Adaptive Nonlinear PID Control for the Industrial Wastewater Treatment Plant (Case study: Africa Juice Tibila S.C).

Gure Olfuda Feyisa

A Thesis submitted to the Department of Electrical Power and Control Engineering

School of Electrical Engineering and Computing

Presented in Parial Fulfillment of the of the Requirements for the Degree of Masters' of Science in Electrical Power and Control Engineering (Control)

Office of Graduate Studies
Adama Science and Technology University

March, 2024

Adama, Ethiopia

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Declaration

I hereby declare that this thesis masters entitled "Adaptive Nonlinear PID control for the industrial wastewater treatment plant (Case study: Africa Juice Tibila S.C)." is my original work. That is, it hasn't been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledge through citation.

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We, the undersigned, members of the board of examiners of the thesis by Gure Olfuda have read and evaluated the thesis entitled “ Adaptive Nonlinear PID Control for the Industrial Wastewater Treatment Plant(Case study: Africa Juice Tibila S.C) ” and examined the candidate during the open defence. This is , therefore, to certify that the tesis is accepted for partial fulfillment of the requirement of the degree of Masters of Science in Electrical Power and Control Engineering (Control).

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Abbreviations

Abbreviation	Definition
WHO	World Health Organization
DO	Dissolved Oxygen
PH	Potential Hygdrogen
ASP	Activated Sludge Process
WWT	Wastewater Treatment
WW	Wastewater
WWTP	Wastewater Treatment Plant
WWTS	Wastewater Treatment System
FAO	Food and Agriculture Organizational
SDGs	Sustainable Development Goals
TTC	Sludge Activity
SCADA	Supervisory Control and Data Acquiition
PLC	Programmable Logic Controller
NN	Neural Network
RBF	Radial Basis Function
PI	Proportional Integral
PID	Proportional Integral Derivative
NLPID	Nonlinear PID
ANLPID	Adaptive Nonlinear PID
IMC	Internal Mobile Control
IWWTP	Industrial Wastewater Treatment Plant
BP	Biological Process
SO	Concentration of Dissolved Oxygen
AS	Activated Sludge
X_S	Slowly biodegradable biomass
$X_{B,H}$	Active heterotrophic biomass
$X_{B,A}$	Active autotrophic biomass
S_{NO}	Nitrate and nitrite nitrogen
S_{NH}	NH^{+}+ NH3 nitrogen

S_{ND}	Soluble biodegradable organic nitrogen
X_{ND}	Particulate biodegradable organic nitrogen
W	Air flow rate
SP	Set Point
PV	Process Variable
ASM1	Activated Sludge Model no 1
ARBFNNPID	Adaptive Radial Basis Function Neural Network PID
MPID	Multivaiable PID
LQC	Linear Quadratic control
MPC	Model Predictive Control
BOD	Biological Oxygen Demand
COD	Chemical Oxygen Demand
TTS	Total Suspended Solid
TDS	Total Dissolved Solid

ABSTRACT

Wastewater is released liquid from any collection of industrial, agricultural, domestic or commercial work places. It contain harmful chemicals, bactrerias or fungi and others toxic pollutants which are dangerous for the society if it didn't treated before released back into the society and environment. The activated sludge process of biological process contain some parameters dissolved oxygen (DO), chemical oxygen demand (COD), biological oxygen demand (BOD), potential hydrogen (PH), total dissolved soluble (TDS), total soluble solid (TSS), ammonia (NH_3), nitrate or nitrite (NO_3) and others breakdown organic matters in wastewater. The dissolved oxygen is the major critical in wastewater treatment plant for aquatic life and biological or chemical oxygen demand process,so, it must been maintained at a certain level for the bacteria to function properly. If industrial wastewater is not well treated the impacts of the untreated released cause healthy problem for community, environmental pollution and odor odour which pollute the air. So, the world health organization, sustainable development goals and others envrimontal based regulator bodies punish the company released the waste to community. Adaptive nonlinear proportional integral derivative(PID) controller can manages the wastewater parametrs as standard. In additional using with radial basis function neural network algorithm as parameters estimator , when PID is the main controller. The radial based function neural network (RBFNNPID) algorithm is a control algorithm that has shown to the effective for controlling the amount of DO, BOD, COD, PH, TDS, TSS, NH3 and NO3 interms of sensor signals feedback for the PID and radial based function neural network (RBFNN) algorithm parameters estimating and give response for PID. The RBFNNPID algorithm is able to tracking the desired paramters more accurately and has a stronger anti disturbance abilty than traditional or linear PID. The simulation results demonstrate that the adaptive nonlinear proportional integral derivative (ANLPID) controller exhibits excellent performance in terms of tracking and anti jamming capabilities. Furthermore, it shows significant improvements compared to traditional PID control methods. Using nonlinear PID with RBFNN best controller all parameters easily by controlling the discharging valve opening depending the feedback from PID by comparing set value with actual values. It has the abilty to be improve the industrial wastewater treatment plant effectiveness and efficiency.

Keywords: *wastewater treatment plant, activated sludge model (ASM 1), industrial wastewater treatment plant, adaptive nonlinear PID, Radial Basis Function Neural Network PID (RBFNNPID)*

CHAPTER ONE

INTRODUCTION

1.1 Background of study

Industrial Wastewater is any water that has used in industry for cleaning, sanitations, cooling and others. It contains a variety of pollutants, organic or in organic matters, byproducts, damped products, pathogens and chemicals. As general wastewater classified into three main types depending from released: domestic, industrial and agricultural wastewater. Domestic wastewater is wastewater that comes from homes and businesses. It includes sewage from toilets, gray water from showers, baths, laundry and rainwater runoff from streets and parking lots. Industrial wastewater is wastewater that comes from factories and other industrial facilities. It can contain a variety of pollutants, depending on the industry. Agricultural wastewater is wastewater that comes from farms. It includes manure from livestock, irrigation runoff and chemicals used in crop production. Wastewater can be a major source of pollution. It can contaminate drinking water, rivers, lakes and oceans. It can also spread diseases and disturb the environmental. (Ayele, B. G., & Assefa, E., 2022).

Africa JUICE is a Dutch company established in 2007 with a mission to sustainably grow and process tropical fruits in Africa. They recognized the rising global demand for these delicious and nutritious products and aimed to fill the gap while empowering local communities and protecting the environment. This company established for agro industry to export passion juice and mango pure for localmarket. Wastewater released in Africa juice during production contains some chemicals (caustic soda, phosphoric acid, grease and other chemicals for micro media preparation …). Solid parts like passion fruit skin, fibers, mango skins and seeds and liquids like damped juice, agent used for micro biological process.

The quality of water resources is obiligation for human being health, all living things and the ecosystem. However, water pollution is a major problem and it is getting worse due to climate change. Uncontrolled discharges of wastewater can contaminate drinking water sources, overload water bodies with organic or in organic matter, accumulate minerals, heavy metals and others. This can lead to many health problems, including gastrointestinal diseases, respiratory infections, cancer & external bodies fugal diseases. It can also damage ecosystems and impact biodiversity. The world is facing a water crisis and climate change is making it worse. Water problem is affecting every continent, two third (2/3) or 75% of the world populations are living under conditions of critical water shortage for a minimum one month per year. (WHO, 2023) So,improving wastewater managing monitoring and treating is essential to address the water crisis. However, the voluntary state to pay for wastewater accumulation, treatment and monitoring is low, especially in undeveloped and developing countries with low health & environmental standards.

Treated wastewater is a valuable resource that be used in domestic, industry, agriculture and energy generation or hydro plant. A model shift wanted in wastewater handling to better protecting drinking water resourses and aquatic ecosystems to contribute for sustainable development and climate change mitigation & adaptation. (Kvist, M., & Vikstrand, J., 2022).

Wastewater treatment is a multi-step process that removes pollutants from wastewater. (von Seidlein, L., Alabaster, G., Deen, J., & Knudsen, J., 2021), The four main steps are:

Preliminary treatment:

- ✓ Screening: This is done by passing the wastewater through a series of screens with different sized mesh removes large solids, such as rags, sticks, and other debris, from the wastewater.
- ✓ Grit removal: This removes sand, grit and other inorganic solids from the wastewater. This is done by passing the wastewater through a tank with a sloping bottom. The solids settle to the below of the tank, while the water flows out of the top.
- ✓ Oil/grease separation: This removes oil and grease from the wastewater. This is done by passing the wastewater through a series of baffles, which cause the oil and grease to float to the surface. The oil and grease are then skimmed off the surface of the wastewater.

Primary treatment:

- ✓ Sedimentation: This removes suspended solids from the wastewater. Sedimentation is done by passing the wastewater through a tank where, the settle at bottom of the tank and dispose.
- ✓ Clarification: This clarifies the wastewater by removing any remaining suspended solids. This is done by adding chemicals to coagulate and flocculate the solids. The coagulated and flocculated solids then settle to the bottom of the tank, where the solid are removed.

Secondary treatment:

- ✓ Aerobic treatment is a WWT process that involves the use of bacteria to decompose organic substances present in wastewater. These bacteria rely on oxygen to break down the organic matter, which ultimately leads to the production of carbon dioxide and water. Aerobic treatment is recognized as the primary method of biological treatment and is extensively used in wastewater treatment applications. (a, a, & a, April 2022)

Tertiary treatment:

- ✓ Filtration: This removes remaining suspended solids from the wastewater. This is done by passing the wastewater through a filter, which traps the solids.
- ✓ Disinfection: This kills any harmful bacteria or viruses in the wastewater. This is done by adding chlorine or other disinfectants to the wastewater.
- ✓ Nutrient removal: This removes nutrients from the wastewater. This is done by passing the wastewater through a series of processes, such as ion exchange, reverse osmosis, and electro dialysis.

The microorganisms are suspended in wastewater are called activated sludge which, are providing the microorganism with oxygen. The microorganism then breakdown the organic matter in the wastewater, producing CO_2 & H_2O. Microorganisms play a crucial role in the cycling of materials and the decomposition of organic substances in WW. Wastewater contains a variety of organic compounds, such as proteins, carbohydates and fats , which ara considered pollutants and need to be removed before the water can be safely discharged or used. So, the secondary treatment process is very essential. Without microorganisms, the wastewater would not be able to be treated effectively. Here are some of the microorganisms that are used in secondary treatment:

- ✓ Bacteria: Bacteria are the most common microorganisms used in secondary treatment, it able to breakdown a wide variety of organic matter.
- ✓ Protozoa: Protozoa are single-celled organisms that feed on bacteria. They help to control the growth of bacteria in the activated sludge.
- ✓ Fungi: Fungi can able to breakdown organic matter. Fungi are often used in tertiary treatment to remove dissolved solids & nutrients from the wastewater. (Mcineka, 2019)

The growth of microorganisms, which form a biological floc. The floc aids in reducing the organic content of the sewage through microbial degradation. The treated wastewater along with the biological flocs, is then transferred to a clarifier where the floc settles to the bottom and the clarified water is separated. The microorganisms present in the settled floc are recycled back to the aeration tank, ensuring their continued activity in treating the wastewater. Developed in 1912 by British researchers Clark and Gage, the activated sludge process is widely regarded as one of the most effective methods for wastewater treatment, helping to significantly reduce the organic content and making the treated water safer for environmental dischage. (Sun, 2021)

The concentration of dissolved oxygen(DO) performes the cruicial roles in effectiveness of wastwarer treatment(WWT) processes. DO is vital for supporting the growth and activities of microorganisms responsible for breaking down organic matter in WW. Insufficientl DO levels can hinder the proper functioning of microorganisms, leading to inefficiencies in the treatment process. The optimal DO concentration for WWT varies depending on the specific process employed. It is important to maintain an appropriate DO level to ensure optimal microbial activity and efficient degradation of organic pollutants in wastewater. (Bo, 2018)

In general, it is recommended to maintain DO levels within the range of 1 to 3mg/L in wastewater systes(WWTS). If DO levels drop below 2mg/L, the treatment process can be significantly impaired. Several factors can influence DO levels in WWTS, including the temperature of the wastewater, the amount of organic matter present and the specific type of treatment process being employed. To ensure stable DO levels, regular monitoring is essential, allowing for timely adjustments as needed to maintain optimal DO concentrations for effective microbial activity and efficient treatment of organic pollutants in wastewater. (K, Avinash, Jaleel, Mujeeb, & Sharanappa, 2018). (Drewnowski, 2019)

The researchers presented a a study on the application of Ziegler Nichols methods for PID tuning using the Benchmark Simulation Model N01(BSM1) to control the concentration of DO in a wastewater treatment process. They introduced an adaptive controller that utilizes these tuning methods and allows for real time tuning. The control algorithm includes adaptive rules that update controller parameters to changes in process dynamics and disturbances. The study also proposed two PID auto- tuning methods: an extension of the relay feedback PID auto-tuner and a model predictive control (MPC) approach. The performance of these auto tuning methods was evaluated on a wastewater treatment process. The findings demonstrated that the adaptive controller with real time tuning achieved better performance compared to standard PID tuning methods. The PID auto tuning methods also exhibited good performance, but the MPC approach was computationally more intensive. Additionally, the researchers noted that the wastewater released from domestic sources had a greater impact on the process than wastewater from industries.

Overall, the study highlighted the effectiveness of adaptive control and PID auto tuning methods in optimizing DO control in wastewater treatment processes. The results suggested that real time tuning and adaptive strategies can improve the performance of the control system, leading to more efficient and reliable wastewater treatment operations. (Du, X., Wang, J., Jegatheesan, V., & Shi, G., 2018).

The control system for a wastewater treatment facility follows a two step are: process identification and controller design. In the first step, the dynamics of the wastewater treatment process are determined by analyzing data and creating a second order model. This model represents the behavior of the process. In the second step, a PID controller is designed using internal model control (IMC) tuning rules. The PID controller is tuned based on the process model obtained in the first step. The goal is to optimize control performance by making the controller mimic the process model. This approach ensures effective control of the wastewater treatment facility by using the process model to guide the controller design. (Van Gerven, 2017), (Anyim, 2018) .

Multivariable PID(MPID) control has been explored using various types of PID tuning methods. These MPID tuning methods aim to decouple the system at different frequency points, requiring information solely from simple step or frequency response tests. To further enhance the control system, a supervisory control algorithm has been proposed for decision making regarding setpoints. This algorithm simultaneously estimates the respiration rate during the identification step and adjusts the DO setpoint proportionally to the respiration rate. Different supervisory control tecnques such as cascade control and feed forward control have been applied. (Wang, Hu, Zhao, & Qiao, 23 December 2021)

Control algorithms typically rely on process models to construct control systems. These models can take the form of process equations, such as the activated sludge model 1(ASM1) or they can be represented as black box models. The control algorithm aims to optimize the controller output based on an objective function that is defined using the process model. The objective function is typically designed to minimize a cost function, which can be mathematically formulated based on the model. (von Seidlein, L., Alabaster, G., Deen, J., & Knudsen, J., 2021)

The control algorithm takes into account this cost function and attempts to find the best solution to the optimization problem while considering any given constraints. One example of the a feedback model based control algorithm is Linear Quadratic Control(LQC). LQC minimizes a cost function that is typically defined in terms of the model equations. It aims to find the optimal control input that minimizes the cost function while considering the system dynamic and constraints. Another example is model predictive control(MPC), which is a form of predictive control. MPC utilizes a process model to predict the system behavior over a future time horizon. It then optimizes the control inputs based on these predictions, taking into account the defined cost function and constraints. MPC continuously updates the control inputs based on real time measurements, allowing for adaptive and optimal control. These model based control algorithms, such as LQC and MPC provide effective strategies for optimizing control systems by considering process models, cost and energy efficiency in various applications, including wastewater treatment process. The MPC has the ability to handle constraits and multivariable . (Hasanlou, H.1,Torabian, A.1, Mehrdadi, N.1Kosari, A. R.2 and Aminzadeh, B.1*, 2019). . (Daoliang Lia, 2022)

The MPC controllers that were compared to the set-point controller in the paper are more complex and require knowledge of the underlying process dynamics. However, they can potentially achieve better performance than the set-point controller in some cases. For example, if the process dynamics are nonlinear, then the MPC controllers may be able to track the desired DO level more closely than the set-point controller. (Panagiotis G. Asteris 1, 28 December 2022)

The choice of wether to use a set point controller or MPC controller for DO control depends on the factors including the complexity of the process, the desired performance and the cost of implementation. In general , the set point controller is a good choice for simple processes where good performance is not critical. However, if the process is complex or if good performance is critical and then MPCcontroller may be a better choice. Further , enhancement of the nonlinear adaptive PID controller is aimed for effective industrial wastewater control strategy. (Charlebois, 2021).

Method adaptive nonlinear PID controller with radial basis function neural network is good for Africa Juice wastewater treatment for automatic controlling before releasing to the community.

1.2 Statement of the problem

Wastewater treatment in industrial processes presents a significant challenge with implications for human health and the environment. The characteristics of wastewater entering treatment plants vary depending on the industry, such as food processing, textiles, or metals. Achieving proper management of wastewater in industrial wastewater treatment plants (IWWTPs) is challenging due to its time-dependent nature and the difficulty of achieving uniformity and homogeneity. Incorrect operation and control of WWTPs can result in operational risks and severe consequences for the environment and public health. Regulatory bodies, including environmental and health organizations, may impose penalties for non-compliance. Therefore, it is crucial for companies to carefully consider various parameters before discharging wastewater into rivers or the surrounding environment. Africa Juice Tibila S.C wastewater treatment plant has only the separation of solid part from liquid and annually external laboratory parameters analysis , but as the results showed 2019 G.C, 2021 GC, 2022 GC by NEMA Analysis Report for parameters such as, total dissolved oxygen (TDS), biological oxygen demand (BOD), chemical oxygen demand (COD), total suspended solids (TSS), electrical conductivity and colour are higher. The company haven't actual control by modern control daily for checking the parameters. International organizations such as the World Health Organization (WHO), Food and Agriculture Organization (FAO), and Sustainable Development Goals (SDGs) have established guidelines and environmental regulations that specify the quality standards for effluent water from WWTPs. Ensuring effective operation, control, and compliance with regulations, this thesis proposes the implementation of an adaptive nonlinear PID controller. By employing MATLAB simulation, this research investigates the performance of an industrial wastewater treatment plant in terms of parameters such as dissolved oxygen, BOD, COD, and total suspended solids. The aim is to develop an intelligent system using an adaptive nonlinear control algorithm that optimizes the operation of the control system for the plant. By adopting this approach, it is expected that the WWTP can enhance its performance, maintain the desired effluent water quality, and mitigate the risks associated with improper operation. This intelligent control system offers a promising solution for efficient and effective wastewater treatment in industrial processes

1.3 Objective of the study

1.3.1 General objective

The general objective of this study is to improve the efficiency and effectiveness of wastewater treatment at Africa Juice Tibila S.C by implementing an adaptive nonlinear PID controller in the industrial wastewater treatment plant.

1.3.2 Specific objectives

The specific objectives of this thesis are:

i. To model a wastewater treatment plant (WWTP)
ii. To design adaptive PID Nonlinear controller for wastewater treatment plant.
iii. To design RBFNN based PID controller for wastewater treatment plnat.
iv. To Evaluate and analysis the performance of the controller using Matlab simulation.

1.4 Significance of the study

Wastewater is a major bottleneck around the world and it is especially challenging to treat wastewater released from industrial areas. This is because industrial wastewater often contains harmful chemicals that can be difficult to remove. The development of a control mechanism for wastewater treatment is an important ways in improving the quality of the water. So, the proposed controller adaptive nonlear PID controller with RBFNN can overcomes shows promise for improving the performance of Africa Juice wastewater treatment systems. The simulation a result has shown are very encouraging. The proposed controller was able to achieve better performance than the conventional PID controllers.

1.5 Scope and limitation of the study

The scope of this thesis focuses on adaptive nonlinear PID control for the Africa Juice Tibila S.C industrial wastewater treatment plant as major controller and tuning used adaptive nonlinear neural network PID controller. Designing new proposed of treatment with some modification on existing adding automatic controller and new basis for chemical enjection had done. At the end of this thesis study, a new method of industrial wastewater treatment plant for Africa Juice S.C Company is proposed.

1.6 Organization of the thesis

This thesis is organized into four chapters, followed by a conclusion, recommendations, references, and appendices. Chapter 1 introduces the topic by providing a background study of industrial wastewater treatment plants, stating the problems addressed in the research, outlining the objectives, and highlighting the significance of the study. Chapter 2 focuses on the literature review of industrial wastewater treatment plants, including related works, identifying research gaps, and providing an overview of the wastewater treatment plant used by Africa Juice sc. In Chapter 3, the methodology is described, encompassing materials and methods, the design of the wastewater treatment plant, the design of controllers, and the proposed model or new treatment specifically tailored for Africa Juice s.c. Chapter 4 presents the results and discussion, analyzing the obtained results and providing a comprehensive interpretation. The conclusion summarizes the main findings, while the recommendations offer practical suggestions for addressing the identified problems or improving the wastewater treatment plant. The references list all the cited sources, and the appendices include supplementary information to support the thesis.

CHAPTER TWO

LITERATURE REVIEW

2.1 Literature review of related works

The Eastern Industrial Park is a good example of how industrial development should impact on society and environment if proper waste treatment measures are not in place. Dongfang textile industry is released high concentration of phosphorus can contribute to eutrophication, which is the excessive growth of algae in water bodies. This can push to a decline in water quality and the death of aquatic life.The dark color wastewater and offensive odor from the communal treatment plant are also signs that the wastewater is not being properly treated. This wastewater may contain harmful pollutants that could pose a health risk to people who come into contact with it, either directly or through the consumption of contaminated food. The use of wastewater from the industries as irrigation water is also a cause for concern. This wastewater may contain harmful pollutants that could contaminate the vegetables grown with it. This could lead to health problems for people who are eat the vegetables.

It is important that the authorities take action to address the problem of industrial liquid waste pollution in the Eastern Industrial park which is located at Dukem town. It will require the implementation of stricter regulations and the enforcement of the the regulations. It is also important to provide financial assistance to the industries to help them upgrade their waste treatment facilities. (Ayele, B. G., & Assefa, E., 2022)

Sustainable development goals(SDG) Indicator 6.3.1 is a crucial tool in the fight for clean water and sanitation for all. Monitoring this indicator helps us understand the state of wastewater treatment globally and identify areas where progress is needed. This, in turn, empowers decision makers and stakeholders to take informed actions towards improving water quality, protecting public health and achieving SDG 6.3.1. There are some purposes monitering indicates: such tracking progress by measuring the proportion of wastewater that is treated ,identifying challenges to monitoring effectively then promoting accountability monitoring progress against indicator 6.3.1 holds counties accountable for the commitments. The data collected through monitoring can be used to inform decision making at all levels, from national governments to local communities. This can help stakeholders make informed choices about investments in water and sanitation infrastructure, the wastewater technologies development and the implementation of policies to reduce water pollution.

The author provides a comprehensive overview of the common situation of WWT globally, for the acceleration needs to SDG indicator 6.3.1. The authors highlight the importance of increasing investment in wastewater treatment infrastructure, as well as improving the quality of wastewater data collection and reporting. They also call for increased international cooperation to support the development and implementation of sustainable wastewater management solutions. (Alabaster, Johnston, & Shantz, 2021).

Classic Aeration Control the authors has seen as tradtitional aeration control & model based simulation. Traditional Aeration Control relies on an NH4 sensor to measure ammonium levels and adjust aeration based on DO concentration in activated sludge systems. Model based simulation focus on a calibrated model of the "Klimzowiec" WWTP was used to simulate NH4 probe measurements, offering a virtual alternative. Relies on an ammonium (NH4) sensor to measure NH4 concentration in the aerobic zone of the bioreactor. Controller adjusts aeration based on NH4 readings and dissolved oxygen (DO) levels.

Simulated NH4 Probe Concentration:

- ✓ Calibrated model of the "Klimzowiec'' WWTP used to simulate NH4 probe readings.
- ✓ Calculations generated every 15 minutes based on previous month's data.
- ✓ "Virtual" NH4 measurements provide redundancy and reduce risk of errors from faulty probes.

SCADA data integrated with simulation software for comprehensive analysis. Overall, the use of a calibrated model to simulate NH4 probe concentration demonstrates a promising approach to enhance aeration control in WWTPs, leading to improved wastewater treatment quality and compliance with environmental regulations. (Kvist, M., & Vikstrand, J., 2022) .

The simulation system is used to predict the behavior of the WWTP the information correctly flow to be used to improve of the operation and optimize the energy use. The SCADA control system is used to monitor and control the WWTP. This system receives information from the simulation system and other sources, and it uses this information to adjust the operation of the WWTP. (Drewnowski, 2019).

Wastewater treatment is a valuable process for protecting human and environmental health. Wastewater contains pathogens, nutrients, solids, chemicals and even hazardous substances. These can pollute our water supplies, cause algae blooms and create a foul odor. Wastewater treatment facilities use a different of technics to remove these contaminants from wastewater. Wastewater treatment is an essential part of our water infrastructure. It helps to protect our health and the environment. We all have a responsibility to make sure that our wastewater is treated properly. (K, Avinash, Jaleel, Mujeeb, & Sharanappa, 2018).

This study investigated of activated sludge of three WWTP in Hungary using two methods: the Sludge activity (TTC) Screening method and microscopic examination. The results showed that only two of the five samples taken were above the minimum acceptable sludge activity measurement range. The chemical tests also showed that the system with the highest enzyme activity had the lowest cleaning efficiency. Microscopic examination of the activated sludge showed that Nocardia bacterial species were present in large numbers in this system, which indicates unfavorable circumstances. The researcher concluded that it is important to use all three methods together to determine how a wastewater treatment system works. The Sludge activity (TTC) Screening method can be used to quickly assess the state of activated sludge, while microscopic examination can provide more detailed information about the composition of the sludge. Chemical tests can also be used to assess the cleaning efficiency of the system.

The study's findings have implications for the operation and management of WWTP. The results show that it is important to monitor the sludge activity and enzyme levels in the system to ensure that it is operating effectively. The presence of Nocardia bacterial species can also be an indicator of problems in the system, so it is important to monitor for these organisms. As generally the author indicate the valuable insights into the use of activated sludge in WWT. The reults of the study to be used to improve the operation and management of WWTPs and to ensure that they are able to effectively remove pollutants from wastewater. (Mcineka, 2019)

In general, literature reviewed from researchers most of journal shows the SCADA, MPC and fuzzy logic only shows NH4 & DO but there is no indication of parameters BOD, COD, TSS, PH and total suspended solid.

2.1.1 Related work and Research gaps

- Graham Alabaster (2021): Focuses on the global status of wastewater treatment progress and identifies the need for accelerating efforts towards SDG 6.3.1. While it mentions feasibility studies on wastewater analysis and standard water quality, it doesn't delve(go down deep) into specific treatment methods.
- Bekele Girma Ayele et al. (2022): Examines the impact of industrial wastewater on various aspects including society, water bodies, and soil. They emphasize the importance of modern and efficient technologies but don't explicitly explore specific solutions like adaptive PID controllers.
- Jakub Drewnowski (2019): Presents a case study of implementing an advanced supervisory control system in a full-scale WWTP. While it focuses on optimization and energy balance using fuzzy logic controllers, it only showcases control for NH4, neglecting other crucial parameters like dissolved oxygen (DO), PH, COD, and BOD.

Utilizing adaptive nonlinear PID controllers addresses some key limitations of the existing research:

- ✓ Real time optimization: These controllers adjust the treatment process dynamically based on real time data, ensuring consistent adherence to discharge standards for various parameters including DO.
- ✓ Improved water quality: Maintaining adequate DO levels fosters a healthy aquatic ecosystem by minimizing COD and BOD.
- ✓ Enhanced efficiency and substainability**:** precise control optimizes resourse utilization, minimize energy consumption and potentially reduces operational costs.

2.2 Overview of Africa Juice Tibila S.C

Africa JUICE is a Dutch company established in 2007 with a mission to sustainably grow and process tropical fruits in Africa. They recognized the rising global demand for these delicious and nutritious products and aimed to fill the gap while empowering local communities and protecting the environment. The Tibila project, nestled in Ethiopia's Upper Awash Valley, stands as a pioneering example of Africa JUICE's dedication to sustainable and ethical tropical fruit production in Africa. This first Fairtrade certified juice business in sub-Saharan Africa is more than just a farm and processing facility; it's a beacon of hope for farmers, workers and the environment.

Their first major project was the Africa JUICE Tibila Share Company, launched in 2009 in Ethiopia's Upper Awash Valley. This ambitious undertaking transformed a former state-owned fruit farm into a modern, thriving tropical fruit plantation. A brand-new processing facility was also constructed, equipped with cutting-edge technology for producing high-quality juices and purees. The initial investment of US$10 million laid the foundation for a successful venture.

Africa JUICE's dedication to sustainability and quality has paid off. Since late 2010, they have been exporting passion fruit NFC juice and mango purees, catering to international, regional, and local markets. They also support local bottlers and are constantly innovating, planning to introduce emulsions and compounds for regional beverage companies in 2020.

Diversifying Products and Practices: Their commitment to local communities and environmental well-being extends to their product range. Africa JUICE recently added papaya products to their local offerings, further catering to diverse tastes and preferences. Furthermore, they are finalizing plans to introduce organic products starting mid-2021, demonstrating their dedication to responsible agricultural practices.

A Promising Future: Africa JUICE's journey is a testament to the potential of sustainable tropical fruit production in Africa. Their success in Ethiopia paves the way for expansion into other regions, offering exciting opportunities for economic growth, environmental conservation and community development.

Fair Trade: Ensuring Equity and Sustainability at its core, the Tibila project champions Fairtrade principles. This globally recognized certification system guarantees:

Fair prices for farmers and workers: This ensures they receive a living wage and have access to social and economic benefits.

Good working conditions: Safe and healthy work environments are prioritized, promoting human dignity and well-being.

Environmental protection: Sustainable agricultural practices are employed to conserve biodiversity and safeguard the ecosystem.

Exporting high-quality products: Since late 2010, Africa JUICE has been exporting delicious passion fruit NFC juice and mango purees to international and regional markets.

Supporting local producers: The project supplies local bottlers with essential ingredients, fostering stronger value chains within the region.

Investing in innovation: In 2020, the company expanded its capabilities by adding new processing facilities to produce emulsions and compounds for local and regional beverage companies.

Cultivating economic opportunities: The project has successfully introduced passion fruit as a new commercial crop in Ethiopia, creating jobs and boosting local income.

Empowering communities: With over 1,000 hectares under cultivation and nearly 2,000 people employed, the Tibila project is a vital source of livelihood and development for the surrounding communities.

Promoting local consumption: By focusing on mango puree for the growing local beverage market, Africa JUICE is contributing to import substitution and fostering a self-sufficient food system.

A Model for the Future:

The Tibila project is a testament to the transformative power of sustainable and ethical business practices. By prioritizing Fairtrade principles, Africa JUICE has created a model for how tropical fruit production can benefit both people and the planet. With their dedication to continuous improvement and expansion, they are paving the way for a brighter future for the entire industry in Africa.

2.2.1 Africa juice wastewater treatment plant process

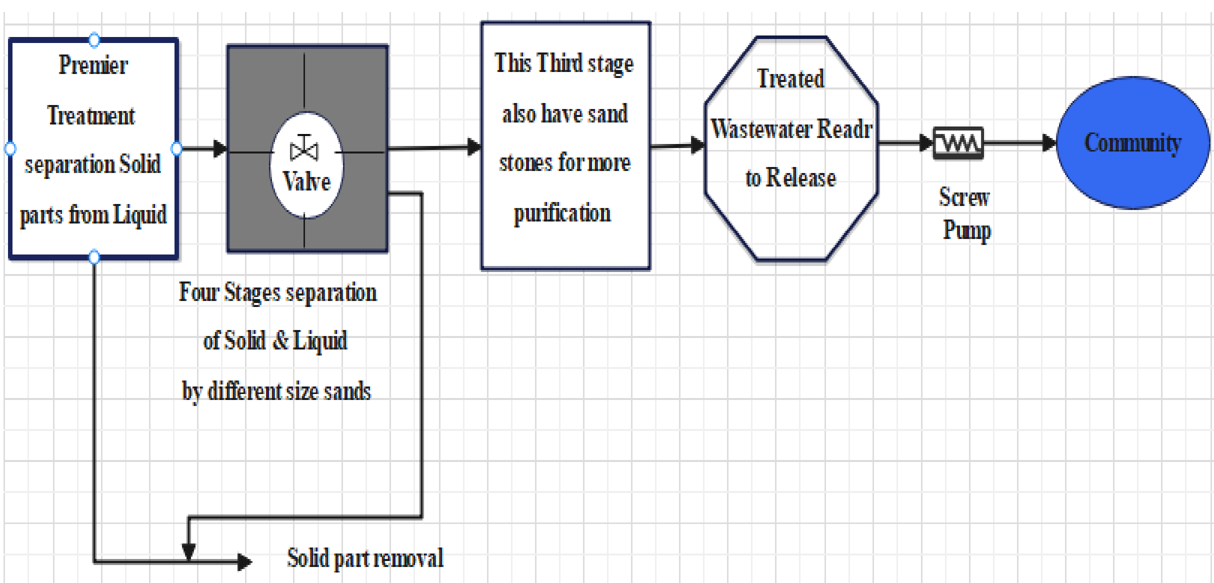

Figure 2.1 Existing system of wastewater treatment plant for Africa Juice

Description of the plant processs flow

- ✓ **Premier treatment (1st stage)** have little pond or silo with screen sieve for the separation of a big sized solid parts like passion fruit seed, passion fruit seeds and others reject fruits, mango seed and skins.
- ✓ **Four stages separation (2nd stage)** is the big stage and has four partitions; the four partitions are filled with different sizes of sand stones for filtration particles passed with wastewater from the **1st stage**. Form one partition to others partition the wastewater transferred slowly.
- ✓ **3rd stage** this stage is last treatment also this treatment is similar with 2nd stage. But it is far from the second 30 meters. The wastewater treated at the flow slowly from 2nd to 3rd stage and this treatment method also uses stones. There were no chemicals used to treat the wastewater treatment.
- ✓ **Storage Reservoir** this storage application only for collection the treated wastewater released from factory and ready for release using motor pump screw type environment. Solid parts collected manual by man power.

2.2.2 Africa Juice effluent water and international standard parameters

Standard parameters of Africa juice effluent water or waste water and international standards Parameters guide in below table,

Table 2.1 Africa juice effluent water (wastewater) and international standard parameters.

Parameter	Unit	Guide Low	*Guide High*	Method
PH		6.50	*8.50*	Potentiometric
Electrical Conductivity	Ms/cm		*<1.50*	Potentiometric
Total dissolved solid	Ppm		*< 1200*	Potentiometric
Total suspended solid	Ppm		*< 30.0*	Gravimetric
Colour	H.U		*< 15.0*	Colorimetric
BOD	Ppm		*< 30.0*	Incubation
COD	Ppm		*< 50.0*	Reflux
DO	Mg/L	1	3	

Ammonium	Ppm			Colorimetric
Nitrate N	Ppm			Colorimetric
*Nitrite N	Ppm			Colorimetric
*Total N	Ppm		< 100	Colorimetric
Chloride	Ppm		< 250	Colorimetric
Fluoride	Ppm		< 1.50	Colorimetric
*Oil & Grease	Ppm		< 0.05	Gravimetric
E.Coli	cfu/100 m		*ND*	CN-TM-W 18
Total Coliforms	cfu/100 m		< 1000	CN-TM-W 18

Table 2.2 Ethiopian Standard Agency (ESA) effluent discharginges to inland waters

Parameter	Emission limit value mg/L	Parameter	Emission limit value mg/L
PH	6-9	Selenium (as Se)	1
Temperature	$40c^0$	Silver as (as Ag)	1
Biochemical oxygen demand (as BOD) at 20 cent	80	Tin (as Sn)	5
Chemical oxygen demand (as COD)	250	Zinc (as Zn)	5
Total dissolved solid	3000	Total heavy metals(combined)	15
Total suspended solid	100	Calcium (as Ca)	100
Total Nitrogen	80	Chloride (as Cl)	1000
Total Ammonium as N	30	Chlorine (total residual, as Cl)	1.5
Total Ammonium as free nitrate N	5	Fluoride (as F)	20
*Nitrite N	20	Sulphide (as S)	10
Dissolved phosphorus (as P)	5	Sulphate (as SO4)	100
Total phosphorus as P	10	1,1,1-Trichloroethene	0.5
Fats, oils and grease	20	1,1,1-Dichloroethyelene	0.2
Aluminium (as Al)	0.2	1,1,2-Trichloroethene	0.06
Arsenic (as As)	0.25	1,2-Dichloroethene	0.04
Barium (as Ba)	10	1,3-Dichloropropene	0.2
Boron (as B)	5	Dichloromethane	0.2

Cadmium (as CD)	1	Cis-1.2-Dichloroethylene	0.4
Chromium (as total Cr)	0.5	Tetrachloroethylene	0.1
Cobalt (as Co)	1	Tetrachloromethane	0.02
Copper (as Cu)	2	Tricholoroethylene	0.3
Cyanide (as CN)	0.5	Polychlorinated Biphenyls(PCB's)	0.003
Iron (as Fe)	10	Polycyclin Aromatic hydrocrabons (as benzene)	0.1
Lead (as Pb)	0.5	Absorbable organic halogen compound	2
Magnesium (as Mg)	100	Dioxins	0.002
Manganese (as) Mn)	5	Benzene	0.2
Mercury (as Hg)	0.001	An-ionic detergent (as MBAS)	15
Nickle (as Ni	3	Pesticides, herbicides, & insecticides	0.1
Phenolic compounds (as C6H5OH)	1	Alpha emitters	10-7yc/ml
Formaldehyde	1	Betta emitters	10-6yc/ml
Totatal coliform bacteria (100per/ml	400		

Table 2.3 Ethiopian Standard Agency (ESA) effluent discharginges to land

Parameter	Emission limit value mg/L	Parameter	Emission limit value mg/L
PH	5.5-9	Lead (as Pb)	0.5
Biochemical oxygen demand (as BOD) at 20 cent	500	Manganese (as) Mn)	5
Total dissolved solid	2100	Mercury (as Hg)	0.001
Fats, oils and grease	30	Nickel (as Ni)	3
Arsenic (as As)	0.25	Selenium (as Se)	1
Barium (as Ba)	10	Silver as (as Ag)	1
Boron (as B)	5	Tin (as Sn)	5
Cadmium (as CD)	1	Zinc (as Zn)	5
Chromium (as hexavalentl Cr)	0.5	Total heavy metals (combined)	15
Cobalt (as Co)	1	Chloride (as Cl)	1000
Copper (as Cu)	2	Fluoride (as F)	20
Cyanide (as CN)	0.5	Sulphate (as SO4)	100

CHAPTER THREE

METHODOLOGY

This chapter has covered material, methods and mathematical modeling of the industrial wastewater treatment plant design using adaptive nonlinear PID controller.

3.1 Materials

MATLAB/Simulink: Is a programming platform that serves as a valuable tool for engineers and scientists in analyzing, designing and modeling systems. It offers a graphical environment specifically designed for modeling and simulating dynamic systems. MATLAB utilizes a unique programming language that is centered around matrics, mathematical expressions, graphics and block diagrams. This language provides a flexible and powerful means of implementing algorithm and performing computations. This feature rich environment allows users to construct models by visually connecting blocks that represent system components and their interactions. Simulink also offers solvers that enable the simulation of these dynamic systems.

Math Type 6.0 : Is a software tool specifically designed for writing mathematical formulas and equations in Microsoft office word and power points. It provides a user friendly interface and a comprehensive set of mathematical symbols, templates and functions to create complex mathematical expressions easily. With math type 6.0, users can seamlessly integrate mathematical equations into their word documents or power point presentations. It offers a range of formatting options, such as adjusting font styles, sizs and colors to ensure the equations are visually appealing and aligned with the document's overall design.

EdrawMax: To create flow charts, mind maps, organs chats, network diagrams and floor phase. So, edrawmax used in this thesis to draw block diagrams, figures, flow chats and designs.

3.2 Method of the Study

The procedure methods of the thesis as below :

a. Introduction:

- ✓ Provide a brief overview of the IWWTP (Industrial Wastewater Treatment Plant) and the need for an adaptive nonlinear PID (Proportional-Integral-Derivative) controller.

- ✓ Explain the objectives of the thesis and the significance of developing an adaptive nonlinear PID controller for the IWWTP.

b. Literature Review:

- ✓ Conduct a comprehensive review of existing literature related to adaptive control techniques, nonlinear control strategies and PID controllers in the context of wastewater treatment.
- ✓ Summarize the strengths and limitations of previous approaches and highlight the research gaps.
- ✓ Briefly explain the existing system of Africa Juice Tibila S.C wastewater treatment plant.

c. Methodology:

- ✓ Describe mathematical model of the wastewater system and controller in detail.
- ✓ Explain the challenges and complexities associated with controlling the IWWTP process, emphasizing the need for an adaptive approach.
- ✓ Explain the selection criteria for the adaptive algorithm and the rationale behind choosing a nonlinear controller.
- ✓ Explain the modifications of the existing Africa Juice Tibila S.C using adaptive nonlinear PID controller.

d. Result and Discussion

- ✓ Conduct simulations to validate the performance of the adaptive nonlinear PID controller using appropriate software tools (e.g., MATLAB, Simulink).
- ✓ Compare the simulation nonlinear PID results with Simulink result on RBFNNPID the controller's effectiveness.

e. Conclusion and Recommendation

- ✓ Summarize the wastewater problems on environmental, human and aquatics.
- ✓ Explain the adaptive nonlinear PID controller and RBFNNPID for the IWWTP.
- ✓ Suggest future research directions to further enhance the controller's performance.
- ✓ Discuss the potential impact of the wastewater on the environment, human safety, and other relevant factors.

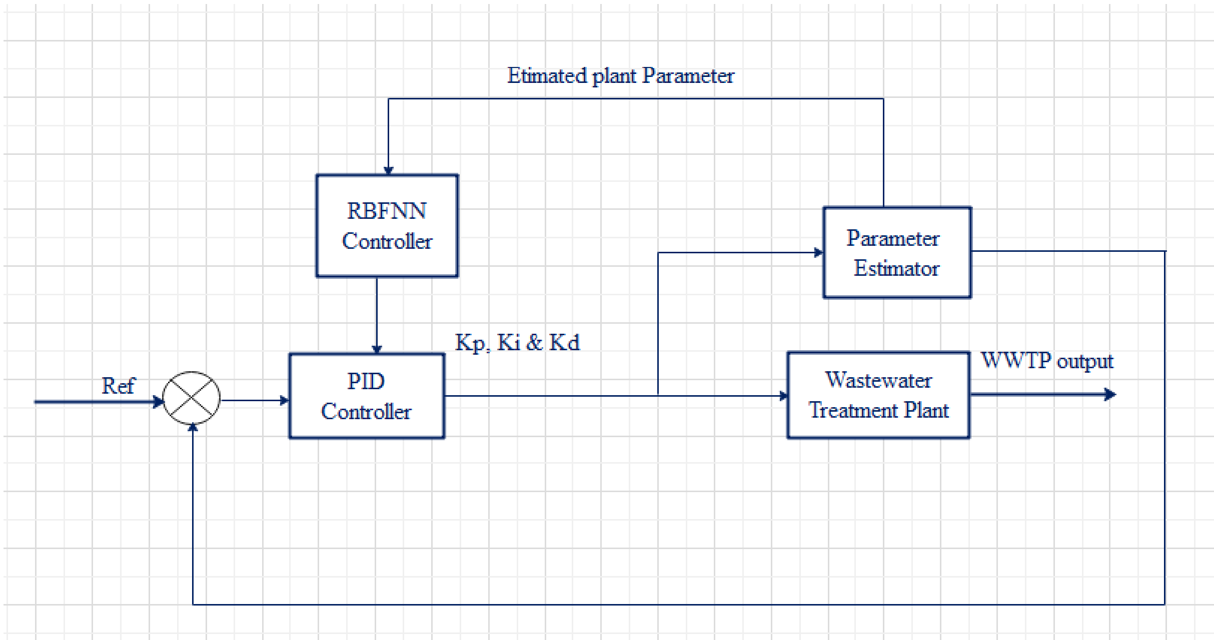

Figure 3.1 Block diagram of the wastewater treatment plant controlled system

Explanation of the components

1. **Input Reference** the desired behavior or setpoint for the industrial wastewater treatment plant is specified as the input reference signal. It represents the target value that the control system aims to achieve.
2. **PID Controller** the input reference signal is compared with the output measurement obtained from the feedback sensors. The PID controller calculates the control actions based on the error between the input reference and the output measurement. The control actions are determined using the proportional, integral, and derivative terms of the PID controller.
3. **RBFNN Adaptation Algorithm** the control error, which is the difference between the input reference and the output measurement, is passed through the RBFNN adaptation algorithm. This algorithm updates the parameters of the RBFNN, such as the weights and centers of the radial basis functions, to improve the accuracy of the RBFNN model in approximating the nonlinear relationship between the process inputs and outputs.
4. **Nonlinear System Model** the adaptive RBFNN model captures the nonlinear behavior of the process. It takes the control actions as inputs and approximates the corresponding process outputs based on the adapted model parameters. The nonlinear system model represents the estimated output based on the current inputs.

5. **Process Plant** the control actions generated by the PID controller are applied to the industrial wastewater treatment plant. The process plant represents the physical system and its dynamics. It converts the control actions into changes in the process inputs, resulting in an updated process output.
6. **Feedback Sensors** the actual process output is measured by the feedback sensors. The feedback signals are sent back to the control system to compare against the input reference and compute the control actions. The feedback signals provide information about the real-time behavior of the process and are used for control and adaptation.
7. **Output Measurement** the output measurement represents the actual process output obtained from the feedback sensors. It is fed back to the control system for comparison with the input reference and to facilitate control action calculation.

The control loop continues iteratively, with the PID controller adjusting the control actions based on the error between the input reference and the output measurement, the adaptive RBFNN updating its model parameters based on the control error, and the process plant responding to the control actions and producing updated process outputs. The goal is to minimize the difference between the actual process output and the desired input reference over time, achieving effective control of the industrial wastewater treatment plant.

3.3 Mathematical model of wastewater treatment plant

The ASM 1 is a mathematical model that provides an inclusive description of the biological and chemical transformations occurring in activated systems. It is a 13 state model, meaning that it encompasses 13 different variables to represent various components within the system. These variables includes biomass concentrations, biodegradable and non biodegradable and inert material. ASM1 incorporates a wider range of biological and chemical processes. This increased complexity allows mathematical model to provides more accurate predictions regrading the performance of activated sludge (AS) systems.

The study mentioned in the context utilized a simulation model based on the BSM1, which is a validated model built upon ASM1. BSM1 has demonstrated its ability to accurately forecast the performance of activated sludge systems. In this study, BSM1 was employed to simulate the operation of activated sludge WWTP under various operating conditions. The simulation results indicated that BSM1 consistently and accurately predicted the performance of the plant across all tested operating conditions. Consequently, the study concluded that BSM1 is a reliable and accurate simulation model for predicting the performance of AS wastewater treatment plants. (Nimir, Ibrahim Mahmoud Nawai, 2021)

3.3.1 Activated sludge model No.1 (ASM1)

The ASM1 model proven to be a valuable tool in studying various processes within activated sludge systems, including nitrification, denitrification, phosphorus removal and sludge production. It has enabled the optimization of design and operation of AS for WWTPs. (Nelson, M. I., Sidhu, H. S., Watt, S. & Hai, F. I., 2019)

The BSM1 represents a five compartment process AS error, consisting two anoxic tanks and three aerobic tanks. These tanks connected in series with the influent wastewater being fed into the first anoxic tank. The effluent from the first anoxic tank then flows into the second anoxic tank before entering the three aerobic tanks. Finally, the effluent from the last aerobic tank is directed to a secondary clarifier, where the sludge is separated from the treated water. Although BSM1 is a simplified representation of a real WWTP, it captures the essential features of the ASP. This model is particularly useful for studying the performance of different control strategies for WWTPs. (Jens Alex, 2018)

In the context of controlling DO, the controller in the BSM1 model manipulates K_{La5}, which represents the oxygen transfer process from the aerator to the activated sludge within the biological reactor. A simplified diagram of the BSM1 model is shown in Figure 3.4. (Nelson, M. I., Sidhu, H. S., Watt, S. & Hai, F. I., 2019)

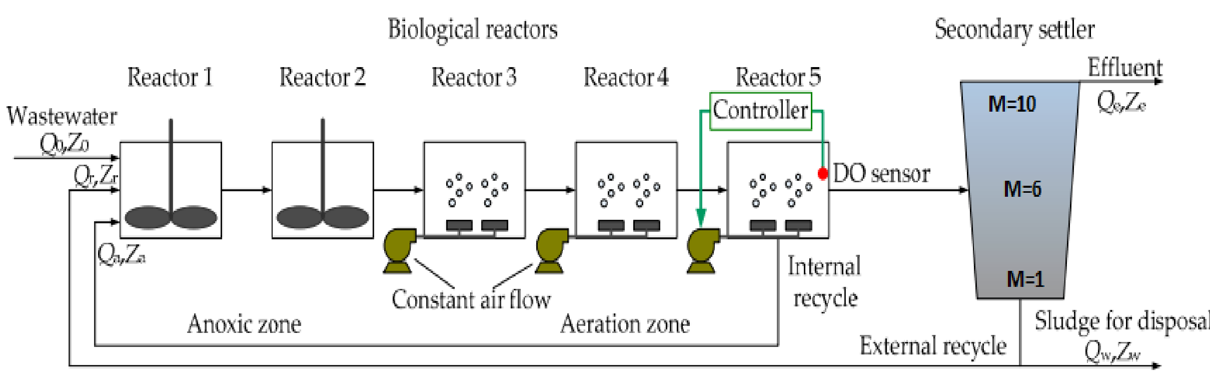

Figure 3.2 Benchmark Simulation Model No. 1 (**Seshagiri Rao, 2020)**

The benchmark simulation model 1 is a biological WWTP. It is has five biological reactors arranged in series with the first two being anoxic and the last three being aerated. The only control input is for DO in the last reactor, so,the first four reactors are essentially the same.

The reason for this is that the first two reactors are used for denitrification converting nitrate to nitrogen gas. The process does not require dissolved oxygen, so the reactors can be operated without aeration. The last three reactors are used for nitrification are the process of ammonia converting into nitrate. This process does require dissolved oxygen, so the reactors need to be aerated.

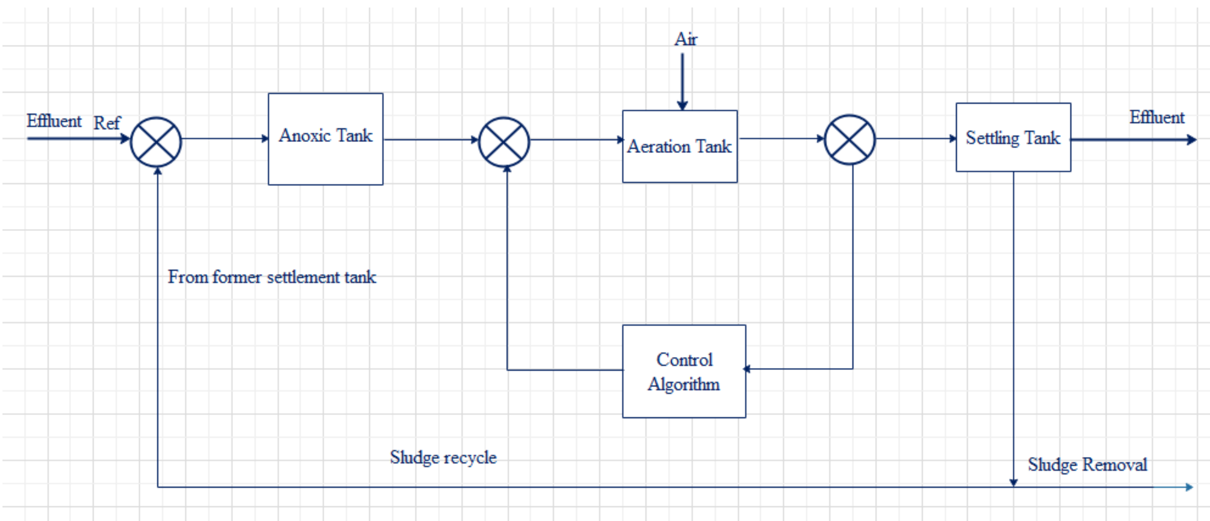

Figure 3.3 Block diagram representation of Benchmark simulation for internal model of WWTP

The above figure 3.3 shows that physical process with electrical as general by simplifying, because anoxic tank contain the three processes (1st , 2nd and 3rd reactions) in biological and aeration process contain 4th stage reaction and 5th stage reaction. This simplifies the model and makes it easier to analyze. It also means that the control input for DO in the last reactor be used to control the performance of the entire system. Mathematic model of the biological reactor is: (Jens Alex, 2018)

$$\frac{dS_{I,k}}{dt} = \frac{1}{V_k}(Q_{kI}S_{I,kI} + rS_{I,k}V_k - Q_k S_{I,k}) \tag{3.1}$$

$$\frac{dS_{S,k}}{dt} = \frac{1}{V_k}(Q_{kI}S_{S,kI} + rS_{S,k}V_k - Q_k S_{S,k}) \tag{3.2}$$

$$\frac{dX_{I,k}}{dt}=\frac{1}{V_k}(Q_{kI}X_{I,kI}+rX_{I,k}V_k-Q_kX_{I,k}) \tag{3.3}$$

$$\frac{dX_{S,k}}{dt}=\frac{1}{V_k}(Q_{kI}X_{S,kI}+rX_{S,k}V_k-Q_kX_{S,k}) \tag{3.4}$$

$$\frac{dX_{B,H,k}}{dt}=\frac{1}{V_k}(Q_{kI}X_{B,H,kI}+rX_{B,H,k}V_k-Q_kX_{B,H,k}) \tag{3.5}$$

$$\frac{dX_{B,A,k}}{dt}=\frac{1}{V_k}(Q_{kI}X_{B,A,kI}+rX_{B,A,k}V_k-Q_kX_{B,A,k}) \tag{3.6}$$

$$\frac{dX_{P,k}}{dt}=\frac{1}{V_k}(Q_{kI}*X_{P,kI}+rX_{P,k}*V_k-Q_k*X_{P,k}) \tag{3.7}$$

$$\frac{dS_{O,k}}{dt}=\frac{1}{V_k}(Q_{kI}S_{O,kI}+rS_{O,k}V_k-Q_kS_{O,k}) \tag{3.8}$$

$$\frac{dS_{NO,k}}{dt}=\frac{1}{V_k}(Q_{kI}S_{NO,kI}+rS_{NO,k}V_k-Q_kS_{NO,k} \tag{3.9}$$

$$\frac{dS_{NH,k}}{dt}=\frac{1}{V_k}(Q_{kI}S_{NH,kI}+rS_{NH,k}V_k-Q_kS_{NH,k}) \tag{3.10}$$

$$\frac{dS_{ND,k}}{dt}=\frac{1}{V_k}(Q_{kI}S_{ND,kI}+rS_{ND,k}V_k-Q_kS_{ND,k}) \tag{3.11}$$

$$\frac{dX_{ND,k}}{dt}=\frac{1}{V_k}(Q_{kI}X_{ND,kI}+rX_{B,H,k}V_k-Q_kX_{ND,k}) \tag{3.12}$$

$$\frac{dS_{ALK,k}}{dt}=\frac{1}{V_k}(Q_{kI}S_{ALK,kI}+rS_{ALK,k}V_k-Q_kS_{ALK,k}) \tag{3.13}$$

Where the Table 3.1 shows the 13 state variables, such as, Constant $k \in$ [1, 2, 3, 4 and 5] and labels of the reactor numbers. Thus V_k is the constant volume of the K^{th} reactor. From equation 3.2, Q_{kI} represents the input flow with concentration S_{IkI} while Q_k represents the output flow with concentration S_{Ik} the conversion rates are given.

Table 3.1 List of ASM1 input variable with standard

S.N	Notation	Definition	Range of standard values
1	S_I	Soluble inert organic matter	50-150mg/L
L	S_S	Readily biodegradable substrate	100-300mg/L
3	X_I	Particulate inert organic matter	100-200mg/L
4	X_S	Slowly biodegradable substrate	50-100mg/L
5	X_{BH}	Active heterotrophic biomass	500-3000mg/L
6	$X_{B,A}$	Active autotrophic biomass	10-100mg/L
7	X_P	Particulate products arising from biomass decay	20-50mg/L
8	S_O	dissolved Oxygen	>2mg/L
9	S_{NO}	Nitrate and nitrite nitrogen	<1-30mg/L
10	S_{NH}	N H $^+$ + NH3 nitrogen	<1-100mg/L
11	S_{ND}	Soluble biodegradable organic nitrogen	10-50mg/L
12	X_{ND}	Particulate biodegradable organic nitrogen	50-100mg/L
13	S_{ALK}	Alkalinity	>100mg/L

The observed conversion rates (r_i)results from combinations of the basic processes. $r_i = \sum_j v_{ij} p_j$

$$S_I(i=0) \qquad r_1 = 0 \tag{3.14}$$

$$S_s(i=2) \qquad r_2 = -\frac{1}{Y_H}P_1 - \frac{1}{Y_H}P_2 + P_7 \tag{3.15}$$

$$X_I(i=3) \qquad r_3 = 0 \tag{3.16}$$

$$X_s(i=4) \qquad r_4 = (1-f_P)P_4 + (1-f_P)P_5 - P_7 \tag{3.17}$$

$$X_{BH}(i=5) \qquad r_5 = P_1 + P_2 - P_4 \tag{3.18}$$

$$X_{BA}(i=6) \qquad r_6 = P_3 - P_5 \tag{3.19}$$

$$X_P(i=7) \qquad r_7 = f_P P_4 + f_P P_5 \tag{3.20}$$

$$S_O(i=8) \qquad r_8 = \frac{1-Y_H}{Y_H}P_1 - \frac{4.57-Y_A}{Y_A}P_3 \tag{3.21}$$

$$S_{NO}(i=9) \qquad r_9 = \frac{1-Y_H}{2.86Y_H}P_2 + \frac{1}{Y_A}P_3 \tag{3.22}$$

$$S_{NH}(i=10) \qquad r_{10} = -i_{XB}P_1 - i_{XB}P_2 - (i_{XB} + \frac{1}{Y_A})P_3 + P_6 \tag{3.23}$$

$$S_{ND}(i=11) \qquad r_{11} = -P_6 + P_8 \tag{3.24}$$

$$X_{ND}(i=12) \qquad r_{12} = (i_{XB} - f_P i_{XP})P_4 + (i_{XP} - f_P i_{XP})P_5 - P_8 \tag{3.25}$$

$$S_{ALK}(i=13) \qquad r_{13} = -\frac{i_{XB}}{14}P_1 + (\frac{1-Y_H}{14-2.86Y_H} - \frac{i_{XB}}{14})P_2 - (\frac{i_{XB}}{14} + \frac{1}{7Y_A})P_3 + \frac{1}{14}P_6 \tag{3.26}$$

Where each biological process represents P and there are 8 basic processes that are used to describe the logical behavior of the system.

1. Aerobic growth of heterotrophis

$$P_1 = \mu H(\frac{S_S}{K_S + S_S})(\frac{S_O}{K_{O,H} + S_O})X_{B,H} \tag{3.27}$$

2. Anoxic growth of heterotrophs

$$P_2 = \mu H(\frac{S_S}{K_S + S_S})(\frac{K_{O,H}}{K_{O,H} + S_O})(\frac{S_{NO}}{K_{NO} + S_{NO}})\eta_g X_{B,H} \tag{3.28}$$

3. Aerobic growth of autotrophs

$$P_3 = \mu A(\frac{S_{NH}}{K_{NH} + S_{NH}})(\frac{S_O}{K_{O,A} + S_O})X_{B,A} \tag{3.29}$$

4. Decay of heterotrophs

$$P_4 = b_H X_{B,H} \tag{3.30}$$

5. Decay of autotrophs

$$P_5 = b_A X_{B,A} \tag{3.31}$$

6. Ammonification of soluble organic nitrogen

$$P_6 = k_a S_{ND} X_{B,H} \tag{3.32}$$

7. Hygrolysis of entrapped organics

$$P_7 = k_h \frac{X_S / X_{B,H}}{K_x + (X_S / X_{B,H})}[(\frac{S_O}{K_{O,H}+S_O}) + \eta_h (\frac{K_{O,H}}{K_{O,H}+S_O})(\frac{S_{NO}}{K_{NO}+S_{NO}})]X_{B,H} \quad (3.33)$$

8. Hydrolysis of entrapped organic nitrogen

$$P_8 = k_h \frac{X_S / X_{B,H}}{K_x + (X_S / X_{B,H})}[(\frac{S_O}{K_{O,H}+S_O}) + \eta_h (\frac{K_{O,H}}{K_{O,H}+S_O})(\frac{S_{NO}}{K_{NO}+S_{NO}})]X_{B,H}(X_{ND} / X_S) \quad (3.34)$$

Stoichiometric parameters and kinetic parameters are given by Table 3.2 and Table 3.3. From Figure 3.4, we can see that the controller that uses fixed oxygen transfer k_{La5} is the reactor 5. Thus, the dissolved oxygen (DO or SO) rate for reactor 5 is given by:

$$\frac{dS_{O,k}}{dt} = \frac{1}{V_k}(Q_{k,I} S_{O,k-1} + r_k V_k + (K_{La})_k V_k (S_O^* - S_{O,k}) - Q_k S_{O,k}) \quad (3.35)$$

Table 3.2 Stoichiometric Parameters

Parameter	*Unit*	*Value*
Y_A	*g cell COD formed.(g N oxidized)* $^{-1}$	*0.24*
Y_H	*g cell COD formed.(g COD oxidized)* $^{-1}$	*0.67*
f_P	*Dimensionless*	*0.08*
I_{XB}	$g\ N.(gCOD)^{-1}$ *in biomass*	*0.08*
i_{XP}	$g\ N.(gCOD)^{-1}$ *in particulate products.*	*0.06*

Table 3.3 Kinetic Parameters

Parameter	*Unit*	*Value*
μ_H	d^{-1}	*4.0*
K_S	$gCOD.m^{-3}$	*10.0*
$K_{O,H}$	$g(-COD).m^{-3}$	*0.2*
K_{NO}	$gNO_3 - N.m^{-3}$	*0.05*
B_H	d^{-1}	*0.3*
η_g	*Dimensionless*	*0.8*

η_h	*Dimensionless*	*0.8*
k_h	*g slowly biodegradable COD.(g cell COD.d)*$^{-1}$	*3.0*
K_X	*g slowly biodegradable COD.(g cell COD)*$^{-1}$	*0.1*
μ_A	d^{-1}	*0.5*
K_{NH}	*g* NH_3*-N.*m^{-3}	*1.0*
b_A	d^{-1}	*0.5*
$K_{O,A}$	*g (-COD).*m^{-3}	*0.4*
K_a	m^3*.(gCOD.d)*$^{-1}$	*0.05*

Where the atuation concentration for oxygen is S_O^* = 2g.m^{-3}. Note there is a fixed oxygen transfer coeffiecient (K_{La}=10h^{-1}=240d^{-1}) in the reactor 3 and reactor 4. For each biological reactor, the general equation from mass balancing is given by:

$$\frac{dZ_j}{dt} = \frac{1}{V_k}(Q_{j,k,I}Z_{j,k,I} + r_j V_k - Q_j Z_j) \tag{2.36}$$

Where Z_j is the jth state variable, $Q_{j,k,I}$ represents the jth input flow with jth concentration $Z_{j,k,I}$ in the kth bioreactor, $Q_{j,k}$ represents the jth output flow with jth concentration $Z_{j,k}$ in the kth bioreactor, r_j means the jth conversion rate and volume V_k is a constant, which is given as example for volumes of both non aerated or aerated compartment.

- Anoxic (Non aerated) compartments: $V_1 = V_2 = 1000m^3$
- Aerated compartments: $V_3 = V_4 = V_5 = 1333m^3$

The biological reactors are followed by a secondary settler the tank which separates the treated WW from the activated sludge using gravity. The 2nd settler in the BSM 1 activate sludge process uses gravity to separate the treated wastewater from the activated sludge. It has 10 layers without any biological reaction and the 6th layer is the feed layer where the mixed liquor from the biological reactors enters.

3.4 New proposed industrial wastewater treatment plant for Africa Juice

Africa juice wastewater had released from factory without any modern wastewater treatment. But the DO, COD, BOD, PH, TSS, TDS, Ammonia and others most commonly should be monitored and controlled variables in ASP. Wastewater parameters sensors are used to monitor and to give signal for measurements to PID controller.

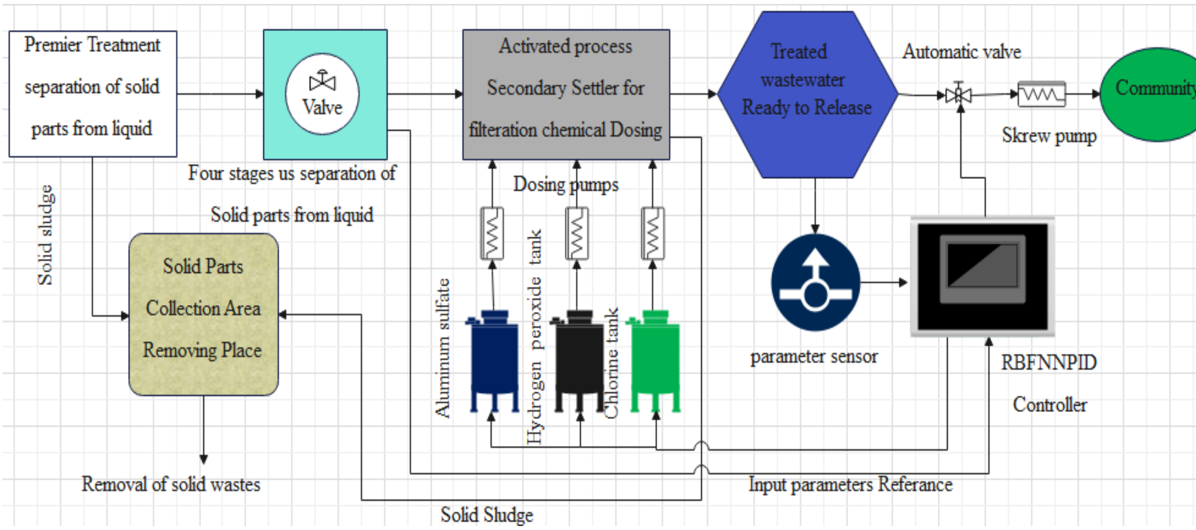

Figure 3.4 Proposed design for Africa Juice WWTP

Explanation of the designed by Edraw Max 2D drawing

The existing Africa Juice wastewater treatment was mechanical treatment or solid parts selection from liquid parts. But the proposed new design is electrical automation controlling using parameters testing using different types of sensors .

1. The first silo or tank is the same with the old system treatment only separate big sized solid parts and release after separate to the next stages
2. The second silo or pond had four parts as the old wastewater treatment plant separate solid parts under sized with different sized filled sands in four partitions. After that middle there was the control valve inside it to control wastewater in pond. There is new place for take the parameters as a reference at middle. But the old system hasn't check point.
3. Depending on the second result if necessary give command for Chemical dosing pump start in order eject aluminum sulfate(turbidity), Hydrogen peroxide (for DO control),Chlorine…..
4. This stage the accumulation treated wastewater and ready for release. So, at this sensors give feed signal for PID like COD sensor, BOD sensor, TSS sensor, TDS sensor, ammonia and nitrate sensor and others. Dissolved Oxygen (Model 499A TrDO sensor) was giving the signal to parameters analyzer with PID controller(ANNRBFPID) which control the automatic diaphragm valve which order the screw type pump release to community or others for aquatic or plant

5. Types of parameters sensor with their specification

I. PH Sensor: Measures the acidity or alkalinity of a solution by detecting the concentration of hydrogen ions.

- Measurement Range: 0-14 pH units
- Accuracy: ±0.01 pH units
- Resolution: 0.01 pH units
- Calibration: Single, double, or triple point calibration
- Response Time: Less than 30 seconds
- Temperature Compensation: Automatic
- Output Signal: Analog or digital (e.g., 4-20 mA, Modbus, etc.)
- Maintenance: Regular cleaning and calibration required
- Brands : Hanna Instruments, Mettler Toledo, Yokogawa, Sensorex

II. TDS Sensor: Measures the total dissolved solids in water, indicating the concentration of dissolved substances, such as salts and minerals.

- Measurement Range: 0-2000 ppm (parts per million)
- Accuracy: ±2% of reading
- Resolution: 1 ppm
- Output Signal: Analog or digital (e.g., 4-20 mA, Modbus, etc.)
- Maintenance: Regular cleaning and calibration required
- Brands : HM Digital, Milwaukee Instruments, Eutech Instruments, Apera Instruments

III. TSS Sensor: Measures the total suspended solids in water, indicating the concentration of particles that remain in suspension.

- Measurement Range: Not applicable (depends on the specific sensor)
- Accuracy: Not applicable (depends on the specific sensor)
- Resolution: Not applicable (depends on the specific sensor)
- Output Signal: Not applicable (depends on the specific sensor)
- Maintenance: Regular cleaning and calibration required
- Brands : Hach, YSI, In-Situ, oakton Instruments

IV. COD Sensor: Measures the chemical oxygen demand, which indicates the amount of oxygen required to oxidize organic and inorganic substances in water.

- Measurement Range: 0-2000 mg/L (milligrams per liter)

- Accuracy: ±5% of reading
- Resolution: 1 mg/L
- Output Signal: Analog or digital (e.g., 4-20 mA, Modbus, etc.)
- Maintenance: Regular cleaning and calibration required
- Brands : Hach, Lovibond, Hanna Instruments, LaMotte

V. BOD Sensor: Measures the biological oxygen demand, which indicates the amount of oxygen required by microorganisms to decompose organic matter in water.

- Measurement Range: 0-500 mg/L
- Accuracy: ±5% of reading
- Resolution: 1 mg/L
- Output Signal: Analog or digital (e.g., 4-20 mA, Modbus, etc.)
- Maintenance: Regular cleaning and calibration required
- Brands : Hach, Lovibond, Hanna Instruments, LaMotte

VI. DO Sensor: Measures the dissolved oxygen concentration in water, which is crucial for assessing water quality and the health of aquatic environments.

- Measurement Range: 0-20 mg/L (milligrams per liter) of dissolved oxygen
- Accuracy: ±0.2 mg/L
- Resolution: 0.01 mg/L
- Response Time: Less than 3 minutes
- Temperature Compensation: Automatic
- Output Signal: Analog or digital (e.g., 4-20 mA, Modbus, etc.)
- Maintenance: Regular cleaning and calibration required
- Brands : Hach, YSI, In-Situ, Honey well

VII. Ammonia Sensor: Measures the concentration of ammonia (NH_3) in water, which is important in assessing water pollution and treatment processes.

- Measurement Range: 0-500 mg/L
- Accuracy: ±5% of reading
- Resolution: 1 mg/L
- Output Signal: Analog or digital (e.g., 4-20 mA, Modbus, etc.)
- Maintenance: Regular cleaning and calibration required
- Brands : Hach, YSI, Hanna Instruments, Sensorex

VIII. Nitrate Sensor: Measures the concentration of nitrate ions (NO3-) in water, which is important for monitoring water quality and evaluating nutrient levels.

- Measurement Range: 0-100 mg/L
- Accuracy: ±5% of reading
- Resolution: 1 mg/L
- Output Signal: Analog or digital (e.g., 4-20 mA, Modbus, etc.)
- Maintenance: Regular cleaning and calibration required.
- Brands : Hach, YSI, Hanna Instruments, LaMotte

3.5 Mathematical model of controllers

3.5.1 Mathematical Model of the adaptive nonlinear PID Controller

Adaptive nonlinear PID controller is best for highly nonlinear process. Three main parts of PID (P,I and D) union can haddle error by calculate depending on the setpoint and desired value. It is often used in conjunction with other control elements, such as filters, compensators, and selectors, to improve their performance. The continuouos development of new control control algorithms ensures that the PID controller will remain a viable option for process control in the future. Nonlinear PID controllers are a type of PID controller that incorporates nonlinear functions into the main linear PID equation. This allows them to better handle nonlinear processes, which are often more difficult to control than nonlinear to control than linear processes. Nonlinear PID controllers can be more complex to design than linear PID controllers, but they can offer significant performance improvements in some cases.

Let see the below Figure 3.6 to understand their typical implementation

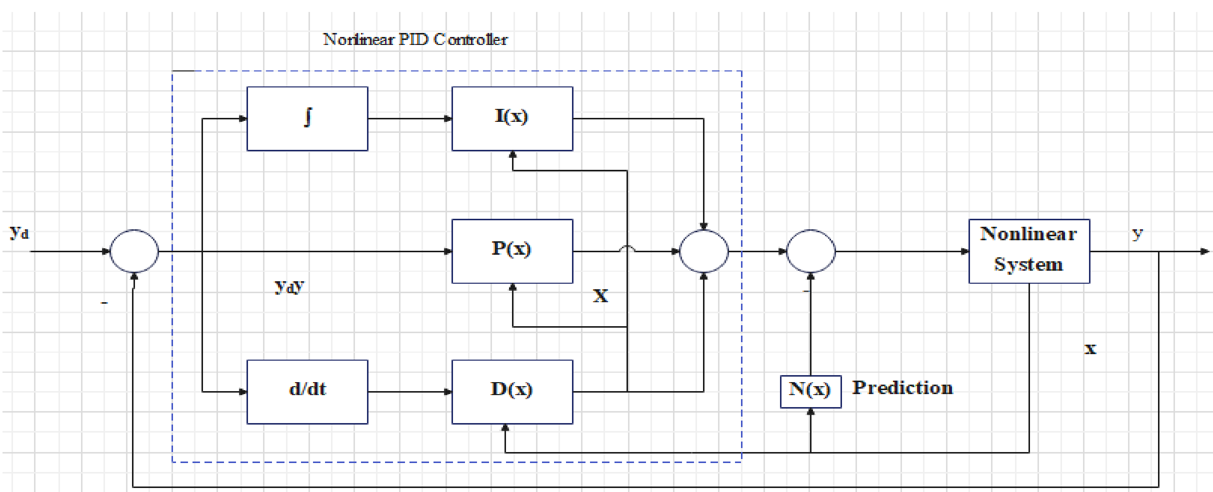

Figure 3.5 Closed loop nonlinear PID controller

Depening on the above Figure 3.5 the nonlinear PID equation can be written as follw

$$\varepsilon_0(t) = x_{11}(t) - x_{21}(t) \tag{3.37}$$

$$\varepsilon_1(t) = \int_0^t [x_{11}(t) - x_{12}(t)]d(t) \tag{3.38}$$

$$\varepsilon_2(t) = x_{12}(t) - x_{22}(t) \tag{3.39}$$

$$\dot{x}_{11}(t) = x_{12}(t) \tag{3.40}$$

$$\dot{x}_{12}(t) = x_{21}(t) \quad , \quad \dot{x}_{21}(t) = x_{22}(t) \tag{3.41}$$

$$\dot{x}_{22}(t) = -M_2 sign(x_{21}(t) - y(t) + \frac{x_{22}(t)\,|\,x_{22}(t)\,|}{2M_2}) \tag{3.42}$$

$$u(t) = K_p \,|\, \varepsilon_0(t) \,|^{ap} \; sign(\varepsilon_0(t)) + K_i \,|\int_0^t \varepsilon_0(t)dt\,|^{ai} \; sign(\int_0^t \varepsilon_0(t)dt) + K_d \,|\int_0^t \frac{d\varepsilon_0(t)}{dt}dt\,|^{ad} \; (sign\int_0^t \frac{d\varepsilon_0(t)}{dt}dt) \tag{3.43}$$

Where $\int_0^t \varepsilon_0(t)dt = \varepsilon_1(t)$ and $\frac{de(t)}{dt}dt = \varepsilon_2(t)$

Then the equation (3.43) can be represented in a general form as:

$$u(t) = K_p\, fal(\varepsilon_0, a_p, \delta_p) + K_i\, fal(\varepsilon_1, a_i, \delta_i) + K_d\, fal(\varepsilon_2, a_d, \delta_d) \tag{3.44}$$

Where

$$fal(\varepsilon_0, a_p, \delta_p) = \begin{Bmatrix} |\,\varepsilon_0\,|^{ap} \; sign(\varepsilon_0); |\,\varepsilon_0\,| > \delta_p \\ \dfrac{\varepsilon_0}{\delta_p^{\;1-ap}}; |\,\varepsilon_0\,| \le \delta_p \end{Bmatrix} \tag{3.45}$$

$$fal(\varepsilon_1, a_i, \delta_i) = \begin{Bmatrix} |\,\varepsilon_1\,|^{ai} \; sign(\varepsilon_1); |\,\varepsilon_1\,| > \delta_i \\ \dfrac{\varepsilon_1}{\delta_i^{1-ai}}; |\,\varepsilon_1\,| \le \delta_i \end{Bmatrix} \tag{3.46}$$

$$fal(\varepsilon_2, a_d, \delta_d) = \begin{Bmatrix} |\,\varepsilon_2\,|^{ad} \; sign(\varepsilon_2); |\,\varepsilon_2\,| > \delta_d \\ \dfrac{\varepsilon_2}{\delta_d^{\;1-ad}}; |\,\varepsilon_2\,| \le \delta_d \end{Bmatrix} \tag{3.47}$$

It can be seen from the Equations (3.43) or (3.44) to (3.47) the nonlinear PID controller shows the WWTP. The process of DO concentration is nonlinear more complex. So, to overcome such type complex nonlinear of the IWWTP in this thesis using neural network with PID controller is good.. There are some controller types adaptive nonlinear PID controller

a. Model Reference Adaptive Control (MRAC): This type of nonlinear PID uses a reference model to guide control actions. Handles uncertainties and changing conditions and ensures desired performance but it requires an accurate reference model. Can be computationally intensive.
b. Sliding Mode Control (SMC) : Drives the system to a desired state using a sliding surface. Robust to disturbances and nonlinearities, insensitive to parameter variations. Can lead to chattering (high-frequency oscillations) if not designed carefully.
c. Fuzzy Logic PID Control: Employs fuzzy logic reasoning for nonlinear mapping. Handles imprecise and uncertain information effectively. Adapts to changing conditions. |Requires expert knowledge to design fuzzy rules and membership functions.
d. Neural Network-based PID Control: Uses neural networks to learn system dynamics. Can model complex nonlinearities. Adapts to variations without model knowledge and requires significant training data. Computationally intensive for large networks.

Understanding the specific WWTP process and its key characteristics is crucial for selecting the most suitable controller. Consider desired accuracy, robustness and adaptability in relation to specific control objectives.Continuous Research: Research in adaptive nonlinear PID control for WWTPs is ongoing, aiming to develop more efficient, robust and adaptive controllers to address the unique challenges of wastewater treatment processes.

The nonlinear PID controller with adaptive nonlinear Neural Network-based PID was able to overcome this limitation by adapting its behavior to the nonlinear characteristics of the process.

3.5.2 Adaptive Neural Network PID controller mathematical model

The Adaptive Neural Network PID (ANNPID) controller is a robust control system tool that combines the strengths of traditional PID controllers with the adaptability of neural networks. It is particularly useful for handling complex nonlinear systems by leveraging adaptive neural networks to learn and implement specific input/output mappings from data. The ANNPID can employ various types of adaptive nonlinear neural networks, such as feedforward networks, recurrent neural networks, convolutional neural networks, radial basis function neural networks, deep neural networks. Generative adversarial networks and others to effectively trackle the control problem at hand. (R. Bouzaiene, 2021)

Radial Basis Function (RBF) networks are a type of neural network that have certain characteristics that make them preferable for certain applications, including industrial wastewater treatment plant (IWWTP) control. Here are a few reasons why RBF networks may be favored in this context:

a. Nonlinearity: RBF networks are capable of modeling complex nonlinear relationships between input and output variables. In the context of IWWTP control, there may be nonlinearities present in the system dynamics, and RBF networks can effectively capture and represent these nonlinearities.
b. Universal approximation: RBF networks have been shown to have universal approximation capabilities, meaning they can approximate any continuous function to an arbitrary degree of accuracy. This property is desirable in control applications where the underlying relationship between variables may be highly complex and difficult to model accurately.
c. Localized representation: RBF networks use localized basis functions that are centered at specific points in the input space. Each basis function represents the influence of a specific input pattern on the network's output. This localized representation can be advantageous in IWWTP control because it allows the network to focus its modeling efforts on specific regions of the input space that are most relevant to the control task, potentially leading to more efficient and accurate control.
d. Training efficiency: RBF networks typically have fewer parameters compared to other types of neural networks, such as multilayer perceptrons (MLPs). This can result in faster training times and reduced computational complexity, which can be advantageous in real-time control applications like IWWTP control.
e. Interpolation: RBF networks inherently perform interpolation between the training data points. This means that even if the network has not been explicitly trained on a specific operating condition, it can still provide reasonable output predictions for similar, unseen conditions. This interpolation property can be useful in IWWTP control, where the operating conditions may vary over time and it may not be feasible to train the network for every possible condition.

It's important to note that the choice of neural network architecture depends on the specific requirements and characteristics of the control problem at hand. While RBF networks have certain advantages, other types of neural networks, such as MLPs or recurrent neural networks (RNNs), may be more suitable for different control applications. The structure of an RBF neural network consists of three layers: the input layer, the hidden layer and the output layer.

The input layer receives the raw input data representing the features or variables of the problem. The neurons in this layer act as conduits, passing the input values to the hidden without any alteration or transformation.

The hidden layer comprises a set of RBF neurons, each characterized by a center and a width parameter. These neurons measures the distance between the inputs and respective centers, resulting in a response that diminishes as the distance increases.

The output layer receives the weighted outputs from the hidden layer. It combines these outputs linearly to produce the final prediction or decision, which represents the outcom of the RBF network's computation. The layers relation shown on figure (3.6) (Husin1, Rahmat2, & Sabri1, May 25, 2021.).

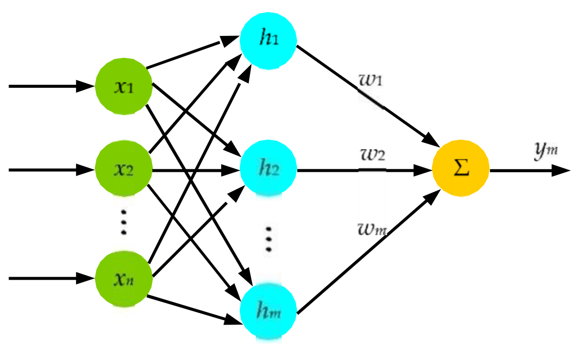

Figure 3.6 Topology of a radial basis function (RBF) neural network (Pan & Ying and Qi, 2023)

In Figure 3.6 the input vector of the input layer of the neural network is represented as:

$$X = [x_1, x_2, ..x_s, ..., x_n]^T \tag{3.48}$$

Where, $x_s = [u_s(k), y_s(k), y_s(k-1), s = 1, 2, ..., n; u(k)]$, s = 1, 2, . . . , n; $u(k)$ is the output of the controller, y(k) is the present or measured output of the system (process) and y(k-1) is the measured value of the last output from the process. The middle layer is the hidden layer. The activation function of the hidden layer is composed of radial basis functions. Each array of computing units of hidden layers is called node. The daial basis vector of the nodes in the RBFNN is shown in equations (3.49).

$$T = [h_1, h_2, ..., h_j, ..., h_m]^T \tag{3.49}$$

Where h_j is a Gaussian function

$$h_j = \exp((\frac{\| x - c_j \|}{2b_j^2})) \tag{3.50}$$

Where, j = 1, 2, 3…, m, c_j is neural network center when j[th] node of the hidden layer of the RBF

$$c_j = [c_{j1}, c_{j2}, ..., c_{ji}, ..., c_{jn}]^T \tag{3.51}$$

Where, I = 1, 2,3…, n. The basic width vector of the hidden layer node of the RBFNN is

$$B = [b_1, b_2, ..., b_j, ..., b_m]^T \tag{3.52}$$

Where, bj is the parameters is the first j node and j = 1, 2…, m. the weight vector of RBFNN weight W is given by:

$$W = [w_1, w_2, ..., w_j, ..., w_m]^T \tag{3.53}$$

Then, the estimated output of the RBF network is defined as:

$$y_m = w_1 b_1 + w_2 b_2 + ... + w_m \tag{3.54}$$

The performance index function of the RBF neural network is set as follows:

$$E_1 = \frac{1}{2}(y(k) - y_m(k))^2 \tag{3.55}$$

From the above equations, the three most critical parameters C, W and B of a RBF neural network obtained by learning algorithm.

$$w_j(k) = w_j(k-1) + \eta(y(k) - y_m(k))h_j + \alpha(w_j(k-1) - w_j(k-2)) \tag{3.56}$$

$$\Delta b_j = (y(k) - y_m(k)) w_j h_j \frac{\| x - c_j \|^2}{b_j^3} \tag{3.57}$$

$$b_j(k) = b_j(k-1) + \eta \Delta b_j + \alpha(b_j(k-1) - b_j(k-2)) \tag{3.58}$$

$$\Delta c_{ji}(k) = (y(k) - y_m(k)) w_j \frac{x - c_{ji}}{b_j^2} \tag{3.59}$$

$$c_{ji}(k) = c_{ji}(k-1) + \eta \Delta c_{ji} + \alpha(c_{ji}(k-1) - c_{ji}(k-2)) \tag{3.60}$$

The jacobian matrix:

$$\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{ji} - x_1}{b_j^2} \tag{3.61}$$

So, if this RBF neural network with PID algorithm applied it is more realized .

3.5.3 Adaptive Nonlinear PID Radial Basis Function Neural Network algorithm.

Wastewater treatment plant (WWTP) processes are complex and dynamic, characterized by nonlinearity, time varying behavior and disturbances. Traditional PID controllers with fixed parameters struggle to maintain optimal performance in each conditions. To overcome these challenges adaptive PID controllers are employed allowing for parameter adjustments over time. This adaptive capability enables them to handle the dynamic and uncertain nature of WWTP processes ensuring statisfactory tracking performance across different operating conditions.The RBFNNID algorithm is a neural network based adaptive PID control method commonly used in WWTPs to regulate the dissolved oxygen concentration and other wastewater parameters. This algorithm leverages RBFNN to calculate weighting cooefficients and parameter gradient information. These values are then used to update the PID controller's parameters in real time. By repeatedly executing this process, the algorithm achieves adaptive parameter adjustment and effective control of the dissolved oxygen concentration. (Du, X., Wang, J., Jegatheesan, V., & Shi, G., 2018)

Compared to traditional PID control algorithms, the RBFNNPID algorithm offers several advantages. Firstly, the RBFNN allows the algorithm to learn and adapt to the specific operating conditions of the DO control system enhancing robustness against disturbances and system changes. Secondly, the algorithm demonstrates improved accuracy in tracking the desired dissolved oxygen concentration. The effectiveness of the RBFNNPID algorithm has been demonstrated in controlling the dissolved oxygen concentration in WWTPs. It provides enhanced robustness, accuracy and efficiency, thereby improving the overall performance of wastewater treatment processes. (Renqiang Wang 1, 18 March 2020)

In general, the RBNNPID algorithm provides a promising solution for effective control of the DO concentration in WWTPs. Its adaptive nature and integration of NN with the PID controller make it well suited to handle the complexities of WWTP processes and achieve optimal control over the wastewater parameters.

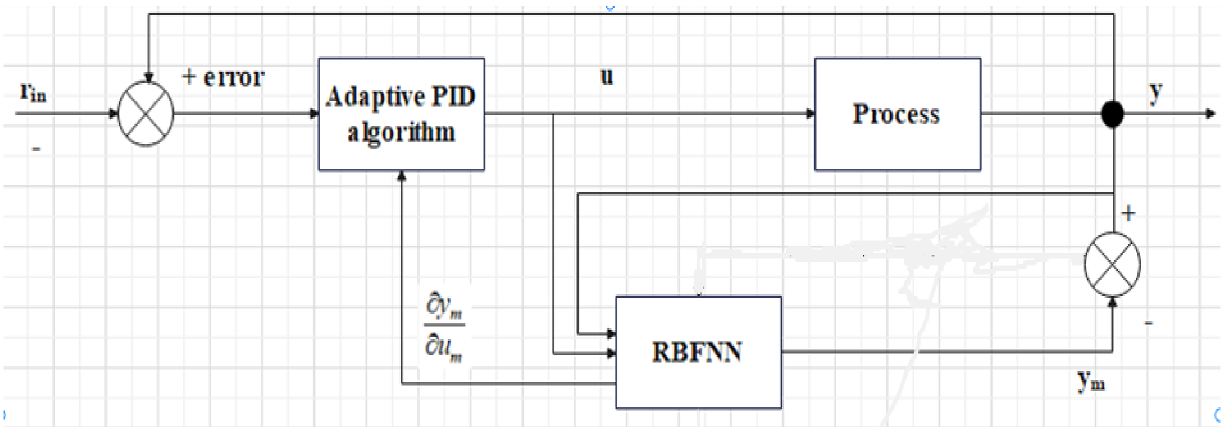

Figure 3.7 Block diagram of RBFNNPID Controller

a. Block diagram of propesd adaptive RBFNNPID algorithms. (Xianjun Du 1,2,3,4,, 2018) . The incremental PID controller and the control error as below:

$$error(k) = r_{in}(k) - y(k) \tag{3.62}$$

Where, r_{in} is the desired process value or setpoint of DO concentration: y(t) is the measured process value of DO. The input of the PID is three errors, which are defined as:

$$xc(1) = error(k) - error(k-1) \tag{3.63}$$

$$xc(2) = error(k) \tag{3.64}$$

$$xc(3) = error(k) - 2error(k-1) + error(k-2) \tag{3.65}$$

The output of the PID algorithm is:-

$$u(k) = u(k-1) + \Delta u(k) \tag{3.66}$$

$$\Delta u(k) = k_p xc(1) + k_i xc(2) + k_d xc(3) \tag{3.67}$$

where, K_p (proportion), K_i (integration) and K_d (differentiation) of are the three parameters of the PID controller. The performance is defined as:

$$E(k) = \frac{1}{2}(error(k))2 \tag{3.68}$$

According to the gradient descent method, the adjustment rules of three parameters are give as:

$$\Delta k_p = -\eta \frac{\partial E}{\partial k_p} = -\eta \frac{\partial E * \partial y * \partial u}{\partial y * \partial u * \partial k_p} = -\eta_{error} \frac{\partial y}{\partial u} xc(1) \tag{3.69}$$

$$\Delta k_i = -\eta \frac{\partial E}{\partial k_i} = -\eta \frac{\partial E * \partial y * \partial u}{\partial y * \partial u * \partial k_i} = -\eta_{error} \frac{\partial y}{\partial u} xc(2) \tag{3.70}$$

$$\Delta k_d = -\eta \frac{\partial E}{\partial k_d} = -\eta \frac{\partial E * \partial y * \partial u}{\partial y * \partial u * \partial k_d} = -\eta_{error} \frac{\partial y}{\partial u} xc(3) \quad (3.71)$$

The Jacobian matrix of a in which, $\partial y/\partial u$ controlled object is a matrix that describes how the output of the object changes in response to changes in the input online calculate at reat time. In RBFNNPID Control: The Jacobian matrix Online Adaptation can be calculated in real time to estimate how changes in input variables (e.g., dissolved oxygen concentration) will affect system outputs. PID Parameter Tuning: This information is used to adjust the PID controller's parameters (P, I, D) adaptively, ensuring optimal control responses under varying conditions.

Learning System Dynamics: The RBFNN can incorporate the Jacobian matrix into its learning process to better model the system's nonlinear behavior and improve control accuracy over time. Overall Significance:The Jacobian matrix is a fundamental tool for understanding and controlling complex systems, both in traditional control engineering and neural network-based approaches. Its ability to quantify local sensitivities and guide optimization processes makes it invaluable for designing effective and adaptive controllers, even for highly nonlinear and uncertain systems.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

In this thesis, MATLAB/Simulink was utilized for simulating the model and implementing the controller. Before industrial wastewater is released into the community or environment, it is crucial to consider various parameters to ensure its compliance with standards and minimize its impact on the ecosystem. Parameters commonly addressed include dissolved oxygen (DO), chemical oxygen demand (COD), biological oxygen demand (BOD), PH, total soluble solid (TSS), total dissolved solid (TDS), ammonia (NH3) and nitrates (NO3).

Among these parameters, the concentration of dissolved oxygen (DO) in the aeration tanks plays a significant role in determining the treatment efficiency, operational costs and overall stability of the WWTS. Adequate levels of DO are essential for the survival and activity of aerobic microorganisms responsible for biodegradation processes in the treatment tanks. Insufficient DO levels can lead to reduced treatment efficiency and increased energy consumption due to the need for additional aeration. On the other hand, excessive DO levels can cause inefficiencies and operational challenges such as foaming, which can disrupt the treatment process and increase maintenance requirements.

Moreover, the concentration of DO in the wastewater effluent has implications beyond the treatment process itself. When the effluent is discharged into aquatic environments, low DO levels can negatively impact aquatic life, leading to oxygen depletion and potentially causing harm to the ecosystem. Aquatic organisms, such as fish and aquatic organisms, require adequate DO levels for their survival and well being. Therefore, maintaining appropriate DO concentrations in the treated wastewater is crucial to minimize the ecological impact of the discharge.Considering these factors, monitoring and controlling the DO concentration in industrial wastewater treatment processes are vital for ensuring effective treatment, minimizing operational costs, maintaining system stability and preserving the health of the surrounding ecosystem.

4.2 Result of mathematical model of plant and controller

Bench mark simulation no 1 has 5 biological reactors, 8 biological process and 13 ASM1 input variables. From 8 basic biological process using constant schoichiometric parameters, kinetic parameters and ASM1 input variables standard range value the P values as below.

Table 4.1 Biological process Result

Process	P value when ASM1 13 variables Minimum value	P value when ASM1 variables Maximum value
P_1	1,652.9	10,557.2
P_2	125.9	84.3
P_3	83.33	990.4
P_4	150	900
P_5	5	50
P_6	250	7,500
P_7	1,453	39.3
P_8	1,453	39.3

The 8 basic biological process for activated sludge process, which is five reactor process for wastewater treatment plant. The 13 variables result as below table 4.5

Table 4.2 Biologial reactor result

Biological Reactor		Value of r when value of p Minimum value	Value of r when value of p Maximum value
Reactor	Conversion rate		
S_I	r_1	0	0
S_S	r_2	1201.9	-1584.4
X_I	r_3	0	0
X_S	r_4	-1310.4	834.7
X_{BH}	r_5	1628.8	9741.5
X_{BA}	r_6	78.33	940.4

X_{XP}	r_7	12.4	76
S_O	r_8	-855.96	436
S_{NO}	r_9	368.89	4141.18
S_{NH}	r_{10}	-246.18	-2557.21
S_{ND}	r_{11}	1203	-2460.7
X_{ND}	r_{12}	-1441.44	31.44
S_{ALK}	r_{13}	-38.9	-475.12

Depending on the reactor and biological ASM1 the conversion rates, variables likes soluble inert organic matter, readily biodegradable substrate particulate inert organic matter, slowly biodegradable substrate, dissolved oxygen, active heterotrophic and autotrophic biomass and others calculation results using the biological process .

Using the biological process and ASM1 various calculation results can be obtained, including the rates of substrate utilization, biomass growth, decay and transformation. These results provide insights into the performance and efficiency of the biological treatment process in the reactor system.

4. 3 Block diagrams using adaptive nonlinear PID controller

Nonlinear PID controllers can provide a number of benefits over linear PID controllers for the ASM1 model in a WWTP. These benefits include improved control performance, better compensation of nonlinearities, increased robustness, and greater flexibility in controller design and tuning. Here is a more detailed explanation of each of these benefits:

- ✓ Improved control performance: Nonlinear PID controllers can provide better control performance compared to linear PID controllers, especially in systems with highly nonlinear dynamics, such as the ASM1 model. This is because nonlinear PID controllers can take into account the nonlinearities in the system when calculating the control signal. As a result, nonlinear PID controllers can achieve better tracking of the setpoint & faster response to disturbance.

- ✓ Nonlinear compensation: NLPID controllers can compensate for the nonlinearities in the system, such as saturation, dead zones, and hysteresis, which can affect the performance of linear controllers.
- ✓ Robustness: Nonlinear PID controllers are more robust to changes in the process dynamics, such as changes in the operating conditions or the presence of disturbances, compared to linear controllers. Nonlinear PID controllers can typically handle these variations better than linear PID controllers, which can help to prevent the system from going out of control.
- ✓ Flexibility: Nonlinear PID controllers offer more flexibility in the design and tuning of the controller parameters, allowing for better adaptation to the specific requirements of the process. This can lead to a more optimized control strategy and improved overall performance of the WWTP.

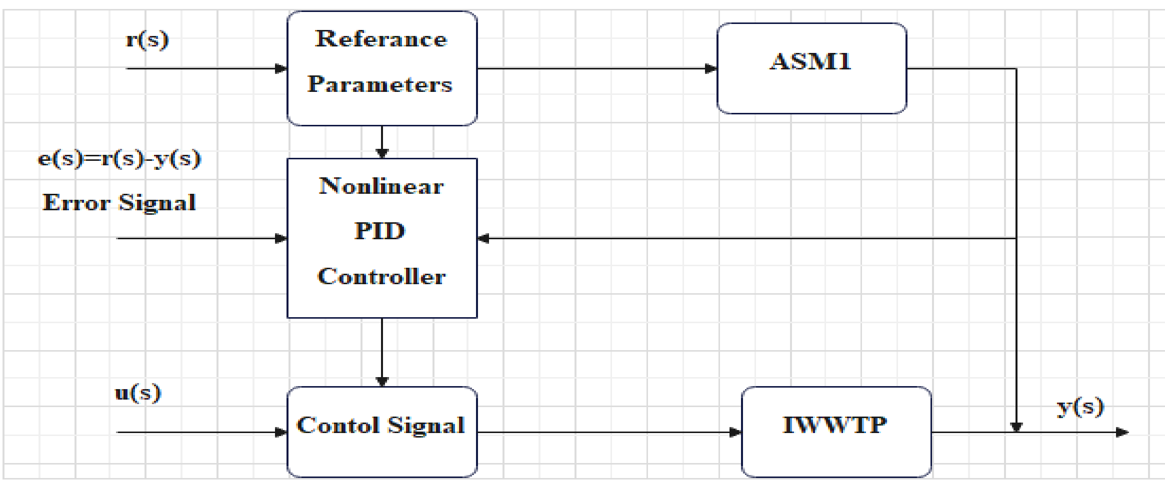

Figure 4.1 Block Diagram of ASM1 Using Nonlinear PID Controller

Overall, nonlinear PID controllers can provide a number of benefits over linear PID controllers for the ASM1 model in a WWTP. These benefits include improved control performance, better compensation of nonlinearities, increased robustness, and greater

4.3.1 MATLAB code simulation results using adaptive nonlinear PID controller algorisim.

The provided code defines the plant and a nonlinear PID controller for regulating its set value. The plant is simulated using the ode45 solver, which takes the system of differential equations (dx/dt) and the control input (u) as inputs. The nonlinear PID controller is implemented as a function that takes the current time(t), the current system value (sv) and the setpoint value (r). The controller calculates the control output based on the relationship between the setpoint proportional, integral and derivative terms .

In this thesis 8 ASM1 main parameters for industrial wastewater treatment plant are selected. These parameters are includes DO, TDS, TSS, COD, NH3, BOD, NO3 and PH. Figure 4.2 shows each parameters of setting point with blue color and the actual value with red color.

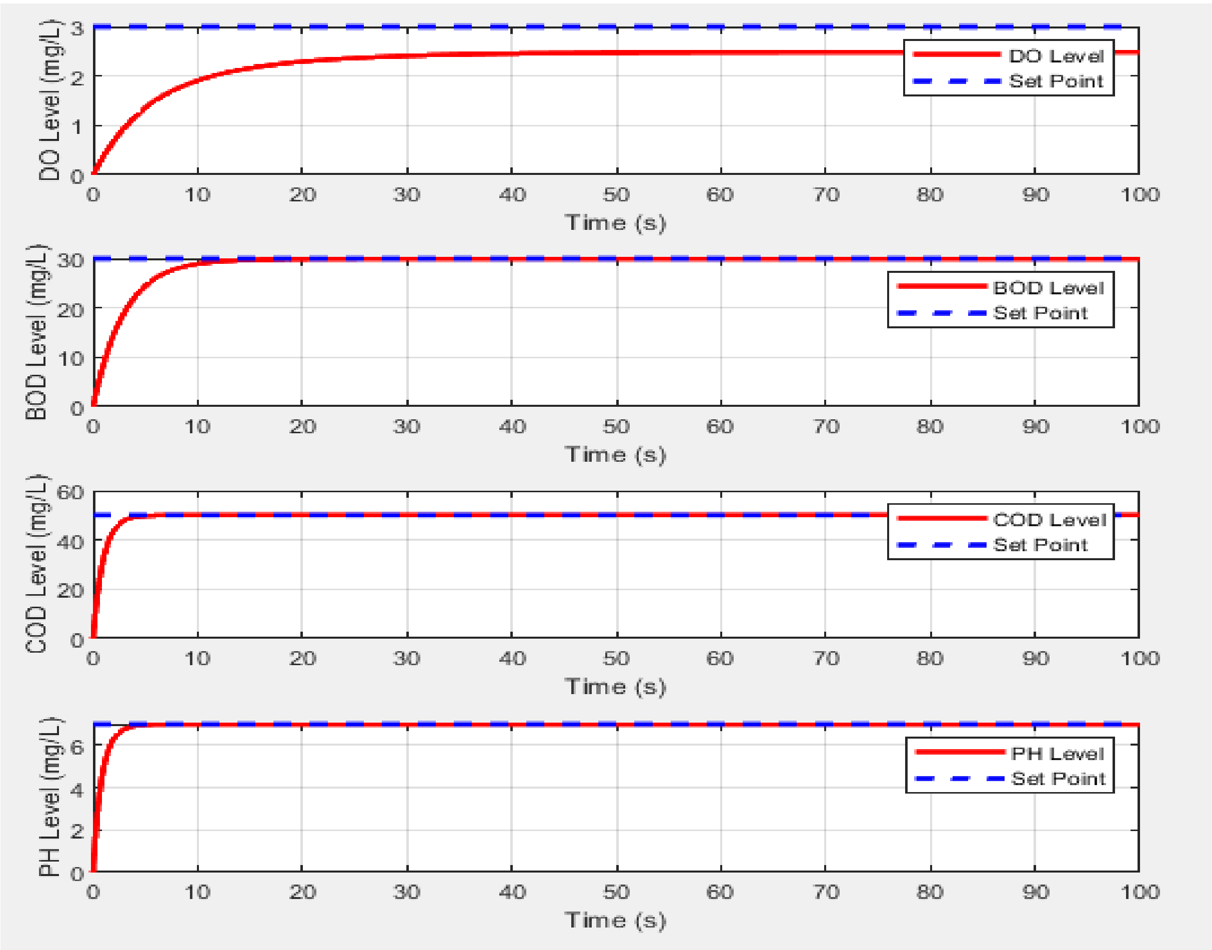

Figure 4.2 Simulink results of DO, BOD, COD and PH

As industrial wastewater treatment plant is the basic to control enffuellent water release to community or society after checking DO, BOD, COD, PH for aquatic living . DO international standard for IWWTP before discharge from 1-3mg/l. BOD less than(<30mg/l), COD less than (<50mg/l). All are in range and best tuned, specially DO is at average.

Simulation results of these parameters using a nonlinear PID controller involve running a model or simulation that represents the dynamics of the system being controlled. The PID controller is implemented in the simulation, and its parameters (proportional, integral, and derivative gains) are tuned to achieve the desired control performance. The simulation results will show how the nonlinear PID controller responds to changes in the system and how it maintains the desired set points for DO, BOD, COD, and ph. The results can include plots or data showing the control signals generated by the PID controller, the actual values of the parameters over time, and any deviations from the set points. The others parameters shown on figure 4.3

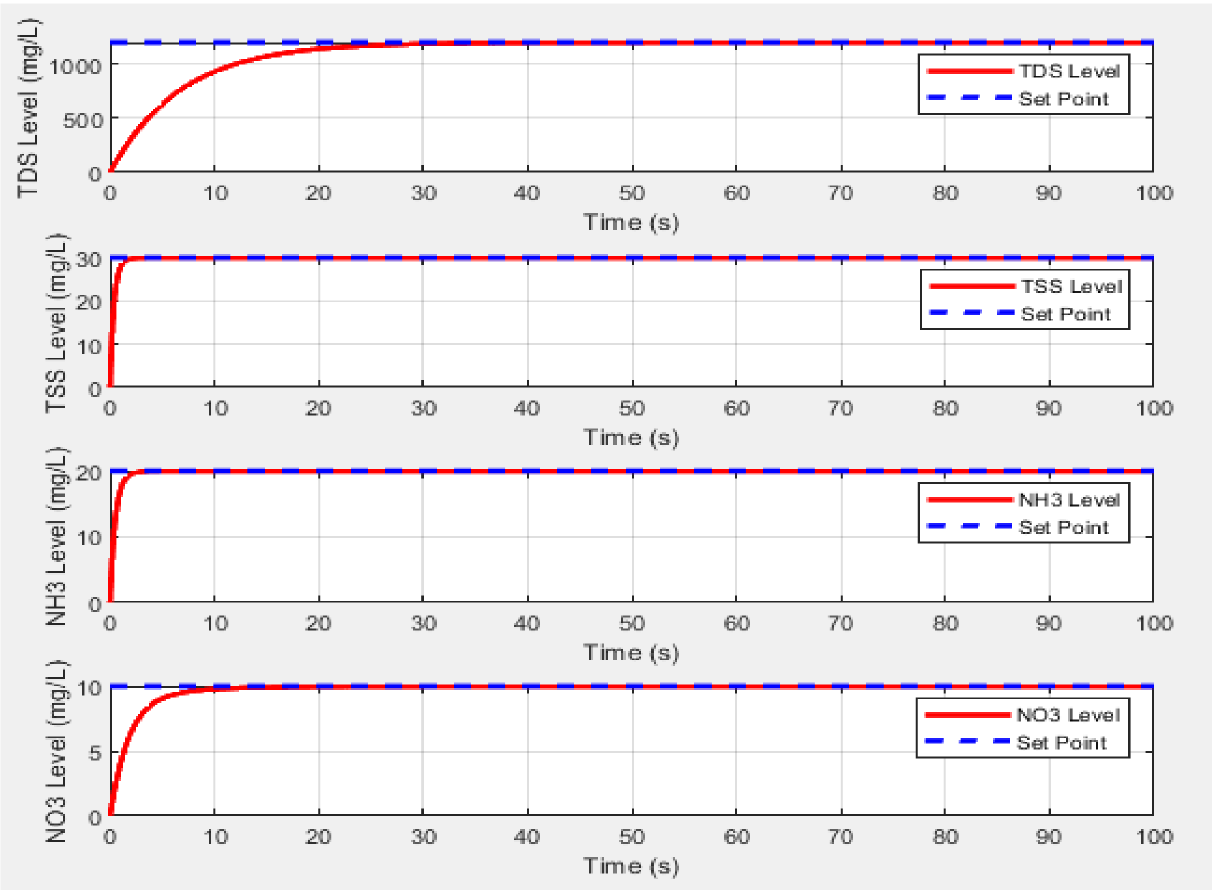

Figure 4.3 simulink results of TDS, TSS, NH3 & NO3

Adaptive nonlinear PID controller good for tuning such type complex nonlinear because IWWTP by itself a complex nonlinear, the setting point value and the actual alomost similary. The set pint value shown by blue color and the red color is actual value. uncontrolling DO can affect the others parameters. The simulation results of Total Dissolved Solids (TDS), Total Suspended Solids (TSS), Ammonia (NH_3), and Nitrate (NO_3) using a nonlinear PID controller, the desired set points for TDS, TSS, NH_3, and NO_3 are 30 mg/L, 1200 mg/L, 20 mg/L, and 10 mg/L, respectively, with the simulation.

a. Total Dissolved Solids (TDS): TDS refers to the total concentration of dissolved solids in water. Nonlinear PID control can be used to regulate TDS levels by adjusting control variables such as water treatment processes or reverse osmosis systems. The PID controller will receive feedback on TDS levels and adjust the control signal to maintain the desired TDS set point of 30 mg/L.
b. Total Suspended Solids (TSS): TSS represents the concentration of suspended particles in water. Nonlinear PID control can be used to regulate TSS levels by adjusting control variables such as sedimentation or filtration processes. The PID controller will receive feedback on TSS levels and adjust the control signal to achieve the desired TSS set point of 1200 mg/L.
c. Ammonia (NH3): NH3 is a form of nitrogen present in water, often originating from wastewater or agricultural runoff. Nonlinear PID control can be used to regulate NH3 levels by adjusting control variables such as aeration or biological treatment processes. The PID controller will receive feedback on NH3 levels and adjust the control signal to maintain the desired NH3 set point of 20 mg/L.
d. Nitrate (NO3): NO3 is another form of nitrogen in water, typically originating from agricultural activities or fertilizer use. Nonlinear PID control can be used to regulate NO3 levels by adjusting control variables such as denitrification or nutrient removal processes. The PID controller will receive feedback on NO3 levels and adjust the control signal to achieve the desired NO3 set point of 10 mg/L.

In a simulation, the results for TDS, TSS, NH3, and NO3 over time can be plotted on a graph, typically with time on the x-axis and the parameter values on the y-axis. Each parameter would have its own separate graph. For example, the graph for TDS might show the actual TDS values over time, as well as the desired set point of 30 mg/L. The nonlinear PID controller will work to keep the actual TDS values as close to the set point as possible.

Similarly, the graphs for TSS, NH3, and NO3 would show the actual values of each parameter over time, along with their respective set points of 1200 mg/L, 20 mg/L, and 10 mg/L. The PID controller will adjust the control signal to maintain these set points..

4.4 Block diagram of Radial Basis Function Neural Network PID controller

The RBFNNPID controller is a type of adaptive nonlinear PID controller that combines the advantages of PID controllers and neural network. In Figure 3.2, the PID controller functions as the primary controller, while the neural network algorithm serves as a parameter estimator. Both components are adaptive nonlinear controllers. The PID controller receives signals from sensors and feeds them into the neural network for estimation purposes. The neural network enhances the robustness and performance of the controller. The radial basis function neural network (RBFNN) is particularly suitable for nonlinear control applications. It learns a mapping from the input signal to the output signal enabling composition for the nonlinearities inherent in the process. To regulate the process, the RBFNN's output is passed through a linear output layer, which converts it into a control signal. This control signal is carefully adjusted to ensure it remains within the safe operating limits of the process. The RBFNNPID controller has proven to be effective in controlling various processes, including the ASM1 process.

In summary, the RBFNNPID controller is an adaptive nonlinear PID controller that combines the strengths of PID controllers and neural networks. The neural network functions as a parameter estimator to improve the robustness and performance of the controller, while the PID controller serves as the primary controller. The RBFNNPID controller has demosstrated effectiveness in controlling nonlinear processes such as the ASM1 process.

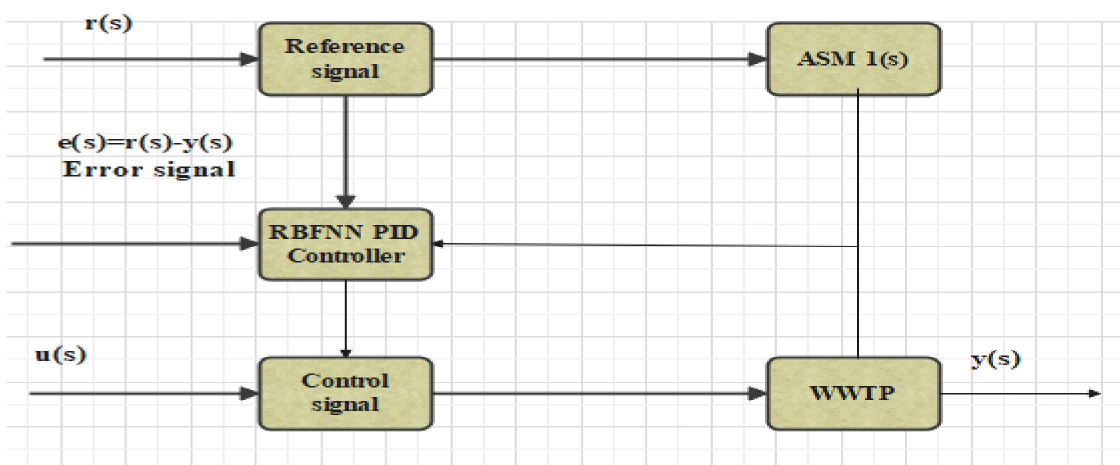

Figure 4.4 Block diagram of ASM1 of WWTP Using RBFNNPID Controller

The combination of a nonlinear PID controller and RBFNN compensator proves to be a highly effective control strategy for the ASM1 process in wastewater treatment. The ASM 1 process plays a crucial role in ensuring proper treatrment of WW, making effective control essential. Here are additional details about the RBFNN compensator:

- The RBFNN is a neural network epecifically designed for modeling nonlinear systems. It employs radial basis functions (RBFs) to approximate the nonlinear relationship between input and output sgnals accurately.
- In this application, the RBFNN compensator takes the error signal and its derivatives behavior of the ASM 1 process more precisely than a traditional PID controller alone.
- The linear output layer of the controller combines the outputs of both the RBFNN compensator and the PID controller, resulting in the generation of the final control signal. This integration ensures that the controller remains robust in the face of chaning process dynamics .

Overall, the RBFNN compensator serves as a valuable tool for enhancing the performance of controllers in nonlinear systems. In the case of the ASM 1 process, combining the RBFNN compensator with a PID controller creates a powerful hybrid controller capable of effectively controlling the process.

4.4.1 Matlab simulink of radial basis function neural network PID controller

The MATLAB Simulink model developed for WWTPs follows international standard values for input variables (influent) and output variables (effluent) before releasing them into the community or society. The model incorporates key parameters such as DO, PH, COD, BOD, TDS, TSS, NH3 and NO3. The Simulink model utilizes an ANLPID as the primary controller and RBFNN controller as the parameter estimator. This combination allows for effective control and estimation of the wastewater treatment process.

Figure 4.5 displays the complete general Simulink model implemented in MATLAB. The model includes the adaptive nonlinear PID controller and the RBFNN controller. Simulation reults from the model are represented in the subsequent section, covering aspects such as the comparison of simulation results using the RBFNNPID controller, tracking performance tests, anti- disturbance performance and robustness. The matlab simulation code generated the below the Simulink figure 4.5 had attatched on appendix.

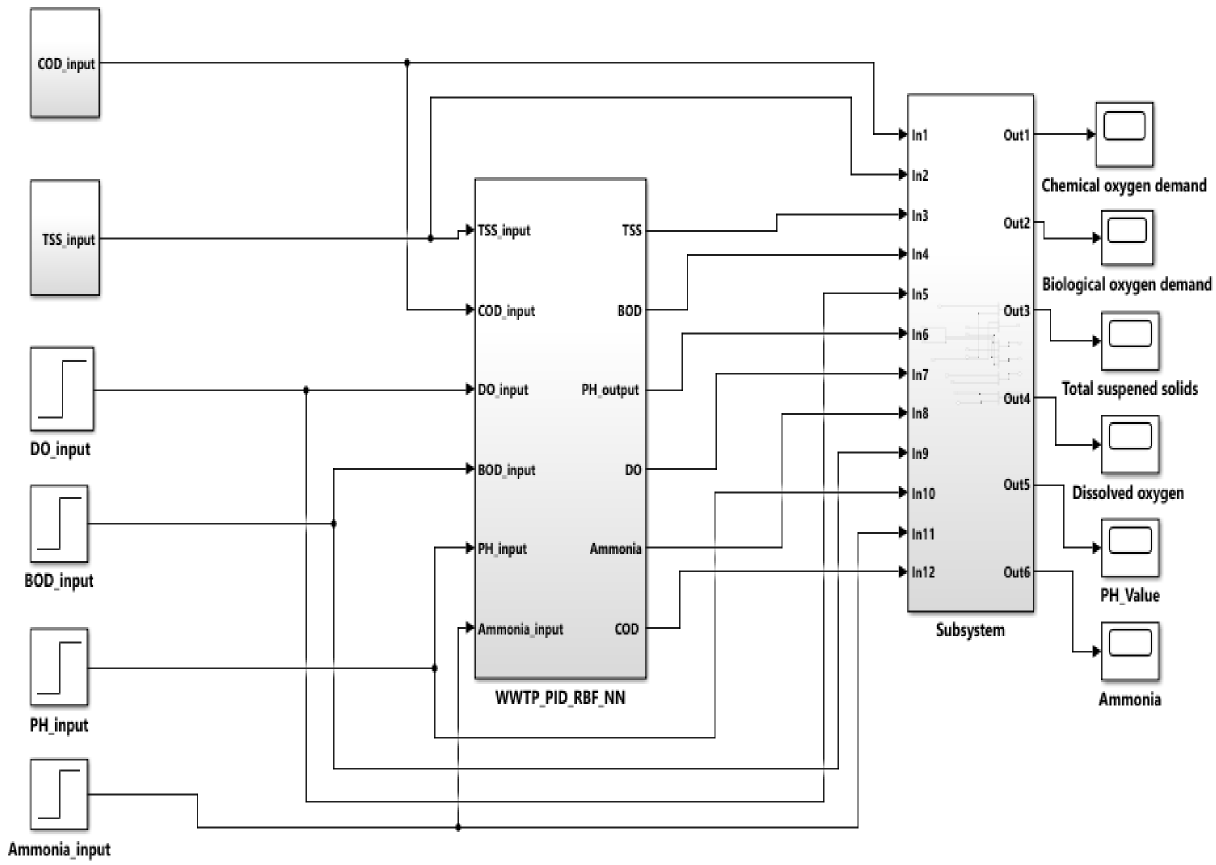

Figure 4.5 General structural Simulink model for Wastewater treatment plant

The Simulink model serves as a comprehensive tool for analyzing and ev
aluating the performance of the RBFNNPID controller in WWTP, providing valuable insights into its effectivess and robustness. This general block diagram shows that the inut part , .the processing and the result or output part of the system as general.WWTP PID with PID RBFNN contains internally wastewater parameters, Grit chamber, Coagulation Basis and Sedimentation Basis. Let us see one by one double clicking on parameters on WWTP PIDRBFNN, then there are some groups of it.

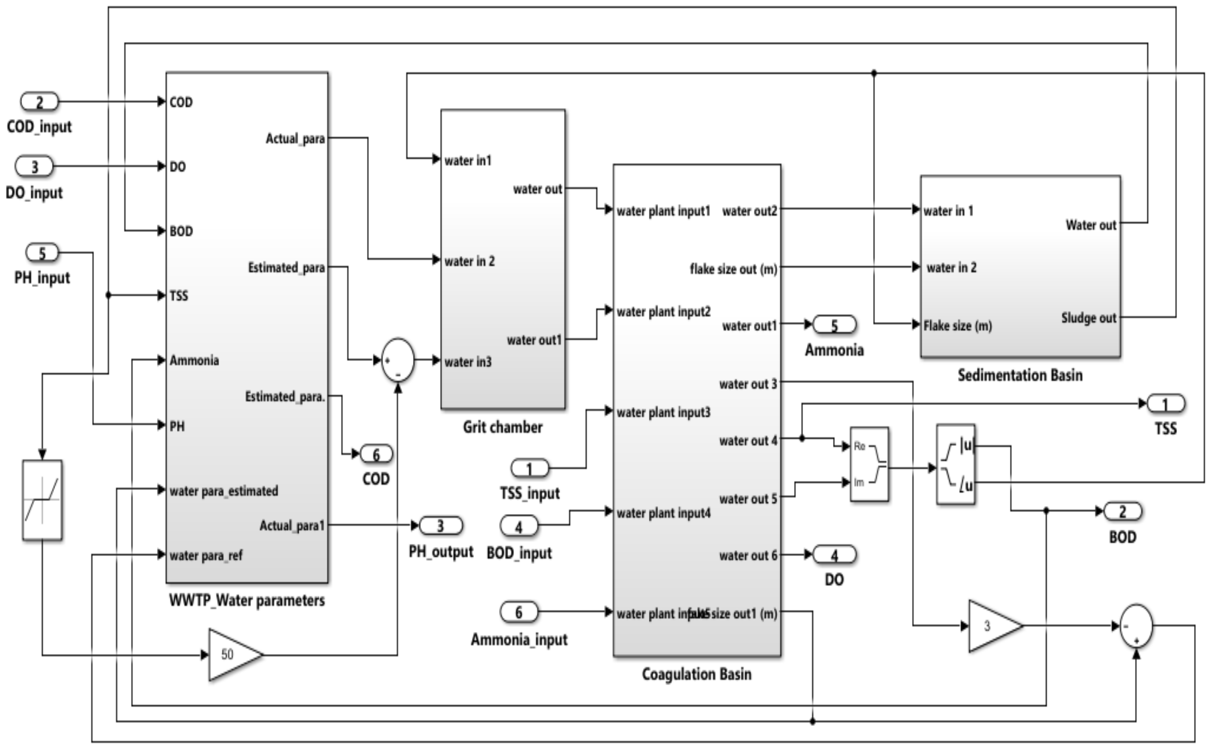

Figure 4.6 Simulink model of Wastewater treatment plant parameters

The Simulink of WWTP as example it contain 6 input parameters like DO, COD, BOD, TSS,NH3, PH . so, this simulation contain basic wastewater treatment stages pirmarly treatmetment, primary, secondary and tertiary treatment components inside like grit chamber, sedimentation, colguration,wastewater paarameters

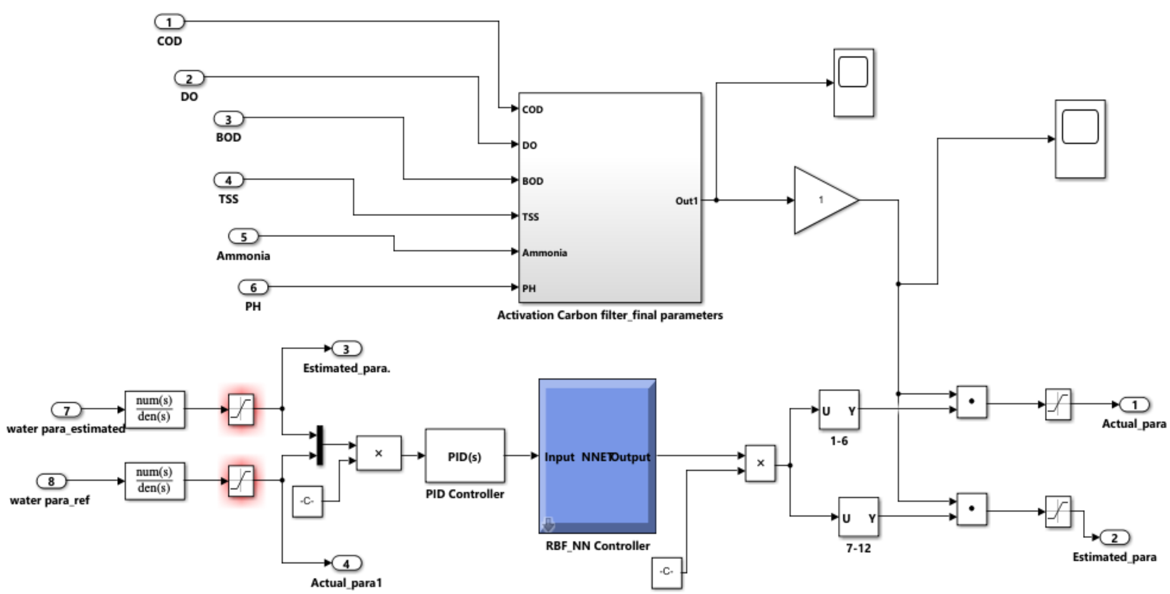

Figure 4.7 Simulink Model of RBFNNPID Controller for WWTP

The PID controller is a widely used control algorithm that calculate a control signal based on the error between a desired set point. In this case the PID controller is taking the reference water parameter (the desired value) and the estimated water parameter (obtained from a sensor or estimator) as inputs. The PID controller process this input and generated an output, which is then fed into a Radial Basis Function Neural Network (RBFNN). The outputs of the RBFNN the actual water parameter (measured parameter) and the estimated water parameter. Step by step an overview of PID with RBFNN controller

- ✓ **Reference and Estimated Water Parameter** the reference water parameter represent the desired value that the system aims to achieve. The estimated water parameter is obtained from a sensor or an estimator, which is provide an estimation of the current value of the water parameter.
- ✓ **PID Controller** the PID controller takes the reference and the estimated water parameter as inputs. It has compared the estimated value with the reference value and then calculated an error signal, which represented the deviation between the desired value and the estimated value. The PID controller used this error signal to compute a control output that aims to minimize the error and control the system towards the desired state.
- ✓ **RBFNN** The control output from the PID controller is then fed into the RBFNN. The RBFANN is a type of artificial neural network that used radial basis functions as activation functions. It process the control output and generated two outputs such as the actual water parameter and the estimated water parameter. The actual water parameter represented the measured value.

Simulink model of RBFNNPID controller input (reference) values chemical oxygen demand(DO), dissolved oxygen(DO), biological oxygen demand (BOD), total soluble solid (TSS), ammoinia and PH references to show as input for activation carbon filter final parameters. The out result generate actual parameter value and estimated parameters. The neural network part have input parameters as actual and estimated, then there was nonlinear PID tuner to give information for RBFNNcontroller .

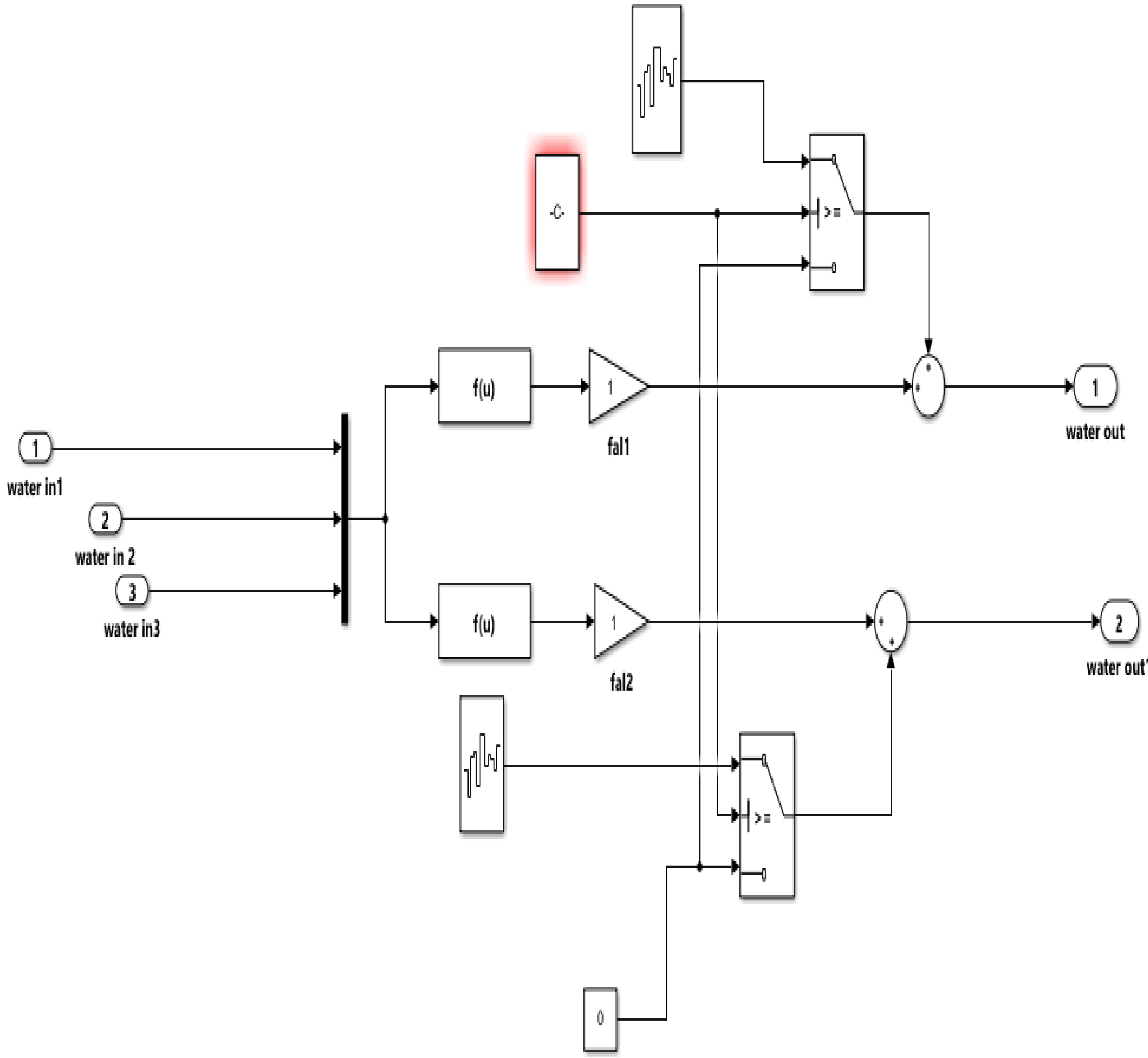

Figure 4.8 Grit chamber Simulink Model for WWTP

Grit chamber is the component of awastewater treatment plant designed to remove heavy solids, such as sandm gravel and grit from wastewater before it undergoes further treatment processes. It provides a controlled environment where the flow velocity of the wastewater is reduced, allowing the heavy solids to settle to the bottom. Grit chambers protect downstream equipment, such as pumps and pipes, from abrasion and damage caused by these abrasive materials.

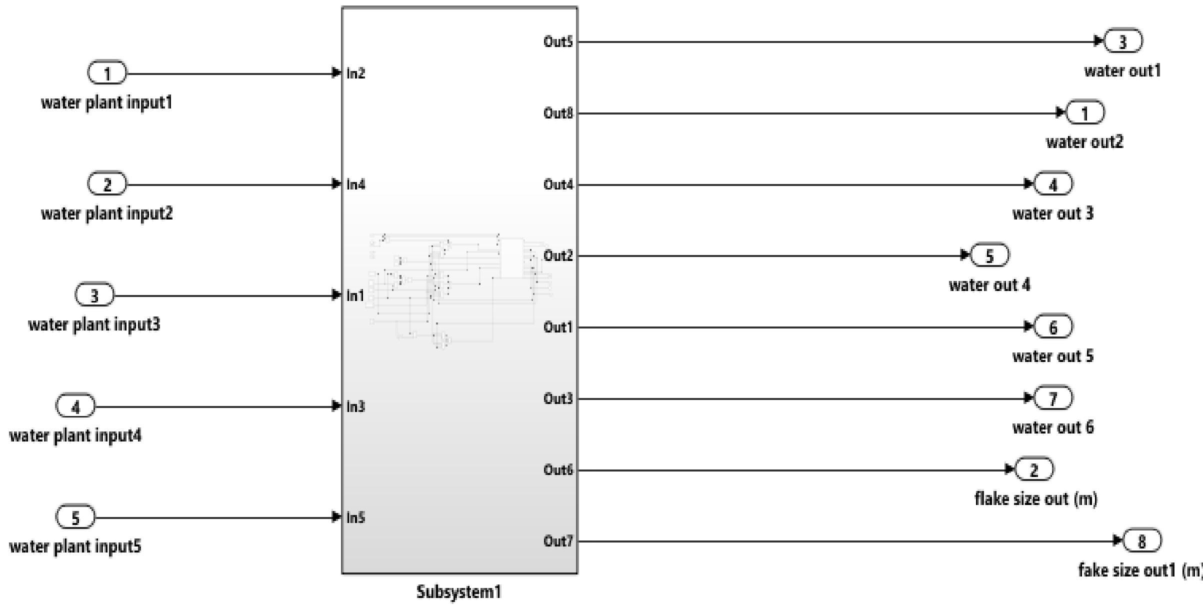

Figure 4.9 Coagulation wastewater Simulink model

Coagulation is a process used in water or wastewater treatment to destabilize and aggregate small suspended particles into large particles called flocs. It involvs the addition of a chemical coagulant, such as aluminum sulphate (alum) or ferric chloride, to the water or wastewater. The coagulant forms positively charged ions that neutralize the negative charges on the particles, promoting their collision and aggregation. As the particles come together they form larger flocs that can be more easily removed through sedimentation or filteration processes.

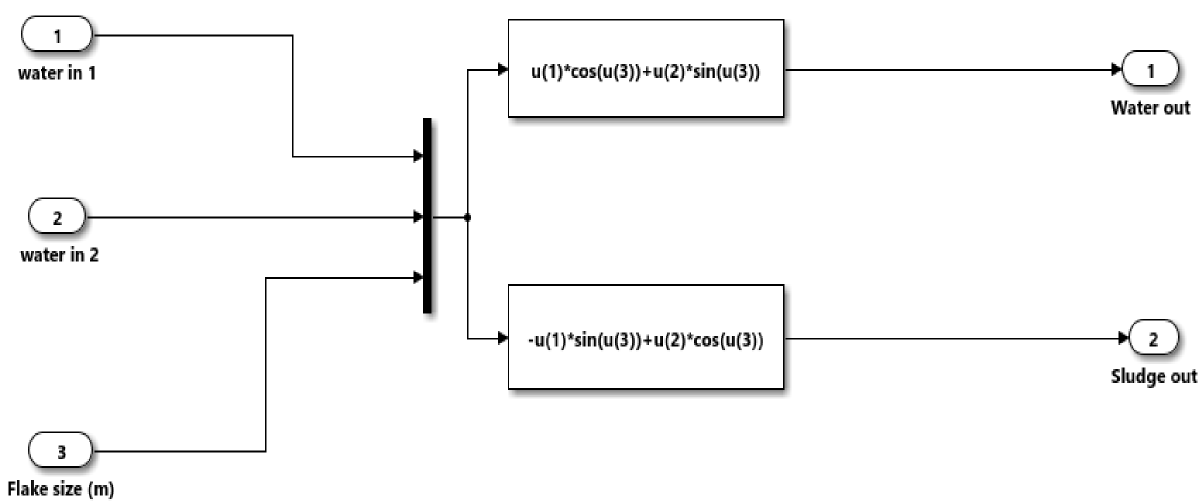

Figure 4.10 Sedimantation Simulink Model for WWTP

Sedimentation is the physical water treatment process that involves the settling of suspended particles or flocs under the influence of gravity. After coagulation or other treatment processes, the water or wastewater is allowed to flow into a sedimentation basin or clarifier. In basin, the flow velocity is reduced, allowing the particles or flocs to settle to the bottom due to their increased weight. The settled particles from a layer of sludge, while the clarified water is colleted from the top or overflow of the basin. Sedimentation is an essential step in water and wastewater treatment for the removal of suspended solids, reducing turbidity and improving water quality.

In the simulation there are two subsystems (subsystem and WWTP subsystem1) both them have internal diagrams. But the simulation only select three parameters DO, BOD and COD of wastewater major parameters. This simulation tracking performance tests, the RBFNNPID controller consistently demonstrated superior accuracy in tracking both constant and sinusoidal set points compared to other controllers, specifically the traditional PID controller. The error exhibited by the RBFNNPID controller was significantly smaller than the error observed with the traditional PID controller.

In anti-disturbance tests, the RBFNNPID controller showcased enhanced disturbance rejection capabilities compared to other controllers, particularly the traditional PID controller. When subjected to a continuously variable influent, the RBFNNPID controller effectively maintained the set point within a narrow range, whereas other controllers, such as the traditional PID controller, struggled to achieve the same level of control.

Furthermore, in robustness tests, the RBFNNPID controller demonstrated greater resilience to changes in the influent compared to other controllers, including the traditional PID controller. Even when the maximum growth rate of the influent was varied, the RBFNNPID controller successfully kept the set point within a narrow range, while other controllers, such as the traditional PID controller, could not achieve the same level of control.

The results clearly indicate that the RBFNNPID controller outperforms other controllers in terms of tracking performance, anti-disturbance capabilities and robustness. It excels in accurately tracking set points, effectively rejecting disturbances, and maintaining control in the face of changing influent condition

4.4.2 Matlab Simulation Results Using RBFNNPID algorithm.

This matlab simulation result has done using RBFNNPID controller basic 6 industrial wastewater treatment parameters which are directly the community and aqualife. These parameters are COD, DO, BOD, TSS, PH, and ammonia . let see the generated simulation results for each parameters using RBFNNPID algorithm (controller).

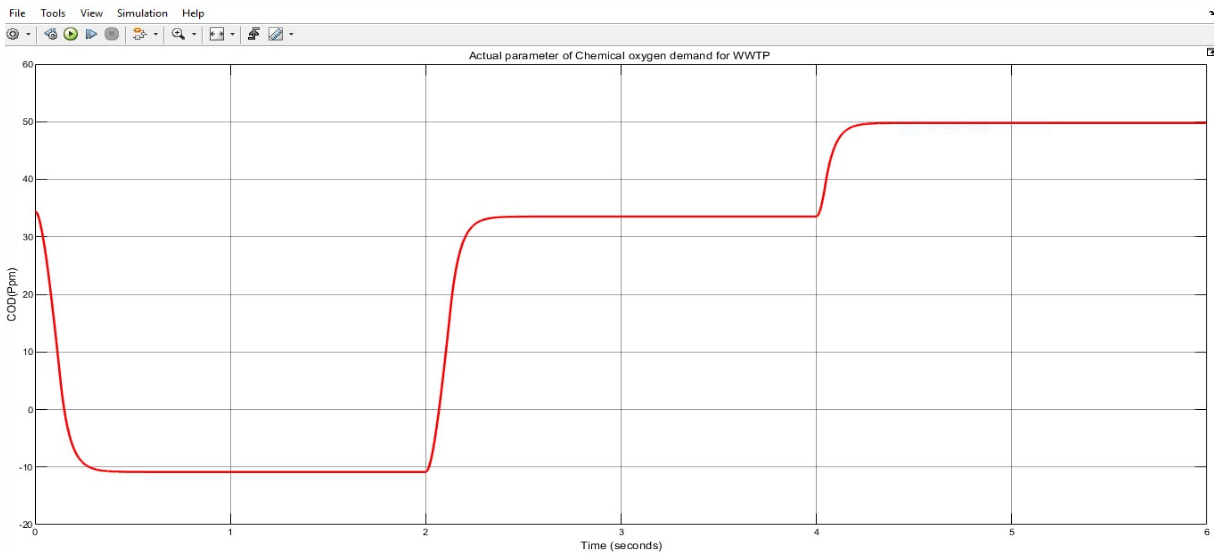

Figure 4.11 Simulation Results of COD

When the actual value of the Chemical Oxygen Demand (COD) parameter is stable at a value of 50, it suggests that the wastewater treatment process is effectively reducing the organic pollutants present in the wastewater to a level that meets the standard requirements. Chemical Oxygen Demand is a measure of the amount of organic matter present in the wastewater. It quantifies the oxygen required to chemically oxidize the organic compounds in the wastewater. Lower COD values indicate a higher level of organic pollutant removal.

By maintaining a stable COD value of 50, it implies that the wastewater treatment process is successfully removing a significant portion of the organic pollutants, resulting in a treated effluent that meets the standard requirements

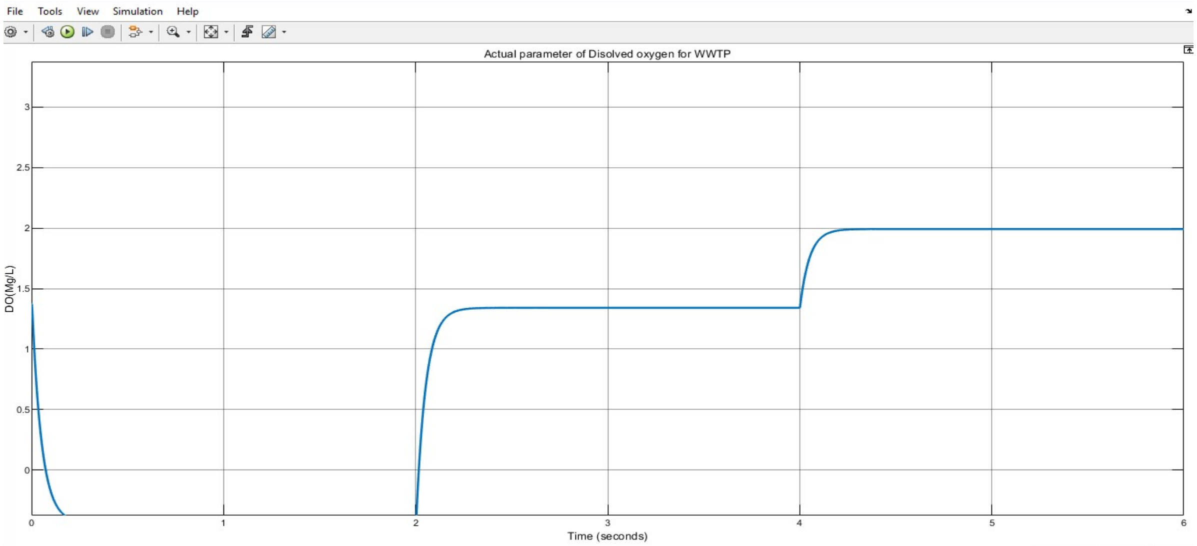

Figure 4.12 Simulation Results of DO

When the actual value of dissolved oxygen (DO) shown on the graph falls within the range of 1-3 mg/L, it indicates that the wastewater treatment process is meeting the standard requirement for DO concentration during release. Maintaining an appropriate level of dissolved oxygen is crucial in wastewater treatment as it directly affects the survival of aquatic organisms and indicates the overall health of the water body into which the treated wastewater is discharged.

By utilizing the RBFNNPID controller, the simulation results demonstrate that the controller is able to regulate the system and keep the DO concentration within the desired range. This suggests that the controller is effectively adjusting the relevant parameters, such as aeration or oxygen supply, to maintain the appropriate DO level

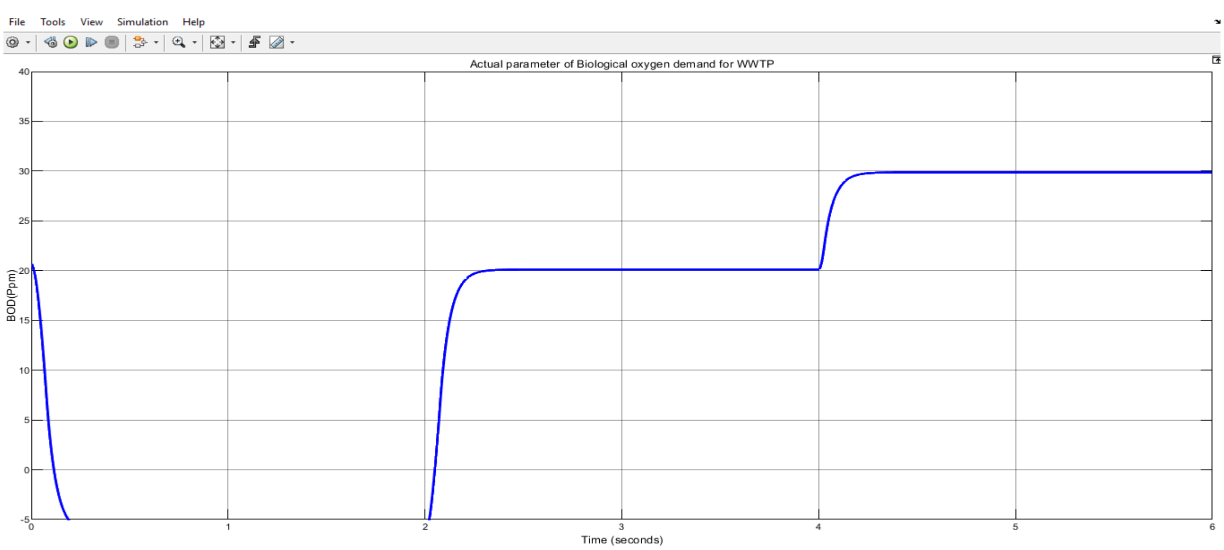

Figure 4.13 Simulation Results of BOD

The graph for Biological Oxygen Demand (BOD) initially shows fluctuations but stabilizes after 4 seconds and remains constant below the set standard of 30 mg/L, it indicates that the wastewater treatment process is effectively reducing the biodegradable organic pollutants present in the wastewater. BOD is a measure of the amount of oxygen required by microorganisms to decompose the organic matter in the wastewater. High BOD levels indicate a high concentration of biodegradable organic pollutants, which can deplete the dissolved oxygen in the receiving water body and harm aquatic life. The graph's initial fluctuations may be attributed to the dynamic nature of the treatment process as it adjusts and adapts to changes in influent conditions or system disturbances. However, once the process stabilizes, it indicates that the treatment system is consistently achieving the desired level of organic pollutant removal, keeping the BOD concentration below the set standard of 30 mg/L.

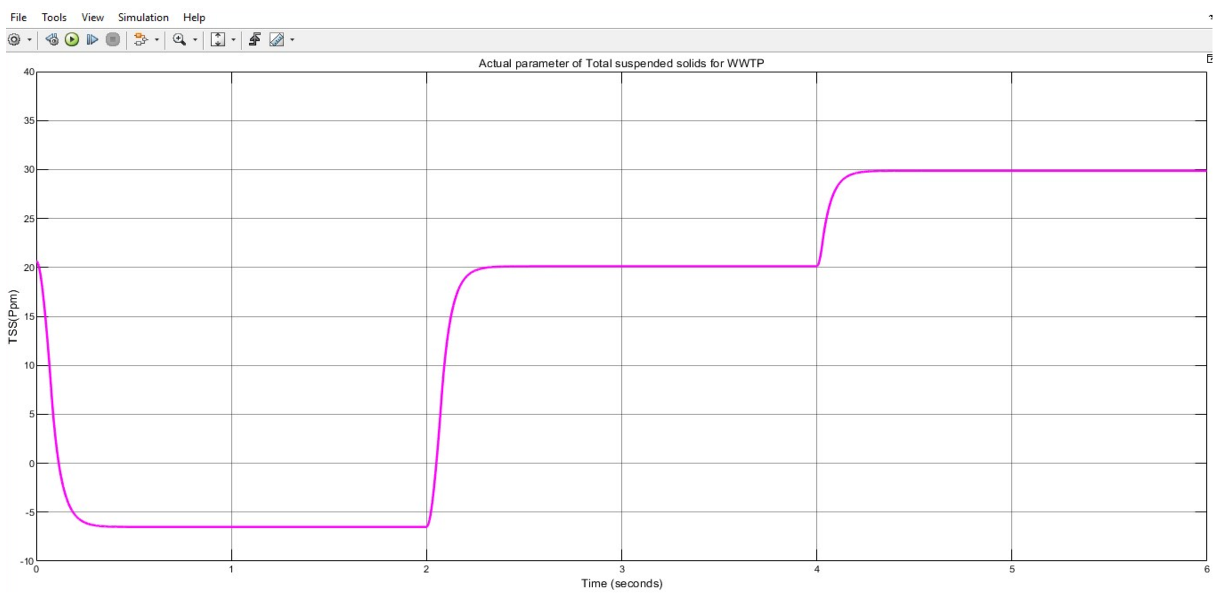

Figure 4.14 Simulation Results of TSS

The above graph shows that the actual value of Total Suspended Solids (TSS) in the industrial wastewater is within the range of the maximum standard of 30 mg/L, it indicates that the wastewater treatment process is effectively removing solid particles and meeting the regulatory requirements for TSS concentration. Total Suspended Solids refers to the concentration of solid particles (both organic and inorganic) that are suspended in the wastewater. High TSS levels can negatively impact water quality, hinder light penetration, and disrupt aquatic ecosystems. By keeping the TSS concentration within the acceptable range, the wastewater treatment process ensures that the treated effluent is free from excessive suspended solids before it is released into the environment or used for community purposes. This helps safeguard water quality and protect The receiving water bodies. the above graph shows the actual value in range.

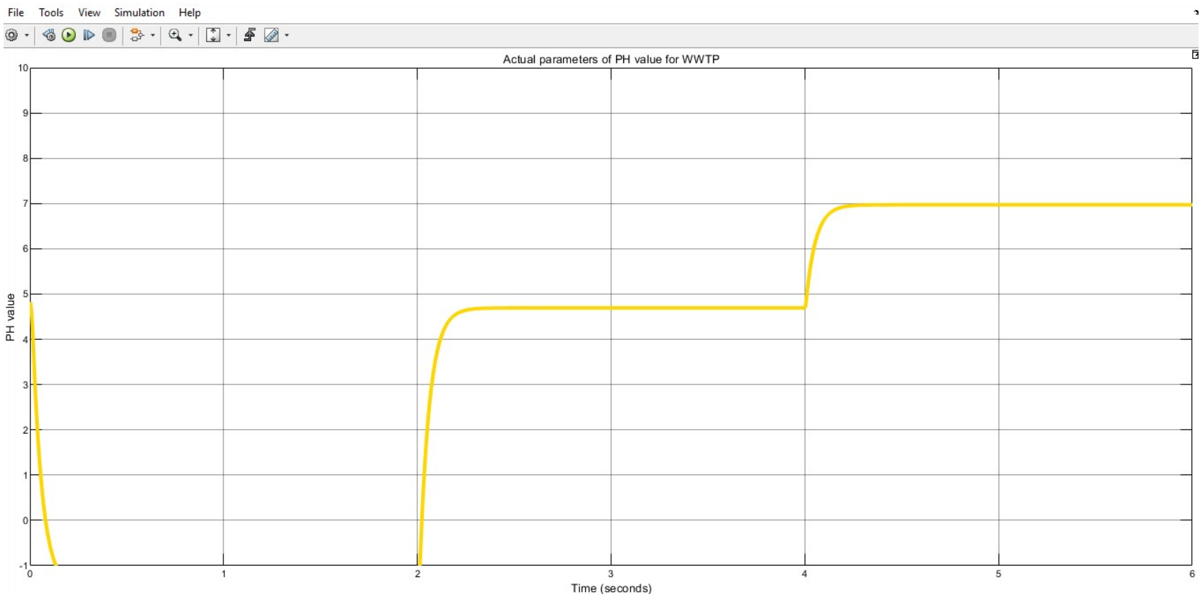

Figure 4.15 Simulation Results of PH

The actual value of PH in the wastewater treatment process is stable at 7, it indicates that the treatment system is successfully maintaining the pH within the acceptable range for both drinking water and wastewater treatment. PH is a measure of the acidity or alkalinity of a solution, and it is an important indicator of water quality. pH values outside the standard range of 6.5-8.5 can have adverse effects on aquatic life and human health.

By stabilizing the pH at 7, the wastewater treatment process ensures that the treated effluent or the water being prepared for drinking purposes is within the acceptable pH range. This helps to meet the water quality standards and ensures that the treated water is safe for consumption or environmentally compatible for release into the environment.

It's worth noting that maintaining proper pH levels in wastewater treatment is important not only for the protection of human health but also for the performance of biological treatment processes. Different pH values can affect the activity of microorganisms involved in biological treatment, and therefore, controlling and stabilizing pH is crucial for overall treatment efficiency.

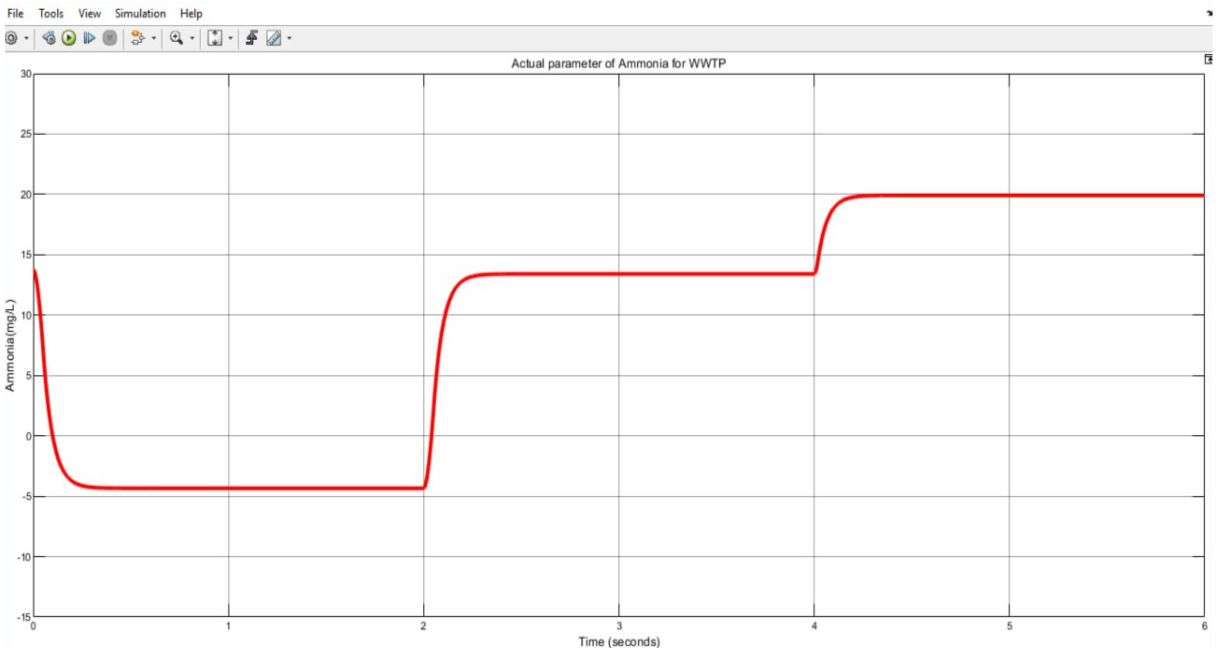

Figure 4.16 Simulation Results of Ammonia

If the above graph shows that the concentration of Ammonia (NH3) in the wastewater is below the standard limit of 20 mg/L, it indicates that the wastewater treatment process is effectively reducing the ammonia content and meeting the regulatory requirements. Ammonia in wastewater primarily exists in two forms: un-ionized ammonia (NH3) and ammonium ion (NH4+). The total ammonia concentration is the sum of these two forms. High levels of ammonia in wastewater can be toxic to aquatic organisms and can indicate inadequate treatment of nitrogenous compounds.

By keeping the concentration of ammonia within the acceptable range, the wastewater treatment process demonstrates its ability to effectively remove nitrogenous pollutants and ensure the treated effluent's compliance with regulatory standards.

Regarding the RBFNNPID algorithm, it is a powerful control strategy that combines the advantages of radial basis function neural networks (RBFNNs) and Proportional Integral Derivative (PID) controllers. RBFNNs can capture and model nonlinear relationships, while the PID controller provides feedback control and tuning capabilities.

In the context of wastewater treatment, the RBFNNPID algorithm can be beneficial in handling the nonlinearity present in the treatment process. It can adapt and adjust control actions based on the dynamic behavior of the system, leading to improved control performance and the ability to meet desired setpoints or target values for various parameters.

4.5 Comparing the result of adptive nonlinear PID with adaptive nonlinear RBFNNPID

Both controllers offer automatic error haddling capabilities to improve control performance and robustness.

i. Adaptive Nonlinear PID(ANLPID) controller result

- ✓ Combines the traditional PID control algorithm with adaptive tuning methods to handle errors in a nonlinear system.
- ✓ The adaptive tuning mechanism continuously updates the PID parameters based on the system's behavior and the error between the desired setpoint and the actual value of the controlled variable.
- ✓ If there is an error, the adaptive tuning mechanism analyzer the system's response and adjusts the PID parameters to optimize control performance. This adaptation allows he controller to self tune and adapt to changes in system dynamics, disturbances or operating conditions.
- ✓ The adaptive tuning in ANLPID enables the controller to handle errors by dynamically adjusting the control action based on the system's behavior and the error information.
- ✓ By continuous monitoring and adapting the PID parameters, ANLPID can automatically handle errors, improve control performance and enhance the stability and robustness of the control system.

ii. Radial Basis Function Neural Network PID (RBFNNPID)

- ✓ The PID controller calculates the control signal based on the error between the desired setpoint and the output of the RBFNN. The error is typically computed as the difference between the desired value and the actual value of the controlled variable.
- ✓ The RBFNN component approximates the nonlinear dynamics of the system and provides an estimates of the atual value of the controlled variable.
- ✓ If there is an error between the desired setpoint and the RBFNN output, the PID controller adjusts the control signal to minimize the error and bring the system closer to the desired setpoint.
- ✓ The PID controller's proportional, integral and derivative terms contribute to error handling and control action adjustment. The proportional term responds to the instantaneous error, the integral term handles accumulated errors over time and the derivative term accounts for

the rate of change of the error.

- ✓ By continuously monitoring the error and adjusting the control action, the RBFNNPID control an automatically handle errors and maintain control performance even in the presence of disturbances, nonlinearity and uncertainities.

Both controllers RBFNNPID and ANLPID provides automatic error handling mechanisms through their respective adaptive tuning approaches. These mechanisms enable the controllers to continuously monitor the error, adjust control actions and adapt to changing system conditions. Thereby improving control performance and robustness in the presence of nonlinearity, uncertainities and disturbances. Because during combination PID is giving feedback for RBFNN algorithm for handling the error got from wastewater parameter sensor at input(reference) value and output values.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

This thesis adaptive nonlinear PID control algorithm based on RBF neural network to control parameters of WWTP in activated sludge bioreactors in wastewater treatment plants (WWTP). From these parameters the measures are DO, COD, BOD, PH, TSS, TDS, NH3, nitorogen and nitrate. But DO is the measure one can enfulence the other parameters. The activated sludge process is known for its high nonlinearity and multivariable dynamic behavior, which makes it very challenging to control. The proposed algorithm uses the ASM1 model to describe the activated sludge process, and it takes DO as the major variable that affects the others. The algorithm is able to adapt to changes in the system and to disturbances, and it has been shown to be effective in controlling DO in WWTPs. Wastewater treatment plants are complex systems, and the concentration of dissolved oxygen (DO) is a critical parameter that needs to be tightly controlled. An ANLPID controller could be a very effective way to achieve this goal.

Based on the simulation code results the adaptive nonlinear PID controller algorithm and Simulink result of RBFNNPID control algorithms demonstrates several advantages over conventional PID controller for controlling various parameters DO concentration, including BOD, COD, PH, NH3, NO, TDS and TSS concentrations. The matlab simulation code result shows that the actual values DO 2mg/l, COD is 50 mg/lm, BOD is 30 mg/l, TSS is 30mg/l, PH is 7mg/l and ammonia is 20mg/l.

The RBFNNPID algorithm effectively maintains desired concentrations around the set points, even if when there are significant changes in influent flow rate and quality. It achieves this by smoothly adjusting the air flow, resulting in a more stable status within the aeration tank while using less air supply. In terms of tracking performance and anti-disturbance ability the RBFNNPID algorithm output performs the conventional PID controller. It increases the parameters estimation of the plant by training the historical data which received from PID feedback. The RBFNNPID algorithm is also robust as it adapts more effectively to changes in set points and disturbances. This ensures consistent and reliable control in dynamic environments. In general the RBFNNPID algorithm is a more effective and robust controller for DO, BOD, COD, PH, TDS, TSS, NH3 and NO3 concentration control compared to the adaptive nonlinear PID controller.

Recommendations

The wastewater treatment process is a critical part of public health and environmental protection my be the implementation is costs. If adaptive nonlinear PID controller is once established and widely used to control the discharging parameters of wastewater with standard the community can use for irrigation and others purposes. This thesis had done only by simulation and designing new treatment plant by comparing with the old Africa Juice S.C treatment.

It is also important to tes the controller on the real time plant to see hoiw it performs under actual conditions. This will help to ensure that the cotroller is effective and that it does’t has any negative impacts on the plant’s performance.

In addition to cost and energy efficiency, other design considerations for a wastewater treatment controller include robustness, flexibility, and ease of use. The controller should be able to handle a wide range of operating conditions and should be easy to adjust as needed.

Finally, it is important to note that the wastewater treatment plant at Final Africa Juice Company is not designed to meet current environmental standards. A new plant is needed to ensure that the effluent does not pose a danger to the community or aquatic life.

Overall, I believe that the cost analysis and energy calculation for the proposed controller and the PID controller are important steps in the design of a wastewater treatment controller. The controller should also be tested on the real plant to ensure that it is effective and does not have any negative impacts on the plant's performance. Other design considerations include robustness, flexibility, and ease of use.

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APPENDICES

APPENDIX A: MATLAB Program code

Appendix A **Nonlinear PID controller for industrial waste water treatment plant**

```
%Parameter Prediction
% Plant Parameters
Kp_DO = 0.5; % Proportional Gain for DO
Ki_DO = 0.05; % Integral Gain for DO
Kd_DO = 0.025; % Derivative Gain for DO
Kp_BOD = 0.5; % Proportional Gain for BOD
Ki_BOD = 0.03; % Integral Gain for BOD
Kd_BOD = 0.05; % Derivative Gain for BOD
Kp_COD = 1.1; % Proportional Gain for COD
Ki_COD = 0.5; % Integral Gain for COD
Kd_COD = 0.025; % Derivative Gain for COD
Kp_PH = 1.5; % Proportional Gain for PH
Ki_PH = 0.02; % Integral Gain for PH
Kd_PH = 0.2; % Derivative Gain for PH
Kp_TDS = 0.5; % Proportional Gain for TDS
Ki_TDS = 0.05; % Integral Gain for TDS
Kd_TDS = 0.025; % Derivative Gain for TDS
Kp_TSS = 2.25; % Proportional Gain for TSS
Ki_TSS = 0.3; % Integral Gain for TSS
Kd_TSS = 0.15; % Derivative Gain for TSS
Kp_NH3 = 1.5; % Proportional Gain for AMONIA
Ki_NH3 = 0.2; % Integral Gain for AMONIA
Kd_NH3 = 0.1; % Derivative Gain for AMONIA
Kp_NO3 = 0.75; % Proportional Gain for NITRATE
Ki_NO3 = 0.1; % Integral Gain for NITRATE
Kd_NO3 = 0.05; % Derivative Gain for NITRATE
% Time Parameters
t0 = 0; % Start Time
tf = 100; % End Time
dt = 0.01; % Time Step
t = t0:dt:tf; % Time Vector
N = length(t); % Number of Time Steps
% Set Points
SP_DO = 3; % Desired DO Level
SP_BOD = 30; % Desired BOD Level
SP_COD = 50; % Desired COD Level
SP_PH = 7; % Desired PH Level
SP_TDS = 1200; % Desired TDS Level
SP_TSS = 30; % Desired TSS Level
SP_NH3 = 20; % Desired NH3 Level
SP_NO3 = 10; % Desired NO3 Level
% Initial Conditions
y_DO_0 = 100; % Initial DO Level
e_DO_0 = SP_DO - y_DO_0; % Initial Error for DO
ie_DO_0 = 0; % Initial Integral Error for DO
y_BOD_0 = 50; % Initial BOD Level
e_BOD_0 = SP_BOD - y_BOD_0; % Initial Error for BOD
ie_BOD_0 = 0; % Initial Integral Error for BOD
y_COD_0 = 100; % Initial COD Level
e_COD_0 = SP_COD - y_COD_0; % Initial Error for COD
```

```
ie_COD_0 = 0; % Initial Integral Error for COD
y_PH_0 = 7; % Initial Erroe PH level
e_PH_0 = SP_PH - y_PH_0; % Initial Error for PH
ie_PH_0 = 0; % Initial Integral Error for PH
y_TDS_0 = 30; % Initial Error TDS level
e_TDS_0 = SP_TDS-y_TDS_0; % Initial Error for TDS
ie_TDS_0 = 0; % Initial Integral Error for TDS
y_TSS_0 = 30; % Initial TSS level
e_TSS_0 = SP_TSS - y_TSS_0; % Initial Error for TSS
ie_TSS_0 = 0; % Initial Integral Error for TSS
y_NH3_0 = 20; % Inital Error AMONIA level
e_NH3_0 = SP_NH3 - y_NH3_0; % Initial Error for AMONIA
ie_NH3_0 = 0; % Initial Integral Error for AMONIA
y_NO3_0 = 10; % Initial Error NITRATE level,
e_NO3_0 = SP_NO3 - y_NO3_0; % Initial Error for NITRATE
ie_NO3_0 = 0; % initial Integral Error for NITRATE
% Controller Parameters
alpha_DO = 0.05; % Nonlinear Parameter for DO
beta_DO = 0.5; % Nonlinear Parameter for DO
alpha_BOD = 0.02; % Nonlinear Parameter for BOD
beta_BOD = 0.5; % Nonlinear Parameter for BOD
alpha_COD = 0.01; % Nonlinear Parameter for COD
beta_COD = 0.5; % Nonlinear Parameter for COD
alpha_PH = 0.05; % Nonlinear Parameter for PH
beta_PH = 0.5; % Nonlinear Parameter for PH
alpha_TDS = 0.05; % Nonlinear Parameter for TDS
beta_TDS = 0.5; % Nonlinear Parameter for TDS
alpha_TSS = 0.05; % Nonlinear Parameter for TSS
beta_TSS = 0.5; % Nonlinear Parameter for TSS
alpha_NH3 = 0.05; % Nonlinear Parameter for NH3
beta_NH3 = 0.5; % Nonlinear Parameter for NH3
alpha_NO3 = 0.05; % Nonlinear Parameter for NO3
beta_NO3 = 0.5; % Nonlinear Parameter for NO3
% Parameter Predictions
Kp_DO_hat = 0.6; % Predicted Proportional Gain for DO
Ki_DO_hat = 0.06; % Predicted Integral Gain for DO
Kd_DO_hat = 0.03; % Predicted Derivative Gain for DO
Kp_BOD_hat = 0.25; % Predicted Proportional Gain for BOD
Ki_BOD_hat = 0.025; % Predicted Integral Gain for BOD
Kd_BOD_hat = 0.0125; % Predicted Derivative Gain for BOD
Kp_COD_hat = 0.15; % Predicted Proportional Gain for COD
Ki_COD_hat = 0.015; % Predicted Integral Gain for COD
Kd_COD_hat = 0.0075; % Predicted Derivative Gain for COD
Kp_PH_hat = 0.6; % Predicted Proportional Gain for PH
Ki_PH_hat = 0.06; % Predicted Integral Gain for PH
Kd_PH_hat = 0.03; % Predicted Derivative Gain for PH
Kp_TDS_hat = 0.6; % Predicted Proportional Gain for TDS
Ki_TDS_hat = 0.06; % Predicted Integral Gain for TDS
Kd_TDS_hat = 0.03; % Predicted Derivative Gain for TDS
Kp_TSS_hat = 0.6; % Predicted Proportional Gain for TSS
Ki_TSS_hat = 0.06; % Predicted Integral Gain for TSS
Kd_TSS_hat = 0.03; % Predicted Derivative Gain for TSS
Kp_NH3_hat = 0.6; % Predicted Proportional Gain for NH3
Ki_NH3_hat = 0.06; % Predicted Integral Gain for NH3
Kd_NH3_hat = 0.03; % Predicted Derivative Gain for NH3
Kp_NO3_hat = 0.6; % Predicted Proportional Gain for NO3
Ki_NO3_hat = 0.06; % Predicted Integral Gain for NO3
```

```
Kd_NO3_hat = 0.03; % Predicted Derivative Gain for NO3
% Preallocate Vectors
y_DO = zeros(1, N); % DO Level
e_DO = zeros(1, N); % Error for DO
ie_DO = zeros(1, N); % Integral Error for DO
y_BOD = zeros(1, N); % BOD Level
e_BOD = zeros(1, N); % Error for BOD
ie_BOD = zeros(1, N); % Integral Error for BOD
y_COD = zeros(1, N); % COD Level
e_COD = zeros(1, N); % Error for COD
ie_COD = zeros(1, N); % Integral Error for COD
u_DO = zeros(1, N); % Control Signal for DO
u_BOD = zeros(1, N); % Control Signal for BOD
u_COD = zeros(1, N); % Control Signal for COD
y_PH = zeros(1, N); % PH Level
e_PH = zeros(1, N); % Error for PH
ie_PH = zeros(1, N); % Integral Error for PH
y_TDS = zeros(1, N); % TDS Level
e_TDS = zeros(1, N); % Error for TDS
ie_TDS = zeros(1, N); % Integral Error for TDS
y_TSS = zeros(1, N); % TSS Level
e_TSS = zeros(1, N); % Error for TSS
ie_TSS = zeros(1, N); % Integral Error for TSS
y_NH3 = zeros(1, N); % NH3 Level
e_NH3 = zeros(1, N); % Error for NH3
ie_NH3 = zeros(1, N); % Integral Error for NH3
y_NO3 = zeros(1, N); % NO3 Level
e_NO3 = zeros(1, N); % Error for NO3
ie_NO3 = zeros(1, N); % Integral Error for NO3
% Loop through Time Steps
for i = 1:N
 % Calculate Error for DO
 e_DO(i) = SP_DO - y_DO(i);
 % Calculate Integral Error for DO
 ie_DO(i) = ie_DO_0 + e_DO(i)*dt;
 % Calculate Derivative Error for DO
 if i == 1
 de_DO = 0;
 else
 de_DO = (e_DO(i) - e_DO(i-1))/dt;
 end
 % Calculate Nonlinear Parameter for DO
 alpha_DO = beta_DO*(1 - exp(-abs(e_DO(i))));
 % Calculate Control Signal for DO
 u_DO(i) = Kp_DO*(1 + alpha_DO)*e_DO(i) + Ki_DO*ie_DO(i) + Kd_DO*(1 -
alpha_DO)*de_DO;
 % Update DO Level
 y_DO(i+1) = y_DO(i) + (u_DO(i) - Kp_DO_hat*e_DO(i))*dt;
 % Calculate Error for BOD
 e_BOD(i) = SP_BOD - y_BOD(i);
 % Calculate Integral Error for BOD
 ie_BOD(i) = ie_BOD_0 + e_BOD(i)*dt;
 % Calculate Derivative Error for BOD
 if i == 1
 de_BOD = 0;
 else
 de_BOD = (e_BOD(i) - e_BOD(i-1))/dt;
```

```
 end
 % Calculate Nonlinear Parameter for BOD
 alpha_BOD = beta_BOD*(1 - exp(-abs(e_BOD(i))));
 % Calculate Control Signal for BOD
 u_BOD(i) = Kp_BOD*(1 + alpha_BOD)*e_BOD(i) + Ki_BOD*ie_BOD(i) + Kd_BOD*(1 -
alpha_BOD)*de_BOD;
% Update BOD Level
 y_BOD(i+1) = y_BOD(i) + (u_BOD(i) - Kp_BOD_hat*e_BOD(i))*dt;
 % Calculate Error for COD
 e_COD(i) = SP_COD - y_COD(i);
 % Calculate Integral Error for COD
 ie_COD(i) = ie_COD_0 + e_COD(i)*dt;
 % Calculate Derivative Error for COD
 if i == 1
 de_COD = 0;
 else
 de_COD = (e_COD(i) - e_COD(i-1))/dt;
 end
 % Calculate Nonlinear Parameter for COD
 alpha_COD = beta_COD*(1 - exp(-abs(e_COD(i))));
 % Calculate Control Signal for COD
 u_COD(i) = Kp_COD*(1 + alpha_COD)*e_COD(i) + Ki_COD*ie_COD(i) + Kd_COD*(1 -
alpha_COD)*de_COD;
 % Update COD Level
 y_COD(i+1) = y_COD(i) + (u_COD(i) - Kp_COD_hat*e_COD(i))*dt;
  % Calculate Error for PH
 e_PH(i) = SP_PH - y_PH(i);
 % Calculate Integral Error for PH
 ie_PH(i) = ie_PH_0 + e_PH(i)*dt;
 % Calculate Derivative Error for PH
 if i == 1
 de_PH = 0;
 else
 de_PH = (e_PH(i) - e_PH(i-1))/dt;
 end
 % Calculate Nonlinear Parameter for PH
 alpha_PH = beta_PH*(1 - exp(-abs(e_PH(i))));
 % Calculate Control Signal for PH
 u_PH(i) = Kp_PH*(1 + alpha_PH)*e_PH(i) + Ki_PH*ie_PH(i) + Kd_PH*(1 -
alpha_PH)*de_PH;
 % Update PH Level
 y_PH(i+1) = y_PH(i) + (u_PH(i) - Kp_PH_hat*e_PH(i))*dt;
 % Calculate Error for TDS
 e_TDS(i) = SP_TDS - y_TDS(i);
 % Calculate Integral Error for TDS
 ie_TDS(i) = ie_TDS_0 + e_TDS(i)*dt;
 % Calculate Derivative Error for TDS
 if i == 1
 de_TDS = 0;
 else
 de_TDS = (e_TDS(i) - e_TDS(i-1))/dt;
 end
 % Calculate Nonlinear Parameter for TDS
 alpha_TDS = beta_TDS*(1 - exp(-abs(e_TDS(i))));
 % Calculate Control Signal for TDS
 u_TDS(i) = Kp_TDS*(1 + alpha_TDS)*e_TDS(i) + Ki_TDS*ie_TDS(i) + Kd_TDS*(1 -
alpha_TDS)*de_TDS;
```

```
 % Update TDS Level
 y_TDS(i+1) = y_TDS(i) + (u_TDS(i) - Kp_TDS_hat*e_TDS(i))*dt;
 % Calculate Error for TSS
 e_TSS(i) = SP_TSS - y_TSS(i);
 % Calculate Integral Error for TSS
 ie_TSS(i) = ie_TSS_0 + e_TSS(i)*dt;
 % Calculate Derivative Error for TSS
 if i == 1
 de_TSS = 0;
 else
 de_TSS = (e_TSS(i) - e_TSS(i-1))/dt;
 end
 % Calculate Nonlinear Parameter for TSS
 alpha_TSS = beta_TSS*(1 - exp(-abs(e_TSS(i))));
 % Calculate Control Signal for TSS
 u_TSS(i) = Kp_TSS*(1 + alpha_TSS)*e_TSS(i) + Ki_TSS*ie_TSS(i) + Kd_TSS*(1 -
alpha_TSS)*de_TSS;
 % Update TSS Level
 y_TSS(i+1) = y_TSS(i) + (u_TSS(i) - Kp_TSS_hat*e_TSS(i))*dt;
 % Calculate Error for NH3
 e_NH3(i) = SP_NH3 - y_NH3(i);
 % Calculate Integral Error for NH3
 ie_NH3(i) = ie_NH3_0 + e_NH3(i)*dt;
 % Calculate Derivative Error for NH3
 if i == 1
 de_NH3 = 0;
 else
 de_NH3 = (e_NH3(i) - e_NH3(i-1))/dt;
 end
 % Calculate Nonlinear Parameter for NH3
 alpha_NH3 = beta_NH3*(1 - exp(-abs(e_NH3(i))));
 % Calculate Control Signal for NH3
 u_NH3(i) = Kp_NH3*(1 + alpha_NH3)*e_NH3(i) + Ki_NH3*ie_NH3(i) + Kd_NH3*(1 -
alpha_NH3)*de_NH3;
 % Update NH3 Level
 y_NH3(i+1) = y_NH3(i) + (u_NH3(i) - Kp_NH3_hat*e_NH3(i))*dt;
 % Calculate Error for NO3
 e_NO3(i) = SP_NO3 - y_NO3(i);
 % Calculate Integral Error for DO
 ie_NO3(i) = ie_NO3_0 + e_NO3(i)*dt;
 % Calculate Derivative Error for NO3
 if i == 1
 de_NO3 = 0;
 else
 de_NO3 = (e_NO3(i) - e_NO3(i-1))/dt;
 end
 % Calculate Nonlinear Parameter for NO3
 alpha_NO3 = beta_NO3*(1 - exp(-abs(e_NO3(i))));
 % Calculate Control Signal for NO3
 u_NO3(i) = Kp_NO3*(1 + alpha_NO3)*e_NO3(i) + Ki_NO3*ie_NO3(i) + Kd_NO3*(1 -
alpha_NO3)*de_NO3;
 % Update NO3 Level
 y_NO3(i+1) = y_NO3(i) + (u_NO3(i) - Kp_NO3_hat*e_NO3(i))*dt;
end
% Plot Results
figure;
subplot(4,1,1);
```

```
plot(t, y_DO(1:end-1), 'r', 'LineWidth', 2);
hold on;
plot(t, SP_DO*ones(1, N), 'b--', 'LineWidth', 2);
xlabel('Time (s)');
ylabel('DO Level (mg/L)');
legend('DO Level', 'Set Point');
grid on;
subplot(4,1,2);
plot(t, y_BOD(1:end-1), 'r', 'LineWidth', 2);
hold on;
plot(t, SP_BOD*ones(1, N), 'b--', 'LineWidth', 2);
xlabel('Time (s)');
ylabel('BOD Level (mg/L)');
legend('BOD Level', 'Set Point');
grid on;
subplot(4,1,3);
plot(t, y_COD(1:end-1), 'r', 'LineWidth', 2);
hold on;
plot(t, SP_COD*ones(1, N), 'b--', 'LineWidth', 2);
xlabel('Time (s)');
ylabel('COD Level (mg/L)');
legend('COD Level', 'Set Point');
grid on;
subplot(4,1,4);
plot(t, y_PH(1:end-1), 'r', 'LineWidth', 2);
hold on;
plot(t, SP_PH*ones(1, N), 'b--', 'LineWidth', 2);
xlabel('Time (s)');
ylabel('PH Level (mg/L)');
legend('PH Level', 'Set Point');
grid on;
subplot(5,1,1);
plot(t, y_TDS(1:end-1), 'r', 'LineWidth', 2);
hold on;
plot(t, SP_TDS*ones(1, N), 'b--', 'LineWidth', 2);
xlabel('Time (s)');
ylabel('TDS Level (mg/L)');
legend('TDS Level', 'Set Point');
grid on;
subplot(5,1,2);
plot(t, y_TSS(1:end-1), 'r', 'LineWidth', 2);
hold on;
plot(t, SP_TSS*ones(1, N), 'b--', 'LineWidth', 2);
xlabel('Time (s)');
ylabel('TSS Level (mg/L)');
legend('TSS Level', 'Set Point');
grid on;
subplot(5,1,3);
plot(t, y_NH3(1:end-1), 'r', 'LineWidth', 2);
hold on;
plot(t, SP_NH3*ones(1, N), 'b--', 'LineWidth', 2);
xlabel('Time (s)');
ylabel('NH3 Level (mg/L)');
legend('NH3 Level', 'Set Point');
grid on;
subplot(5,1,4);
plot(t, y_NO3(1:end-1), 'r', 'LineWidth', 2);
```

```
hold on;
plot(t, SP_NO3*ones(1, N), 'b--', 'LineWidth', 2);
xlabel('Time (s)');
ylabel('NO3 Level (mg/L)');
legend('NO3 Level', 'Set Point');
grid on;
```

Appendix B **Nonlinear PID controller for industrial waste water treatment plant**

```
%%Watewater treatment plant parameters estimation using RBFNN
training = 0;
% training = 1)
% Plant parameters for wastewater treatment
COD =50;
BOD =30;
TSS =30;
DO = 2;
Ts = 1e-4;
wc = 1/Ts;
PH = 7.0;
Ammonia = 100;
if training == 0
    load net_rbf.mat
    open('wwtp_rbf_nn.slx');
    disp('Simulating a wastewater treatment plant parameters');
    set_param('wwtp_rbf_nn','SimulationCommand','start');
    return
end
k = 1;
norm_input = max(abs(inputRBFNN'))';
norm_inputRBFNN = repmat(norm_input',max(size(inputRBFNN)),1)';
norm_output = max(abs(outputRBFNN'))';
norm_outputRBFNN = repmat(norm_output',max(size(outputRBFNN)),1)';
X = inputRBFNN./norm_inputRBFNN;
Y = outputRBFNN./norm_outputRBFNN;
s1 = 3;
s2 = 5;
[s3,pom] = size(Y);
%
net = feedforwardnet([s1,s2]);
net.layers{1}.transferFcn = 'tansig';
net.layers{2}.transferFcn = 'tansig';
net.layers{3}.transferFcn = 'purelin';
net.divideFcn='dividetrain';
net.trainParam.show = 6;
net.trainParam.epochs = 100;
disp('Training...');
net = train(net,X,Y);
```

APPENDIX B STANDARDS

C . Africa juice effluent water (wastewater) and international standard parameters.

Parameter	Unit	Guide Low	Guide High	Method
Ph		6.50	8.50	Potentiometric
Electrical Conductivity	mS/cm		< 1.50	Potentiometric
*Total Dissolved Solids	Ppm		< 1200	Potentiometric
*Total Suspended Solids	Ppm		< 30.0	Gravimetric
*Colour	H.U		< 15.0	Colorimetric
*B.O.D	Ppm		< 30.0	Incubation
*C.O.D	Ppm		< 50.0	Reflux
Ammonium	Ppm			Colorimetric
Nitrate N	Ppm			Colorimetric
*Nitrite N	Ppm			Colorimetric
*Total N	Ppm		< 100	Colorimetric
Chloride	Ppm		< 250	Colorimetric
Fluoride	Ppm		< 1.50	Colorimetric
*Oil & Grease	Ppm		< 0.05	Gravimetric
E.Coli	cfu/100 m		ND	CN-TM-W 18

C2. SDGs Output standard Ranges discharging

S.N	*Notation*	*Definition of Enffluent*	*Standard range*
1	S_I	*Soluble inert organic matter*	*10-50mg/L*
2	S_S	*Biomass substrate concentration*	*1000-3000mg/L*
3	X_I	*Particulate inert organic matter*	*<20mg/L*
4	X_S	*Slowly biodegradable substrate*	*<20mg/L*
5	$X_{B,H}$	*Active heterotrophic biomass*	*<50mg/L*
6	$X_{B,A}$	*Active autotrophic biomass*	*<5mg/L*
7	X_P	*Particulate products arising from biomassdecay*	*<5mg/L*
8	S_O	*dissolved Oxygen*	*>2mg/L*

9	S_{NO}	*Nitrate and nitrite nitrogen*	*<10mg/L*
10	S_{NH}	*NH^{+} + NH3 nitrogen*	*<1mg/L*
11	S_{ND}	*Soluble biodegradable organic nitrogen*	*<5mg/L*
12	X_{ND}	*Particulate biodegradable organic nitrogen*	*<10mg/L*
13	S_{ALK}	*Alkalinity*	*>50mg/L*

D. Poposed costs

N0	Spares	Unit measurement	Quantity	Unity price	Total costs
1	Universal sensor	Pcs	1	15,600	15,600
2	5.5 kW motor pump	Pcs	1	39,000	39,000
3	MODEL 54ea Analyzer/Controller	Pcs	1	52,000	52,000
4	PID	Pcs	1	18,200	18,200
5	Power cable copper 4x6	Meter	40	250	10,000
6	Wire 1.5	Meter	100	4,200ETB	4,200
7	Wire 2.5	Meter	100	2,600ETB	2,600
10	Contactor 3C/25A	Pcs	3	4,500	13,500
11	Accessory				10,000
12	Man power			3,000	10,000
	Total costs				156,900ETB