Addis Ababa University

Addis Ababa Institute of Technology

School of Electrical and Computer Engineering

NON-LINEAR ADAPTIVE ARTIFICIAL NEURAL NETWORK CONTROL OF MUNICIPAL WASTEWATER TREATMENT PLANTS

A thesis submitted to Addis Ababa Institute of Technology, School of Graduate Studies, Addis Ababa University

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By

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Declaration

I, the undersigned, declared that this MSc title **"Non-linear Adaptive Artificial Neural Network Control of Municipal Wastewater Treatment Plants"** is my original work, has not been presented for fulfillment of a degree in this or any other University and all sources and materials used for the thesis is acknowledged.

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This thesis work has been submitted for examination with my approval as a University Advisor.

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Acknowledgment

First of First and foremost, praise and thanks to God, the Almighty, for the showers of blessings throughout my entire life.

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Solomon Baye Ayalew

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List of Symbols, Abbreviations, and Nomenclature

Symbol	Definition
ASP	Activated Sludge Process
WWTP	Wastewater Treatment Plant
ANN	Artificial Neural Network
RBF	Radial Basis Function
PI	Proportional Integral
PID	Proportional Integral Derivative
PD	Proportional Derivative
$X(t)$	Biomass Concentration
$S(t)$	Substrate Concentration
$\mathrm{DO}(t)$	Dissolved Oxygen Concentration
$X_r(t)$	Recycled Biomass
S_I	Soluble inert organic matter
S_S	Readily biodegradable substrate
X_I	Particulate inert organic matter
X_S	Slowly biodegradable biomass
$X_{B,H}$	Active heterotrophic biomass
X_{B_A}	Active autotrophic biomass
X_P	Particulate products arising from biomass decay
S_O	Oxygen
S_{NO}	Nitrate and nitrite nitrogen
S_{NH}	$NH_4^+ + NH_3$ nitrogen
S_{ND}	Soluble biodegradable organic nitrogen

X_{ND}	Particulate biodegradable organic nitrogen
S_{ALK}	Alkalinity
W	Air flow rate
WWTP	Wastewater Treatment Plant
BSM	Bench mark simulation model
ASM1	Activated Sludge Model no 1
ASM3	Activated Sludge Model no 3
RBF	Radial Basis Function
ANNRBF	Adaptive Neural Network Radial Basis Function
MPID	Multi Variable PID
LQC	Linear Quadratic control
MPC	Model Predictive Control
BNN	Biological Neural Network
BP	Back propagation
hj	Gaussian function
SIMBA#	Software package

Abstract

Wastewater is used water from any combination of domestic, industrial, commercial or agricultural activities, surface runoff or stormwater, and any sewer inflow or sewer infiltration. The characteristics of wastewater vary depending on the source. Types of wastewater include domestic wastewater from households, municipal wastewater from communities (also called sewage) or industrial wastewater from industrial activities.Wastewater treatment is the process of treating contaminants prior to releasing wastewater into the environment or reusing. Basically, there are four steps to remove contaminants in sewage wastewater which are; pretreatment, primary treatment, secondary treatment and tertiary treatment.The activated sludge process is a biological process and an essential secondary treatment in wastewater treatment , where bacteria plays a role of degrading organic substances based on the the crucial process control parameter, dissolved oxygen (DO) concentration. The DO concentration in the aeration tank(s) is maintained at the desired level by manipulation of airflow rate, applying a Neural network based adaptive Proportional-Integral-Derivative (PID) controller.

In this thesis work, an Adaptive Neural Network Radial Basis Function PID (ANNRBFPID) control strategy is implemented to control a DO concentration in aerated bioreactors which update the set point of DO adaptively and withstand uncertain disturbances. Two models are selected to represent an activated sludge process. The first one is the simplified model with only four state variables. The second model is the Activated Sludge Model no.1(ASM1) the more realistic and accepted model with 13 state variables. Matlab/Simulink and SIMBA# software used for simulating the designed mathematical model and control of the activated sludge process for the simplified model and ASM1 respectively. The powerful learning and adaptive ability of the RBF neural network make the adaptive adjustment of the PID parameters to be realized. Hence, when the wastewater quality and quantity fluctuate, adjustments to some parameters online can be made by ANNRBFPID algorithm to improve the performance of the controller.

The Matlab/Simulink simulation result show that the DO can be maintained at 2mg/L or any desired setpoint with the presence of uncertain disturbances and continuously variable influents with ANNRBFPID control algorithm and the simulation result shows that ANNRBFPID achieve better control performance than conventional PID. On the other hand, SIMBA# simulation results show that the international standard limit for Ntot (Total Nitrogen), CODtot (Total Chemical Oxygen Demand), SNH (NH4(+) and NH3 nitrogen), TSS(Total Suspended Solids) is given by < 18g, < 100g, < 4g, < 30g respectively and the simulation result obtained is 11.04 g N/m^3, 23.82 g COD/m^3, 0.5421 g N/m^3, 5.061 g/m^3 respectively.

Keywords: dissolved oxygen concentration; adaptive PID; radial basis function(RBF); SIMBA#

Chapter One

1 Introduction

1.1 Introduction of Wastewater Treatment

Wastewater (or wastewater) is any water that has been affected by human and animal use. Wastewater is "used water from any combination of domestic, industrial, commercial or agricultural activities, surface runoff or stormwater, and any sewer inflow or sewer infiltration". The characteristics of wastewater vary depending on the source. Types of wastewater include domestic wastewater from households, municipal wastewater from communities (also called sewage) or industrial wastewater from industrial activities. Wastewater can contain physical, chemical and biological pollutants. Households may produce wastewater from flush toilets, sinks, dishwashers, washing machines, bathtubs, and showers. Households that use dry toilets produce less wastewater than those that use flush toilets [36].

Wastewater treatment includes 4 steps [**3**], which are pretreatment, primary treatment, secondary treatment, and tertiary treatment. Secondary treatment is a substantially biological process; the activated sludge uses oxygen and a large inventory of microorganisms. Microorganisms play an important role in the cycling of materials and in the decomposition of organic substances in the wastewater.

Activated sludge removes organic pollutants in wastewater with condensation, absorption, oxidation, decomposition and precipitation effects. In an activated sludge method, the air is continuously bubbled into the wastewater, and after a certain time (because of aerobic microbial growth) flocs are formed. Microorganisms habitat on the flocs, which have a strong ability to absorb and oxidize organic matter. The basic concept of the activated sludge process (ASP) came from British researchers Clark and Gage in 1912 [4]. They found that after a long period of time aerating air into wastewater, the quality of wastewater significantly improved. Arden and Lackett's further research [9] found that the sidewall of the experimental container could not be washed clean, thus leaving a residue on the container, which had an active effect on improving the quality of the wastewater; this discovery led to the development of the activated sludge process.

From a control system's perspective, the biggest challenge is to maintain the stability of the bioreactor while minimizing the amount of energy used for aeration. Oxygen is required in the aerobic zone of the activated sludge process to allow the microorganisms to grow and to consume the organic compounds present in the wastewater. An insufficient supply of oxygen may result in poor water quality, or could even result in the death of some of the microorganisms in an activate sludge process; yet an oversupply of oxygen is a waste of both energy and money [27]. On the other hand, concentration (pollution load) and uncertain disturbances from the incoming wastewater varies depending upon the time of the day and seasonally. Consequently, even though it is desirable to identify optimal values for all state variables, these optimal values will vary periodically. Therefore, a proper control system for an activated sludge process requires a periodical adjustment of the set-point values for the states, while ensuring that those set-points are efficiently tracked. In this thesis, it is assumed that appropriate, or optimal set point values are known. Consequently, the objective is to design a control system which is capable of tracking the desired set points, while ensuring the dynamic system remains stable.

1.2 Background and Literature Review

The premise of how the wastewater treatment process can perform stable will depend on how effectively the concentration of DO is be maintained within a reasonable range [6]. Due to the complex nature of microbial activities that are present in an activated sludge process, even a small change introduced to the system (for example, change in flow rate, the water quality of the influent, the temperature of the wastewater in the reactors and so on) can affect the concentration of DO. The air supplied to aeration tanks by blowers allows the oxygen to be transferred from the air to the liquid phase (wastewater). The oxygen transfer is a complex process characterized by large time-delays as well as strong nonlinearity, coupling, and disturbance, which further increases the difficulty of controlling the concentration of DO [7,8]. A large number of studies have been carried out and achievements have been made by researchers all over the world to control the concentration of DO level; a series of control methods to control the concentration of DO have been put into practice and they have achieved some good effects. An appropriate DO setpoint is identified either by experienced operators or automatically through computer algorithms. The control task is challenging since the operating conditions of the system are always changing. Large disturbances in the input of the system and weather conditions such as rain, dry and storms can affect the operating condition substantially and the control system must respond properly. Some proposed control methods in the literature are reviewed in the following paragraphs.

In [9] standard PID tuning methods such as Ziegler-Nichols and relay, tuning has been evaluated for DO control using Benchmark Simulation Model no. 1 (BSM1). The paper also presents an adaptive controller that uses the tuning methods and describes how to perform real-time tuning. Adaptive rules in the control algorithm update controller parameters in order to adapt to changes in the process dynamic or disturbances. PID autotuning methods are proposed as well.

A controller based on an extension of the relay-feedback PID auto-tuner is applied to a wastewater treatment process in [10]. There are two steps in the proposed method: process identification and controller design. From the identification a second order model is obtained which is used for controller design. The PID controller is designed based on internal model control (IMC) tuning rules. A PID auto-tuning method is also investigated in [11] for the control system of a wastewater treatment facility. This paper also considers the identification step and, moreover, presents a set-point decision algorithm for choosing an appropriate set-point of DO concentration for the optimal aeration. Slightly improved efficiency of the conventional DO PI control is found in [4]. In the paper, the model-based estimation method is proposed to estimate the respiration rate. Then a parameter scheduling (gain scheduling) PI control is proposed. The changes in PI controller parameters are related to the scheduling variable, the estimated respiration rate, with the aim of compensating for the process nonlinearities. In [12] multivariable PID (MPID) control has been considered for an activated sludge wastewater treatment process. Different PID tuning methods are compared. All methods for MPID tuning, which are based on decoupling the system at different frequency points, require information only from a simple step or frequency response tests. In [13] some process identification methods of PID auto-tuning for DO control are compared. Moreover, a supervisory control algorithm is proposed for set-point decision making. The respiration rate is estimated simultaneously during the identification step. The DO set-point is considered to be proportional to the respiration rate. The supervisory control reduces the aeration cost. Cascade control is another classical control method, which is well known for DO set-point tracking. Feedforward control in combination with cascade control has also been investigated recently. The idea is to use a feedforward of ammonia in the influent to handle disturbance rejection. Examples of cascade control combined with feedforward can be found in [14]. In these studies, different types of feedforward controllers are applied to the process and the feedforward term is modeled in a linear or nonlinear way. Simulation results and, in some cases, pilot plant testing is provided within the studies. In [15] feedforward of influent ammonia is combined with feedback control for maintaining the DO concentration set-point.The combined controller outperforms the feedback control in suppressing ammonia peaks. The same results are found with a combined ammonia cascade and feedforward control method in [16]. With this method, a 45% reduction was obtained in airflow compared to conventional PI control. A pilot plant was used to verify the results. In addition, only cascade ammonia control (without feedforward) reduced the air flow by 23%. Another example can be found In [17]. It describes a full-scale evaluation of a modified cascade controller at Kappala WWTP in Sweden. Certain control algorithms use some of the process models in order to develop the control system. The model can be either the process equations proposed in the models such as ASM1 (activated sludge model number 1) or a black-box. The controller output will optimize some objective function that is defined based on the model. The control algorithm considers the cost function that must be mathematically minimized and finds the best solution to the optimization problem with the given constraints. Linear Quadratic Control (LQC) is an example of feedback model-based control, which minimizes a cost function. Another example is predictive control, such as Model Predictive Control (MPC). The MPC ability to include multiple variables and handle constraints has made it a popular control method. The classical MPC method has been also developed. Robust MPC, adaptive MPC, and nonlinear MPC are extensions. In [3] results from an MPC for aeration control is presented. It is a case study application of MPC for a wastewater treatment process in Lancaster, North England. BOD-removal improvement in an activated sludge process is achieved by considering a black-box model of the aeration and using feedforward of the influent BOD load. The previous on/off control strategy for the surface aerators are improved and the compared results indicate a reduction of energy usage and an increase in the plant efficiency.

MPC is also used for DO set-point determination in [19]. The dissolved oxygen model is created by sub-space identification. A PI controller with constant DO set-point is compared with three different MPC controllers. It is shown by comparing system settling time and overshoot that a set-point controller Improves the performance. The authors also conclude that the set-point controller is easy to implement. MPC application for maintaining and tracking the DO set-point is investigated in [20]. The effect of some MPC tuning parameters, such as sampling time, is also investigated. The proposed control is applied to the benchmark simulation and compared to a standard PI controller; the MPC controller shows marginal improvements. The comparison of different model-based controllers and the PI control can be found in two publications. The first one is [21] in which results based on different model-based controllers are compared with conventional PI control with fixed DO set-point and a set-point found through PI ammonia control. The control variables were the DO set-point, internal recycle flow rate, returned activated sludge flow rate and external carbon dosing. LQC, DMC (Dynamic Matrix Control) and NPC (Nonlinear Predictive Control) is the model-based controllers included in the study. The model-based controllers (LQC, DMC, and NPC) improved control performance compared to PI control and the best results were obtained by the NPC controller. Another comparison between different model-based controllers is found in [22]. In this study, three model-based controllers are considered: DMC, Quadratic DMC (QDMC) and nonlinear MPC. Improved results did not obtain with QDMC compared to DMC. The nonlinear MPC improved the performance, yet the energy consumption increased as well. Feedforward for disturbance rejection is also investigated in combination with DMC. Both the ammonia concentration feedforward and inflow rate feedforward are considered and the ammonia concentration feedforward results in better results. With feedforward, the performance is also improved at the cost of increased energy consumption. A similar study in [27] compared nonlinear MPC, QDMC, and QDMC with feedforward. It is concluded that non-linear MPC outperforms other controllers in the handling of the disturbances with acceptable energy consumption. Decentralized PI controllers are compared with model-based controllers in two different studies. The controllers are applied to the Benchmark Simulation Model. In [28] PI loops for nitrate recycle and airflow rate are compared to two model-based controllers; an LQ controller and a DAC (disturbance accommodation controller). PI control achieved better results. Performance of a multi-loop PI controller to a multivariable controller in a single aerated reactor is compared in [29]. The control variables were DO and substrate concentration. The results in a step response test are comparable for the two controllers. Genetic algorithm has been also used for model-based control in [30, 31]. In [30] a cost minimization control is evaluated using the benchmark simulation model. A hierarchical control structure is proposed. The set-point of the process is obtained in the higher-level control by an optimization that used the simplified process model and genetic algorithms. In the aeration control, the PI controller in a low-level control follows the ammonia set-point which is determined by the optimizer in a higher-level control. A genetic algorithm was also used in [31] for set-point optimization in aerobic zones and energy reduction is obtained without sacrificing the treatment performance. A MIMO robust MPC, Extended Kalman filter, grey box parameter estimation or Weighted Least Squares with Moving Measurement window is involved in the control. A nonlinear SISO MPC is proposed based on the oxygen dynamics in [32] and an improvement to the algorithm is published in [33] where a fuzzy predictive controller increased the computational efficiency. In [34] an Adaptive Model Reference controller and a nonlinear MPC are compared. In another work which is described in [35].

1.3 Statement of the Problem

During the past few years, the control of bioprocesses has been a significant problem attracting the world's attention, because it directly impacts human lives. Specifically, wastewater treatment has been one of the major problems in bioprocessing. The behavior of influents of WWTPs differs from one plant to another based on the living standards of the community. On the other way, the type of influent for any plant is highly time-dependent and it is very challenging to have a uniform and homogeneous influent to a WWTP. This may lead to an operational risk impact on the plant. Additionally, serious environmental and public health problems may result from improper operation and control of WWTPs. Thus, environmental regulations set restrictions on the quality of effluent that must be met by every WWTP.

Unless the plant is properly operated and controlled, it will result in diseases to human beings and aquatic-dependent animals and leads to public health problems. A best operation and control of WWTP can be achieved by developing an intelligent and adaptive controller algorithm for the developed mathematical models. To this end, in this thesis work, an artificial neural network of radial basis function is employed with PID controller to set the dissolved oxygen concentration on the international standard limit and to withstand with any environmental condition. Even though the conventional PID is still a better controller for many industries, it does not perform well for a highly nonlinear and uncertain system like WWTPs. Thus, an intelligent system specifically an adaptive neural network PID algorithm should be employed for the proper operation of the control system for the plant.

1.4 The objective of the thesis

1.4.1 General Objective

The main objective of this research is to design a Neural Network based Adaptive PID control algorithm, capable of stabilizing the system and making the output track the desired set points in spite of unknown parameters and disturbances in order to improve the performance of the wastewater treatment process.

1.4.2 Specific Objective

- To study the mathematical model of waste water treatment plants for control design
- To select an appropriate manipulation parameters for the control of WWTP.
- To design an Adaptive Neural Network Radial Basis Function PID (ANNRBFPID) controller
- To simulate the controller in MATLAB/Simulink and SIMBA#.
- To compare the performance of the ANNRBFPID and conventional PID controller.

1.5 Contribution of the Thesis

As we know wastewater is a major problem around municipals especially in Addis Ababa due to household wastes such as food and flush toilets. So, developing a control mechanism for waste treatment plays a big role and creates foresight for developing a waste treatment system and wastewater recovery system for every town. This thesis can also be an input for peoples engaged in the work of the wastewater treatment system. Even if it does not tested on the real wastewater plant the simulation result shows the effectiveness of the controller. The proposed controller ANNRBF PID shows better performance than the conventional PID controller.

1.6 Outline of the Thesis

Chapter one presents the background and introduction of WWTP, statement of the problem, the objective of the thesis and contribution of the thesis. Chapter two begins by introducing wastewater and a mathematical model of the simplified model and benchmark simulation model BSM briefly discussed and plant layout detail and biological processes are given. In chapter three a controller is designed. Which is A Neural Network Based Adaptive PID Algorithm is discussed. In chapter four the results and discussion are given and the performance of the proposed ANNRBF PID and conventional PID is compared in terms of setpoint tracking, anti-disturbance capability, and robustness. Following this, an activated sludge model which is more realistic and complex one simulated in SIMBA software and the results and the design is given. The last chapter presents the conclusion and recommendation.

CHAPTER 2

2 Mathematical Model of Wastewater Treatment Plant

2.1 Wastewater

Wastewater (or wastewater) is any water that has been affected by human and animal use. Wastewater is "used water from any combination of domestic, industrial, commercial or agricultural activities, surface runoff or stormwater, and any sewer inflow or sewer infiltration". The characteristics of wastewater vary depending on the source. Types of wastewater include domestic wastewater from households, municipal wastewater from communities (also called sewage) or industrial wastewater from industrial activities. Wastewater can contain physical, chemical and biological pollutants. Households may produce wastewater from flush toilets, sinks, dishwashers, washing machines, bathtubs, and showers. Households that use dry toilets produce less wastewater than those that use flush toilets [36].

Figure 2. 1 Greywater (a type of wastewater) [36]

All sewage requires treatment before draining directly into major watersheds [37]. When wastewater is untreated, some constitutes in wastewater have a serious impact on the health of human beings and on the quality of the environment, for example, pathogens can cause a variety of illnesses. Some chemicals have a potential risk even at very low concentrations and can remain a threat for long periods of time, because of bio circulation and bioaccumulation in animal or human tissue. Consequently, the following constitutes must be removed [38] in a wastewater treatment system:

- Pathogens, such as bacteria;
- Organic particles, such as organic food, vegetable materials;
- Soluble organic materials, such as proteins, drugs;
- Inorganic particles such as sand, grit, metal particles;
- Soluble inorganic material, such as ammonia;
- Gases, such as hydrogen sulfide, carbon dioxide, methane;
- Toxins, such as pesticides, poisons, herbicides;

2.1.1 Wastewater Treatment

Wastewater treatment is the process of treating contaminants prior to releasing wastewater into the environment or reusing. This thesis looks specifically at sewage treatment. Sewage mainly consists of household wastewater (as opposed to industrial wastewater which is contaminated by industry). Basically, there are four steps to remove contaminants in sewage wastewater [39]:

- Pretreatment: Pretreatment is a process to remove all large materials, which are commonly gathered from the raw sewage before they damage or clog the pumps. Contaminants that are easily removed during pretreatment include grit, rags, leaves, branches and other large objects.
- Primary Treatment: Primary treatment is a physical process driven by gravity. Sewage flows through large tanks, and the tanks are used to settle sludge. All fat, grease, and oils are skimmed off.
- Secondary Treatment: Secondary treatment is a substantially biological process,

which removes biological content from human waste and food waste. When sewage enters the secondary tank, bacteria in activated sludge (according to an aerobic biological process) degrades organic substances. The bacteria rely on dissolved oxygen and convert degradable organic matter into bacterial cells. The sewage is then filtered by separating treated water from the bacterial cells.

- Tertiary Treatment: Tertiary treatment is a final step to improve the quality of the effluent before it is discharged into the environment. Membrane filters are used for removing much of the residual suspended matter. Advanced oxidization is required for further nutrient removal, including nitrogen and phosphorus removal. Finally, an ultraviolet system disinfects wastewater.
- Heat: Heat that comes from the original wastewater can be captured during the treatment and utilized to warm the facility. Another method of using excess heat energy is to distribute it to the local community for heating up homes and buildings.
- Solids: Solids in wastewater can be treated as a valuable source of nutrients. The pretreatment treatment process provides several opportunities for resource recovery for future use.
- Phosphate: During the residual solids treatment process, phosphate can be extracted and used in fertilizer.
- Biosolids: Biosolids can be used to kill pathogens and used as a fuel substitute for cement kilns or for other beneficial uses.
- Irrigation: Treated wastewater can be used as irrigation for urban vegetation and agriculture.

2.2 Activated Sludge Process

The biological reactor or aeration tank is filled with a mixture of activated sludge and influent, known as “mixed liquor”. The aeration equipment (either surface aerators or compressors connected to submerged air diffusers) transfers the oxygen necessary for the oxidation of organic material into the reactor, while simultaneously introducing enough turbulence to keep the sludge flocs in suspension. The continuous introduction of new influent results in a continuous discharge of mixed liquor to the final settler (or secondary clarifier), where phase separation of solids and liquid takes place. The liquid leaves the system as treated effluent, whereas the sludge is recirculated to the aeration tank and for that reason is called “return sludge”. A primary settler (or primary clarifier) may be introduced to remove part of the suspended solids present in the influent. This reduces the organic load to the biological reactor. The settled suspended solids (“primary sludge”) are often sent to an anaerobic digester, together with the activated sludge that is discharged from the biological reactor: the excess sludge. In the anaerobic digester, the volatile suspended solids in the excess sludge are partly degraded, in the absence of oxygen, into methane and carbon dioxide. Without the discharge of excess sludge, there would be a continuous growth of sludge in the reactor and consequently, an increase of the sludge concentration in the process. In practice, the activated sludge concentration must not be allowed to exceed a certain maximum value in order to guarantee the proper functioning of the final settler (secondary clarifier). Sludge age is the most important operational and design variable. Additional to the organic material removal, nitrification was introduced in the activated sludge process. Nitrification is a two-step biological oxidation of ammonium, using oxygen as an oxidant: the first step is the oxidation of ammonium to nitrite, while the second step is the oxidation of nitrite to nitrate. Nitrification was initially applied only to reduce the effluent oxygen demand. The general arrangement of activated sludge processes is shown in Figure 2.2, including an aeration tank and a settling tank [40].

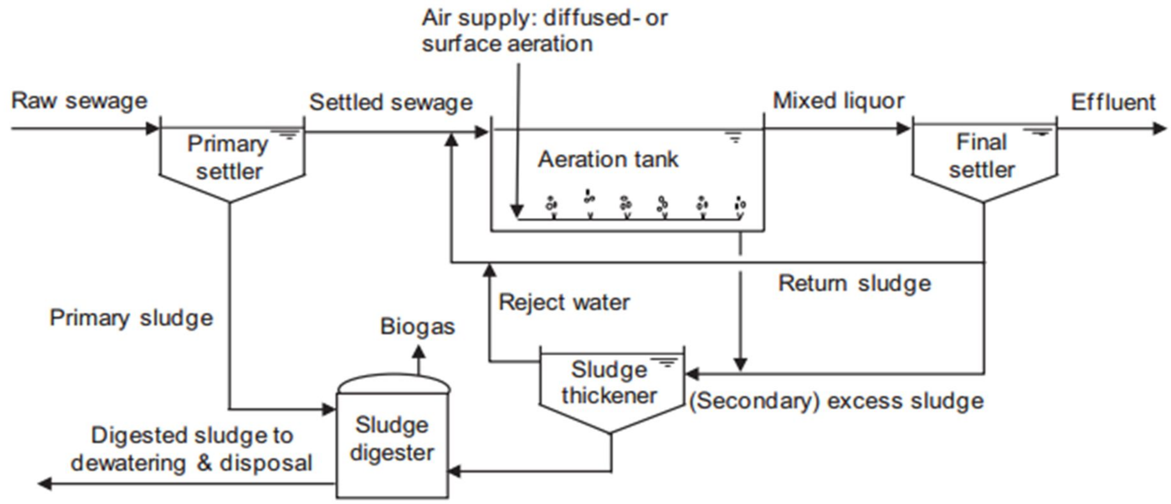


Figure 2. 2 Activated Sludge system representation [40]

2.3 Simulation Model

There are two well-known models to describe the characteristics of an activated sludge process in a biological wastewater treatment plant; one is a 4x4 model from Nejjari's paper [41], another is the activated sludge model no.1 (ASM1) [42].

The first model is a (4x4 model) four-state model, which captures the essential dynamic behavior in an aerated bioreactor. Thus, a control algorithm can be designed based on this simpler model for dissolved oxygen concentration control in the bioreactor. The other model is called activated sludge model no.1 (ASM1). In this model, thirteen state variables are considered in order to describe the biological process happening in a bioreactor. ASM1 is more detailed and complex. A simulation model that can be considered for a real treatment plant simulation should be based on a more detailed model like the ASM1. The simulation model that has been used in this study to model an activated sludge wastewater treatment plant is based on the benchmark simulation model no. 1 (BSM1), in which ASM1 is used in order to model the activated sludge process. In the following first the four-state model will be introduced then the simulation model and ASM1 are described.

2.3.1 Four by Four (4x4) Model

The principle scheme of Figure1 was considered for the mathematical modeling of the biological wastewater treatment process.

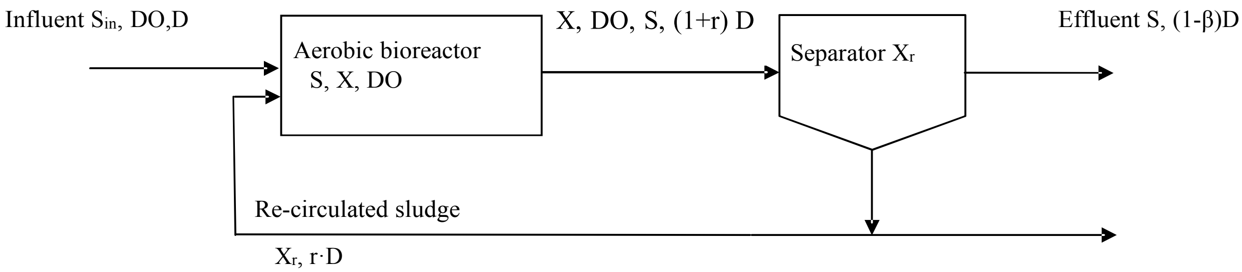


Figure 2. 3 The block-scheme of the process

The process is mainly constituted by two sequential tanks, an aerated tank, and a settler. In the aerated tank (also called the aerobic biological reactor), bacteria and other micro-organisms feed on the organic matter contained in the incoming wastewater that is to be discharged in the tank, thus reducing the level of degradation. The clarifier tank or settler is a gravitational sedimentation tank, where the sludge and the clean residual water are separated. Part of the settled active sludge is re-circulated from the settler into the aeration reactor, so that the content (population) of micro-organisms in the aerobic reactor could be maintained at an appropriate level, in order to continue the wastewater treatment process. The excess of active sludge is discharged from the biological wastewater treatment system. The provisions below tackle with a simplified model of the installation for the biological wastewater treatment plant. The model is based on the following hypotheses:

- the aeration tank is continuously stirred and mixed;
- no bio-reaction is taking place in the settler and the sludge is the only component re-circulated in the aerobic biological reactor;
- the oxygen and substrate concentrations are neglected along with re-circulation flow;
- the exit flow rate from the aeration tank equals the sum between the exit

flow rate from the separator and the flow rate of re-circulated sludge. For model determination purposes there are four fundamental equations, which aim at carrying out the processes by separating the effects

1) the equation linked to the balance of the active sludge at the level of the aeration tank – the process of increasing the active mass of the sludge:

$$\dot{X} = \mu\,(S, C)\,X - D\,(1 + r)\,X + rDX_r \qquad (2.1)$$

2) the equation linked to the mass balance of the substrate – the process of degradation of the carbon-based organic compounds:

$$\dot{S} = -\mu\,(S, C)\,X/Y - D\,(1 + r)\,S + DS_{in} \qquad (2.2)$$

3) the equation linked to the mass balance of the oxygen in the water mass the oxygen consumed by the biochemical degradation of the organic matters, the oxygenation process performed by the oxygen transfer from the air supplied with specific equipment in the water:

$$\dot{C} = -\mu\,(S, C)\,K_0X/Y - D\,(1 + r)\,C + DC_{in} + (C_s - C)\,\alpha W \qquad (2.3)$$

4) the equation linked to the balance of the active sludge at the level of the settling tank:

$$\dot{X}_r = \mathrm{D}\,(1 + r)\,X - D\,(b + r)\,X_r \qquad (2.4)$$

where the 4 states in the system are

$X(t)$ – biomass concentration,

$S(t)$ – substrate concentration,

$DO(t)$ – dissolved oxygen concentration,

$Xr(t)$ – recycled biomass,

where,

- D is the dilution rate
- b = (waste flow)/(influent flow)
- r = (recycled flow)/(influent flow)

- W is the air flow rate
- S_{in} is the substrate concentration in the influent load
- C_{in} is the dissolved oxygen concentration in the influent load
- C_s is the maximum dissolved oxygen concentration
- Y is the cell mass
- K_0 is a positive constant

The air flow rate (W) and the recycled rate (r) are the manipulated (input) variables. μ is the specific growth rate, which is a complex function of chemical and biological factors in the tank such as the biomass concentration, the substrate concentration, and the dissolved oxygen concentration. μ is the key parameter in order to explain the biomass growth. For this model, a Monod law is used to define this parameter and it is assumed that the specific growth rate depends on the dissolved oxygen concentration, the substrate concentration, and several kinetic parameters.

It is given by:

$$\mu\,(S, C) = \mu_{max} \frac{S}{K_S + S} \frac{C}{K_C + C} \tag{2.5}$$

where, μ_{max}, K_S and K_C are positive constants.

2.3.2 ASM1 Model

Activated sludge Model n.1(ASM1) has been considered to describe dynamic behavior within biological reactors [9]. The model contains 13 state variables. In Table 2.1, a list of state variables and their definitions is given.

2.3.2.1 List of state variables and their definitions

Table 2. 1 list of state variables and their definitions

	Notation	Definition

1	S_I	Soluble inert organic matter
2	S_S	Readily biodegradable substrate
3	X_I	Particulate inert organic matter
4	X_S	Slowly biodegradable substrate
5	$X_{B,\ H}$	Active heterotrophic biomass
6	$X_{B,\ A}$	Active autotrophic biomass
7	X_P	Particulate products arising from biomass decay
8	S_O	Oxygen
9	S_{NO}	Nitrate and nitrite nitrogen
10	S_{NH}	$NH^+ + NH_3$ nitrogen
11	S_{ND}	Soluble biodegradable organic nitrogen
12	X_{ND}	Particulate biodegradable organic nitrogen
13	S_{ALK}	Alkalinity

2.3.2.2 Observed Conversion Rates and Basic Processes

In ASM1 eight basic processes ($\rho_1, ..., \rho_8$) are introduced in order to describe biological behavior in bioreactors. The observed conversion rate (r_i and i = 1, ..., 13) is defined for each variable and describes the dynamic behavior of the variable when there is no input. The observed conversion rates result from a weighted sum of the basic processes. The observed conversion rates for 13 variables are given in the following equations:

$$(S_I)\ r_1 = 0 \tag{2.6}$$

$$(S_s)r_2 = -\frac{1}{Y_H}\rho_1 - \frac{1}{Y_H}\rho_2 + \rho_7 \tag{2.7}$$

$$(X_I)\ \ r_3 = 0 \tag{2.8}$$

$$(X_S)\ r_4 = (1-f_P)\rho_4 + (1-f_P)\rho_5 - \rho_7 \tag{2.9}$$

$$(X_{B,\ H})\ r_5 = \rho_1 + \rho_2 - \rho_4 \tag{2.10}$$

$$(X_{B,\ A})\ \mathrm{r}_6 = \rho_3 - \rho_5 \tag{2.11}$$

$$(X_P)\ \mathrm{r}_7 = f_p\rho_4 + f_p\rho_5 \tag{2.12}$$

$$(s_o)r_8 = -\frac{1-Y_H}{Y_H}\rho_1 - \frac{4.57-Y_A}{Y_A}p_3 \tag{2.13}$$

$$(S_{NO})r_9 = -\frac{1-Y_H}{2.86Y_H}\rho_2 + \frac{1}{Y_A}\rho_3 \tag{2.14}$$

$$\left(S_{NH}\right)r_{10} = -i_{XB}\rho_1 - i_{XB}\rho_2 - (i_{XB} + \frac{1}{Y_A})p_3 + p_6 \tag{2.15}$$

$$(S_{ND})\ r_{11} = -\rho_6 + \rho_8 \tag{2.16}$$

$$(X_{ND})\ \ r_{12} = (i_{XB} - f_P\, i_{XP})\rho_4 + (i_{XB} - f_P\, i_{XP})\rho_5 - \rho_8 \tag{2.17}$$

$$(SALK)r_{13} = \frac{i_{XB}}{14}\rho_1 + (1-Y_H\,14-2.86Y_H - \frac{iXB}{14})\rho_2 - (i_{XB}14 + \frac{1}{7Y_A})\rho_3 + \frac{1}{14}\rho_6 \tag{2.18}$$

The following describes the basic processes:

1 - Aerobic growth of heterotrophs:

$$\rho_1 = \mu_H \quad \frac{S_S}{K_S + S_S} \quad \frac{S_O}{K_{O,H} + S_O} X_{B,H} \tag{2.19}$$

2 - Anoxic growth of heterotrophs

$$\rho_2 = \mu_H \quad \frac{S_S}{K_S + S_S} \quad \frac{K_{O,H}}{K_{O,H} + S_O} \quad \frac{S_{NO}}{K_{NO} + S_{NO}} \eta_g X_{B,H} \tag{2.20}$$

3 - Aerobic growth of autotrophs

$$\rho_3 = \frac{S_{NH}}{K_{NH+}S_{NH}} \frac{S_o}{K_{o,A} + S_o} \text{ (2.21)} \qquad (2.21)$$

4 - Decay of heterotrophs

$$\rho_4 = b_H X_{B,H} \qquad (2.22)$$

5 - Decay of autotrophs

$$\rho_5 = b_A X_{B,A} \qquad (2.23)$$

6 - Ammonification of soluble organic nitrogen

$$\rho_6 = k_a S_{ND} X_{B,H} \qquad (2.24)$$

7 - Hydrolysis of entrapped organics

$$\rho_{7=k_H} \frac{X_s / X_{B,H}}{K_x + X_s / X_{B,H}} [(\frac{s_o}{K_{o,H} + s_o}) + \eta_h (\frac{K_{o,H}}{K_{o,H} + s_o})(\frac{s_o}{K_{NO} + s_{NO}})] X_{B,H} \qquad (2.25)$$

8 - Hydrolysis of entrapped organic nitrogen

$$\rho_{8=k_H} \frac{X_s / X_{B,H}}{K_x + X_s / X_{B,H}} [(\frac{s_o}{K_{o,H} + s_o}) + \eta_h (\frac{K_{o,H}}{K_{o,H} + s_o})(\frac{s_o}{K_{NO} + s_{NO}})] X_{B,H} ({}^{X_{ND}} / {}_{X_s}) \qquad (2.26)$$

2.1.1 Biological parameter values

In the above equations, there are stoichiometric and kinetic parameters. The unit and value of the parameters are given in Tables 2.2 and 2.3. In ASM1 there is a range for the value of each parameter and here the exact value for each parameter is the same as the values that are chosen in BSM1. In BSM1 the temperature is considered to be about 15 degrees Celsius.

Table 2. 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 2. 3: Kinetic parameters

Parameter	Unit	Value
μ_H	d^{-1}	4.0
K_S	g $COD.m^{-3}$	10.0
$K_{O,H}$	g $(-COD).m^{-3}$	0.2
K_{NO}	g $NO_3\text{-}N.m^{-3}$	0.05
b_y	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 $NH_3\text{-}N.m^{-3}$	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

2.3.3 Detailed Plant Layout

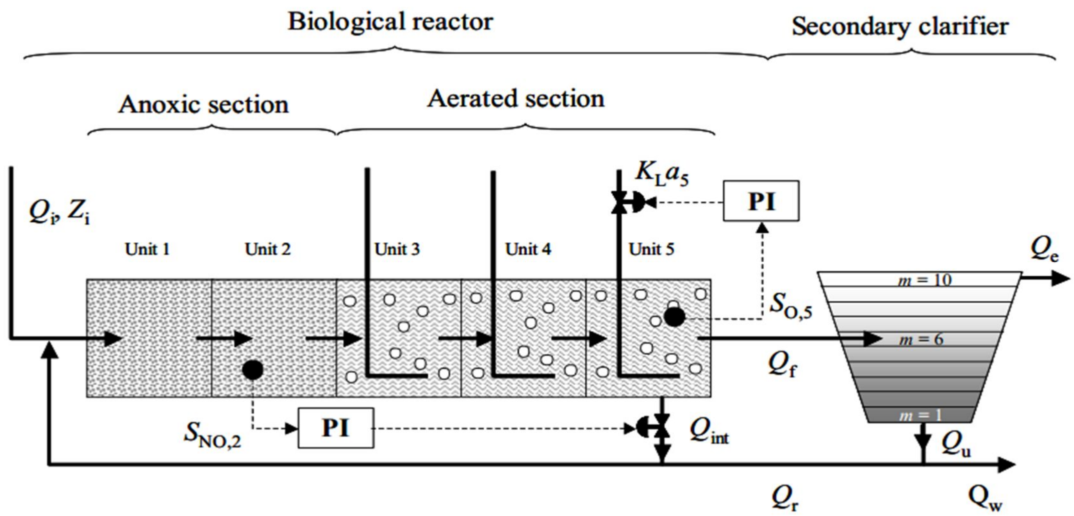


Figure 2.4. Benchmark Simulation Model no.1 [42]

2.3.3.1 General Characteristics of the Bioreactor

As it is shown in Figure 2.4 the bioreactor has a non-aerated compartment followed by an aerated one. Manipulation of the oxygen transfer coefficient (K_La) controls the DO level in the second tank. For each compartment consider these definitions:

Flow rate: Q_k, Concentration: Z_k, Volume: V_k, Reaction rate: r_k.

2.3.3.2 General Formula for Reactor Mass Balance

For the first tank:

$$\frac{dZ_1}{dt} = \frac{1}{V_1}\left(Q_r Z_r + Q_{in} Z_{in} + r_Z V_1 - Q_1 Z_1\right) \tag{2.27}$$

$$Q_1 = Q_r + Q_{in}$$

For the second tank:

$$\frac{dZ_2}{dt} = \frac{1}{V_2}(Q_1 Z_1 + r_Z V_2 - Q_2 Z_2) \tag{2.28}$$

$$Q_2 = Q_1$$

special case for oxygen: ($S_{O,2}$)

$$\frac{dS_{O,2}}{dt} = \frac{1}{V_2}\left(Q_1 S_{O,1} + r_8 V_2 + (K_L a)_2 V_2 (S_O^* - S_{O,2}) - Q_2 S_{O,2}\right) \tag{2.29}$$

$$\dot{S}_I = r_1 + D(S_{I,1} - S_{I,2}) \tag{2.30}$$

$$\dot{S}_S = r_2 + D(S_{S,1} - S_{S,2}) \tag{2.31}$$

$$\dot{X}_I = r_3 + D(X_{I,1} - X_{I,2}) \tag{2.32}$$

$$\dot{X}_S = r_4 + D(X_{S,1} - X_{S,2}) \tag{2.33}$$

$$\dot{X}_{B,H} = r_5 + D(X_{B,H,1} - X_{B,H,2}) \tag{2.34}$$

$$\dot{X}_{B,A} = r_6 + D(X_{B,A,1} - X_{B,A,2}) \tag{2.35}$$

$$\dot{X}_P = r_7 + D(X_{P,1} - X_{P,2}) \tag{2.36}$$

$$\dot{S}_I = r_9 + D(S_{I,1} - S_{I,2}) \tag{2.37}$$

$$\dot{S}_{NO} = r_1 0 + D(S_{NO,1} - S_{NO,2}) \tag{2.38}$$

$$\dot{S}_{NH} = r_1 1 + D(S_{NH,1} - S_{NH,2}) \tag{2.39}$$

$$\dot{S}_{ND} = r_1 2 + D(S_{ND,1} - S_{ND,2}) \tag{2.40}$$

$$\dot{S}_{ALK} = r_1 3 + D(S_{ALK,1} - S_{ALK,2}) \tag{2.41}$$

Where D $= Q_2/V_2$

2.3.4 Secondary Settler

There is no biological reaction in the secondary settler. In BSM1 the secondary settler has been modeled with 10 layers. The following describes the secondary settler that has been modeled in BSM1. The solid flux due to gravity is $J_s = v_s(X)X$ where X is the total sludge concentration. The settling velocity function, $v_s(X)$ is a double-exponential function:

$$v_s(X) = max\,[0, min\{v_0, v_0(e^{-r_h(X-Xmin)} - e^{-r_p(X-Xmin)}\}] \tag{2.42}$$

Table 2. 4: Settling parameters

Maximum settling velocity	v_0	$m.d^{-1}$	250.0
Maximum Vesilind settling velocity	v_0	$m.d^{-1}$	474
Hindered zone settling parameter	r_h	$m^3.(gSS)^{-1}$	.000576
Flocculant zone settling parameter	r_p	$m^3.(gSS)^{-1}$	0.00286
Non-settleable fraction	f_{ns}	dimensionless	.00228

With $X_{min} = F_{ns}X_f$. The parameter values for the settling velocity function are given in Table 2.4. With these notations, the mass balances for the sludge in different layers of the settler are written as: For the bottom layer (m=1)

$$\frac{dX_m}{dt} = \frac{v_{dn}(X_{m+1} - X_m) + min\,(J_{s,m}, J_{s,m+1})}{z_m} \tag{2.43}$$

For the intermediate layers below the feed layer (m=2 to m=5)

$$\frac{dX_m}{dt} = \frac{v_{dn}(X_{m+1} - X_m) + min(J_{s,m}, J_{s,m+1}) - min(J_{s,m}, J_{s,m-1})}{z_m} \tag{2.44}$$

For the feed layer (m=6)

$$\frac{dX_m}{dt} = \frac{\frac{Q_f X_f}{A} + J_{clar,m+1} - (v_{up} - v_{dn})X_m - min(J_{s,m}, J_{s,m-1})}{z_m} \tag{2.45}$$

For the intermediate clarification layers above the feed layer(m=7 to m=9)

$$\frac{dX_m}{dt} = \frac{v_{dn}(X_{m-1} - X_m) + J_{clar,m+1} - J_{clar,m}}{z_m} \tag{2.46}$$

$$\frac{dX_m}{dt} = \frac{v_{dn}(X_{m-1} - X_m) - J_{clar,m}}{z_m} \tag{2.47}$$

$$J_{clar,j} = \begin{cases} \min(v_{s,j}X_j, v_{s,j-1}X_{j-1}) ... if, x_{j-1} > x_t \\ v_{s,j}X_j .. if, x_{j-1} \leq x_t \end{cases}$$

Each layer for the soluble components (including dissolved oxygen) represents a completely mixed volume and the concentrations of soluble components are given as:

For the layers m=1 to 5

$$\frac{dZ_m}{dt} = \frac{v_{dn}(Z_{m+1} - Z_m)}{z_m} \tag{2.48}$$

For the feed layer, m = 6

$$\frac{dZ_m}{dt} = \frac{\frac{Q_f Z_f}{A} - (v_{dn} - v_{up})Z_m}{z_m} \tag{2.49}$$

For the layers m=7 to 10

$$\frac{dX_m}{dt} = \frac{v_{up}(Z_{m-1} - Z_m)}{z_m} \tag{2.50}$$

The concentration in the recycle and wastage flow are equal to those of the first layer bottom layer). The sludge concentration into the settler can be calculated from concentrations in the second compartment of the activated sludge reactor:

$$X_f = 0.75(X_{S,2} + X_{P,2} + X_{I,2} + X_{B,H,2} + X_{B,A,2}) \tag{2.51}$$

The same principle is applied for X_u (in the settler underflow) and X_e (at the plant exit). Across the settler, the ratio of a particulate concentration to the total solid concentration is assumed to remain constant:

$$\frac{X_{S,2}}{X_f} = \frac{X_{S,u}}{X_u}$$

Similar equations hold for $X_{P,u}$, $X_{I,u}$, $X_{B,H,u}$, $X_{B,A,u}$ and $X_{ND,u}$. This assumption means that the dynamics of the fractions of particulate concentrations in the inlet of the settler will be directly propagated to the settler underflow and overflow, without taking into account the normal retention time in the settler.

In the steady-state case the sludge age calculation is based on the total amount of biomass present in the reactor and the settler:

$$Age = \frac{TX_a + TX_s}{\varphi_e + \varphi_w} \tag{2.52}$$

where TX_a is the total amount of biomass present in the reactor:

$$TX_a = \sum_{i=1}^{2} (X_{B,H,i} + X_{B,A,i}).V_{i\Sigma\Sigma} \tag{2.53}$$

TX_s is the total amount of biomass present in the settler:

$$TX_s = \sum_{i=1} (X_{B,H,i} + X_{B,A,i}).z_j.A \tag{2.54}$$

where V is the volume of the tank and A is the area of the settler which is constant. φ_e is the loss rate of biomass in the effluent:

$$\varphi_e = (X_{B,H,m} + X_{B,A,m}).Q_e \tag{2.55}$$

with m = 10 and φ_w is the loss rate of biomass in the wastage flow

$$\varphi_w = (X_{B,H,u} + X_{B,A,u}).Q_w \tag{2.56}$$

In an actual plant, the sludge age is measured based on the total amount of solids present in the system.

$$Age = \frac{TX_{fa} + TX_{fs}}{\varphi_{fe} + \varphi_{fw}} \tag{2.57}$$

where TS_{fa} is the total amount of solids present in the reactor

$$TX_{fa} = \sum_{i=1}^{2} X_{f,i}.V_i \tag{2.58}$$

$$X_{f,i} = 0.75(X_{S,i} + X_{P,i} + X_{I,i} + X_{B,H,i} + X_{B,A,i})$$

TX_{fs} is the total amount of solids present in the settler:

$$TX_{fs} = \sum_{j=1}^{1} 0X_{f,i}.z_j.A \tag{2.59}$$

$$X_{f,j} = 0.75(X_{S,j} + X_{P,j} + X_{I,j} + X_{B,H,j} + X_{B,A,j})$$

φ_{fe} is the loss rate of solids in the effluent:

$$\varphi_{fe} = X_{f,m}.Q_e \tag{2.60}$$

with $X_{f,m} = 0.75(X_{S,m} + X_{P,m} + X_{I,m} + X_{B,H,m} + X_{B,A,m})$ for m=10, and φ_w is the loss rate of solids in the wastage flow:

$$\varphi_w = X_{f,u}.Q_w \tag{2.61}$$

$$X_{f,u} = 0.75(X_{S,u} + X_{P,u} + X_{I,u} + X_{B,H,u} + X_{B,A,u})$$

This chapter describes the details of two models for an activated sludge process. It is unrealistic to assume that the parameters of these models can be known for control design purposes. Thus, the objective of this thesis is to design an adaptive ANNRBFPID controller, capable of stabilizing the system and making the output track the desired set points in spite of unknown parameters and disturbances.

CHAPTER THREE

3 Review of Neural Network and algorithm design

3.1 Artificial neural network

Artificial neural networks (**ANN**) or **connectionist systems** are computing systems vaguely inspired by the biological neural networks that constitute animal brains. The neural network itself is not an algorithm, but rather a framework for many different machine learning algorithms to work together and process complex data inputs.[6] Such systems "learn" to perform tasks by considering examples, generally without being programmed with any task-specific rules. For example, an image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images. They do this without any prior knowledge about cats, for example, that they have fur, tails, whiskers and cat-like faces. Instead, they automatically generate identifying characteristics from the learning material that they process.[43]

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it.

In common ANN implementations, the signal at a connection between artificial neurons is a real number, and the output of each artificial neuron is computed by some non-linear function of the sum of its inputs. The connections between artificial neurons are called 'edges'. Artificial neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Artificial neurons may have a threshold such that the signal is only sent if the aggregate signal crosses that threshold. Typically, artificial neurons are aggregated into layers. Different layers may perform different kinds of transformations on their inputs. Signals travel from the first layer (the input layer) to the last layer (the output layer), possibly after traversing the layers multiple times.[44]

3.1.1 A Single Neuron

The basic unit of computation in a neural network is the **neuron**, often called a **node** or **unit**. It receives input from some other nodes, or from an external source and computes an output. Each input has an associated **weight** (w), which is assigned on the basis of its relative importance to other inputs. The node applies a function ***f*** (defined below) to the weighted sum of its inputs as shown in Figure 1 below:

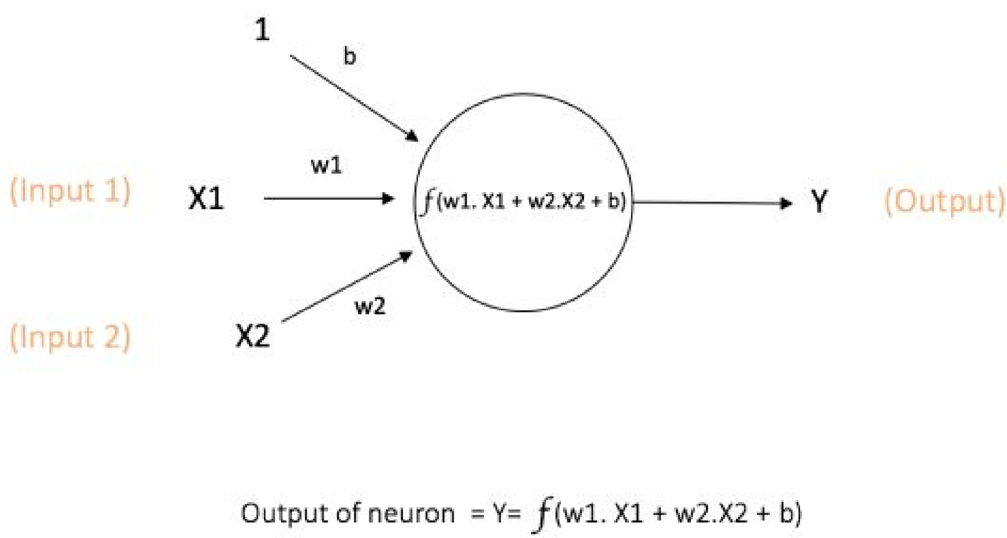


Figure 1: a single neuron [45]

The above network takes numerical inputs **X1** and **X2** and has weights **w1** and **w2** associated with those inputs. Additionally, there is another input **1** with weight **b** (called the **Bias**) associated with it. We will learn more details about the role of the bias later.

The output **Y** from the neuron is computed as shown in Figure 1. The function ***f*** is non-linear and is called the **Activation Function**. The purpose of the activation function is to introduce non-linearity into the output of a neuron. This is important because most real-world data are nonlinear and we want neurons to *learn* these nonlinear representations.

Every activation function (or *non-linearity*) takes a single number and performs a certain fixed mathematical operation on it [45]. There are several activation functions you may encounter in practice:

- **Sigmoid:** takes a real-valued input and squashes it to range between 0 and 1

  $\sigma(x) = 1 / (1 + \exp(-x))$

- **tanh:** takes a real-valued input and squashes it to the range [-1, 1]

  $\tanh(x) = 2\sigma(2x) - 1$

- **ReLU**: ReLU stands for Rectified Linear Unit. It takes a real-valued input and thresholds it at zero (replaces negative values with zero) $f(x) = \max(0, x)$

3.1.2 Feedforward Neural Network

The feedforward neural network was the first and simplest type of artificial neural network devised [45]. It contains multiple neurons (nodes) arranged in **layers**. Nodes from adjacent layers have **connections** or **edges** between them. All these connections have **weights** associated with them. An example of a feedforward neural network is shown in Figure 3.

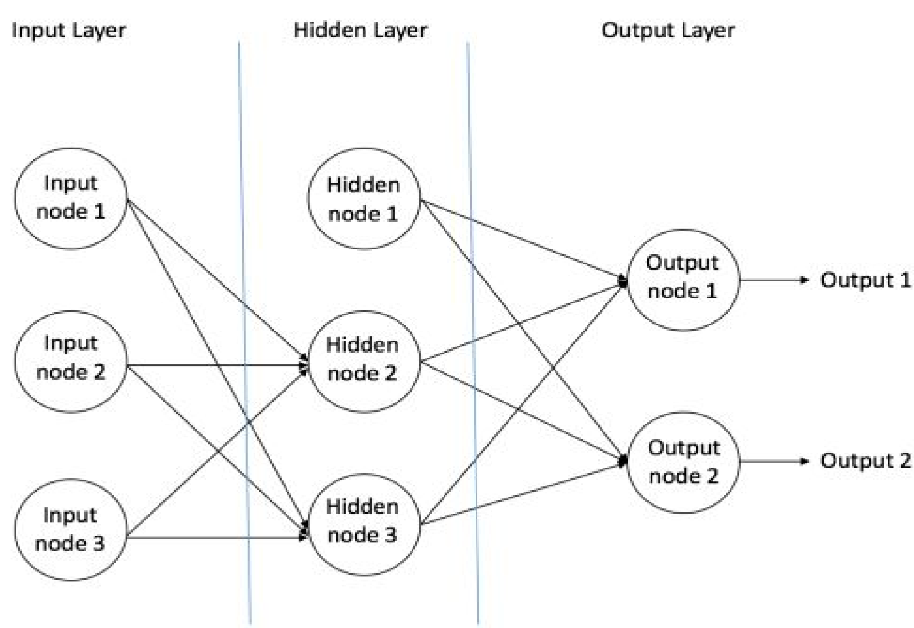


Figure 3: an example of feedforward neural network [45]

A feedforward neural network can consist of three types of nodes:

1. **Input Nodes –** The Input nodes provide information from the outside world to the network and are together referred to as the "Input Layer". No computation is performed in any of the Input nodes – they just pass on the information to the hidden nodes.

2. **Hidden Nodes –** The Hidden nodes have no direct connection with the outside world (hence the name "hidden"). They perform computations and transfer information from the input nodes to the output nodes. A collection of hidden nodes forms a "Hidden Layer". While a feedforward network will only have a single input layer and a single output layer, it can have zero or multiple Hidden Layers.

3. **Output Nodes –** The Output nodes are collectively referred to as the "Output Layer" and are responsible for computations and transferring information from the network to the outside world. In a feedforward network, the information moves in only one direction – forward – from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network [47] (this property of feedforward networks is different from Recurrent Neural Networks in which the connections between the nodes form a cycle).

Two examples of feedforward networks are given below: **Single Layer Perceptron** – This is the simplest feedforward neural network and does not contain any hidden layer. **Multi-Layer Perceptron** – A Multi-Layer Perceptron has one or more hidden layers. We will only discuss Multi-Layer Perceptrons below since they are more useful than Single Layer Perceptions for practical applications today.

3.1.2.1 Multi-Layer Perceptron

A Multi-Layer Perceptron (MLP) contains one or more hidden layers (apart from one input and one output layer). While a single layer perceptron can only learn linear functions, a multi-layer perceptron can also learn non – linear functions.

Figure 4 shows a multi-layer perceptron with a single hidden layer. Note that all connections have weights associated with them, but only three weights (w0, w1, w2) are shown in the figure.

Input Layer: The Input layer has three nodes. The Bias node has a value of 1. The other two nodes take X1 and X2 as external inputs (which are numerical values depending upon the input dataset). As discussed above, no computation is performed in the Input layer, so the outputs from nodes in the Input layer are 1, X1 and X2 respectively, which are fed into the Hidden Layer.

Hidden Layer: The Hidden layer also has three nodes with the Bias node having an output of 1. The output of the other two nodes in the Hidden layer depends on the outputs from the Input layer (1, X1, X2) as well as the weights associated with the connections (edges). Similarly, the output from another hidden node can be calculated. Remember that ***f*** refers to the activation function. These outputs are then fed to the nodes in the Output layer.

3.1.3 Backpropagation

Backward Propagation of Errors, often abbreviated as Backprop is one of the several ways in which an artificial neural network (ANN) can be trained. It is a supervised training scheme, which means, it learns from labeled training data (there is a supervisor, to guide its learning). To put in simple terms, Backprop is like “learning from mistakes “. The supervisor corrects the ANN whenever it makes mistakes. An ANN consists of nodes in different layers; input layer, intermediate hidden layer(s) and the output layer. The connections between nodes of adjacent layers have “weights” associated with them. The goal of learning is to assign correct weights for these edges. Given an input vector, these weights determine what the output vector is. In supervised learning, the training set is labeled. This means, for some given inputs, we know the desired/expected output (label). Backpropagation Algorithm**:** Initially all the edge weights are randomly assigned. For every input in the training dataset, the ANN is activated and its output is observed. This output is compared with the desired output that we already know, and the error is “propagated” back to the previous layer. This error is noted and the weights are “adjusted” accordingly. This process is repeated until the output error is below a predetermined threshold.

3.2 Radial Basis Function (RBF) Neural Network

Artificial neural network (ANN) is an artificial intelligence system to imitate biological neural networks (BNN). It uses the nonlinear processing unit to simulate biological neurons for simulating the behavior of biological synapses among neurons by adjusting the variable weights between connected units. The specific topological structure of the network is organized from each processing unit in a certain connected form. Parallel processing ability and distributed storage are the main features of ANN. Furthermore, it has strong fault tolerance and nonlinear mapping ability with self-organization, self-learning and adaptive reasoning ability [34].

BP (backpropagation) network and RBF network are the most widely used forms of ANN. It is easy to be seen in the widely uses of pattern recognition, prediction, automatic control, etc. [35]. BP algorithm, a supervised learning algorithm, is based on a gradient descent algorithm. The drawbacks of BP include an easy fall into local optimum, slow convergence speed, and disunity network structure. RBF network is a feedforward network based on the function approximation theory. It has strong global approximation ability, which can guarantee the network to approximation any kind of nonlinear function with arbitrary accuracy. It can fundamentally overcome the problem of local optimum occurs in the BP network. The RBF network has the advantages of simple structure, fast convergence speed and strong generalization ability [36].

Radial basis function (RBF) neural network used in this paper is a three-layer forward network, which is a local approximation method of neural networks. The RBF neural network is composed of three layers, the input layer, the hidden layer and the output layer as shown in Figure3. The mapping of the input layer to the output layer is nonlinear and the mapping of the space from the hidden layer to the output layer is linear. This kind of mapping configuration itself can speed up the learning rate and avoid the problem of local minima [24].

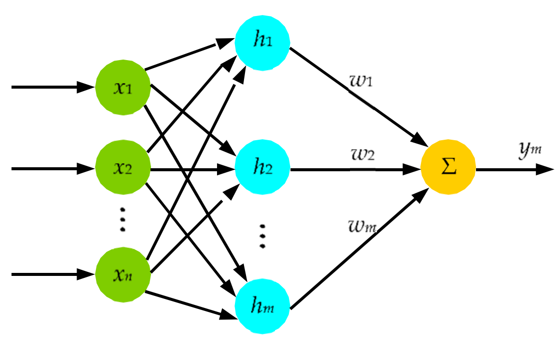


Figure 3. 1 Topology of a radial basis function (RBF) neural network. [48]

In Figure 3.1, the input vector of the input layer of the neural network is represented as:

$$X = [x_1, x_2, \cdots x_s, \cdots, x_n]^T \tag{3.0}$$

where, $x_s = [u_s(k), y_s(k), y_s(k-1)]$, s = 1, 2, . . . , n; $u(k)$ is the output of the controller; $y(k)$ is the present (measured) output of the system (or process), that is, the measured value of DO concentration; $y(k-1)$ is the last measured value of DO concentration 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

radial basis vector of the nodes in the RBF neural network is shown in Equation (3.1).

$$T = [h_1, h_2, \cdots, h_j, \cdots, h_m]^T \tag{3.1}$$

Wher hj is a Gaussian function

$$h_j = \exp((\frac{\| x - c_j \|}{2b_j^2})) \tag{3.2}$$

Where, j= 1, 2…., m. c_j is the central vector of the first j node of the hidden layer of the RBF neural network,

$$c_j = [c_{j1,} c_{j2,} ..., c_{ji,} ..., c_{jn}]^T \tag{3.3}$$

Where, i=1, 2…, n. The basic width vector of the hidden layer node of the RBF neural network is

$$B = [b_1, b_2, \cdots, b_j, \cdots, b_m]^T \tag{3.4}$$

where, b_j is the parameter of the first j node and j = 1, 2, . . ., m. The weight vector of RBF neural network W is given by:

$$W = [w_1, w_2, \cdots, w_j, \cdots, w_m]^T \tag{3.5}$$

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

$$y_m = w_1 h_1 + w_2 h_2 + \cdots + w_m h_m \tag{3.6}$$

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

$$E_1 = \frac{1}{2} (y(k) - y_m(k))^2 \tag{3.7}$$

From the above equations, the three most critical parameters C, W and B of a RBF neural network obtained by learning algorithm. In this paper, the gradient descent method is employed to obtain those three parameters of the nodes. The iterative algorithm used is as follows.

$$w_j(k) = w_j(k-1) + \eta(y(k) - y_m(k))h_j + \alpha(w_j(k-1) - w_j(k-2)) \tag{3.8}$$

$$\Delta b_j = (y(k) - y_m(k))w_j h_j \frac{\| x - c_j \|^2}{b_j^3} \tag{3.9}$$

$$b_j(k) = b_j(k-1) + \eta\Delta b_j + \alpha(b_j(k-1) - b_j(k-2)) \tag{3.10}$$

$$\Delta c_{ji} = (y(k) - y_m(k))w_j \frac{x - c_{ji}}{b_j^2} \tag{3.11}$$

$$c_{ji}(k) = c_{ji}(k-1) + \eta\Delta c_{ji} + \alpha(c_{ji}(k-1) - c_{ji}(k-2) \tag{3.12}$$

and the Jacobian matrix:

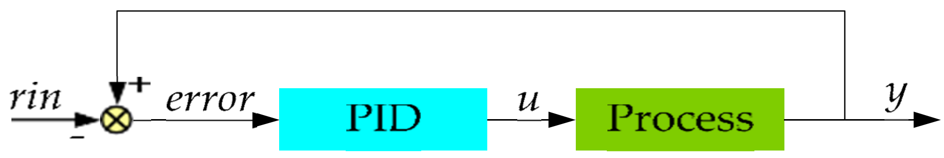
$$\frac{\partial y(k)}{\partial u(k)} \approx \frac{\partial y_m(k)}{\partial u(k)} = \sum_{j=1}^{m} w_j h_j \frac{c_{ji} - x_1}{b_j^2} \tag{3.13}$$

3.3 An Adaptive Neural Network Based Radial Basis PID Algorithm

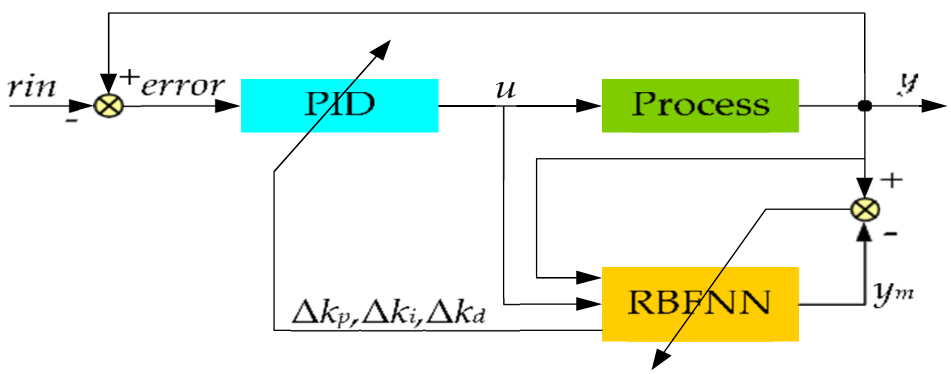
In the past decades, Proportional-Integral-Derivative (PID) is the main control method for the DO level [36,37]. However, owing to the WWTP's time-varying feature, strong nonlinearity, significant perturbations, and large uncertainty, a fixed parameter linear controller is not able to maintain a satisfactory tracking performance under the full range of operating conditions [1,38].

The structure of the RBF neural network-based adaptive PID (RBFNNPID) algorithm is shown in Figure 3.2. The RBF neural network will adaptively calculate the weighting coefficient and the parameter gradient information according to the operating state of the dissolved oxygen control system, by its own great learning ability. These results will be used to update the parameters of the

PID controller in real time. Hence, such a repeated execution process realizes the adaptive adjustment of PID parameters and achieves the control of DO concentration.



(a) Block diagram of a traditional PID controller in a feedback loop [48]



(b) Block diagram of proposed RBF Adaptive Neural Network Based Radial Basis PID Algorithm (ANNRBF PID). PID: Proportional-Integral-Derivative. [48]

Figure 3. 2 Block diagram comparing PID and ANNRBFPID controllers

We have adopted the incremental PID controller and the control error is:

$$error(k) = rin(k) - y(k) \tag{3.14}$$

where, rin is the desired process value or setpoint of DO concentration; $y(k)$ is the measured process value of DO.

The input of the PID algorithm is three errors, which are defined as:

$$xc\,(1) = error(k) - error\,(k-1) \tag{3.15}$$

$$xc\,(2) = error(k) \tag{3.16}$$

$$xc\ (3) = error(k) - 2error\ (k-1) + error\ (k-2) \tag{3.17}$$

The output of the PID algorithm is:

$$u(k) = u\ (k-1) + \Delta u(k) \tag{3.18}$$

$$\Delta u(k) = k_p xc\ (1) + k_i xc\ (2) + k_d xc\ (3) \tag{3.19}$$

where, k_p, k_i and k_d are the three parameters of the PID controller, which represents the proportion, integration and differentiation. The performance function is defined as:

$$E(k) = \frac{1}{2}\left(error(k)\right)2 \tag{3.20}$$

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

$$\Delta k_p = -\eta \frac{\partial E}{\partial k_p} = -\eta \frac{\partial E \partial y \partial u}{\partial y \partial u \partial k_p} = -\eta error(k) \frac{\partial y}{\partial u} xc(1) \tag{3.21}$$

$$\Delta k_i = -\eta \frac{\partial E}{\partial k_i} = -\eta \frac{\partial E \partial y \partial u}{\partial y \partial u \partial k_i} = -\eta error(k) \frac{\partial y}{\partial u} xc(2) \tag{3.22}$$

$$\Delta k_d = -\eta \frac{\partial E}{\partial k_d} = -\eta \frac{\partial E \partial y \partial u}{\partial y \partial u \partial k_d} = -\eta error(k) \frac{\partial y}{\partial u} xc(3) \tag{3.23}$$

in which, $\partial y/\partial u$ is the identification information for the Jacobian matrix of the controlled object and it can be obtained through the identification process of the neural network. The Jacobian matrix reflects the sensitivity of the output of the controlled object to the change of the input of the control.

The steps of the proposed RBFNNPID control strategy are as follows:

Step 1: Initializing the network parameters, including the number of nodes in input layers and hidden layers, learning rate, inertia coefficient, the base width vector, and the weight vector.

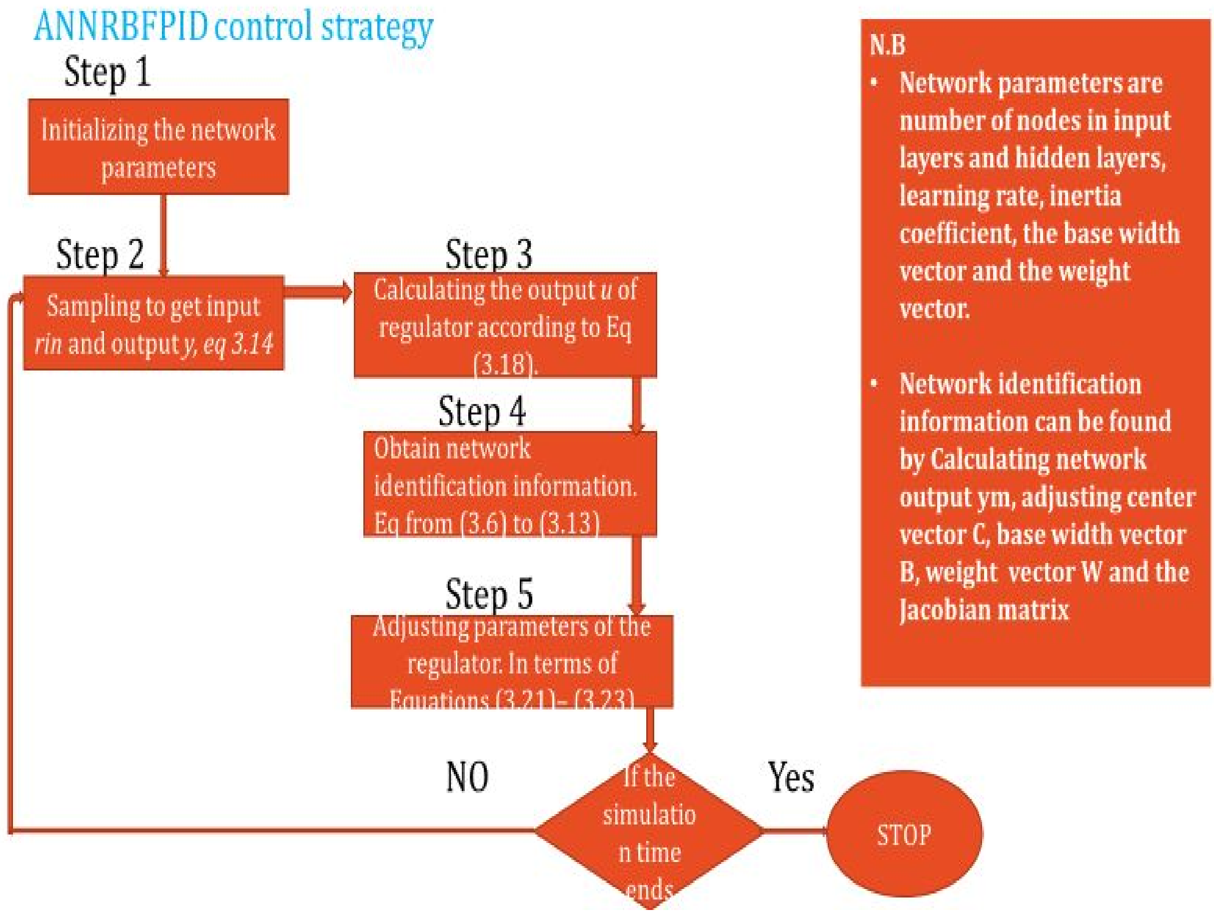
Step 2: Sampling to get input *rin* and output *y*, calculating error in terms of Equation (3.14).

Step 3: Calculating the output *u* of regulator according to Equation (3.18).

Step 4: Calculating network output y_m, adjusting center vector *C*, base width vector B, weight vector *W* and the Jacobian matrix in terms of Equations from (3.6) to (3.13) to obtain network identification information.

Step 5: Adjusting parameters of the regulator in terms of Equations (3.21)– (3.23).

Step 6: Back to *Step 2* and repeat the subsequent steps until the end of the simulation time.



CHAPTER FOUR

4 RESULTS AND DISCUSSION

4.1 Introduction

In this thesis, the simulation of the model and controller was performed using MATLAB/Simulink and SIMBA# software packages. The concentration of Dissolved oxygen (DO) in the aeration tanks has a great effect on treatment efficiency, operational cost, and system stability.

As the DO drops

- The quantity of filamentous microorganisms increases and this affects the settle-ability of activated sludge.
- The continuous drop of DO seriously affects treatment efficiency by increasing effluent turbidity and leads to treatment deterioration.
- The efficiency of organic matter degradation reduced.

Higher DO

Excessive DO leads to

- The problem in settling of sludge due to shearing of flocks and re-suspension of inert materials.
- Makes the denitrification less efficient.
- Waste of energy.

Thus, how the wastewater treatment process can perform stable will depend on how effectively the concentration of DO is maintained within a reasonable range.

How DO maintained in a reasonable range

- Due to a complex nature of microbial activities, even a small change of (change of in flow rate, the water quality of influent, the temperature of wastewater) can affect the concentration of DO.
- The air supplied to aeration tanks by blowers allow the oxygen to be transferred from air to liquid phase.

4.2 The wastewater-free dynamics model in Simulink and overall model simulation and results

The table below shows the initial values of model coefficients the simplified waste water obtained experimentally from previous studies.

Table 4. 1 The simplified model coefficients [43]

Parameters	Values
DO_{max}	10mg/l
S_{in}	200mg/l
DO_{in}	0.5mg/l
Y	0.65
A	0.018/m3
R	0.6/h
$\mu_{\max}$	0.15/h
B	0.2
K_S	100mg/l
K_0	0.5
K_{DO}	2mg/l

The simulation block diagram for the open loop simplified wastewater treatment model can be seen in Figure 4.1. It comprises four states in the system: $X(t)$ – biomass concentration, $S(t)$ – substrate concentration, $DO(t)$ – dissolved oxygen concentration, $Xr(t)$ – recycled biomass. And manipulated variables and reaction components such as:

- D is the dilution rate
- b = (waste flow)/ (influent flow)
- W is the air flow rate
- S_{in} is the substrate concentration in the influent load
- C_{in} is the dissolved oxygen concentration in the influent load
- C_s is the maximum dissolved oxygen concentration
- Y is the cell mass

- K_0 is a positive constant

The air flow rate (W) and the recycled rate (r) are the manipulated (input) variables.μ is t the specific growth rate.

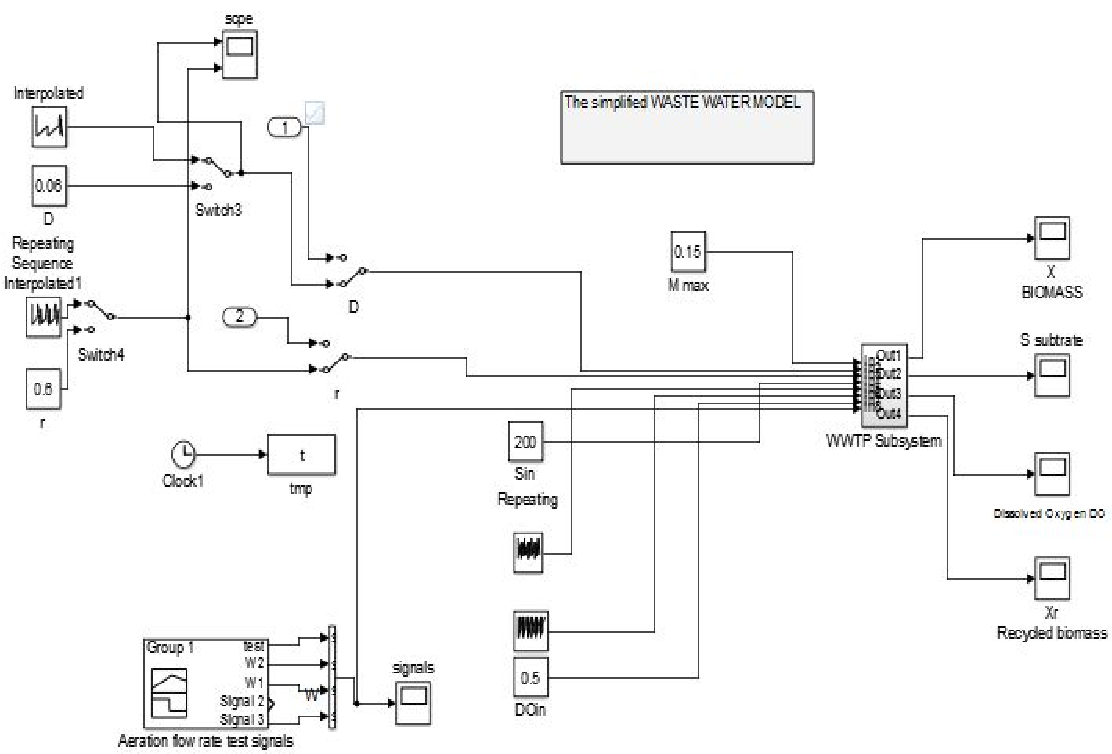


Figure 4. 1 The Simulink model corresponds to the equations and parameters listed in the previous sub-section 2.3.1

The internal block structure of WWTP subsystem of figure 4.1 can be seen in appendix of figure B.2. First, the free dynamics of the model without any controller is tested and how it responds for the change of some influent parameters such as: recycle rate(r), dilution rate(D), the substrate in the influent(Sin) and Dissolved oxygen in the influent(DOin).

4.3 Dissolved oxygen response for continuously varying influent parameters

1. How the change of recycling rate r and dilution rate D affects the concentration of dissolved oxygen DO.

    Case 1: constant r and variable D

Case 2: constant D and variable r

Case 3: both varying r and D

Figure 4.2 shows how the DO concentration varies when recycling flow (r) and Dilution rate D) varies. DO changes rapidly whenever r and D changes.

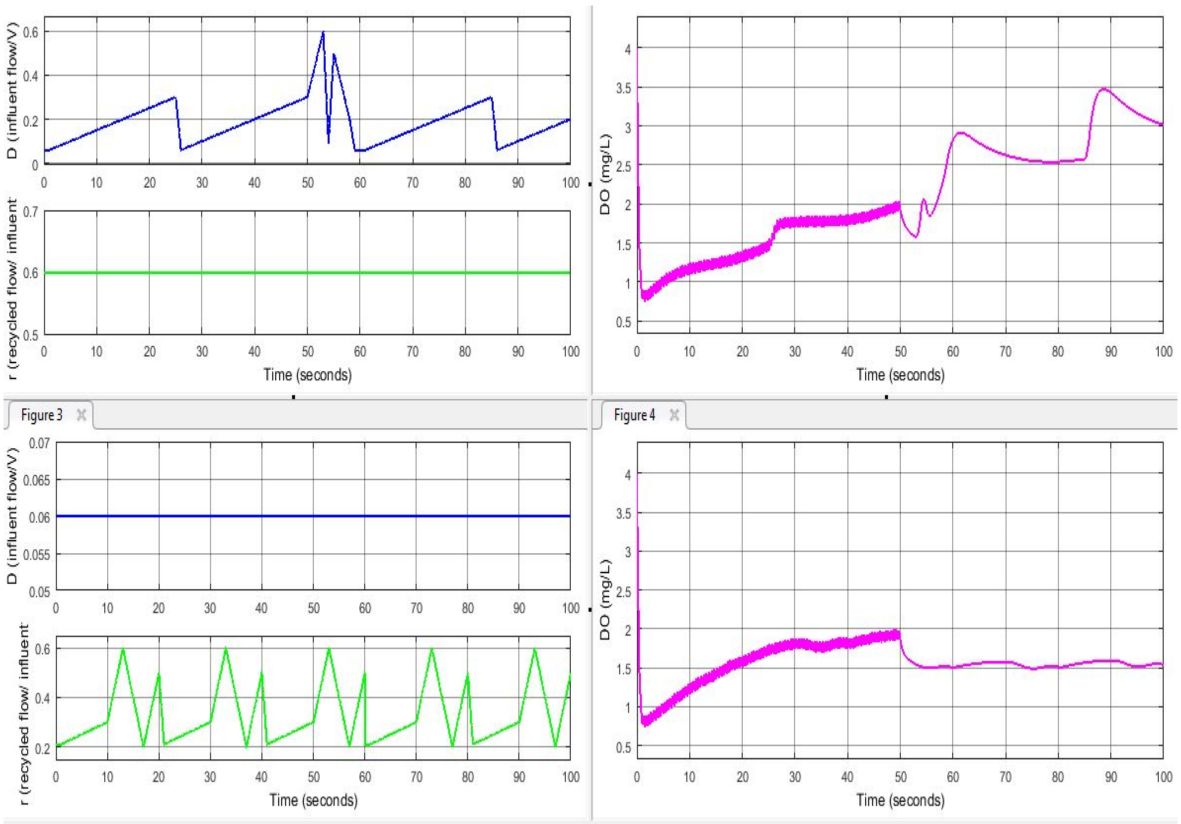


Figure 4. 2 The response of DO for the continious change of r and constant D

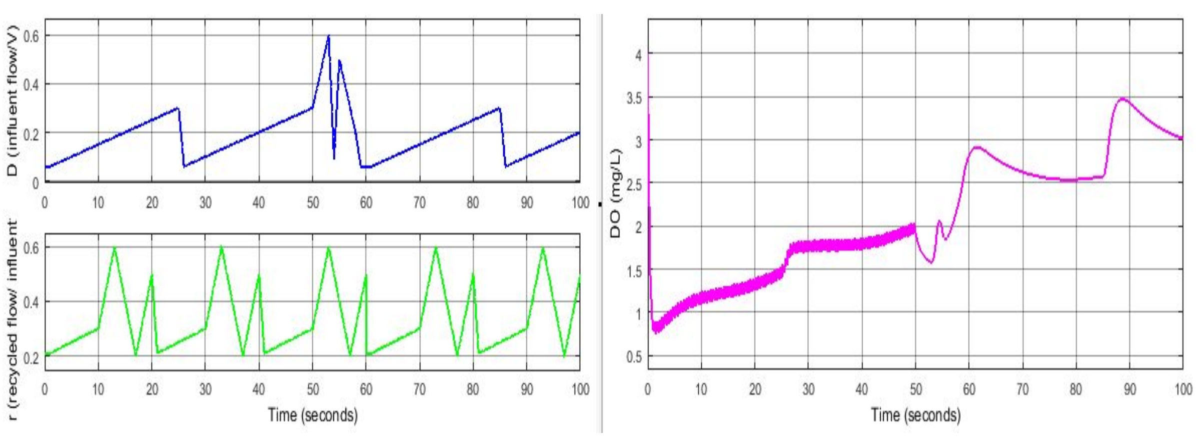


Figure 4. 3 The response of DO for the continious change of r and D

2. How the change of S_{in} is the substrate concentration in the influent load, DOin dissolved oxygen in the influent effects DO.

1. Constant Sin and variable DOin
2. Constant DOin and variable Sin
3. Variable r, D, SOin and DOin

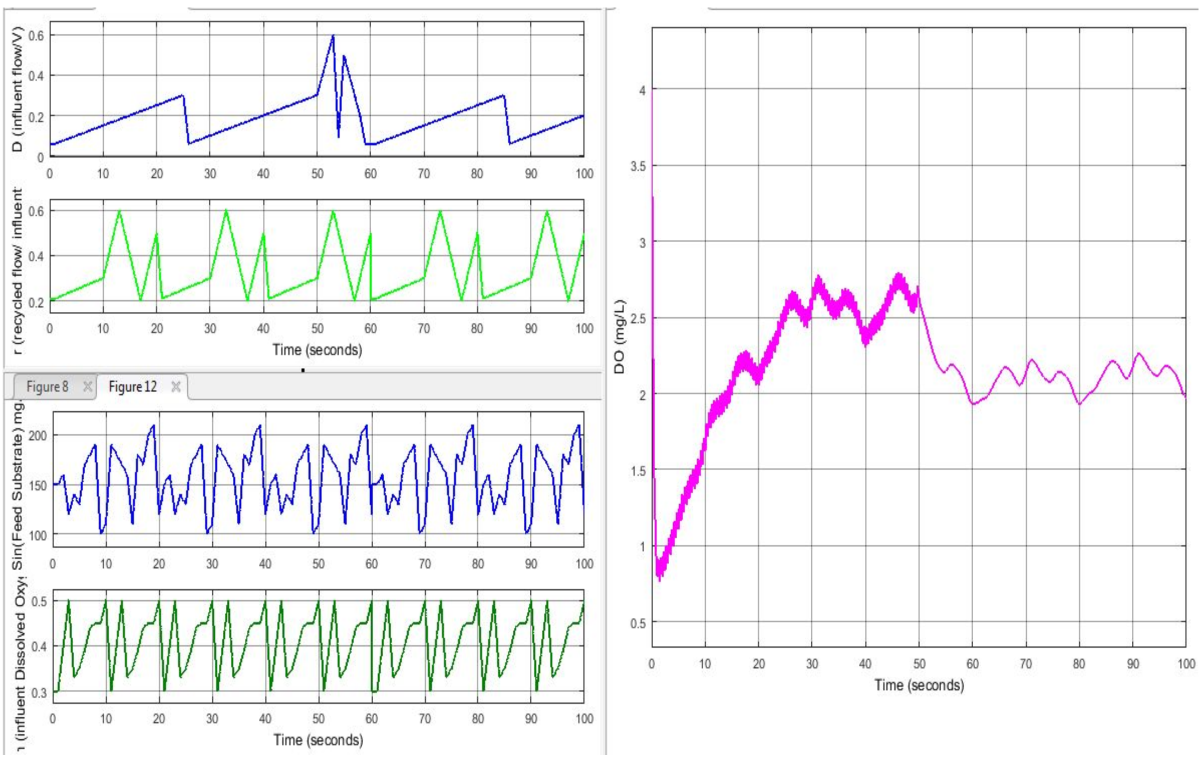


Figure 4. 4 The response of DO for the continious change r, D, SOin and DOin.

Figure 4.4 above and Figure 4.5below shows how DO concentration affected whenever r, D, SOin, and DOin varies. This shows how a controller is necessary for DO to secure the DO concentration in the desired set point.

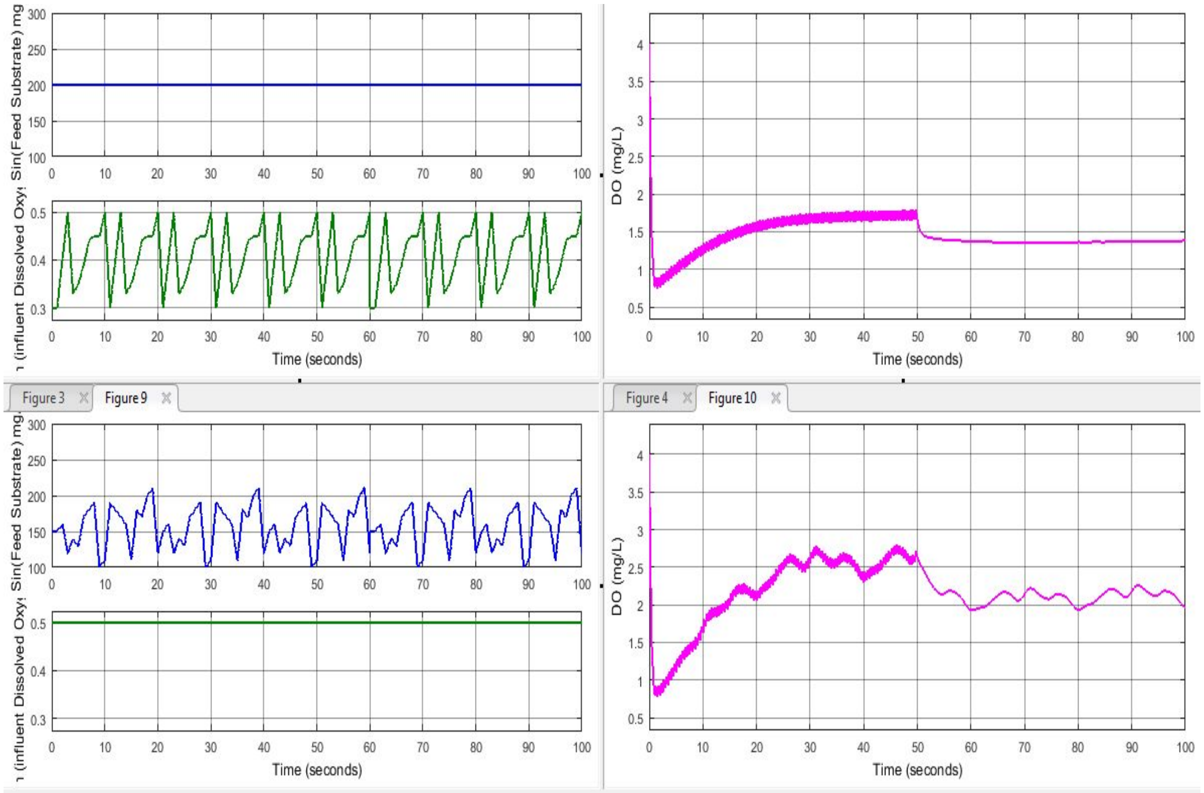


Figure 4. 5 The response of DO for the continious change SOin and DOin.

4.4 Biomass and Substrate sensitivity

How the change of recycler rate r and dilution rate affects the substrate(S) and biomass (X) concentration.

1.1 Constant r and D and the response of S and X.

1.2 Variable r and D and the response of S and X.

Figure 4.6 below shows, on the left half of the figure, when constant D and r are given S Substrate concentration and X biomass concentration become somehow constant, and the right side shows how variable D and r affects the X and S concentration. In reality, X and S concentration is not measurable rather they are observable but limiting the DO concentration at 2mg/l lets the whole wastewater treatment process performance at the desired concentration.

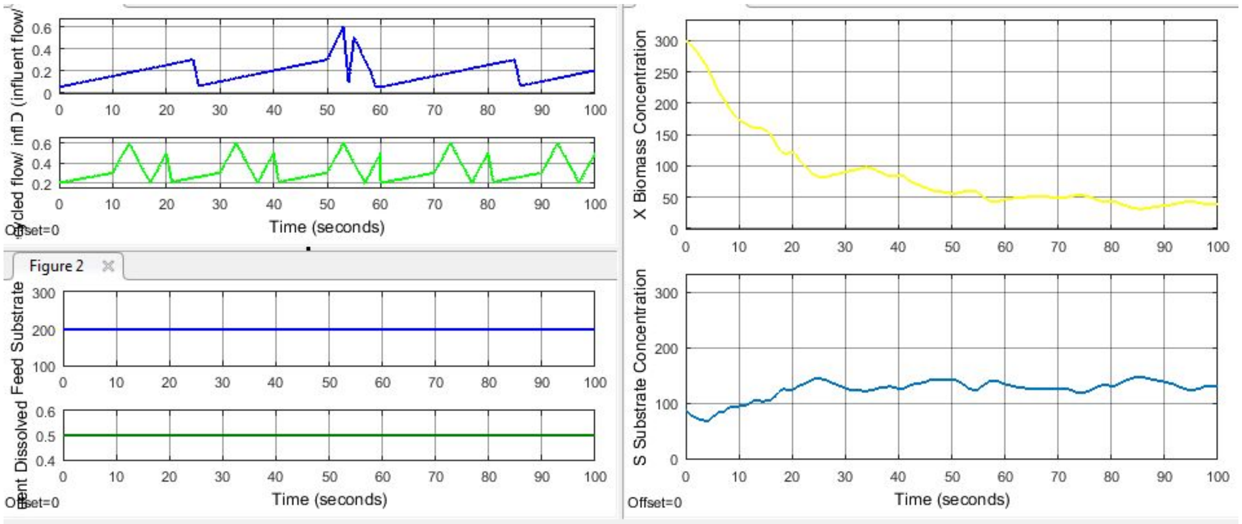


Figure 4. 6 The response of S Substrate and Biomass X for Constant Sin, DOin and Variable D,r

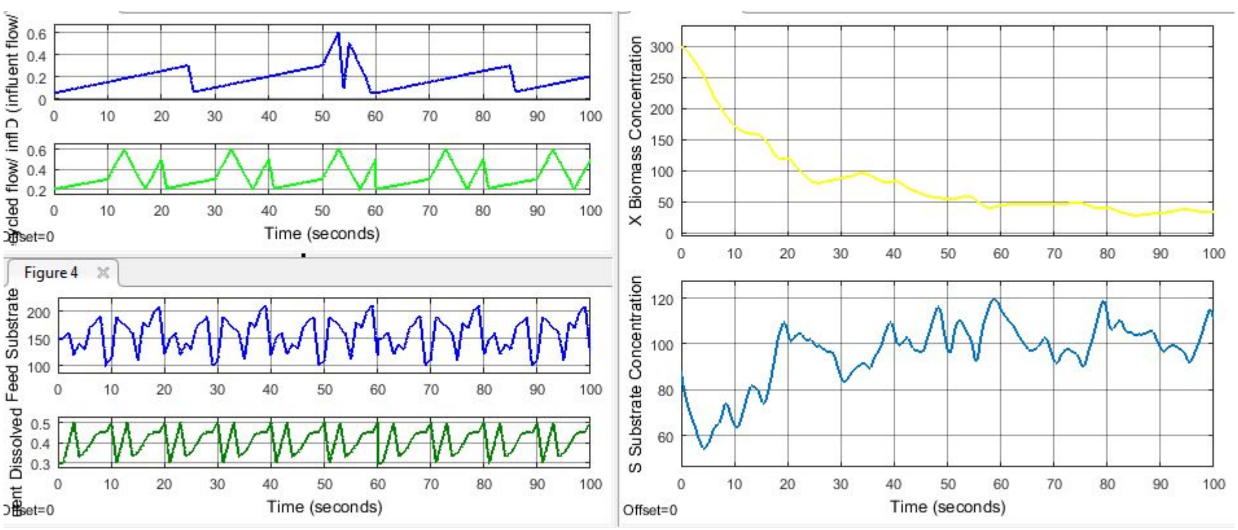


Figure 4. 7 The response of S and X for Variable r, D, Sin, and DOin

Note that: As shown above, the dilution rate and recycle rate has a great influence on state variables, and it is observed that when the dilution rate decreases X increases and DO concentration also increase. On the other hand, when r increases biomass concentration increases and the DO concentration decreases.

In reality, the only measurable parameter is DO and the other 3 state variables are observable rather than measurable. The objective of this thesis is to make the DO concentration at the desired set point (2mg/l) in any weather condition and disturbances. But this is achieved by manipulation of aeration from blowers according to the current DO concentration.

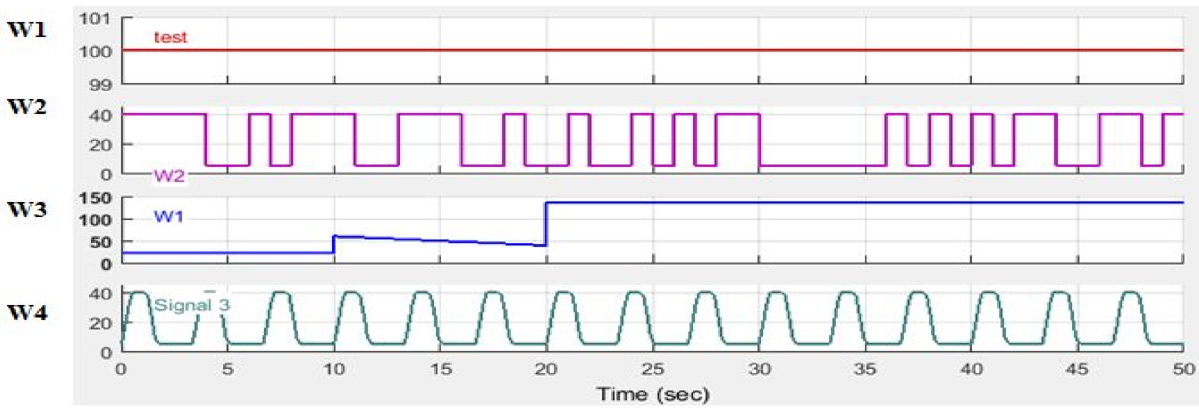
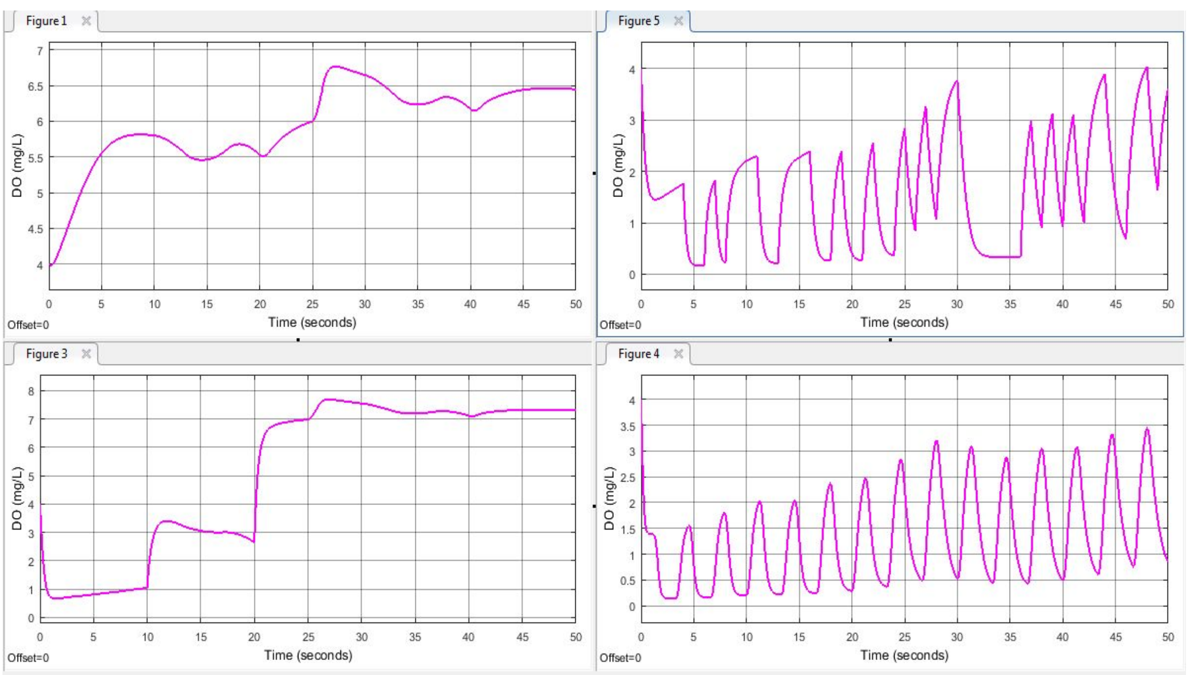


Figure 4. 8 Four aeration test signals, w reperesents for air flow rate



Test-Figure1   W2-Figure3   W1-Figure5 Signal 3-Figure4

Figure 4. 9 The response of DO for four aeration test signals

As mentioned in the previous sections, the only possible way to control the Dissolved Oxygen(DO) is by controlling the amount of aeration released from the blowers. So, four different aeration signals constant signal, pseudo random signal and sampled sign wave signals are given and how DO respond for each is analyzed in Figure 4.8. When constant signal given the DO become not constant this is due to different non -linear and uncertain input parameters which affect DO also as shown from Fig 4.2 to 4.5. But DO increases as aeration increase and decreases as aeration decreases non-linearly.

The objective of this research is to maintain the DO level at 2 mg/l no matter how continuously varying input parameters and disturbances present and to follow any kind of set-point. As mentioned in many previous research papers keeping the DO level at desired point keeps all unmeasured parameters within an acceptable range. In the following section, the results obtained by integrating the proposed intelligent controller is discussed.

4.5 Results when Adaptive Neural Network Radial Basis Function PID (ANNRBF PID) and conventional PID integrated into the waste water model

The effectiveness and feasibility of proposed Adaptive Neural Network Radial Basis Function PID (ANNRBF PID) algorithm for DO concentration control of activated sludge process in wastewater treatment system is validated by comparison of simulation of ANNRBF PID and conventional PID.

The complete Simulink® model implemented on MATLAB® is shown in Figure 4.9. whose simulation results for comparison of simulation of ANNRBF PID and conventional PID, tracking performance test, anti-disturbance performance and robustness are given in the next sections.

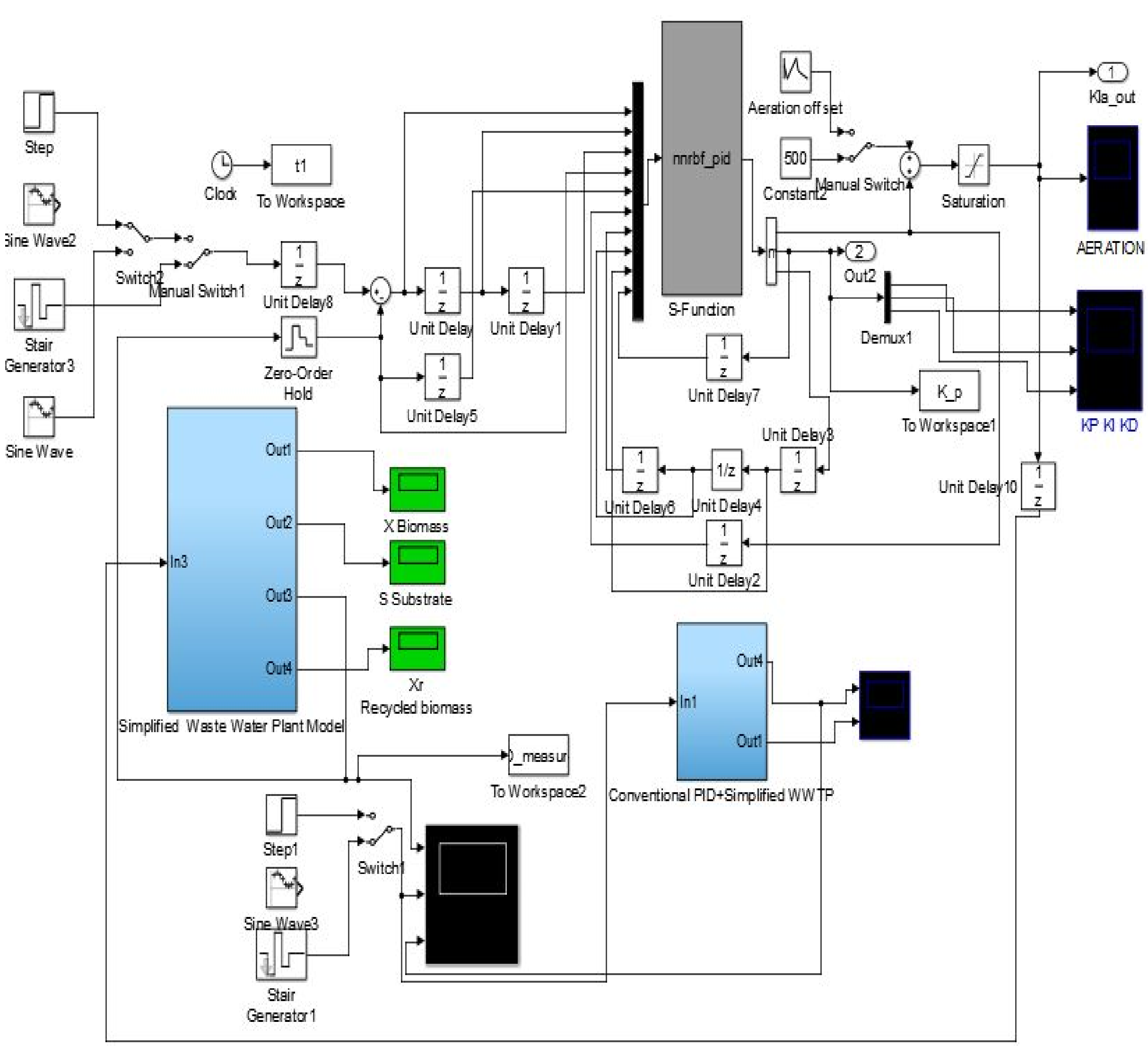


Figure 4. 10 The complete Simulink® wastewater treatment process model and controller

The ANNRBF PID controller complete Simulink® model is shown in Figure 4.10 below, which shows all important blocks and ANNRBFPID S- function written in MATLAB and loaded on the block.

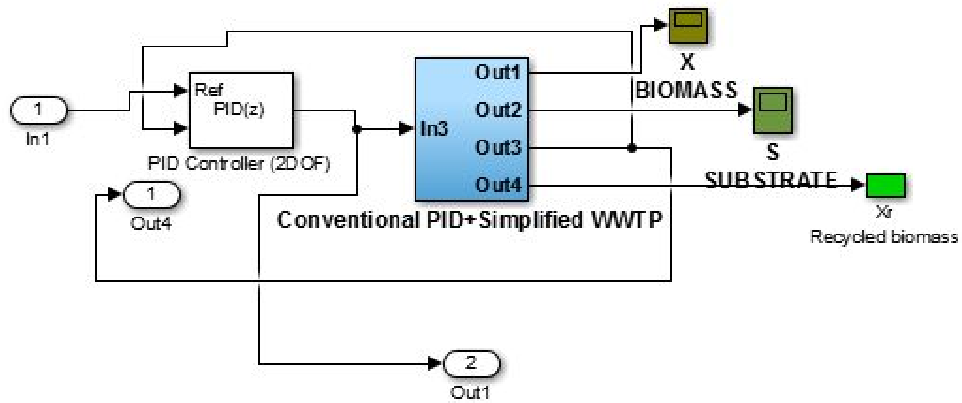


Figure 4. 11 Conventional PID controller of simplified WWTP

In the coming sections the tracking performance of tests, anti-disturbance tests, and robustness tests performed and compared to the traditional PID and how the KP KI and KD parameters update to adapt themselves for the sake of tracking the actual set-point and leads the manipulated variable (W) to provide the required amount of aeration signal.

In the simulation, the three parameters of both the conventional incremental PID algorithm and the proposed ANNRBFPID algorithm are set as $KP = 5$, $k_i = 1$, $KD = 0.5$ based on the experiment; the learning rate, η of the three parameters of PID is 0.2; the momentum factor α is 0.05; the network sampling period is 0.001 s; the structure of the RBFNN is defined as "3-6-1", that is to say, the input layer has three nodes, the hidden layer has six nodes and the output layer has one node.

4.5.1 Tracking Performance Test

Case i. In Figure 4.11: below 2mg/L DO setpoint is given to the plant and how the controller handles the uncertain and continuously varying input variables and ANNRBF PID shows a better performance than the PID and the error for both controllers also shown in Figure 4.12.

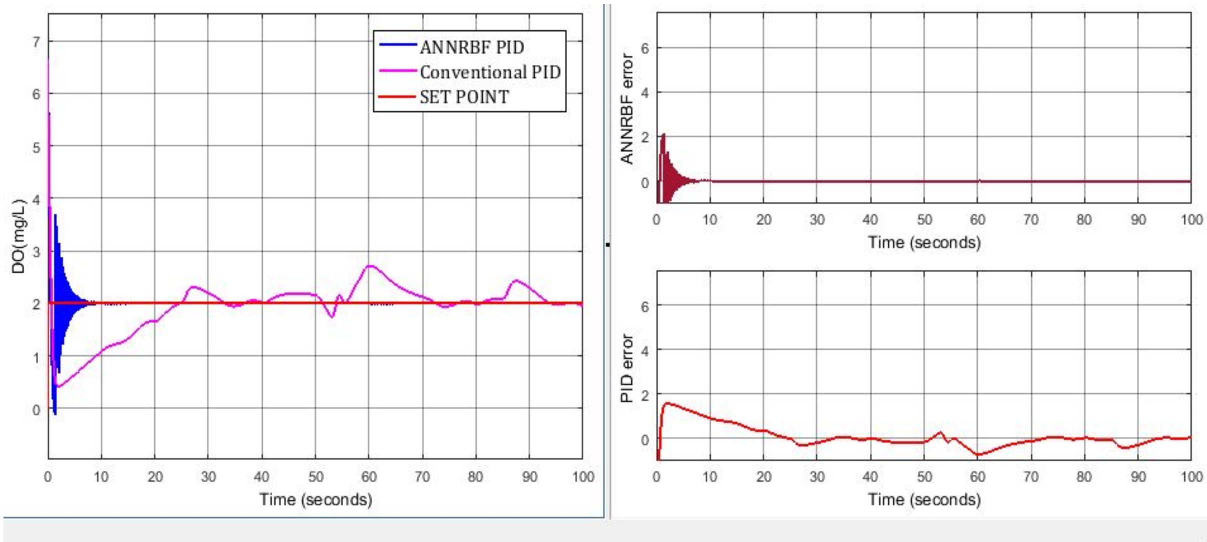


Figure 4. 12 constant setpoint response of ANNRBFPID and PID controller and corresponding errors

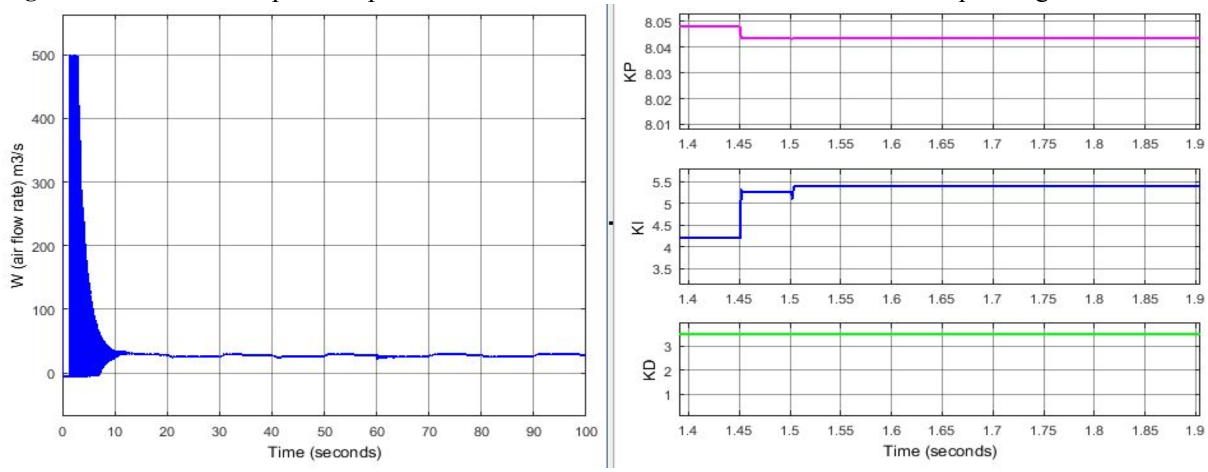


Figure 4. 13: Dynamic Aeration change and Dynamic adaptive adjustments of the three parameters KP, KI and KD

The error of ANNRBF PID is very small close to zero with some oscillation during starting time. The error recorded for PID controller is continuously varying and very large error. The aeration signal which is the manipulated variable and gives as a feedback to the plant and an adaptive adjustment is done and the PID parameters updated to let the process to abide with the set point as shown above in figure 4.12.

Case ii. Tracking performance test of both ANNRBF PID and conventional PID for sampled Sinusoidal set point input is shown in Figure 4.13. Here also the proposed controller performs efficiently than the PID and the corresponding errors also shown below.

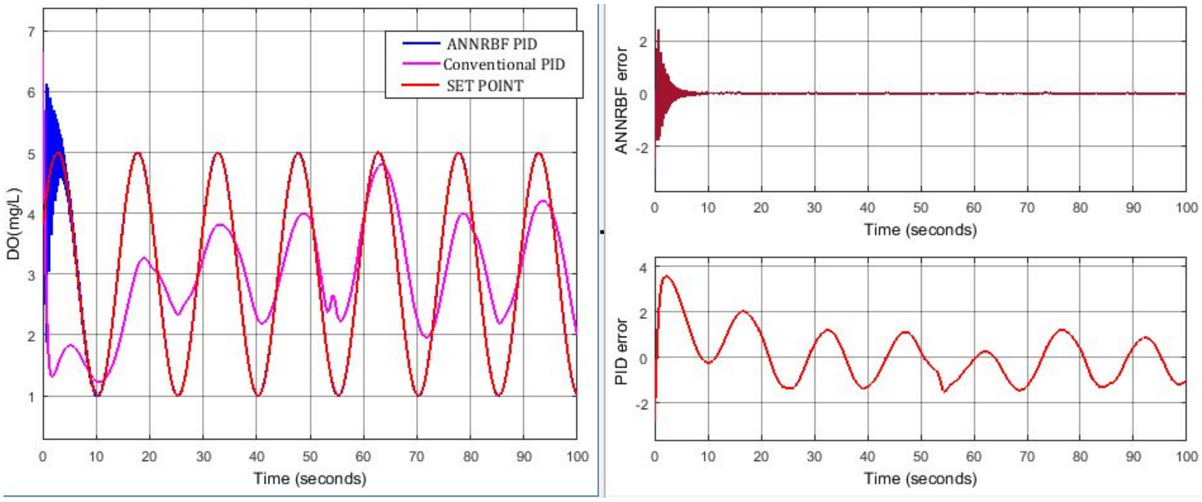


Figure 4. 14: sampled sinusoidal setpoint response and error of ANNRBFPID and PID controller

The aeration signal which is the manipulated variable and gives as a feedback to the plant and an adaptive adjustment is done and the PID parameters updated to let the process to abide with the set point as shown above in figure 4.14. Biomass concentration and substrate concentration during this process are as shown below in Figure 4.15. But practically this parameters are not measurable.

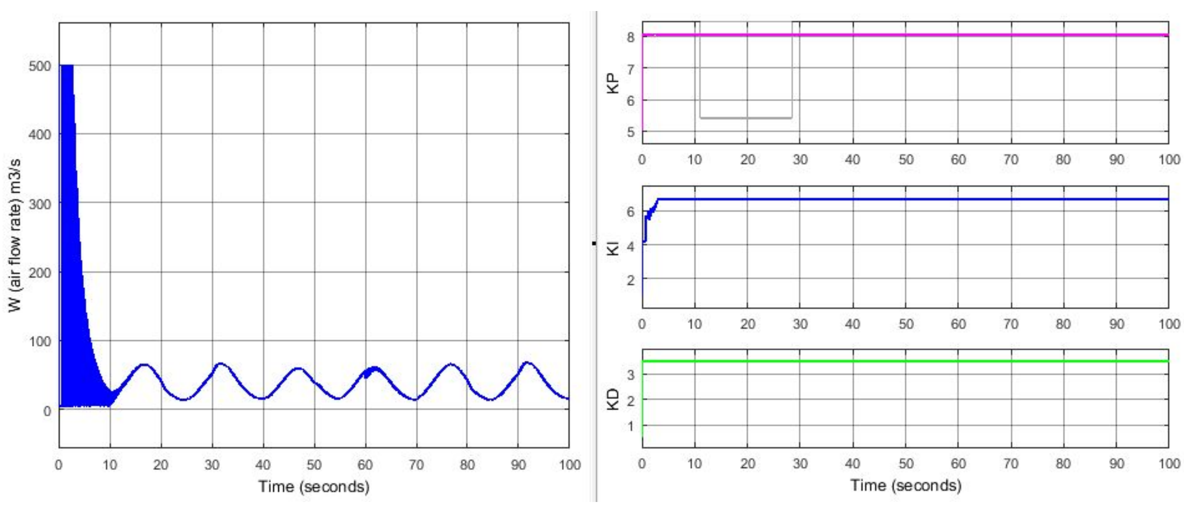


Figure 4. 15: Dynamic Aeration change and adaptive adjustments of the three parameters KP, KI and KD

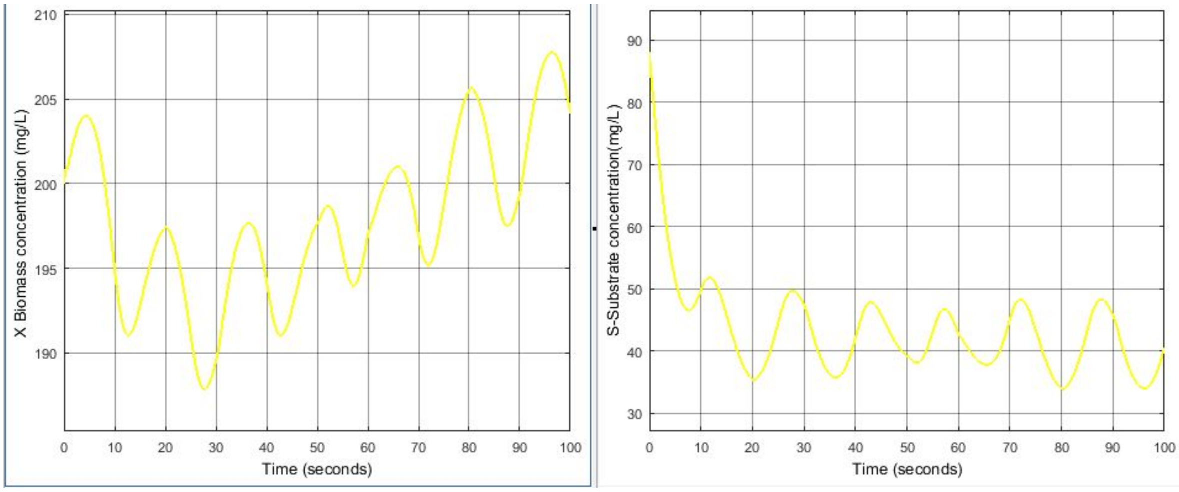


Figure 4. 16: Biomass and substrate response for Sinusoidal set point input

Case iii The last tracking performance test is done by giving a built-in the pseudo signal which changes its set point unexpectedly and remarkable tracking performance obtained by ANNRBF PID and compared to conventional PID and errors corresponding also shown in figure 4.16 below.

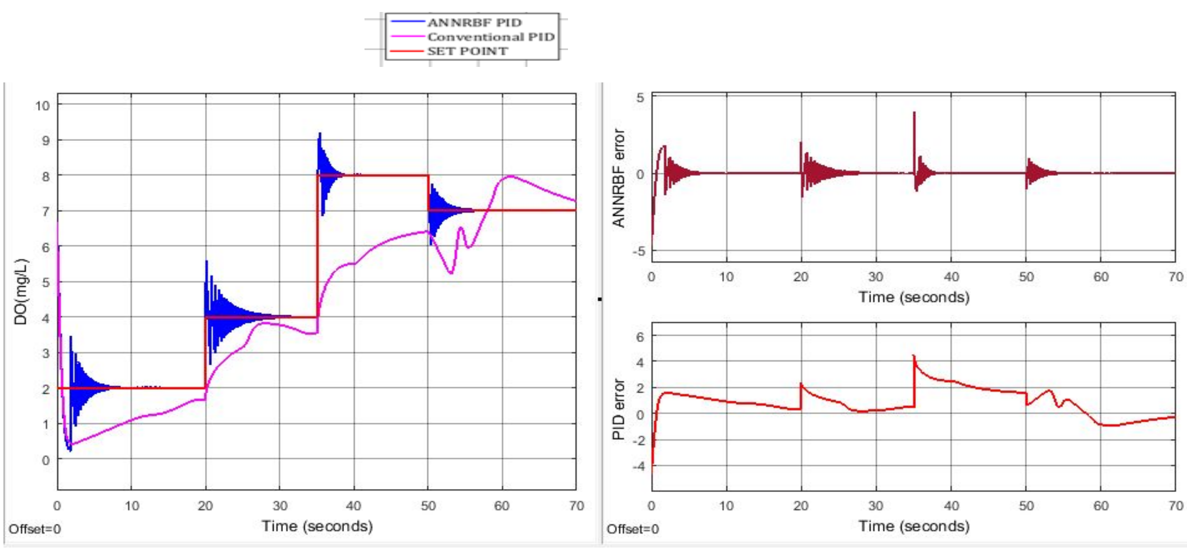


Figure 4. 17: pseudo-random signal setpoint response of ANNRBFPID and PID and error

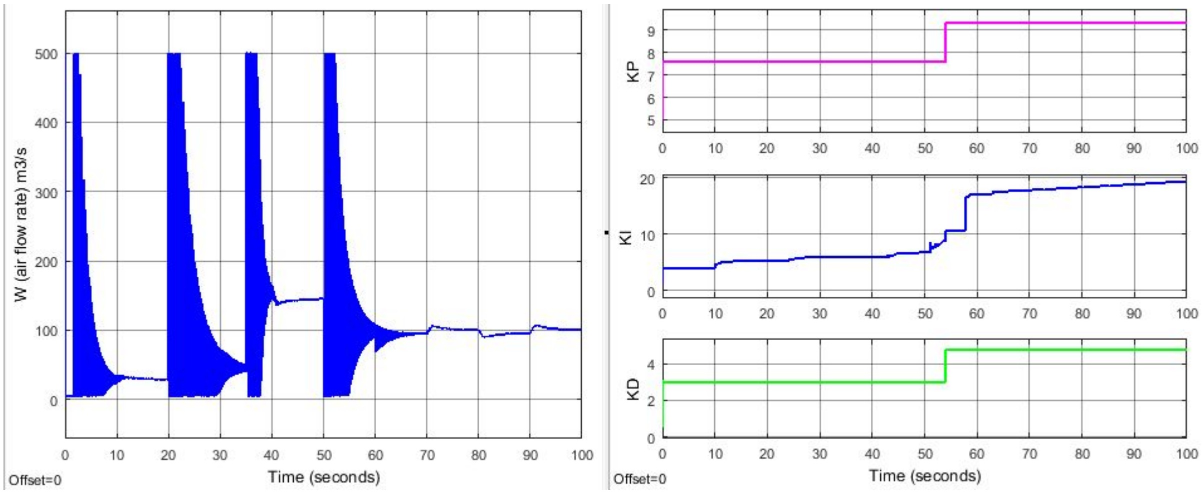


Figure 4. 18: Dynamic Aeration change and Dynamic adaptive adjustments of the three parameters KP, KI, KD

4.5.2 Ability to withstand a continuously variable influent change and Disturbance rejection Analysis

Here the controller tracking performance and the ability to keep the set point as desired while a continuously variable and uncertain influent is coming, as shown in the figure 4.18 the proposed ANNRBF PID shows an excellent adaptation ability even in the time of every weather condition. On the other hand, conventional PID is not suited well for this process.

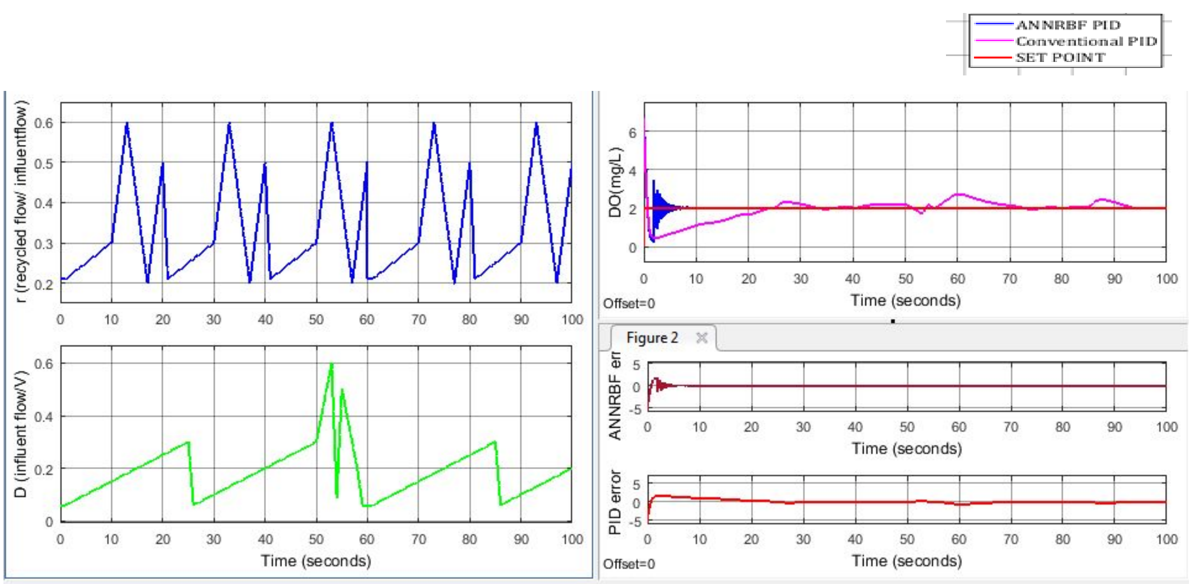


Figure 4. 19: Ability to withstand a continuously variable influent change

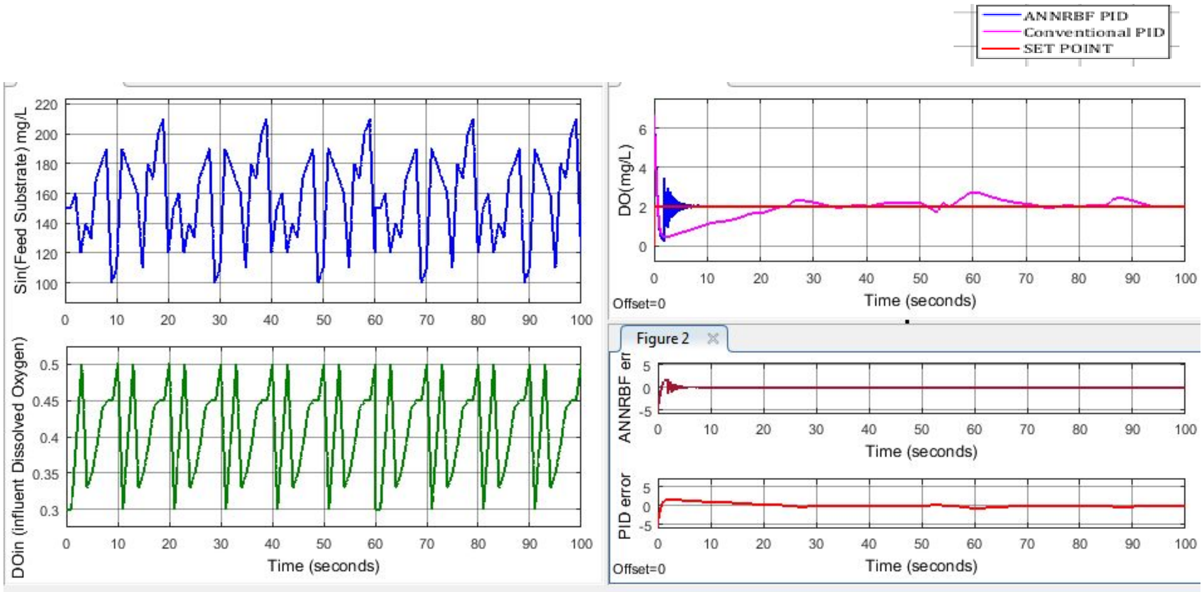


Figure 4. 20: Disturbance rejection capability

When the maximum growth rate varies between 0.15 and 0.17 the following result shows how the controller performs this. From this result, we can conclude that the proposed controller ANNRBF PID has great robustness.

4.5.3 Uncertainty rejection performance test

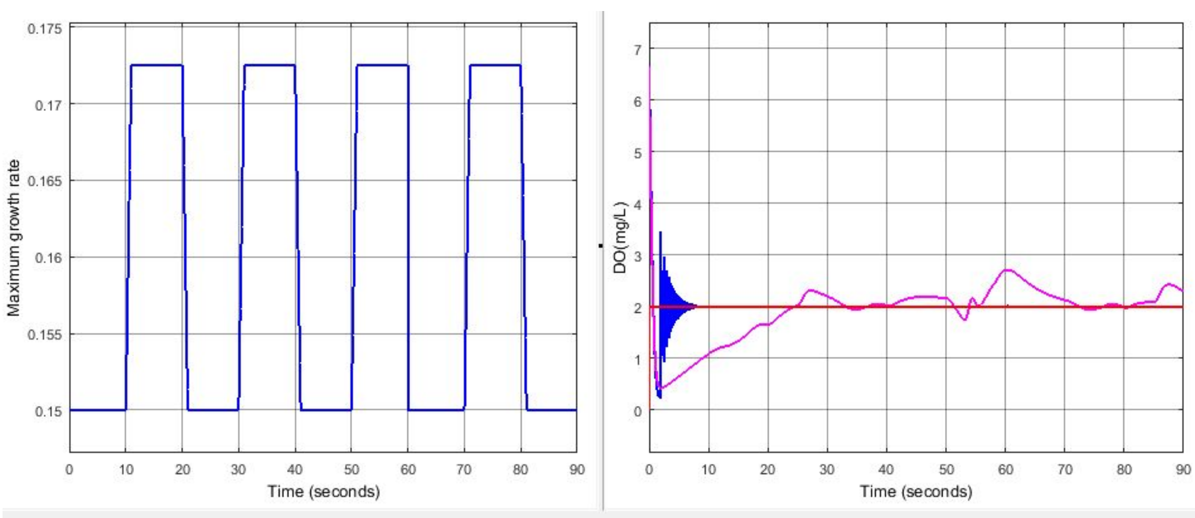


Figure 4. 21: Uncertainity rejection performance test

4.6 Activated Sludge Model 3 (ASM3) Simulation results based on SIMBA Software

SIMBA software: SIMBA is a simulation system constituted of versatile software useful not only for modeling but also in dynamic simulations relating to the wastewater-engineering field. The basis of SIMBA is both Simulink and MATLAB, which enable it to fulfill most of the common needs relating to the simulation of wastewater processes In extending both Matlab and Simulink, SIMBA applies block libraries and chemical and biological treatment processes. The control window of SIMBA and a sample block library for SIMBA are shown in Figure 4.20

4.6.1 Design of influent data

When using the dynamic simulation for fine tuning of the design of activated sludge plants diurnal variations of influent data are required. For this application usually, only data from the design process and no measured data are available. This Excel workbook implements the method described in Langergraber et al. (2008) and Langergraber et al. (2009) to generate diurnal variations of wastewater flow and concentrations. The aim is to generate realistic influent data in terms of flow, concentrations and TKN/COD ratios and not to predict the influent of the activated sludge tank in detail.[41]

4.6.2 Parameters and configuration

I have designed an influent data for a town which have 4 million people of population.

Table 4. 2: Total Influent Characteristics

People Equivalents			
PE =	4000000	[-]	
Daily influent dry weather flow			
Qm =	1714	[m3/d]	
Daily mean concentrations			
CODm =	467	[mg/l]	
TKNm =	58.3	[mg/l]	
TPm =	9.3	[mg/l]	

Table 4. 3: Influent Fractions Parameters

Fraction and concentration of infiltration water			
fQinf =	0.3	[-]	Fraction of infiltration water

CODinf =	25	[mg/l]	
TKNinf =	5	[mg/l]	
TPinf =	0.5	[mg/l]	
Fraction and concentration of urine			
fQu =	0.1	[-]	*Fraction of urine in (Qm-Qinf)*
CODu =	300	[mg/l]	
TKNu =	400	[mg/l]	
TPu =	30	[mg/l]	

4.6.3 Graphical representation

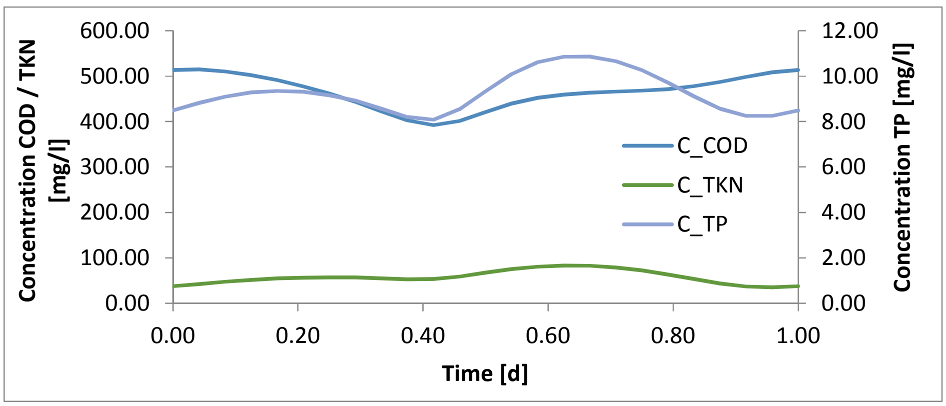


Figure 4. 22: influent concentration

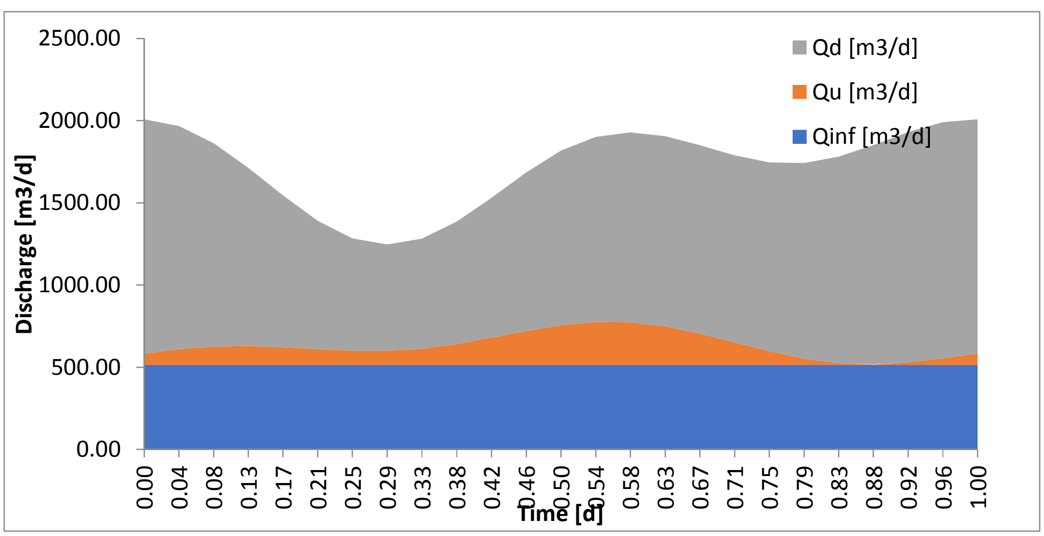


Figure 4. 23: Influent discharge stacked

The data shown in APPENDIX 1 is the generated diurnal variation and this data is used as an input for the model designed in SIMBA software. The following figure shows the model of the whole process designed in SIMBA and the internal detail structure is shown in APPENDIX 1.

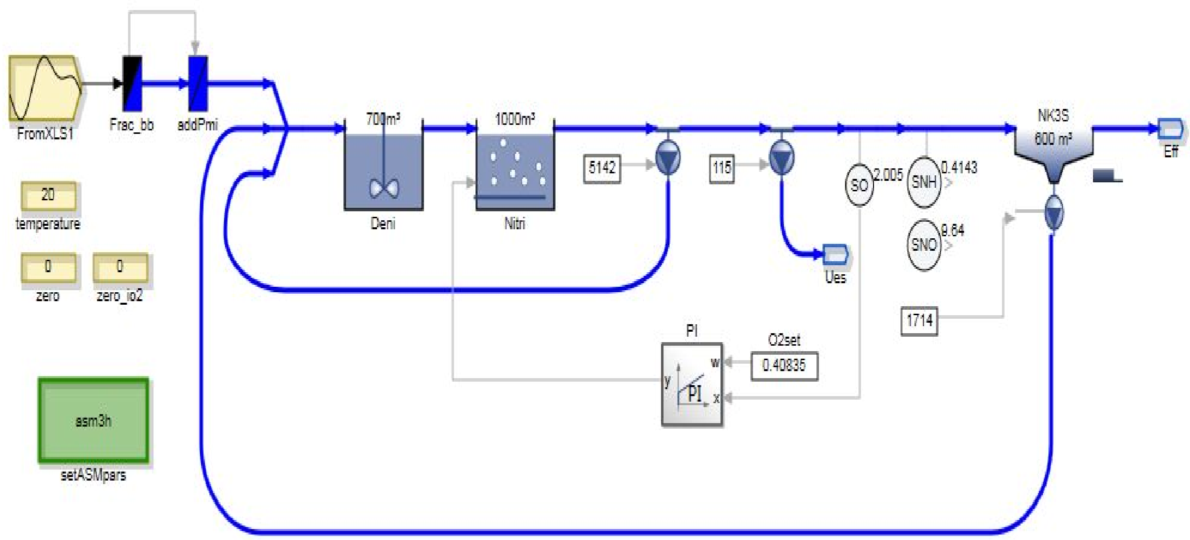
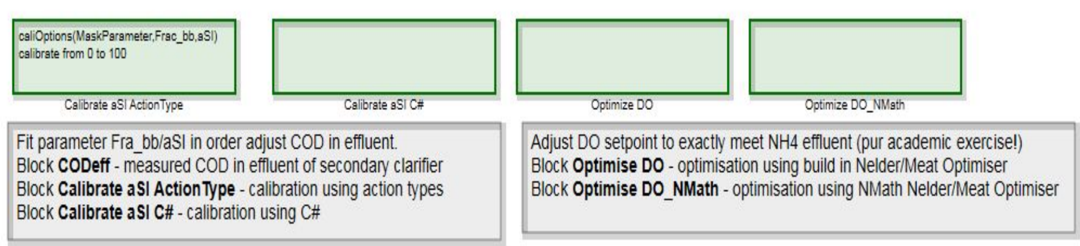


Figure 4. 24: The Waste Water Treatment Plant Model designed in SIMBA

Simba script blocks are shown below and called green blocks, used to automate simulation tasks and the blocks are not part of the simulation model they are written independently based on C# programming language



The three lines connected to the denitrification are influent from outside, influent from returned sludge and influent from internal recirculation respectively. The sum of the three influents is as shown below.

Table 4. 4: Sum of the influents

	Value	Unit
SO	1.65	g O2/m³
SS	13.85	g COD/m³
SNH	7.29	g N/m³
SNO	7.929	g N/m³
SN2	32.11	g N/m³
SALK	7.013	mol/m³
SI	23.58	g COD/m³
XI	744	g COD/m³
XS	65.34	g COD/m³
XH	892	g COD/m³
XSTO	10.89	g COD/m³
XA	62.55	g COD/m³
XMI	608.4	g/m³
Flow rate	8326	m³/d
TSS: Total Suspended Solids	1941	g/m³
VSS: Volatile Suspended Solids	1274	g/m³
ISS: Inorganic Suspended Solids	666.8	g/m³
TN: Total Nitrogen	114.4	g N/m³
TKN: Total Kjeldahl Nitrogen	106.5	g N/m³
N_fil: Filtered Nitrogen (incl. colloidals)	16.85	g N/m³
N_sol: Soluble Nitrogen (w/o colloidals)	0	g N/m³
NOx-N: Sum of NO2 and NO3	7.929	g N/m³
TP: Total Phosphorus	0	g P/m³
COD: Total Chemical Oxygen Demand	1812	g COD/m³
COD_fil: Filtered Chemical Oxygen Demand (incl. colloidals)	70.1	g COD/m³

Table 4. 5: The load's concentration per day basis

Load	Value	Unit
SO	13.74	kg O2/d
SS	115.3	kg COD/d
SNH	60.57	kg N/d
SNO	66.43	kg N/d
SN2	269.7	kg N/d
SALK	58.36	kmol/d
SI	196.3	kg COD/d
XI	1.105e+04	kg COD/d
XS	546.6	kg COD/d
XH	7643	kg COD/d

XSTO	91.25	kg COD/d
XA	542	kg COD/d
XMI	8356	kg/d
TSS: Total Suspended Solids	2.329e+04	kg/d
VSS: Volatile Suspended Solids	1.443e+04	kg/d
ISS: Inorganic Suspended Solids	8857	kg/d
TN: Total Nitrogen	1164	kg N/d
TKN: Total Kjeldahl Nitrogen	1097	kg N/d
N_fil: Filtered Nitrogen (incl. colloidals)	140.6	kg N/d
N_sol: Soluble Nitrogen (w/o colloidals)	0	kg N/d
NOx-N: Sum of NO2 and NO3	66.43	kg N/d
TP: Total Phosphorus	0	kg P/d
COD: Total Chemical Oxygen Demand	2.018e+04	kg COD/d
COD_fil: Filtered Chemical Oxygen Demand (incl. colloidals)	584.9	kg COD/d

The controller used here is a conventional PID controller with a fixed setpoint and a Dissolved Oxygen-DO optimizer written on C# and the source code is shown in APPENDIX 1. The first tank is the denitrification tank with a 700m3 reactor volume and 4 m depth and no aeration is taking place in it. Parameter block of nitrification tank is as shown on figure 27.and the aeration is taking place here and the PID controller controls to let the concentration of DO close to 2mg/l.

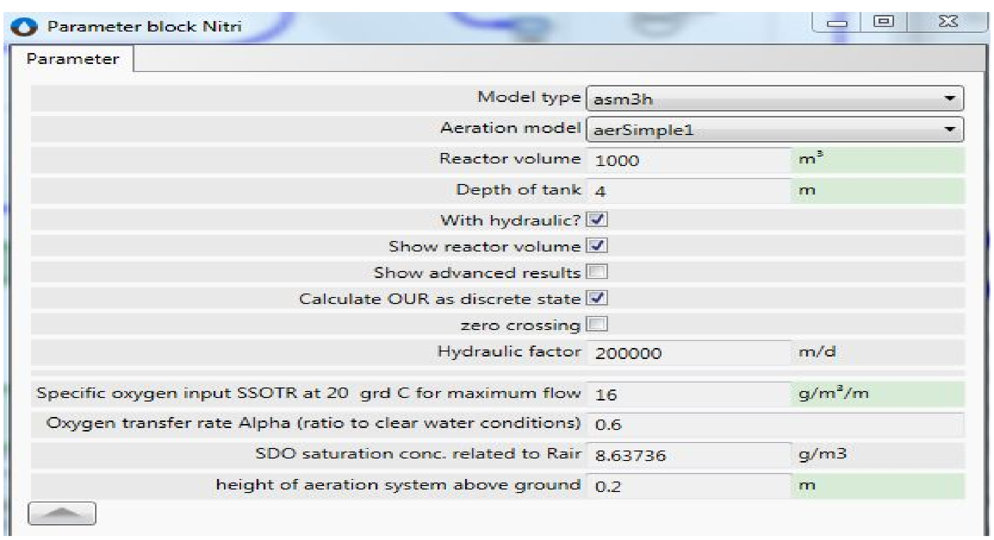


Figure 4. 25: Nitrification tank block parameter

PID block parameter is shown below the initial values of PID are experimental results and taken from BSM1.

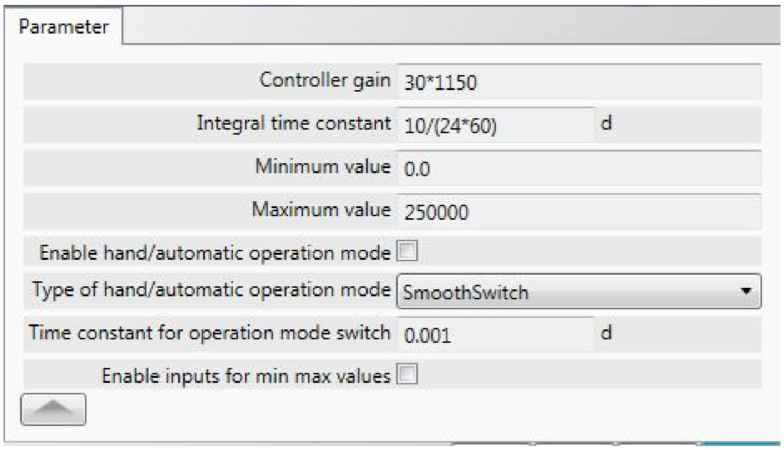


Figure 4. 26: PID block parameters

The final tank is called a settler it is a place for the final treated effluent obtained, and the parameters are set as shown below in figure 4.29

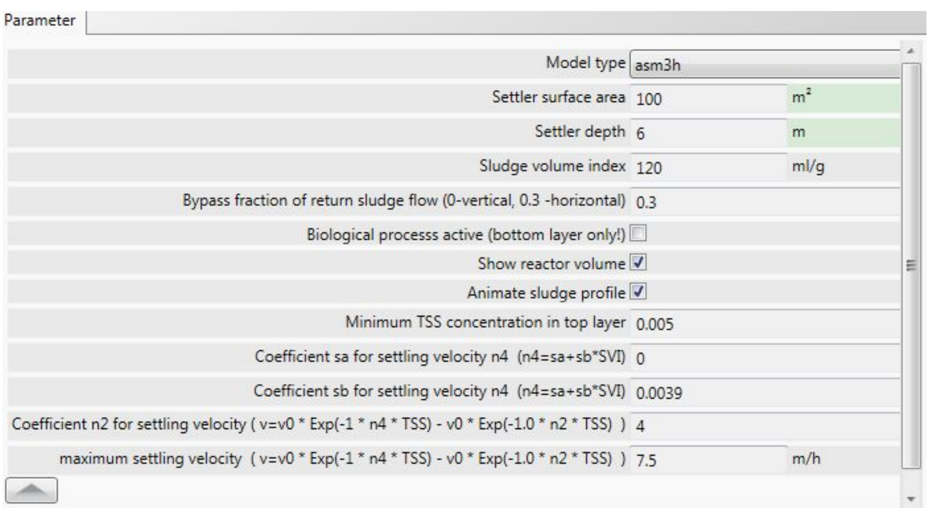


Figure 4. 267: The settler block parameters

The following table shows the effluent or the wastewater chemical composition. The treated water that is safe for release to the water bodies is the top layer as shown below.

Table 4. 6: Top Middle and Bottom concentration of the settler

State	Top(effluent)	Middle	Bottom		
SO	2.0006	2.0032	2.0019	g O2/m³	Dissolved oxygen
SS	0.24972	0.2335	0.23954	g COD/m³	Readily biodegradable substrate
SNH	0.5421	0.46371	0.47904	g N/m³	NH4(+) and NH3 nitrogen
SNO	9.9994	9.6334	9.6634	g N/m³	nitrate and nitrite nitrogen
SN	38.84	38.954	38.913	g N/m³	Dinitrogen
SALK	6.3467	6.3743	6.3737	mol/m³	Alkalinity as H2CO3
SI	23.54	23.717	23.71	g COD/m³	Soluble inert organic matter
XI	1.9656	860.48	2020	g COD/m³	Particulate inert organic matter
XS	0.064988	27.302	65.248	g COD/m³	Slowly biodegradable substrate
XH	2.3546	1029.9	2418.4	g COD/m³	Heterotrophic biomass
XSTO	0.03035	12.933	30.829	g COD/m³	Organic storage products
XA	0.16847	73.25	172.13	g COD/m³	Autotrophic biomass
XMI	1.5973	699	1641.1	g/m³	particulate mineral fraction
V	470.28	100.06	30	m³	
TSS	5.1	2213.3	5197.7	g TSS/m³	

Graphical representation of the effluent and how the result is abode with the standard effluent assessment limit is discussed in the following sections.

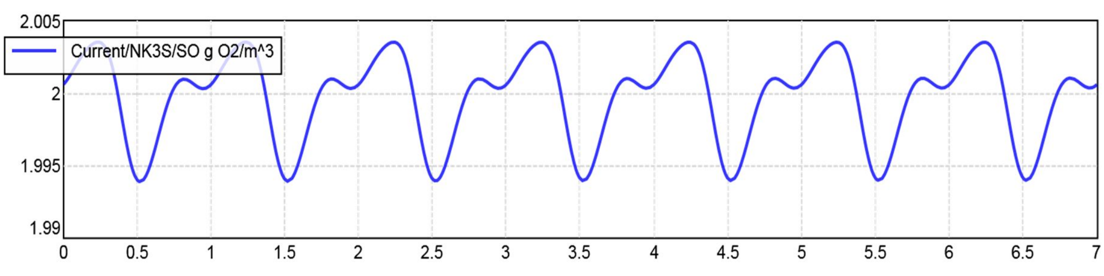


Figure 4. 278: Dissolved Oxygen Concentration when the PI controller performs for 7 days.

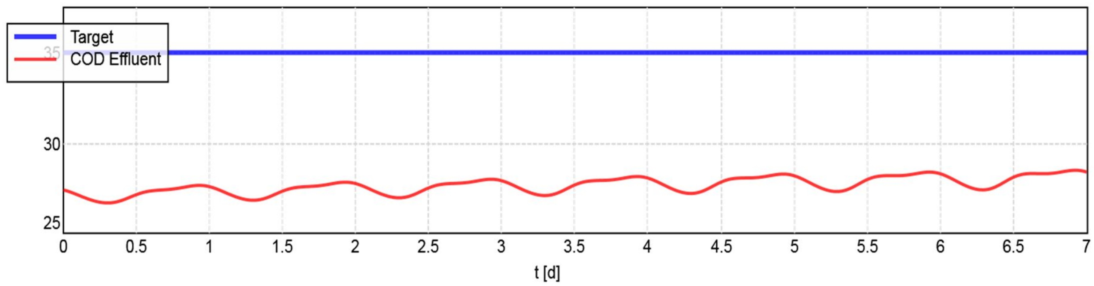


Figure 4. 289: COD Effluent for 7 days

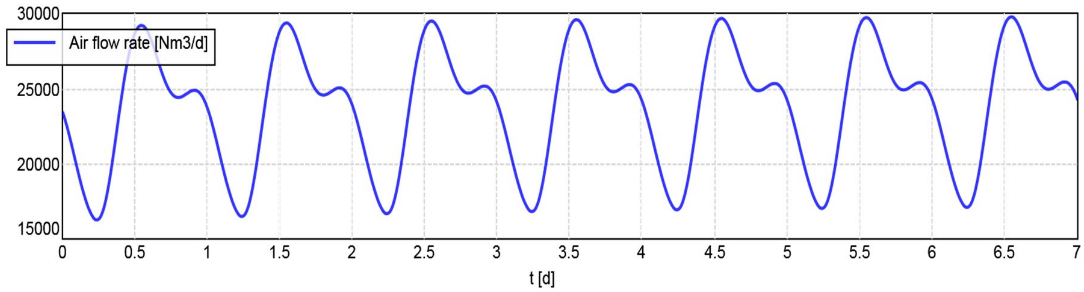


Figure 4.30: Air flow rate for 7 days

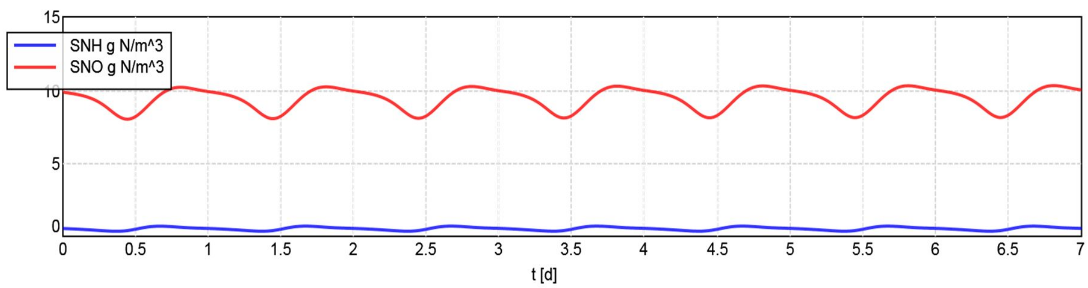


Figure 4. 291: SNH(NH4(+) and NH3 nitrogen) SNO(nitrate and nitrite nitrogen)

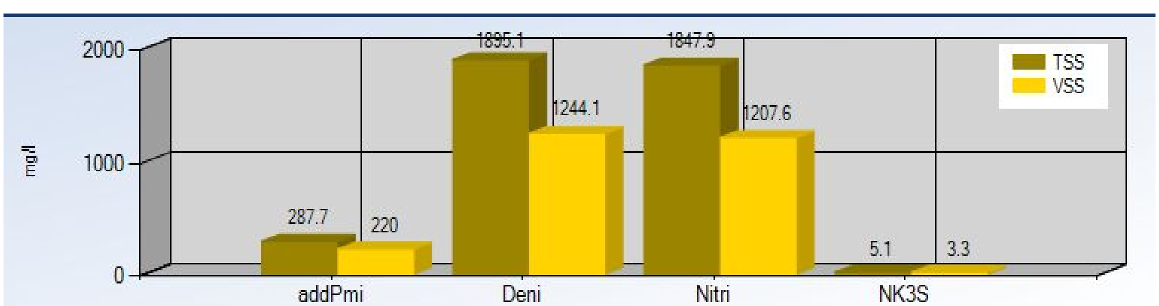


Figure 4. 302: The total and volatile suspended solids, SO, SNH and SNO in each reactor and settler

Table 4. 7: Performance Assessment and Effluent Quality Standard Limits

Variable	Standard Value	Result obtained
Ntot (Total Nitrogen)	< 18g	11.04 g N/m³
CODtot (Total Chemical Oxygen Demand)	< 100g	23.82 g COD/m³
SNH (NH4(+) and NH3 nitrogen)	< 4g	0.5421 g N/m³
TSS(Total Suspended Solids)	< 30g	5.061 g/m³

Comparing our results to the standard limits shows that the controller performs satisfactorily and provide acceptable results.

The above PI control controls the DO concentration to 2mg/l setpoint value. In the following section DO setpoint adjusted to exactly meet NH4 effluent by writing an algorithm using C# and the results are shown below simulated for 200days.

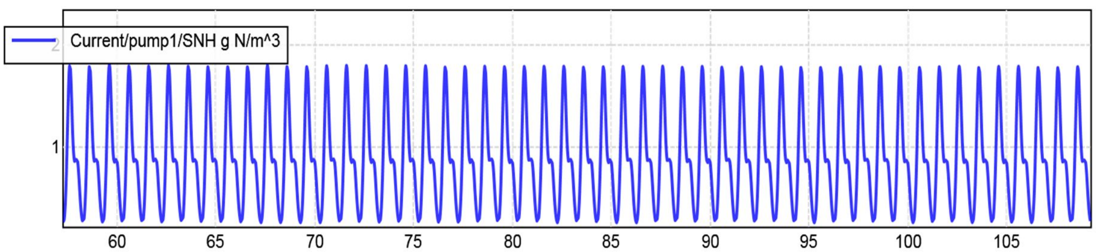


Figure 4. 313: SNH

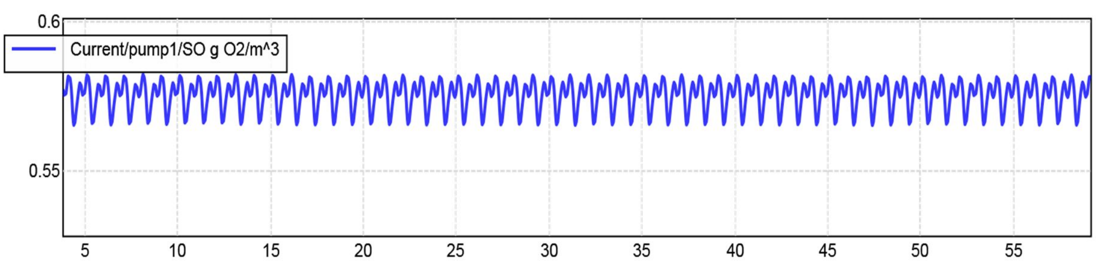


Figure 4. 324: DO setpoint adjusted to exactly meet NH4 effluent

Table 4. 8: effluent concentration

Id	Value	Unit
SO	0.5716	g O2/m³
SS	0.1841	g COD/m³
SNH	0.6654	g N/m³
SNO	6.074	g N/m³
SN2	42.01	g N/m³

SALK	6.706	mol/m³
SI	23.15	g COD/m³
XI	3.751	g COD/m³
XS	0.04729	g COD/m³
XH	2.936	g COD/m³
XSTO	0.02645	g COD/m³
XA	0.2034	g COD/m³
XMI	2.868	g/m³
Flow rate	2231	m³/d
TSS: Total Suspended Solids	8.134	g/m³
VSS: Volatile Suspended Solids	5.074	g/m³
ISS: Inorganic Suspended Solids	3.06	g/m³
TN: Total Nitrogen	7.348	g N/m³
TKN: Total Kjeldahl Nitrogen	1.274	g N/m³
N_fil: Filtered Nitrogen (incl. colloidals)	6.977	g N/m³
N_sol: Soluble Nitrogen (w/o colloidals)	0	g N/m³
NOx-N: Sum of NO2 and NO3	6.074	g N/m³
TP: Total Phosphorus	0	g P/m³
COD: Total Chemical Oxygen Demand	30.3	g COD/m³
COD_fil: Filtered Chemical Oxygen Demand (incl. colloidals)	23.36	g COD/m³

CHAPTER 5

5 CONCLUSIONS AND FUTURE WORK

5.1 Conclusions

This thesis work proposes an adaptive PID control algorithm based on Radial Basis Function (RBF) neural network to control dissolved oxygen concentration within the activated sludge bioreactors in wastewater treatment plants (WWTP). The activated sludge process is known for its high nonlinearity and multivariable dynamic behavior. Large disturbances and uncertain feed stream make the system very challenging to control. Two models are applied in this thesis to describe the activated sludge process. The first one is a simplified 4x4 model and the second one is BSM1. The main objective of this thesis is to design an adaptive Neural Network PID controller to control the concentration of DO at a specific limit in order to get an excellent effluent quality by stabilizing this complex nonlinear dynamic system.

The most important factor in the biological treatment process is the dissolved oxygen concentration in the plant. Moreover, the aeration system is the most energy consuming part wastewater treatment facility, which initiates the researchers to propose various control methods for dissolved oxygen concentration which are most robust, adaptive and energy efficient.

Chapter four is all about the results obtained for two wastewater models. The first one is the simplified wastewater treatment model which has four state variable sand two basic input variables introduced first by Nejjari [41]. First, the model is validated by simulating in MATLAB/SIMULINK and the free dynamics response without a controller is tested. The Dissolved Oxygen Concentration easily affected by influent from outside and internal recirculated, figure 4.2 up to figure 4.5 shows how dissolved oxygen affected and varies nonlinearly by the change of dilution rate (D), recycle flow rate(r), dissolved oxygen in the feed stream (DOin) and substrate concentration in the feed stream (Sin). But these parameters are not measurable and cannot be adjusted to set the concentration of DO at the desired level. The possible way to control is the manipulation of aeration from blowers. When aeration increase and decreases the amount of DO also increases and decreases non-linearly respectively as indicated on figure 4.8 and figure 4.9. Thus, it is required to propose a controller which enables to adapt any weather condition and keep the concentration of DO concentration at the desired point in the presence of non-linearly varying and uncertain influent inputs. PID may fail to achieve the control goal or effect of the process while using the traditional PID control algorithm due to unknown and unexpected disturbances as well as significant changes in operating conditions, such as a significant change in the (1) quality of influent; (2) weather, etc. Therefore, in general, the parameters of the traditional PID controller need to be adjusted under different operating environments. In this paper, an adaptive PID control algorithm based on RBF neural network is proposed. The ANNRBF PID algorithm combines the good learning and adaptive ability of neural networks and the practical advantages of the PID algorithm. The gradient descent method is used to adaptively adjust the increment of the three parameters of the PID controller to achieve an optimal control effect on the control of DO concentration.

The simulation results in Figures 4.13 to 4.18 show that the DO concentration is difficult to maintain a set point under the control of the conventional incremental PID controller when the influent flow rate and quality changed greatly. On the other hand, ANNRBF PID can effectively maintain the DO concentration around the set value with a relatively low error by adjusting the air flow (which can be seen in Figures 4.13, 4.15 and 4.18. It can be seen that the dynamic changes of the manipulated variable W are smooth under the control of ANNRBF PID. This means we can get a more stable status by using less air supply to the aeration tank.

According to the result r, D, Sin and DOin , which can be considered as the disturbances of the influent, shown in Figures19 and 20, compared with the conventional PID controller, the ANNRBF PID controller can quickly and accurately track the desired output trajectory values, which means it not only has a good tracking performance but also has a stronger anti-disturbance ability with the changes to the set points. Figures4.13, 4.15, 4.18 show the curves of the PID parameters are being adjusted adaptively. Parameters adjusted rapidly at the start of the simulation and small adjustments took place as the simulation goes on. The simulation results show that the ANNRBF PID algorithm not only has a better performance of tracking and anti-jamming but also has a great improvement to the robustness compared to conventional PID.

The second model is an activated sludge model no.1 ASM1 which is a more realistic and complex model contains 13 variables and designed by International Water Association. The model is simulated in SIMBA software. The data shown in APPENDIX 1 is the generated diurnal variation and this data is used as an input for the model designed in SIMBA software. The controller used here is a conventional PID controller with a fixed setpoint and a Dissolved Oxygen-DO optimizer written on C# and the source code is shown in APPENDIX1. Performance Assessment and Effluent Quality Standard Limits for Ntot (Total Nitrogen), CODtot (Total Chemical Oxygen Demand), SNH (NH4(+) and NH3 nitrogen) and TSS (Total Suspended Solids) is given in Table 4.6 and the result shows the controller performs satisfactorily and provide an acceptable result.

5.2 Future Work

The wastewater treatment process is highly in need of budget. So, the cost analysis and energy calculation for the proposed controller and the PID controller and comparison can be worked. Since it is not tested on the real plant, it will be best if it is tested on the real plant and see how the controller improves the plant performance. As future work, additional research is required to more accurately control the activated sludge process. The most important design consideration is energy-efficiency. In this thesis only two controllers have been checked; However, some other controllers should be designed to choose the most energy-efficient controller. The adaptive ANNRBF PID control should be tested under real plant conditions and redesigned if necessary.

References

[1]. Bo, Y.C.; Zhang, X. Online adaptive dynamic programming based on echo state networks for dissolved oxygen control. Appl. Soft Comput. 2017.

[2]. Holenda, B.; Domokos, E.; Rédey, Á.; Fazakas, J. Dissolved oxygen control of the activated sludge wastewater treatment process using model predictive control. Comput. Chem. Eng. 2008, 32, 1270–1278.

[3]. OBrien, M., J. Mack, B. Lennox, D. Lovett, and A. Wall. "Model Predictive Control of an activated sludge process: A case study." Control Engineering Practice 19, no. 1 (2011): 54-61.

[4]. Gerksic, S., D. Vrecko, and Nadja Hvala. Improving oxygen concentration control in Activated sludge process with the estimation of respiration and scheduling control. Vol. 53, no. 4. 2006.

[5] Vreko, D., Nadja Hvala, and Bengt Carlsson. "Feedforward-feedback control of an activated sludge process: a simulation study." Water Science Technology 47, no. 12 (2003): 19-26.

[6]. Zhang, P.; Yuan, M.; Wang, H. Study on Dissolved Oxygen Control Method Based on International Evaluation Benchmark. Inf. Control 2007, 36, 199–203.

[7]. Yu, K.; Muhetaer, A.; Wei, L. Evaluation indexes of sewage stabilization from the municipal wastewater treatment plant. China Water Wastewater 2016, 5, 93–97.

[8]. Chen, C.S. Robust self-organizing neural-fuzzy control with uncertainty observer for MIMO nonlinearsystems. IEEE Trans. Fuzzy Syst. 2011, 19, 694–706.

[9]. Tzoneva, Raynitchka. "Optimal PID control of the dissolved oxygen concentration in the wastewater treatment plant." In AFRICON 2007, pp. 1-7. IEEE, 2007.

[10]. Nascu, Ioan, Grigore Vlad, Silviu Folea, and Tudor Buzdugan. ”Development and application of a PID auto-tuning method to a wastewater treatment process.”In Automation, Quality and Testing, Robotics, 2008. AQTR 2008. IEEE International Conference on, vol. 2, pp. 229-234. IEEE, 2008.

[11]. Yoo, ChangKyoo, and Min Han Kim. ”Industrial experience of process identification and set-point decision algorithm in a full-scale treatment plant.” Journal of environmental management 90, no. 8 (2009): 2823-2830.

[12]. Wahab, Norhaliza A., Reza Katebi, and Jonas Balderud.”Multivariable PID control Design for activated sludge process with nitrification and denitrification.” Biochemical Engineering Journal 45, no. 3 (2009): 239-248.

[13]. Yoo, ChangKyoo, Ho Kyung Lee, and I. Beum Lee. ”Comparison of process Identification methods and supervisory control in the full-scale wastewater treatment plant.” In 15 the IFAC World Congress, Barcelona. 2002.

[14]. Ingildsen, P., U. Jeppsson, and Gustaf Olsson. ”Dissolved oxygen controller based on on-line measurements of ammonium combining feed-forward and feedback.” Water Science Technology 45, no. 4 (2002): 453-460.

[15]. Krause, K., K. Becker, and J. London. ”Simulation of a nitrification control concept considering influent ammonium load.” Water Science Technology 45, no. 4-5 (2002): 413-420

[16]. Vreko, D., Nadja Hvala, Aljaz Stare, Olga Burica, M. Strait, Meta Levstek, Peter Cerar, and S. Podbevek. ”Improvement of ammonia removal in activated sludge process with feedforward-feedback aeration controllers.” Water Science Technology 53, no. 4-5 (2006):125-132.

[17]. Thunberg, A., A. M. Sundin, and B. Carlsson. ”Energy optimization of the aeration Process at KŁppala wastewater treatment plant.” In 10th IWA Conference on

Instrumentation, Control Automation, pp. 14-17. 2009

[18] Meyer, Ulrich, and H. Perl. ”Fuzzy-control for improved nitrogen removal and Energy saving in WWT-plants with pre-denitrification.” Water Science Technology 47, no. 11 (2003): 69-76.

[19]. Sanchez, A., and M. R. Katebi. ”Predictive control of dissolved oxygen in an Activated sludge wastewater treatment plant.” In Proc. European Control Conference ECC. 2003.

[20]. Holenda, B., E. Domokos, A. Reddy, and J. Fazakas. ”Dissolved oxygen control of the activated sludge wastewater treatment process using model predictive control.” ComputersChemical Engineering 32, no. 6 (2008): 1270-1278.

[21]. Steffens, M. A., and P. A. Lant. ”Multivariable control of nutrient-removing activated Sludge systems.” Water Research 33, no. 12 (1999): 2864-2878.

[22]. Shen, Wenhao, Xiaoquan Chen, M. N. Pons, and J. P. Corriou. ”Model predictive control for wastewater treatment process with feedforward compensation.” Chemical Engineering Journal 155, no. 1 (2009): 161-174.

[23] Yong, Ma, Peng Yongzhen, and Wang Shuying. ”Feedforward-feedback control of Dissolved oxygen concentration in a denitrification system.” Bioprocess and biosystems Engineering 27, no. 4 (2005): 223-228.

[24]. Zhang, Ping, Mingzhe Yuan, and Hong Wang. ”Improvement of nitrogen removal and reduction of operating costs in an activated sludge process with feed-forward cascade control strategy.” Biochemical Engineering Journal 41, no. 1 (2008): 53-58.

[25]. Thornton, A., N. Sumner, and M. Haeck. ”Real-time control for reduced aeration and chemical consumption: a full-scale study.” (2010).

[26] Yong, Ma, Peng Yongzhen, and Wang Shuying. ”Feedforward-feedback control of Dissolved oxygen concentration in a denitrification system.” Bioprocess and biosystems engineering 27, no. 4 (2005): 223-228.

[27]. Shen, Wenhao, Xiaoquan Chen, and Jean Pierre Corriou. ”Application of model Predictive control to the BSM1 benchmark of the wastewater treatment process.”Computers Chemical Engineering 32, no. 12 (2008): 2849-2856.

[28]. Zarrad, W., J. Harmand, M. Devisscher, and J. P. Steyer. ”Comparison of advanced control strategies for improving the monitoring of activated sludge processes.” Control Engineering Practice 12, no. 3 (2004): 323-333.

[29]. Vilanova, Ramon, R. Katebi, and V. Alfaro. ”Multi-loop PI-based control Strategies for the Activated Sludge Process.” In Emerging Technologies Factory Automation, 2009. ETFA 2009.IEEE Conference on, pp. 1-8. IEEE, 2009.

[30]. Yamanaka, O., T. Obara, and K. Yamamoto. ”Total cost minimization control scheme For the biological wastewater treatment process and its evaluation based on the COST Benchmark process.” Water Science Technology 53, no. 4-5 (2006):.

[31]. Beraud, Benoit, Cyrille Lemoine, and Jean-Philippe Steyer. ”Multiobjective Genetic algorithms for the optimization of wastewater treatment processes.”In Computational Intelligence Techniques for Bioprocess Modelling, Supervision and Control, pp. 163-195. Springer Berlin Heidelberg, 2009.

[32]. Chotkowski, W., Mietek A. Brdys*, and K. Konarczak. ”Dissolved oxygen control for activated sludge processes.” International Journal of Systems Science 36, no. 12 (2005).

[33]. Brdys, M.A.,W.Chotkowski, K.Duzinkiewicz, K.Konarczak, and R. Piotrowski.”Two-level dissolved oxygen control for activated sludge processes.” In 15th IFAC World Congress Barcelona, July, pp. 21-26. 2002.

[34]. Chotkowski, W., Mietek A. Brdys*, and K. Konarczak. ”Dissolved oxygen control for activated sludge processes.” International Journal of Systems Science 36, no. 12 (2005): 727-736.

[35]. Xianjun Du, Junlu Wang, Veeriah Jegatheesan * and Guohua Shi.’’ Dissolved Oxygen Control in Activated Sludge Process Using a Neural Network-Based Adaptive PID Algorithm.’’ Appl. Sci. 2018, 8, 261,1-21.

[36]. From Wikipedia, the free encyclopedia.

[37]. Wang. UASB-CASS joint technology applied to the treatment of brewery wastewater. In Computer Distributed Control and Intelligent Environmental Monitoring, pages 330–333, Changsha, 2011. IEEE.

[38]. Zhenliang Liao. Study on the wastewater treatment mode of three islands of Chongming. In Bioinformatics and Biomedical Engineering, IEEE, number 10063202, pages 2734–2738, Shanghai, China, 2008.

[39]. Langergraber, G., Spering, V., Alex, J., Ahnert, M., Cernochoca, L., Dürrenmatt, D.J., Frehmann, T., Hobus, I., Weissenbacher, N., Winkler, S., Yücesoy, E. (2009). Using numerical simulation to optimize control strategies during the activated sludge plant design. International Conference on Instrumentation, Control, and Automation (ICA).

[40]. Handbook of Biological Wastewater Treatment Design and Optimisation of Activated Sludge Systems.

[41]. F. Najjar, B. Dahhou, A. Benhamou, and G. Roux. Non-linear multivariable adaptive control of an activated sludge wastewater treatment process. Int. J. Adapt. Contr. Signal Pro-cess., 13:347–365, 1999.

[42]. M. Henze, W. Gujer, T. Mino, and M. Loosdrecht. Activated Sludge Models, ASM1, ASM2, ASM2d, and ASM3. Number 1 900222 24 8. IWA Publishing in it's Scientific and Technical Report Series, TJ International (Ltd), Padstow, Cornwall, UK, 2000.

[43]. "Artificial Neural Networks as Models of Neural Information Processing | Frontiers Research Topic". Retrieved 20 February 2018.

[44]. "Encephalos Journal". www.encephalos.gr. Retrieved 26 March 2019.

[45]. Neural-Adaptive Control of a Biological Wastewater Treatment Process.

[46]. https://www.willamette.edu/~gorr/classes/cs449/ann-overview.html.

[47]. http://cs231n.github.io/neural-networks-1/.

[48] Dissolved Oxygen Control in Activated Sludge Process Using a Neural Network-Based Adaptive PID Algorithm, 9 February 2018.

APPENDIX

APPENDIX A: Detailed SIMBA blocks representation and C# code for adjusting DO set-point

Table A.1 Diurnal variation of the discharge and of the concentrations and loads of COD, TKN, and TP.

	Discharge				Concentrations			Loads		
Time	Qinf	Qu	Qd	Qtot	C_COD	C_TKN	C_TP	F_COD	F_TKN	F_TP
[d]	[m3/d]	[m3/d]	[m3/d]	[m3/d]	[mg/l]	[mg/l]	[mg/l]	[kg/d]	[kg/d]	[kg/d]
0.00	514.20	69.99	1424.78	2008.98	513.97	37.69	8.49	1032.56	19.37	0.32
0.04	514.20	95.89	1356.91	1967.00	514.69	42.41	8.81	1012.39	21.83	0.37
0.08	514.20	111.81	1237.82	1863.83	510.64	47.44	9.10	951.75	24.22	0.43
0.13	514.20	115.25	1084.59	1714.04	502.58	51.69	9.28	861.44	25.98	0.48
0.17	514.20	108.07	922.87	1545.14	491.29	54.74	9.35	759.12	26.89	0.51
0.21	514.20	95.78	781.07	1391.05	477.49	56.54	9.31	664.21	27.00	0.53
0.25	514.20	85.82	683.78	1283.80	461.64	57.22	9.16	592.66	26.41	0.52
0.29	514.20	85.29	646.09	1245.58	443.52	56.83	8.92	552.43	25.20	0.51
0.33	514.20	98.74	670.28	1283.22	422.58	55.20	8.57	542.27	23.33	0.47
0.38	514.20	126.67	745.75	1386.62	402.51	53.26	8.20	558.13	21.44	0.44
0.42	514.20	165.09	852.16	1531.45	392.20	53.38	8.08	600.63	20.94	0.43
0.46	514.20	206.36	964.86	1685.42	401.22	58.67	8.54	676.22	23.54	0.50
0.50	514.20	241.07	1061.23	1816.50	420.80	67.15	9.34	764.39	28.26	0.63
0.54	514.20	260.42	1126.27	1900.89	439.42	75.19	10.09	835.29	33.04	0.76
0.58	514.20	258.57	1155.82	1928.60	452.27	80.67	10.61	872.24	36.49	0.86
0.63	514.20	234.25	1156.82	1905.27	459.72	83.08	10.86	875.90	38.19	0.90
0.67	514.20	191.20	1144.40	1849.80	463.66	82.44	10.86	857.68	38.23	0.90
0.71	514.20	137.38	1136.80	1788.38	465.91	78.89	10.65	833.23	36.75	0.84
0.75	514.20	83.04	1149.48	1746.72	468.08	72.54	10.26	817.60	33.95	0.74
0.79	514.20	38.33	1190.01	1742.54	471.62	63.74	9.72	821.81	30.06	0.62
0.83	514.20	10.80	1255.36	1780.36	477.79	53.42	9.10	850.64	25.53	0.49
0.88	514.20	3.74	1332.12	1850.06	487.08	43.59	8.56	901.13	21.23	0.37
0.92	514.20	15.55	1399.85	1929.60	498.19	36.94	8.25	961.30	18.40	0.30
0.96	514.20	40.40	1436.55	1991.15	508.09	35.19	8.25	1011.69	17.88	0.29
1.00	514.20	69.99	1424.78	2008.98	513.97	37.69	8.49	1032.56	19.37	0.32

Table A. 1

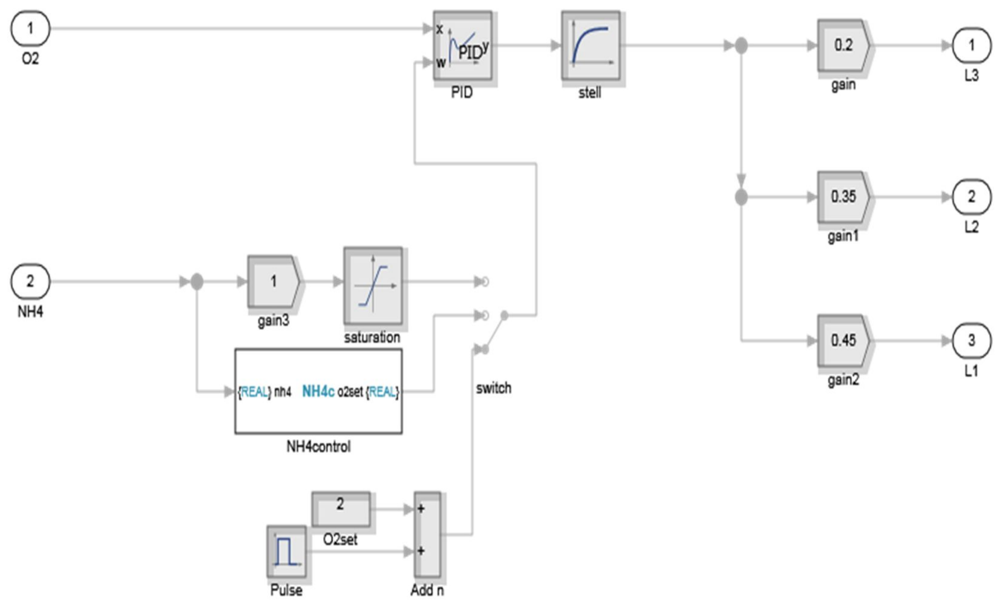


Figure A. 1: PID control block diagram for DO and NH4 control

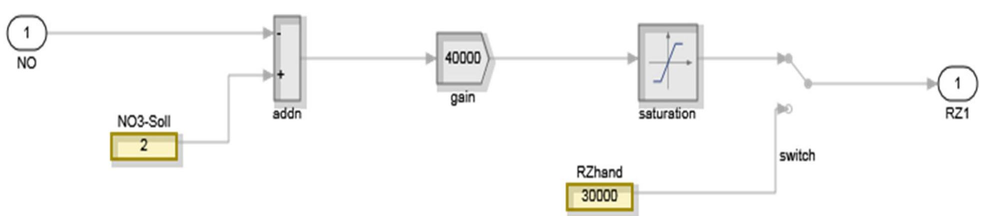


Figure A. 2: Nitrate and nitrite Nitrogen Regulator internal diagram

C# code for limiting DO based on ammonium concentration

```
public double gfun(matrix x, params object[] funargs) {
        sisiAPIint api = (sisiAPIint)funargs[0];
        matrix res1;
        double opt;
```

```
        //DO set point
        x[0] = Math.Min(Math.Max(x[0], 0.0), 10.0);
        api.con.writeLn("x: " + aConv.d2s(x[0], 3));
        api.dia_setParam("O2set", "Constant_0", aConv.double2string(x[0]));

        // Run Simulation
        api.resetState();
        api.prepareSim(0.0, 200.0);

        while (true) {
          if (api.step()) break;
          api.updateGuiAsync(false);
        }

        // user stop!
        if (api.isSimError()) throw new sisiException("User abort!");

        res1 = api.getResultMatrix("NK3S", "yef", "SNH");

        opt=Math.Abs(res1[-1,1]-1.0);

        api.con.writeLn("x=" + aConv.d2s(x[0], 3)+", gfun=" + aConv.d2s(opt, 6));

        return opt;
      }

public override void userCodeAsync(sisiAPIint api) {

  fMinSearch cali = new fMinSearch();
  cali.funfcn = this.gfun;

  // Do calibration
  matrix startVal = new matrix(1, 1, new double[1] { 2.0 });
  matrix optVal = cali.search(startVal, api);

  // Write to console
  api.con.writeLn("optVal: " + aConv.d2s(optVal[0], 6));
}
```

APPENDIX: B

MATLAB/Simulink S-function code and S-function Block parameters

```
function [sys, x0, str, ts] = nnrbf_pid(t,x,u,flag,T,nn,K_pid, eta_pid, xite, alfa, beta0, w0)

switch flag,
case 0, [sys, x0, str, ts] = mdlInitializeSizes(T,nn);
case 2, sys = mdlUpdates(u);
case 3, sys = mdlOutputs(t, x, u, T,nn, K_pid,eta_pid, xite, alfa, beta0, w0);
case {1, 4, 9}, sys = [];
otherwise, error (['Unhandled flag = ' , num2str(flag)]);
end

function [sys,x0,str,ts] = mdlInitializeSizes(T, nn)
sizes = simsizes;
sizes. NumContStates = 0;
sizes.NumDiscStates = 3;
sizes. NumOutputs = 4 + 5* nn;
sizes.NumInputs = 9 + 15* nn;
sizes. DirFeedthrough = 1;
sizes. NumSampleTimes =1;
sys = simsizes(sizes) ;
x0 = zeros(3, 1);
str = [];
T=0.0001;
ts = [T 0];
function sys = mdlUpdates(u)
sys = [ u(1) - u(2); u(1); u(1) + u(3) - 2* u(2)];
function sys = mdlOutputs(t, x, u,T, nn, K_pid, eta_pid, xite, alfa, beta0, w0)
% Initialization of the radial basis centers
ci3 = reshape(u(7: 6 + 3* nn), 3, nn);
ci2 = reshape(u(7 + 5* nn: 6 + 8* nn), 3, nn);
ci1 = reshape(u(7 + 10* nn: 6 + 13* nn), 3, nn);
% Initialization of the radial basis width
bi3 = u(7 + 3* nn: 6 + 4* nn);
bi2 = u(7 + 8*nn: 6 + 9* nn);
bi1 = u(7 + 13* nn: 6 + 14* nn);
% Initialization of the weights
w3 = u(7 + 4* nn: 6+ 5* nn) ;
w2 = u(7 + 9* nn: 6+ 10* nn) ;
w1 = u(7 + 14* nn: 6+ 15* nn) ;
if t== 0
% Initialize the PID parameters
ci1 = w0(1) * ones(3, nn);
bi1 = w0(2) *ones(nn, 1);
w1 = w0(3) * ones(nn, 1);
K_pid0 = K_pid;
```

```
else
% Update the PID parameters
K_pid0 = u(end-2: end);
end
%h= zeros(nn,1);
for j = 1: nn
% Gaussian
h(j,1) = exp(-norm(xx-ci1( : , j))^2/(2* bi1(j) * bi1(j)));
end
% Dynamic of gradient descent method
dym = u(4) - w1'* h;
w = w1 + xite* dym* h + alfa* (w1 - w2) + beta0*(w2 - w3) ;
%dbi=zeros(nn,1);
%dci=zeros(nn,1);
for j = 1: nn
dbi(j,1) = xite* dym* w1(j) * h(j) * (bi1(j) ^(-3)) * norm(xx - ci1(:,j))^2;
dci( : ,j) = xite*dym* w1(j)* h(j) * (xx - ci1(:,j)) * (bi1(j)^(-2));
end
% Jacobian
dJac = sum(w.*h.*(-xx (1) + ci (1,:)') ./bi.^2);
% adjustments of the PID parameters
KK(1) = K_pid0(1) + u(1) * dJac* eta_pid(1)* x(1);
KK(2) = K_pid0(2) + u(1) * dJac* eta_pid(2)* x(2);
KK(3) = K_pid0(3) + u(1) * dJac* eta_pid(3)* x(3);
sys= [ u(6) + KK* x; KK'; ci( : ) ; bi( : ) ; w( : ) ] ;
```

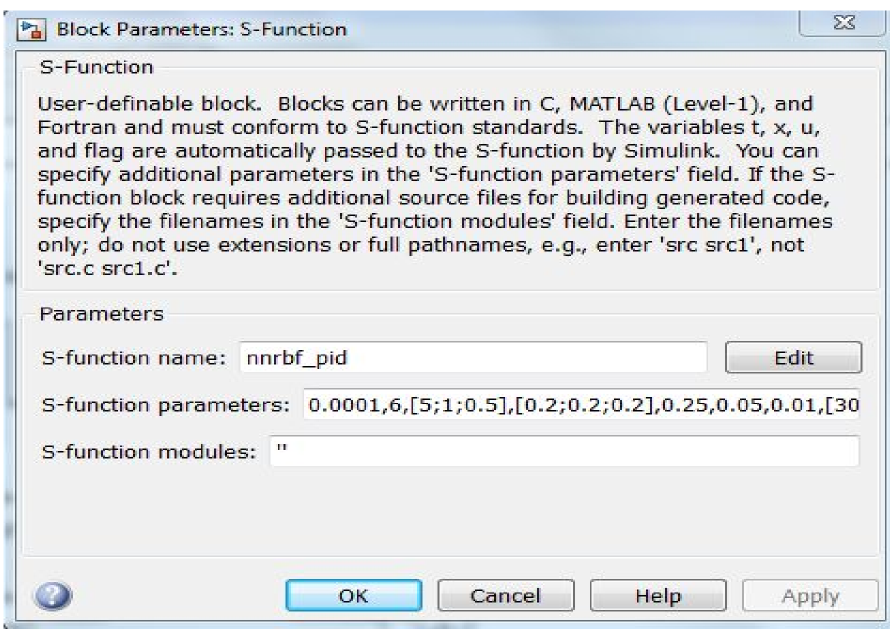


Figure B. 1 S-function initial parameter sets

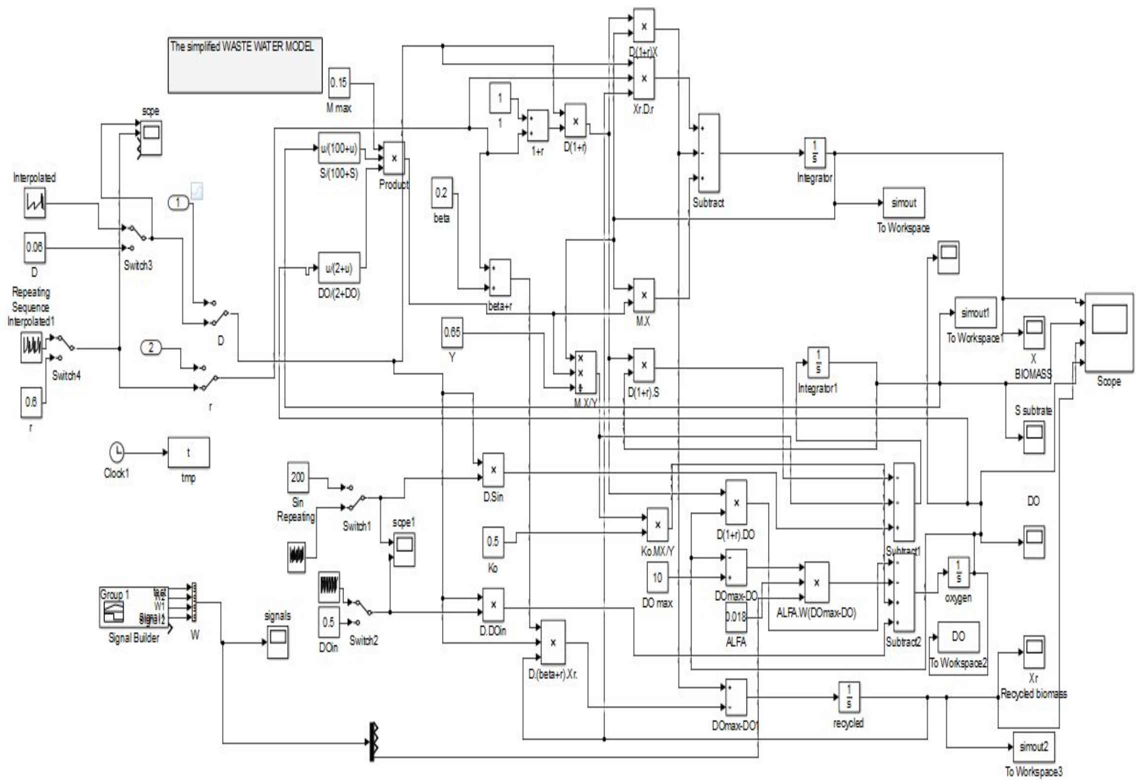


Figure B.2 Internal subsystem structure of the WWTP model block of figure 4.1

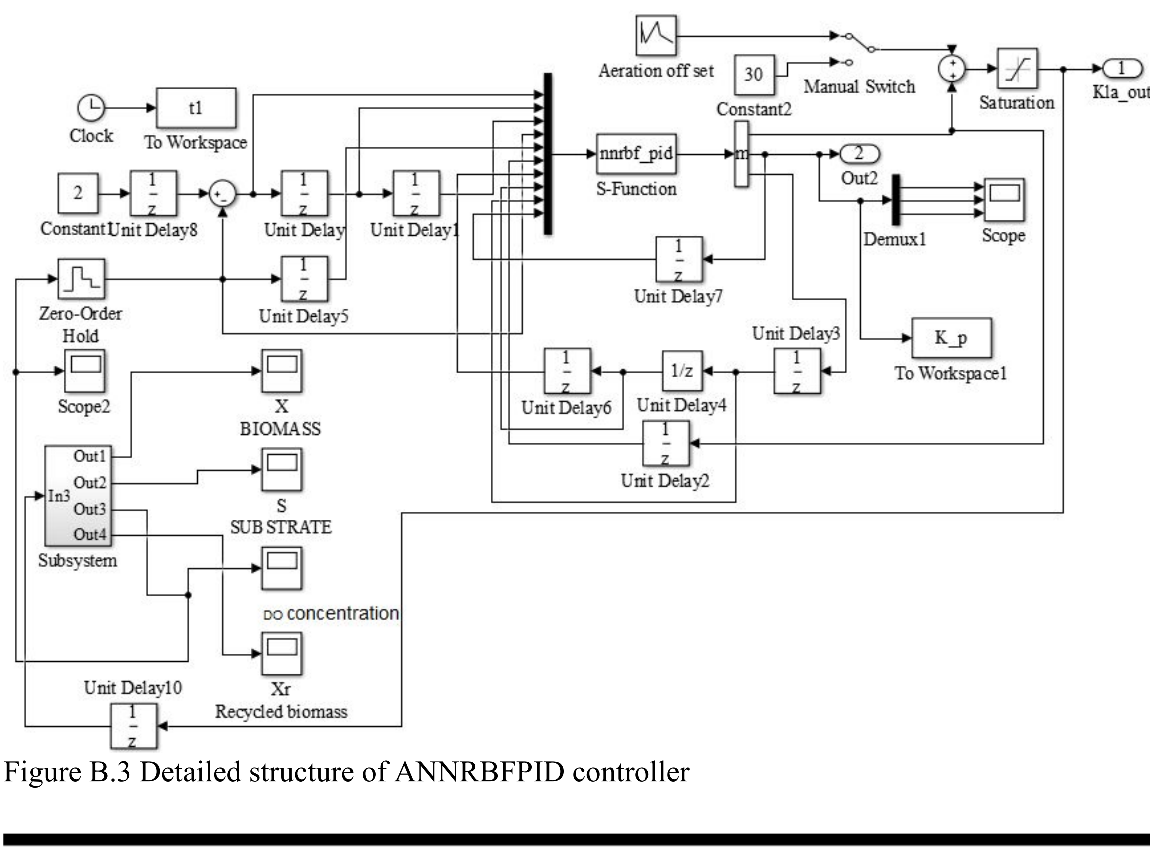


Figure B.3 Detailed structure of ANNRBFPID controller