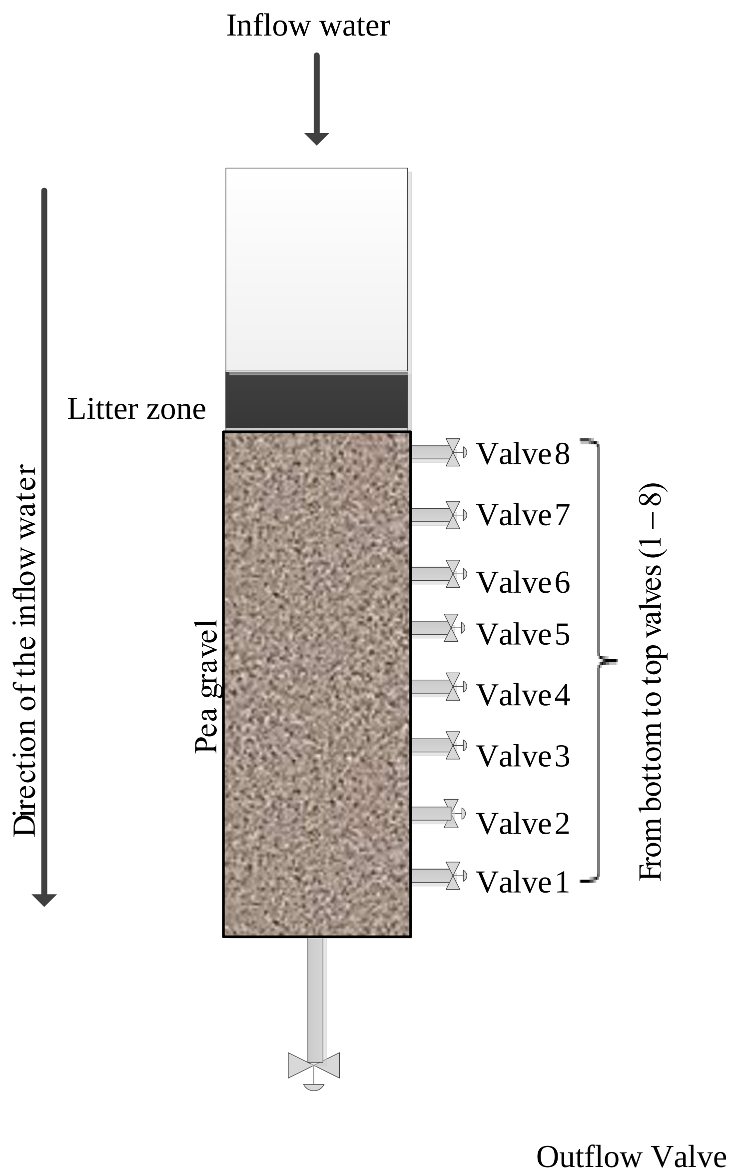


Figure 3.5: Schematic diagram of a constructed wetland filter

Drainage pipes should be cleaned occasionally to remove sludge and some microorganism that might block the passage and valve. The concentration of solids in the wastewater should be reduced to bearest minimum before loading into the system to ensure the effectiveness of the primary treatment and avoid clogging. Also, the weeds growing were avoided by removing it as it starts germinating in the area that it can compete with the planted wetland vegetation, as their roots can affect the growth of the wetland plant leading to lower performance treatment. Routine obstruction observations and water quality sampling, monitoring and analysis were carried out by guidelines in the standard laboratories and base on the specification of American Public Health Association APHA (2005), to monitor the treatment performance and clogging unless stated otherwise.

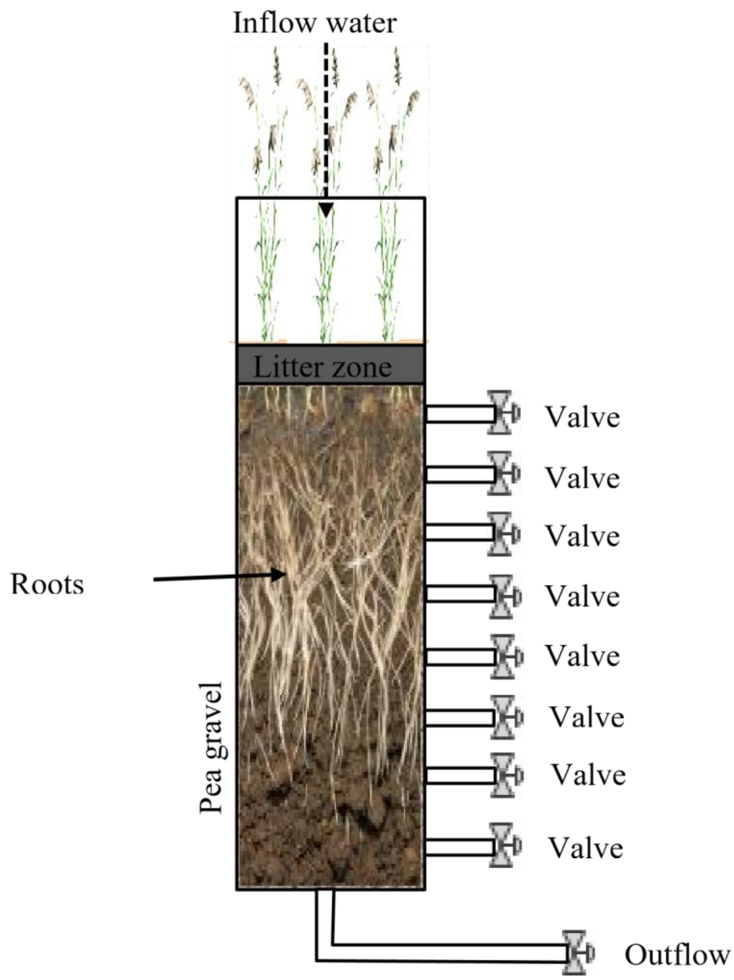


Figure 3.6: Schematic Diagram of treatment of process of VFCW

3.3 Stage II: Treatment Performance Analysis

3.3.1 Experimental Apparatus used for water quality parameters analysis

The combined water quality analysis was conducted from December 2014 to February 2018 (39 months), with a sampling rate at least five times per week for different water quality parameters. Determination of the physical, biological and chemical parameters of the quality of a wastewater sample was performed base on standard APHA (Federation & Association, 2005). The treatment of wastewater in constructed wetland systems is based on physical, biological and chemical methods taking place in the soil, gravel and water environment using common reed as wetland plants (Bcef & Ad, 2017).

Throughout the period of the experiment and operational system, Water samples were collected regularly from the wastewater inflow and the treated outflow of each treatment filter of vertical flow constructed wetland systems. Samples were taken carefully using containers and taken directly to the laboratory for immediate analysis of water quality parameters. Analysis of water quality parameters in the laboratory is conducted by the procedures and specification outlined in the Standard Methods for the Examination of Water and Wastewater of American Public Health Association (APHA) (Federation & Association, 2005). The parameters that were analyse in the laboratory include: Turbidity (TBD), Suspended Solid (SS), Temperature (T), Dissolved Oxygen (DO), Electrical Conductivity (EC), Oxidation-Reduction Potential (ORP), pH, Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Nitrate-Nitrogen (NO3-N), Ammonia-Nitrogen (NH_4-N), and Orthophosphate-Phosphorus (PO_4-P).

The portable spectrophotometer DR 2800 Hach Lange ((Figure 3.5 (g)) and more can be found in www.hach.com) was used for standard analysis of different water quality parameters; this includes nitrate-nitrogen (NO3-N), ammonia-nitrogen (NH_4-N), chemical oxygen demand (COD), orthophosphate-phosphorus (PO4-P) and suspended solids (SS). A spectrophotometer is a machine for measuring the intensity of light and is used to measure and detect light absorption illumination and light intensity, it also runs analytical method automatically, as the machine has a barcode to read any test that is being run when the tube was inserted into the photometer. All the remaining water quality parameters were analysed and measured using standard laboratory method and procedure, to get accurate results.

Moreover, for more reliable results, samples were analysed as soon as possible.

3.3.1.1 COD Measurement

COD is measured using spectrophotometer needed for the standard calibration curve by measuring the concentration of dichromate and their absorbance. It involves heating the samples in the laboratory to estimate the COD contents. Inflow wastewater and treated outflow sample are prepared, tested, analysed aimed at measuring the amount of organic matter present. The required volume of sample is added into the test tube and digested as it has pre-measured reagent present, containing sulphuric acid and potassium dichromate in the presence of a silver sulphate catalyst under closed reflux conditions. Each test tube was labelled according to their respective samples (Filters), and deionised water test tube for calibration. The calibration test tube was required using LCK 314 (15-150) mg/l, while if the test tube used is LCL 400 (0-1000) mg/l, it does not require a calibration test tube.

The samples were mixed thoroughly before use; this will digest the sample and course colour change, test tube was inserted fume cabinet (Figure 3.5a), place the test tubes into a reactor and set time to 150^o C temperature and time approximately 2 hours, the test tubes are removed and allowed to cool in a crate (Figure 3.5i). Before analysing the sample using photometer, the system was calibrated using the calibration test tube. The sample was then inserted in a spectrophotometer (Figure 3.5 c) and read bottom was pressing to display the reading of COD in mg/L. The displayed values were then recorded. The test tubes were wiped and clean before inserting into the photometer. The process was repeated for another test tube of the filters, and make sure the photometer has a fitting for the test tubes sizes select the correct COD program for the of absorbance specific COD range. COD values were recorded, as this model is a direct reading user-friendly photometer pre-programmed for Palin test-tube water tests.

3.3.1.2 BOD Measurement

Although there exist many methods for BOD measurement, the principle for all of them is the same. If the sample is expected to have a low content of microorganism, an inoculum should be added. Also, an extra nutrient solution is added to ensure that the growth of the microorganism is not limited. BOD value increase over time as the organic matter is progressively biodegraded. However, after five days most of the organic matter contained in the sample has already been degraded, for that reason, BOD_5 that is measured after five days of incubation is the most widely used method.

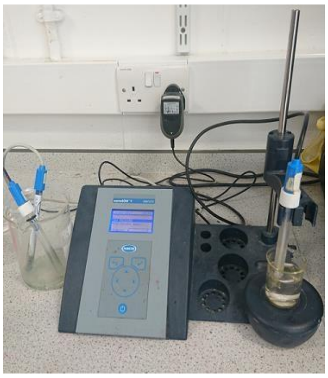
The oxidation of the water sample present in the water sample can also contribute to the consumption of oxygen nitrification could interfere in the measurement of BOD leading to an overestimation of its value, to prevent this the use of an inhibitor is required.

To determine BOD values in the laboratory for all wetland filters, treated wastewater sample by the constructed wetland was collected 300ml of the sample for inflow and 100ml for outflow is prepared and poured in a respirometric bottle (Figure 3i) sealed with a manometer. Each BOD bottle is then placed into an incubator (Figure 3.2h) at 20°C temperature in constant tension in a dark condition for five days, after which all bottle was removed, and the values were recorded and stored. A monomeric measurement device, supplied by the Wissenschaftlich-Technische Werkstätten (WTW), Weilheim, Germany is an instrument used to measure the declining pressure inside the bottle caused by oxygen consumption and to measure the effect of water sample on a beam of light. Sodium hydroxide (NaOH) is added to absorb the carbon dioxide produced in the process, which might interfere in the pressure measurement, firstly magnet stirrer is introduced in the bottle so that when they are placed in the magnetised tray, they stay stressed continuously. To determine the quantity number of sample in the bottle, for that purpose estimation is made of the expected BOD range of the sample. The exact volume required was measured using burette, which was then introduced into the bottles. Three drops of nitrification inhibitor were then added for the inflow sample while seven drops for the outflow samples. The nest is to put Sodium hydroxide (NaOH) into the plastic enclosure located within the monomeric cap. The bottles are firmly close with a monomeric lid to guarantee airtight environment inside; monomeric caps should be reset to zero to start measuring again. If the value is out of range, no results will be displayed. Once the values are noted down, to get the final BOD_5 value, the following equation is used.

$$BOD_5(mgo_2{}^{-L}) = \text{value x-Factor} \qquad 2.2$$

Where the term factor appearing in the formula corresponding to the figure obtained from the standard table for the specific sample volume, multiply the factor with the value of monomeric cap displayed after which all the values were recorded and stored.


(a) (b) (c)




(d) (e) (f)

(g) (h)

(i)

(j) (k) (l)

Figure 3.7: Apparatus used in the laboratory for analysis

3.3.1.3 Nutrient Measurement

Nutrients measurements were conducted in order to evaluate the quality of the water sample. Measurements of the nutrients were conducted employing colourimetry methods using a Palin test tube with product code LCK 339 for nitrate, LCK 303 for ammonia and LCK 049 for other-phosphate phosphorus. A water sample was added into the Palin test tube, and Nitrate was reduced to nitrite by cadmium and determined as an azo dye at 540 nm (using a Perstorp Analytical EnviroFlow 3000 flow injection analyser) following diazotisation with sulfanilamide and subsequent coupling with N-1-naphthyl ethylenediamine dihydrochloride. The mixture of the sample with the reagent was then shaken well to allow reaction take place. The sample was then allowed to equilibrate and settled at room temperature before placing it into the spectrophotometer for measuring the nutrients content.

Ammonia-nitrogen and ortho-phosphate-phosphorous were determined by automated precision colourimetry in all water samples from reaction with hypochlorite and salicylate ions in solution in the presence of sodium nitro-sopentacyanoferrate (nitroprusside), and reaction with acidic molybdate to form a phosphor-molybdenum blue complex, respectively. The coloured complexes formed were measured spectrometrically by a photometer, which automatically detects any nutrient to be measured.

3.3.1.4 Dissolve Oxygen (DO) Measurement

Dissolved oxygen is one of the most important parameters that determine water quality because it indirectly points out if there is pollution in the water (Jorge G. Ibanez; Margarita Hernandez-Esparza; Carmen Doria-Serrano; Mono Mohan Singh, 2013).

Dissolved oxygen (DO) is a measure of the number of free oxygen molecules in water. The concentration of DO is a significant indicator of the health of an aquatic ecosystem as oxygen is vital for almost all forms of life. Dissolve oxygen is measured in milligrams per litre (mg/l)**.** A dissolved oxygen meter (DO meter) in 3.2k is used to determine the DO in a water sample. The DO meter can measure dissolved oxygen in water in the range of 0 – 50 mg/l.

3.3.1.5 Turbidity Measurement

Turbidity is the quantity of cloudiness in a given sample of water which is an expression of the suspension in the sample. Turbidity in water is caused by suspended matter such as clay, mud, silt, finely divided organic compound and chemical precipitates. Turbidity is analysed and measured in the laboratory using an infrared instrument called Turbi-check, Turbidity Meter as shown in Figure 3.2e, (Lovibond Water Testing, Tintometer Group, available at www.lovibond.com), the machine is designed to allow fast, precise on-site testing and is suitable for regulatory monitoring and process control. Some treatment systems, such as sediments, coagulators and gravel pre-filters are designed to remove turbidity. It is very accurate and stable instrument for measurement of turbidity up to 1000 NTU; it is very accurate for measuring very low turbidity values (less than 5 NTU). Turbidity is measured in nephelometric turbidity units (NTU) or Formazin turbidity units (FTU), depending on the method and equipment used. **2.32.7 pH Measurement** pH is a measure of H^+ concentration in a given water sample. The pH value varies between o to 14 with, with 7 as a value of neutral water. pH value is an indirect measure of acidity and alkalinity present in water. The values less than 7 indicate present of alkalinity, whereas values higher than 7 indicate the presence of acidity in water (Jurgen Schleicher, 2007). The commonly employed method to measure the pH value of water in the laboratory is an electrometric method. Where a pH metre is used, pH meter comprises of a potential meter, temperature compensating device and pH electrode. They should be appropriately connected to the potential meter. The pH meter is calibrated using pH buffers solution of known-values (4, 7, and 9) by inserting the electrode in the buffers one after the other from pH of 4 to 9 until the instrument is correctly calibrated. The water sample is then poured in the beaker, and the electrode is inserted to measure its pH value (Figure 3.2d). At the measuring electrode, hydrogen ions create a potential that depends on the pH value of the sample (Jurgen Schleicher, 2007). The pH value is taken and recorded. pH value has no unit

3.3.1.6 Suspended Solid (SS) Measurement

Suspended solids refer to small solid particles, which remain in suspension in water that does not dissolve and separable using filtration. It is used as one of the indicators of water quality; SS is analysed and measured in the laboratory using a spectrophotometer Hach DR 2800 which has a suspended solid method in it. It sends a concentrated light beam through the water sample.

Before starting the SS measurement, the instrument has to be calibrated with the standard solution. Bootle needs to be clean by rinsing with distilled water; the water sample is put into a bottle, and insert into the sample holder of the spectrophotometer for the SS analysis as shown in the Figure 3.2c. Reading is taken and recorded. The unit of SS is mg/l.

3.3.1.7 Oxidation Redox potential (ORP) Measurements

ORP is measured to determine the oxidising or reducing potential of a water sample. ORP is determined by measuring the potential of a chemically-inert (platinum) electrode which is immersed in the solution. The sensing electrode potential is read relative to the reference electrode of the pH probe, and the value is presented in millivolts (mV)**.** Redox potential (ORP) can be analyzed and measured using potentiometer with Oxidation reduction potential (ORP) electrode (Weight & Chandler, 2010), also known as redox potential instruments as shown in Figure 3.2b, redox potential measurements are used to monitor chemical reactions (Schüring, Schulz, Fischer, Böttcher, & Duijnisveld, 2013). The instrument measured the ability of a solution to act an oxidising agent and to measure ion activity.

3.3.1.8 Temperature Measurement (T)

Temperature is an important parameter when evaluating the quality of water, temperature effects numerous other water quality parameters and can change the physical and chemical properties of water. In this respect, the temperature of the water should be considered when analysing pH, DO, EC ORP

Temperature is a measure of the internal thermal energy state of a substance. It represents how much vibrational energy exists in the molecules of a liquid or solid, or the translational energy (speed of movement) of molecules in a gas. There are various temperature scales for measuring temperature. The one used by scientists is the Kelvin scale. The thermometer is an instrument used to measure temperature in this study, which is placed in and outside the greenhouse.

3.3.1.9 Electrical conductivity (EC) Measurement

This parameter is one of the parameters used to evaluate the quality of water; procedures can also be used to monitor in the treatment of wastewater that causes changes in the concentration of total salt and therefore changes the conductivity (Levlin, 2010). The electrical conductivity is used an indication of how contaminant or pure the sample is. Consequently, measuring the conductivity of water can specify the concentration of electrolytes. Electrical conductivity is measured with continuous measurement device called electrical conductivity meter know an EC meter (Figure 3.2f) by measuring the conductance of the water sample. The measurement is conducted by dipping the electrode of the metre in a given sample to measure a quantitative reading of the amount of the conductivity that is taking place in the sample. Electrical Conductivity (EC) is measured in Siemens per meter or micro Siemens per centimetre (μS/cm) or micro Siemens per metre (μS/m)

3.3.2 Experimental Data Parameters

An experimental investigation has been carried out, and the data generated were collected by monitoring the influent and effluent concentrations of 11 water quality parameters. The parameters or variables include Turbidity, Suspended Solids (SS), Dissolve oxygen (DO), Ammonium Nitrogen (NH_4-N), pH, and Electrical conductivity. Others include oxidationreduction potential (OPR), chemical oxygen demand (COD), biological oxygen demand (BOD), orthophosphate phosphorus (PO_4-P), Nitrate (NO_4-N) and Temperature. The recorded data of the variables were collected and recorded for the assessment of the system. The input variables were selected based on their goodness of correlation with the target output variables (Meyer et al., 2015). Usually, target output variables (variables to be predicted) are compared with cost-effective and more accessible to measure input variable for easier prediction (Zare Abyaneh, 2014). Name of the water quality parameters used and their chemical formula, units and their respective ranges are presented Table 3.2.

3.3.3 Data analysis

The process of inspecting and applying formal statistical procedure, to describes and evaluates data for analysis and support decision-making to achieve research aims and objectives of discovering useful information. The data generated from the analysis is recorded in a Microsoft Excel sheet is used for the general data storage, missing values were filled in using the simple statistical technique, including mean estimates and linear regression models while outliers and error values from the experiment were filtered and removed to enhance the quality of raw data. After data collection, data were subjected to a normality test before validation and subsequent analysis. Because of high variability, the data were not normally distributed even after transformations, and as a result, easy statistical tools that will fit the abnormally distributed data such as non-parametric tools were sought and applied. The non-parametric Mann-Whitney U-test was computed using IBM SPSS Statistics Version 20 and used to compare the medians of two (unmatched) samples since virtually all sample data (even after data transformation) were not normally distributed.

Table 3.2: Ranges of parameters used for the experiment

Parameters	Chemical Formula	Unit	Good water quality	Poor water quality
Biological Oxygen Demand	BOD	Mg/l	1 to 10	13 to 100
Ortho-phosphate Phosp	PO_4-P	Mg/ l	0.01	0.02 to 0.05
Ammonium Nitrogen	NH_4-N	Mg/ l	0 – 0.5	1 - 6
Nitrate Nitrogen	NO_3^-N	Mg/ l	$0.01 \leq 10$	0 to 0.06
Oxidation reduction potential	ORP	mV	-50 to +50	+75 to +250
Electrical conductivity	EC	µS/cm	150 to 500	0 to 50
Dissolve Oxygen	DO	Mg/ l	5 to 11	0 to 4
Suspended Solid	SS	Mg/ l	0 - 19	20-40
Chemical oxygen Demand	COD	Mg/ l	0 - 3	10 - 30
Turbidity	TBD	NTU	$0 \leq 5$	5 and above
pH	pH	no	6.5 to 8.5	1 to 5

Temperature	T	^{o}C, K	9 to 25	

3.3.4 The removal rate of water quality parameters

The treatment of wastewater using vertical flow constructed a wetland to remove pollutants is modelled employing probability to predict the total removal and performance efficiency. This process occurs in the natural wastewater treatment system. Assuming that hydrological phenomena such as rainfall, percolation and evaporation are negligible and that the inflow and outflow rates are equal, the behaviour of a wastewater treatment system based on Common reed can be represented by the global mass balance equations for each of the components of the system. The system considers the inflow concentration (C_I) and outflow concentration (C_P) of the water quality parameters. The input concentration of the water quality parameters has a direct proportion with the output concentration. Therefore, this relation can be express as:

$$C_{I_i} = KC_{P_i} \qquad 2.3$$

Where C_I and C_P is the input and output concentration of i^{th} components water quality parameters respectively. The K is the constant of proportionality defined as:

$$K = \frac{C_{I_i}}{C_{P_i}} \qquad 2.4$$

The total removal of the i^{th} components which is the change in concentration divided by the input concentration is given as:

$$R = \frac{C_{I_i} - C_{P_i}}{C_{I_i}} X\ 100 \qquad 2.5$$

Where R is the total removal of the west from the wastewater sample. The total removal of water quality which is the amount of waste removed from the wastewater using constructed vertical wetland. For example, it can be used to calculate how much BOD was removed in the primary clarifier. This concept can be applied to the removal of total suspended solids (TSS) and ammonia (nitrification). Combining equation (2) and (3) yield the following equation:

$$R = \frac{C_{P_i}(K-1)}{C_{I_i}} \qquad 2.6$$

Therefore, considering the boundary conditions of $0 \leq R \leq 1$, and $P(R) \leq 1$ and $\lim_{I \to C_P}(R) = 0$; $\lim_{C_P \to 0}(R) = 1$ then equation (4) transformed into:

$$R = \sum_{i=1}^{n} \frac{C_{P_i}(K-1)}{C_{I_i}} \qquad 2.7$$

Equation (5) is called percentage removal efficiency (removal rate) formula is used to calculate the differential change in concentration between inflow water and outflow treated water is also as First order kinetics removal model**.** To calculate how many amounts of the contaminant was removed in wastewater. Removal efficiencies formula are often used in this study research to evaluate the performance of pollutants removal in wastewater by vertical flow constructed wetland (VFCW) of every water quality parameter excluding DO, because the concentration of dissolved oxygen in outflow is greater than that of inflow

Thus the % removal efficiency is given as:

$$E = 100\% * R \qquad 2.8$$

Where E is the efficiency

Treatment performance is continuously evaluated a, d comparisons concentration of pollutants between inflow wastewater and outflow treated water indicated clear improvements (see Table 4.2)

3.4 Stage III: Model Development and Evaluation

3.4.1 Vertical flow Constructed wetland modelling using data mining technique

The discussion focuses on the ability of designed models (multiple linear regression and multilayer perceptron artificial neural network) to predict the removal of water quality parameters (output) given other available water quality parameters as inputs and understanding their gained and correlation to each other beyond the laboratory experiment and design impacts on the predicted values fate.

3.4.1.1 The Methodological Framework

Before the data is used for further analysis, data preparation was carried out. The existing or available data from the database are used, and the data exists in a spreadsheet (excel file), and the data were transformed into useful information which was used for the general data analysis. The source of our data is primary (source collected from the researcher). The data are selected from the existing raw data to have useful information, which must be processed correctly. If data has not been carefully screened and analysed, this can produce misleading results. The next step in data analysis processes is to prepare data for further analysis. Data for five years of referenced parameters have been obtained from the experiment. The idea behind the framework is to help in analysing the data and structure it into mining form.

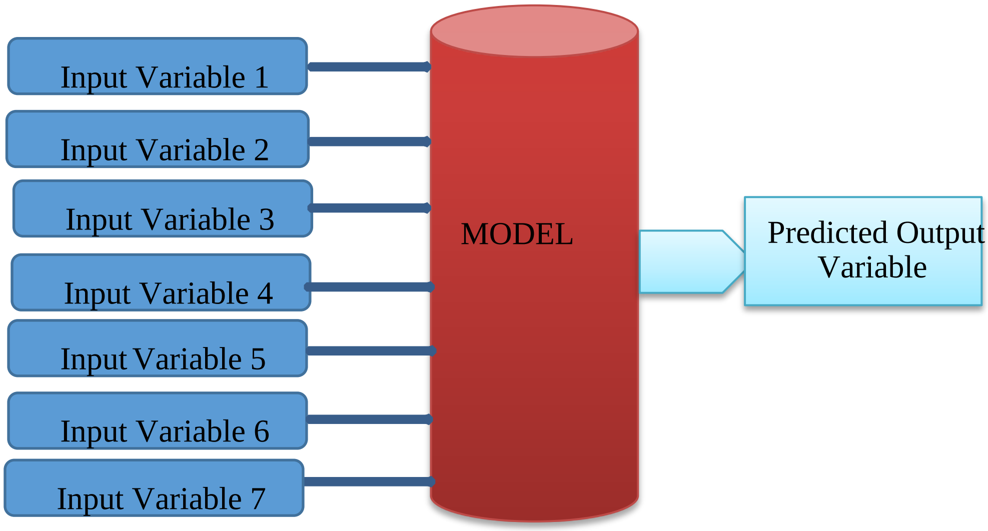


Figure 3.8: Methodological framework diagram

3.4.2 Model development and Evaluation

3.4.2.1 Correlation Analysis

Before developing a prediction model, correlation analysis was conducted to ensure that the variables are relevant to include in the model development. The selection of an appropriate set of input variables from all possible input variables in hydrological modelling is essential for obtaining accurate and efficient prediction model, mainly when it involves modelling of the dataset (Panagoulia, Tsekouras, & Kousiouris, 2017). Correlation analysis is used to have a good idea on which input variables are relevant to select for an accurate and straightforward output prediction model. The essential and highly correlated parameter is the one to be considered and remove the unnecessary ones before model development (Abba & Elkiran, 2017). Input and output variables were selected from the parameters used in the vertical flow constructed wetlands system in the present research. The correlation between the output variable (dependent) and input variables (independents) was then determined.

The highly correlated input parameters were used as an independent variable in the development of the prediction model for accuracy on the predicted variable (output) which is the dependent parameter. Therefore, using many independent input parameters to construct multiple linear regression (MLR) may results in overfitting if the variables are not correlated. Hence, choosing the best and highly correlated input parameters for the model, yield better results. However, input variables may likely correlate each other, and this phenomenon is called Multicollinearity. Due to multicollinearity and overfitting, conducting correlation analysis is needed between input and output parameters before model development. The accuracy of the prediction model's outcome depends on how good output dependent parameter is correlated with the independent input parameters.

Variable selection is made using common sense knowledge of correlating variables in addition to checking correlation using statistical analysis such as using correlation matrix analysis, to check for statistically significant variables (p-value < 0.01). Starting with correlation analysis, one can determine the number of input variables for MLR or ANN models. Scaling or normalising of input variables is often done to reduce unintended influencing of the weights occurring due to the different magnitudes of input variables used, for example, TP (in the range of hundreds) versus TSS (in the range of 10 thousand).

Water quality parameters are predicted base on the highly correlated they are with their corresponding input parameters. Before getting into the model prediction development, data ware inspected and checks to eliminate outlier values, determine their validity, missing values ware also checked. The monitoring dataset of all the parameters used was generated, and the correlation is determined.

3.4.2.2 Model development

This thesis employs the use of data mining technique to develop the predictive model that will estimate the future treatment performance of vertical flow constructed wetlands systems (VFCWs), the techniques used include multiple linear regression (MLR) Multilayer Perceptron. Development of a predictive model that will help to achieve the target goal requires a suitable data from which the model can learn, and predicting a target output based on given input, needs a suitable data comprising past input-output parameters.

The model development provides a framework in which the process can be interpreted and understood. This involves the definition of predictive model objectives. Before developing a prediction model, it will ensure some common data requirements and practical considerations of which input variables are relevant and suitable to include in the model development. The model development framework comprises the following stages.

3.4.2.3 Data Pre-processing

As far as the data mining process is a concern, in the estimate data pre-processing consumes a large part of the project which spends up to 70% of the entire processing time. Rough data is highly susceptible to noise, missing values and inconsistency. The quality of data affects the data mining result. To improve the quality of data and that of the mining result accordingly, row data is pre-processed to enhance the effectiveness and easy in the mining process. The four significant tasks in data pre-processing include data cleaning, integration, transformation and reduction. Data cleaning routines can be used to fill missing values, smooth noisy data, identify outliers and correct data inconsistencies. Data integration combine data from multiple sources to form a coherent data store. Data transformation routine confirm the data into an appropriate form for mining. Data reduction technique has been helpful in analysing the compressed representation of the dataset without compromising the integrity of the original data and yet producing the quality knowledge. In the real world data is always redundant, missing, uncertain and inconsistent data, data mining cannot be implemented before pre-processing (Pyle, Cerra, Wade, & Breyer, 1999).

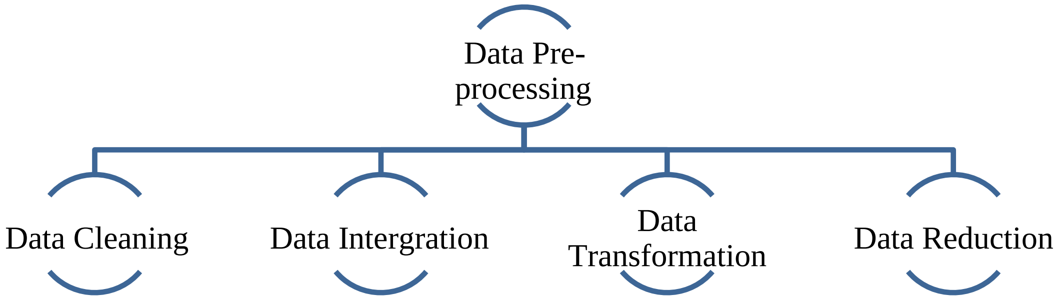


Figure 3.9: Four significant tasks of data pre-processing

3.4.2.4 Preparing the Input

Preparing input parameters for data mining search usually, consume the majority of the work done in the whole data mining process. Consequently, adequate and relevant input parameters are needed, to adequately identify the significant relationship between the input parameters and output predicted parameter (Mas & Ahlfeld, 2007). Quality of data mining results decisively depends on the quality of input data. The collected and prepared data is presented in a spreadsheet.

3.4.2.5 Data Collection

To start the work on data mining issues and to determine what data to collect, it is mandatory too, first of all, bring together all the data into a set of instances. Because of the complexity to choose the suitable data of the data, it must be assembled, integrated and cleaned up considered the representation and quality of data is first and foremost before running an analysis (Pyle et al., 1999).

3.4.2.6 Data Analysis

The collected data need to be inspected, cleaned and transformed from noise and unrelated data for the purpose of discovering useful information, it is expected that the programme will generate a large body of quantitative experimental data that will be analysed by appropriate methodologies and summarising the computational tool and techniques in data analysis (Witten et al., 2011). After data collection, data were subjected to a normality test before validation and subsequent analysis. Microsoft Excel was used for the data analysis. Before modelling, the data is checked for errors, outliers, missing values and invalid data entries to ensure proper usability for modelling

3.4.3 Modelling

This is where modelling algorithm is applied to processed data. Once it is confirmed that the data is suitable and ready for modelling. It requires selecting a data mining algorithm and identifying relevant aspects of a situation in the real world and turning the parameters using different types of models for different aims (Witten et al., 2011). This is a process of translating real-life situations into a mathematical model. The modelling tool is going to automate the entire process of modelling data for discovering useful information, suggesting conclusions, and supporting decision-making (Pyle et al., 1999). The data is partition into two parts for the training and testing process by considering70% of the data as a training set, and the remaining 30% of the data as a testing set, which are common divisional percentages in the data-driven model. The output of the model is entirely determined by the parameter values and the initial conditions.

3.4.4 Implementation

For the entire data of the experiment in question, if the final results are not implemented, it is impossible for any project to be successful. On the other hand, mining preparation, surveying, and modelling—traditionally takes most of the time in any project. However, after the importance of implementing the result, the two most significant contributors to success are solving an appropriate problem and preparing the data. While implementing the result is of the first importance to success, it is almost invariably outside the scope of the data exploration project itself. As such, implementation usually requires organisational or procedural changes inside an organisation, which is well outside the scope of this discussion.

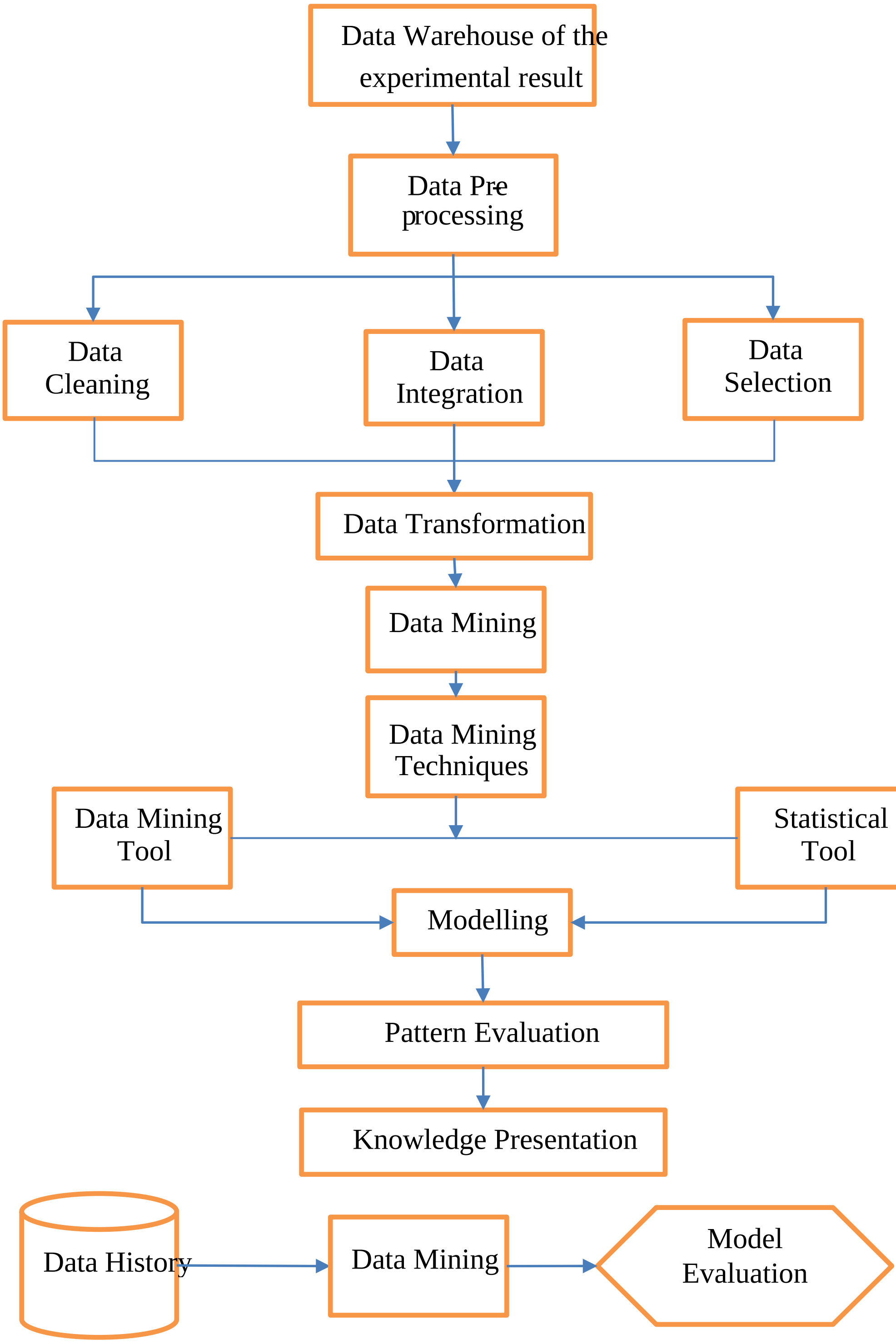


Figure 3.10: Framework for VFCW Implementation

3.4.4.1 Data Partitioning

Using all the dataset for training to generate a predictive model and evaluate the performance of the model with the same training data used is not possible, the accuracy of the model results will be incorrect. However, there is no guarantee how good the model will perform when it applied with a new dataset. However, Evaluating the performance of the model with the entire data used as training data as the same testing data is not suitable in data mining because it can easily produce predictive models that are overfitted. To build confidence for the model build, there is a need to test the model build. MLR and MLP models are considered to be data dependent during their development, especially when they subjected to the new dataset in the coming future. Using part of the data to generate a predictive model and holding the remaining to test the model build provide the ability of how well the model will predict when using testing data in a controlled environment (the dataset that the model never seen before). Data partitioning is a significant part of assessing the performance of data mining technique models, the entire history dataset is divided into two different parts randomly using R language using a random split command, major part of the data (70%) is used for training while the remaining smaller portion of the data (30%) is used as testing dataset, which is the is important aspect in developing and evaluating data mining techniques models. Both training and testing datasets came from a similar data source (figure 3.3) It is significant to have an appropriate portion of training and testing dataset to achieve a model generalisation performance to new data. The ultimate target is to achieve high model accuracy

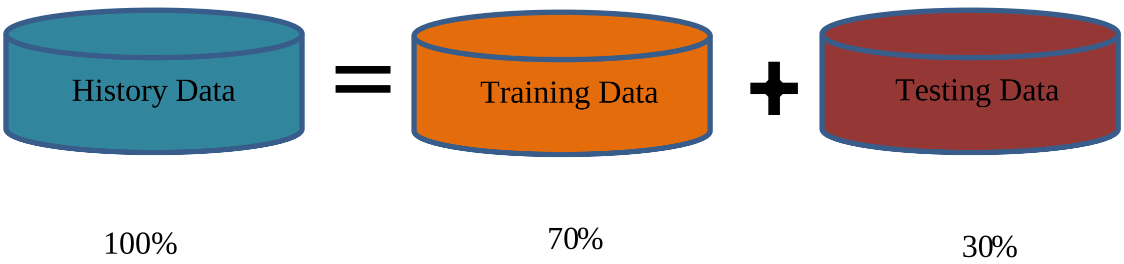


Figure 3.11: Partition of complete monitoring dataset

3.4.4.2 Training dataset

The dataset used for training purpose is called the training dataset. The training dataset is the data use to is build data mining model. The role of training dataset is to provide a data in which the predictive model is constructed. The models were built a base on the training dataset. The high the training dataset (70%) the better the prediction model performs. the quality and quantity of the training data has to do with the success of the data

3.4.4.3 Testing dataset

The dataset used to test the model is called testing dataset. After the model has been processed by using the training set (the training is completed). Testing dataset is then uncovered to model, the model built is tested by making predictions against the test dataset. Training dataset advises a model on how it should work and make its prediction. Because the data in the testing set already comprises known values for the attribute to be predicted, it is very simple to verify if the model's predictions are correct. Before applying the model built for predictions, there is a need to evaluate the predictive performance of the models‘ quality and accuracy. To assess the quality of the models (MLR and MLP) predictions, this has been with data the models have not seen before

3.4.5 Building multiple linear regression Model (MLR)

Multiple linear regression (MLR) models are suitable statistical tools used to estimate complex relationships involving prediction parameters (Baffi, Martin, & Morris, 1999). The multiple linear regression model used in this study was designed using R-language for the prediction of real values of water quality parameters. This model is used to simulate the behaviour of water quality parameters used for investigating and modelling the relationship between input and output variables applicable for predicting the performance of vertical flow constructed wetlands water quality, due to its simplicity, and best fits. Output, independent or target variable estimation can also be performed using a multiple linear regression model (MLR) in R-language, which explain the relationship between the input and output parameters

3.4.6 Building a multilayer perceptron (MLR) Model

The multilayer perceptron is a branch of the artificial neural network, was the tool used to build a prediction model. It is a three-layer network consist of the input layer, a hidden layer and output layer the model used in this research is designed and built using machine learning software WEKA, which is also a robust data mining tool for resolving data mining problems by taking out and analysing useful information from the database. It comprises a group of graphical representation and numbers for data analysis and development of prediction models.

A perceptron consists of weight (including bias), the summation processor and an activation function. However, a perceptron takes a weighted sum of inputs and output as following

- If the weighted sum is larger than the adjustable threshold, then the output is one otherwise the output is zero as contained in the equations below

$$W_1X_1 + W_2X_2 + \ldots .. + W_nX_n > \Theta \qquad 2.9$$

$$W_1X_1 + W_2X_2 + \ldots .. + W_nX_n \quad \Theta \qquad 2.10$$

- The input and connection weights sum are typically real values

The input values are presented to the perceptron, and if the predicted output is the same as the desired output, then the performance is considered satisfactory, and no changes to weight are needed. However, if the predicted output does not match the actual output of the instances, the weights need to be changed to reduce the error

$$W \quad *d*X \qquad 2.11$$

$$D = \text{predicted output} - \text{actual measured output} \qquad 2.12$$

X input data, η learning rate

Perceptron can only use in linearly separable data, if the data in nonlinear separable, the perceptron will not work. A multilayer perceptron is used to handle nonlinearly separable data; it has the same structure of single layer perceptron with one or more hidden layer. Inputs and weights are used to work out the activation function for any node as learned before (i.e. weighted sum and transfer function). This is achieved for the hidden layer as it has direct links to the actual input layer, the output is used from the hidden layer nodes to work out the activation function for an output node (they are the input to the output layer nodes). Sigmoid is used as a non-linear separable function; it is also used because it is differentiable.

When the main available data attributes and other necessary information are collected and stored to develop a database. The data is arranged base on the format and structures that are needed. Also, to load data into WEKA, the dataset is transformed into an ARFF file (Attribute-Relation File Format) format to process in WEKA. An ARFF file is an ASCII text file that describes a list of instances sharing a set of attributes, ARFF is the format that WEKA software understands and prepared. The type of data fed to the system can then be defined, then supply the data itself. In the file, column and what each column contains are also described.

After processing the ARFF file in WEKA, the list of all characteristics, statistics and other factors can be visualised as shown in the figure. ARFF format is essentially the same as comma-separated values (CSV) format used in the R language. The already prepared data can be analysed in Weka using different data mining techniques like multilayer perceptron artificial neural network (MLP-ANN).

An ARFF (Attribute-Relation File Format) file is an ASCII text file that describes a list of instances sharing a set of attributes. The Machine Learning Project developed ARFF files uses by WEKA data mining tool.

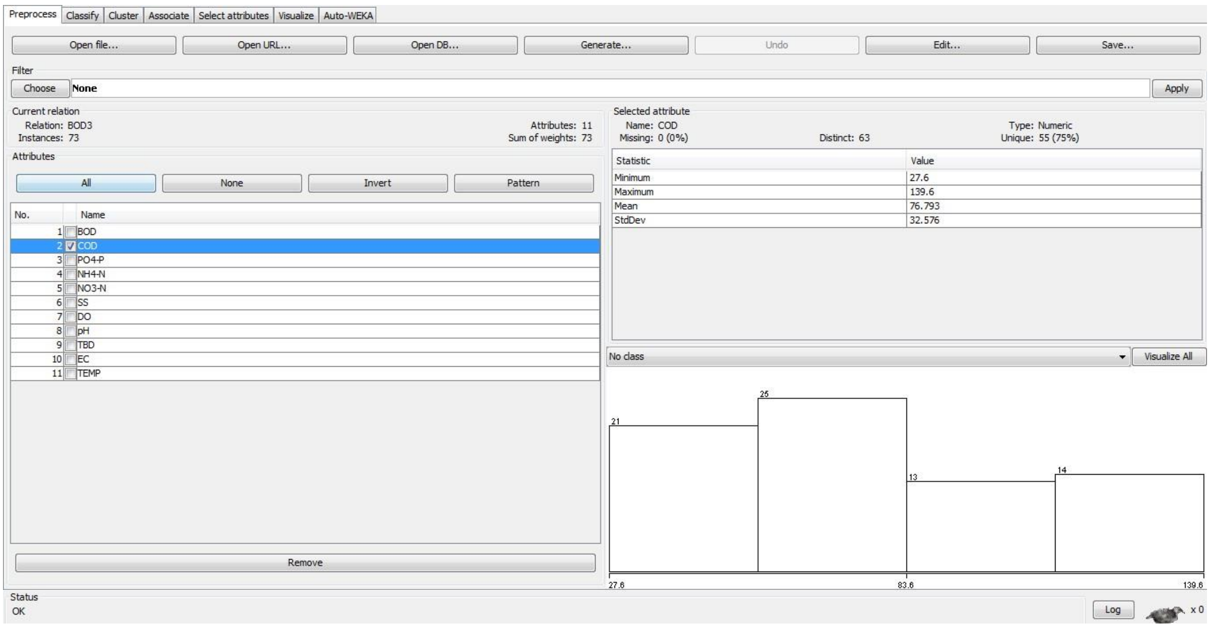


Figure 3.12: Display of WEKA platform

3.4.7 Model Evaluation Criteria

After the model is built, specific evaluation performance about the prediction model parameters is useful used to evaluate the predictive accuracy of the model and error (Ruby & David, 2015). The performance of the models built were evaluated based on two model evaluation performance methods these include graphical visualisation evaluation (using scatter plots and hydrographs) and numerical model evaluation using five different error measures which are a very significant step to understanding the strengths and weaknesses of the model built (Steyerberg et al., 2010). Several measures of goodness of fit were used to evaluate the predictive performance and quality of a model (Khadr & Elshemy, 2016). The five statistical error measures criteria to interpret the results include Root Mean Square Error (RMSE), correlation coefficient (r), Relative Absolute Error (RAE), Mean Absolute Error (MAE) and Root Relative Squared Error (RRSE).

3.4.7.1 Graphical Model Evaluation

To predict the performance of constructed wetland by predicting water Thus, it seems that plotting the data and showing the dispersion of the values is essential. Graphical representation model evaluation is a process of visualising the relationships between measured and predicted values. Assessing model performance through graphical evaluation, scatter plot and hydrograph play a vital role. The use of scatter plots of predicted and measured (or vice versa) values is one of the most common alternatives to evaluate the performance of prediction models and is still the most commonly used method.

3.4.7.2 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is the most typically used evaluation measures to manipulate mathematically and used in model valuation (Chai & Draxler, 2014, Witten, Frank, & Hall, 2011) to measure the difference between predicted values by a model and the actual measured values, which is choose in many iterative prediction and performance (Emamgholizadeh et al., 2014). RMSE is expressed as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(av - pv)^2} \qquad 2.13$$

Where av is an actual value, pv is the predicted value, and n is some instances

3.4.8 Correlation Coefficient (r)

Correlation Coefficient (r) is a measured number that describes statistical relationship between two or more continuous variables (Mukaka, 2012) example is how much actual value and predicted value are linearly related to each other. The correlation coefficient values range is from -1 to +1. A correlation value of 0 means no relationship exists, a correlation of 1 means there is a very strong positive linear relationship, a correlation of −1 it shows there is a negative linear relationship and if a correlation value is larger than 1 or smaller than -1, a mistake has occurred when calculation. When RMSE and MAE values are low, this indicates satisfied fitness among data (Sharifi, Delirhasannia, Nourani, Sadraddini, & Ghorbani, 2009).

$$r = \frac{N\sum xy - (\sum x)(\sum y)}{\sqrt{[N\sum x^2 - (\sum x)^2][N\sum y^2 - (\sum y)^2]}} \qquad 2.14$$

Where N is the total number of parameters used, $\sum xy$ is the sum of the product of parameters used, $\sum x$ is the sum of the input independent parameters, $\sum y$ is the sum of the output dependent parameters, $\sum x^2$ = sum of squared input parameters, $\sum y^2$ = sum of squared output parameters.

3.4.9 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is one of the most straightforward measure criteria used to evaluate model prediction performance accuracy and is the absolute value of the difference between the predicted value and the actual value (Cimbala, 2011). It compares between models whose errors are measured in the same units. MAE indicates how large an error is expected on average from the prediction. It is similar in magnitude to Root Mean Square Error (RMSE) but slightly smaller. MAE is the mean of all absolute errors and measures the closeness of predictions to the similar observation (Sharifi et al., 2009). The formula is express as:

MAE $\sum$ni 1 pv_____n-av 2.15

$$MAE\ \frac{1}{n}\sum_{i\ 1}^{n} ei \qquad 2.16$$

Where pv is a predicted value, av is actual measured value, ei is the absolute error and n is number of instances

3.4.10 Relative absolute error (RAE)

Relative absolute error (RAE) is the total absolute error with a similar type of normalisation and is the magnitude of the difference between the exact value and the prediction value (Witten et al., 2011).

The Relative absolute error is given by:

$$RAE\ \frac{\sum_{i\ 1}^{n} pv\text{-}av}{\sum_{i-1}^{n} |\bar{a}\text{-}av} \qquad 2.17$$

3.4.11 Root relative squared error (RRSE)

Root relative squared error (RRSE) is relative to what it would have been if a simple predictor had been used. Relative squared error takes the total squared error and normalises it by dividing by the total squared error of the default independent input variables (Witten et al., 2011).

Therefore, lower values of RRSE are better but larger values higher than 100% indicate a system is doing worse instead of predicting the mean.

Mathematically, the Root Relative Squared Error (RRSE) of an individual program was evaluated by the equation:

$$RRSE\ \sqrt{\frac{\sum_{i\ 1}^{n} pv\text{-}av}{\sum_{i-1}^{n} \bar{a}\text{-}av}} \qquad 2.18$$

Where pv is a predicted value by the individual program, av is actual value and $\bar{}$ is

3.4.12 Limitations of the experimental research

The vertical flow constructed wetlands required expert participation in its design and construction; the system requires regular maintenance, and constant electricity is also needed for the water circulation along the system, the temperature will be increased when required to maintain the higher temperature in heating cycle and to decrease the temperature for the cooling mode. Not all part of the system is locally available, example Titan 350 aqua Medic machine.

The vertical flow constructed wetlands monitored and evaluated in this experimental research are located the greenhouse under the enabling environments that are semi-controlled by a human being (researchers), which is incomparable with natural wetlands in reality. Moreover, however, the research results and finding can serve as a prototype to be used in the design and construction in further research finding and improving new wetlands system to be operated in different climates condition. Furthermore, considering natural wetlands employ large area of land and natural energy inputs in abundance (sunlight) for its uses, which serves as an avenue for various types of microorganisms to reside, the constructed wetland set-up used in this study could not represent the actual requirement of the enormous land area involved in the natural field.

3.5 Chapter summary

This chapter explains the vertical flow constructed wetland systems experimental set-up used for the research, which includes design and mode operation. It also explains how the treatment performance of the constructed wetland is conducted and evaluated by using the removal rate formula. It also describes the method employed to develop and design two data mining predictive model to predict the wastewater treatment performance of vertical flow constructed wetland system (VFCWs) by predicting water quality parameters used in the study.

Chapter 4: Assessment of General Treatment Performance of the system

4.1 Introduction

This chapter summarises and explains the overall wastewater treatment performance often (10) different filters of vertical-flow constructed wetlands system. It also summaries results and discussion of the critical water quality parameters and their statistical differences for the period of the study, these include influent and effluent water quality, based on the methods described in Chapter 3.

4.2 Inflow water qualities

Study on water quality was conducted in order to determine the water quality of the inflow concentration. The investigations were also performed using water samples, which were collected on a weekly basis from December 2014 to March 2018. The raw sample of the collected wastewater quality was examined and tabulated in this section. The resulting tabulation was then interpreted and analyses.

The average mean Inflow 1 concentrations of water quality parameters in the wastewater sample were monitored and measured for more than three (3) years of operation. The inflow sample was investigated and analysed and then compare with treated outflow sample to check the performance of the constructed wetlands and the quality of the water sample. The composition of the wastewater inflow usually varied throughout the experiment. Inflow values fluctuated across for all the water quality parameters. Moreover, the source of the water comes mainly from the household, food stalls, laundry services and groundwater run up.

Table 4.1 shows the overall mean inflow concentrations of the water quality variable for the wetland Filters 1 to 4 and Filter 9 and 10. The inflow for these filters was composed of 50% wastewater and 50% de-chlorinated tap water for the four (4) experimental period. The wastewater quality was variable during the collection period and was contained most of the domestic wastewater (wastewater mixed surface water runoff and minimum percentage of the industrial wastewater constituent) dilute with clean dechlorinated water. COD was used as a criterion to differentiate between low and high loads of the inflow concentration. An inflow COD of about 105 mg/l (usually between a range of 43 and 120 mg/l) was set for wetlands with a low loading rate base on this research finding (Filters 1, 2, 3, 9 and 10). The remaining Filters 7 and 8 received raw wastewater without dilution.

Table 4.1: Overall mean inflow 1 water quality of the raw domestic wastewater dilute with clean dechlorinated tap water (50% wastewater + 50% fresh water) from 03/12/14 to 28/03/18

Inflow 1						
Parameter	Unit	Number	Mean	Maximum	Minimum	SD
Chemical oxygen demand	mg/l	210	155.79	196.8	84.8	25.46
Biological oxygen demand	mg/l	212	88.35	108	32	12.371
Ortho-phosphate-phosphorus	mg/l	205	9.01	15.3	5.76	1.54
Nitrate-nitrogen	mg/l	199	1.12	1.99	0.54	0.2651
Ammonia-nitrogen	mg/l	214	7.75	9.94	5.02	1033
Suspended solid	mg/l	221	13.59	17	5	1.351
Turbidity	NTU	223	15.77	19	10.4	2,445
Electrical conductivity	mS/m	222	682	987	270	113.16

Table 4.2 shows the overall mean inflow 2 concentrations of the water quality variable for the wetland filters 7 and 8. These filters were loaded with raw domestic wastewater without dilution for the experimental period from 03/12/14 to 28/03/18.

Generally, the recorded data of the water quality parameters as observed shows a relatively high variability. This variability indicates the use of high concentration of real urban wastewater (Sani et al., 2013; Al-Isawi et al., 2015; Rawaa H K Al-Isawi, Scholz, & Al-Faraj, 2016). Out of the eleven water quality parameters used in this research, COD was used as a criterion to differentiate between low and high loads of the inflow concentration. An inflow COD of about 232 mg/l (usually between a range of 122 and 620 mg/l) was set for wetlands with a high loading rate (Filters 7 and 8).

The remaining Filters 1 to 4 and Filters 9 and 10 received wastewater diluted with de-chlorinated tap water.

Table 4.2 and 4.3 indicated the yearly mean inflow of water quality parameters concentration before feeding into the different filters of the wetland systems. It also includes yearly minimum and maximum values as well as standard deviation values for the eight different water quality parameters used in the study. The composition of the wastewater varied over time and the range of pollutant concentration in the inflow wastewater to the CWs were BOD (62 – 195 mg/l), COD (140 – 312 mg/l) , PO4-P (5.5 – 28.60 mg/l), NO3-N (0.86 – 2.98 mg/l), NH4-N (7.79 – 24.76 mg/l), suspended solid SS (13 – 38 mg/l), turbidity (12.12 – 36.5NTU), electrical conductivity (EC) (710- 1252 mS/m). It was discovered that the characteristics of the source wastewater did not change over time as wastewater is pre-treated from wastewater treatment plant: base on the water quality monitoring data, this show how the inflow concentration is in its state of pollution. High concentration of different water quality parameters was observed in the flow, which suggests the water quality control, and hence management of the inflow becomes an issue of great concern.

Table 4.2: Overall mean inflow 2 water quality of the raw domestic wastewater without dilution (100% wastewater) from 03/12/14 to 28/03/18

Inflow 2						
Parameter	Unit	Number	Mean	Maximum	Minimum	SD
Chemical oxygen demand	mg/l	210	265	313	54	36.968
Biological oxygen demand	mg/l	212	154	193	52	29.935
Ortho-phosphatephosphorus	mg/l	205	17.13	44.4	2.89	4.596
Nitrate-nitrogen	mg/l	199	1.895	2.98	0.864	0.418
Ammonia-nitrogen	mg/l	214	15.81	18.94	6.1	2.331

Turbidity	mg/l	221	23.97	36.5	12.12	2.578
Suspended solid	NTU	223	25.34	38	13	3.099
Electrical conductivity	mS/m	222	980.28	1252	588	86.67

Table 4.3 showed the statistics of the overall inflow 1 after dilution for the four experimental periods during these investigations. Each of the water quality for the inflow 1 was statistical analyses and presented in the table according to each of the stage or periods, because of the variability nature of the water quality parameters in the sample.

Table 4.3: Overall mean inflow water quality parameters of the raw domestic wastewater mixed with dechlorinated tap water (after dilution) starting from 03/12/14 to 28/03/18

Inflow 1						
The first stage of the experiment 03/12/2014 to 25/09/2015						
Parameter	Unit	Number	Mean	Maximum	Minimum	SD
COD	mg/l	49	158.5	192	106.3	19.396
BOD	mg/l	46	89.33	102	58	8.937
PO4-P	mg/l	52	8.41	9.89	6.3	0.796
NO3-N	mg/l	44	1.24	1.88	0.81	0.279
NH4-N	mg/l	46	7.83	9.94	6.23	0.922
SS	mg/l	58	12.71	18	5	2.067

TBD	NTU	58	12.71	14.9	8.05	1.779
EC	mS/m	58	651.28	835	270	97.243
The second stage of the experiment 26/09/2015 to 25/09/2016						
COD	mg/l	54	152.23	186.8	88.3	22.72
BOD	mg/l	56	89.31	104	56	12.483
PO4-P	mg/l	59	8.87	11.6	5.76	0.979
NO3-N	mg/l	60	1.15	1.91	0.823	0.253
NH4-N	mg/l	60	0.872	9.7	5.19	1.0734
SS	mg/l	68	13.7	17	10	1.333
TBD	NTU	67	13.63	14.98	8.4	1.253
EC	mS/m	69	717.76	896	514	106.74
The third stage of the experiment 26/09/2016 to 25/09/2017						
COD	mg/l	65	153.6	189.8	84.8	29.76
BOD	mg/l	64	83.34	108	32	14.232
PO4-P	mg/l	64	9.542	15.3	5.76	1.735
NO3-N	mg/l	65	1.017	1.99	0.54	0.213
NH4-N	mg/l	68	7.941	9.746	5.23	0.919
SS	mg/l	70	13.971	16	9	0.963
TBD	NTU	70	13.379	15.17	10.45	1.138
EC	mS/m	70	711.909	987	532	102.632

Table 4.3: Cont.

The fourth stage of the experiment 26/09/2017 to 28/03/2018						
COD	mg/l	29	158.036	196.8	80.6	31.197
BOD	mg/l	30	88.324	100	45	10.565
PO4-P	mg/l	31	10.279	14.7	7.3	1.867
NO3-N	mg/l	30	1.065	1.621	0.761	1.065
NH4-N	mg/l	33	7.795	9.4	5.23	1.101
SS	mg/l	35	14.059	16	9	1.413
TBD	NTU	35	12.55	14.77	9.39	1.474
EC	mS/m	35	606.54	789	334	106.34

Table 4.4 showed the statistics of the overall inflow 2 water for the four experimental periods during these investigations. Each of the water quality for the inflow 2 was statistical analyses and presented in the table according to each of the stage or periods, because of the variability nature of the parameters in the sample. This inflow was used for Filter 7 and 8, which is highly variable and was comprised mainly of domestic wastewater and surface water runoff, the component of industrial wastewater was minimal. The wastewater was in its raw state without dilution.

Table 4.4: Mean inflow 2 water quality parameters of the raw domestic wastewater (without dilution) starting from 03/12/14 to 28/03/18

Inflow 2						
Parameter	Unit	Number	Mean	Maximum	Minimum	SD
COD	mg/l		276	312	268	11.639
BOD	mg/l		165.28	194	124	18.485
PO4-P	mg/l		18.1	44.8	11.3	4.595
NO3-N	mg/l		1.703	2.949	1.065	0.3643
NH4-N	mg/l		16.52	22.87	12.76	2.2692
SS	mg/l		25.7	28	21	2.9615
TBD	NTU		23.49	36.5	12.12	4.003
EC	mS/m		974.441	1252	710	73.944
The second stage of the experiment 26/09/2015 to 25/09/2016						
COD	mg/l		270.99	313	178.5	21.4811
BOD	mg/l		161.36	196	124	17.129
PO4-P	mg/l		15.4	26.78	7.52	3.341
NO3-N	mg/l		1.9532	2.954	0.864	0.3977
NH4-N	mg/l		16.13	24.7	12.5	2.4368
SS	mg/l		25.38	38	14	3.2789
TBD	NTU		23.633	26.7	13.64	1.9749
EC	mS/m		970.143	2204	780	67.2943
The third stage of the experiment 26/09/2016 to 25/09/2017						

COD	mg/l	65	260.274	311.8	145.6	36.551
BOD	mg/l	64	141.61	188	63.6	25.85
PO4-P	mg/l	64	17.015	28.9	2.89	4.1657
NO3-N	mg/l	65	1.0169	2.98	0.98	0.4027
NH4-N	mg/l	68	15.135	24.76	7.79	2.467
SS	mg/l	70	25.2609	31	16	2.791
TBD	NTU	70	24.642	27.7	20.43	1.535
EC	mS/m	70	980.603	1183	588	107.52
The fourth stage of the experiment 26/09/2017 to 28/03/2018						
COD	mg/l	29	254.243	306.8	136.6	47.628
BOD	mg/l	30	140.09	168	62	20.095
PO4-P	mg/l	31	19.492	28.65	14.43	3.758
NO3-N	mg/l	30	2.159	2.98	1.32	0.4307
NH4-N	mg/l	33	14.81	18.93	12.67	1.4024
SS	mg/l	35	24.824	32	13	3.267
TBD	NTU	35	24.175	28.43	21.6	1.571
EC	mS/m	35	1021.34	1192	830	81.23

Note above features are for filter 7 and filter 8 only which received a full dose of inflow sample (wastewater only). The remaining six filters received wastewater mixed with water

(half dose wastewater and half dose de-chlorinated tap water). The undiluted influent concentrations for COD, BOD, ammonia nitrogen, nitrate-nitrogen, Ortho-phosphatephosphorus, SS, DO and turbidity were 256 mg/l, 138 mg/l, 23 mg/l, 14 mg/l, 16 mg/l, 21 mg/l, 8.5 mg/l, 20 NTU respectively.

4.3 Pollutants removal and water quality improvement

4.3.1 Comparison of outflow water qualities

Vertical flow constructed wetland wastewater treatment performance was calculated and evaluated by yearly and seasonal performance and temperature effect using, removal rate also known as modified first-order kinetic model or KC* model. It is designed base on first order equation and was first introduced by Kadlec & Knight, (1996), which was tested and broadly applied to be efficient, and a robust model for evaluating wastewater treatment performance of a constructed wetland. Many contaminants concentration reduce drastically in the wastewater inflow when they pass through the constructed wetland (Robert H Kadlec, 2000).

Three years and four months (40 months) of performance data from a vertical flow constructed wetland system receiving urban wastewater were used to determine treatment performance. The built wetland performance was evaluated by yearly and seasonal performance and temperature effect using first order-order based model as contained in equation 3 (Robert H Kadlec, 2000; Robert H Kadlec & Wallace, 2008). The performance of the constructed wetland stabilised, and a significant reduction in pollutant concentration of the outflow treated water was obtained when compared with the pollutant concentration of inflow wastewater. Also, a considerable increase of dissolved oxygen was obtained.

4.3.2 Assessment of organic matter Parameters removal (COD and BOD)

Constructed wetland system is proved to be removing several pollutants including organic matter. Biological matter parameters (COD and BOD) are the parameters used to assess and analyse organic matter concentration present in wastewater. Moreover, they are the two most popular parameters used to identify the wastewater composition (Abdalla & Hammam, 2014). Organic matter removal mechanism in constructed wetlands include deposition, aerobic, anaerobic, adsorption, filtration, and microbial metabolism (Hamzah & Jailani, 2002; Stefanakis, Akratos, Gikas, & Tsihrintzis, 2009). BOD and COD function in a similar way, they both measure the organic matter level in wastewater. However, COD is more common, measuring all the organic matters that are oxidised chemically. BOD precisely aims biodegradable compounds. According to many research literatures, confirm that constructed wetland systems are effective in removing BOD, COD from wastewater these include urban, industrial and agricultural wastewater, landfill leachate, acid mine water and urban storm runoff. In this study, the overall assessment of wastewater treatment performance of water quality parameters is also shown in Table 4.2 these include the organic matter parameters (COD and BOD) and other water quality parameters.

4.3.2.1 Biological Oxygen Demand (BOD) removal

BOD is a numerical measurement of the amount of oxygen consumed by microorganisms to oxidise of organic matter, and it comprises nitrogenous and carbonaceous oxidation (Mazumder, 2013). The BOD is oxygen-consuming is considered as significant pollutants in wastewater. The supply of oxygen is, therefore, a recommendable matter regarding constructed wetlands, particularly in the treatment of strong wastewaters. BOD removal is calculated and evaluated by a first-order model, relatively, the according to average removal results, a significant reduction in BOD concentration of the effluent wastewater was obtained. BOD was used to evaluate organic matter concentration in constructed wetlands used in the present research.

Many research studies indicated that constructed wetlands are very useful in eliminating BOD, after some pre-treatment, to achieve outflow quality (Kadlec & Knight, 1996). The result shows that all filters performed relatively well in term of COD and BOD removal as depicted in Figure 4.1. This can be explained by the fact that, the biological activity necessary for microbial degradation takes time to develop and as such, the treatment efficiency can be expected to improve after microbial adjustment as confirmed by (Zidan et al. 2015; Sani et al., 2013; R. H K Al-Isawi et al., 2015). The BOD removal performance efficiencies generally improved over time. This improvement can be attributed to the development of mature biomass adjusted to the environmental boundary conditions of the constructed wetland system (L. Zhang et al., 2010). BOD removal in the constructed wetland is typically considered to be more of a microbial mediated process specifically executed by attached aerobic and anaerobic bacteria.

It was discovered that BOD removal efficiency was greater than 60 % in almost all the season of the year (Table 4.6), but during the summer season, it recorded higher than that. The BOD5 which was considered as significant pollutants in wastewater reduced significantly in

VFCW. This reduction indicates that the wetlands were able to considerably reduce the level of BOD in the raw wastewater outflow. The outflow concentration of BOD pollutant was directly connected to the inflow pollutant load concentration. The plot (Figure 4.1) shows that the changes in the inflow and outflow concentration for the BOD during the experimental process was very high symbolising the ability of a constructed wetland to remove BOD from wastewater.

The reason for the excellent performance observed in the current study by the wetland system might be connected to the ongoing capability of the microorganism to biodegrade the organic matter particles which accumulated over time in different filters of the system. However, to the intermittent aeration that might have enhanced the biodegradation of the pollutants and averting aggregation of the organic particles in the substrate media, subsequently leading to within bed clogging abatement of the wetland systems. This phenomenon has been backed and confirmed by Al-Isawi et al., (2015) in their dedicated research. However, the litter zone formed on top of each filter which was due to both the high strength and SS load of the wastewater, but mainly due to the dead and dry macrophyte plant material. The harvested (trim) macrophyte plant material in the winter season and later returned to the corresponding wetland when they are completely dry filters as confirmed by Sani et al., (2013) and Scholz & Lee, (2005).

Because of the previous presence of diesel (period of petroleum hydrocarbon contamination) into the inflow of filters 1, 3, 5 and 7, there was a sharp decrease in overall pollutant removal performance observed. The plant (common reed) died, which were attributed to the presence of hydrocarbon contamination. New common reed plant was re-planted for those filters on Monday 12th September 2016 base on the result analysis conduct in the laboratory. It was observed that within the first three months the treatment performance of new the plants was recorded very low (start-up time). After that, the performance was found to be very significant in pollutant removal than the first three (3) months before they adopt, become mature and continue treating the wastewater properly like the remaining filter that was not previously by the artificial contribution of hydrocarbon.

Removal efficiency for BOD generally improved over time (Tables 4.5). This enhancement can be credited to the mature biomass growth modified to the environmental boundary conditions of the constructed wetland system. The overall performance of mean BOD removal for Filters 7 and 8 (both designed to received high pollutant loading rate) were recorded to be greater mean BOD removal for filters 3 and 4 (both designed to accepted low pollutants loading rate). The statistically significant difference between them was indicated as revealed in Table 4.14, which summarises an evaluation of the statistically significant differences among outflow water quality parameters of different constructed filters using the non-parametric Mann-Whitney U-test. Filters 3 and 4 were compared with Filter 9 provides an understanding of the consequence of contact time on the wastewater treatment performance by the constructed wetland. The overall removal performance efficiency of the parameters by the wetland filters was irrespective of the aggregate size was slightly different. The Filters 1 to 4 mean removals of BOD were also related, demonstrating that the size of the gravel (porous media) may not change (Al-Isawi et al., 2015; Al-isawi et al., 2015; Almuktar, Scholz, Al-Isawi, & Sani, 2015; Sani et al., 2013a) and the performance efficiency of the vertical flow constructed wetland of each filter. As can be seen in table 4.3, the removal of pollutants performance efficiency of vertical flow constructed wetland indicated a good result, with all or many water quality parameters used in the research, which showed a considerable decrease of pollutants. The treatment performance efficiency of wastewater by constructed wetland has improved, from results of BOD5 and COD and other water quality parameters in Table 4.6 in comparison with UK water quality standard.

Water quality data for all wetland influents and effluents for the monitoring period from December 2014 to March 2018 are tabulated and summarised in Tables 4.5. The overall removal performance of water quality parameter concentration was generally higher than 60% except for the second stage of the experimental period, where 32% are recorded due to the presence of hydrocarbon contamination. Table 4.14 is the summary of the overall assessment and statistically significant differences between inflow and outflow water quality parameters of different filters had improved the wastewater quality significantly. This indicates that after treatment it was removed entirely to be microbiologically safe for human consumption. The high value of BOD indicates a decrease in DO level because oxygen is consumed by aerobic bacteria that make the aquatic life survival difficult.

Table 4.5: Comparison of outflow water quality for experimental phases of filter 1 from 03/12/2014 to 28/03/2018

Filter 1								
The first stage of the experiment 03/12/2014 to 25/09/2015								
Parameter	Unit	Number	MI	MO	RE (%)	Maximum	Minimum	SD
COD	mg/l	57	158.505	49.511	68.764	74.000	21.500	15.475
BOD	mg/l	57	89.328	35.242	60.547	58.000	12.000	13.749
PO4-P	mg/l	56	8.409	4.457	47.005	7.500	1.930	1.458
NO3-N	mg/l	57	1.240	0.457	63.143	0.921	0.011	0.177
NH4-N	mg/l	57	7.832	4.252	45.712	8.750	1.010	1.744
SS	mg/l	57	12.684	3.386	73.306	9.000	0.000	2.641
TBD	NTU	57	12.706	3.433	72.979	8.200	0.850	1.663
EC	mS/m	57	651.276	314.246	51.749	504.000	120.000	125.212
The second stage of the experiment 26/09/2015 to 25/09/2016								
COD	mg/l	70	150.817	115.351	23.516	189.600	28.500	47.927
BOD	mg/l	70	90.058	60.347	32.991	94.000	22.000	21.624
PO4-P	mg/l	71	8.883	6.092	31.425	9.310	2.580	1.996
NO3-N	mg/l	70	1.149	0.756	34.217	1.433	0.294	0.285
NH4-N	mg/l	70	7.766	5.556	28.454	8.230	2.620	1.540

SS	mg/l	69	13.700	6.580	51.973	11.000	0.000	2.287
TBD	NTU	69	13.626	5.931	56.476	14.060	1.640	3.153
EC	mS/m	70	717.757	442.800	38.308	690.000	195.000	136.937
The third stage of the experiment 26/09/2016 to 25/09/2017								
COD	mg/l	71	153.613	67.697	55.930	477.000	16.600	55.537
BOD	mg/l	70	83.324	44.610	46.462	88.000	12.000	20.083
PO4-P	mg/l	69	9.309	6.031	35.216	9.780	2.010	1.710
NO3-N	mg/l	70	1.017	0.580	43.012	0.987	0.101	0.261
NH4-N	mg/l	70	7.940	5.078	36.048	8.140	1.050	1.899
SS	mg/l	69	13.971	6.116	56.224	15.000	0.000	3.512
TBD	NTU	70	13.379	5.293	60.440	12.040	0.950	3.116
EC	mS/m	71	711.909	413.225	41.955	791.000	104.000	164.426
Fourth stage of the experiment 26/09/2017 to 28/03/2018								
COD	mg/l	35	157.288	55.123	64.954	79.800	32.700	14.575
BOD	mg/l	36	88.086	32.000	63.672	48.000	20.000	8.165
PO4-P	mg/l	32	10.039	4.097	59.195	6.860	2.060	1.391
NO3-N	mg/l	35	1.064	0.547	48.618	0.796	0.304	0.139
NH4-N	mg/l	37	7.795	4.299	44.845	7.120	2.070	1.392
SS	mg/l	35	14.059	4.114	70.735	9.000	1.000	1.953
TBD	NTU	36	12.778	4.109	67.839	7.060	1.940	1.310
EC	mS/m	35	619.676	354.143	42.850	589.000	190.000	120.226

The traditional UK standard measurement for BOD removal from pre-treated wastewater is 20 mg/l and 25 mg/l for sensitive and less sensitive (e.g., many coastal discharges) areas, respectively (Royal Commission on Sewage Disposal, 1915).

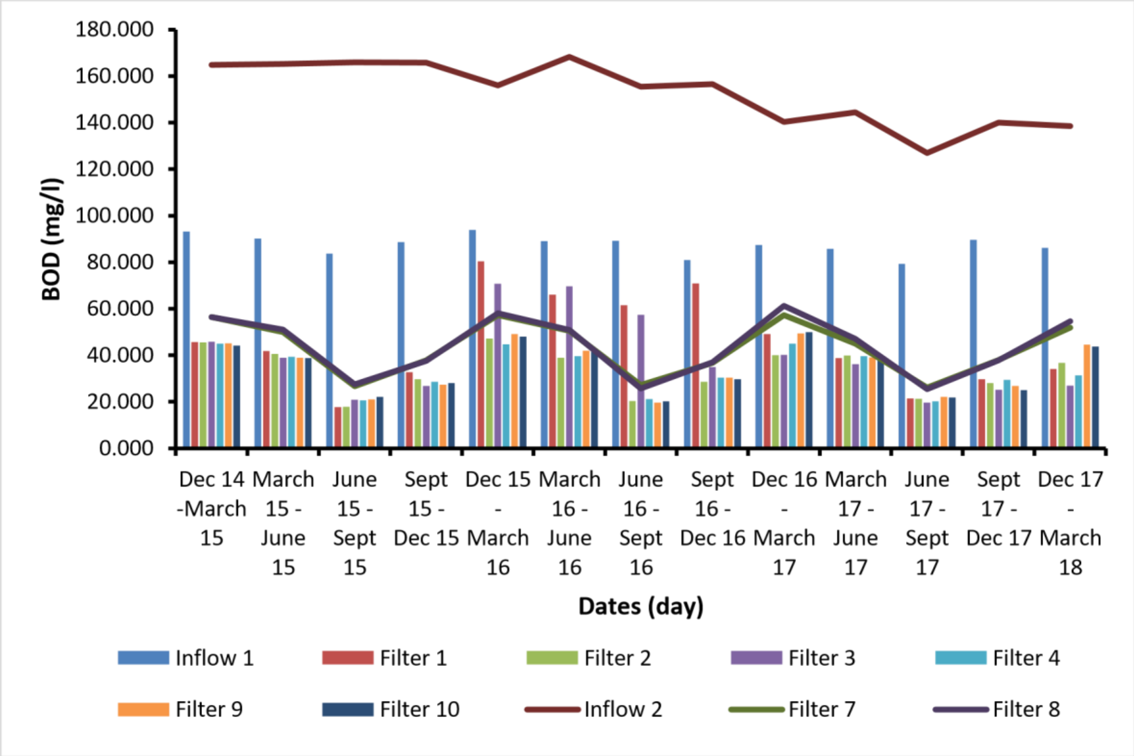


Figure 4.1: Overall variation in BOD for inflow and outflow

4.3.2.2 Chemical oxygen demand (COD) removal

COD is a measure of oxygen requirement of a sample that is needed to oxidise soluble and organic matter particles in wastewater by the strong chemical oxidant. Similar to BOD, COD was also used to evaluate the concentration of organic matter in constructed wetlands. The wastewater organic contaminants commonly measured as regards to COD, BOD (Devi & Dahiya, 2006). The COD removal is determined by the amalgamation of physical and microbial mechanisms (Darajeh et al., 2016). The high removal percentages for COD recorded in the research is due to sedimentation of suspended solids and decomposition processes.

The result shows that all filters demonstrated relatively good COD removal (excluding the time close to the start-up and period of petroleum hydrocarbon contamination) as depicted in Figure 4.2. This can be explained by the fact that, close to the start-up period, the biological activity necessary for microbial degradation takes time to develop and as such, the treatment efficiency can be expected to improve after microbial acclimatisation.

The wastewater treatment performance results of VFCWs regarding removal of significant pollutants from urban wastewater is presented in Table 4.2-4.8

Which is the basic statistics of the water quality variable measured during the monitoring period December 2014 to March 2018 in vertical flow constructed wetland treating domestic wastewater. As can be seen in the tables 4.1, 4.2, 4.3 and 4.4 1, the standard deviations (SD) of all the parameters measured is relatively normal. SD values of the parameters are higher or lower in comparison with other studies. The study conducted by Abyaneh H.Z RSD concentration of COD is 0.35, and that of BOD is 0.28. Such differences may be attributed to climate change, concentration difference of the sample as well water quality of the region (Zare Abyaneh, 2014).

To compare the effect of different operational conditions on the performance of the wetland, the removal efficiency and mass removal rate were calculated and are provided in the tables. The constructed wetland performs exceptionally well in treating domestic wastewater. The constructed wetland can handle raw domestic wastewater without any dilution

The outcomes of BOD and COD removal of this research study was confirmed with other findings of the previous research study. In research study of Stefanakis & Tsihrintzis, (2009), they studied the effect of various design parameters of constructed wetland such as Several types of porous media materials (carbonate material, material from river bed, zeolite and bauxite), two vegetation types (common reeds and cattails) and three total thicknesses of the porous media were used in 10 constructed wetlands. After one year of monitoring treatment performance of wetland systems, the result obtained indicated that removal Organic matter pollutants were recorded in all units, as it reached on the mean average of 71,1 % and 66,9 % for BOD and COD, respectively. It was discovered in the research study of (Vymazal, 2010), that high removals performance of organics matter load was recorded in all filters of constructed wetlands this is due to the aerobic microbial degradation processes.

In many previous research COD values are always measured and recorded to be higher than BOD5 values, and the ratio between them will differ subject to the features of the wastewater.

This ratio is used generally as an indicator of biodegradation ability (Hill, 2003).

Table 4.6: Comparison of outflow water quality for experimental phases of filter 2 from 03/12/2014 to 28/03/2018

	Filter 2							
	First stage of the experiment 03/12/2014 to 25/09/2015							
Parameter	Unit	Number	MI	MO	RE (%)	Maximum	Minimum	SD
COD	mg/l	57	158.505	49.989	68.462	76.500	22.700	14.717
BOD	mg/l	57	89.328	34.865	60.970	55.000	12.000	13.423
PO4-P	mg/l	56	8.409	4.529	46.141	7.650	1.980	1.435
NO3-N	mg/l	57	1.240	0.432	65.181	0.779	0.022	0.193
NH4-N	mg/l	57	7.832	4.320	44.848	8.480	1.030	1.881
SS	mg/l	57	12.684	4.281	66.252	9.000	0.000	2.469
TBD	NTU	57	12.706	3.490	72.532	7.510	0.870	1.671
EC	mS/m	57	651.276	308.018	52.706	508.000	115.000	123.861
	The second stage of the experiment 26/09/2015 to 25/09/2016							
COD	mg/l	70	150.817	45.821	69.618	72.700	14.900	16.995
BOD	mg/l	70	90.058	33.986	62.262	52.000	12.000	10.963
PO4-P	mg/l	71	8.883	4.329	51.264	7.980	1.840	1.443
NO3-N	mg/l	70	1.149	0.448	60.987	1.231	0.120	0.255
NH4-N	mg/l	70	7.766	4.284	44.844	7.410	1.010	1.658

SS	mg/l	69	13.700	4.449	67.524	9.000	0.000	2.350
TBD	NTU	69	13.626	3.279	75.937	5.890	0.790	1.338
EC	mS/m	70	717.757	302.186	57.899	528.000	109.000	110.071
The third stage of the experiment 26/09/2016 to 25/09/2017								
COD	mg/l	71	153.613	48.014	68.743	88.600	17.600	16.309
BOD	mg/l	70	83.324	32.443	61.064	52.000	14.000	10.004
PO4-P	mg/l	69	9.309	4.785	48.599	6.850	2.090	1.129
NO3-N	mg/l	70	1.017	0.439	56.879	0.768	0.119	0.185
NH4-N	mg/l	70	7.940	3.906	50.807	7.470	1.010	1.743
SS	mg/l	69	13.971	4.420	68.361	9.000	0.000	2.428
TBD	NTU	70	13.379	3.184	76.201	5.520	0.790	1.290
EC	mS/m	71	711.909	289.000	59.405	511.000	110.000	115.421
Fourth stage of the experiment 26/09/2017 to 28/03/2018								
COD	mg/l	35	157.288	55.451	64.745	88.600	34.800	15.043
BOD	mg/l	36	88.086	32.583	63.010	52.000	20.000	9.323
PO4-P	mg/l	32	10.039	4.243	57.741	6.890	2.090	1.374
NO3-N	mg/l	35	1.064	0.529	50.328	0.770	0.242	0.188
NH4-N	mg/l	37	7.795	4.204	46.072	6.460	1.210	1.345
SS	mg/l	35	14.059	3.600	74.393	9.000	1.000	1.808
TBD	NTU	36	12.778	3.889	69.563	5.920	1.940	1.277
EC	mS/m	35	619.676	325.086	47.539	516.000	171.000	116.825

SD: Standard deviation, RSD: relative standard deviation, RE: removal efficiency

Table 4.7: Comparison of outflow water quality for experimental phases of filter 3 from 03/12/2014 to 28/03/2018

Filter 3								
The first stage of the experiment 03/12/2014 to 25/09/2015								
Parameter	Unit	Number	MI	MO	RE (%)	Maximum	Minimum	SD
COD	mg/l	57	158.505	51.600	67.446	76.700	25.000	14.957
BOD	mg/l	57	89.328	35.316	60.465	58.000	12.000	12.311
PO4-P	mg/l	55	8.409	4.534	46.085	8.780	1.670	1.891
NO3-N	mg/l	57	1.240	0.434	64.972	0.838	0.144	0.173
NH4-N	mg/l	56	7.832	4.298	45.124	7.440	1.020	1.768
SS	mg/l	57	12.684	4.333	65.837	9.000	1.000	2.219
TBD	NTU	57	12.706	3.357	73.580	5.420	0.750	1.350
EC	mS/m	57	651.276	313.842	51.811	499.000	111.000	124.929
The second stage of the experiment 26/09/2015 to 25/09/2016								
COD	mg/l	70	150.817	107.874	58.474	164.000	29.100	42.383
BOD	mg/l	70	90.058	56.343	47.437	90.000	20.000	23.485
PO4-P	mg/l	71	8.883	5.909	33.483	9.950	2.460	2.133
NO3-N	mg/l	70	1.149	0.707	38.510	1.346	0.211	0.258
NH4-N	mg/l	70	7.766	5.554	48.491	8.770	2.250	1.660
SS	mg/l	69	13.700	7.290	76.789	14.000	2.000	2.543
TBD	NTU	69	13.626	5.728	57.961	12.130	1.990	2.665
EC	mS/m	70	717.757	449.386	37.390	670.000	211.000	131.299

The third stage of the experiment 26/09/2016 to 25/09/2017								
COD	mg/l	71	153.613	60.313	60.737	108.900	18.700	25.099
BOD	mg/l	70	83.324	32.814	60.618	80.000	12.000	14.826
PO4-P	mg/l	69	9.309	6.201	33.390	8.930	2.330	1.259
NO3-N	mg/l	70	1.017	0.541	46.822	0.983	0.110	0.255
NH4-N	mg/l	70	7.940	5.025	57.720	8.640	1.010	2.177
SS	mg/l	69	13.971	6.029	86.846	16.000	0.000	3.226
TBD	NTU	70	13.379	5.226	60.940	9.890	0.780	2.987
EC	mS/m	71	711.909	411.944	42.135	2558.000	109.000	237.839
Fourth stage of the experiment 26/09/2017 to 28/03/2018								
COD	mg/l	35	157.288	51.914	66.994	74.700	28.900	13.156
BOD	mg/l	36	88.086	26.083	70.389	44.000	17.000	5.997
PO4-P	mg/l	32	10.039	4.843	51.765	8.840	2.260	1.425
NO3-N	mg/l	35	1.064	0.377	64.569	0.717	0.218	0.136
NH4-N	mg/l	37	7.795	3.204	58.891	6.110	1.510	1.321
SS	mg/l	35	14.059	3.257	76.832	9.000	0.000	1.872
TBD	NTU	36	12.778	3.910	69.400	7.320	1.840	1.252
EC	mS/m	35	619.676	377.286	39.116	533.000	189.000	109.825

Table 4.8: Comparison of outflow water quality for experimental phases of filter 4 from 03/12/2014 to 28/03/2018

Filter 4								
The first stage of the experiment 03/12/2014 to 25/09/2015								
Parameter	Unit	Number	MI	MO	PR (%)	Maximum	Minimum	SD
COD	mg/l	57	158.505	72.302	54.385	741.900	24.000	113.454
BOD	mg/l	57	89.328	35.018	60.799	54.000	14.000	12.415
PO4-P	mg/l	57	8.409	4.534	46.084	8.340	1.870	1.710
NO3-N	mg/l	57	1.240	0.454	63.360	0.890	0.043	0.184
NH4-N	mg/l	57	7.832	4.558	41.806	6.980	1.110	1.574
SS	mg/l	57	12.684	4.298	66.113	9.000	1.000	2.302
TBD	NTU	57	12.706	3.392	73.307	5.580	0.890	1.404
EC	mS/m	57	651.276	303.982	53.325	531.000	111.000	143.341
The second stage of the experiment 26/09/2015 to 25/09/2016								
COD	mg/l	70	150.817	47.603	68.437	78.500	18.900	15.549
BOD	mg/l	70	90.058	33.571	62.722	54.000	14.000	10.980
PO4-P	mg/l	71	8.883	4.106	53.783	7.290	1.300	1.583
NO3-N	mg/l	70	1.149	0.401	65.111	0.752	0.110	0.184
NH4-N	mg/l	69	7.766	4.085	47.403	6.870	1.010	1.488
SS	mg/l	69	13.700	4.449	67.524	8.000	0.000	2.411
TBD	NTU	69	13.626	3.442	74.741	5.370	0.790	1.106
EC	mS/m	70	717.757	301.486	57.996	508.000	108.000	114.868

The third stage of the experiment 26/09/2016 to 25/09/2017								
COD	mg/l	71	153.613	47.335	69.185	69.500	19.500	14.682
BOD	mg/l	70	83.324	33.800	59.435	52.000	12.000	10.371
PO4-P	mg/l	69	9.309	4.554	51.076	7.730	1.970	1.399
NO3-N	mg/l	70	1.017	0.408	59.881	0.654	0.113	0.165
NH4-N	mg/l	70	7.940	4.243	46.563	7.050	1.120	1.569
SS	mg/l	69	13.971	4.029	71.162	8.000	1.000	2.092
TBD	NTU	70	13.379	3.229	75.863	5.780	0.820	1.435
EC	mS/m	71	711.909	298.169	58.117	463.000	102.000	110.651
Fourth stage of the experiment 26/09/2017 to 28/03/2018								
COD	mg/l	35	157.288	52.154	66.842	81.500	30.500	13.870
BOD	mg/l	36	88.086	30.425	65.460	54.000	20.000	8.255
PO4-P	mg/l	32	10.039	4.575	54.429	7.090	1.640	1.337
NO3-N	mg/l	35	1.064	0.401	62.371	0.649	0.152	0.145
NH4-N	mg/l	37	7.795	4.600	40.982	7.280	1.650	1.513
SS	mg/l	35	14.059	3.057	78.255	8.000	1.000	1.912
TBD	NTU	36	12.778	3.839	69.954	5.780	1.490	1.264
EC	mS/m	35	619.676	368.457	40.540	533.000	186.000	110.927

Table 4.9: Comparison of outflow water quality for experimental phases of filter 9 from 03/12/2014 to 28/03/2018

Filter 9								
The first stage of the experiment 03/12/2014 to 25/09/2015								
Parameter	Unit	Number	MI	MO	RE (%)	Maximum	Minimum	SD
COD	mg/l	73	158.505	74.504	52.996	756.000	15.800	132.444
BOD	mg/l	72	89.328	58.000	35.070	58.000	12.000	12.644
PO4-P	mg/l	78	8.409	4.567	45.690	6.980	1.650	1.437
NO3-N	mg/l	72	1.240	0.452	63.536	0.782	0.102	0.186
NH4-N	mg/l	73	7.832	4.103	47.608	6.980	1.030	1.698
SS	mg/l	73	12.684	4.438	65.009	8.000	0.000	2.526
TBD	NTU	74	12.706	3.389	73.329	5.640	0.720	1.417
EC	mS/m	73	651.276	307.534	52.780	498.000	104.000	124.841
The second stage of the experiment 26/09/2015 to 25/09/2016								
COD	mg/l	90	150.817	48.478	67.857	80.500	18.500	15.017
BOD	mg/l	91	90.058	62.000	31.155	62.000	12.000	12.776
PO4-P	mg/l	88	8.883	4.713	46.951	7.210	2.110	1.149
NO3-N	mg/l	89	1.149	0.434	62.210	0.773	0.119	0.168
NH4-N	mg/l	91	7.766	4.106	47.128	7.760	1.070	1.592
SS	mg/l	89	13.700	4.404	67.850	9.000	0.000	2.316
TBD	NTU	91	13.626	3.159	76.814	5.620	0.230	1.387
EC	mS/m	88	717.757	304.739	57.543	519.000	102.000	121.247

Table 4.9: Cont.

The third stage of the experiment 26/09/2016 to 25/09/2017								
COD	mg/l	89	153.613	54.052	64.813	79.100	37.400	10.290
BOD	mg/l	88	83.324	62.000	25.592	62.000	12.000	11.496
PO4-P	mg/l	88	9.309	4.575	50.850	7.070	1.970	1.345
NO3-N	mg/l	87	1.017	0.428	57.958	0.760	0.048	0.146
NH4-N	mg/l	90	7.940	4.003	49.584	6.890	1.030	1.635
SS	mg/l	90	13.971	4.456	68.109	8.000	0.000	2.237
TBD	NTU	90	13.379	3.196	76.115	5.680	0.810	1.317
EC	mS/m	88	711.909	289.091	59.392	512.000	101.000	121.275
Fourth stage of the experiment 26/09/2017 to 28/03/2018								
COD	mg/l	44	157.288	54.895	65.099	79.100	38.500	13.759
BOD	mg/l	42	88.086	54.000	38.696	54.000	16.000	10.218
PO4-P	mg/l	41	10.039	3.756	62.591	6.670	1.180	1.559
NO3-N	mg/l	44	1.064	0.492	53.799	0.837	0.274	0.137
NH4-N	mg/l	44	7.795	4.511	42.131	7.281	2.220	1.618
SS	mg/l	44	14.059	4.636	67.022	9.000	1.000	2.365
TBD	NTU	44	12.778	3.770	70.497	5.680	1.950	1.264
EC	mS/m	42	619.676	345.286	44.280	522.000	193.000	128.476

Table 4.10: Comparison of outflow water quality for experimental phases of filter 1 from 03/12/2014 to 28/03/2018

Filter 10								
The first stage of the experiment 03/12/2014 to 25/09/2015								
Parameter	Unit	Number	MI	MO	PR (%)	Maximum	Minimum	SD
COD	mg/l	91	158.505	50.457	68.167	366.000	14.000	37.853
BOD	mg/l	88	89.328	55.000	38.429	55.000	12.000	12.201
PO4-P	mg/l	86	8.409	4.890	41.850	6.910	1.870	1.403
NO3-N	mg/l	93	1.240	0.439	64.562	0.736	0.051	0.181
NH4-N	mg/l	93	7.832	4.238	45.895	6.980	1.020	1.764
SS	mg/l	95	12.684	4.421	65.145	8.000	0.000	2.610
TBD	NTU	96	12.706	3.369	73.487	5.650	0.860	1.276
EC	mS/m	92	651.276	326.370	49.888	497.000	106.000	122.895
The second stage of the experiment 26/09/2015 to 25/09/2016								
COD	mg/l	113	150.817	48.002	68.172	76.000	18.900	15.034
BOD	mg/l	108	90.058	60.000	33.376	60.000	10.000	12.402
PO4-P	mg/l	113	8.883	4.961	44.159	7.020	2.180	1.194
NO3-N	mg/l	107	1.149	0.443	61.436	0.791	0.093	0.190
NH4-N	mg/l	117	7.766	4.255	45.210	7.960	1.090	1.746
SS	mg/l	119	13.700	4.294	68.656	9.000	0.000	2.454
TBD	NTU	114	13.626	3.135	76.995	5.670	0.450	1.299
EC	mS/m	113	717.757	314.407	56.196	522.000	102.000	124.370

The third stage of the experiment 26/09/2016 to 25/09/2017								
COD	mg/l	105	153.613	53.944	64.883	80.500	4.300	11.418
BOD	mg/l	112	83.324	64.000	23.191	64.000	12.000	11.511
PO4-P	mg/l	109	9.309	6.315	32.166	75.620	2.520	6.741
NO3-N	mg/l	116	1.017	0.413	59.409	0.796	0.087	0.192
NH4-N	mg/l	114	7.940	4.115	48.169	7.120	1.320	1.565
SS	mg/l	117	13.971	4.376	68.678	8.000	0.000	2.279
TBD	NTU	116	13.379	3.297	75.356	5.830	0.760	1.321
EC	mS/m	114	711.909	302.974	57.442	515.000	103.000	124.984
Fourth stage of the experiment 26/09/2017 to 28/03/2018								
COD	mg/l	51	157.288	54.898	65.097	79.400	35.500	13.946
BOD	mg/l	52	88.086	60.000	31.885	60.000	16.000	11.716
PO4-P	mg/l	49	10.039	6.221	38.032	8.540	3.720	1.325
NO3-N	mg/l	55	1.064	0.539	49.405	1.502	0.263	0.208
NH4-N	mg/l	58	7.795	4.708	39.598	7.470	1.590	1.751
SS	mg/l	59	14.059	4.000	71.548	9.000	1.000	2.270
TBD	NTU	57	12.778	3.922	69.309	5.890	1.600	1.355
EC	mS/m	54	619.676	371.037	40.124	526.000	191.000	122.607

Table 4.11: Comparison of outflow water quality for experimental phases of filter 7 starting from 03/12/2014 to 28/03/2018

	Filter 7							
	The first stage of the experiment 03/12/2014 to 25/09/2015							
Parameter	Unit	Number	MI	MO	RE (%)	Maximum	Minimum	SD
COD	mg/l	57	275.634	47.646	82.714	92.000	22.400	18.664
BOD	mg/l	57	165.281	44.421	73.124	70.000	14.000	15.441
PO4-P	mg/l	56	18.100	5.613	68.988	8.980	1.630	1.693
NO3-N	mg/l	57	1.703	0.437	74.348	0.789	0.111	0.164
NH4-N	mg/l	56	16.516	4.340	73.723	6.750	1.080	1.704
SS	mg/l	57	25.702	4.526	82.389	8.000	0.000	2.500
TBD	NTU	57	23.492	3.329	85.831	5.600	0.760	1.325
EC	mS/m	57	974.441	316.895	67.479	527.000	104.000	131.370
	The second stage of the experiment 26/09/2015 to 25/09/2016							
COD	mg/l	70	270.991	164.117	39.438	264.000	2.000	88.987
BOD	mg/l	70	161.364	43.314	73.157	68.000	16.000	13.206
PO4-P	mg/l	71	15.472	7.048	54.446	14.960	1.530	2.903
NO3-N	mg/l	71	1.953	0.871	55.421	2.299	0.091	0.698
NH4-N	mg/l	70	16.134	6.853	57.522	14.870	1.670	3.023
SS	mg/l	69	25.386	9.261	63.519	21.000	1.000	5.495
TBD	NTU	69	23.633	9.157	61.253	19.990	2.130	6.030
EC	mS/m	70	970.143	515.186	46.896	952.000	192.000	189.425

The third stage of the experiment 26/09/2016 to 25/09/2017								
COD	mg/l	71	260.274	61.307	76.445	207.300	18.900	33.953
BOD	mg/l	70	141.606	41.171	70.925	70.000	12.000	13.899
PO4-P	mg/l	69	16.838	7.898	53.094	15.330	0.040	2.904
NO3-N	mg/l	70	1.908	0.674	64.689	2.573	0.066	0.454
NH4-N	mg/l	70	15.135	6.001	60.351	15.610	1.080	3.371
SS	mg/l	69	25.261	8.130	67.814	19.000	0.000	5.376
TBD	NTU	70	24.642	6.964	71.741	19.290	0.790	6.390
EC	mS/m	71	980.603	463.634	52.720	851.000	102.000	217.567

Table 4.11: Cont.

Fourth stage of the experiment 26/09/2017 to 28/03/2018								
COD	mg/l	35	254.203	57.763	77.277	84.800	36.600	16.787
BOD	mg/l	36	140.086	45.333	67.639	64.000	22.000	10.975
PO4-P	mg/l	32	17.491	10.014	42.748	14.770	2.780	2.877
NO3-N	mg/l	35	2.159	0.509	76.405	0.789	0.245	0.183
NH4-N	mg/l	37	14.810	4.591	69.001	7.080	2.570	1.328
SS	mg/l	35	24.824	5.543	77.671	9.000	3.000	2.234
TBD	NTU	36	24.309	3.308	86.393	12.380	1.590	1.844
EC	mS/m	35	1021.343	373.686	63.412	557.000	192.000	121.141

Table 4.12: Comparison of outflow water quality for experimental phases of filter 8 from 03/12/2014 to 28/03/2018

Filter 8								
The first stage of the experiment 03/12/2014 to 25/09/2015								
Parameter	Unit	Number	MI	MO	PR (%)	Maximum	Minimum	SD
COD	mg/l	57	275.634	47.314	82.835	79.600	19.000	15.808
BOD	mg/l	57	165.281	45.105	72.710	68.000	16.000	14.598
PO4-P	mg/l	56	18.100	5.672	68.665	8.650	1.380	1.688
NO3-N	mg/l	57	1.703	0.447	73.740	0.770	0.114	0.198
NH4-N	mg/l	57	16.516	4.780	71.061	25.200	1.190	3.166
SS	mg/l	57	25.702	4.596	82.116	8.000	0.000	2.427
TBD	NTU	57	23.492	3.736	84.097	18.090	0.860	2.433
EC	mS/m	57	974.441	303.263	68.878	510.000	101.000	124.362
The second stage of the experiment 26/09/2015 to 25/09/2016								
COD	mg/l	70	270.991	53.863	80.124	545.900	20.100	61.109
BOD	mg/l	70	161.364	43.171	73.246	70.000	12.000	14.245
PO4-P	mg/l	71	15.472	6.794	56.092	14.970	1.640	3.110
NO3-N	mg/l	71	1.953	0.363	81.401	0.954	0.116	0.164
NH4-N	mg/l	70	16.134	4.126	74.428	6.910	1.090	1.603
SS	mg/l	69	25.386	4.348	82.873	8.000	0.000	2.289

TBD	NTU	69	23.633	3.967	83.214	52.440	1.090	5.987
EC	mS/m	70	970.143	303.157	68.751	497.000	104.000	117.633

Table 4.12: Cont.

The third stage of the experiment 26/09/2016 to 25/09/2017								
COD	mg/l	71	260.274	52.210	79.940	567.100	19.500	64.216
BOD	mg/l	70	141.606	42.600	69.916	72.000	12.000	14.911
PO4-P	mg/l	69	16.838	7.874	53.236	15.110	2.560	2.796
NO3-N	mg/l	70	1.908	0.432	77.370	0.784	0.087	0.184
NH4-N	mg/l	70	15.135	4.362	71.179	7.440	1.030	1.634
SS	mg/l	69	25.261	4.696	81.411	9.000	0.000	2.538
TBD	NTU	70	24.642	3.078	87.509	5.350	0.740	1.161
EC	mS/m	71	980.603	307.169	68.675	558.000	102.000	120.316
Fourth stage of the experiment 26/09/2017 to 28/03/2018								
COD	mg/l	35	254.203	72.677	71.410	643.500	32.000	99.030
BOD	mg/l	36	140.086	46.694	66.667	67.000	18.000	11.460
PO4-P	mg/l	32	17.491	10.669	39.005	14.060	7.010	2.277
NO3-N	mg/l	35	2.159	0.547	74.679	0.784	0.278	0.173
NH4-N	mg/l	37	14.810	4.760	67.861	7.440	2.450	1.584
SS	mg/l	35	24.824	5.829	76.520	9.000	2.000	2.236
TBD	NTU	36	24.309	3.661	84.938	5.910	2.010	1.131
EC	mS/m	35	1021.343	373.943	63.387	558.000	189.000	121.040

The above table for the overall mean outflow and inflow values and standard deviation show variation in the influent and effluent concentrations of the constructed vertical wetlands and this indicated the flowing treatment rate that the constructed vertical wetlands had a high capacity to remove pollutants. The vertical constructed wetlands generally had similar ranges of removal efficiency, with the following values: 54.19 – 84.82% for COD, 63.09 – 75.5% for BOD_5, 56.69 – 83.09% for NH4-N, 56.66 – 86.86% for PO4-P, 42.01 – 50.18% for NO3N, 40.91 – 79.31% for SS, 39.87 – 63.98% for DO, 33.89 – 54.80% for EC and 33.89 –

54.80% for Turbidity. Performance of the vertical constructed wetland system for filters 1 – 4, 7 and 8, 9 and 10 were generally recorded high removal efficiency performance.

The traditional UK standard for BOD removal from secondary wastewater is not more than 20 mg/l and 25 mg/l for sensitive and less sensitive (e.g., many coastal discharges) areas, respectively (Royal Commission on Sewage Disposal, 1915). Depending on receiving water or type of industry under consideration but the range will exceed 60mg/l.

Table 4.13: Comparison of outflow water quality and air temperature for the control filters

Filter 5 (Control A)								
Fourth stage of the experiment 26/09/2017 to 28/03/2018								
Parameter	Unit	Number	MI	MO	PR	Maximum	Minimum	SD
COD	mg/l	35		63.286	n/a	96.500	51.500	11.583
BOD	mg/l	36		26.056	n/a	35.200	8.000	7.334
PO4-P	mg/l	32		5.418	n/a	8.780	2.380	2.237

NO3-N	mg/l	35		0.325	n/a	0.576	0.030	0.159
NH4-N	mg/l	37		2.530	n/a	6.720	-0.036	1.891
SS	mg/l	35		5.000	n/a	9.000	2.000	2.070
TBD	NTU	36		3.765	n/a	5.860	1.300	1.191
EC	mS/m	35		473.466	n/a	596.000	342.000	66.740
AT	C							
	FILTER 6 (Control B)							
	Fourth stage of the experiment 26/09/2017 to 28/03/2018							
Parameter	Unit	Number	MI	MO	PR	Maximum	Minimum	SD
COD	mg/l	35		60.009	n/a	95.000	52.400	11.469
BOD	mg/l	36		26.967	n/a	48.000	8.000	8.816
PO4-P	mg/l	31		5.058	n/a	8.870	1.170	1.889
NO3-N	mg/l	32		0.440	n/a	0.762	0.025	0.183
NH4-N	mg/l	37		2.380	n/a	6.830	-0.047	2.073
SS	mg/l	35		2.829	n/a	4.000	2.000	0.774
TBD	NTU	36		3.583	n/a	5.340	2.310	1.030
EC	mS/m	35		440.666	n/a	565.000	229.000	105.158
AT	C	304		16.3762		34	3	7.092182
				4				

AT air temperature C degree Celsius

The wastewater treatment process in a vertical flow constructed wetland of this research improved the water quality by water quality standard. The possible reason for this excellent performance observed in the current study could be attributed to gradual microorganism‘s ability to biodegrade the accumulated organic matter particles overtime in addition to the intermittent aeration that might have enhanced the biodegradation of the pollutants and averting aggregation of the organic particles in the substrate media. Constructed wetlands systems influent and effluent variation of COD concentrations are shown in figure 4.1

The COD test measures requirement of oxygen by organic and inorganic compounds, it clearly indicates that presence of these compounds also decreases the DO level in river water.

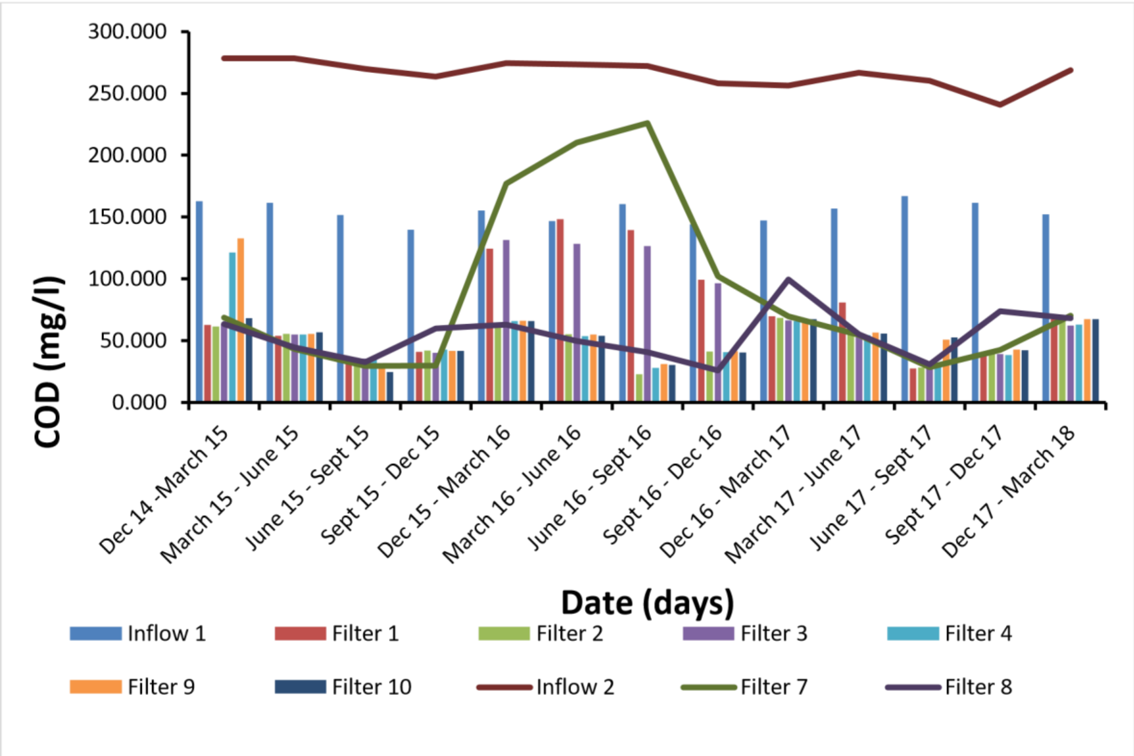


Figure 4.2: Overall variation for COD inflow and outflow

Figure 4.4 is the concentration of chemical oxygen demand (COD) in the wastewater inflow and the corresponding values of treated water outflow of VFCWs throughout the monitoring experiment.

4.3.3 Evaluation of nutrients Parameters

The processes that affect removal and retention of nitrogen during wastewater treatment in constructed wetlands (CWs) are manifold and include NH_3 volatilization, nitrification, denitrification, nitrogen fixation, plant and microbial uptake, mineralization (ammonification), nitrate reduction to ammonium (nitrate-ammonification), anaerobic ammonia oxidation (ANAMMOX), fragmentation, sorption, desorption, burial, and leaching.

Nutrient removal is one of the main factors in determining and maintaining how clean or contaminant the wastewater is as human interventions and increase in population growth and demand of clean water impose the need for domestic wastewater treatment as an alternative source of water globally (Jariwala, Syed, & Pandya, 2017). Nitrogen and phosphorus are crucial elements for micro-organism's growth used in the treatment of wastewater; consequently, during the treatment process, a considerable level of a nutrient is removed.

Nutrients removal in constructed wetlands is commanding, due to their health and environmental repercussions. Receiving watercourses by the plants become eutrophic when they receive large amounts of these nutrients subsequently promoting enormous plant growth that leads to the depletion of oxygen in the receiving water environment the decay of which kills animal life by depriving it of oxygen. Nitrogen removal in constructed wetlands is primarily by microbial nitrification and denitrification (Jan Vymazal, 2014a) (Fan, Liang, et al., 2013).

Constructed Wetlands are capable of eliminating nitrogen and phosphorus in wastewater via a mixture of the process. These include physical, chemical, and biological processes. These natural processes occur in the system consists of: adsorb/absorb, transform, sequester, and remove the nutrients and other chemicals as wastewater pass slowly down the constructed wetland. Nitrogen compounds used in this research study include ammonia nitrogen (NH4N), nitrate nitrogen (NO3-N) and orthophosphate phosphorus (PO4-P) proved to be capable of effectively removing nutrients from wastewater.

This study research, Tables 4.2, 4.3, 4.4 and 4.5 comparisons of the overall mean nutrients outflow and percentage removal of the nutrient compound water quality parameters conducted were tabulated in different experimental phases, while Table 4.6 summarizes an assessment of the statistically significant differences between outflow water quality variables of different filters using the non-parametric Mann-Whitney U-test.

4.4 Ammonia-nitrogen

Ammonium nitrogen is one of the nitrogen family compound and nutrient parameters found in wastewater, that when in surplus can cause water eutrophication (Liikanen & Martikainen, 2003). The removal of ammonium nitrogen from wastewater has been of substantial worry for many years (T. Zhang, Ding, Ren, & Xiong, 2009). The ammonium ion ($NH4^{+}$) is a significant member of nitrogen-containing compounds that perform as nutrients for aquatic plants and algae. In surface water, most of the ammonia, NH3, is originate in the form of ammonium ion, $NH4^{+}$. This will help approximate the concentration of all of the nitrogen in the ammonia and ammonium combined form, commonly called ammonia nitrogen, by measuring only the concentration of the ammonium ions. Ammonium nitrogen NH4-N in moderate municipal wastewaters vary depending on the concentration within the range of 1250 mg/l representing low and high to concentrated wastewater respectively (Henze, Harremoes, la Cour Jansen, & Arvin, 2001).

Wastewater containing ammonium nitrogen causes a severe pollution problem to people and can be harmful to human and animal health. Removal of nitrogen from wastewater can be realised by biological or physicochemical procedures (Capodaglio, Hlavínek, & Raboni, 2015).

The wastewater containing ammonia nitrogen would inhibit the natural nitrification, cause water hypoxia, result in fish poisoning, decrease the water purification capacity, and finally do great harm to the water environment. Ammonia is said to oxidise largely to nitrate in the process of nitrification, (Cola, 2009). By the oxidation of ammonia to nitrate, nitrate is reduced to the gaseous form of nitrogen by the process called denitrification. However, the removal is inadequate without active and passive aeration, this due to insufficient oxygen readily for aerobic biodegradation (Scholz et al., 2010; H. Wu et al., 2015; Vymazal, 2014).

The process of removing ammonia in constructed wetlands is difficult as it involves a sequence of chemical, physical and biological reactions within the wetland media. However, previous journals have confirmed that high aeration which promotes the build-up of ammonia-oxidizing bacteria leads to high ammonia nitrification (Fan, Liang, Zhang, & Zhang, 2013; H. Wu et al., 2013).

In this research work, evaluation of the overall nutrients outflow of all filters of the wetland of water quality in different experimental phases is shown in table 4.2, 4.3, 4.4, 4.5. The total removal rates of ammonia-nitrogen (NH4-N) were relatively high in comparison (figure 4.6) with other parameters, partially due to temperatures usually being above 15°C in the greenhouse-controlled environment during the warm seasons and aeration (Fan, Liang, et al., 2013). It was observed removal efficiencies of some of the filters of wetland system were low if undiluted wastewater was used (filter 1, 2,3,4,9 and 10). However, aggregate size, resting time and contact time were not that significant for the overall removal of ammonia nitrogen. Previous study research reported high removal of ammonium nitrogen by constructed wetland such as in a study of Yongzhen, Shouyou, Shuying, & Lu, (2007) stated that nitrification/denitrification process, can remove about 95% of NH4 –N level in domestic wastewater (Purwono, Hibbaan, & Budihardjo, 2017).

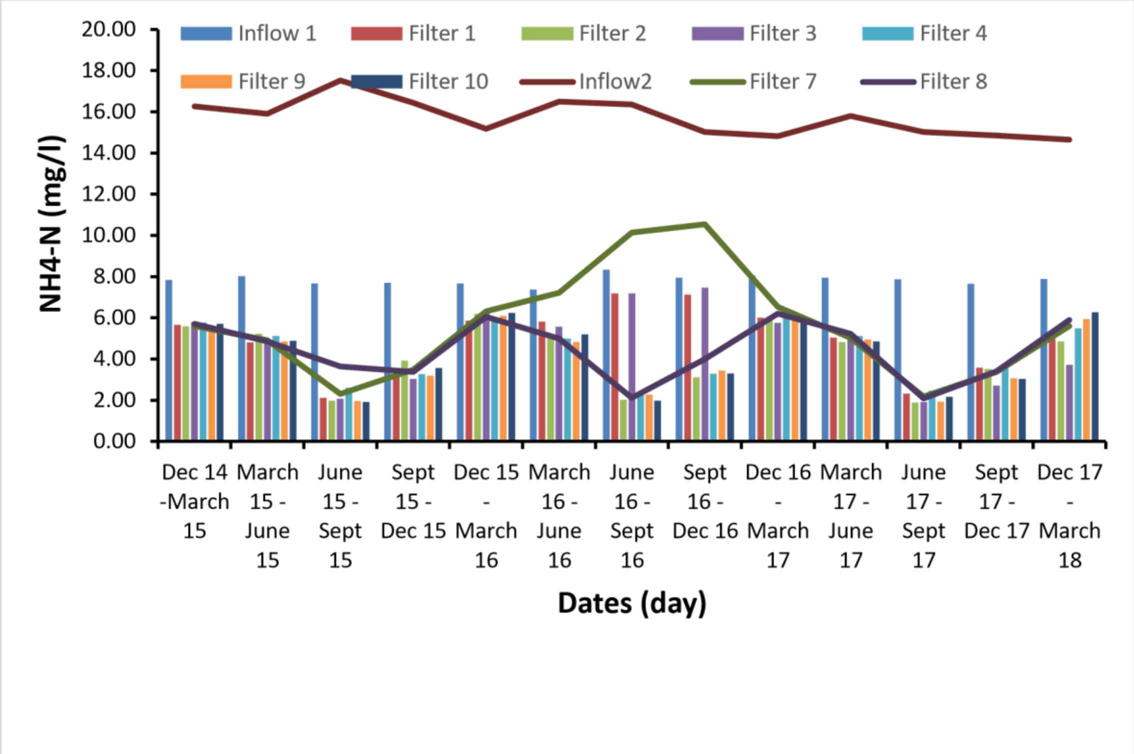


Figure 4.3: Net variations for ammonia-nitrogen of inflow and outflow relationship

Denitrification in wetlands has been described in many publications and positively correlated with organic carbon supply from macrophytes and temperature (Miklas Scholz et al., 2010). Though the concentration of nitrate-nitrogen present in the inflow was recorded to be relatively low (Table 4.1), the outflow concentrations of nitrate nitrogen were relatively high for all filters (Tables 4.2, 4.3, 4.4 and 4.5). Only Filters 3, 4, 7, 8, 9 and 10 had favorable removal efficiencies (though very small). In contrast, other filters functioned as sources for nitrate-nitrogen in the first experimental phase. In the second and third preliminary phases, however, Filters 1, 2, 7, 8 and Filters 1, 2, 3, 4, 7 and 8 had low favorable removal efficiencies respectively. However, the outflow concentration of other filters served as a source for nitrate-nitrogen. However, the necessary conditions for denitrification to take place were not directly observed within the entire pilot constructed wetlands, because this can lead to high damage to the system (Sani et al., 2013b).

A typical standard by UK regulations (UK Government, 1994) was not set for ammonia nitrogen that would relate to the treatment system used in this experiment. However, a practical guideline threshold value concerning secondary wastewater treatment in this experiment would be 20 mg/l (Sani et al., 2013b) as shown in figure 4.3. In comparison, a common standard set by environment agencies for the second nitrogen variable, nitrate-nitrogen, concerning the secondary treatment of wastewater is 50 mg/l (Sani et al., 2013). All filters were obedient with rules and standard.

General performance of constructed wetland filters concerning the nutrients parameters indicates that all the nutrients were relatively removed from all filters. The overall removal efficiency was relatively excellent (Table 4.6).

4.5 Orthophosphate phosphorus Removal

A phosphate is a form of phosphorus that is found in wastewater and is one of the most significant parameters that is used mainly to determine how pollutant the wastewater is, usually called orthophosphate phosphorus (PO4-P). Phosphorus or phosphate analysis is an essential measurement in the monitoring and control of inflow wastewater treatment. The removal of phosphate in constructed wetlands is achieved by biological transformation and physical-chemical separation (Mazumder, 2013). In a research study of Kadlec & Knight, (1996), it was indicated that PO4-P removal is mostly by plant uptake through the root and adsorption on the gravel (porous media). Orthophosphates phosphorous is among the common forms of phosphorous found in wastewater presented for biological metabolism without additional breakdown.

However, the effectiveness of constructed wetlands to remove Orthophosphate phosphorus contaminants by the constructed wetland system were recorded to cover between 49 and 45%, 49 and 50%, 42 and 45%, 45% and 50% for filters 1 and 2, 3 and 4, 7 and 8, 9 as well as 10 respectively. Regardless of the loading rate in the experiment (Table 4.6), resting time and aggregate size of the gravel were not crucial parameters regarding overall Orthophosphate-phosphorus removal. This can be explained by the fact that phosphorus is always present in the form of a particulate, and does not dissolve well in filters that are not yet saturated by phosphorus or other compounds competing for adsorption sites (Miklas Scholz et al., 2010).

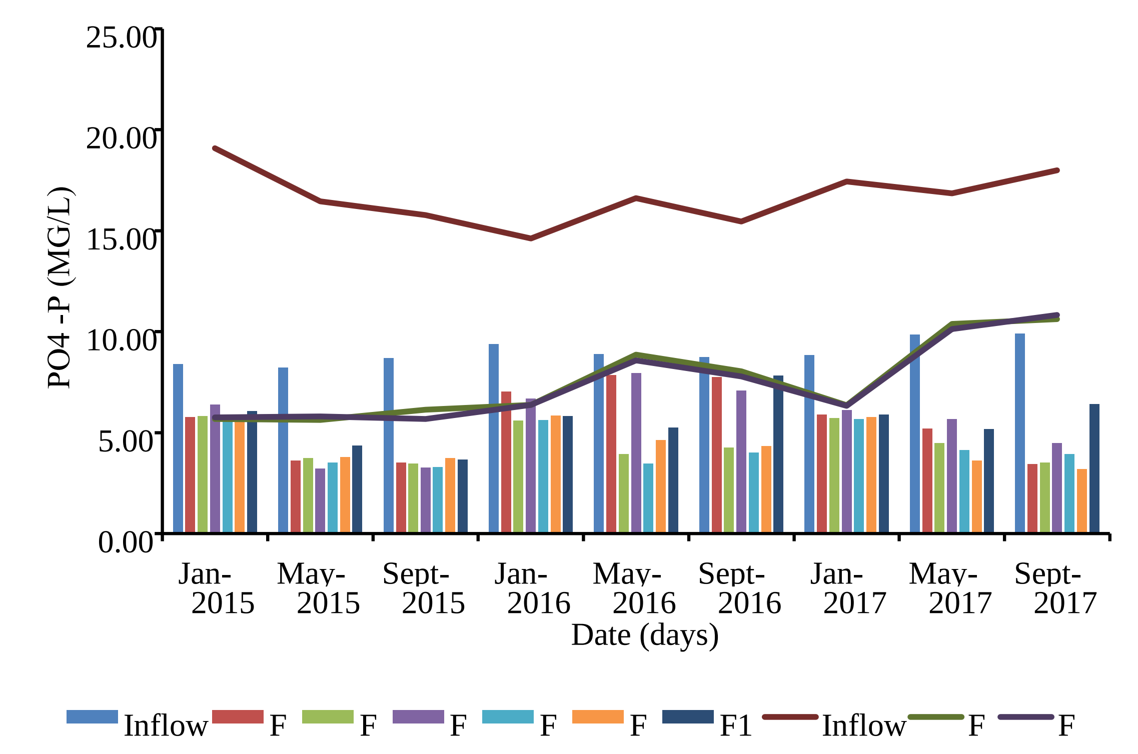


Figure 4.4: Net variations for ortho-phosphate phosphorous of inflow and outflow concentration

Phosphorus removal mechanisms in vertical flow constructed wetland constructed wetland systems were designed to contain plant as reported by Jan Vymazal, (2011b) and Jan Vymazal, (2013) in their respective research study. Moreover, microbial uptake and accretions in porous media of the constructed wetland (Gikas & Tsihrintzis, 2012), retention by system gravel and precipitation in different wetland filters (Gikas, Akratos, & Tsihrintzis, 2007). Also, many types of research have shown that phosphorus is one of the most difficult pollutants to remove by constructed wetlands (Fia, Vilas Boas, Campos, Fia, & Souza, 2014; Vera, Araya, Andrés, Sáez, & Vidal, 2014).

Phosphorus removal mechanisms in vertical flow constructed wetlands system have been designated to contain plant and microbial uptake and accretions in constructed wetland filters (Sharma et al., 2014) retention by gravel and precipitation in water filters (G D Gikas et al., 2007). Moreover, numerous research publication has revealed that phosphorus is one of the hardest water quality parameters to be removed in wastewater by constructed wetlands (Fia et al., 2014; Pant, Reddy, & Lemon, 2001; Vera et al., 2014).

All filters of the constructed wetland performed insufficiently regarding phosphorus removal in comparison to other key water quality parameters such as COD and ammonia-nitrogen. Findings confirmed by several studies (Smith, Joye, & Howarth, 2006; Sani et al., 2013) indicating that constructed wetlands were not efficient in removing phosphate in north Europe and Atlantics countries, especially during winter season.

Removal mechanisms of phosphorus in constructed wetland systems have been reported to include plant uptake (Vymazal, 2011c, 2013a), microbial uptake and accretions in wetland media (Gikas & Tsihrintis, 2012), retention by wetland substrate and precipitation in the water column (Gikas et al., 2007). Furthermore, several publications have shown that phosphorus is one of the most difficult pollutants to remove by constructed wetlands (Pant, Reddy, & Lemon, 2001; Fia et al., 2014; Vera et al., 2014).

Phosphorus particles are linked to suspended solids in constructed wetlands and are reported to be removed because of wastewater adsorption, settlement, and microbial. However, the increase of these suspended solids through the adhesion of biofilms due to microorganism growth contributes (Hua, Zeng, Zhao, Cheng, & Chen, 2014; W. Zhang, Qu, Li, Wang, & Wu, 2012) as a result of that limiting the effectiveness and productivity of the constructed wetland systems. In this research, the overall wetland performance in removing the phosphorus good in all filters of the wetland (Tables 4.2, 4.3, 4.4, 4.5 and 4.6). This has been established in a respective work of Almuktar et al., (2015), who recorded high performance efficiency in phosphorus removal in their constructed wetland systems. They credited better performance achieved by the system to the microbial activity and high aeration that endorsed the high phosphorus biodegradation. Also, hydraulic conductivity, porosity and both high strength and SS load of the wastewater, among others. And dead macrophyte plant material that was harvested in winter and returned to the corresponding wetland filters.

These results of the nutrient removal were also achieved in other study researches. IStefanakis & Tsihrintzis, (2009) discovered that, after one year of monitoring operation of the constructed wetland systems the result obtained indicated that removal nutrients pollutants were recorded in all units, as removal of nitrogen recorded satisfactory removal and 42.2% for ammonium nitrogen (NH4-N) removal, ortho-phosphate retention rates recorded about 36.9% and 37.9%, respectively. In the research study of

4.5.1.1 Comparison of particles

Suspended solids are the minor solid particles that continue in suspension in wastewater. It is one of the parameters that contribute to the worsening the quality of water, and it is abbreviated as SS. The number of suspended solids indicates how cloudy the wastewater is. The SS removal also leads in a sharp decrease of organic load content in wastewater, generally demonstrated as biochemical oxygen demand (BOD) or chemical oxygen demand (COD) (Jover-Smet, Martín-Pascual, & Trapote, 2017). Previous research of well-designed constructed wetland have recorded high efficiency of suspended solid removal performance from wastewater (Dębska et al., 2015; Manios et al., 2003; Torrens Armengol, 2016). The suspended solid present in wastewater, possibly contain many pollutants like nutrient and organic compound family and trace of heavy metal that may be found in particulate form (Jiang, 2015).

Several studies confirmed that solids and particulate matter removal are achieved (Kadlec & Knight, Green et al., 1997; Leonard, 2000; ITRC, 2003; Garcia et al., 2010; Hua et al., 2013) via settling and sedimentation, adsorption, and microbial degradation in wetland systems.

Previous Studies reported that sedimentation, filtration, aggregation and surface adhesion are the primary removal mechanisms for large suspended solids from wastewater before feeding into the constructed wetland for treatment (Vymazal, 2014; Jan Vymazal & Kröpfelová, 2008). Some studies at the past confirmed that solids and particulate matter removal are achieved through settling and sedimentation, adsorption, and microbial degradation in constructed wetland systems (Garcia et al., 2010; R H Kadlec & Knight, 1996a; Zou et al., 2012).

The overall performance efficiencies for Suspended Solid SS removal were recorded to be adequately high for all the filters of the wetland (table 4.2 too). A loading rate is higher with a significant p-value of 0.05 had impacted negatively on the general treatment performance of the system, finding discovered that suspended solids collected in the top part of the filters. As a resulting deposit of dry litter layer creation for years of the treatment operation and monitoring. This is confirmed by the study research of Scholz, (2010) and Sani et al., (2013c). The presence of different porous media gravel sizes in the wetland filters did not seem to have any impact on solids holding. During the early periods of treatment operation and monitoring.

The overall performance efficiencies for SS removal were recorded to be high for all the filter of the system (Tables 4.2, 4.3, 4.4 and 4.5). A higher loading rate had a significantly (P 0.05) negative impact on the overall treatment performance before petroleum hydrocarbon contamination (Table 4.6). Suspended solids accumulated in the top part of the filters as a result of litter layer formation two years later, confirming findings by Hua et al. (2010), Scholz (2010) and Sani et al. (2013b). The presence of different aggregates did not seem to have an influence on solids retention, at least in the early stages of operation.

It was reported in a research study of Vymazal et al., (1998), that suspended solids are mostly eliminated by physical processes like filtration and sedimentation. Filtration takes place by the particles influence the roots and stems of the plants and porous media particles in Constructed wetland systems. The effect of the feeding mode on the removal of suspended solids may be explained by its impact on the sedimentation rate of the suspended particles. In the batch mode of feeding the wetland system is filled with wastewater for a determined period and subsequently drained entirely before the next batch of effluent is applied.

Overall, all constructed wetland filters 1 to 8 were 8, 12, 4, 7, 14, 10, 9 and 13 times noncompliant with the regulation, respectively. More recently, the regulations (UK Government, 1994) have reset SS value of 35 mg/l. Filters 1 to 8 were 5, 9, 4, 7, 11, 10, 8 and 8 times noncompliant, respectively (Figure 4.5). Moreover, authorities try to respect the more rigid traditional guideline.

The UK standard for SS removal from secondary wastewater (treated water from constructed wetland) set 30 mg/l (Royal Commission on Sewage Disposal, 1915). Figure 4.5 is diagram representation that depicted a net variation of suspended solids of inflow and outflow concentration during the operation period in different vertical-flow constructed wetlands filters.

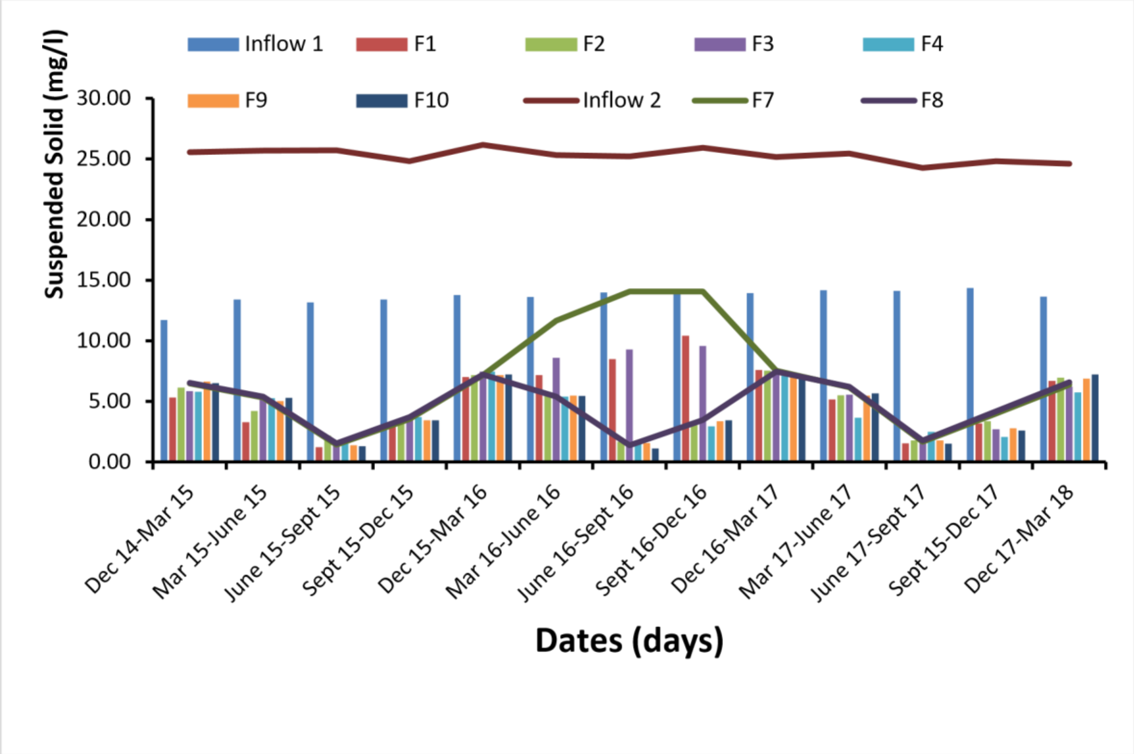


Figure 4.5: Net variations of Suspended Solid of inflow and outflow concentration during the operation period

Figure 4.4 is the concentration of suspended solids in the wastewater inflow and the corresponding values of treated water outflow of VFCWs throughout the monitoring experiment

4.6 Evaluation of Dissolve oxygen (DO) Parameters

The assessment of dissolve oxygen was evaluated graphically by the plot of the monthly mean inflow and outflow. A significant increase of dissolved oxygen was observed in the plot (i.e. concentration of dissolve of outflow is higher than of inflow). The constant low concentration of dissolved oxygen is observed in inflow wastewater whereas in outflow treated water the concentration of dissolved oxygen is recorded to higher. This an indication of wastewater treatment improvement performance by constructed wetland as dissolved oxygen concentration increased. It was also noticed that the preliminary unpleasant odour of the raw wastewater was no more perceptible, and the colour of the outflow treated water is clearer than the inflow wastewater. Figure 4.6 is the seasonal mean inflow and outflow of the dissolved oxygen concentration for the complete monitoring period of the research timeframe

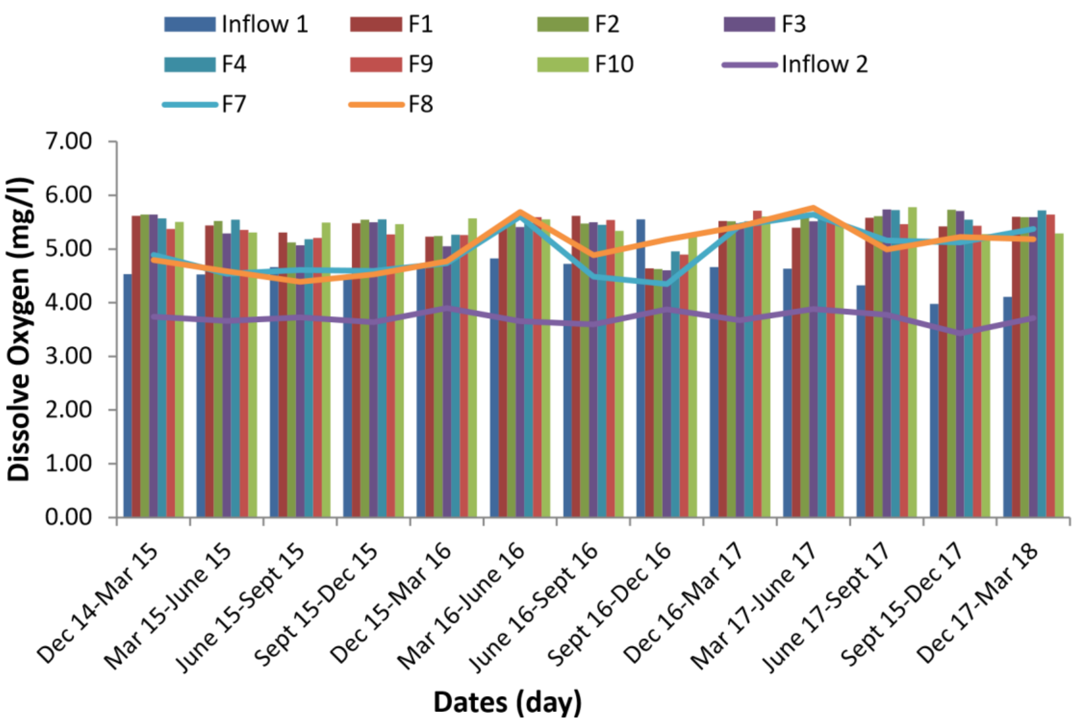


Figure 4.6: Trend of dissolve oxygen for inflow and outflow concentration during the monitoring period

Figure 4.4 is the concentration of dissolved oxygen in the wastewater inflow and the corresponding values of treated water outflow of VFCWs throughout the monitoring experiment. It was observed that from the figure 4.7 that dissolve oxygen has significantly increased from inflow to outflow, as can be seen the amount dissolve oxygen in both inflow 1 and inflow 2 samples were low, however treatment of the wastewater (inflow 1 and 2) improved the content of DO in all the filters of the CW. The results recommend the vital role of oxygen guiding the treatment processes as well as the possibility of constructed wetlands for wastewater treatment. This an indication that the DO significantly improves the treatment performance of constructed wetland by effectively treat pollutant concentration as DO is an essential parameter since most important degradation processes need aerobic situation, and therefore sufficient oxygen supply is of high importance. Dissolve oxygen increase could be credited to the nature of constructed wetland that provides adequate aeration and longer contact time for the reduction of organic matter parameter. This is the reason that VFCWs are suggested a system to treat highly polluted wastewater with little amount dissolve oxygen (Villar et al., 2012). Oxygen plays an important role in achieving nitrification;

Table 4.14: Overview of the statistically significant differences between outflow water quality variables of different wetland filters using the non-parametric Mann-Whitney U-test

(03/12/14-28/03/18)

Parameter	Unit	Statistics	Aggregate Diameter[a]	Contact Time[b]	Resting Time[c]	COD[d]
First to third experimental phase (03/12/2014 – 25/09/2017)						
COD	mg/l	P-value	0.185	0.000	0.825	<0.000
		h	0	1	0	1
BOD	mg/l	P-value	0.000	0.000	0.003	<0.000
		h	1	1	1	1
PO4-P	mg/l	P-value	0.088	0.000	0.000	<0.000
		h	1	1	1	1
NO3-N	mg/l	P-value	0.198	0.000	0.948	<0.000
		h	0	1	0	1
NH4-N	mg/l	P-value	0.412	0.000	0.266	<0.000
		h	0	1	0	1
SS	mg/l	P-value	0.465	0.040	0.461	<0.000
		h	0	1	0	1
TBD	NTU	P-value	0.833	0.000	0.867	<0.000
		h	0	1	0	1
Parameter	Unit	Statistics	Aggregate	Contact Time[f]	Resting	COD[h]

			Diameter[e]		Time[g]	
Fourth experimental phase (26/09/2017 – 28/03/2018)						
COD	mg/l	P-value	0.706	0.156	0.926	0.200
		h	0	0	0	0
BOD	mg/l	P-value	0.000	0.019	0.455	0.532
		h	1	1	0	0
PO4-P	mg/l	P-value	0.003	0.000	0.017	0.001
		h	1	1	1	0
NO3-N	mg/l	P-value	0.001	0.000	0.369	0.049
		h	1	1	0	0
NH4-N	mg/l	P-value	0.261	0.000	0.472	0.230
		h	0	1	0	0
SS	mg/l	P-value	0.029	0.006	0.162	0.321
		h	1	1	0	0
TBD	NTU	P-value	0.604	0.921	0.485	0.221
		h	0	0	0	0
Parameter	Unit	Statistics	Aggregate Diameter[i]	Contact Time[j]	Resting Time[k]	COD[l]
Fourth experimental phase (26/09/2017 – 28/03/2018)						
COD	mg/l	P-value	0.174	0.090	0.926	0.231
		h	0	0	0	0

BOD	mg/l	P-value	0.048	0.004	0.623	0.129
		h	0	1	0	0
PO4-P	mg/l	P-value	0.004	0.001	0.010	0.121
		h	0	1	1	0
NO3-N	mg/l	P-value	0.044	0.007	0.369	0.896
		h	1	1	0	0
NH4-N	mg/l	P-value	0.126	0.423	0.472	0.638
		h	0	0	0	0
SS	mg/l	P-value	0.123	0.001	0.205	0.937
		h	0	1	0	0
TBD	NTU	P-value	0.858	0.751	0.458	0.321
		h	0	0	0	0

4.7 Evaluation of pH Parameters on the treatment performance of VFCWs

pH is the measurement of the strength of acidity or alkalinity and quantifies the concentration of hydrogen ion in water. The Nature of inflow wastewater samples is always continuous change between acidic and alkaline. The range of pH value recorded in this study research of inflow wastewater was 7.28, and after wastewater treatment, it became 6.9 on the average as can be seen from figure 4.4 which shows the neutral nature of wastewater.

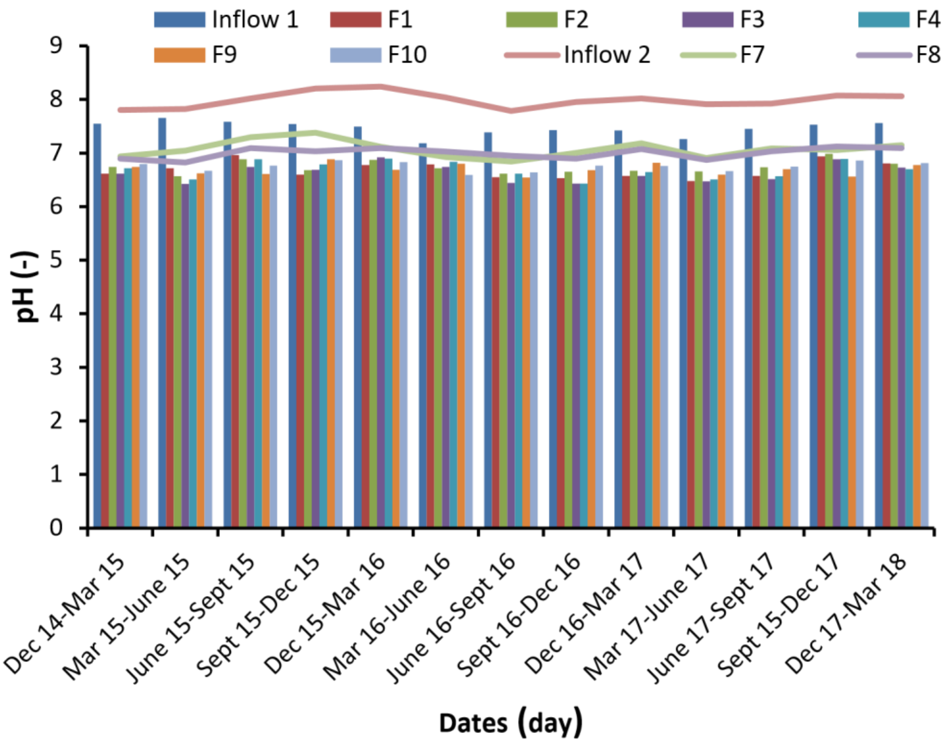


Figure 4.7: Trend of pH for inflow and outflow concentration during the monitoring period

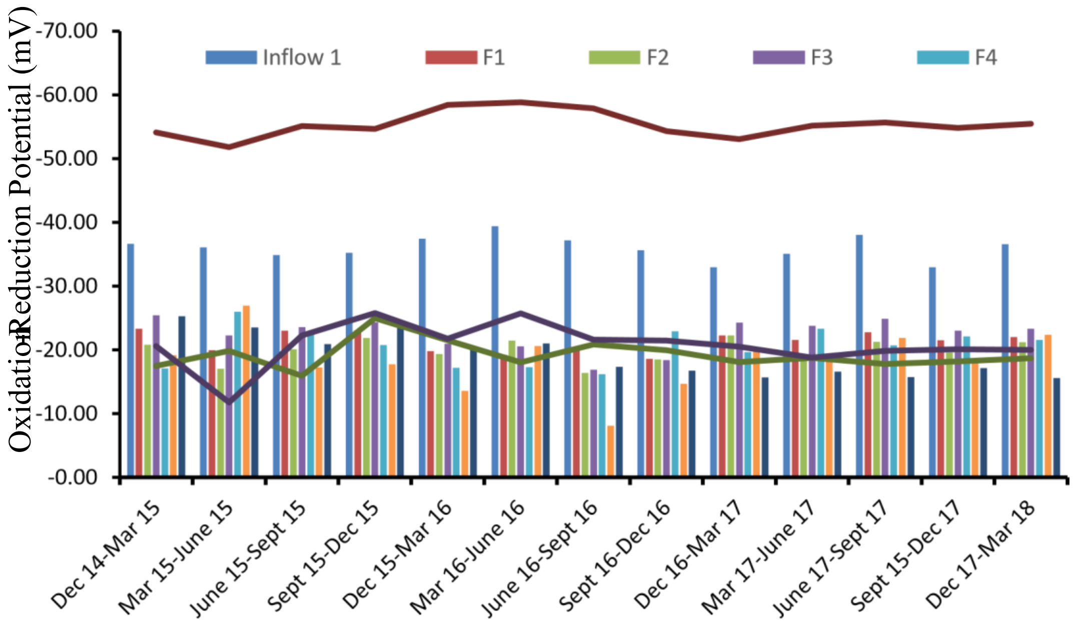
In the research study of Tchobanoglous, Burton, & Stensel, (2003) observed that the ideal range value of pH for the heterotrophic bacteria growth is between 6.5 and 7.5 while in the research study of Von Sperling, (2007) showed that the most appropriate pH value range is between 7 and 8 for all bacteria decomposition and organic carbon, nitrogen and phosphorus removal. pH value above 8, the removal of nutrient is still possible, but the removal rate of the nutrient can be very different from the ideal one.

The recorded mean pH values were found to be between the ranges of 7 to 8 which shows that the wastewater and treated water samples are slightly alkaline. The values are within the maximum permissible pH value limit and in compliance with the recommendation range of pH values as prescribed by WHO

According to Kadlec et al., (2000) indicated that the idle pH range needed for ammonification is (6.5 – 8.5), nitrification by ammonium-oxidizing bacteria (AOB) and nitrite-oxidizing bacteria (NOB) at the pH value range of 7.6 – 8.6, denitrification by anaerobic oxidizing bacteria at the range 7-8 and phosphorus removal

4.8 Evaluation of oxidation-reduction potential (ORP) Parameters

Oxidation-reduction potentials or redox conditions can be used as an indirect measurement of the anaerobic and aerobic conditions frequent in the wastewater treatment by constructed wetland system systems. Oxidation-reduction processes can be related to content of oxygen, which characterized by the loss (oxidation) or gain (reduction) of electrons. But, as it is not the only element that can amend it, some other considerations have to be made, like aerobic bacteria presence (Dušek, Picek, & Číţková, 2008) Oxidation-reduction conditions are also crucial for the capacity of constructed wetlands to retain inorganic phosphorus (Bezbaruah & Zhang, 2004). Detailed analyses and measurements reporting of ORP would permit better characterisation and understanding of the physicochemical and biological interdependence of wastewater treatment method.



Date (day)

Figure 4.8: Graphical representation of ORP for inflow and outflow concentration during the monitoring period

As can be seen Generally, ORP values were observed to be negative in the constructed wetland indicating the reducing conditions. ORP values were observed to differ between -49 mV and –21 mV for inflow 1 while -81 mV and -35 mV for inflow 2. Likewise, for the outflow filters the range of ORP values are between -36 and -8. It was observed that ORP decreased with increasing organic pollutant loading. This variation values of ORP validates that it is affected by the created oxygen by the macrophyte during the wastewater treatment process. This phenomenon could be explained by the fact that more oxygen would be consumed by biological oxidation of excess organic matter removal (Fei et al., 2016)

ORP values lower than −100 mV shows decrease in sulphates content and organic substances (fermentation). However, to make it standard, all ORP values recorded are described with regards to the standard hydrogen electrode (Eh) (Guido-Zárate, Buitrón, Mijaylova-Nacheva, & Duránde-Bazúa, 2007). The measurement of redox potential has widely been used to characterise oxidation-reduction conditions of wetland soils (Michael J Vepraskas, Richardson, Vepraskas, & Craft, 2000). The biological reduction of nitrate, denitrification, is an vital water purification process that transforms nitrate into nitrogen gas. This process is highly active in constructed wetlands for swine wastewater treatment (Hunt et al., 2003).

Anaerobic and aerobic environments can be distinguished by the ORP in a Constructed wetland system. Generally, an ORP value greater than 100 mV is considered as an aerobic environment, whereas an amount less than − 100 mV indicates an anaerobic condition (Ong,

Uchiyama, Inadama, Ishida, & Yamagiwa, 2010) So, an ORP range from − 100 to 100 mV can be considered an anoxic environment. The aerobic and anoxic/anaerobic regions in CW bed would influence the activity of microbes in the biodegradation of organic matter, nitrification, and denitrification (Liu et al., 2018). Evaluation of Electrical conductivity Parameters

4.9 Overall wastewater Treatment Performance of vertical flow constructed wetland system

The levels of each parameter in the wastewater influent and the resultant treated water outflow throughout the experiment were averaged. To compare the effect of the treatment performance of the constructed wetland, the removal efficiency was calculated and are provided in the tables.

Because of the diesel that was poured into filters 1, 3, 5 and 7 the common reed plants that were planted on these filters were gradually diminishing and finally dead, new common reed plant were re-planted on Monday 12th September 2016 base on the result analysis conduct in the laboratory, it was observed that within the first three months the treatment performance of new plants was recorded very low (start-up time), after that it was recorded to be a bit higher than the first 3 months before they adopt, become mature and continue treating the wastewater properly.

Table 4.15: Overall water quality parameters for all the wetland filters from 3rd December to 28th March 2018

	Overall Performance						
	From 03/12/2014 to 28/03/2018						
Parameter	Unit	Number	MO	RE (%)	Maximum	Minimum	SD
	Inflow 1						
COD	mg/l	231.000	154.547	N/A	196.800	80.600	25.853
BOD	mg/l	233.000	87.528	N/A	108.000	32.000	11.472
PO4-P	mg/l	225.000	9.051	N/A	15.300	5.760	1.337
NO3-N	mg/l	232.000	1.119	N/A	1.990	0.540	0.259
NH4-N	mg/l	231.000	7.840	N/A	9.940	5.190	0.999
SS	mg/l	230.000	13.583	N/A	18.000	5.000	1.569
TBD	NTU	231.000	13.200	N/A	15.170	8.050	1.482
EC	mS/m	231.000	684.882	N/A	987.000	270.000	114.128
	Filter 1						
COD	mg/l	233.000	75.676	51.034	477.000	16.600	49.434
BOD	mg/l	233.000	45.098	48.476	94.000	12.000	20.938

PO4-P	mg/l	228.000	5.392	40.432	9.780	1.930	1.909
NO3-N	mg/l	232.000	0.598	46.581	1.433	0.011	0.262
NH4-N	mg/l	234.000	4.897	37.540	8.750	1.010	1.770
SS	mg/l	230.000	5.274	61.172	15.000	0.000	3.064
TBD	NTU	232.000	4.842	63.317	14.060	0.850	2.796
EC	mS/m	233.000	389.021	43.199	791.000	104.000	157.585
	Filter 2						
COD	mg/l	233.000	48.956	68.323	88.600	14.900	16.267
BOD	mg/l	233.000	33.521	61.703	55.000	12.000	11.166
PO4-P	mg/l	228.000	4.504	50.237	7.980	1.840	1.360
NO3-N	mg/l	232.000	0.453	59.479	1.231	0.022	0.213
NH4-N	mg/l	234.000	4.167	46.851	8.480	1.010	1.706
SS	mg/l	230.000	4.270	68.566	9.000	0.000	2.349
TBD	NTU	232.000	3.397	74.265	7.510	0.790	1.425
EC	mS/m	233.000	303.034	55.754	528.000	109.000	118.229
			Filter 3				
COD	mg/l	233.000	71.209	53.924	164.000	18.700	37.449
BOD	mg/l	233.000	39.455	54.923	90.000	12.000	20.128
PO4-P	mg/l	227.000	5.514	39.078	9.950	1.670	1.883
NO3-N	mg/l	232.000	0.540	51.743	1.346	0.110	0.255

NH4-N	mg/l	233.000	4.720	39.796	8.770	1.010	1.981
SS	mg/l	230.000	5.565	59.027	16.000	0.000	2.993
TBD	NTU	232.000	4.712	64.302	12.130	0.750	2.536
EC	mS/m	233.000	393.987	42.474	2558.000	109.000	205.629
Filter 4							
COD	mg/l	233.000	54.247	64.899	741.900	18.900	58.518
BOD	mg/l	233.000	33.508	61.718	54.000	12.000	10.900
PO4-P	mg/l	229.000	4.413	51.244	8.340	1.300	1.545
NO3-N	mg/l	232.000	0.416	62.813	0.890	0.043	0.174
NH4-N	mg/l	233.000	4.330	44.770	7.280	1.010	1.552
SS	mg/l	230.000	4.074	70.006	9.000	0.000	2.267
TBD	NTU	232.000	3.427	74.036	5.780	0.790	1.325
EC	mS/m	233.000	311.146	54.569	533.000	102.000	121.933
Filter 9							
COD	mg/l	296.000	57.526	62.777	756.000	15.800	67.493
BOD	mg/l	293.000	35.102	59.896	62.000	12.000	12.035
PO4-P	mg/l	295.000	4.500	50.281	7.210	1.180	1.382
NO3-N	mg/l	292.000	0.445	60.201	0.837	0.048	0.163
NH4-N	mg/l	298.000	4.134	47.267	7.760	1.030	1.643
SS	mg/l	296.000	4.463	67.143	9.000	0.000	2.355
TBD	NTU	299.000	3.317	74.871	5.680	0.230	1.372

EC	mS/m	291.000	306.560	55.239	522.000	101.000	124.340
Filter 10							
COD	mg/l	360.000	51.333	66.785	366.000	4.300	22.499
BOD	mg/l	360.000	34.839	60.197	64.000	10.000	11.983
PO4-P	mg/l	357.000	5.530	38.903	75.620	1.870	3.936
NO3-N	mg/l	371.000	0.447	60.064	1.502	0.051	0.195
NH4-N	mg/l	382.000	4.278	45.432	7.960	1.020	1.710
SS	mg/l	390.000	4.305	68.304	9.000	0.000	2.419
TBD	NTU	383.000	3.360	74.547	5.890	0.450	1.332
EC	mS/m	373.000	322.062	52.976	526.000	102.000	125.973
Inflow 2							
COD	mg/l	230.000	266.492	N/A	313.000	136.600	32.380
BOD	mg/l	233.000	153.105	N/A	196.000	62.000	23.633
PO4-P	mg/l	223.000	16.829	N/A	44.800	6.300	4.088
NO3-N	mg/l	234.000	1.907	N/A	2.980	0.864	0.421
NH4-N	mg/l	228.000	15.743	N/A	24.760	7.790	2.378
SS	mg/l	230.000	25.343	N/A	38.000	13.000	3.072
TBD	NTU	228.000	24.001	N/A	36.500	12.120	2.551
EC	mS/m	232.000	982.026	N/A	1252.000	588.000	86.208
Filter 7							

COD	mg/l	233.000	88.320	66.858	264.000	2.000	73.152
BOD	mg/l	233.000	43.253	71.749	70.000	12.000	13.772
PO4-P	mg/l	228.000	7.369	56.211	15.330	0.040	2.983
NO3-N	mg/l	233.000	0.651	65.862	2.573	0.066	0.501
NH4-N	mg/l	233.000	5.634	64.213	15.610	1.080	2.864
SS	mg/l	230.000	7.183	71.659	21.000	0.000	4.874
TBD	NTU	232.000	6.156	74.353	19.990	0.760	5.495
EC	mS/m	233.000	429.712	56.242	952.000	102.000	201.990
Filter 8							
COD	mg/l	233.000	54.583	79.518	643.500	19.000	63.061
BOD	mg/l	233.000	44.017	71.250	72.000	12.000	14.227
PO4-P	mg/l	228.000	7.389	56.094	15.110	1.380	3.037
NO3-N	mg/l	233.000	0.432	77.354	0.954	0.087	0.190
NH4-N	mg/l	234.000	4.456	71.696	25.200	1.030	2.117
SS	mg/l	230.000	4.739	81.300	9.000	0.000	2.441
TBD	NTU	232.000	3.595	85.023	52.440	0.740	3.584
EC	mS/m	233.000	315.039	67.920	558.000	101.000	123.929

4.10 Chapter Summary

This chapter discussed the overall treatment performance of vertical flow constructed wetland. These include quality of inflow wastewater, comparison of the outflow water quality parameters, which contains organic matter parameters (COD and BOD), nutrients parameters, (PO_4-P, NH_4-N) and particles parameters (Suspended Solid). Overall, high removal rate was achieved for most of the parameters throughout the monitoring process for water quality enhancement. Thus, the removal rate of the system operation indicated that wetlands system was relatively effective with high efficiency in treating and removing pollutants from wastewater. The results demonstrated the potential of vertical flow constructed wetlands to clean treated domestic wastewater for irrigation, other agricultural and human purposes.

Chapter 5: Water Quality Parameters Prediction Using Data Mining Techniques

5.1 Overview

The data mining technique model to predict wastewater treatment performance of VFCWs were discussed in this chapter. The model was build using relevant and highly correlated input parameters obtained in various combinations, using correlation analysis. It also explained and outlines how the entire experimental dataset was partition into training data to build the data mining models and testing data to test the model build.

Additionally the chapter presented and discusses the designed and developed two data mining predictive models namely: Multiple Linear Regression (MLR) and Multilayer Perceptron (MLP) that were employed in this study to predict the performance of vertical flow constructed wetland systems (VFCWs) treating domestic wastewater, by predicting output dependent parameter based on the given values of input dependent variable. R language was employed to construct multiple linear regressions (MLR) while WEKA was used to develop the multilayer perceptron model. However, the criteria used to evaluate and compare the models prediction performance are also presented and discussed in this chapter.

5.2 Correlation

One of the requirements listed in this chapter is to choose the suitable input parameters required to develop water quality prediction with absolute accuracy. To achieve good prediction model, prior to model development correlation analysis is employed. Correlation measured the strength and direction of the linear and multiple dependencies. It measure the relationship between two or more variables (Pianosi et al., 2016). Correlation analysis result can be supplied to the model under construction to make predictions about the parameters under study, the aim was to determine the most suitable input parameters to be used for the model development to get accurate model. In this study out of all the 11 water quality parameters used for the experiment only five parameters are selected to use and considered for the prediction model development, these include COD, BOD, PO4-P, NH4-N and SS. For the COD dataset of filter 2 is chosen and used (as Filter 1 and 2 are replicated, having the same design, mode of operation contact time and resting time), for BOD dataset of filter 3 is used (as Filter 3 and 4 are replicated), for PO4-P filter 9 dataset is used for NH4-N filter 10 dataset is used (Filter 9 and 10 are not replicated) for the SS, filter 8 dataset is used (as filter 7 and 8 are replicated, as such they are all considered for the model development) filters 1, 3 and 8 are replicated (have the same design, mode of operation contact time and resting) while filters 5 and 6 are served as control receiving only clean dechlorinated tap water, therefore they are left out for the model development. Prior to model development correlation analysis was conducted investigate to the relationship between each of COD, BOD, PO4-P, NH4-N and SS as output parameters to be predicted by the model with other water quality as input parameters. This was done to give a greater understanding and select suitable input parameters to be used for MLR and MLP model‘s development. The input parameters were selected based on their relative importance in assessing water quality and the possibility of being able to predict final outflow concentration from data obtained in real time, or from other parameters that are inexpensive, simple and/or faster to analyse in the laboratory. In this study research two type of correlation analyses are employed namely: graphical and numerical correlation analysis. SPSS software has been applied to determine the statistical correlation between variables while scatter plot was used in R language for the graphical correlation analysis.

5.2.1 Numerical correlation analysis

Is a numerical analysis that measures the strength and direction of a linear relationship between numerical variables and displays the result numerically, it numerical values vary from 1 through -1 values

The correlation coefficient (R) between the output variable (dependent) and input variables (independents) for different filters of constructed wetland ware calculated as shown. Table 5.1 – 5.5 summarises the finding from numerical correlation analysis by SPSS software comparing input variables and output target variable. The input parameters are selected based on their goodness with their corresponding output variables. Some of the correlations were weak while others are strongly correlated. Therefore, significant input variables were selected base on their highly correlated and with their corresponding output parameters. Understanding the relationship between the output parameter (under investigation) and input parameters is required to achieve a more practical and accurate model.

5.2.2 Correlation analysis of COD and its corresponding input parameters

Correlation analysis was conducted between COD as an output parameter, and all the water quality parameters used in the experiment as inputs. The result of the correlation analysis is presented in Table 5.1, and data obtained from Filter 2 is used for this purpose. As shown in Table 5.1, the correlation analysis indicated a high correlation between BOD, PO4-P, NO3N, SS, turbidity, electrical conductivity and temperature as input parameters and COD as an output parameter. However, DO, and pH shows no correlation tendency with COD. Therefore, the highly correlated parameters show a significant trend to be used as a variable for COD prediction. Thus, their deployment in the model development. And it's corresponding input parameters. The correlation analysis of the parameters was used as a tool for the parameters interaction among the water quality parameters and hence their influence on COD concentration prediction.

Table 5.1: Correlation analysis between COD as an output variable and other water quality parameters as input parameters

Filter 2		
Input Parameter	Output Parameters	Correlation Values
	BOD	0.68646
	PO4-P	0.62410
	NH4-N	0.57630
	NO3-N	0.63136
	SS	0.54149
COD	DO	0.01440
	TBD	0.55272
	pH	-0.12113

	EC	0.58959
	TEMP	0.57577

5.2.3 Correlation analysis of BOD and its corresponding input parameters

Table 5.2 shows the correlation analysis results obtained between all the water quality parameters used in the present study and BOD. Filter 3 and 4 have the same design criteria (aggregate size, mode of operation, contact time and resting time). Therefore, data obtained from Filter 4 was used for the correlation analysis between BOD and the water quality parameters.

The correlation analysis results obtained show that the input parameters including: COD, PO4-P, NH4-N, NO3-N, SS, TBD and EC are found to holds significant positive correlation with BOD. However, DO and pH shows negative correlation with BOD and hence insignificant variables for BOD model development. These parameters with higher positive correlation values was used for the BOD prediction model using both MLR and MLP. To see the parameter interaction among the water quality parameters, correlation analysis was employed and the one that shows high positive correlation values with BOD was used for the BOD concentration prediction model.

Table 4.2: Correlation analysis between BOD as output variable and other input water quality parameters

Filter 4		
Input Parameter	Output Parameters	Correlation Values
	COD	0.79646
	PO4-P	0.73620
	NH4-N	0.76387
	NO3-N	0.78618

BOD	SS	0.74142
	DO	-0.07296
	TBD	0.73343
	pH	-0.09664
	EC	0.77851
	TEMP	0.60793

5.2.4 Correlation analysis of NH4-N and its corresponding input parameters

The correlation analysis between NH4-N as output parameters and water quality parameters used in the current work is shown in Table 5.3. Water quality parameters data obtained from Filter 9 was used for NH4-N correlation. All water quality parameters in the present work were used as input parameters while NH4-N was used as an output parameter. To develop the model that will predict the NH4-N accurately a highly correlated water quality parameter with NH4-N is needed.

From the correlation analysis results as shown in Table 5.3, the input parameters including COD, BOD, PO4-P, SS, TBD and EC shows a significant and positive correlation with the output parameter NH4-N. The remaining parameters including NO3-N, DO, EC, pH and Temp shows an insignificant correlation with the output parameter NH4-N. Therefore, COD, BOD, PO4-P, SS, TBD and EC were used in predicting NH4-N concentration employing the two data mining techniques adopted in the present investigation.

Table 5.2: Correlation analysis NH4-N as an input variable and other water quality parameters as an output variable

Filter 9		
Input Parameter	Output Parameters	Correlation Values
	COD	0.79812
	BOD	0.83269

	PO4-P	0.68065
	NO3-N	0.03536
NH4-N	SS	0.86246
	TBD	0.88325
	pH	0.01902
	EC	0.79226
	DO	0.12014
	TEMP	0.15652

5.2.5 Correlation analysis of PO4-P and its corresponding input parameters

Table 5.4 shows the correlation analysis results obtained between PO4-P as an output parameter and all the water quality parameters used in the current investigation as inputs variables. The VFCWs data obtained from Filter 10 was used for the PO4-P parameter interaction with the water quality parameters.

The results obtained for the PO4-P correlation analysis shows that the input variables COD, BOD, NH4-N, SS, TBD and EC were highly correlated with the output variable PO4-P, while NO3-N, pH, DO and Temp shows a weaker correlation with PO4-P. Thus, the highly correlated variables were employed in the model development for PO4-P prediction using MLR and MLP.

Table 5.3: Correlation values for PO4-P as input variable and other water quality parameters as output variable

Filter 10		
Input Parameter	Output Parameters	Correlation Values
	COD	0.62048
	BOD	0.50708
PO4-P	NO3-N	0.08563

	NH4-N	0.69876
	SS	0.54019
	TBD	0.74125
	pH	0.01717
	EC	0.51358
	DO	0.12860
	TEMP	0.14300

5.2.6 Correlation analysis of SS and its corresponding input parameters

Table 5.5 shows the correlation analysis results obtained between SS and the water quality parameters used in the present work. The SS was used as an output variable while the input variables consists of all the water quality parameters considered in the current research. Filter 7 and 8 are similar in design parameters and operational variables, and therefore, filter 8 data was used for the SS correlation with other water quality parameters.

The results of the correlation analysis of SS as an output parameter with other input water quality parameters are presented in Table 5.5, indicated that BOD, NO3-N, PO4-P NH4-N, TBD and EC has higher positive correlation and very significant with SS as an output variable. COD and DO shows a weaker correlation while pH and Temp shows a negative correlation, thus term as insignificant input variable with SS. The highly significant and positive input variables were used in the model development for SS prediction using the data mining techniques employed for conducting the present investigation.

Table 5.4: Correlation values for SS as output variable and other water quality parameters as output variable

FILTER 8		
Input Parameter	Output Parameters	Correlation Values
SS	COD	0.18467
	BOD	0.78655
	NO3-N	0.65254
	PO4-P	0.60677
	NH4-N	0.53187
	TBD	0.75379
	pH	-0.00382
	EC	0.78852
	DO	0.06424
	TEMP	-0.16053

The correlation analysis results as summarises in Table 5.1 – 5.5 were obtained from SPSS by comparing input variables with output variable as targeted parameter. The input parameters that are highly correlated with the corresponding output variable are selected for the prediction model. Also, input parameters that shows weaker or insignificant correlation with the output or targeted parameter were discarded or not included in the model development.

5.3 Graphical correlation analysis

After calculating the numerical correlation analysis between the output and input variables, representing such relationship (correlation) pictorially, graphical correlation methods are employed. To describe in a step-by-step procedure graphically, scatter plot is used, visual summaries of the correlation data. To confirm the result of the numerical correlation analysis conducted in Figure 5.1 to 5.5, graphical correlation analysis is depicted and presented using scatter plot to pictorially represent such relationship to reaffirm the result obtained. The aim of the graphical representation is to graphically support and back up the already obtained results of the correlation analysis that can be used to predict the output variable by establishing the relationship with the input variable. Scatter plot is used for the graphical analysis usually drawn to obtain a correlation, scatterplot depicts the strength, direction, relationship between two parameters are linear or curved, and supports the interpretation of the correlation (Fu & Wang, 2012). The value of output parameter appears on the y axis of the plot while the values of input parameters appear on the x axis. Each value of the data appears as a point on the graph.

To plot graphical representation of all parameters used in the COD prediction data (Filter 2 data). For the complete picture of all parameter‘s relationships, rather than just a single one, pairwise scatterplot in R language is employed. The output of the preceding function is pictured below; the plot run on an entire of the variable the interest is to visualize all the scatterplots at once, to diagnose the various relationships present in the entire COD dataset and produce a matrix of scatter plots. Figure 5.1 is the pairwise matrix scatter plot, which visualise the relationship between all the parameters of the COD dataset in one single image. It was observed according to the visual representation that some of the parameters are correlated to each other.

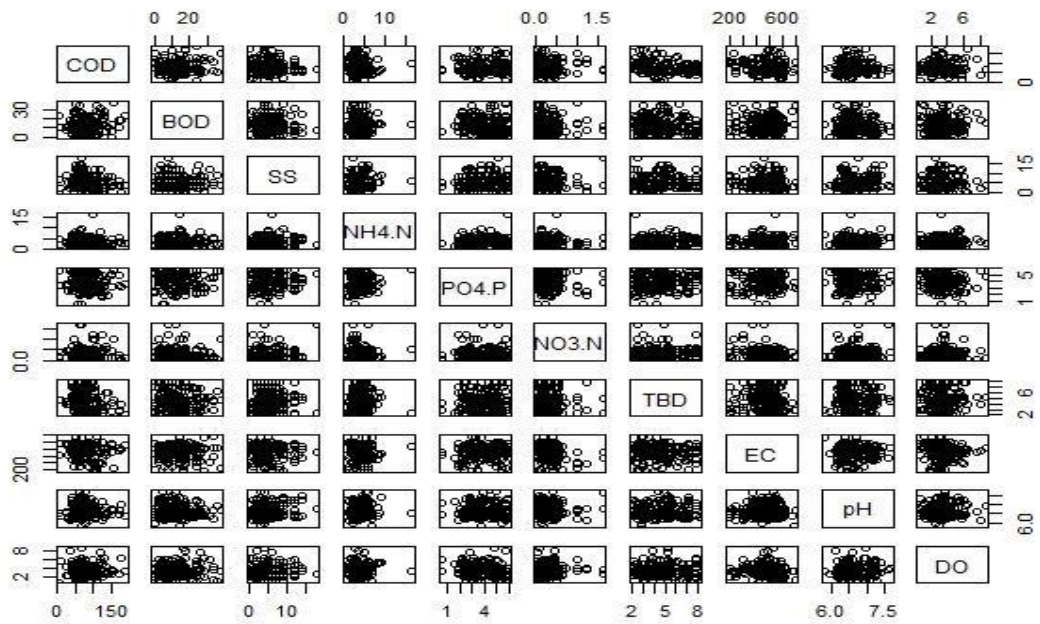
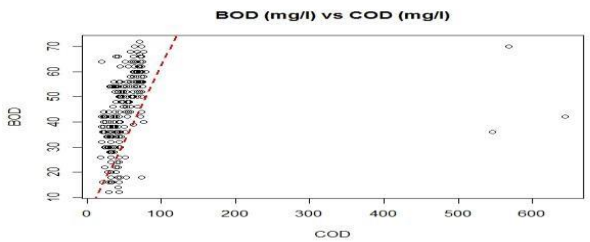
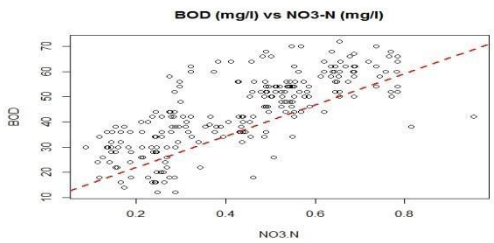


Figure 5.1: matrix scatterplot for all the variables in COD dataset

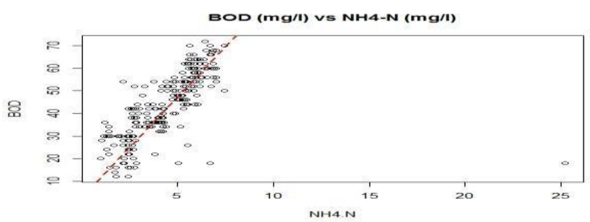
However, the matrix scatter plot did not depict graphical correlation relationship between them clearly for proper illustration. Hence, the need of individual graphical correlation as contain in Figure 5.2 to 5.6

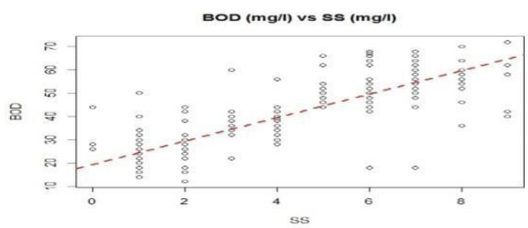




a

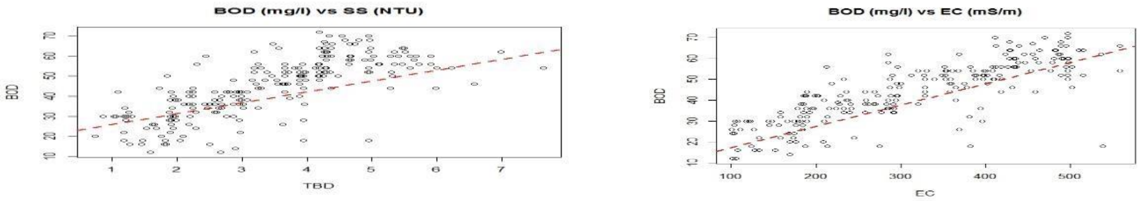
b





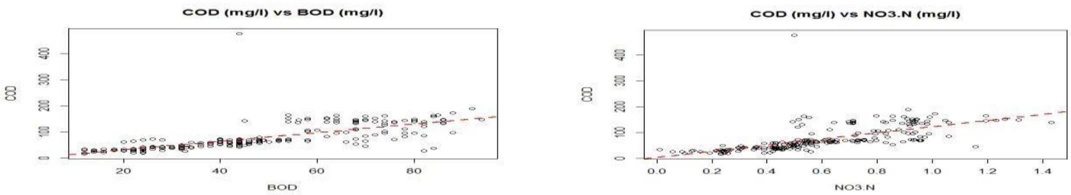
c

d

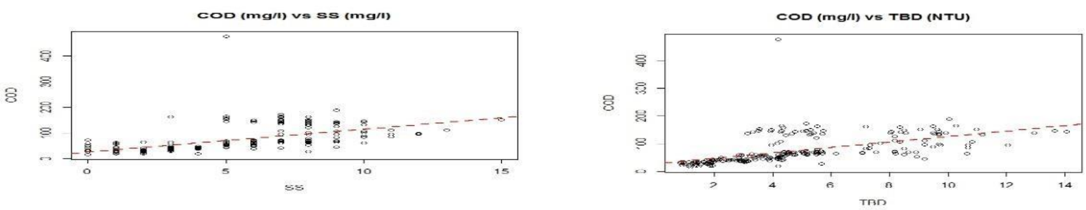


e f

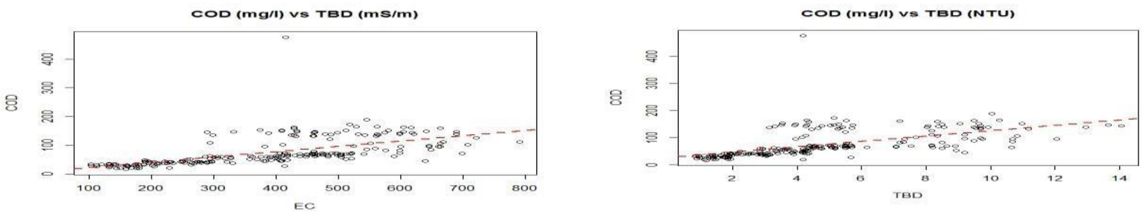
Figure 5.2: Graphical correlation between BOD and corresponding correlated input parameters



a b



c d



e f

Figure 5.3: Graphical correlations between COD and its corresponding correlated input parameters

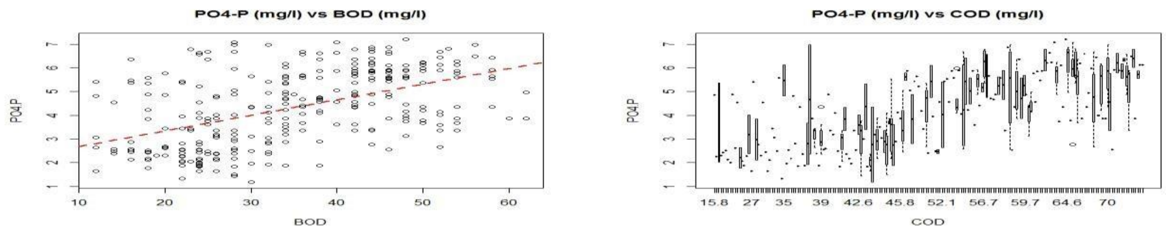
From Figure 5.2 and 5.3 are graphical correlation analysis for the BOD and COD output parameter and their respective input parameters respectively to check the picture of the relationship between them before embarking on real analysis. From the plots it was discovered that the scatter plot reaffirms the result of the numerical correlation already calculated. However, Figure 5.3 and 54 are the graphical correlation analysis for NH4-N and PO4-P output parameters and their respective highly correlated input parameters. As can be seen from the graphs, that they indicated NH4-N was in good agreement with COD, BOD,

PO4-P, SS, TBD and EC this is confirm by numerical correlation in table 5.3. However, as can be seen from the scatter plot that PO4-P as an output parameter it was discovered to be highly correlated with BOD, COD, NH4-N, SS, TBD and EC and this confirm the result of numerical correlation analysis in Table 5.3. The plot indicates that the procedure is making progress with the linear model and is likely to achieve a good model.

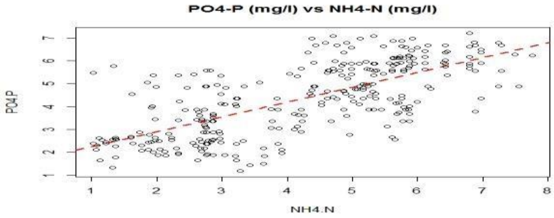
However, as can be seen from the scatter plot in Figure 5.3 that PO4-P as an output parameter is discovered to display positive high correlation with BOD, COD, NH4-N, SS, TBD and EC and this confirm the result of numerical correlation analysis obtained in table 5.3. Let start by plotting two variables (BOD and COD). The relationship between COD and BOD is depicting below.

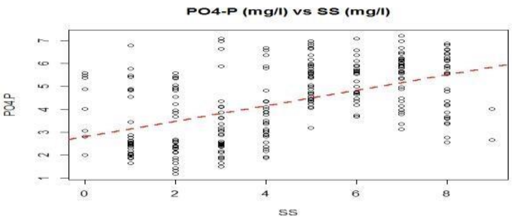
Scatter plots of the output variable against their respective individual input variables. Figure

Fig. 5.3 above suggests that NH4-N is linearly related with its corresponding input variables.

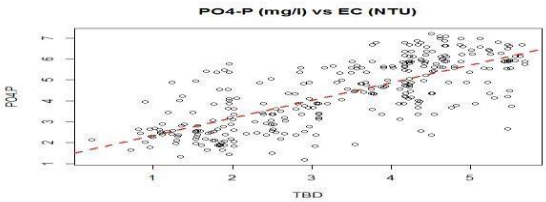


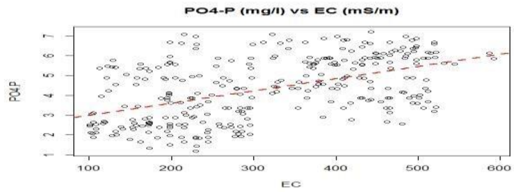
a b





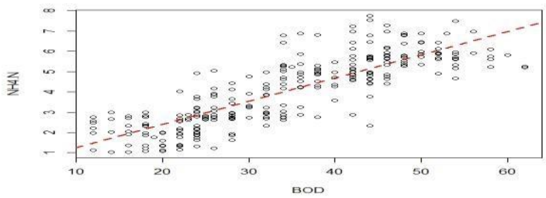
c d

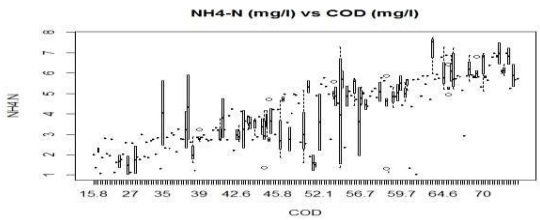




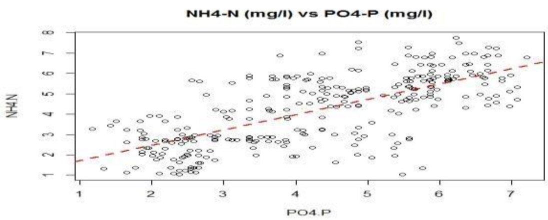
e f

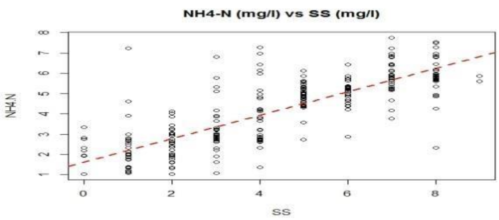
Figure 5.4: Graphical correlations between PO4-P and its corresponding correlated input parameters



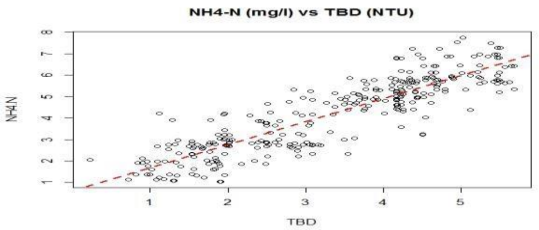


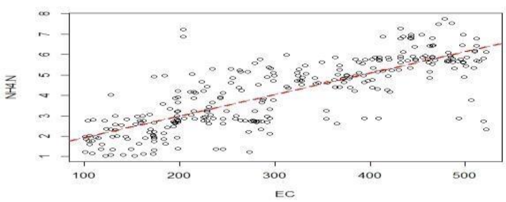
a b





c d



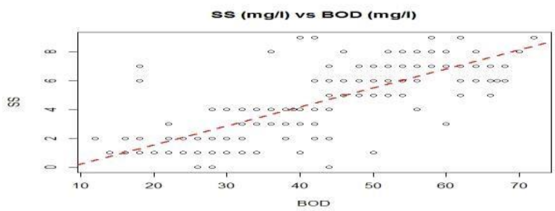


e f

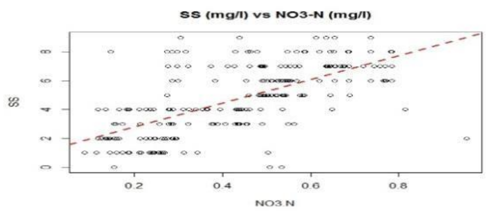
Figure 5.5: Graphical correlations between NH4-N and its corresponding correlated input parameters

Figure 5.6 is the scatter plot graphical correlation analysis representation for suspended solid (SS) as output parameters and their respective highly correlated input parameters. As can be seen from the graphs, that SS is visually indicated to be in good agreement and linearly related with BOD, NO3-N, NH4-N, PO4-P, TBD and EC as an input water quality parameters and this confirm the values obtained from numerical correlation in Table 5.5 which showed positive and significant correlation between them and suggested a linear increasing relationship between output parameters and input parameters. The scatter plot of all the out parameters in Figure 5.1 to 5.5 indicated good correlation with their respective input parameters this is sign of likely to achieve a good model. The assumptions of linearity and constant variance do seem to hold on the above scatter plots. When highly correlated input parameters are used for the model development tendency for the values of output parameters to increase or decrease as the values of the input parameters increase or decrease

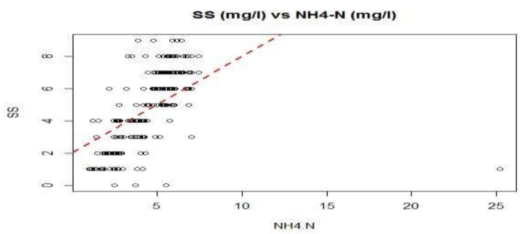
Having selected the highly correlated input parameters for their respective output model development, next step is to develop the models namely MLR and MLP.



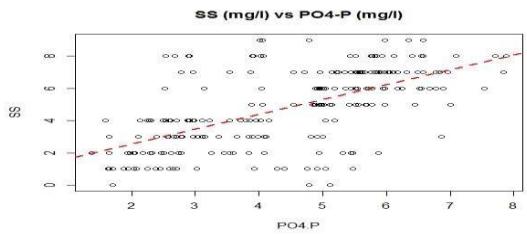
a



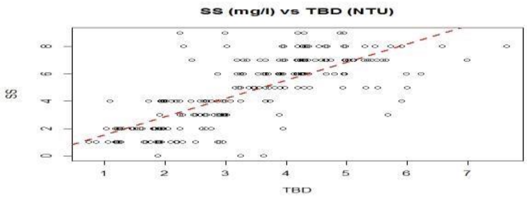
b



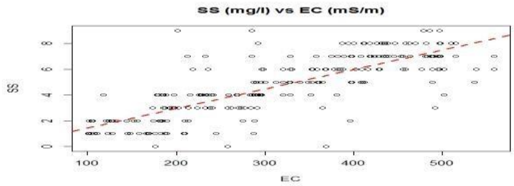
c



d



e



f

Figure 5.6: Graphical correlations between suspend solid (SS) and its corresponding highly correlated input parameters

5.4 The building of Data mining models

The models were developed and validated based on the quantitative data collected during monitoring performance of the experiment for over three years (forty months) that were used in this research study obtained from 3rd December 2014 to 28th March 2018. Two different data mining models were employed to carry out the task; these include multiple linear regression developed using R language and Multilayer Perceptron (MLP) constructed using WEKA data mining tool.

5.4.1 Building Multiple linear regression Model (MLR)

Multiple linear regression used in thesis was developed using R language. However, the function used in building a regression model in R language is lm () function, which takes in two, main argument, they are Data and Formula (regression equation). After building the models and establishing a highly significant relationship between output and input variables in a formula form. The regression equations can be used to predict the pollutant concentration (water quality parameters) present in wastewater or treated water base on the given known input values.

5.4.1.1 Building multiple linear regression (MLR) for COD

To model, the COD output parameter, highly correlated input dependent parameter is used for the model development. It was discovered from correlation analysis that seven input parameters were recorded to have a positive and strong correlation with COD, these include parameters BOD, PO4-P, NO3-N, SS, turbidity, electrical conductivity and temperature. Hence, they will be used to develop COD prediction model. The multiple linear regression equations are presented in equation 5.1.

$COD = b_o + b_1BOD + b_2NO3\text{-}N + b_3PO_4\text{-}P + b_4SS + b_5TBD + b_6EC + b_7TEMP$ 5.1

The regression equation in equation 1 will be used to find a line that best fits the COD data test and find a line that minimises the distance from all the data points to that line. COD is the output parameter to be predicted while the highly correlated input parameters were used to develop the prediction model

ˆ = bo + b1X1 + b2X2 + b3X3 + b4X4 + b5X5 + b6X6 + b7X7 5.2

Where ˆ = COD, X_1 = BOD, X_2 = NO3-N, X_3 = PO4-P, X_4 = SS, X_5=Turbidity, X_6 = EC and X_7 = TEMP, X_1 to X_7 are the input parameters, while b_o to b_7 are coefficient

The model is defined using lm () function in R, to estimate regression coefficient for a multiple linear regression equation. Having execute the lm () function, next is to use summary function is used to get the summary of the model performance

Since there are seven independent parameters from X_1 to X_7, seven regression coefficients are expected b_1 to b_7 plus Y intercept b_o, making eight estimates of regression coefficients, they will converge together in a regression equation. The regression model summary of predicting for a whole data is:

```
Call:
lm(formula = COD ~ BOD + PO4.P + NO3.N + SS + TBD + EC + TEMP,
    data = cod)

Residuals:
    Min      1Q  Median      3Q     Max
-50.068  -4.763   0.125   6.181  30.379

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -11.516201   2.444041  -4.712 4.29e-06 ***
BOD           0.753885   0.065359  11.534  < 2e-16 ***
PO4.P         3.261922   0.768542   4.244 3.20e-05 ***
NO3.N        30.392055   5.514923   5.511 9.70e-08 ***
SS           -0.328440   0.463301  -0.709  0.47911
TBD          -1.647551   0.552170  -2.984  0.00316 **
EC            0.007574   0.011347   0.667  0.50516
TEMP          1.683973   0.194605   8.653 9.48e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11.06 on 226 degrees of freedom
Multiple R-squared:  0.888,     Adjusted R-squared:  0.8846
F-statistic: 256.1 on 7 and 226 DF,  p-value: < 2.2e-16
```

Figure 5.7: Generated multiple regression summary for the whole dataset of COD used in the study using R language

From the above summary of the R language for the prediction of COD, the eight different coefficient regression estimates from equation 5.2 have values as calculated where bo = 11.516, b1 = 0.7539, b2 = 3.2619, b3 = 30.3921, b4 = -0.3284, b5 = -1.6476, b6 = 0.0076, and b7 = 1.6840, the coefficients are substituted with the actual values, therefore the multiple linear regression equation model to predict COD concentration in R language will be as;

$$COD = -11.5162 + 0.7539BOD + 3.262PO4\text{-}P + 30.392NO3\text{-}N + (-0.3284SS) + (-1.6476TBD) + 0.0076EC + 1.6840TEMP \quad 5.3$$

To get the legitimate COD prediction in the R model that was created in equation 5.3, the prediction function command is used. After feeding the data frame of highly correlated input parameters, the COD prediction result for whole data generated by multiple linear regression models was generated as presented in table 5.6 as

Table 5.5: Measure and prediction table of entire COD data

S/N	Actual COD	Predicted COD	Error	S/N	Actual COD	Predicted COD	Error	S/N	Actual COD	Predicted COD	Error
1	40.2	41.67	-1.47	28	54.6	61.10	-6.50	55	32.00	31.38	0.62
2	48.5	41.31	7.19	29	69.6	62.50	7.10	56	33.80	37.37	-3.57
3	40	46.80	-6.80	30	48.6	63.33	-14.73	57	35.20	40.82	-5.62
4	41.4	39.21	2.19	31	61.6	61.33	0.27	58	41.20	50.79	-9.59
5	54.7	66.78	-12.08	32	56.6	56.83	-0.23	59	55.60	56.32	-0.72
6	67	65.61	1.39	33	55.6	54.73	0.87	60	42.60	54.27	-11.67
7	72.3	67.23	5.07	34	52	62.60	-10.60	61	42.90	52.11	-9.21
8	68.8	70.50	-1.70	35	56	60.20	-4.20	62	42.00	50.01	-8.01
9	65	69.25	-4.25	36	64.2	63.58	0.62	63	39.00	42.06	-3.06
10	73.8	67.80	6.00	37	66.7	61.45	5.25	64	44.80	51.10	-6.30
11	60	69.42	-9.42	38	58.2	54.95	3.25	65	49.80	49.94	-0.14

12	74	78.15	-4.15	39	50.8	46.84	3.96	66	42.80	34.48	8.32
13	65	65.87	-0.87	40	50.5	44.16	6.34	67	42.20	46.66	-4.46
14	65	74.82	-9.82	41	36.5	18.76	17.74	68	57.20	56.15	1.05
15	66	78.00	-12.00	42	34	38.11	-4.11	69	49.00	51.04	-2.04
16	64.6	75.40	-10.80	43	26.2	34.04	-7.84	70	47.00	51.40	-4.40
17	75	72.17	2.83	44	35	40.95	-5.95	71	46.50	49.11	-2.61
18	73	82.10	-9.10	45	24	31.86	-7.86	72	40.40	44.44	-4.04
19	74	69.34	4.66	46	34.4	27.94	6.46	73	43.20	40.19	3.01
20	64.6	66.80	-2.20	47	35.5	33.44	2.06	74	98.00	93.32	4.68
21	64	63.10	0.90	48	34	37.26	-3.26	75	84.30	81.32	2.98
22	56.6	57.48	-0.88	49	35	26.63	8.37	76	103.00	98.11	4.89
23	57	58.76	-1.76	50	31.8	27.95	3.85	77	94.60	88.36	6.24

24	56.2	64.33	-8.13	51	28.89	31.45	-2.56	78	122.00	117.89	4.11
25	55.6	62.12	-6.52	52	29.9	27.93	1.97	79	104.00	94.89	9.11
26	50.5	55.30	-4.80	53	31.2	33.83	-2.63	80	103.12	96.09	7.03
27	60.8	69.66	-8.86	54	27	26.28	0.72	81	122.20	112.31	9.89
S/N	Actual COD	Predicted COD	Error	S/N	Actual COD	Predicted COD	Error	S/N	Actual`1 COD	Predicted COD	Error
82	126.80	117.25	9.55	109	127.7	118.86	8.84	136	109.2	106.78	2.421
83	137.40	128.63	8.77	110	124	112.48	11.52	137	102.8	106.88	-4.078
84	116.00	109.75	6.25	111	122	109.88	12.12	138	126.5	119.33	7.170
85	123.20	121.71	1.49	112	126	110.92	15.08	139	96.6	120.43	-23.833
86	126.30	98.74	27.56	113	126.5	112.95	13.55	140	84	120.67	-36.674
87	100.40	89.37	11.03	114	135.8	118.93	16.87	141	96.5	117.82	-21.323
88	123.00	111.68	11.32	115	139.6	145.07	-5.47	142	71.8	121.87	-50.068
89	122.00	107.75	14.25	116	124.5	113.47	11.03	143	109.6	104.71	4.888

90	118.50	105.17	13.33	117	122.7	109.64	13.06	144	92.8	103.62	-10.824
91	122.00	115.43	6.57	118	139.6	123.17	16.43	145	91.8	106.24	-14.439
92	138.50	123.06	15.44	119	125.6	106.89	18.71	146	74.7	104.85	-30.147
93	113.00	99.77	13.23	120	133.6	118.07	15.53	147	66	104.59	-38.594
94	113.20	109.73	3.47	121	117.7	113.30	4.40	148	92.7	116.77	-24.066
95	128.00	105.11	22.89	122	122.7	112.80	9.90	149	79.6	102.64	-23.036
96	116.30	112.81	3.49	123	112.6	122.64	-10.04	150	99.6	100.61	-1.014
97	121.20	113.64	7.56	124	129.6	139.95	-10.35	151	109.6	103.12	6.478
98	135.60	127.36	8.24	125	139.6	138.85	0.75	152	87.7	84.96	2.744
99	111.00	110.76	0.24	126	86.7	120.98	-34.28	153	72.4	72.58	-0.183
100	117.30	114.92	2.38	127	132.7	121.88	10.82	154	82.7	81.36	1.344

101	122.00	123.70	-1.70	128	97.6	133.62	-36.02	155	89.6	84.44	5.160
102	135.80	122.97	12.83	129	106.5	98.76	7.74	156	99.6	85.32	14.278
103	129.60	99.22	30.38	130	96.5	101.74	-5.24	157	89.6	85.73	3.869
104	113.00	106.38	6.62	131	96.5	128.29	-31.79	158	89.8	82.80	7.002
105	112.70	104.51	8.19	132	99.8	106.97	-7.17	159	82.7	85.58	-2.879
106	113.60	120.85	-7.25	133	112.7	114.65	-1.95	160	77.6	78.28	-0.681
107	114.90	125.91	-11.01	134	107.6	103.96	3.64	161	71.8	76.30	-4.501
108	139.70	123.69	16.01	135	121.8	115.43	6.37	162	77.7	77.09	0.613
S/N	Actual	Predicted	Error	S/N	Actual	Predicted	Error	S/N	Actual	Predicted	Error
	COD	COD			COD	COD			COD	COD	
163	69.6	64.07	5.53	190	29.7	38.75	-9.05	217	64.7	50.42	14.28
164	72	74.97	-2.97	191	30.6	35.44	-4.84	218	72.7	48.70	24.00
165	75.8	73.09	2.71	192	27.6	38.64	-11.04	219	69.6	48.08	21.52

166	59.6	64.38	-4.78	193	35.1	36.73	-1.63	220	69.6	53.11	16.49
167	67.5	73.37	-5.87	194	34.5	35.68	-1.18	221	69.6	60.96	8.64
168	72.7	73.04	-0.34	195	32.5	34.91	-2.41	222	79.8	68.56	11.24
169	64.5	70.03	-5.53	196	30.8	28.79	2.01	223	77.6	72.11	5.49
170	72.9	73.14	-0.24	197	29.7	29.01	0.69	224	62.7	61.33	1.37
171	69.7	67.62	2.08	198	35.98	37.43	-1.45	225	58.4	67.89	-9.49
172	72.7	70.69	2.01	199	37.8	43.20	-5.40	226	72.7	69.18	3.52
173	69.6	69.60	0.00	200	52.7	51.30	1.40	227	69.6	71.10	-1.50
174	70.8	71.22	-0.42	201	42.8	42.79	0.01	228	69.6	66.41	3.19
175	79	75.57	3.43	202	42.5	44.55	-2.05	229	69.6	79.08	-9.48
176	60.5	66.17	-5.67	203	42.6	44.72	-2.12	230	69.8	66.85	2.95
177	60	61.90	-1.90	204	44	42.34	1.66	231	62.7	64.68	-1.98

178	69.6	77.43	-7.83	205	36.5	35.92	0.58	232	67.8	70.36	-2.56
179	61	61.13	-0.13	206	38.5	38.78	-0.28	233	67.7	68.68	-0.98
180	62.7	58.58	4.12	207	36.5	44.43	-7.93	234	84.68	57.79	26.89
181	59.6	51.61	7.99	208	42.8	41.46	1.34				
182	53.6	58.22	-4.62	209	44.8	41.39	3.41				
183	49.6	50.09	-0.49	210	42.7	43.98	-1.28				
184	47.7	50.64	-2.94	211	42.8	46.32	-3.52				
185	41.9	44.76	-2.86	212	37.6	47.25	-9.65				
186	36.6	33.66	2.94	213	39.6	48.15	-8.55				
187	29.6	33.84	-4.24	214	44.6	49.31	-4.71				
188	20.6	33.72	-13.12	215	42.6	51.49	-8.89				
189	56.7	48.97	7.73	216	62.7	40.24	22.46				

The COD data from constructed wetland system were 234 data points, which were later divided randomly into two parts consisting of 161 data points (70%) of the total data points as training data and 73 data points (30%) of the entire data points as testing data which was presented in the table.

Table 5.6:

Data partition	Relative size	Number of entries
Entire data	100%	244
Training data	70%	161
Testing data	30%	73

5.5 Data partitioning for model development

To achieve a good prediction model, the monitoring dataset is split randomly into two parts training and testing dataset, 70% of the data were used as training set data while the remaining 30% of data were used as testing set.

5.5.1 Training dataset

Training dataset is used to train (build) the prediction model. During model training, particular structures are selected out from the training dataset. These structures are then merged into the model built. The multiple linear regression model summary generated in R language for the training dataset of COD is presented in figure 5.10

```
Call:
lm(formula = COD ~ BOD + PO4.P + NO3.N + SS + TBD + EC + TEMP,
    data = tdata)

Residuals:
    Min      1Q  Median      3Q     Max
-46.468  -4.477   0.681   6.238  32.231

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -9.0847888  3.1392065  -2.894 0.004400 **
BOD          0.6033082  0.0979952   6.157 7.10e-09 ***
PO4.P        3.9151181  1.0528875   3.718 0.000287 ***
NO3.N       32.4843623  7.4317030   4.371 2.36e-05 ***
SS           0.1187805  0.5392908   0.220 0.825988
TBD         -1.5537863  0.6709917  -2.316 0.021999 *
EC           0.0004191  0.0137116   0.031 0.975657
TEMP         1.5855498  0.2482968   6.386 2.24e-09 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 11.18 on 143 degrees of freedom
Multiple R-squared:  0.8791,    Adjusted R-squared:  0.8732
F-statistic: 148.6 on 7 and 143 DF,  p-value: < 2.2e-16
```

Figure 5.8: generated multiple regression summary for the training dataset of COD by R language

The multiple regression equation for the training dataset of COD is presented in equation 5.3 below

$$COD = -9.0848 + 0.6033BOD + 3.9151PO4\text{-}P + 32.484NO3\text{-}N + 0.1187SS + (-1.553TBD) + 0.0004EC + 1.5855TEMP \quad 5.3$$

5.5.2 Testing dataset

Once the training stage is completed, testing dataset will introduce to the model built. the less the test data (30%) the more accurate the error estimate of the model will be. The model is test using training dataset, and check how modes built are doing, because testing data were not seen by the model built. If the results of the prediction model are as expected, then it is discovered that the model is built enough to make correct prediction. The multiple regression model summaries for the testing dataset of COD is presented in figure 5.7

```
Call:
lm(formula = COD ~ BOD + PO4.P + NO3.N + SS + TBD + EC + TEMP,
    data = vdata)

Residuals:
    Min      1Q  Median      3Q     Max
-35.937  -4.535   0.295   4.781  28.664

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -13.66040    3.91046  -3.493 0.000804 ***
BOD           0.92626    0.09560   9.689 7.36e-15 ***
PO4.P         3.23696    1.11330   2.908 0.004788 **
NO3.N        24.55579    8.14249   3.016 0.003498 **
SS           -2.36392    1.01288  -2.334 0.022285 *
TBD          -0.42502    1.07794  -0.394 0.694488
EC            0.02220    0.02055   1.080 0.283418
TEMP          1.59915    0.32001   4.997 3.70e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 10.37 on 75 degrees of freedom
Multiple R-squared:  0.9157,    Adjusted R-squared:  0.9078
F-statistic: 116.4 on 7 and 75 DF,  p-value: < 2.2e-16
```

Figure 5.9: Generated multiple regression summary for the testing dataset of COD by R language

COD = -13.661 + 0.9263BOD + 3.237PO4-P + 24.556NO3-N + (-2.364SS) + (-0.425TBD) + 0.02226EC + 1.599TEMP 5

The measured values by the laboratory analysis and the predicted values of COD by the multiple linear regression model are presented in table 5.8 and 5.9 for training and testing dataset respectively.

Table 5.7: Measure and prediction table for COD training dataset of MLR

S/N	Measured COD (Y)	Predicted COD (Ȳ)	Error (Y- Ȳ)	S/N.	Measured COD (Y)	Predicted COD (Ȳ)	Error (Y- Ȳ)	S/N	Measured COD (Y)	Predicted COD (Ȳ)	Error (Y- Ȳ)
1	40.20	42.05	-1.85	79	104.00	93.66	10.34	158	89.80	82.67	7.13
2	48.50	41.55	6.95	80	103.12	94.90	8.22	159	82.70	86.36	-3.66
3	40.00	47.86	-7.86	82	126.80	117.75	9.05	160	77.60	77.86	-0.26
4	41.40	38.66	2.74	83	137.40	129.84	7.56	161	71.80	76.52	-4.72
5	64.70	66.34	-1.64	86	136.30	99.29	37.01	164	72.00	77.10	-5.10
6	67.00	64.81	2.19	87	100.40	89.62	10.78	165	75.80	73.79	2.01
7	72.30	66.27	6.03	88	123.00	112.28	10.72	166	59.60	64.72	-5.12
8	68.80	70.57	-1.77	90	118.50	105.52	12.98	167	60.50	73.94	-13.44
9	65.00	68.74	-3.74	91	122.00	116.77	5.23	168	72.70	72.28	0.42
12	74.00	78.01	-4.01	92	138.50	124.84	13.66	169	64.50	71.28	-6.78
13	65.00	65.63	-0.63	93	113.00	102.35	10.65	170	72.90	73.81	-0.91
16	64.60	74.97	-10.37	94	113.20	112.94	0.26	171	69.70	67.18	2.52

17	75.00	72.00	3.00	96	116.30	115.89	0.41	173	69.60	70.12	-0.52
18	73.00	82.70	-9.70	98	135.60	128.55	7.05	174	70.80	71.16	-0.36
19	74.00	70.56	3.44	101	122.00	125.48	-3.48	175	79.00	75.20	3.80
21	64.00	63.23	0.77	102	135.80	126.23	9.57	176	60.50	66.72	-6.22
22	56.60	57.38	-0.78	103	129.60	96.81	32.79	178	62.68	79.04	-16.36
24	56.20	65.11	-8.91	104	113.00	105.08	7.92	179	61.00	61.99	-0.99
25	55.60	63.43	-7.83	105	112.70	104.70	8.00	181	57.90	53.16	4.74
28	54.60	61.80	-7.20	106	113.60	120.81	-7.21	184	47.70	52.40	-4.70
31	46.60	61.23	-14.63	107	118.90	125.40	-6.50	185	41.90	46.01	-4.11
32	56.60	56.90	-0.30	108	139.70	122.35	17.35	187	29.60	34.51	-4.91
33	55.60	54.77	0.83	109	127.70	117.94	9.76	188	32.60	33.74	-1.14
34	52.00	63.09	-11.09	113	126.50	112.36	14.14	190	38.70	39.58	-0.88
37	66.70	61.27	5.43	116	124.50	110.62	13.88	192	39.60	38.87	0.73
38	58.20	55.99	2.21	118	139.60	121.75	17.85	194	36.50	36.30	0.20

39	50.80	47.55	3.25	120	133.60	117.67	15.93	195	37.50	35.05	2.45
40	50.50	45.09	5.41	121	117.70	110.31	7.39	199	39.80	43.22	-3.42
41	36.50	18.23	18.27	123	136.60	122.89	13.71	200	39.75	50.83	-11.08
43	26.20	35.21	-9.01	124	149.60	140.64	8.96	201	42.80	42.59	0.21
44	35.00	42.33	-7.33	125	139.60	138.89	0.71	203	42.60	44.31	-1.71
45	24.00	32.55	-8.55	126	86.70	119.68	-32.98	204	44.00	43.02	0.98
46	34.40	28.64	5.76	127	132.70	121.44	11.26	205	36.50	35.67	0.83
47	35.50	33.88	1.62	128	97.60	133.44	-35.84	207	36.50	44.47	-7.97
48	34.00	38.22	-4.22	129	106.50	96.95	9.55	208	42.80	41.29	1.51
49	35.00	26.85	8.15	130	96.50	97.91	-1.41	209	44.80	42.27	2.53
50	31.80	27.82	3.98	131	96.50	127.38	-30.88	210	42.70	44.34	-1.64
51	22.00	31.62	-9.62	133	112.70	112.30	0.40	211	42.80	46.78	-3.98
52	29.90	28.54	1.36	135	117.80	114.32	3.48	212	37.60	47.02	-9.42
54	27.00	26.10	0.90	136	100.20	105.89	-5.69	213	39.60	47.76	-8.16

55	32.00	32.08	-0.08	137	102.80	105.89	-3.09	214	44.60	48.07	-3.47
57	35.20	41.79	-6.59	138	126.50	118.68	7.82	216	62.70	38.22	24.48
61	42.90	53.05	-10.15	139	96.60	119.29	-22.69	217	64.70	48.84	15.86
62	42.00	49.80	-7.80	141	96.50	116.18	-19.68	220	69.60	52.15	17.45
65	49.80	49.65	0.15	142	71.80	121.59	-49.79	221	69.60	59.88	9.72
66	42.80	35.09	7.71	144	92.80	103.34	-10.54	222	79.80	68.30	11.50
67	42.20	47.06	-4.86	145	91.80	105.57	-13.77	224	62.70	59.86	2.84
70	47.00	51.72	-4.72	147	66.00	102.81	-36.81	225	68.40	67.70	0.70
71	46.50	49.17	-2.67	150	99.60	99.74	-0.14	226	72.70	69.39	3.31
73	43.20	39.16	4.04	151	109.60	104.23	5.37	227	69.60	71.11	-1.51
74	98.00	93.86	4.14	152	87.70	85.80	1.90	230	69.80	71.01	-1.21
76	103.00	98.30	4.70	153	72.40	71.35	1.05	231	62.70	64.28	-1.58
77	94.60	89.18	5.42	154	82.70	81.03	1.67	232	67.80	70.93	-3.13
78	101.00	119.31	-18.31	156	99.60	85.71	13.89	234	69.68	67.13	2.55

Table 5.8: Measured and predicted values for COD testing data of MLR

S/N	Measured COD (Y)	Predicted COD (Ȳ)	Error (Y-Ȳ)	S/N	Measured COD (Y)	Predicted COD (Ȳ)	Error (Y-Ȳ)	S/N	Measured COD (Y)	Predicted COD (Ȳ)	Error Ȳ Y-
10	73.80	67.71	6.09	81	122.20	109.81	12.39	157	89.60	85.74	3.86
11	60.00	68.24	-8.24	84	116.00	107.91	8.09	162	77.70	76.96	0.74
14	65.00	74.05	-9.05	85	133.20	118.49	14.71	163	49.60	62.74	-13.14
15	66.00	79.22	-13.22	89	122.00	107.41	14.59	172	72.70	70.03	2.67
20	64.60	65.92	-1.32	95	128.00	105.59	22.41	177	64.00	61.82	2.18
23	57.00	55.63	1.37	97	121.20	113.02	8.18	180	62.70	58.23	4.47
26	50.50	54.51	-4.01	99	114.00	111.32	2.68	182	53.60	57.61	-4.01
27	60.80	68.58	-7.78	100	117.30	114.12	3.18	183	49.60	50.83	-1.23

29	69.60	59.70	9.90	110	124.00	115.00	9.00	186	36.60	32.45	4.15
30	48.60	60.89	-12.29	111	122.00	113.18	8.82	189	40.70	47.05	-6.35
35	46.00	56.49	-10.49	112	126.00	113.23	12.77	191	34.60	34.93	-0.33
36	64.20	61.25	2.95	114	135.80	121.68	14.12	193	35.10	36.09	-0.99
42	34.00	35.46	-1.46	115	139.60	146.99	-7.39	196	38.80	27.73	11.07
53	31.20	31.87	-0.67	117	122.70	112.78	9.92	197	32.70	28.95	3.75
56	33.80	36.10	-2.30	119	125.60	110.35	15.25	198	36.00	36.08	-0.08
58	41.20	49.40	-8.20	122	113.70	117.56	-3.86	202	42.50	42.76	-0.26
59	55.60	54.41	1.19	132	99.80	110.72	-10.92	206	38.50	37.17	1.33
60	42.60	52.09	-9.49	134	107.60	105.46	2.14	215	42.60	50.02	-7.42
63	39.00	40.96	-1.96	140	84.00	121.79	-37.79	218	72.70	48.46	24.24
64	44.80	50.67	-5.87	143	109.60	106.04	3.56	219	69.60	47.32	22.28
68	57.20	55.30	1.90	146	72.70	104.65	-31.95	223	67.60	66.89	0.71
69	49.00	50.22	-1.22	148	92.70	117.22	-24.52	228	69.60	64.91	4.69

72	40.40	43.10	-2.70	149	79.60	103.09	-23.49	229	69.60	77.98	-8.38
75	84.30	79.56	4.74	155	89.60	84.55	5.05	233	67.70	66.47	1.23

The multiple linear regression equation for the testing dataset for the prediction of COD is presented in equation 5.4.

COD = -13.6604 + 0.92626BOD + 3.237PO4-P + 24.556NO3-N --2.3639SS -0.425SS + 0.0222EC + 1.599TEMP 5.5

All generated multiple linear regression summaries by R language and measured and predicted table in the whole dataset, training and testing dataset of all the remaining output parameters are presented in the appendix section of this thesis.

5.5.3 Multiple linear regression for BOD

The coefficients are substituted with the actual values. Therefore, the multiple linear regression equation models for the whole dataset to predict BOD concentration given other highly correlated input parameters in R language is generated in equation 5.6 as;

BOD = 5.5013 +0.497 COD + (-1.454PO4-P) + 0.04684 NH4-N + 0.563SS + 0.813TBD + 0.631EC + (-0.389TEMP). 5.6

The complete BOD dataset from constructed wetland system dataset were 234 data points, which were divided randomly into two parts consisting of 161 data points which are 70% of the dataset as training dataset and 30% of data as testing dataset consisting of 73 data point as contained in the table

Table 5.9: Partition of BOD dataset

Data partition	Relative size	Number of entries
Entire data	100%	234
Training data	70%	161
Testing data	30%	73

The model is processed by putting 70% training dataset by predicting training test data. Therefore, the multiple linear regression equation models for the training dataset of BOD concentration given other highly correlated known input parameters values in R language is generated in equation 5.6 as

BOD = 7.505 +0.216 COD + 0.491PO4-P + 1.274NH4-N + 1.125SS + 0.404TBD + 0.02751EC + (-0.627TEMP) 5.6

After getting the prediction result from the training dataset, the model build is tested by predicting BOD against the test set. Because the testing dataset already contains known values for the output parameters to predict, to check whether the model's predictions are accurate and correct or not. The multiple regression equation for the testing dataset of the output BOD is presented in equation 5.7 below

BOD = 12.669 +0.216 COD + 1.906PO4-P + 0.278NH4-N + (- 0.0257SS + 1.351TBD + (-0.00281EC + (-0.426TEMP) 5.6

5.5.4 Multiple linear regression for PO4-P

The multiple linear regressions for the R language prediction model are generated for the whole dataset of PO4-P. Therefore, the multiple linear regression equation models for the whole dataset to predict PO4-P concentration given other highly correlated input parameters in R language is generated in equation 5.7 as:

PO4-P = 7.419 + (-0.833COD) + (-0.478BOD) + 1.087NH4-N + 1.359SS + 2.396TBD + 0.026EC 5.7

For proper prediction of the output PO4-P, the overall data is then split randomly using R language into two different subsets training, and testing dataset 70% with 201 data point and 30% with 105 data point respectively as contained in Table 5.8. The training set part of the

PO4-P dataset is used to build up a model, and testing is used to test the model

Table 5.10: Partition of the PO4-P dataset

Data partition	Relative size	Number of entries
Entire data	100%	306
Training data	70%	201
Testing data	30%	105

The multiple linear regression equation models for the training dataset to predict PO4-P concentration given other highly correlated input parameters in R language is generated in equation 5.8 as

PO4-P = 4.6445 + 0.126COD + 0.051BOD + 1.021NH4-N + 1.041SS + 1.973TBD + 0.029EC 5.7

The testing dataset of the whole data is used to validate the model built using training dataset.

The multiple linear regression equation models for the testing dataset to predict PO4-P concentration given other highly correlated input parameters in R language is generated in equation 5.9 as

PO4-P = -0.982 + (- 1.175COD) + (- 0.869BOD) + (-0.021NH4-N) + 3.523SS + 0.136TBD + 0.0424EC 5.9

5.5.5 Multiple linear regression for Ammonium nitrogen (NH4-N)

The multiple linear regression equation model for the whole dataset to predict NH4-N concentration given other highly correlated input parameters in R language is generated in equation 5.10 as follows;

$$NH4\text{-}N = 0.876 + 0.0035BOD + 1.687COD + 0.172PO4\text{-}P + 0.099SS + 0.534TBD + 0.0014EC \quad 5.10$$

To properly create and evaluate NH4-N prediction model the overall data is split into 70% training and 30% testing data randomly as contain in Table 5.9.

Table 5.11: Partition of the NH4-N dataset

Data partition	Relative size	Number of entries
Entire data	100%	293
Training data	70%	202
Testing data	30%	91

The multiple linear regression equation models for the training dataset to predict NH4-N concentration given other highly correlated input parameters in is generated R language as presented in equation 5.11 as follows:

$$NH4\text{-}N = -0.217 + 0.0157BOD + 0.0296COD + 0.122PO4\text{-}P + 0.149SS + 0.265TBD + 0.0088EC \quad 5.11$$

The multiple linear regression equation models for the testing dataset to validate the NH4-N prediction built and compare the result of training dataset model given is generated R language as presented in equation 5.11 as follows:

$$NH4\text{-}N = 0.828 + 1.713BOD + 0.762COD + 0.0079PO4\text{-}P + 0.142SS + 0.0532TBD + 0.8085EC \quad 5.11$$

5.5.6 Multiple liner regression for suspended solid (SS)

To predict SS concentration of the whole dataset using multiple linear regression models in R language, the overall dataset has 294 data points the generated regression equation for the prediction of SS is presented in equation 5.12

SS = -1.185+ 0.0568BOD + (-0.0114NO3-N) + (-0.032PO4-P) + 0.049NH4-N + 0.513TBD + 0.005EC 5.12

To ascertain the performance of the linear regression model for the prediction of SS from overall datasets used. The dataset is divided randomly into two different dataset training, and testing dataset using R language, the allocation of data is 70% and 30% for training and testing dataset respectively Table 5.

Table 5.12: Partition of SS dataset

Data partition	Relative size	Number of entries
Entire data	100%	263
Training data	70%	192
Testing data	30%	71

The training parts a dataset is used to train the model**,** the model itself was created by learning from the training set part, while in another hand test the model from an unseen testing dataset. The detailed structures are selected out from the training set. These structures are then integrated into the model, which should be able to learn from these structures. The total data point of training dataset is 192 entries. The multiple linear regression equation models for the training dataset to predict SS concentration given other highly correlated input parameters in is generated R language as presented in equation 5.13 as follows

SS = 186.024 + 0.083BOD + (-2.573NO3-N) + 118.396PO4-P + (-1.772NH4-N + (-24.285TBD) + 0.278EC 5.13

To assess and test the how well the regression model performs in predicting SS on the training dataset, testing dataset is used (dataset the model has not seen before).

The total data point of training dataset are 71 entries the multiple linear regression equation models for the testing dataset to validate the SS prediction built and compare the result of training dataset model given is generated in R language as presented in equation 5.14 as follows:

SS = 104.713 + 0.143BOD + (-2.672NO3-N) + 51.511PO4-P + 8.854NH4-N + (16.285TBD) + 0.375EC 5.14

5.6 Building a multilayer perceptron (MLR) Model

In this study research, multilayer perceptron (MLP) was build using WEKA data mining tool. The software only accepts and understand data that is arrange in ARFF file format before it processed. The type of data fed to the system can then be defined, then supply the data itself.

In the file, column and what each column contains are also described.

5.6.1 Construction of the Multilayer perceptron for COD

It was discovered from correlation analysis that seven input parameters were recorded to have a positive and strong correlation with COD, these include BOD, PO4-P, NO3-N, SS, TBD, EC and Temp. Hence, they will be used to develop the multilayer perceptron model for the prediction of COD. The model clearly indicates how these inputs are used to generated COD output prediction, how the feedforward algorithms work, where the incoming input get to multiply by weights and sum together and successfully generate an output from hidden layer each neuron computes its net input as weighted sum of its input and pass through activation function to get output. Its assume all neuron use the same activation function the output of the neuron in the output layer are the final output of the networks and build a simple multiple layer perceptron prediction models, that all the pieces of the artificial neural network.

Table 5.13: Measured and predicted data for COD training data of MLP

S/N	Measured COD (Y)	Predicted COD (Ȳ)	Error (Y-Ȳ)	S/N	Measured COD (Y)	Predicted COD (Ȳ)	Error (Y-Ȳ)	S/N	Measured COD (Y)	Predicted COD (Ȳ)	Error Y- Ȳ
1	40.20	42.43	-2.23	79	104.00	99.14	4.86	157	89.60	87.68	1.92
2	48.50	48.82	-0.32	80	103.12	102.08	1.04	158	89.80	86.10	3.70
3	40.00	42.68	-2.68	81	122.20	119.01	3.19	159	82.70	85.78	-3.08
4	41.40	38.23	3.17	82	126.80	125.20	1.60	160	77.60	77.48	0.12
5	64.70	70.53	-5.83	83	137.40	139.11	-1.71	161	71.80	75.77	-3.97
6	67.00	64.55	2.45	84	116.00	115.32	0.68	162	77.70	77.43	0.27
7	72.30	74.99	-2.69	85	133.20	130.08	3.12	163	49.60	61.95	-12.35
8	68.80	65.98	2.82	86	136.30	134.49	1.81	164	72.00	75.41	-3.41
9	65.00	65.29	-0.29	87	100.40	102.77	-2.37	165	75.80	72.16	3.64
10	73.80	76.76	-2.96	88	123.00	124.98	-1.98	166	59.60	62.38	-2.78
11	60.00	61.46	-1.46	89	122.00	120.68	1.32	167	60.50	73.31	-12.81
12	74.00	76.87	-2.87	90	118.50	115.03	3.47	168	72.70	71.08	1.62

13	65.00	65.53	-0.53	91	122.00	120.67	1.33	169	64.50	68.31	-3.81
14	65.00	67.38	-2.38	92	138.50	132.87	5.63	170	72.90	71.48	1.42
15	66.00	72.45	-6.45	93	113.00	111.62	1.38	171	69.70	66.64	3.06
16	64.60	73.77	-9.17	94	113.20	114.68	-1.48	172	72.70	70.78	1.92
17	75.00	78.22	-3.22	95	128.00	129.46	-1.46	173	69.60	68.84	0.76
18	73.00	75.45	-2.45	96	116.30	117.26	-0.96	174	70.80	68.57	2.23
19	74.00	77.79	-3.79	97	121.20	117.99	3.21	175	79.00	75.68	3.32
20	64.60	63.47	1.13	98	135.60	136.78	-1.18	176	60.50	64.68	-4.18
21	64.00	61.45	2.55	99	114.00	109.02	4.98	177	64.00	59.46	4.54
22	56.60	56.18	0.42	100	117.30	112.14	5.16	178	62.68	56.28	4.72
23	57.00	56.74	0.26	101	122.00	125.39	-3.39	179	61.00	62.49	-1.49
24	56.20	60.24	-4.04	102	135.80	130.22	5.58	180	62.70	56.85	5.15
25	55.60	59.97	-4.37	103	129.60	123.59	6.01	181	57.90	50.02	7.88

26	50.50	51.65	-1.15	104	113.00	111.16	1.84	182	53.60	55.92	-2.32
27	60.80	63.51	-2.71	105	112.70	115.44	-2.74	183	49.60	45.82	3.78
28	54.60	58.67	-4.07	106	113.60	111.54	2.06	184	47.70	46.69	1.01
29	69.60	63.48	6.12	107	118.90	115.05	5.85	185	41.90	40.83	1.07
30	48.60	51.98	-3.38	108	139.70	134.73	4.97	186	36.60	38.96	-2.36
31	46.60	60.22	-13.62	109	127.70	128.22	-0.52	187	29.60	27.95	1.65
32	56.60	55.82	0.78	110	124.00	123.00	1.00	188	32.60	29.12	3.48
33	55.60	54.30	1.30	111	122.00	120.15	1.85	189	40.70	37.44	3.26
34	52.00	58.00	-6.00	112	126.00	123.06	2.94	190	38.70	35.40	3.30
35	46.00	53.08	-7.08	113	126.50	124.42	2.08	191	34.60	30.19	5.41
36	64.20	68.80	-4.60	114	135.80	131.22	4.58	192	39.60	36.37	3.27
37	66.70	65.84	0.86	115	139.60	136.23	3.37	193	35.10	30.65	4.45
38	58.20	57.00	1.20	116	124.50	122.55	1.95	194	36.50	29.98	-3.48
39	50.80	46.76	4.04	117	122.70	119.36	3.34	195	37.50	33.04	4.46

40	50.50	45.41	5.09	118	139.60	134.99	4.61	196	38.80	35.11	3.69
41	36.50	39.09	-2.59	119	125.60	122.13	3.47	197	32.70	29.55	3.15
42	34.00	33.61	0.39	120	133.60	133.75	-0.15	198	36.00	34.10	1.90
43	26.20	27.91	-1.71	121	117.70	112.12	5.58	199	39.80	37.99	1.81
44	35.00	36.87	-1.87	122	113.70	113.11	0.59	200	39.75	35.40	4.34
45	24.00	24.48	-0.48	123	136.60	132.75	3.85	201	42.80	37.28	5.52
46	34.40	29.89	4.51	124	149.60	152.93	-3.33	202	42.50	41.37	1.13
47	35.50	36.18	-0.68	125	139.60	135.50	4.10	203	42.60	45.61	-3.01
48	34.00	31.98	2.02	126	86.70	83.37	3.33	204	44.00	38.13	5.87
49	35.00	32.19	2.81	127	132.70	128.42	4.28	205	36.50	33.34	3.16
50	31.80	30.72	1.08	128	97.60	94.17	3.43	206	38.50	34.85	3.65
51	22.00	26.93	-4.93	129	106.50	107.55	-1.05	207	36.50	42.15	-5.65
52	29.90	22.38	7.52	130	96.50	93.24	3.26	208	42.80	37.59	5.21
53	31.20	29.56	1.64	131	96.50	99.05	-2.55	209	44.80	39.19	5.61

54	27.00	28.04	-1.04	132	99.80	102.12	-2.32	210	42.70	38.20	4.50
55	32.00	34.58	-2.58	133	112.70	118.68	-5.98	211	42.80	44.70	-1.90
56	33.80	33.82	-0.02	134	107.60	109.27	-1.67	212	37.60	43.76	-6.16
57	35.20	38.64	-3.44	135	117.80	120.06	-2.26	213	39.60	43.87	-4.27
58	41.20	46.97	-5.77	136	100.20	105.50	-5.30	214	44.60	46.99	-2.39
59	55.60	52.40	3.20	137	102.80	109.48	-6.68	215	42.60	47.91	-5.31
60	42.60	50.28	-7.68	138	126.50	127.03	-0.53	216	62.70	61.06	1.64
61	42.90	47.38	-4.48	139	96.60	97.73	-1.13	217	64.70	65.72	-1.02
62	42.00	46.67	-4.67	140	84.00	85.84	-1.84	218	72.70	73.59	-0.89
63	39.00	35.57	3.43	141	96.50	90.00	6.50	219	69.60	63.49	6.11
64	44.80	47.70	-2.90	142	71.80	71.59	0.21	220	69.60	68.13	1.47
65	49.80	51.39	-1.59	143	109.60	114.60	-5.00	221	69.60	67.82	1.78
66	42.80	39.81	2.99	144	92.80	90.69	2.11	222	79.80	76.85	2.95
67	42.20	42.93	-0.73	145	91.80	82.17	9.63	223	67.60	74.01	-6.41

68	57.20	54.68	2.52	146	72.70	72.78	-0.08	224	62.70	57.87	4.83
69	49.00	47.36	1.64	147	66.00	68.08	-2.08	225	68.40	65.03	3.37
70	47.00	48.46	-1.46	148	92.70	96.63	-3.93	226	72.70	68.14	4.56
71	46.50	48.42	-1.92	149	79.60	79.77	-0.17	227	69.60	72.24	-2.64
72	40.40	38.60	1.80	150	99.60	102.74	-3.14	228	69.60	64.47	5.13
73	43.20	45.27	-2.07	151	109.60	109.74	-0.14	229	69.60	65.82	3.78
74	98.00	100.14	-2.14	152	87.70	88.95	-1.25	230	69.80	71.08	-1.28
75	84.30	81.84	2.46	153	72.40	69.41	2.99	231	62.70	61.56	1.14
76	103.00	100.38	2.62	154	82.70	81.12	1.58	232	67.80	66.51	1.29
77	94.60	91.36	3.24	155	89.60	85.37	4.23	233	67.70	68.28	-0.58
78	101.00	97.16	3.84	156	99.60	96.43	3.17	234	69.68	65.09	4.59

Table 5.14: Measured and predicted values for COD testing data of MLP

COD TRAINING DATA											
S/N	Actual COD	Predicted COD	error	S/N	Actual COD	Predicted COD	error	S/N	Actual COD	Predicted COD	error
1	40.2	40.7	-0.47	42	34	31.29	2.71	87	100.4	90.2	10.16
2	48.5	36.4	12.06	43	26.2	26.19	0.01	88	123	125.9	-2.86
3	40	39.2	0.77	44	35	27.48	7.52	89	122	102.7	19.26
5	54.7	60.1	-5.36	45	24	22.39	1.61	90	118.5	110.9	7.60
7	72.3	64.2	8.10	47	35.5	29.56	5.94	91	122	123.3	-1.30
8	68.8	69.0	-0.22	48	34	31.43	2.57	92	138.5	133.8	4.69
9	65	69.1	-4.11	52	29.9	23.15	6.75	94	113.2	111.7	1.50
10	73.8	65.8	8.01	53	31.2	32.14	-0.94	95	128	118.5	9.45
11	60	62.8	-2.85	54	27	27.31	-0.31	96	116.3	117.8	-1.52
12	74	77.6	-3.60	55	32	29.84	2.17	97	121.2	112.7	8.54
14	65	67.9	-2.90	58	41.2	42.20	-1.00	98	135.6	135.2	0.40

15	66	77.8	-11.84	59	55.6	47.05	8.55	99	111	102.3	8.68
16	64.6	70.4	-5.83	60	42.6	45.84	-3.24	100	117.3	98.2	19.06
19	74	61.2	12.77	61	42.9	43.68	-0.78	101	122	110.6	11.39
21	64	55.7	8.29	62	42	45.00	-3.00	102	135.8	133.0	2.82
23	57	53.3	3.73	63	39	39.15	-0.15	103	129.6	96.2	33.42

24	56.2	54.0	2.18	64	44.8	43.88	0.92	104	113	96.4	16.65
25	55.6	51.8	3.82	67	42.2	40.72	1.48	106	113.6	124.0	-10.39
26	50.5	49.3	1.16	68	57.2	47.04	10.16	107	114.9	126.5	-11.56
29	69.6	55.2	14.40	69	49	44.02	4.98	108	139.7	115.7	24.04
30	48.6	55.2	-6.58	70	47	45.42	1.58	110	124	105.9	18.14
31	61.6	54.8	6.79	71	46.5	39.26	7.24	111	122	115.0	7.00
33	55.6	48.0	7.65	75	84.3	77.44	6.86	112	126	107.8	18.18
35	56	51.0	4.97	77	94.6	84.56	10.04	113	126.5	124.4	2.11
36	64.2	61.6	2.63	79	104	90.26	13.74	114	135.8	120.2	15.60
37	66.7	53.4	13.34	81	122.2	103.93	18.27	115	139.6	136.4	3.19
38	58.2	58.0	0.23	83	137.4	131.20	6.20	117	122.7	108.8	13.87
40	50.5	38.9	11.64	84	116	106.46	9.54	118	139.6	113.2	26.44
41	36.5	31.3	5.245	85	123.2	115.67	7.535	119	125.6	103.53	22.073

S/N	**Actual COD**	**Predicted COD**	**error**	**S/N**	**Actual COD**	**Predicted COD**	**error**	**S/N**	**Actual COD**	**Predicted COD**	**error**
120	133.6	106.97	26.63	160	77.6	76.29	1.314	196	30.8	26.49	4.313
121	117.7	107.04	10.66	162	77.7	66.53	11.17	198	35.98	31.44	4.54
122	122.7	120.00	2.70	163	69.6	61.31	8.29	199	37.8	39.62	-1.82
123	112.6	102.93	9.67	164	72	67.30	4.70	200	52.7	46.46	6.24
124	129.6	127.79	1.81	165	75.8	64.30	11.50	201	42.8	37.81	4.99
126	86.7	104.56	-17.86	166	59.6	57.24	2.36	202	42.5	38.66	3.85
127	132.7	97.29	35.41	167	67.5	66.09	1.41	203	42.6	41.10	1.50

129	106.5	95.98	10.52	168	72.7	70.10	2.60	205	36.5	31.82	4.68
130	96.5	97.39	-0.89	169	64.5	60.80	3.70	206	38.5	33.54	4.96
131	96.5	108.63	-12.13	170	72.9	67.76	5.14	210	42.7	40.13	2.57
133	112.7	98.80	13.90	171	69.7	62.82	6.88	211	42.8	36.82	5.98
134	107.6	94.42	13.18	172	72.7	64.79	7.91	214	44.6	47.03	-2.43
136	109.2	99.09	10.11	173	69.6	65.12	4.48	215	42.6	51.68	-9.08
138	126.5	102.94	23.56	174	70.8	64.26	6.54	216	62.7	52.03	10.67
139	96.6	105.46	-8.86	176	60.5	60.57	-0.07	217	64.7	55.63	9.07
140	84	104.90	-20.90	177	60	56.31	3.69	219	69.6	54.79	14.81
141	96.5	109.49	-12.99	181	59.6	48.79	10.81	220	69.6	63.85	5.75
142	71.8	101.31	-29.51	182	53.6	48.63	4.97	221	69.6	61.48	8.12
143	109.6	97.35	12.25	183	49.6	48.47	1.13	222	79.8	68.88	10.92
145	91.8	96.87	-5.07	184	47.7	44.30	3.40	223	77.6	64.41	13.20

146	74.7	97.01	-22.31	186	36.6	31.65	4.95	227	69.6	61.76	7.84
147	66	97.33	-31.33	187	29.6	29.94	-0.34	229	69.6	71.69	-2.09
148	92.7	100.27	-7.57	189	56.7	43.54	13.16	231	62.7	63.83	-1.13
149	79.6	97.95	-18.35	190	29.7	30.71	-1.01	232	67.8	61.67	6.13
151	109.6	95.00	14.60	191	30.6	30.52	0.08	233	67.7	65.77	1.93
153	72.4	76.54	-4.14	192	27.6	35.19	-7.59	234	84.68	63.03	21.65
155	89.6	87.98	1.62	193	35.1	24.46	10.64				
158	89.8	82.80	7.00	194	34.5	23.97	10.53				
159	82.7	78.80	3.90	195	32.5	28.62	3.88				

The input node is fully connected to every node of the hidden layer, and every node of the hidden layer is connected to every node of the output layer. And the data feed forward to output, each hidden node neuron in hidden layer does something called weighted sum, it takes the input and multiply by the weight and that to the other input and multiply by the weight. At the completion of the weighted sum, the result passes through activation function before it gets to send out to the next connection. The Multilayer perceptron network used to generate COD prediction is shown in figure 5. Seven different inputs enter in the system, the input data feedforward and the output come out.

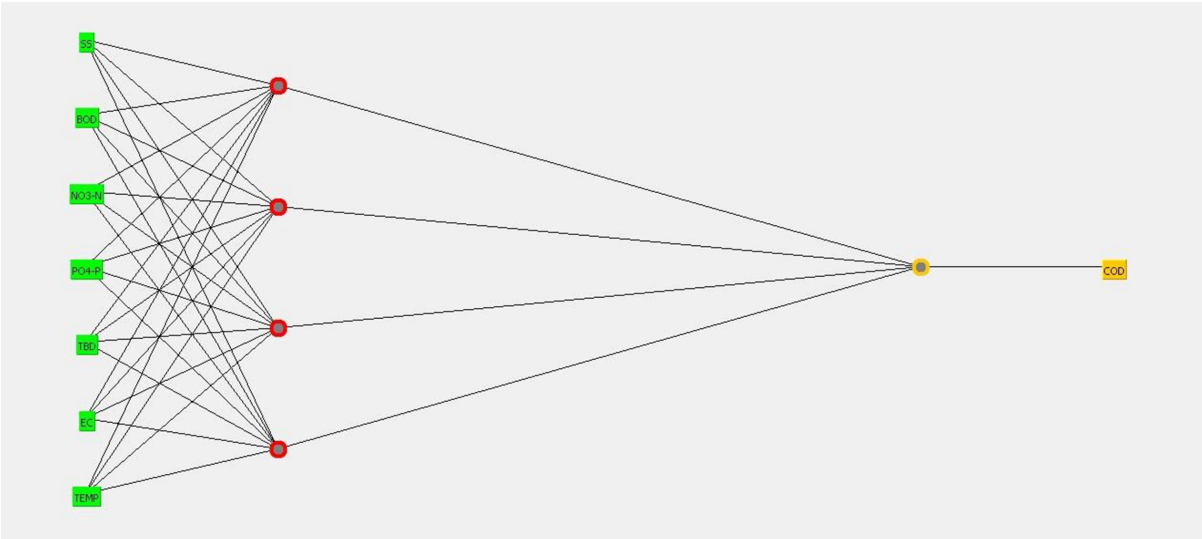


Figure 5.10: MLP generated network model for output COD and its corresponding correlated input parameters

As can be seen, the MLP has seven inputs and one output. The set of inputs (X_1 to X_7) combine with their corresponding weights (weighted sum) W_1 to W_7 or strength of their own plus a bias or error to produce better predictive output. Sometimes the output is either zero or one depending on the weighted sum of the set of inputs that means the inputs are needed to pass to a function called a sigmoid function or a logistic curve, that will produce either one or zero based on a certain threshold. Neurons are fully connected using the connection, and they send a signal to the next neuron. the weighted sum generated from the multilayer perceptron in Figure 5.10 above is

$$Y = \begin{bmatrix} W_{11} & W_{12} & W_{13} & W_{14} & W_{15} & W_{16} & W_{17} \\ W_{21} & W_{22} & W_{23} & W_{24} & W_{25} & W_{26} & W_{27} \\ W_{31} & W_{32} & W_{33} & W_{34} & W_{34} & W_{36} & W_{38} \\ W_{41} & W_{42} & W_{43} & W_{44} & W_{45} & W_{46} & W_{47} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \\ X_7 \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{bmatrix}$$

$$matric = \begin{bmatrix} X_1W_{11} & X_2W_{13} & X_3W_{13} & X_4W_{14} & X_5W_{15} & X_6W_{16} & X_7W_{17} \\ X_1W_{21} & X_2W_{22} & X_3W_{23} & X_4W_{24} & X_5W_{25} & X_6W_{26} & X_7W_{27} \\ X_1W_{31} & X_2W_{32} & X_3W_{33} & X_4W_{34} & X_5W_{34} & X_6W_{36} & X_7W_{38} \\ X_1W_{41} & X_2W_{42} & X_3W_{43} & X_4W_{44} & X_5W_{45} & X_6W_{46} & X_7W_{47} \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{bmatrix}$$

$$COD = \begin{bmatrix} X_1W_{11} & X_2W_{13} & X_3W_{13} & X_4W_{14} & X_5W_{15} & X_6W_{16} & X_7W_{17} \\ X_1W_{21} & X_2W_{22} & X_3W_{23} & X_4W_{24} & X_5W_{25} & X_6W_{26} & X_7W_{27} \\ X_1W_{31} & X_2W_{32} & X_3W_{33} & X_4W_{34} & X_5W_{34} & X_6W_{36} & X_7W_{38} \\ X_1W_{41} & X_2W_{42} & X_3W_{43} & X_4W_{44} & X_5W_{45} & X_6W_{46} & X_7W_{47} \end{bmatrix} = \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \end{bmatrix}$$

The function represents by the above network can be written as

$Y_1 = f_1(X_1W_{11} + X_2W_{13} + X_3W_{13} + X_4W_{14} + X_5W_{15} + X_6W_{16} + X_7W_{17})$

$Y_2 = f_2(X_1W_{21} + X_2W_{22} + X_3W_{23} + X_4W_{24} + X_5W_{25} + X_6W_{26} + X_7W_{27})$

$Y_3 = f_3(X_1W_{31} + X_2W_{32} + X_3W_{33} + X_4W_{34} + X_5W_{35} + X_6W_{36} + X_7W_{37})$

$Y_4 = f_4(X_1W_{41} + X_2W_{42} + X_3W_{43} + X_4W_{44} + X_5W_{45} + X_6W_{46} + X_7W_{47})$

$$\begin{bmatrix} Y_1 = f_1(BODW_{11} + PO4 - PW_{12} + NO3 - NW_{13} + SSW_{14} + TBDW_{15} + ECW_{16} + TEMPW_{17} \\ Y_2 = f_2(BODW_{21} + PO4 - PW_{22} + NO3 - NW_{23} + SSW_{24} + TBDW_{25} + ECW_{26} + TEMPW_{27} \\ Y_3 = f_3(BODW_{31} + PO4 - PW_{32} + NO3 - NW_{33} + SSW_{34} + TBDW_{35} + ECW_{36} + TEMPW_{37} \\ Y_4 = f_4(BODW_{41} + PO4 - PW_{42} + NO3 - NW_{43} + SSW_{44} + TBDW_{45} + ECW_{46} + TEMPW_{47} \end{bmatrix}$$

Where Y1 to Y4 are the sub COD value before final summation, f1 to f4 are the activation of the respective neuron, X_1 = BOD, X_2 = PO4-P, X_3 = NO3-N, X_4 = SS, X_5 = TBD, X_6 = EC, X_7 = TEMP, and W_{11} to W_{57} are the weight of the connector of the respective input, and h_1 to h_2 are the hidden layers

COD

Therefore, COD = $Y_1 + Y_2 + Y_3 + Y_4$

This how the multilayer perceptron network is represented to predict the output COD

5.6.2 Construction of the Multilayer perceptron for BOD

Multilayer Perceptron is used to build BOD predictive models from a set of highly correlated input data to predict output parameter these include COD, PO4-P, NO3-N, NH4-N, turbidity electrical conductivity and temperature. 70% of the data is used to train the network which help the network to learn appropriately and the remaining data set was used to test the model build. The generated MLP network for the estimation of BOD output parameter is presented in figure 5.11, as can be seen from the figure the perceptron produces single output base on seven different input layers, four hidden layers by forming a linear mixture by means of input weights. The signal flow travels from the input layers through the hidden layers and finally to the output layer

Figure 5.11: MLP generated network model for output BOD and its corresponding correlated input parameters

The input-output generated matrix equation from network for both training and testing data set of BOD in Figure 5.11

$\lceil Y_1\ f_1(CODW_{11}+ PO4\text{-}PW_{12}+ NO3\text{-}NW_{13}+ NH4\text{-}NW_{14}+ TBDW_{15}+ ECW_{16}+ TEMPW_{17})\rceil$

$| Y_2\ f_2(CODW_{21}+ PO4\text{-}PW_{22}+ NO3\text{-}NW_{23}+ NH4\text{-}NW_{24}+ TBDW_{25}+ ECW_{26}+ TEMPW_{27})$

$| = BOD$

$| Y_3=f_3(CODW_{31}+ PO4\text{-}PW_{32}+ NO3\text{-}NW_{33}+ NH4\text{-}NW_{34}+ TBDW_{35}+ ECW_{36}+ TEMPW_{37}) |$

$\lfloor Y_4$ $f_4(CODW_{41}+$ $PO4\text{-}PW_{42}+$ $NO3\text{-}NW_{43}+$ $NH4\text{-}NW_{44}+$ $TBDW_{45}+$ $ECW_{46}+$ $TEMPW_{47})$ $\rfloor$

Therefore, $Y_1 + Y_{2\,+}\, Y_{3\,+}\, Y_4 = BOD$

Where f is an activation function w is a corresponding weight of the input

5.6.3 Construction of the Multilayer perceptron for NH4-N

Multilayer Perceptron is used to build NH4-N predictive models from a set of highly correlated input data to predict output parameter these include COD, BOD, PO4-P, SS turbidity and electrical conductivity (EC). The network consists of six different inputs and 3 hidden layer and one single output as contain in figure 5.10

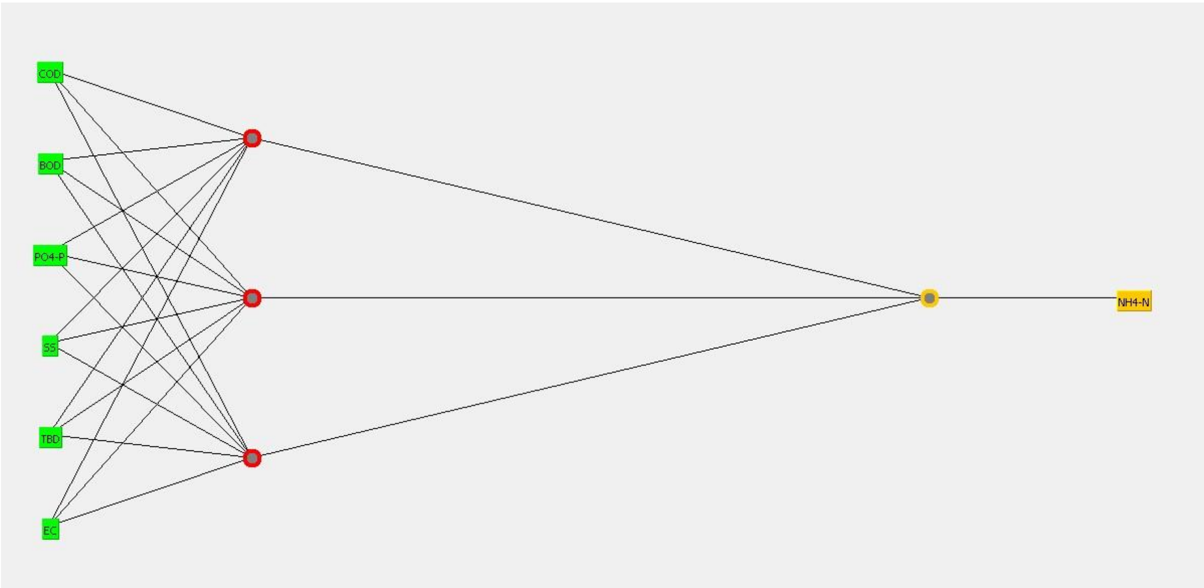


Figure 5.12: MLP generated network model for output NH4-N and its corresponding correlated input parameters

The input-output generated matrix equation from network for both training and testing of NH4-N data in Figure 5.12

Y_1 $f_1(CODW_{11}+ BODW_{12}+ PO4\text{-}PW_{13}+ SSW_{14}+ TBDW_{15}+ ECW_{16})$

NH4-N [Y_2 $f_2(CODW_{21}+ BODW_{22}+$ $PO4\text{-}PW_{23}+ SSW_{24}+ TBDW_{25}+ ECW_{26})$]

Y_3 $f_3(CODW_{31}+ BODW_{32}+ PO4\text{-}PW_{33}+$ $W_{34}+ TBDW_{35}+ ECW_{36})$

Y_4 $f_4(CODW_{41}+ BODW_{42}+ PO4\text{-}PW_{43}+ SSW_{44}+ TBDW_{45}+ ECW_{46})$

Therefore, $Y_1 + Y_2 + Y_3 + Y_4 = NH4\text{-}N$

5.6.4 Construction of the Multilayer perceptron for PO4-P

Multilayer Perceptron is employed to build NH4-N models from a set of highly correlated input data aimed at predicting NH4-N output parameter; the highly correlated input parameters include COD, BOD, NH4-N, SS, turbidity, and electrical conductivity. All the six different inputs parameters are connected to all the 3 hidden layer of the network with processing neurons and all 3 hidden layers are connected to one single output as contain in Figure 5.13.

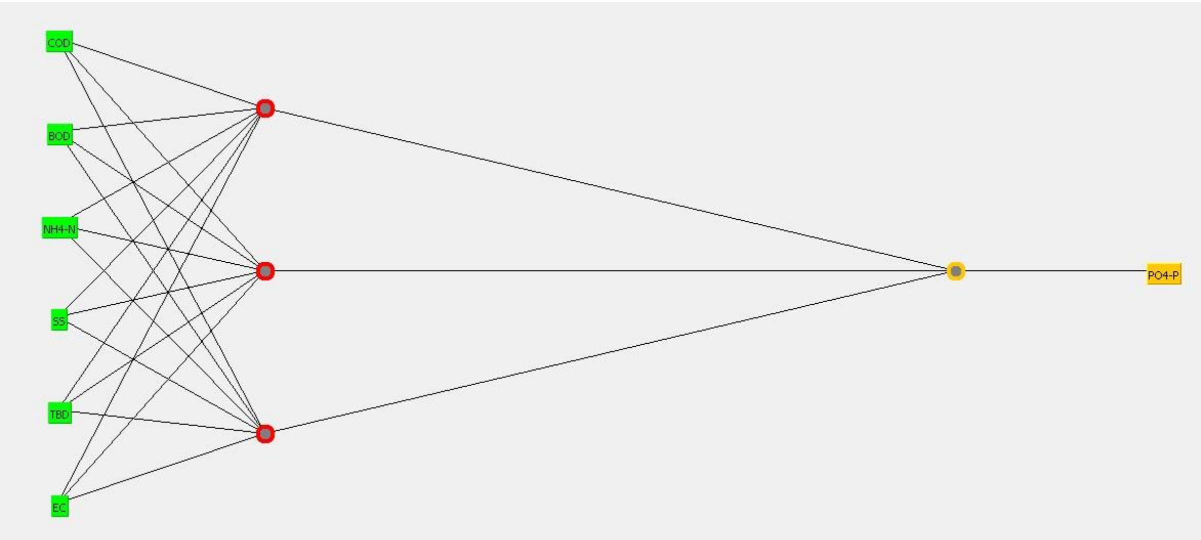


Figure 5.13: MLP generated network model for output PO4-P and its corresponding correlated input parameters

The input-output generated matrix equation from network for training and testing PO4-P dataset in equation

$$PO4\text{-}P \quad \begin{bmatrix} Y_1\ f_1(CODW_{11} + BODW_{12} + NH4\text{-}NW_{13} + SSW_{14} + TBDW_{15} + ECW_{16}) \\ Y_2\ f_2(CODW_{21} + BODW_{22} + NH4\text{-}NW_{23} + SSW_{24} + TBDW_{25} + ECW_{26}) \\ Y_3\ f_3(CODW_{31} + BODW_{32} + NH4\text{-}NW_{33} + SSW_{34} + TBDW_{35} + ECW_{36}) \\ Y_4\ f_4(CODW_{41} + BODW_{42} + NH4\text{-}NW_{43} + SSW_{44} + TBDW_{45} + ECW_{46}) \end{bmatrix} \qquad 5.4$$

Therefore, $Y_1 + Y_2 + Y_3 + Y_4 = PO4\text{-}P$

5.6.5 Construction of the Multilayer perceptron for Suspended solid (SS)

It is a network with six different highly correlated input water quality parameters, three hidden layers with processing neurons and one single output parameters (SS) as shown in Figure 5.14.

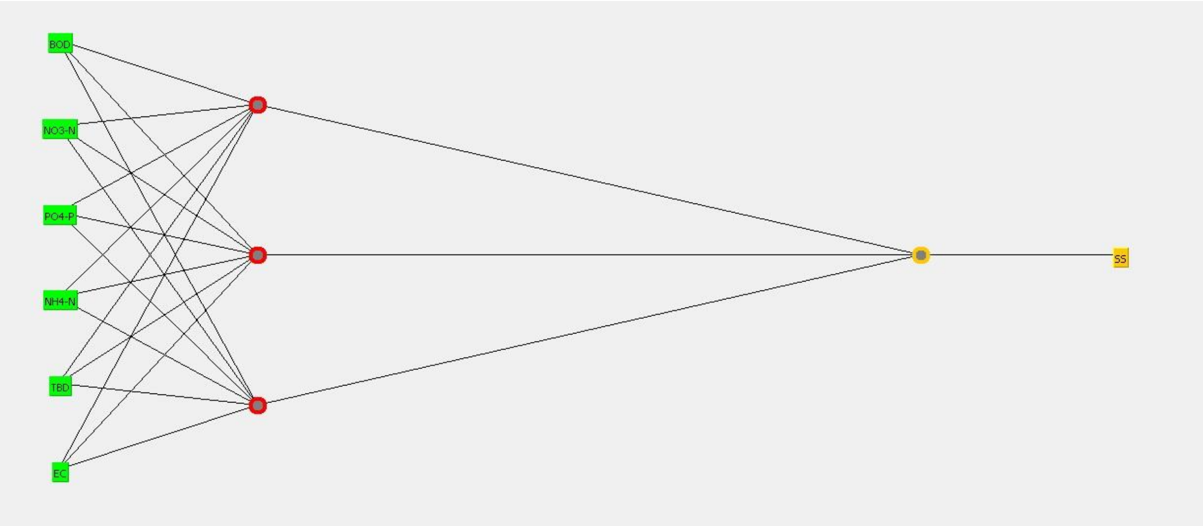


Figure 5.14: MLP generated network model for output SS and its corresponding with correlated input parameters

The MLP generated equation to predict output SS parameter given other know highly correlated input for both training and testing data set is presented in equation

Y_1 f_1(BODW_{11}+ NO3-NW_{12}+ PO4-PW_{13}+ SSW_{14}+ TBDW_{15}+ ECW_{16})

[Y_2 f_2(BODW_{21}+ NO3-NW_{22}+ PO4-PW_{23}+ SSW_{24}+ TBDW_{25}+ ECW_{26})] Y_3 f_3(BODW_{31}+ NO3-NW_{32}+ PO4-PW_{33}+ W_{34}+ TBDW_{35}+ ECW_{36})

Y_4 f_4(BODW_{41}+ NO3-NW_{42}+ PO4-PW_{43}+ SSW_{44}+ TBDW_{45}+ ECW_{46})

Therefore, $Y_1 + Y_2 + Y_3 + Y_4$ =SS

All predicted values are generated, and the results are compared with the actual measure values to compare and evaluate the performance of the prediction model

5.7 Model evaluation performance

Model Evaluation is an integral part of the process of choosing a good model in the data predictive model process. It helps to find the best model among many models build that will predict output parameter accurately in question in a given data set it also indicates how good the chosen model will work in the future. After the model is built, specific evaluation performance about the prediction model parameters is useful in measuring prediction model accuracy and model error. Several measures of goodness of fit were used to evaluate the prediction performance of the regression model (Khadr & Elshemy, 2016). The performance of the models built was evaluated based on two model evaluation performance methods. These methods include graphical visualisation evaluation (using scatter plots and hydrographs) and numerical model evaluation using error measures criteria, the measures that were used to compare the output values of the model, these include root mean square (RMSE), regression coefficient (r), mean average error (MAE), relate absolute error (RAE) and root relative squared error (RRSE)

5.7.1 Graphical Model Evaluation

To predict the performance of constructed wetland by predicting water Thus, it seems that plotting the data and showing the dispersion of the values is important

Graphical representation model evaluation is a process of visualising the relationships between measured and predicted values. Assessing model performance through graphical evaluation, scatter plot and hydrograph play a vital role. The use of scatter plots of predicted and measured (or vice versa) values is one of the most common alternatives to evaluate the performance of prediction models and is still the most commonly used method.

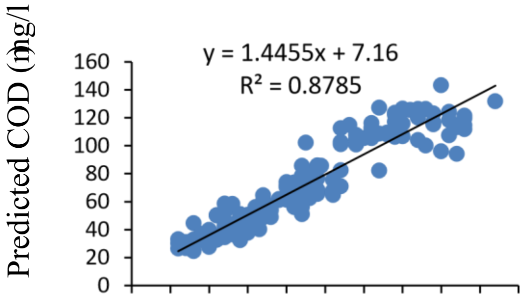
To graphically evaluate the prediction performance of the MLP and MLR models built, actual and predicted values are compared graphically to visualise the difference between them Figs. 4 and 5 are the structures of scatter plot and hydrograph of MLP model, that ware depicted between actual and predicted values of BOD and COD concentrations both in training and testing dataset phases, respectively. From the MLP model structures as shown on a scatter graph, the closer the points of measured and predicted values merge in a straight line the solid and accurate the linear relationship is between actual and predicted values built by the model, likewise hygrograph the closer the measure and predicted curves values are in agreement the accurate the model is

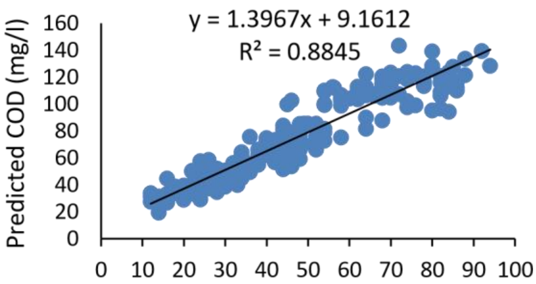
5.7.1.1 Graphical evaluation of BOD and COD model

To graphically evaluate COD build by MLR and MLP model, scatter plots and hydrograph were employed for this task. Figure 5.15 are the scatter plots and hydrograph between predicted values of COD concentration by MLR model versus measured values for training, testing and complete COD data set. As can be seen from It was from Figure 5.15a that the measure and predicted were correlated linearly merged in a straight line. Likewise, in Figure 5.15b hydrograph the measure and predicted COD value curves are in close agreement with each other. COD testing data is used to test the model build, as seen from the scatter plot and hydrograph Figure 5.15 c, and d respectively, that the model predicted COD with high accuracy. Since the MLR model recorded great success, the entire COD data is used for prediction, and the model is evaluated graphically as contain in figure 5.15e for scatter plot and 5.15f for hydrograph, it was observed that the measured and predicted values of COD are linearly fitted to each other on straight line in scatter plot. However, in hydrograph the measured and predicted value curves were in close agreement with each other. This confirms that the MLR model performed considerably well in predicting COD concentration for the entire COD dataset. Hence the accuracy of the MLR model build in predicting COD

concentration was achieved.

(c)

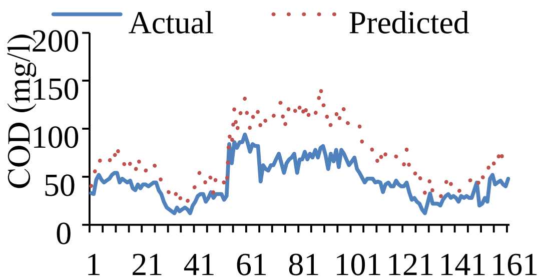




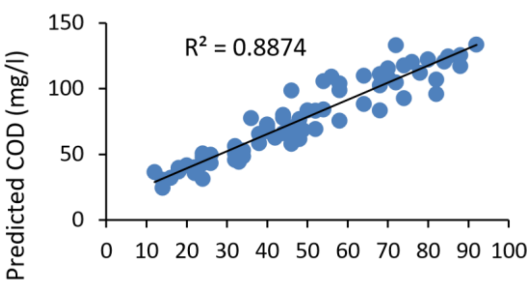
0 10 20 30 40 50 60 70 80 90 100

(e) Measured COD (mg/l)

(a) Measuered COD (mg/l)



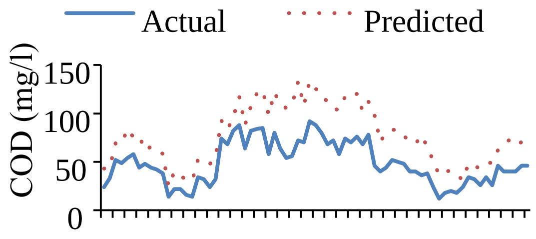
(b) Data Points



y =

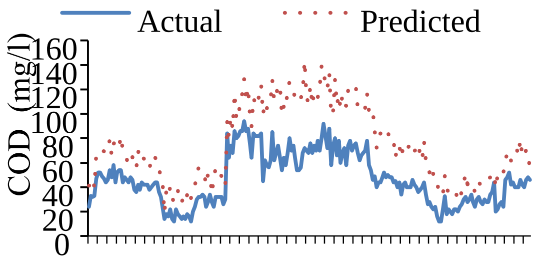
1.3059x + 13.095

Measured COD (mg/l)



1 6 11 16 21 26 31 36 41 46 51 56 61 66 71

(d) Data Points



1 21 41 61 81 101121141161181201221

(f) Data Points

Figure 5.15: MLR model: (a) scatter plot of COD concentration between quantified and predicted values in Training data (b) Hydrograph of COD concentration between actual and predicted values in training data (c) Scatter plot of COD concentration between measured and predicted value in testing data (d) Hydrograph of COD concentration between actual and predicted values in testing data set. (e) Scatter plot of COD concentration for the whole data set (f) Hydrograph of COD concentration for the whole data set

Meanwhile, Figure 5.16 are the designed MLP model structure for the comparison between measured and predicted COD concentration, in training, testing and whole dataset, which depicted in the form of scatter plot and hydrograph. Looking at the scatterplots of the MLP model as shown in Figure 5.16 a and c indicated that the points of measured and predicted of COD values concentration are linearly fitted to each other in both training and testing respectively. The result is confirmed in hydrographs in Figure 5.16 b and d that the lines between measured and predicted values of COD are in close agreement to one another in both training and testing dataset. This also confirms that the MLP model predicts COD correctly. However, in figure 5.16 e and f are the scatter plot and hydrograph between measured and predicted values of COD concentration respectively, as can be seen, that the two graphs indicated that both measured and predicted values points are close together to the line of perfect match and in close agreement between each other. This is an indication that the predicted values fit well to the actual values. Hence MLP model predict COD with reasonable accuracy.

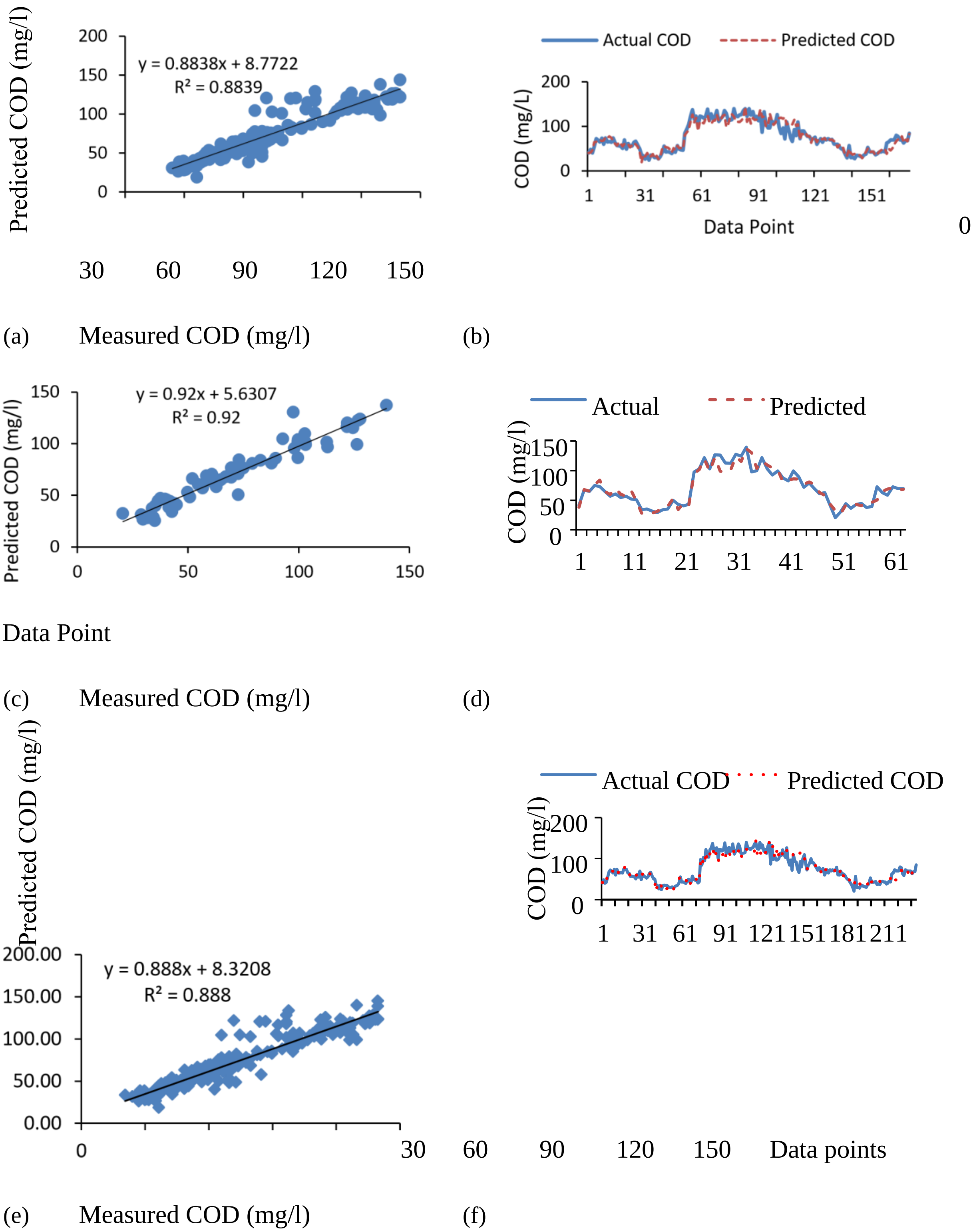
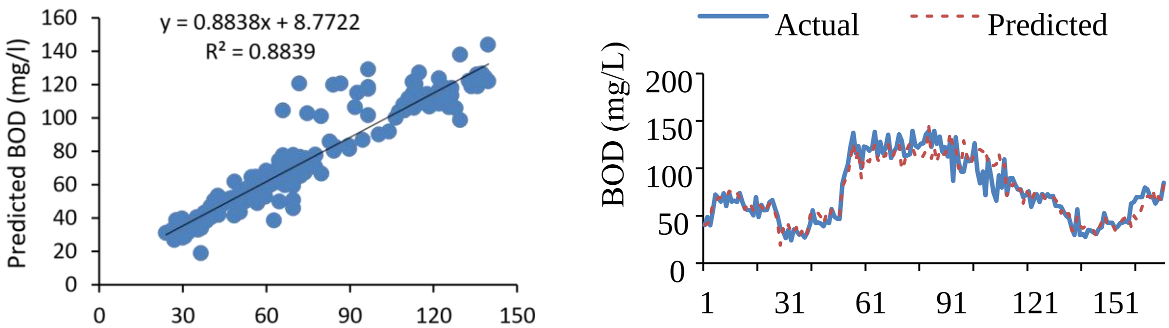
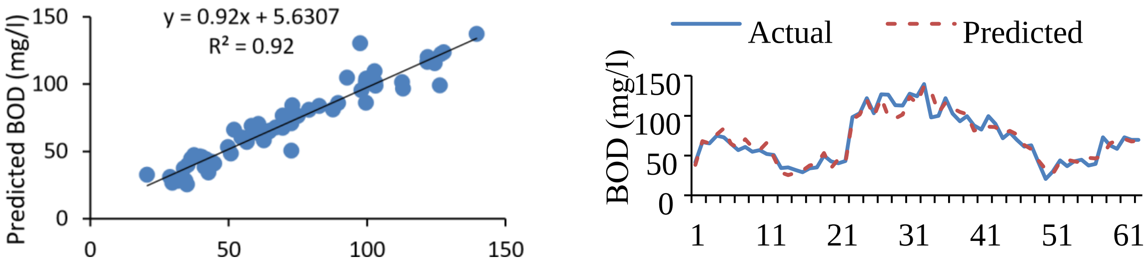


Figure 5.16: MLP model: (a) scatter plot of COD concentration between quantified and predicted values (b) Hydrograph of COD concentration between actual and predicted values (c) Scatter plot of COD concentration between measured and predicted value (d) Hydrograph of COD concentration between actual and predicted values. (e) Scatter plot of COD concentration for the whole data set (f) Hydrograph of COD concentration for the whole data set.

Figure 5.17 scatter plot and hydrograph of measured and predicted BOD concentration value of the MLR model. Figure 5.17 a and c are the scatter plot of training and testing dataset respectively. It was observed that the value points merged in a straight line and also Figure 5.17 b and d are scatter plots and hydrographs of training and testing data of BOD concentration, which indicated that measured and predicted values trend curves were closely together. This trend symbolises the accuracy of the MLR model in predicting BOD concentrations. However, Figure 5.17 e is the scatter plot and f is the hydrograph of measured and predicted values of BOD concentration of the whole BOD dataset respectively. It was observed that the measured and predicted values points of BOD join closer together in a straight line of scatter plot and also curves of hydrograph are closely together between, this symbolise the accuracy of the MLR models in predicting BOD concentrations.



(a) Measured BOD (mg/l) (b) Data Point



(d) Data Point

(c) Measured BOD (mg/l)

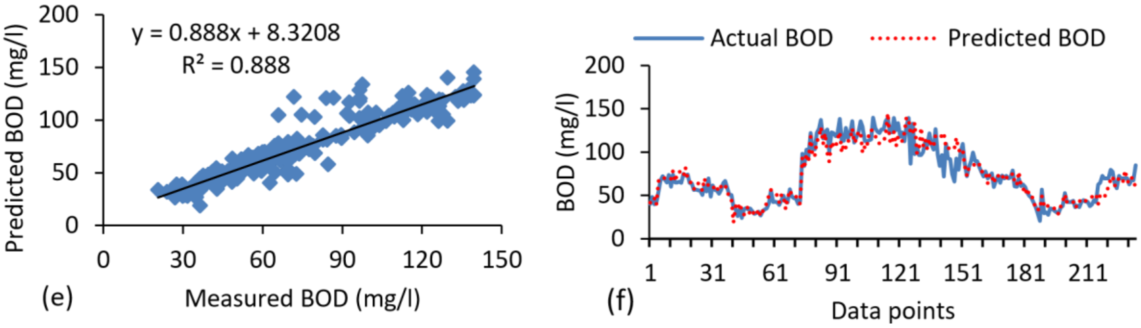
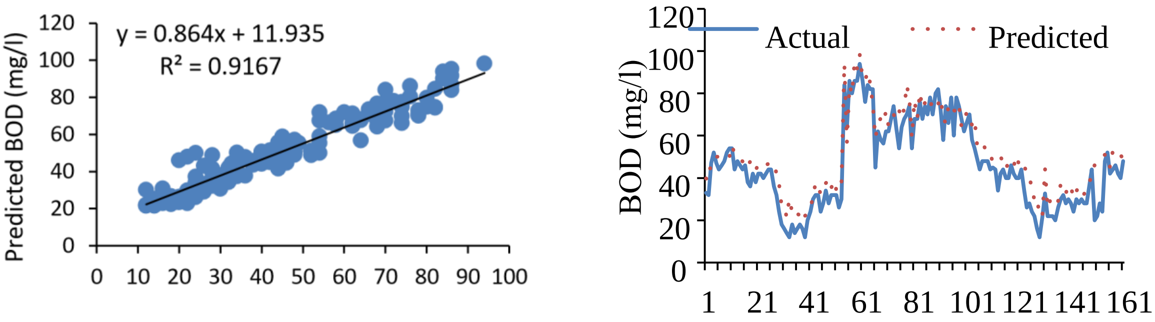


Figure 5.17: MLR model (a) scatter plot of BOD concentration between quantified and predicted values in Training data; (b) Hydrograph of BOD concentration between actual and predicted values in training data; (c) Scatter plot of BOD concentration between measured and predicted value in testing data; (d) Hydrograph of BOD concentration between actual and predicted values in testing dataset; (e) Scatter plot of BOD concentration for the whole data set; and (f) Hydrograph of BOD concentration for the whole data set.

Meanwhile, Figure 5.18 are the graphical evaluation of designed MLP model structure between measured and predicted BOD concentration, in training and testing dataset, which depicted in the form of scatter plot and hydrograph. Looking at the scatterplots shown in Figure 5.18 a and c which indicated that the points of measured and predicted BOD values concentration are linearly fitted to each other in both training and testing data set respectively. This is also reaffirm in hydrograph in figure 5.18 b and d that the line curves of predicted values of BOD concentration are closely followed the measure values and in close agreement to one another in both training and testing dataset respectively. This also confirms that the MLP model predicts BOD correctly.



(a) Measured BOD (mg/l) (b) Data Points

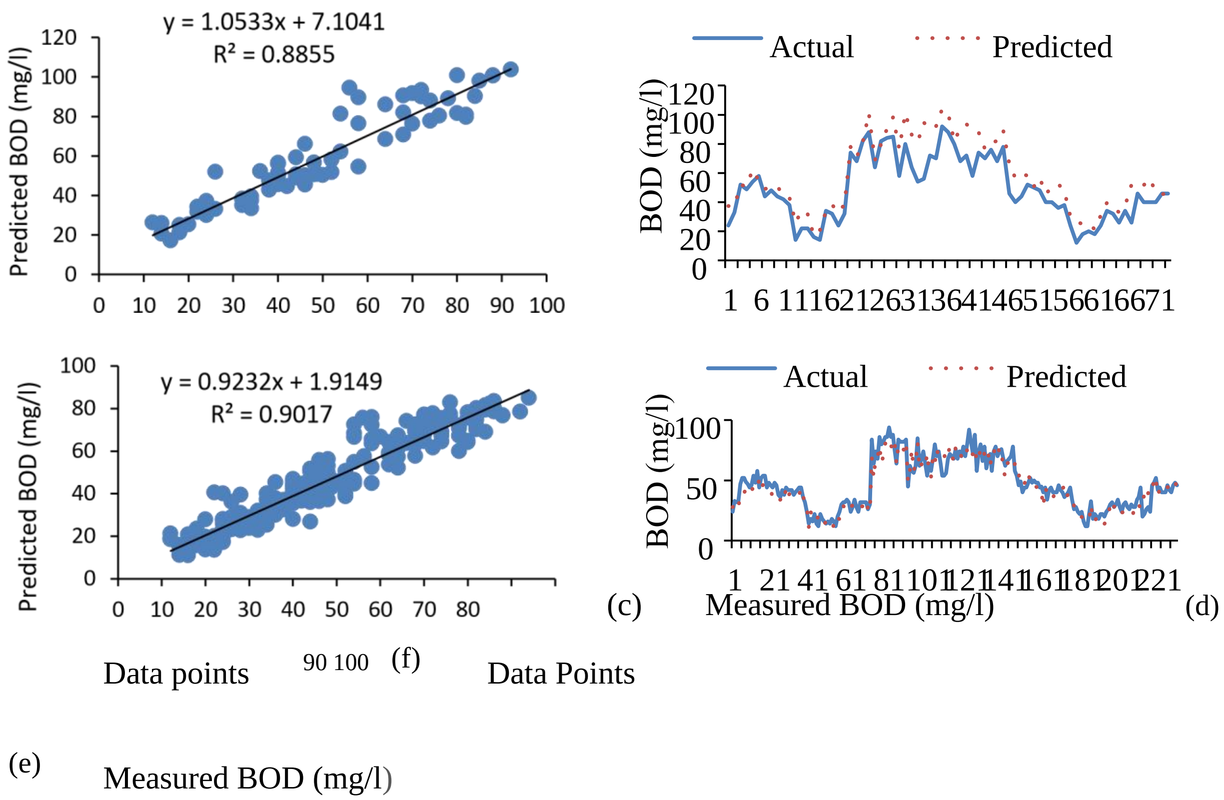


Figure 5.18: MLP model: (a) scatter plot of BOD concentration between quantified and predicted values (b) Hydrograph of BOD concentration between actual and predicted values (c) Scatter plot of BOD concentration between measured and predicted value (d) Hydrograph of BOD concentration between actual and predicted values. (e) Scatter plot of BOD concentration for the whole data set (f) Hydrograph of BOD concentration for the whole data set

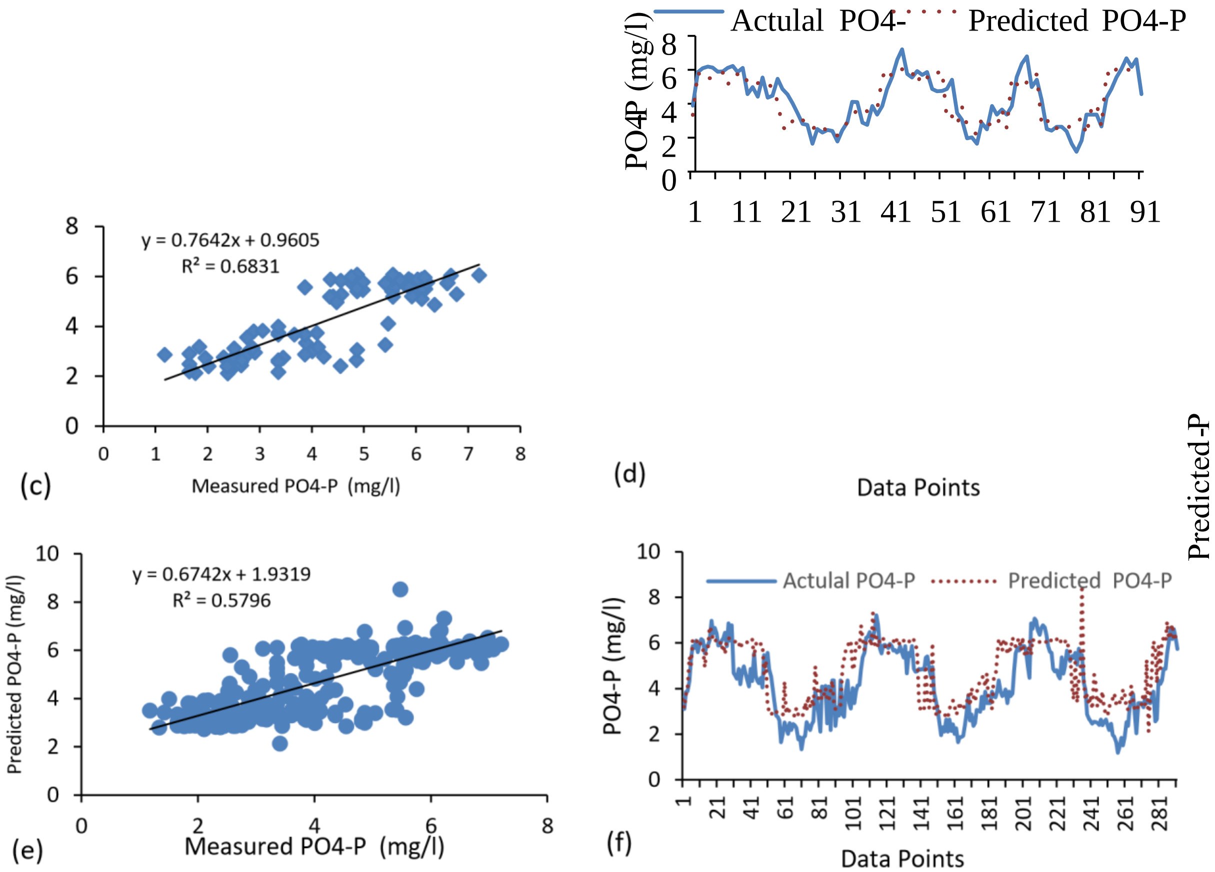
However, in Figure 5.19 e and f are the scatter plot and hydrograph between measured and predicted values of BOD concentration of the whole dataset respectively, as can be seen. that the scatter plot indicated that both measured and predicted values are correlated and in close agreement between each other in hydrograph. This confirm that the MLP model predict COD values concentration accurately.

However, in graphical comparison between two models built MLR and MLP for prediction of organic matter parameters (BOD and COD). It was observed from all the scatter plots that, predicted values data points of BOD and COD in MLP model are closer in a straight line to their corresponding BOD and COD measured values in both training and testing data set than MLR model. This was confirmed in hydrograph that the predicted values curves of BOD and COD are more closely followed the measure values curves beside few instances that deviation occur. Comparably MLP model predicted both COD and BOD better than MLR as contain in the Figures.

5.7.1.2 Graphical evaluation of PO4-P and NH4-N model

MLR and MLP models were built to predict PO4-P and NH4-N concentration, however, to graphically evaluate the performance of the two models built, scatter plots and hydrographs are employed to visualise and evaluate the relationship between measured and predicted values and figure out the best between

Figure 5.19 presented the scatter plot and hydrograph between measured and predicted PO4P values of MLR model. Figure 5.19 a and c are the scatter plots of training and testing dataset respectively. It was observed that the data points of predicted and measured values merged closer together in straight line. likewise Figure 5.19 b and d are hydrographs of training and testing data of PO4-P which indicated that predicted values closely follow the trend of measured PO4-P values and this signifies the accuracy of the MLR model in predicting water PO4-P concentrations in both training and testing data set. However, Figure 5.19 e is the scatter plot and 5.19 f is the hydrograph of measured and predicted values of PO4-P concentration of the entire dataset. It was observed that the measured and predicted value points of PO4-P in a scatter plot are linearly correlated in a straight line, it was also indicated that the measured and predicted values are closely together between in hydrograph, this confirms the accuracy of the MLR model for the prediction of PO4-P concentrations.



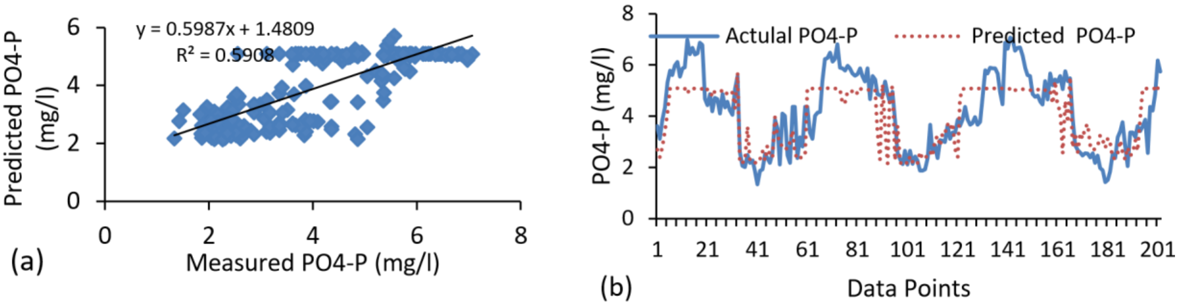
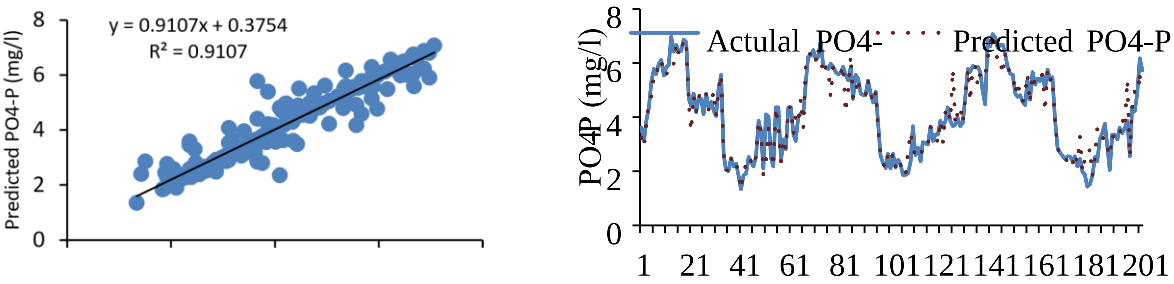


Figure 5.19: MLR model: (a) scatter plot of SS concentration between quantified and predicted values in Training data (b) Hydrograph of PO4-P concentration between actual and predicted values in training data (c) Scatter plot of PO4-P concentration between measured and predicted value in testing data (d) Hydrograph of PO4-P concentration between actual and predicted values in testing data set. (e) Scatter plot of PO4-P concentration for the whole data set (f) Hydrograph of PO4-P concentration for the whole data set.

Furthermore, the MLP model is employed to predict the concentration of PO4-P, to evaluate its performance graphically scatter plot and hydrograph are used as depicted in Figure 5.20, which demonstrate the graphical evaluation of MLP prediction model using scatter plot and hydrograph. As can be seen from the scatter plot in 5.20 a and 5.20 c, that depicted the measured and predicted values of PO4-P in both training and testing dataset were observed to be in good linear correlation between them Also measured and predicted PO4-P concentration in Figure b and d is the hydrograph of training and testing data respectively of the MLP model, it was discovered that their trend follows closely to each. This is an indication that the MLP model was able to predict PO4-P concentration correctly, due to the effectiveness of the MLP built. MLP model is employed to predict the entire PO4-P data set; the graphical model evaluation revealed that the measured and predicted values PO4-P in scatter plot and hydrograph as depicted in Figure e and f respectively are correlated and in close agreement with each other.



a 0 Measured PO42 -P (mg/l)4 6 8 b Data points

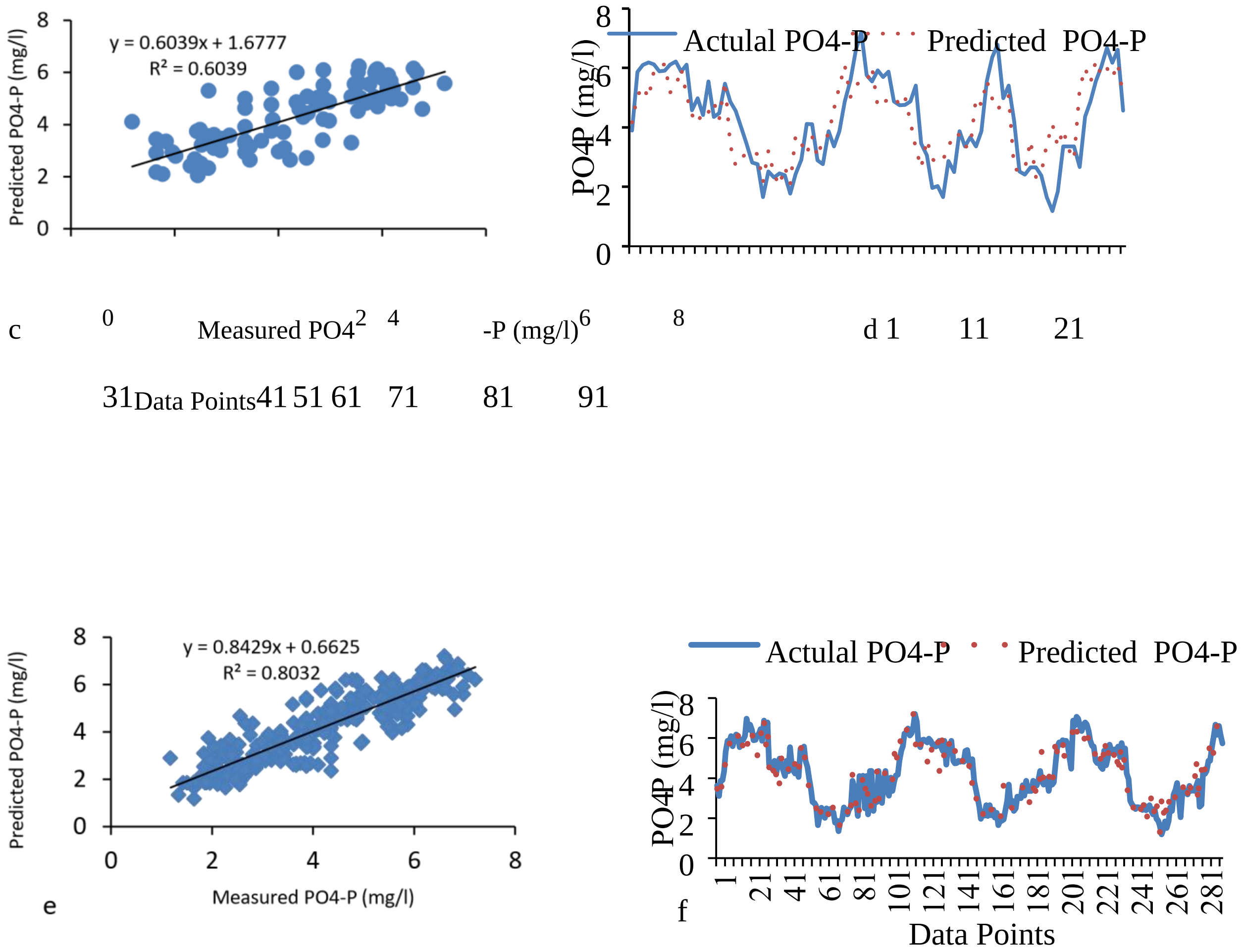


Figure 5.20: MLP model: (a) scatter plot of PO4-P concentration between quantified and predicted values (b) Hydrograph of PO4-P concentration between actual and predicted values (c) Scatter plot of BOD concentration between measured and predicted value (d) Hydrograph of PO4-P concentration between actual and predicted values. (e) Scatter plot of PO4-P concentration for the whole data set (f) Hydrograph of PO4-P concentration for the whole data set

However, to graphically evaluate the performance of the MLR model for the prediction of NH4-N concentrations scatter plot and hydrograph were used as depicted in Figure 5.21 for both training and testing NH4-N dataset. According to the Figures 5.21 a and b for the scatter plot of training and testing NH4-N data respectively, it was discovered that there exists a better linear correlation relationship between measured and predicted values of NH4-N concentration. However, measured and predicted values curves in hydrograph followed closely to each other in both training and testing data set. This confirms that MLR model predicted NH4-N parameter concentration with reasonable accuracy. Likewise, Figure 5.21 e and f are the graphical evaluation of the MLR model to predict NH4-N for the entire data in scatter plot and hydrograph respectively, which showed measures and predicted data points are in close agreement between each other.

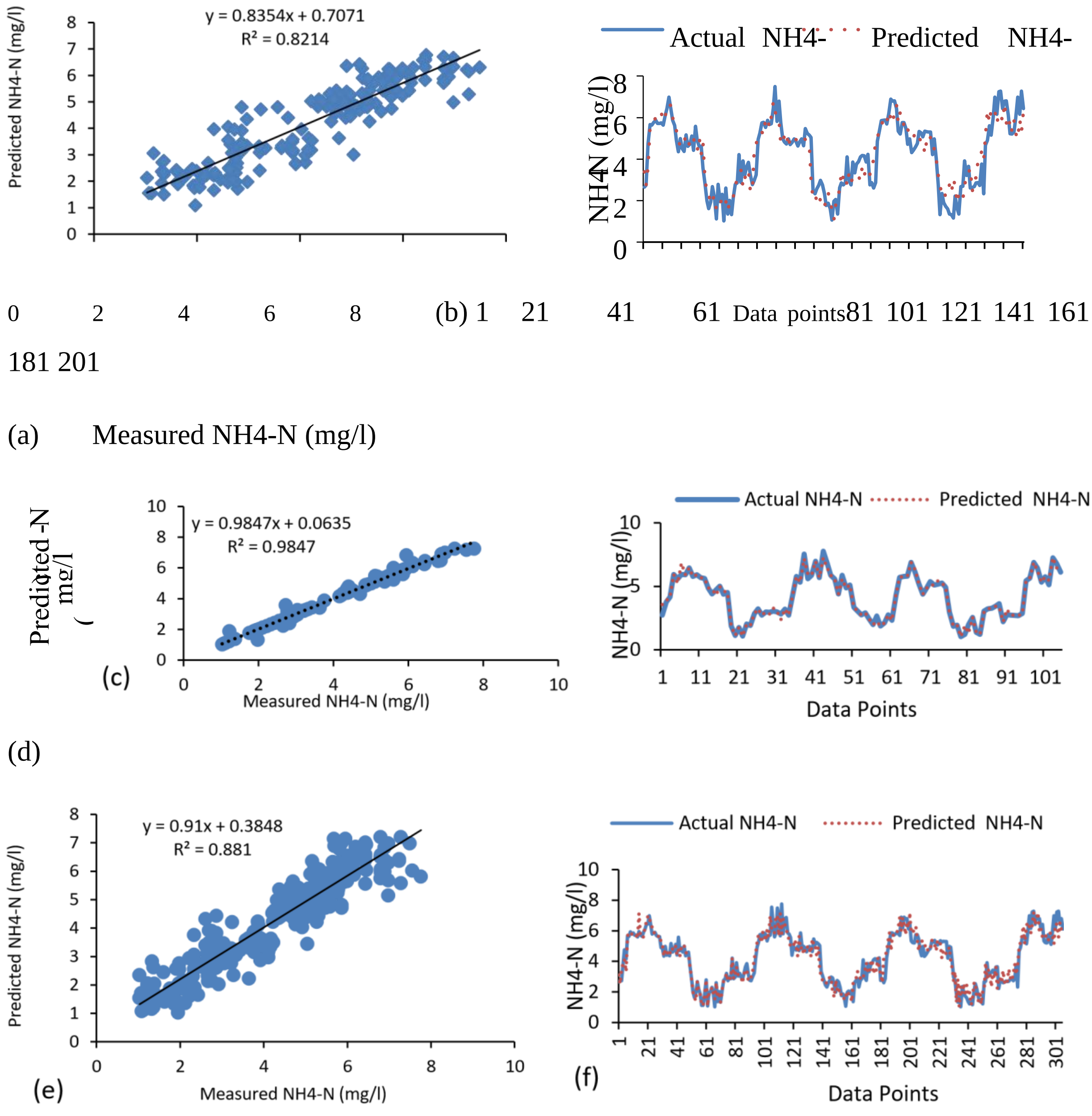


Figure 5.21: MLR model: (a) scatter plot of NH4-N concentration between quantified and predicted values in Training data (b) Hydrograph of NH4-N concentration between actual and predicted values in training data (c) Scatter plot of NH4-N concentration between measured and predicted value in testing data (d) Hydrograph of NH4-N concentration between actual and predicted values in testing data set. (e) Scatter plot of NH4-N concentration for the whole data set (f) Hydrograph of NH4-N concentration for the whole data set

To graphically evaluate the performance of the MLP model for the prediction of NH4-N concentration, measured versus the predicted values were depicted for both training and testing dataset and also for the whole dataset in Figure 5.22. It was discovered in scatter plot in Figure 5.22 a and b for both in training and testing dataset that the measure and predicted values are linearly correlated to each other in a straight line; this was confirmed in hydrograph Figure 5.20 b and d for the of training and testing NH4-N data respectively that the trend lines of measured values curves are in close agreement with predicted values. However, figure 5.22 e and f are the scatter plot and hydrograph between measured and predicted NH4-N concentration of training and testing data of entire data respectively. It was discovered that the measured and predicted data points are in close agreement with each other. This signifies that the MLP model predicted NH4-N concentration perfectly in training and testing of NH4-N data set.

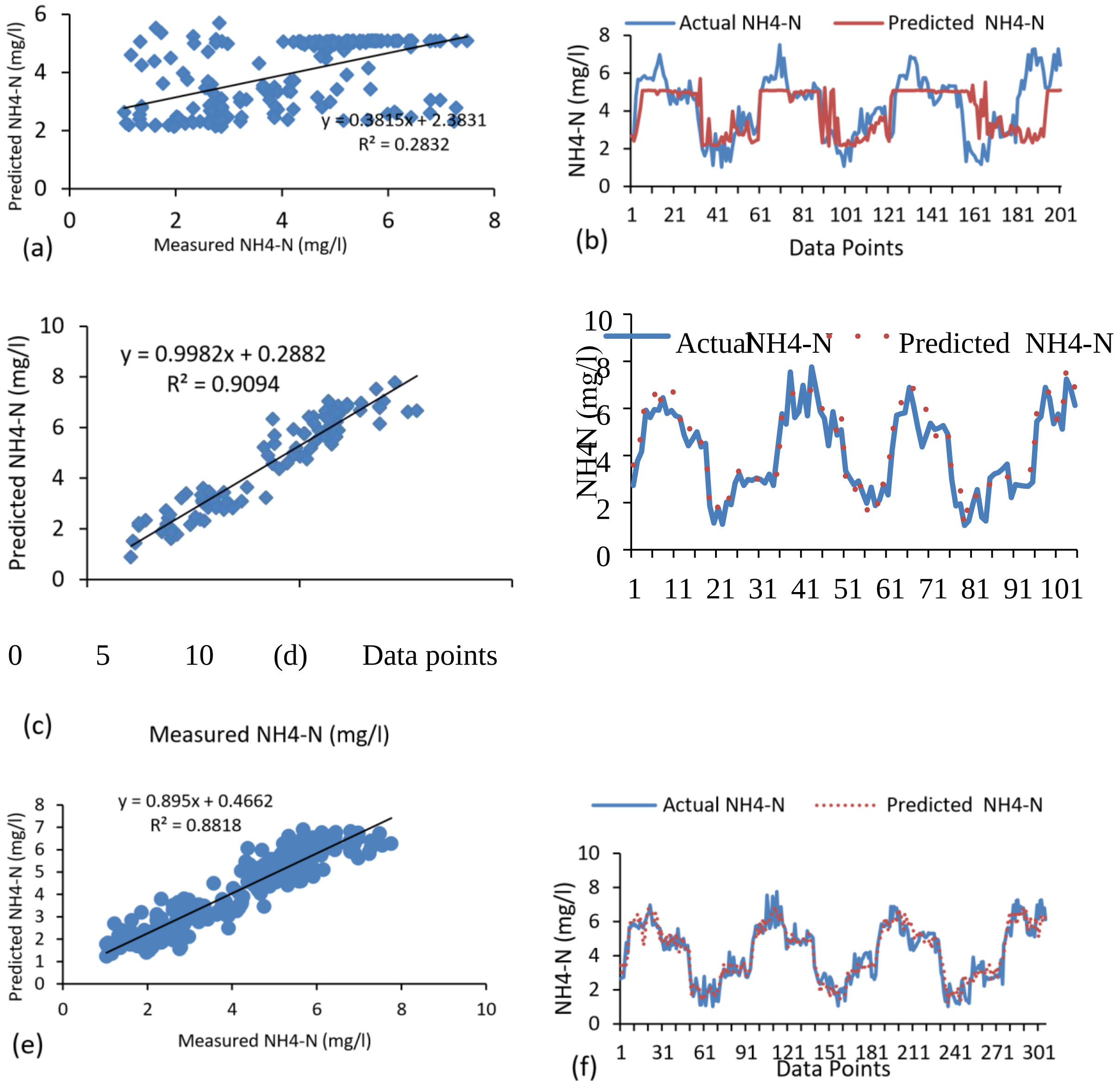


Figure 5.22: MLP model: (a) scatter plot of NH4-N concentration between quantified and predicted values (b) Hydrograph of NH4-N concentration between actual and predicted values (c) Scatter plot of NH4-N concentration between measured and predicted value (d) Hydrograph of NH4-N concentration between actual and predicted values. (e) Scatter plot of NH4-N concentration for the whole data set (f) Hydrograph of NH4-N concentration for the whole data set.

To compare the graphical evaluation performance of MLP and MLR in PO4-P and NH4-N concentrations prediction, scatter plot and hydrograph form are used as shown in Figures 5.18 to 5.21. As can be seen clearly from the graphs that the relationship between measured and predicted values of both PO4-P and NH4-N in scatter plot are closer together in a straight line and in Figure 5.18/19 a, and c for PO4-P for training and 5.20/21 a and c for NH4-N testing data set. The result is confirmed in hydrograph as presented in Figure 5.18/19 b, and d for PO4-P for training and 5.20/21 b and d for NH4-N testing data set which indicated the predicted value curves closely follow the measured values curves in both training and testing data set. These confirmed both MLR and MLP predict PO4-P and NH4-N with considerable accuracy. Thus, MLP had predicted both PO4-P and NH4-N better than MLR. However as can be visualised in the Figures 5.18 to 5.21 that measure and predicted values of PO4-P and NH4-N are more linearly correlated in straight line and in close agreement with each other in MLP than in MLR. Hence predicts MLP predicted both PO4-P and NH4-N better than MLR.

5.7.1.3 Graphical evaluation of SS

To graphically evaluate the performance of the MLR model for the prediction of SS concentration, measured versus the measured values were depicted for both training and testing SS data set and also for the SS complete dataset as one entity in Figure 5.23. It was discovered in scatter plot in Figure 5.23 a and c for both training and testing SS dataset respectively that the measure and predicted values are linearly correlated together; this was confirmed in Figure 5.23 b and d in the hydrograph of training and testing data respectively that the trend lines of measured values are very close to the predicted values. Likewise, figure 5.23 e and f are the graphical evaluation of the MLR model of the entire data for scatter plot and hydrograph respectively, which indicated that MLR estimated SS in whole data set perfectly. Hence all the graphical evaluation of MLR model in training and testing data set as well whole dataset visualised strong relationship and in close agreement between measured and their corresponding predicted values, and this confirms the accuracy of the MLR model built.

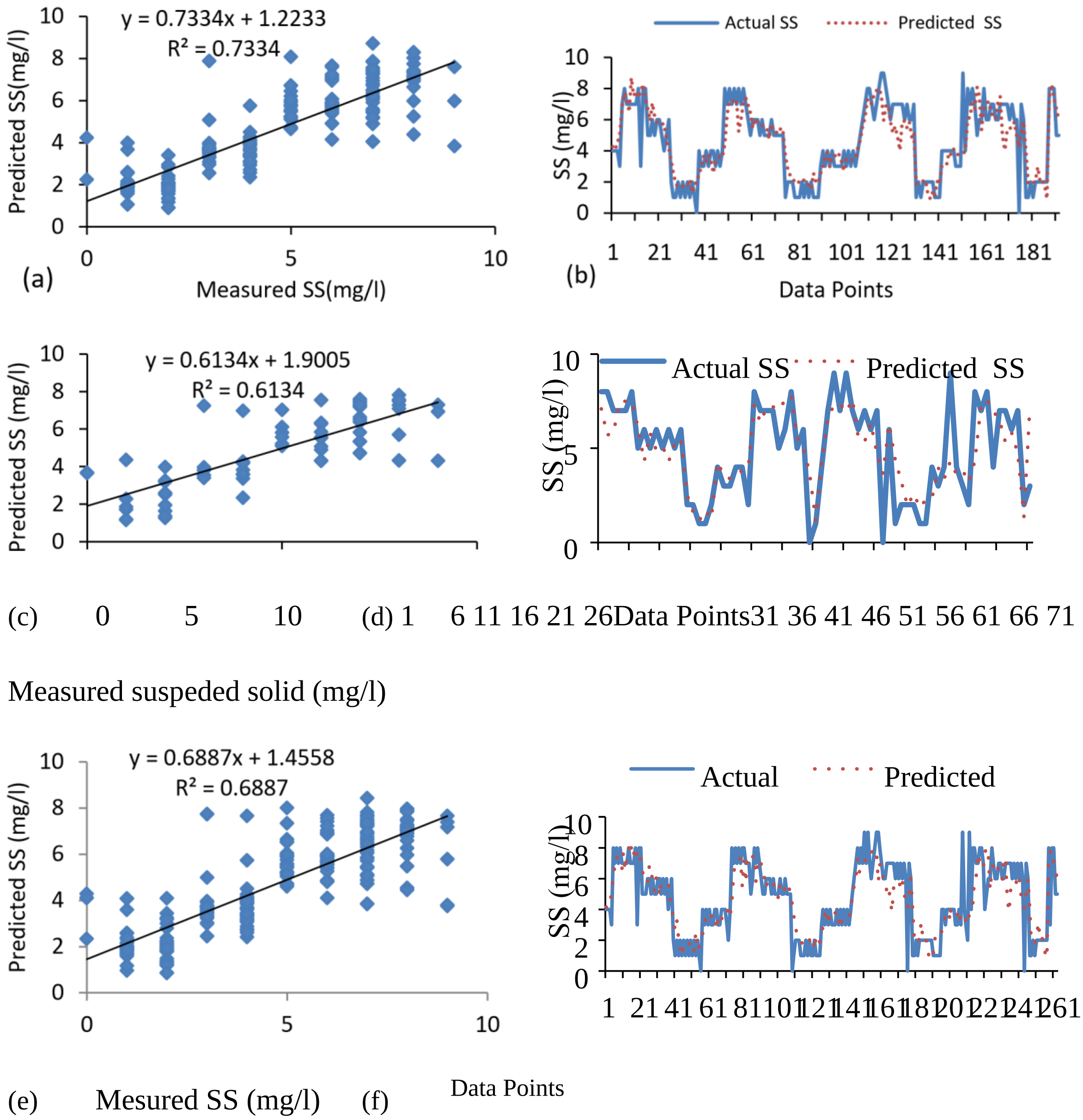


Figure 5.23: MLR model: (a) scatter plot of SS concentration between quantified and predicted values (b) Hydrograph of SS concentration between actual and predicted values (c) Scatter plot of SS concentration between measured and predicted value (d) Hydrograph of SS concentration between actual and predicted values. (e) Scatter plot of SS concentration for the whole data set (f) Hydrograph of SS concentration for the whole data set

To graphically evaluate the performance of the MLP model for the prediction of SS concentration values Figure 5.24 depicted the result of scatter plot and hydrograph between measured and predicted values were depicted for both training and testing SS data set and also for the whole data set. It was discovered that all the scatter points in Figure 5.21 a and c for training and testing data respectively are close together and merge to the line of the perfect match, this symbolise the accuracy of the model. In addition, it was confirmed by hydrographs in Figure 5.21 b and d of the training, and testing SS dataset respectively that predicted value curves of SS followed measured SS value curves closely. This is an indication that MLP model predicted SS value concentration better. However, figure e is scatter plot and f is hydrograph of complete SS data set. It was observed that measured and predicted SS values are merge together in straight line and also in close agreement to each other.

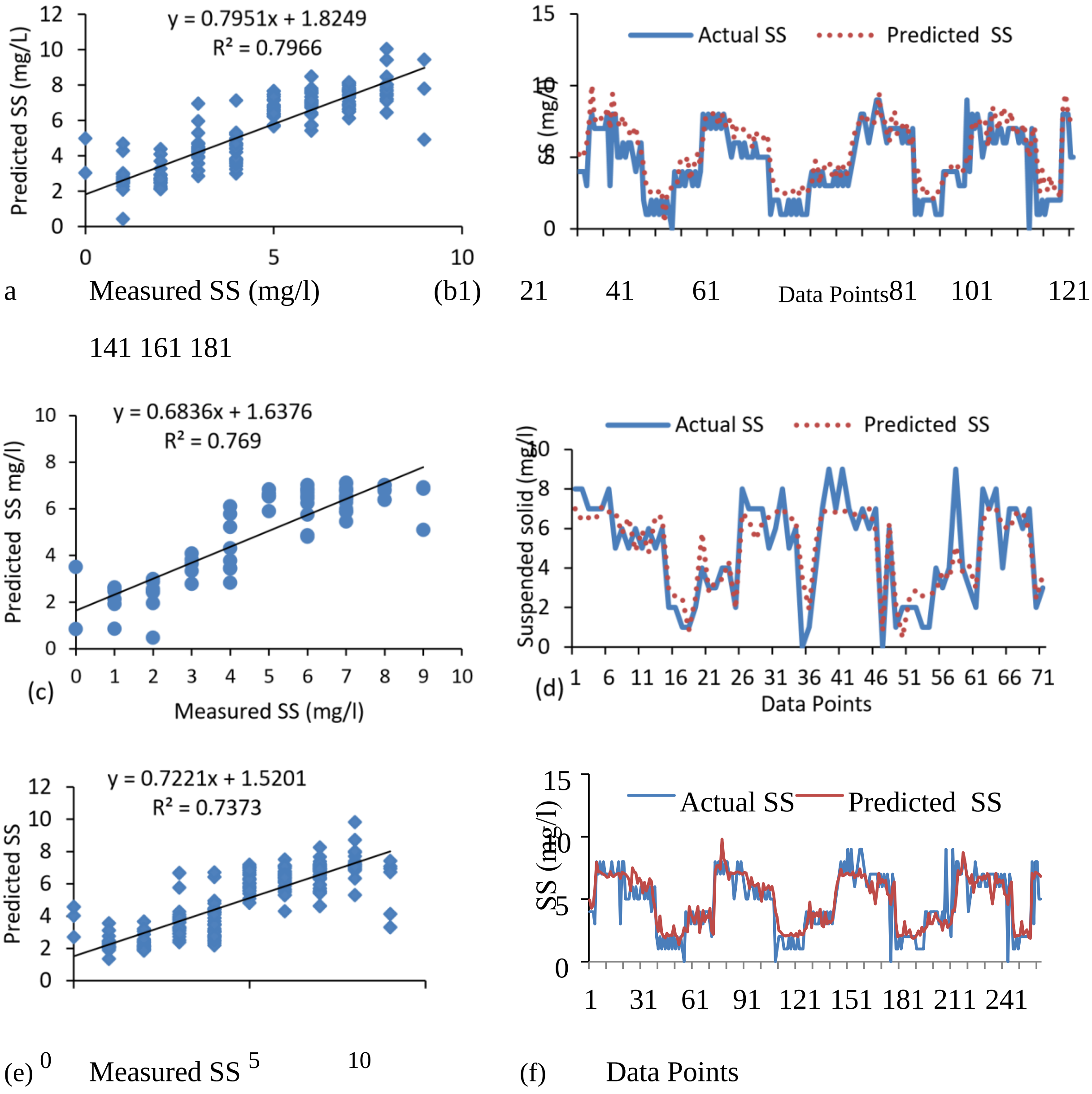


Figure 5.24: MLP model: (a) scatter plot of SS concentration between quantified and predicted values in Training data (b) Hydrograph of SS concentration between actual and predicted values in training data (c) Scatter plot of SS concentration between measured and predicted value in

testing data (d) Hydrograph of SS concentration between actual and predicted values in testing data set. (e) Scatter plot of SS concentration for the whole data set (f) Hydrograph of SS concentration for the whole data set

Comparison between two data mining models MLP and MLP showed that the measure and predicted value curves of SS concentration in MLP model both in training and testing SS data set are closer in agreement in hydrograph Figure 5.22b and d than hydrograph in MLR figure

5.21b and d. This indicated that MLP predicted SS concentration better than MLR.

5.8 Numerical Model Evaluation

To ascertain and confirm the result obtained from model graphical evaluation performance, numerical model evaluation criteria were applied which is the important part of the model development process. This summarises and evaluates the performance of MLP and MLR prediction models build numerically. The numerical model evaluation is done by comparing predicted values by the model with the measured values obtained from constructed wetland experimental analysis. These analyses include regression coefficient (r), root mean square error (RMSE), mean absolute error (MAE), relative absolute error (RAE), and root relative squared error (RRSE).

5.8.1 Numerical Evaluation of COD and BOD

To ascertain the already obtained result of the graphical evaluation of COD and BOD, numerical evaluation is used. As can be seen clearly from Table 5.15, indicates the performance assessment criteria of the MLR model in reference to training and testing of COD and BOD. The values of r, RMSE, MAE, RAE and RRSE were calculated both in training and in testing datasets. The result revealed that the values of r, RMSE, MAE, RAE and RRSE for COD in training stage were 0.8817, 15.394, 11.789, 42.25 and 40.44 respectively and that of the testing stage were 0.8744, 13.63, 10.94, 42.66 and 45.72 respectively. Likewise, the values of r, RMSE, MAE, RAE and RRSE for BOD in training stage were 0.8948, 9.82, 6.68, 40.504, 40.64 respectively and that of the testing stage were 0.8993, 10.695, 8.271, 40.82 and 47.72 respectively. According, the result indicated that the error values of BOD in training and testing of MLR model are lower than that of COD values, and the values of r of BOD for MLR model is higher than that of COD values. Thus, the calculated result obtained indicated that the MLR model predicts both BOD and COD with high accuracy but predicted BOD slightly better than COD.

Table 5.15: Multiple linear regression (MLR) model performance evaluation criteria for computation of chemical oxygen demand (COD) output parameter

MLR						
Variable	Data Partition	r	RMSE	MAE	RAE (%)	RRSE (%)
COD	Training	0.8817	15.39	11.79	42.25	40.44
	Testing	0.8744	13.63	10.94	42.66	45.72
	Whole	0.8618	5.20	11.63	42.26	46.55
BOD	Training	0.8948	9.82	6.68	40.50	40.64
	Testing	0.8993	10.70	8.21	40.82	39.72
	Whole	0.8856	9.57	7.18	41.15	42.38

r, (Pearson) correlation coefficient; RMSE, root mean square error; MAE, mean absolute error; RAE, relative absolute error; RRSE, root relative squared error.

However, Table 5.17 presented five numerical model evaluation performance criteria of the MLP model build. According to the result from the table indicated that the values of r, RMSE, MAE, RAE and RRSE for COD in training stage were 0.9567, 10.621, 7.9713, 28.44 and 32.45 respectively, that of the testing stage the values of COD were 0.9740, 9.138, 7.230, 28.211 and 29.53 respectively. However, the values of r, RMSE, MAE, RAE and RRSE for BOD of MLP model in training data were 0.9594, 8.271, 6.717, 40.13, and 40.45, and the values of for testing data of BOD were recorded for r, RMSE, MAE, RAE and RRSE as

0.9810, 9.02, 6.204, 42.95, and 39.18. The calculated results indicated that the model showed error values are low (lower error estimates) both in training and testing dataset which is a sign that the model predicts both BOD and COD values accurately. Base on the result presented it was indicated that the error values of BOD values in training and testing are lower than that of COD values in MLP model, and the value of r of BOD is higher than that of COD values. Thus, the calculated result obtained indicated that the MLP model predicts both BOD and COD with high accuracy, but predicted BOD slightly better than COD.

Table 5.16: Multilayer perceptron (MLP) model performance evaluation criteria for computation of chemical oxygen demand (COD) output parameter

MLP						
Variable	Data Partition	r	RMSE	MAE	RAE (%)	RRSE (%)
COD	Training	0.9567	10.621	7.971	28.44	32.45
COD	Testing	0.974	9.138	7.23	28.21	29.53
COD	Whole	0.9585	10.192	7.684	28.02	31.37
BOD	Training	0.9594	8.271	6.717	40.13	40.91
BOD	Testing	0.981	9.017	6.204	42.95	39.18
BOD	Whole	0.9696	6.685	5.286	26.04	27.45

r, (Pearson) correlation coefficient; RMSE, root mean square error; MAE, mean absolute error; RAE, relative absolute error; RRSE, root relative squared error

To compare the performance of MLR and MLP models for the prediction of chemical oxygen demand (COD) and biological oxygen demand (BOD), it clearly indicated that multilayer perceptron (MLP) model has slightly higher prediction accuracy than MLP and also it has high r-value and slightly less error value than multiple linear regression (MLR) as shown in Figs. 5.25 and 5.26. Figure 5.25 compares BOD values predicted of by MLR and MLP models for both training datasets in a, and testing datasets in b.

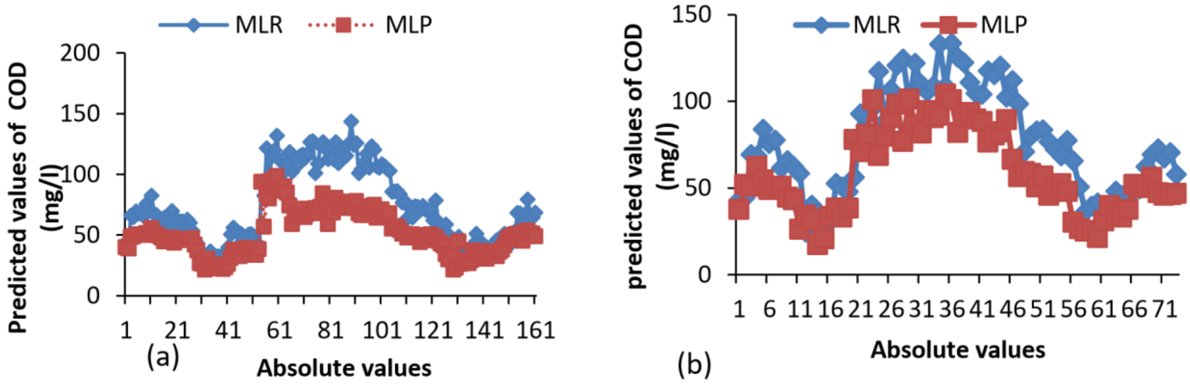


Figure 5.25: Comparison between predicted values of chemical oxygen demand (COD) by multilayer perceptron (MLP) and multiple linear regression (MLR) models for the (a) training data set, and (b) testing dataset

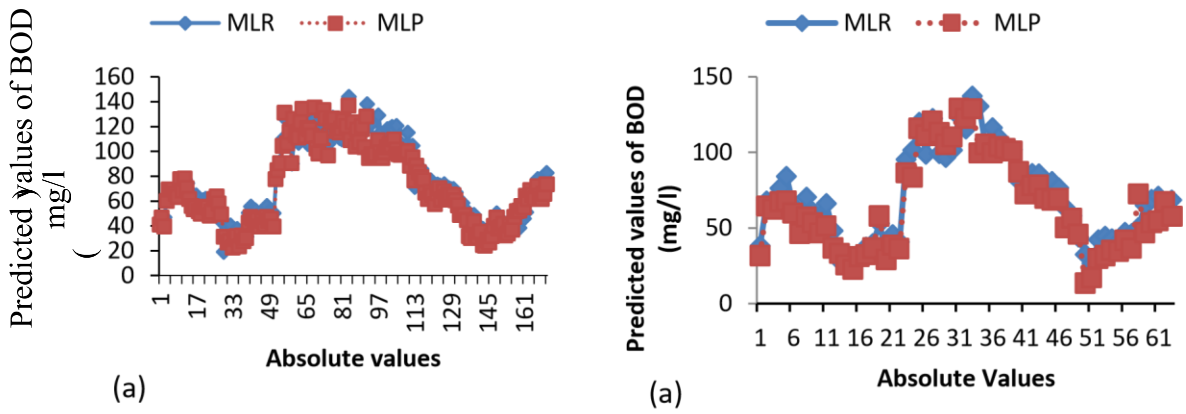


Figure 5.26: Comparison between predicted values of biochemical oxygen demand (BOD) by multilayer perceptron (MLP) and multiple linear regression (MLR) models for the (a) training data set, and (b) testing

Figure 5.26 compares predicted values of COD in MLR and MLP models of training and testing data, it was discovered that the predicted values curves of both COD and BOD in MLR and MLP are in close relationship agreement with each other. Therefore, the overall result presented exposes that MLR and MLP models were accurate in predicting both BOD and COD, but it was discovered that multilayer perpeptron (MLP) outperformed its corresponding multiple linear regression (MLP) slightly better in predicting COD and BOD.,. The prediction result of MLR and MLP of this research study were also recorded acceptable accuracy and considered as best. This result was confirmed by other research result which clearly indicate that MLP model performed better in prediction of water quality parameters in comparison with other prediction model ((Emamgholizadeh et al., 2014; Memarian & Balasundram, 2012; Abyaneh, 2014; Tomenko et al., 2007)

However, in many research studies, multiple linear regression (MLR) models performed prediction better than other prediction models (Babatunde, Zhao, O‘neill, & O‘sullivan, 2008; Georgios et al., 2011; May & Sivakumar, 2008; Obaid et al., 2015).

5.8.2 Numerical Evaluation of PO4-P and NH4-N

As can be observed, Table 5.18 indicates the performance assessment criteria of the MLR model for training and testing of PO4-P and NH4-N. The values of r, RMSE, MAE, RAE, and RRSE were obtained both in training and in testing data sets. The result indicated that the values of r, RMSE, MAE, RAE and RRSE for PO4-P in training stage were 0.6247, 1.178,

0.9508, 42.88 and 48.04 respectively and that of testing stage were 0.7199, 1.059, 0.8353, 39.94 and 49.41 respectively. Likewise, the values of r, RMSE, MAE, RAE and RRSE for NH4-N in training stage of MLP model were 0.8846, 0.7649, 0.6178, 43.42, 46.64 respectively and testing stage were obtained to be 0.889, 0.792, 0.6112, 39.62 and 35.79 for r, RMSE, MAE, RAE and RRSE respectively. Base on the result obtained, it was indicated that the error values of NH4-N in training and testing are lower than that of PO4-P values in MLP model, and the value of r of NH4-N is higher than that of PO4-P values. Thus, the calculated result obtained indicated that MLP model predict both NH4-N and PO4-P with high accuracy, but the model predicted NH4-N slightly better than PO4-P.

Table 5.17: Multiple linear regression (MLR) model performance evaluation criteria for computation of E phosphorous (PO4-P) output parameter

MLR						
Variable	Data Partition	r	RMSE	MAE	RAE (%)	RRSE (%)
PO4-P	Training	0.6247	1.178	0.9508	42.88	48.08
	Testing	0.7199	1.059	0.8353	39.94	49.41
	Whole	0.6544	1.145	0.9144	40.71	45.52
NH4-N	Training	0.8846	0.7649	0.6178	38.42	46.64
	Testing	0.889	0.792	0.6112	36.62	35.79
	Whole	0.8854	0.777	0.6159	39.04	36.48

r, (Pearson) correlation coefficient; RMSE, root mean square error; MAE, mean absolute error; RAE, relative absolute error; RRSE, root relative squared error

Table 5.18: Multiple linear regression (MLR) model performance evaluation criteria for the determination of orthophosphate phosphorous (PO4-P) and ammonium nitrogen (NH4-N) output parameters

MLP						
Variable	Data Partition	r	RMSE	MAE	RAE (%)	RRSE (%)
PO4-P	Training	0.7686	0.9874	0.8117	62.22	65.43
	Testing	0.8265	0.8726	0.6834	51.49	57.19
	Whole	0.7609	1.147	0.9339	51.2	55.08
NH4-N	Training	0.9365	0.6121	0.4984	35.07	37.32
	Testing	0.9536	0.612	0.4849	31.43	35.444
	Whole	0.9391	0.5756	0.4631	31.61	34.44

r, (Pearson) correlation coefficient; RMSE, root mean square error; MAE, mean absolute error; RAE, relative absolute error; RRSE, root relative squared error

To compare the performance of MLR and MLP models for the prediction of suspended solid (SS), it clearly indicated that multilayer perceptron (MLP) recorded high r-value and low error values than multiple linear regression (MLR) as shown in figs. 5.25 and 5.26 compare PO4-P and NH4-N values predicted of by MLR and MLP models for both training datasets in and testing datasets of a and b respectively.

It was discovered that the predicted values curves of both PO4-P and NH4-N in MLR and MLP are in close relationship agreement with each other. Therefore, the overall result presented exposes that MLR and MLP models were accurate in predicting both BOD and COD, but it was discovered that multilayer perpeptron (MLP) outperformed its corresponding multiple linear regression (MLP) slightly better in predicting PO4-P and NH4-N. However, ss can be seen from the two figures (5.25 and 5.26) among the two nutrient parameters predicted, MLP model predicted NH4-N better than PO4-P in both training and testing dataset.

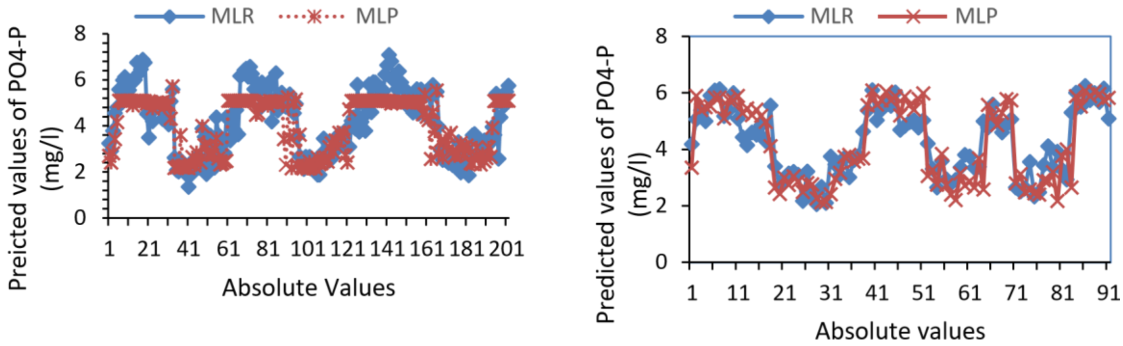


Figure 5.27: Comparison between predicted values of orthophosphate phosphorous (PO4-P) by multilayer perceptron (MLP) and multiple linear regression (MLR) models for the (a) training data set, and (b) testing dataset.

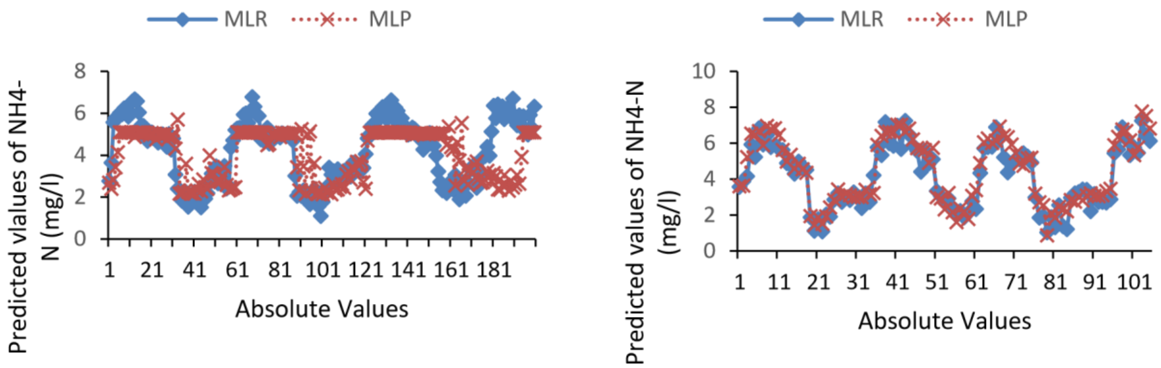


Figure 5.28: Comparison between predicted values ammonium nitrogen (NH4-N) by multilayer perceptron (MLP) and multiple linear regressions (MLR) models for the (a) training data set, and (b) testing dataset

5.8.3 Model Numerical Evaluation of SS

As can be seen clearly in Table 5.21 presented the values of five models statistical evaluation criteria that were calculated and recorded for SS dataset. The model evaluation criteria for SS training data set of MLR were recorded 0.7922, 1.446, 1.085, 52.16, and 61.03 for r, RMSE, MAE, MAE and RRSE respectively, and that of SS testing dataset was recorded as 0.7504, 1.637, 1.164, 54.06, and 66.15 for r, RMSE, MAE, MAE and RRSE respectively. According to the result, it was discovered that the MLR model predicts SS concentration in treated wastewater is considerable accuracy in both training and testing data of SS.

Figure 5.29: Multilayer perceptron (MLR) model performance evaluation criteria for the prediction of suspended solids (SS) output parameter

MLR						
Variable	Data Partition	r	RMSE	MAE	RAE (%)	RRSE (%)
SS	Training	0.7922	1.446	1.085	52.16	61.03
SS	Testing	0.7504	1.637	1.164	54.06	66.15
SS	Whole	0.7688	1.537	1.13	53.57	63.95

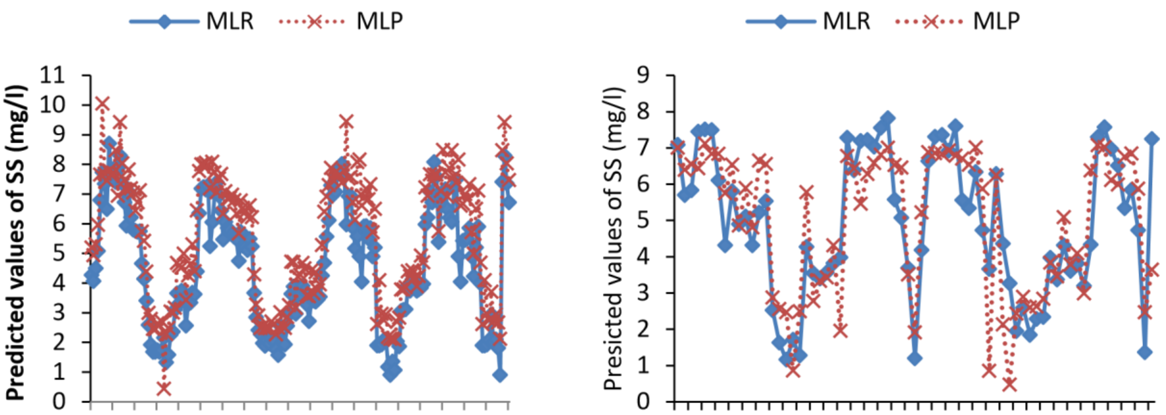
r, (Pearson) correlation coefficient; RMSE, root mean square error; MAE, mean absolute error; RAE, relative absolute error; RRSE, root relative squared error

However, as can be observed from Table 5.21, that the MLP model evaluation criteria for SS training data set were presented and recorded to be 0.8925, 1.3874, 1.1068, 53.2, and 58.55 for r, RMSE, MAE, MAE and RRSE respectively, and that of testing dataset was recorded to be 0.8769, 1.2521, 1.1063, 45.78, and 49.16 for r, RMSE, MAE, MAE and RRSE respectively, based on the result provided, it was discovered that MLP model predict SS concentration with acceptable accuracy in both training an testing data set this is an indication that multilayer perceptron (MLP) is suitable for predicting SS concentration.

Table 5.19: Multilayer perceptron (MLP) model performance evaluation criteria for the prediction of the suspended solids output parameter

MLP						
Variable	Data Partition	r	RMSE	MAE	RAE (%)	RRSE (%)
SS	Training	0.7922	1.4463	1.085	52.16	61.03
SS	Testing	0.7504	1.134	1.164	54.06	66.15
SS	Whole	0.7688	1.537	1.13	53.58	63.95

r, (Pearson) correlation coefficient; RMSE, root mean square error; MAE, mean absolute error; RAE, relative absolute error; RRSE, root relative squared error



1 21 41 61 81 101121141161181 1 6 11 16 21 26 31 36 41 46 51 56 61 66 71

Absolute Values (b) Absolute values

(a)

Figure 5.30: Comparison between predicted values of biochemical oxygen demand (BOD) by multilayer perceptron (MLP) and multiple linear regression (MLR) models for the (a) training data set, and (b) testing data set.

To compare the performance of MLR and MLP models for the prediction of suspended solid (SS), it indicated that multilayer perceptron (MLP) recorded high r-values 0.8925 and 0.8769 in training and testing dataset respectively against MLR with 0.7922 and 0.7504 r values in training and testing data respectively. However, MLP has lower error values than multiple linear regression (MLR) in both training and testing data set as shown in the table. 5.20 and 5.21. This an indication that MLP predicts SS better than MLR. It was discovered that the predicted values curves of both SS in MLP were in close and good agreement with each other than MLR Therefore, the overall result presented exposes that MLR and MLP models were accurate in SS prediction, but it was discovered that multilayer perceptron (MLP) outperformed its corresponding multiple linear regression (MLP) slightly better in predicting SS. Figure 5.26 compares the predicted values of SS in MLR and MLP models of training and testing data. Therefore, the overall result presented reveals that MLR and MLP models were accurate in predicting SS. Thus, it was discovered that multilayer perceptron model (MLP) outperformed its corresponding multiple linear regression model (MLP)

5.9 Chapter Summary

In this research study, two data mining prediction models namely: multiple linear regression (MLR) and multilayer perceptron (MLR) were developed and designed to predict wastewater treatment performance of vertical flow constructed wetland by predicting unknown water quality parameters given other known water quality parameters of wastewater concentration. Input parameters correlating well with outputs were used by the two different for the model development. The performance of these models was studied and evaluated using graphical and numerical model evaluation criteria by comparing predicted values and measured values. It was discovered that the predicted values of both MLR and MLP models for all the selected output parameters used (COD, BOD, PO4-P, NH4-N and SS) were in close and perfect agreement with their corresponding measured values both in training and testing dataset. This is an indication that the two models had performed reasonably well in predicting pollutants concentration, and they could be used to predict wetland removal performance. This will help in reducing future high cost and time for the laboratory analysis of water quality parameters. In a comparison of two models built, it was discovered that the MLP model predicts all the selected output parameters better than the MLR model.

Chapter 6: Conclusion and Recommendation

6.1 Conclusion

In this thesis, experimental monitoring of vertical flow constructed wetland systems treating domestic wastewater has been designed, set up and operated for the period of over three years (thirty-nine months), to investigate and evaluate the performance of different wetland filters treating wastewater. The investigations covered experimental procedures in the green house, laboratory analysis of the wastewater (inflow) and treated water (outflow) conducted for the eleven different water quality parameters. The monitoring data were collected treatment performance of the constructed wetland system were evaluated. The results were revealed, it was discovered that, all constructed wetland filters (filters 5 and 6 excluded) have shown relatively high removal performance for the water quality parameters irrespective of filters set-up and operation. Hence, vertical flow constructed wetland system (VFCWs) can be considered as effective, efficient, economic, environmentally friendly and sustainable systems for wastewater treatment.

However, even though VFCWs have been identify as a promising, robust and reliable tool for wastewater treatment, the great challenges and uncertainty experienced during the course of the monitoring experiment and analysis is lack of complete information and inconsistency of the water quality parameters data used hinder effective treatment evaluation of the system, this is due to high cost of measurement, laboratory tests and sampling uncertainties of machineries used, time consuming for the analysis To properly evaluate the wastewater treatment performance by the constructed wetland, the monitoring data for all the water quality parameters need to be complete and free from missing values, accurate, consistent and up to date so as not to get bias and misleading result. The aim to fill this gap triggered the use of two data mining techniques models namely: multiple liner regression (MLR) and multilayer perceptron (MLP) to predict performance of vertical flow constructed wetland system water quality parameters in a view to evaluate treatment performance of vertical flow constructed wetland effectively.

The data mining predictive models investigated and evaluated (comparison between measured and predicted values) using graphical and numerical model evaluation criteria, it was discovered from the result that, the two models built were able to predict some selected water quality parameters (COD, BOD, PO4-P, NH4-N and SS) with reasonable accuracy, this indicated effectiveness of the model built. In comparison between two models built, it was discovered that MLP model outperform MLR model in predicting all the water quality parameter. The models build could be used as reliable models to treatment performance by predict all water quality parameters, provided that correlation exists between input parameters without any restriction. The models can be used to predict overall treatment performance, monthly yearly and any season of the year. Comparison between MLP and MLR, it was discovered that MLP have highest correlation coefficient values (r) and least error values (RMSE, MAE, RAE, RRSE) in all the water parameters predicted this is indication that MLP had performed better than MLR. In addition, it is not the use of many input parameters that lead to better and improvement of data mining predictive models but the selection of highly correlated ones.

6.2 Recommendations for future work

The findings have significant suggestions for the future operation, monitoring and management of vertical flow constructed wetlands for wastewater treatment. While this study has demonstrated effectiveness of vertical flow constructed wetlands in pollutants removal, however there is an observable need to carry out further studies. Some important future research borderlines are as follows

i. More research is needed to better understand how to improve the processes responsible for the treatment and removal of water quality parameters to achieve highest percentage removal efficiency of pollutants in wastewater.

ii. Determining the role of wetland plants in constructed wetland is very important.

iii. Future experiment work should include investigating the suitability of treated water by constructed wetland to irrigate the edible plant

iv. Moreover, research under controlled laboratory conditions or field scale should be initiated to discover more about the microbial removal processes responsible for ammonia-nitrogen, nitrate-nitrogen orthophosphate phosphorous, as this research study recorded low removal efficiency percentage in nutrient parameter.

v. Although this research has demonstrated the potentiality of CWs to treat wastewater for pollutants the removal without clogging, there is need to investigate and redesign the way of preventing possibility of clogging in the future

Regarding the importance of this type of study research for the development of data mining techniques models to predict wastewater treatment performance of Vertical flow constructed wetland system (VFCWs) by predicting water quality parameters, the following ideas are suggested as future research

i. In the future studies, same MLP and MLR models framework can be applied to another type of constructed wetland for comparison between prediction results obtained and make conclusion about them

ii. The modelling study can be extended for the other water quality parameters

iii. Employing more prediction models, to make better and wider comparison among prediction model, could lead to choosing more accurate model among them

iv. The framework of this research need to be readjusted to expand the scope of the prediction models to include some features of CW to enhance prediction performance like plant, porous media contact and resting time mode of operation etc

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