DESIGN AND PERFORMANCE EVALUATION OF ADVANCED CONTROL STRATEGIES FOR BIOLOGICAL WASTEWATER TREATMENT PLANTS

Submitted in partial fulfillment of the requirement for the award of the degree of

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by

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CERTIFICATE

This is to certify that the thesis entitled **"DESIGN AND PERFORMANCE EVALUATION OF ADVANCED CONTROL STRATEGIES FOR BIOLOGICAL WASTEWATER TREATMENT PLANTS"** being submitted by **Mr. Indranil Dey** for the award of the degree of Doctor of Philosophy (Ph.D) in Chemical Engineering, National Institute of Technology, Warangal, India, is a record of the bonafide research work carried out by him under my supervision. The thesis has fulfilled the requirements according to the regulations of this Institute and in my opinion, has reached the standards for submission. The results embodied in the thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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DECLARATION

This is to certify that the work presented in the thesis entitled "**DESIGN AND PERFORMANCE EVALUATION OF ADVANCED CONTROL STRATEGIES FOR BIOLOGICAL WASTEWATER TREATMENT PLANTS**" is a bonafide work done by me under the supervision of Dr. Seshagiri Rao Ambati and Dr. P Sridhar and is not submitted elsewhere for the award of any degree.

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ABSTRACT

The utilization of biological processes to treat polluted wastewater has become prevalent, encompassing both conventional domestic and industrial wastewater. This approach aims to eliminate nutrients, specifically carbon, nitrogen, and phosphorus, while adhering to regulatory guidelines for reducing nutrient discharge into surface water, as mandated by municipal water directives. There is a growing interest for enhancing the effluent quality (EQ) of sewage wastewater treatment facilities.

Wastewater treatment plants are complex, nonlinear, and slow processes. The lack of adequate instrumentation, stringent environmental regulations, and the need for cost-effective plants have highlighted the significance of automating wastewater treatment processes. However, the process's complexity makes it difficult to successfully implement control systems. The main challenge is developing a control strategy that reduces operational costs (OC) while also improving EQ. This study looks into the development of various control strategies to meet these challenges.

The Benchmark Simulation Model No. 1-P (BSM1-P) and Sequencing Batch Reactor (SBR) serve as test platforms for these control strategies. The primary goal is to prevent violations in effluent ammonia, total nitrogen, and total phosphorus levels while reducing operational costs and improving effluent quality. The proposed control strategies use proportional integral (PI), fractional PI (FPI), fuzzy logic controller (FLC), and model predictive control (MPC).

To meet strict environmental laws, wastewater treatment plants (WWTPs) must balance efficiency and cost-effectiveness in their extremely non-linear operations. The ASM3bioP framework inside a BSM1-P is employed in this study to enable simultaneous nitrogen and phosphorus removal using an activated sludge process model with seven reactor configurations. The activated sludge process is the most complicated and energy-intensive phase of a WWTP. To control dissolved oxygen in aerobic reactors and nitrate levels in anoxic reactors, two robust PI controllers – a classical PI and a non-integer (fractional) order PI – with both integer-order and fractional-order models are designed. The controllers are created and simulated with the use of a mathematical model that has been developed based on the input data. Control theory has actively explored fractional calculus and its applications in recent years. This work regulates DO and NO concentrations in aerobic and anoxic reactors using IMC-based fractional filters cascaded with PI and FPI controls. Based on integer and non-

integer commands, these controllers optimize plant efficiency, longevity, production costs, and effluent nutrient content. IMC fractional PI controllers prioritize maximal sensitivity (Ms) within gain margin (GM) and phase margin (PM) as limitations. Fractional-order calculus advances highlight the dynamic character of real-time complicated processes, reducing complexity while retaining complex system dynamics. The fractional-order PID ($PI^{\lambda}D^{\mu}$) controller, an improved variant of the integer-order PID, adds integration (λ) and differentiation (μ) orders, improving closed-loop response stability with parameter alterations. The lower level Fractional controller with a fractional order model improves both the effluent quality index (EQI) and operational cost index (OCI) significantly. For such biological WWTP, a hierarchical Fuzzy logic controller or a MPC are designed to adjust the dissolved oxygen in the seventh reactor (DO_7) to control ammonia. The implemented supervisory layer control strategy improves EQI while increasing OCI marginally.

The treatment of wastewater is highly challenging due to large fluctuations in flow rates, pollutants, and variable influent water compositions. A sequencing batch reactor (SBR), and Modified SBR Cycle-Step-Feed Process (SSBR) configuration are studied in this work to effectively treat municipal wastewater while simultaneously removing nitrogen and phosphorus. To control the amount of Dissolved Oxygen in a SBR, three axiomatic control strategy (PI, FPI), and Fuzzy logic controllers (FUZZY)) is presented. A biological process and relevant control algorithm has been designed using real-time plant data with the models of biological processes (SBR, and SSBR), and aeration system. ASM2d mathematical modelling framework is considered for development of control relevant simulations. The use of the intricate ASM2d model, as well as the application of a control strategy to a batch process, makes the work significant. A comparison of plant performance concerning PI, FPI and FUZZY control framework is included. A comparison of FPI with the other two control strategies showed a significant reduction in nutrient levels and added an improvement in effluent quality. The SSBR, which is improved by precisely optimizing nutrient supply and aeration, establishes a delicate equilibrium. This refined method reduces oxygen requirements while reliably sustaining important biological functions.

This thesis also proposes a novel supervisory control scheme for SBR based WWTP. It integrates hierarchical fuzzy control, based on ammonia and nitrate observations, in the presence of lower-level PI and FPI controllers, with the dual goal of aeration cost reduction and effluent quality enhancement. In the hierarchical control system, variable DO trajectories are generated by the supervisory fuzzy logic controller and passed to the lower level controller, according to ammonia and nitrate profiles within SBR. It is crucial to adjust this element properly in order to maximize wastewater treatment efficiency and reduce plant costs, especially for the aeration system. A notable aspect of nitrate based hierarchical control scheme is to curtail the fresh oxygen use since nitrate (S_{NO}), a product of nitrification, is utilized for limiting aeration costs. Six distinct control techniques are implemented of which PI and FPI controllers for control of DO at the lower level. Four types of hierarchical ammonia and nitrate-based controllers employing intelligent Fuzzy control are deployed. Addition of Fuzzy controller contributes to an airflow reduction of 40.08% for ammonia control and 31.58% for nitrate control strategies. This study highlights the superiority of the ammonia-based control strategy, particularly coupled with lower level FPI controller, based on its ability to minimize airflow without affecting effluent quality. These findings offer helpful insights for advancing the field of wastewater treatment, improving efficiency, and promoting cost-effective and sustainable practices in SBR.

Another study which aims to investigate the effect of different seasons where the temperature would be different on the performance (phosphorous, nitrogen, and organic matter removal) of SBR based wastewater treatment plants. The modified ASM2d module, including the microbial kinetics is used to simulate the EBPR-based SBR process and the temperature is chosen between 10 to 33°C. Influent data from distinct wastewater treatment plants located in India and Europe are considered. The investigation of the kinetic variables is performed over a wide temperature range, and significant increases are seen as the temperature rises. The effluent parameters are within the government guidelines. It is clear that an increase in temperature results in better effluent quality with reduced COD, BOD, NH, and TN values and a slight increase in TP and TSS. In conclusion, this study highlights the importance of considering the effect of temperature on the performance of SBR-based wastewater treatment plants in different climatic conditions.

Keywords: Activated sludge system, Benchmark simulation model, Effluent quality index, PI controller, FPI controller, Non- integer model, Sequencing batch reactor, Operational cost index.

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Nomenclature

AE	Aeration energy rate (Kwh/d)
ASM1	Activated sludge model No.1
ASM2	Activated sludge model No.2
ASM2d	Activated sludge model No.2d
ASM3	Activated sludge model No.3
BOD_5	Biological oxygen demand
COD	Chemical oxygen demand
CE	Consumed energy
DO	Dissolved oxygen
EQI	Effluent quality index
IQI	Influent quality index
IMC	Internal Model Control
K or K_P	Proportional gain
K_La	Oxygen transfer coefficient
TN	Total nitrogen
NO	Nitrate
TP	Total phosphorus
PE	Pumping energy consumption (kWh/d)
HU_k	Pollutant load corresponding to the component
Qo	Influent flow rate (m^3/d)
Q_{intr}	Internal recycle flow rate (m^3/d)
Q_r	Return sludge flow rate (m^3/d)
Q_w	Waste sludge flow rate (m^3/d)
RGA	Relative gain array
SBR	Sequencing Batch Reactor
S_A	Fermentation products (g COD/m^3)
S_F	Readily biodegradable organic substrate
S_{HCO}	Alkalinity of the waste water (HCO_3/m^3)
S_I	Inert soluble organic material (g COD/m^3)
S_{NH}	Ammonium and ammonia nitrogen (g N/m^3)
S_{NO}	Nitrate and nitrite nitrogen (g N/m^3)

S_{N2}	Dinitrogen (g N/m^3)
S_{PO4}	Inorganic soluble phosphate (g P/m^3)
S_S	Readily biodegradable organic substrate (g COD/m^3)
t_o	Start time
t_f	End time
T_{BOD}	Total BOD concentration
T_{COD}	Total COD concentration
T_{NO}	Nitrate concentration
TN_{tot}	Total N concentration
TP_{tot}	Total phosphorous concentration
T_{TKN}	Total organic N concentration
T_{TSS}	Total suspended solids concentration
WWTP	Wastewater treatment plant
X_A	Nitrifying organisms (g COD/m^3)
X_H	Heterotrophic organisms (g COD/m^3)
X_I	Inert particulate organic material (g COD/m^3)
X_S	Slowly biodegradable substrates (g COD/m^3)
X_{PAO}	Phosphate accumulating organisms (g COD/m^3)
X_{PHA}	Cell internal storage product of PAO's (g COD/m^3)
X_{PP}	Polyphosphate (g P/m^3)
X_{STO}	Cell inner storage product of heterotopy
X_{TSS}	Suspended solids (g SS/m^3)
α_j	Cost factor for components j (j= EQI, AE, PE, and SP)
β_k	Weighting factor for components K (T_k = T_{BOD}, T_{COD}, T_{TKN}, T_{NO3},T_{Ptot}, and T_{TSS})

Introduction

1. INTRODUCTION

In wastewater treatment plants (WWTPs), control techniques are necessary for the plants to run efficiently and meet government standards. This thesis highlights their pivotal role in optimizing treatment processes, ensuring compliance, enhancing resource utilization. Control strategies also make it possible to adapt to changes in wastewater composition and flow rates, lower operating risks, and make decisions based on data. Control strategies are an important part of modern wastewater treatment. They ensure the system works well and sustainably by using advanced tracking, dynamic adjustments, and smart decision-making.

1.1 Wastewater Treatment

Water is the cornerstone of life, an absolute must for the survival of all living beings. In the face of escalating global population growth and widespread urbanisation, sustainable oversight of water resources has arisen as a paramount corner. One of the foremost significant aspects of this quest is the efficient clean-up of wastewater, an intricate process that is required to protect both environmental integrity and the wellness of society. It is critical to comprehend and apply cutting-edge technology for wastewater treatment since growing urbanisation and industrialization continue to put pressure on water bodies. Based on this context, developing countries have to establish initiatives to promote the recycling and reuse of treated wastewater. As a result, several nations are tightening their environmental restrictions. Research into intensifying wastewater treatment plants (WWTPs) is in vogue.

Wastewater, a by-product of domestic, industrial and agricultural operations, contains an intricate array of contaminants ranging from organic matter to toxic substances. Unchecked discharge of untreated wastewater straight into water bodies destroys aquatic ecosystems and increases the danger of waterborne infections, putting public health at risk. As a result, developing and deploying robust wastewater treatment systems has become critical to shield water resources and maintain ecological balance. The exploration towards wastewater treatment is a study of the sensitive balance between anthropogenic activity and aquatic ecosystem resilience. It entails the delicate interaction of creative engineering solutions and environmental preservation. As the world grapples with the effects of pollution and water scarcity, a nuanced understanding of wastewater treatment processes is critical for devising holistic and successful water management policies. Because of the numerous biological, chemical, and physical elements influencing wastewater treatment systems, such as fluctuations, dynamics, disturbances, and uncertainties in the influent, monitoring the wastewater treatment plant is often difficult. Several research materials dedicated to enhancing the wastewater treatment process have been published as a result of significant studies done by the global research community. In recent years, there has been a greater emphasis on the water-energy-food nexus, intending to understand the interconnectedness of these components and analyse their reciprocal requirements. At present, researchers are investigating wastewater treatment plants as potential sources of resource recovery.

1.1.1 Wastewater treatment facility: Water conversion tool

We are in an era where water scarcity is a growing concern, wastewater treatment addresses the challenge by promoting a circular water economy. Its sophisticated treatment methods contribute to environmental conservation while aligning with global sustainability goals. An innovative wastewater treatment facility stands at the forefront of sustainable water management. This cutting-edge water conversion tool integrates advanced technologies to efficiently treat and convert wastewater into high class water resources.

The wastewater treatment process involves a series of steps to remove impurities and contaminants from water, from wastewater collection to grit removal, primary treatment to secondary treatment, sludge treatment, tertiary treatment, and disinfection. The two types of wastewater treatment facilities are chemical or physical WWTPs and biological WWTPs. A biological WWTP uses biological microbes to break down waste (organic material). Through microbial activity, the biological approach is responsible for the removal of organic contaminants and pollutants. The physical method deals with the process of primary treatment like grit, screening, primary sedimentation, and filtration. Physical wastewater treatment plants are frequently used to handle wastewater from industries, factories, and industrial companies, whereas biological treatment facilities are appropriate for dealing with wastewater from municipal and commercial sectors. The chemical approach involves the addition of chemical doses to remove pollutants.

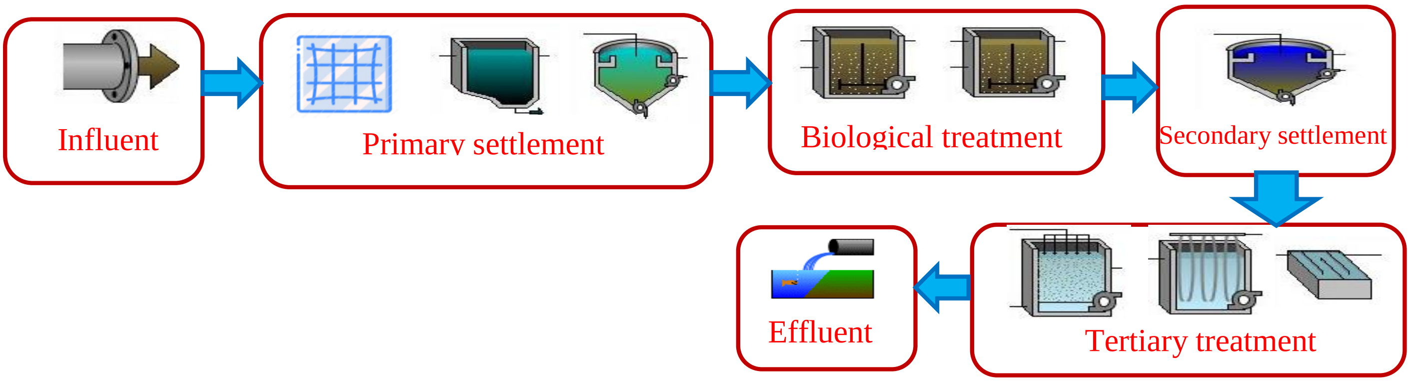


Figure 1.1: Schematic diagram of wastewater treatment facility

Figure 1.1 depicts an intricate wastewater treatment operation. The contaminated influent is collected and passed through primary settlement via screening, gritting, and a primary clarifier before entering the biological treatment process via multiple anaerobic or anoxic and mostly aeration treatments before reaching secondary settlement. Following that, some complex water recycling units known as tertiary treatment takes place. The water has been treated and is now ready for discharge. The complicated chemical and biological interactions within the process, the particular properties of microbes, the progressive nature of the process, and the variations in concentrations and dynamic flow rates all contribute to the complexity of WWTPs. Furthermore, functioning is highly energy-intensive, challenging and complicated the work of controlling WWTPs. Nonetheless, new research reveals that, in addition to water treatment, WWTPs have the potential to produce important resources. It is becoming increasingly clear that wastewater can be used to recover value-added products such as clean water, clean energy, and fertilisers.

1.1.2 Biological wastewater treatment plant

Biological WWTPs are complex and nonlinear systems with interwoven dynamics encompassing a wide range of erratic time constants and several sub-processes. These biological treatment procedures entail the oxidation of organic compounds in wastewater by microbial activities such as lagoons or anaerobic processes, activated sludge, and microalgae photosynthesis. These methods are used to reduce physiological variables like pH, biochemical oxygen demand (BOD), and chemical oxygen demand (COD).

The classic approach for biological treatment of industrial and domestic wastewaters is characterised as activated sludge treatment. The unusual behaviour of microorganisms in biological events occurring within the process is the primary cause of the process's nonlinear and complex dynamics. The primary goal of wastewater treatment is to reduce effluent concentrations prior to disposal. However, only some of the contaminants in wastewater are treated and reduced below the allowable limit by the procedure used. Furthermore, the plant is subjected to a wide range of disturbances and variations in the properties of the influent with magnitudes that exceed those experienced by most other process industries. Even so, the plant must run continually in order to meet the rigorous effluent quality restrictions. Currently, because the process is highly energy-intensive, the plant must be operated in an energy-efficient manner. Thus biological wastewater treatment stands out as a cutting-edge topic of research in the contemporary landscape.

According to the operating mode of biological treatment process it can be classified into two types, Activated Sludge Process (ASP) and Sequencing Batch Reactor (SBR). The activated sludge process is an interrupted treatment method that uses a suspension of microorganisms in wastewater within an aeration tank. This microbial consortia digests and degrades organic contaminants. A portion of the organic matter is completely oxidised, resulting in harmless end products and other inorganic chemicals and giving energy to sustain microbial growth and biomass creation (flocs). A typical activated sludge plant is shown in Figure 1.2.

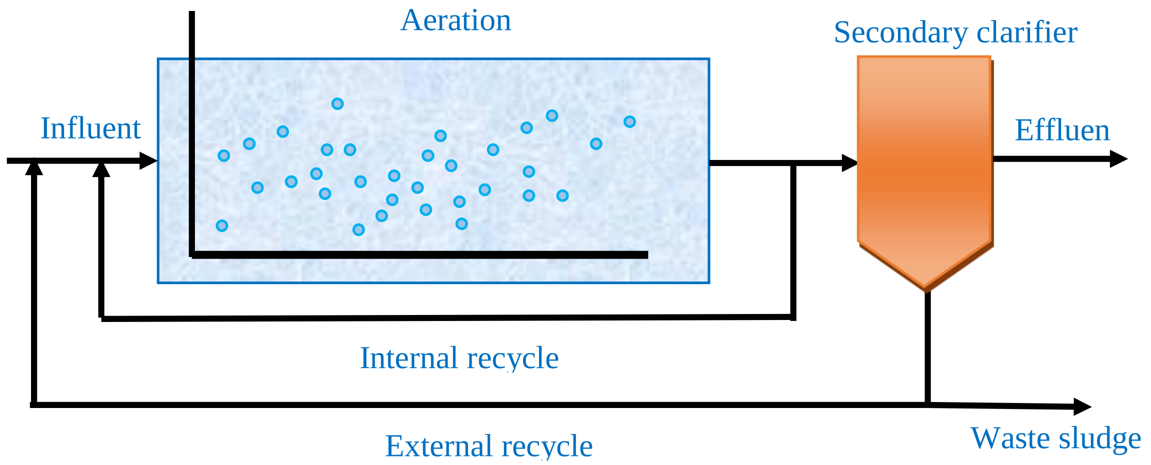


Figure 1.2: Activated sludge Process (ASP)

A SBR is an example of batch-mode wastewater treatment technology. It is intended to treat sewage in a series of steps, with treatment operations taking place in particular time-based stages within a single tank. The SBR system is often divided into the following phases: Fill, React, Settle, Decant, and Idle. In contrast to the ASP scheme, the SBR technology does not require a secondary sedimentation basin to operate. Furthermore, the SBR system, unlike the ASP scheme, does not include sludge return back to the aeration basin. A diagram of time sequence SBR process is shown in Figure 1.3

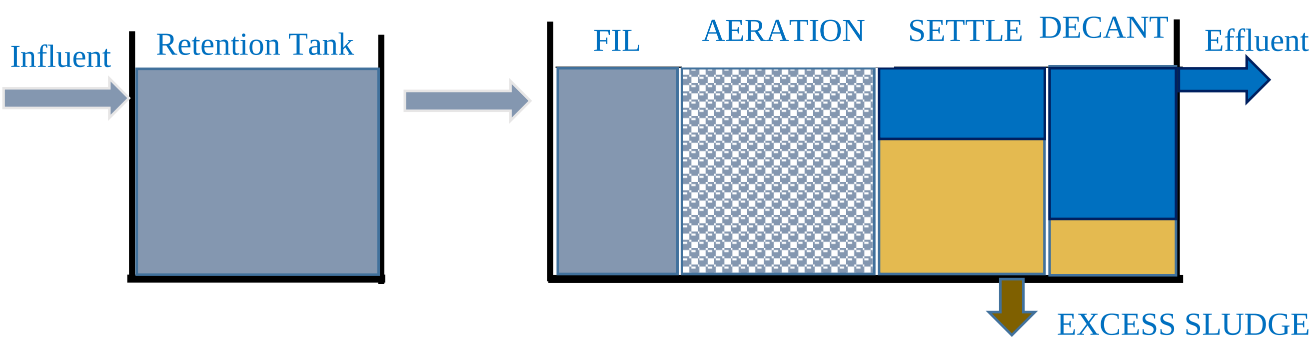


Figure 1.3: Sequencing batch Reactor (SBR)

1.2 Control of Biological Wastewater treatment Plants

Recently, it has become increasingly difficult to achieve any process plant performance standards. Upstretched productivity, severe environmental and safety laws, and rapidly changing economic conditions have all contributed considerably to this complexity. As a result, product quality criteria have become more severe, resulting in a greater emphasis on improving plant profitability. Another degree of complication derives from the present trend towards sophisticated and compactly integrated processes, which makes it difficult to limit disturbances that propagate among interconnected components. Process control has grown in importance as the emphasis on safe and efficient plant operations has grown. Computer-based process control systems have developed as important tools, allowing modern factories to operate safely and profitably while satisfying quality requirements and environmental restrictions. Figure 1.4 illustrates the systematic procedure to operate a WWTP and valuable outcomes.

The control strategies in Biological WWTPs ensure environmental compliance, improve operational efficiency, and optimize treatment processes. In practice, the most commonly utilised control configurations are for dissolved oxygen control, nitrate control, ammonia-based aeration control, orthophosphate control, total suspended solids management, and so on. In recent years, the operation of WWTPs with lower operating costs and improved effluent quality has become critical.

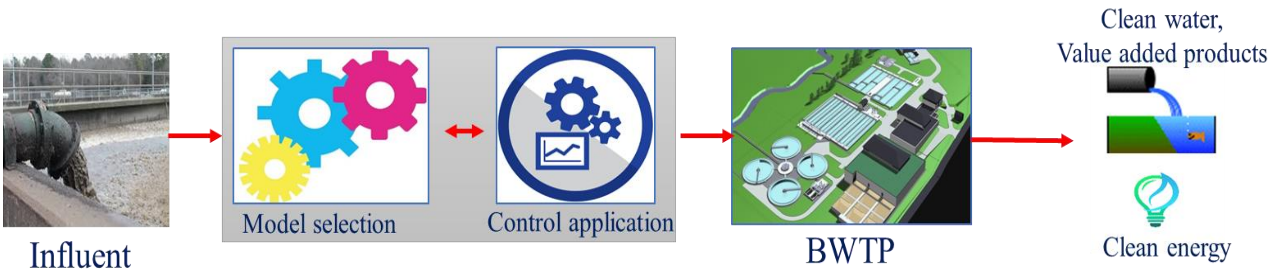


Figure 1.4: Integrated technologies in WWTP and their outcome

1.2.1 Role of Process control engineers in WWTP

Process control engineers play an important role in WWTPs by ensuring that the treatment processes run efficiently and effectively. Their responsibilities include a wide range of tasks geared at improving plant performance, meeting environmental standards, and guaranteeing the facility's general reliability. The following are significant features of process control engineers' roles in WWTPs:

- **Design and setup:** Control engineers are involved in the design and implementation of control systems for various treatment processes. They integrate sensors, programmable logic controllers (PLCs), and other automation technologies to monitor and control the plant's operations.
- **Process optimization:** These engineers constantly analyse and assess the performance of treatment procedures. They attempt to improve the efficiency of biological, chemical, and physical treatment methods by fine-tuning control strategies, modifying set points, and optimising parameters.
- **Dealing with Instrumentation & sensor:** Control engineers are responsible for the calibration and maintenance of the plant's instruments and sensors. For effective control, accurate measurements of important parameters such as flow rates, pH levels, and dissolved oxygen concentrations are required.
- **Troubleshooting and Diagnostics:** When problems or disturbances occur during the treatment process, process control engineers play an important role in diagnosing the issue. They apply their knowledge to troubleshoot control system problems, identify root causes, and put corrective measures in place.
- **Plant safety:** The safety of plant operations is of the utmost importance. Process control engineers seek to put safety precautions and emergency shutdown of systems.
- **Data Analysis and Reporting:** Process control engineers prepare plant performance reports by monitoring and analysing data from control systems. This data-driven strategy aids in the development of informed judgements for process optimisation and regulatory reporting.
- **Adopting new technology:** As technology advances, process control engineers investigate and integrate sophisticated technologies such as artificial intelligence, machine learning, and advanced sensors to improve the efficiency and automation of wastewater treatment processes.

In essence, a process control engineers play an important role in maintain the reliable and sustainable functioning of wastewater treatment plants, thereby contributing to the protection of environmental and public health.

Figure 1.5 displays benefits of controller implementation in WWTP. It becomes vital for the success of a control system to investigate the incentives that can motivate a system or individual to encourage optimal performance.

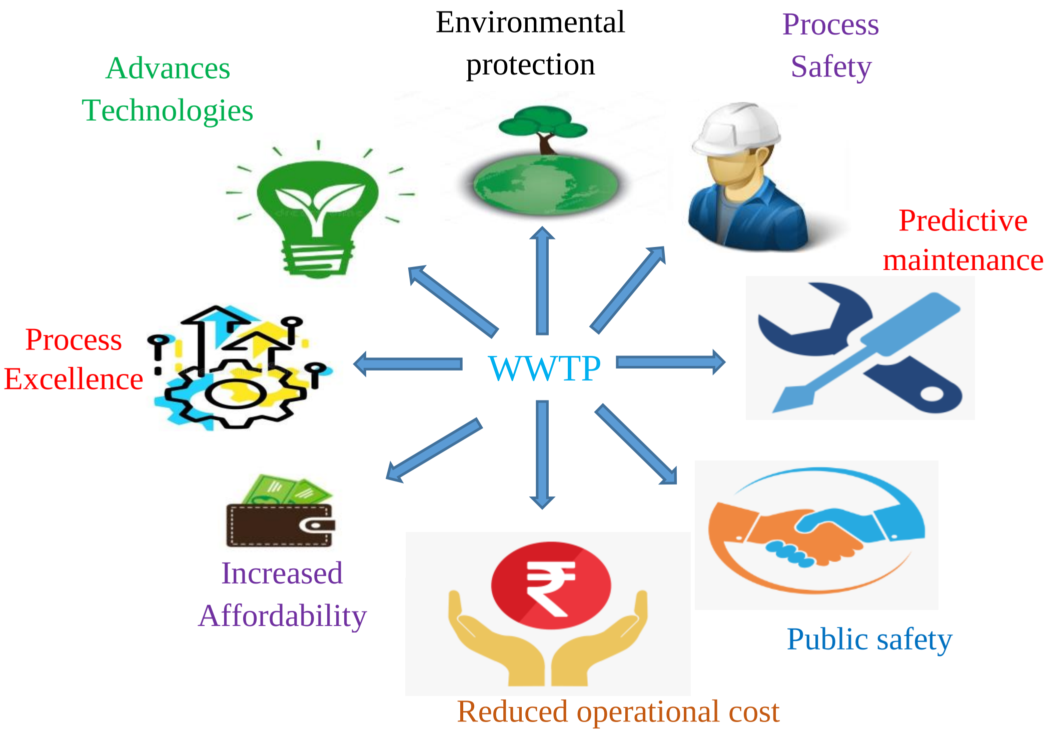


Figure 1.5: Outcomes of controller implementation in a WWTP

It becomes vital for the success of a control system to investigate the incentives that can motivate a system or individual to encourage optimal performance. The use of automatic controllers can improve process monitoring, allowing operations to be more closely aligned with restrictions like effluent assessment and cost considerations. Process control is crucial in wastewater treatment facilities because it assures optimal performance, increasing the plant's lifespan and lowering unit product costs. Wastewater treatment plants are one-of-a-kind, which changes the control strategy and adds complexity to the process. Here are some of the features:

• The amount of wastewater that needs to be treated every day can be very large.

• The disturbances in the influent are very high compared to most industries.

• The influent has to be accepted and treated; it can't be sent back to the supplier.

• The process isn't linear, which makes simple controllers less useful.

• The biological processes involved may have unstable behaviour.

• The amounts of nutrients are very low, making sensors difficult to use.

In addition, the subsequent ones represent a few more reasons why control is not easy to plan or put into place.

• The type of bacteria and how they act and where they live.

• It's hard to separate the effluent from the biomass, and it's easy to mess up the process.

• There are very strict effluent standards that must be met before the wastewater can be released.

Taking all of these things into account, there are set goals and objectives for putting in place the right control methods for biological wastewater. The aims and goals are broken down into three groups: operational goals, process or plant goals, and community or societal goals. The company's community or societal goals include taking care of the environment, its workers, and the people in the neighbourhood where it does business. It is important for the process or plant goals to help reach the bigger group goals. Some of them are meeting limits on effluent discharge, getting good disturbance rejection, and keeping running costs as low as possible. In order for a certain company to meet the process or plant goals, the operational objectives spell out exactly how it should be run. Operational objectives, plant dynamics, and traditional instrumentation and management systems shape control strategy execution. The pyramid in Figure 1.6 shows the hierarchical organisation of instrumentation and management systems. Left of the pyramid classifies hardware, software, and labour; right classifies purpose and duty. Information in diminishing amounts flows up, and operating instructions in larger amounts flow down. All of these are considered while implementing control measures to satisfy biological wastewater treatment facility goals.

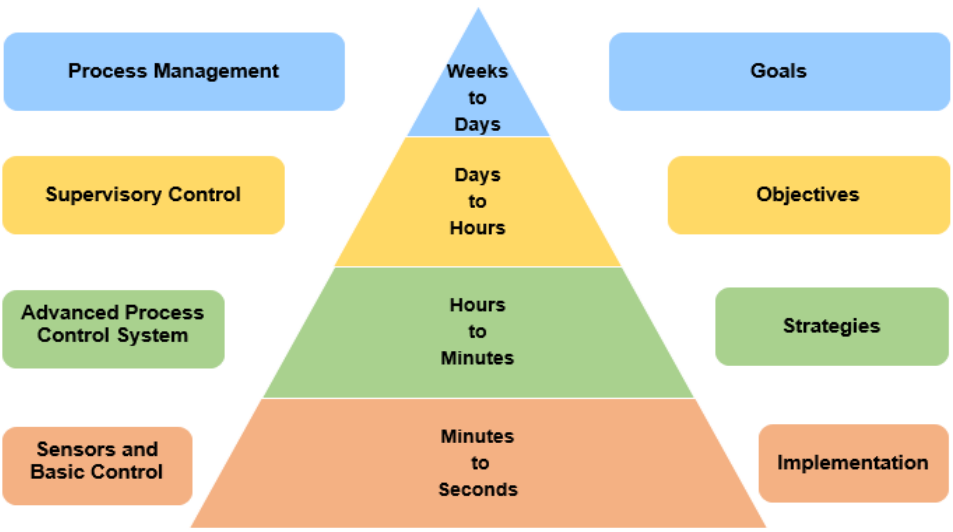


Figure 1.6: Standard Operating and Control Hierarchy

1.2.2 Control structures and algorithms

Different control structures are employed depending on the procedures used to accomplish specific goals. Designing the control system involves determining which variables to manage, and regulate, and how these groups of variables interact to build control loops. Several well-known control structures, such as Feedback Control (FB), Feed-forward Control (FF), Cascade Control, and Supervisory Control, are used and evaluated for WWTPs in this work. The general framework of feedforward, feedback, and cascade control is depicted in Figures 1.7, 1.8, 1.9.

A controller's principal responsibility is to keep the process value at the desired level. The most extensively used control technique for achieving this study is the Proportional-Integral-Derivative (PID) controller (Aström and Hägglund 1995). PID controllers are classified into three types: P (Proportional), PD (Proportional-Derivative), and PI (Proportional-Integral). The proportional section responds to current control errors, the integral section collects previous control errors, and the derivative section predicts future control mistakes by using the control error's derivative.

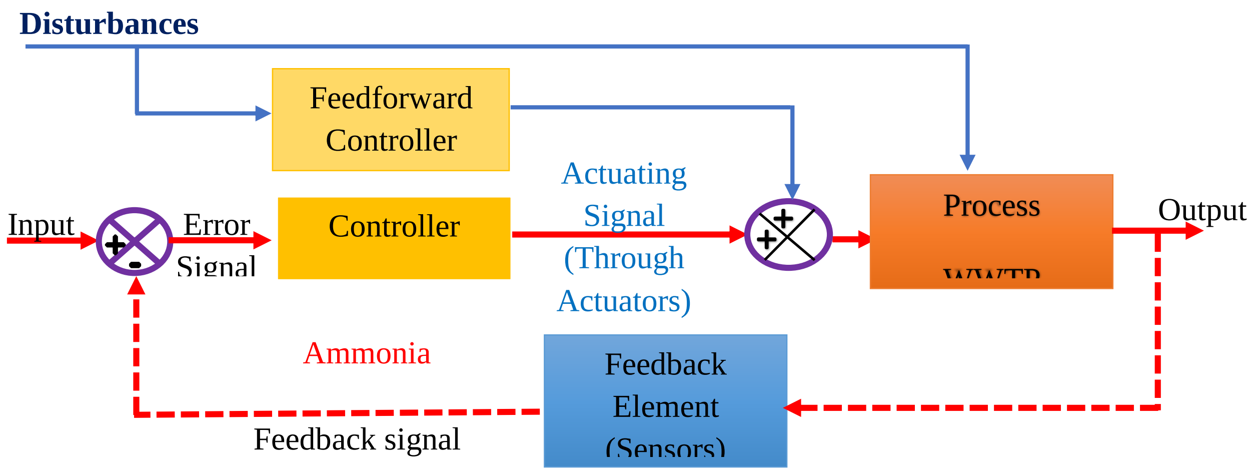


Figure 1.7: Feedback-feedforward control

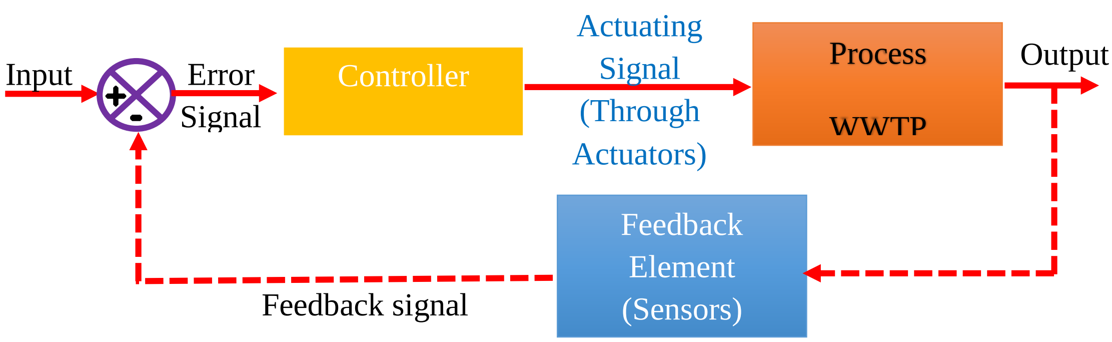


Figure 1.8: Feedback Control

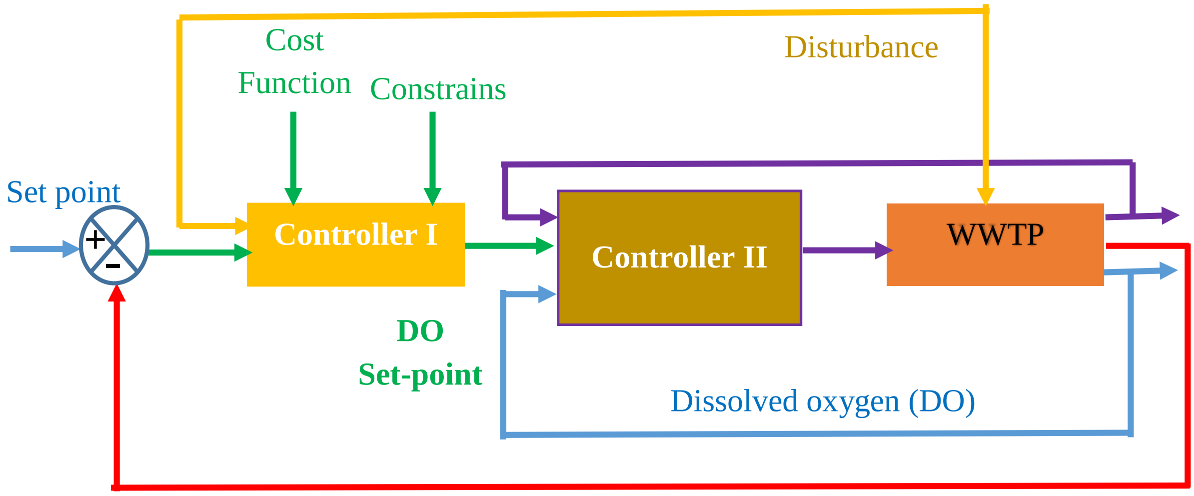


Figure 1.9: A supervisory layer strategy which determines set point to lower loop.

Responsibility for the integral action lies with the integral segment. Alternatively, the steady-state offset can be eliminated via integral action. The main issue with PID is that it is linear, which might not work for complex systems. An expansion of the integer-order PID controller that incorporates the integration (λ) and differentiation (μ) orders is the fractional-order $PI^{\lambda}D^{\mu}$ controller, elucidates in Figure 1.10. The extra tuning options in fractional order controllers are what really make them appealing, they may be used to make the closed-loop system more resilient in general.

Water treatment plants often use advanced control algorithms like MPC, Fuzzy, and ANN. There has been the utilisation of Fuzzy logic control across the entirety of the wastewater treatment process. It was also discovered that the FLCs operate admirably under a range of

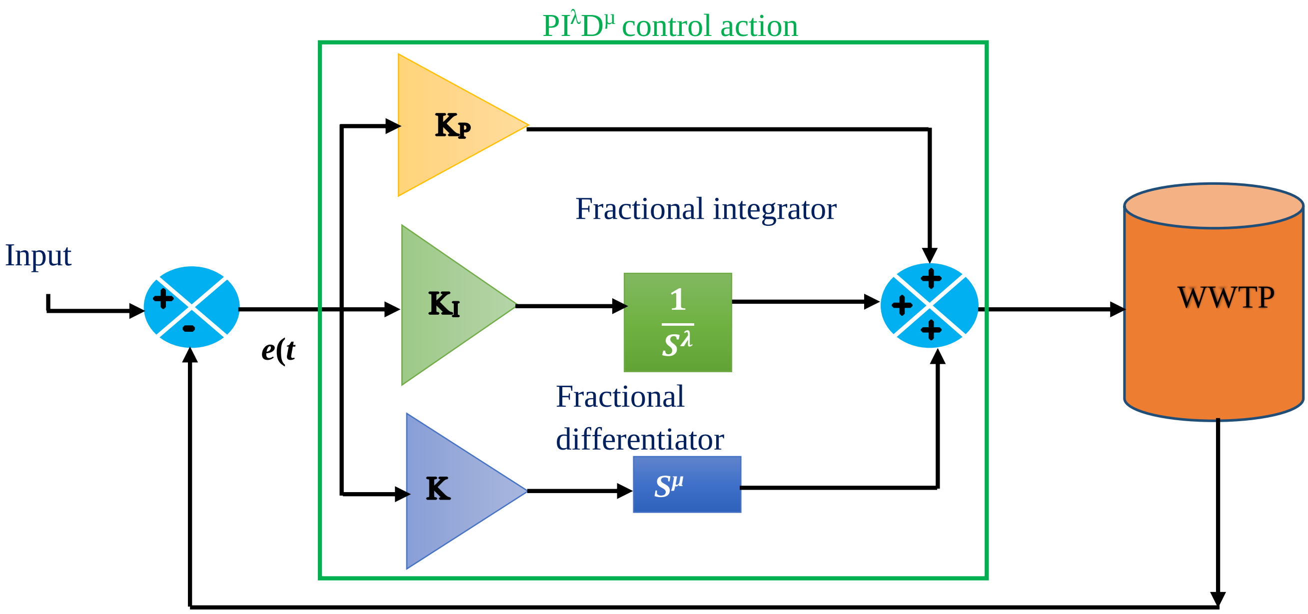


Figure 1.10: Fractional PID block diagram

operational circumstances. The WWTP's basic fuzzy logic controller is shown in Figure 1.11. Recent trends highlight the importance of FLCs in wastewater treatment, however direct control approaches can fail in many ways depending on the sensitivity of the process. In traditional FLC, the control model represents the human body of knowledge. There are three parts to FLC. In the main portion, input values are used to fuzzify membership functions (MFs). In the second section, we'll use the inference process to identify the outputs after connecting the fuzzy inputs and outputs using specified rules. De-fuzzification, the third section, involves computing stringent output values. To control aeration for energy efficiency and reduce nitrous oxide (N_2O) emissions, wastewater treatment plants use fuzzy logic control.

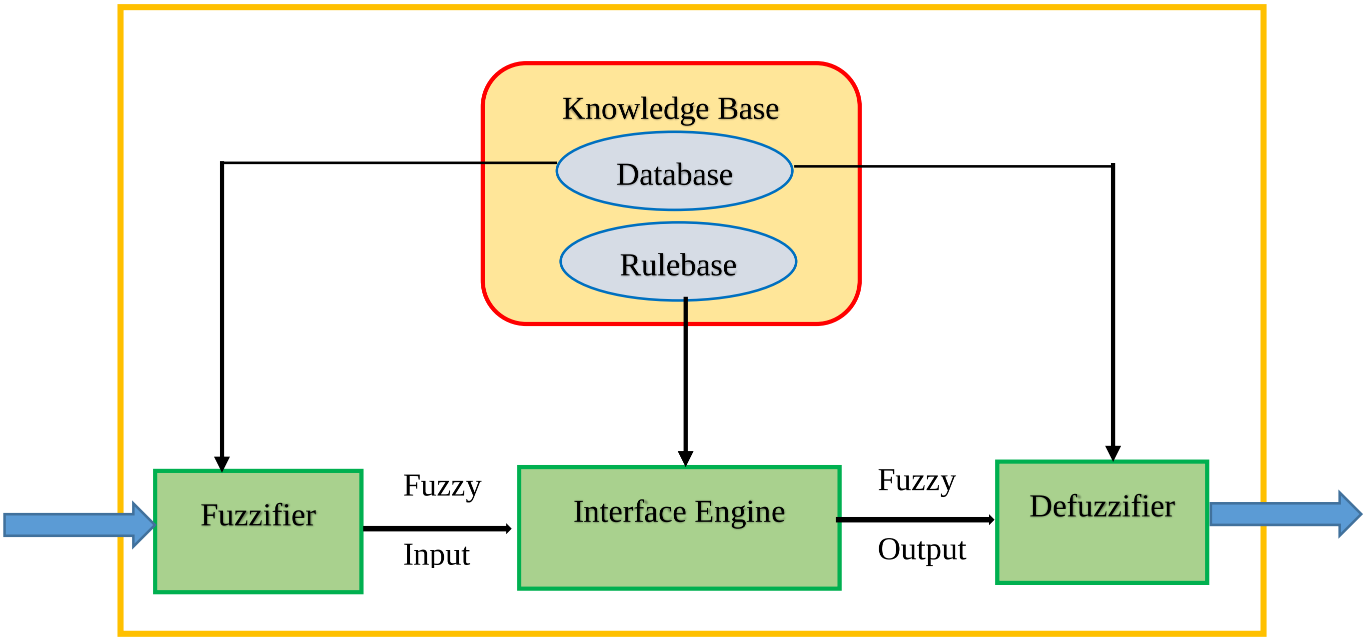


Figure 1.11: Structure of Fuzzy Interface system

wastewater treatment. MPC is a sophisticated control technique that use a dynamic process model to anticipate future system behaviour and optimise control inputs over a predetermined time horizon. The core components of MPC are process models, objective functions, and control rules. The basic MPC controller in the WWTP is shown in Figure 1.12. Several studies have demonstrated that MPC, when applied to a linear process model, is beneficial in treating wastewater (Steffens and Lant (1999), Charef et al. (2000), and Sotomayor et al. (2002)).

We can see how an MPC controller can incorporated with WWTP:

Development of a dynamic model: To initiate the implementation of MPC, the initial step involves constructing a dynamic model of the wastewater treatment process. The model should accurately represent the essential connections and behaviours of the system, encompassing the interplay between different elements like as pumps, valves, tanks, and biological activities. Then defining the Objective Function: It necessitates the use of an objective function that must be minimised across the prediction horizon. Regarding wastewater treatment, the objective function in question may encompass minimising energy usage, maximising efficiency in removing pollutants, or ensuring that the quality of the effluent remains within the limitations set by regulations. Then putting the constraints Statement: Constraints play a crucial role in MPC by ensuring that the control inputs and system states stay within acceptable limits. Limitations in wastewater treatment may encompass restrictions on the dynamics of influent flow, quantities of chemicals used, and other variables within the treatment process.

Real-time optimisation: MPC addresses the optimisation problem in real-time by utilising current measurements and adjusting the control inputs accordingly at each time step. Execution of MPC Controller: The MPC algorithm computes optimal control inputs by considering the present system state and forecasting its future dynamics.

Benefits of Model Predictive Control in the field of Wastewater Treatment adds enhanced process performance by optimising crucial objectives, including pollution removal, energy efficiency, and resource utilisation, thereby improving the overall performance of the wastewater treatment plant. However implementation of MPC in wastewater treatment may pose challenges, including the requirement for precise dynamic models, limitations in sensor capabilities, and the computational intricacy of solving real-time optimisation problems. Nevertheless, achieving its effective execution necessitates a comprehensive comprehension of the distinct attributes of the wastewater treatment facility and the creation of precise dynamic process models.

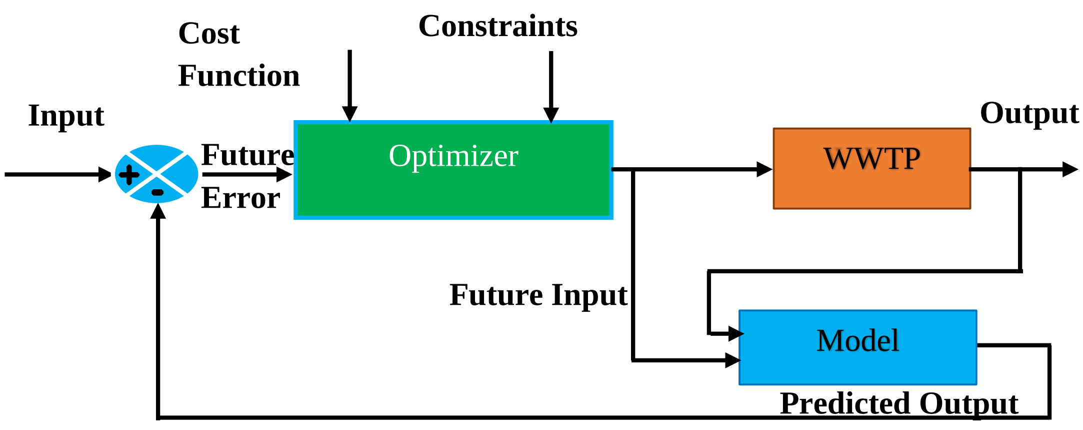


Figure 1.12: Typical structure of model Predictive controller

1.2.3 Sensors

WWTPs utilise a range of sensors to monitor and control the treatment process. These sensors offer real-time information on crucial parameters, enabling operators to enhance treatment efficiency. Here some important sensors frequently adopted in a WWTP.

- Physical sensors: To measure physical attributes of WWTP.

Flow Sensors are used to quantify the rate at which wastewater flows through the treatment facility, like internal & external recycle. Typical varieties comprise of electromagnetic flow metres, ultrasonic flow metres, and open channel flow metres.

Level Sensors monitor the liquid levels in tanks and basins. Level measuring often employs capacitance, ultrasonic, and radar sensors.

Pressure Sensors are used to gauge the pressure levels inside pipes and tanks, aiding in the supervision and regulation of wastewater flow.

Temperature Sensors are used to monitor the temperature of wastewater at different stages of the treatment process. Typical examples comprise thermocouples and resistance temperature detectors (RTDs).

- Chemical sensors: To monitor chemical parameters in treatment facilities.

pH Sensors, are utilised to quantify the level of acidity or alkalinity in wastewater. pH sensors play a vital role in ensuring the ideal conditions are maintained in biological treatment procedures.

Dissolved Oxygen Sensors, are used to quantify the concentration of oxygen that is dissolved in wastewater. Crucial for evaluating the condition of aerobic treatment processes. According to the aspects of our current study to implement aeration control this sensors are very crucial.

Conductivity Sensors are used to measure the electrical conductivity of wastewater, which gives an indication of the concentration of total dissolved solids (TDS).

Turbidity sensors are used to quantify the level of cloudiness or haziness in wastewater, which serves as an indicator of the presence of suspended materials.

- Biological sensors:

Ammonia Sensors are used to gauge the level of ammonia in wastewater, a crucial factor in evaluating the effectiveness of biological treatment methods.

BOD Sensors are used to measure the quantity of organic substances present in wastewater. They assist in evaluating the level of biodegradable material and determining the necessary treatment measures.

- Gas sensors:

Hydrogen Sulphide Sensors are used to quantify the levels of hydrogen sulphide gas, which may arise during anaerobic treatment procedures. Methane Sensors are used to detect the presence of methane gas, which can be generated during anaerobic digestion processes.

The selection of sensors is contingent upon the particular demands and attributes of the treatment facility. By using sophisticated sensor technology and data analytics, the efficiency and performance of WWTPs can be significantly improved.

1.3 Aeration Control

Controlling the level of dissolved oxygen is crucial in the activated sludge process, whether it is in continuous or in alternating or periodic systems. The implementation of aeration control was initially initiated in the 1960s with the objective of conserving energy by preventing excessive aeration during episodes of low load. The influence of the dissolved oxygen (DO) concentration and/or aerobic volume (in a continuous system) or aeration phase length (in a batch system) on the features and performance of a biological wastewater treatment system extends beyond mere cost savings. Indeed, the attention has been directed towards the influence of dissolved oxygen control on the process of removing biological nitrogen and phosphorus. Figure 1.13 delivers a concise overview.

Nitrification: Ammonia is converted to nitrite and then to nitrate in this process by ammonia-oxidizing bacteria (AOB) and nitrite-oxidizing bacteria (NOB). Both are aerobic and rely on oxygen as an electron acceptor. DO provides energy to these bacteria, altering the pace of nitrification. Higher DO levels promote faster nitrification, whereas oxygen deficiency can slow rates and block nitrifying microorganisms. DO level monitoring and control are critical for optimising nitrification rates and overall treatment efficiency.

Denitrification: DO significantly influences denitrification in wastewater treatment. Denitrification, converting nitrate and nitrite into nitrogen gas under anoxic conditions, relies on low oxygen levels. Excessive DO inhibits denitrification, favouring aerobic processes. Maintaining optimal DO concentrations, typically below 0.5 mg/L, is crucial for effective denitrification. Wastewater treatment plants control aeration to balance aerobic and anaerobic needs.

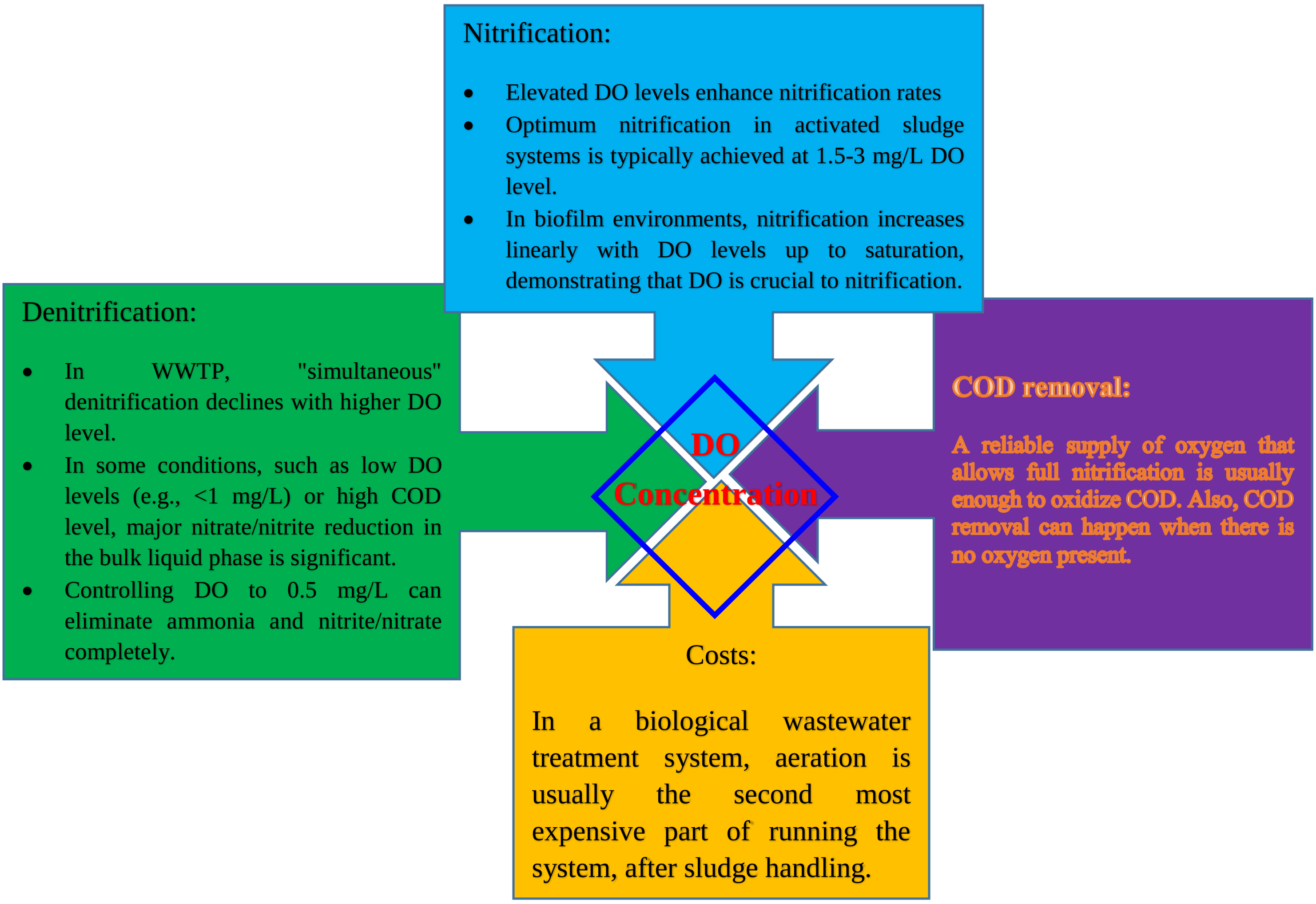


Figure 1.13: Impact of DO level on WWTP performance

1.4 Simulation models

Modelling the biological wastewater treatment process typically presents a complex and multi-faceted task. Essentially, the primary goal of mathematical models in WWTPs is to demonstrate the dynamic characteristics of the plant's operation. WWTPs are known for their complex model development and extensive kinetic, stoichiometric, and state factors correlation. The International Association for Water Quality (IWAQ), formerly IAWPRC, established a task group to create a mathematical model of wastewater treatment plants. This model aims to accurately predict the effectiveness of single sludge systems in carrying out various process operations such as carbon oxidation, hydrolysis, nitrification, denitrification, and the growth of poly accumulating organisms (PAO's). The development of this model is based on the research of Henze et al. (2000), Gujer et al. (2000), Gernaey et al. (2004), and Riger et al. (2001). This section defines BSM1-P as the designated working situations. It platforms of a simulation environment encompass the depiction of the physical arrangement of the plant, a model that simulates the plant's behaviour, the processes for conducting tests, and the criteria used to evaluate performance.

1.4.1 Benchmark simulation models.1-P (BSM1-P)

The BSM1-P framework of a WWTP is shown in Figure 1.14. It is made up of seven bioreactors lined up in a row and one more settling tank. Each of the first two anaerobic reactors is 2000 m³ in volume, and then there are two anoxic reactors, also 2000 m³ in volume, and finally, for every single reactor, complete mixing is taking place. Each of the other three fully mixed and aerated aerobic reactors has a volume of 3,999 m³. The sedimentation tank has 6,000 m³ in volume. Two recycle loops are in operation: one connects the third aeration tank to the anoxic reactor (Q_{intr}) with a flow rate of 34,500 m³/d, and the other connects the sedimentation tank's underflow to the influent flow (Q_r) with a flow rate of 18446 m³/d. During the dry season, the WWTP is expected to operate at a flow rate of 18446 m³/d. The output effluent (Qe) is taken into account, and the sludge flow rate (Qw) is set at 385 m³/d. Out of the 14 days that are accessible, only the last 7 are used for analysis. From day zero until day fourteen, the simulation continues. During the first week, the system reaches and stays in a dynamic "pseudo" steady-state. The remaining seven days are open for the implementation and evaluation of any control method, allowing for a fair comparison of alternative algorithms. It is possible to test the control

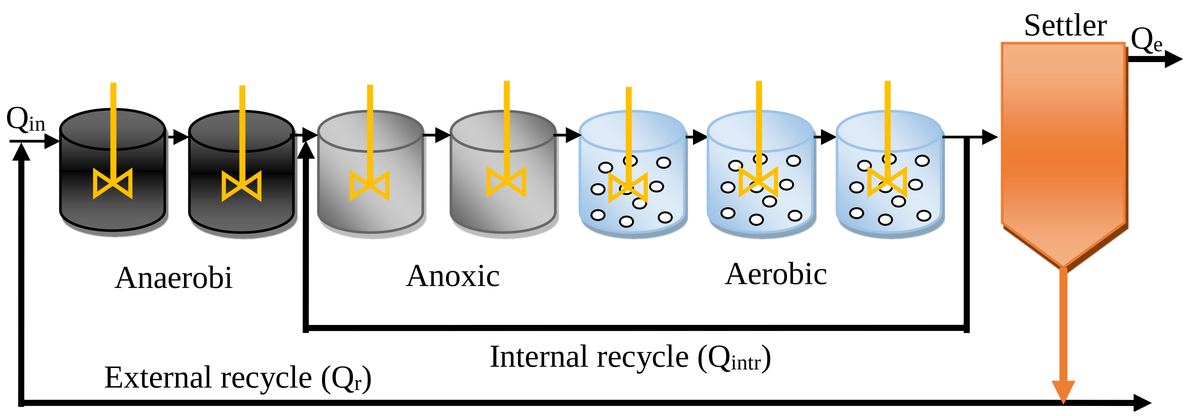


Figure 1.14:BSM1-P framework

algorithms' efficacy by running the dynamic simulation repeatedly. It is possible to test the control algorithms' efficacy by running the dynamic simulation repeatedly.

1.4.2 Overview of the activated sludge model (ASM) and it's factors

The renowned mathematical models responsible for the chemical and biological reactions that occur in ASP are known as activated sludge models. Table 1.1 provides a summary of the literature that is based on the ASM and also displays the reported total parameters, state variables, process equations, and substrates removal for six ASM models. For the process operation, ASM3bioP is chosen in those ASMs. As an additional mathematical model, activated sludge model No. 3 (ASM3) was designed to evaluate the biological WWTP's performance. Its capacity to treat sewage wastewater is dependent on its oxygen consumption rate, nitrification and denitrification rates, and sludge formation rates. In addition to including the chemicals used for internal cellular storage, ASM3 fixes a few additional issues with ASM1, such as the fact that the decay rate of nitrifiers differs under aerobic and anoxic environments (Gujer et al. (2000)). Similarly, Rieger et al. (2001) and Solon (2015) mainly built a modification of the ASM3 model (i.e., ASM3bioP) to forecast biological phosphorus elimination. This model incorporates modified processes from the ASM2d model, but it does not account for the fermentation of easily biodegradable substrates. The biological P elimination mechanism is detailed in Figure 1.15 of the ASM3bioP model. In the cellular internal system, PAOs are represented as a model structure called X_{PHA}. All the by-products of organic matter are integrated into this structure, and the formation of PAOs is what causes it to function as a substrate. In addition, the growth of the PAO is affected by oxygen and nitrate. To address the shortcomings of ASM1 and briefly compare the nitrification lysis rates in anoxic and oxic environments, ASM3 was developed based on the work of Gujer et al. (2000). It also addresses problems with the internal storage of cells. Moreover, the COD rate differs significantly between ASM1 and ASM3.

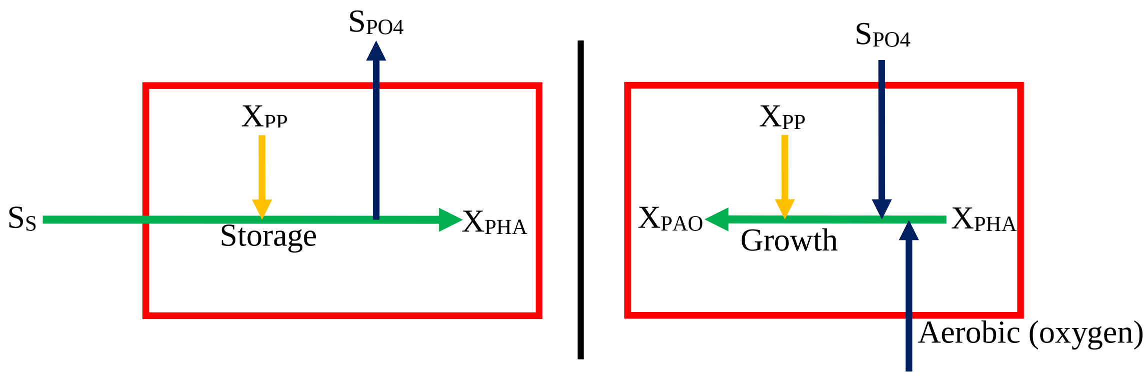


Figure 1.15: P-removal process incorporated in ASM3-bioP

Table 1.1: ASM models with their features

ASM Models	Substrates	Number of Process	State variables	Total kinetic and Stoichiometric parameters	References
ASM1	CN	8	13	26	Henze et al. (2000)
ASM2d	CNP	21	19	74	Henze et al. (2000)
ASM3	CN	12	13	46	Gujer et al. (2000)
AMS3-BioP	CNP	23	17	83	Rieger et al. (2001)
ASM2d+TUD	CNP	22	18	98	Meijer (2004)
UCTPHO	CNP	35	16	66	Hu et al. (2007)

The Sludge Model 3 with bio-phosphorous (ASM3-bioP) is used to simulate the biological process of the reactors. There are 23 biological processes that were assumed to describe what was going on in each reactor. The double exponential settling velocity model represents the vertical transfer between layers in the settler. 13 state variables are already in ASM3, and four more state variables tied to bio-P make the total seventeen number of state variables. In addition, ASM3 techniques are further developed by using the ASM2d process, which includes bio-P reactions but excludes precipitation reactions. The ASM3 model incorporates hydrolysis, heterotrophic, and autotrophic processes. Additionally, it predicts a lower growth rate for phosphorus (P). The ASM3bioP model incorporates the effects of temperature on kinetic parameters, oxygen saturation concentration, and K_{La} (oxygen mass transfer coefficient) at a temperature of 15°C. The state variables, along with their corresponding symbols and units, are displayed in Table 1.2 as presented by Solon (2015). The ASM3-bioP model includes a total of twenty-three biological processes. These processes are based on the stoichiometric parameters matrix for the particulate components of ASM3 (Henze et al., 2000) and the EAWAG Bio-P module (Rieger et al., 2001). Appendix Table A3 displays the kinetic rate expressions for ASM3, as documented by Henze et al. (2000). Additionally, Appendix Table A4 offers the kinetic rate expressions for the EAWAG Bio-P module, as documented by Rieger et al. (2001).

Table 1.2: State variables of ASM3bioP with average influent data

Compound	Symbol	Units	Average influent
Dissolved oxygen	S_O	$g(COD)m^{-3}$	0
Readily biodegradable organic substrate	S_S	$g(COD)m^{-3}$	90.34
Inert soluble organic	S_I	$g(COD)m^{-3}$	30
Ammonia+Nitrogen	S_{NH}	$g(N)m^{-3}$	39.40
Nitrate and nitrite	S_{NO}	$g\ (N)m^{-3}$	0
Dinitrogen	S_N	$g(N)m^{-3}$	0
Primarily orthophosphates	S_{PO4}	$g(P)m^{-3}$	8.86
Alkalinity	S_{HCO}	$mol(HCO3)m^{-3}$	7
Inert Particulate	X_I	$g(COD)m^{-3}$	51.20
Slowly biodegradable substrates	X_S	$g(COD)m^{-3}$	202.34
Heterotrophic Organisms	X_H	$g(COD)m^{-3}$	28.17
Cell internal storage	X_{STO}	$g(COD)m^{-3}$	0
Phosphate accumulating organisms	X_{PAO}	$g(COD)m^{-3}$	0
Polyphosphate	X_{PP}	$g(P)m^{-3}$	0
Primarily polyhydroxy alkanoates	X_{PHA}	$g(P)m^{-3}$	0
Nitrifying Organisms	X_A	$g(COD)m^{-3}$	0
Suspended solids	X_{TSS}	$g(SS)m^{-3}$	215.51

The ASM3-bioP model comprises a total of twenty-three processes, which are outlined below:

1 Hydrolysis
2 Heterotrophic organisms X_H
3 Aerobic Storage of X_{STO}
4 Anoxic Storage of X_{STO}
5 Aerobic growth
6 Anoxic growth
7 Aerobic endogenous Respiration
8 Anoxic endogenous Respiration
9 Aerobic respiration of X_{STO}
10 Anoxic resp. of X_{STO}
11 Aerobic endogenous Respiration

12	Anoxic endogenous Respiration
13	Storage of X_{PHA}
14	Aerobic storage of X_{PP}
15	Anoxic storage X_{PP}
16	Aerobic growth
17	Anoxic Growth
18	Aerobic endogenous Respiration
19	Anoxic endogenous Respiration
20	Aerobic lysis of X_{PP}
21	Anoxic lysis of X_{P}
22	Aerobic respiration of X_{PH}
23	Anoxic resp. of X_{PHA}

The equations defining the mass balance is listed below:

The mass balance equations are given in below:

$$r_1 = \frac{dZ_1}{dt} = \frac{1}{V_1}\left(Q_O Z_O + Q_r Z_r + r_1 V_1 - Q_1 Z_1\right) \tag{1.1}$$

Where $Q_1 = Q_O + Q_r$

$$r_2 = \frac{dZ_2}{dt} = \frac{1}{V_2}\left(Q_1 Z_1 + r_2 V_2 - Q_2 Z_2\right) \tag{1.2}$$

$$r_3 = \frac{dZ_3}{dt} = \frac{1}{V_3}\left(Q_2 Z_2 + Q_a Z_a + r_3 V_3 - Q_3 Z_3\right) \tag{1.3}$$

Where $Q_3 = Q_a + Q_2$

From K = 4 to 7

$$r_K = \frac{dZ_K}{dt} = \frac{1}{V_K}\left(Q_{K-1} Z_{K-1} + r_K V_K - Q_K Z_K\right) \tag{1.4}$$

Z represents the concentration of the process, Qa represents the concentration in the internal recycling rate, Qr represents the concentration in the external recycle, and V represents the volume of the reactors. The flow rates Qr and Q0 represent the influent flow rates, and their sum corresponds to the total influent flow rate into reactor1, denoted as r1. In the third reactor, Qa is introduced to Qo. Equations (1.1-1.4) can be used to write similar equations for the remaining six reactors. Furthermore, equation (1.5) will depict the dynamics of dissolved oxygen in aerated reactors. An additional factor is included in this equation to account for the oxygen concentration provided to aerobic reactors. The oxygen saturation coefficient, denoted as S_O*, is set at 8 mg O_2/L. The variable K_{La} represents the oxygen mass transfer coefficient for the kth reactor. The special scenario for the presence of in the aerobic tanks is being considered:

$$\frac{dS_{O,K}}{dt} = \frac{1}{V}\left(Q_{K-1}S_{O,K-1} + r_K V_K + \left(K_L a\right)_K V_K \left(S_O^* - S_{O,K}\right) - Q_K S_{O,K}\right) \tag{1.5}$$

The oxygen supplied to the aeration tanks must match the oxygen demand of the microorganisms involved in the activated sludge process. This need includes the oxidation of organic waste and the maintenance of appropriate levels of dissolved oxygen (DO). Insufficient oxygen can hinder the growth of microorganisms, leading to an increase in filamentous microorganisms. This can result in poor settleability and reduced quality of activated sludge. Conversely, an overly elevated dissolved oxygen (DO) level, which is often associated with a high flow rate, results in increased energy consumption and can also degrade the quality of the sludge. In aerobic aeration tanks, the DO content should be maintained at 1.5 to 4 mg O_2/L, at 2 being a common range. If nitrate consumption in the final pre-denitrification zone is below a specific threshold, aeration zones need not use excessive air.

For optimal nitrate concentration in anoxic reactors, maintain 1−3 mg N/L with internal recirculation, with 1 mg N/L being the preferred value. Denitrification occurs in anoxic reactors. Ordinary heterotrophs and PAO biomass convert internal recirculation nitrate from aerobic reactor 7 to molecular nitrogen in anoxic reactor 3 (or 4). Autotrophic organisms nitrify ammonium to nitrate in aerobic reactors. In contrast, the internal recirculation flow rate from the final aerobic reactor controls denitrification (nitrate concentration in the anoxic reactor). Table 1.3 listed the stoichiometric parameter.

Table 1.3: stoichiometric parameter values

Parameters	Value
Heterotrophic max specific growth rate	3
Heterotrophic decay rate	0.3
Half saturation coefficient for heterotrophs	10
Oxygen half-saturation for heterotrophs	0.2
Nitrate half-saturation coefficient for denitrifying heterotrophs	0.5

Autotrophic max. specific growth rate	1
Autotrophic decay rate	0.2
Oxygen half-saturation coefficient for autotrophs	0.5
Ammonia half-saturation coefficient for autotrophs	1
Correction factor for anoxic growth of heterotrophs	0.8
Ammonification rate	0.01
Maximum specific hydrolysis rate	9
Half saturation coefficient for hydrolysis of slowly biodegradable substrate	1
Correction factor for anoxic hydrolysis	0.33
Rate constant X_{PHA} storage	6
The rate constant for X_{PP}	1.5
Rate constant lysis of X_{PP}	0.2
Rate constant for respiration of X_{PAO}	0.2
Maximum growth rate X_{PAO}	1

1.4.3 Secondary sedimentation tank

There are no biological interactions in the model of the ten-layer secondary sedimentation tank since it is not reactive. Looking at the stack from top to bottom, the feed layer is the sixth layer. The settler has an area (A) of 1,500 m^2. The height of each layer, denoted as Zm, is 0.4 metres, resulting in a cumulative height of 4 metres. Consequently, the volume of the settler is 6,000 cubic metres. Equation 1.29, proposed by Takas et al. (1991), describes the solid flux caused by gravity using a double exponential velocity. Figure 1.16 illustrates the secondary clarifier model.

$$J_s = v_s\,(X_{sc})\,X_{sc} \tag{1.6}$$

$$v_s\,(X_{sc}) = max\,[\,0, min\{\,v_0', v_0(e^{-r_h(X_{sc}\,-\,X_{min})} - e^{-r_h(X_{sc}\,-\,X_{min})} \tag{1.7}$$

$$X_{min} = f_{ns}\;X_f \tag{1.8}$$

The variables in question are as follows: X_{SC} represents the overall concentration of sludge, v_0 denotes the maximum Vesilind settling velocity, v_0' represents the maximum settling velocity, r_p is the settling parameter for the flocculent zone, r_h is the settling parameter for the hampered zone, and f_{ns} represents the proportion of sludge that does not settle.

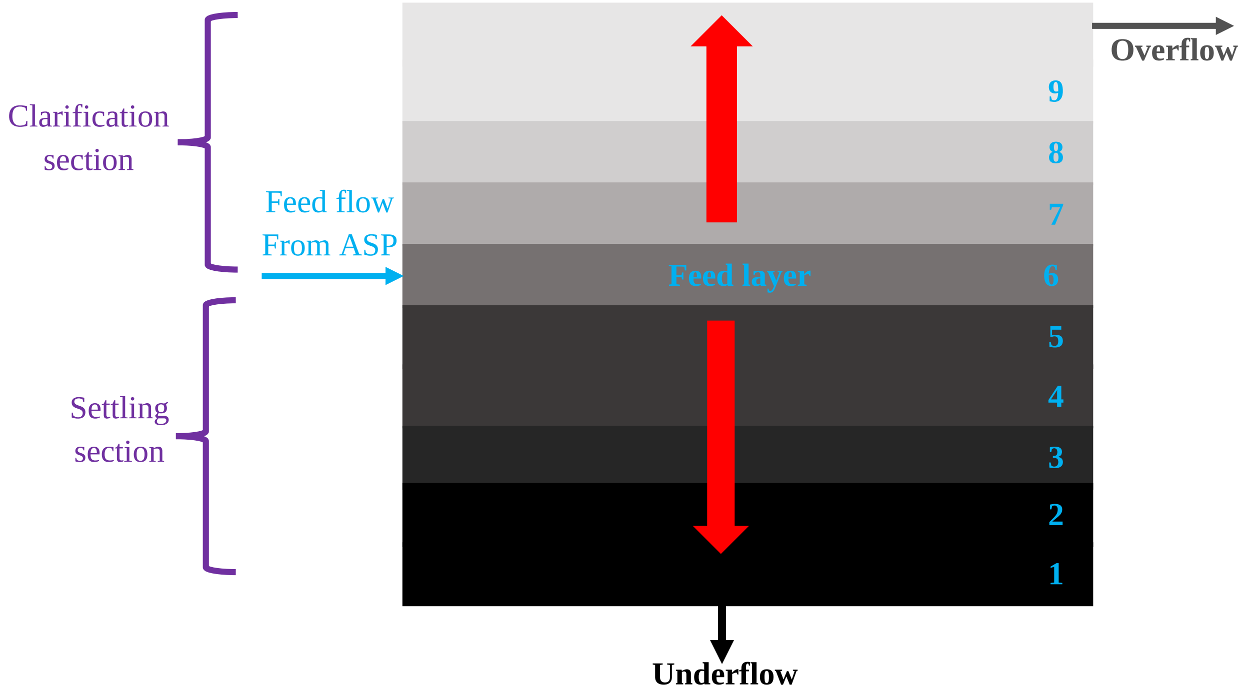


Figure 1.16: Secondary clarifier model (Takacs settler)

The calculations for the upward (v_{up}) and downward (v_{dn}) velocities are determined according to the equations provided.

$$v_{dn} = \frac{Q_u}{A} = \frac{Q_r + Q_w}{A} \tag{1.9}$$

$$v_{up} = \frac{Q_e}{A} \tag{1.10}$$

According to the notations provided, the feed is introduced into the settler at the 6th layer from the bottom. The sludge mass balance equation for the feed layer (m=6) is presented below:

$$\frac{dX_{sc,m}}{dt} = \frac{\frac{Q_f X_f}{A} + J_{sc,m+1} - (v_{up} + v_{dn})X_{sc,m} - min(J_{s,m}, J_{s,m-1})}{z_m} \tag{1.11}$$

For layers m = 2–5, the mass balance of the sludge is:

$$\frac{dX_{sc,m}}{dt} = \frac{v_{dn}(X_{sc,m+1} - X_{sc,m}) + min(J_{s,m}, J_{s,m+1}) - min(J_{s,m}, J_{s,m-1})}{z_m} \tag{1.12}$$

For layer m = 1:

$$\frac{dX_{sc,1}}{dt} = \frac{v_{dn}(X_{sc,2} - X_{sc,1}) + min(J_{s,2}, J_{s,1})}{z_1} \tag{1.13}$$

For layers' m = 7 to 9:

$$\frac{dX_{sc,m}}{dt} = \frac{v_{up}\left(X_{sc,m-1} - X_{sc,m}\right) + J_{sc,m+1} - J_{sc,m}}{z_m} \tag{1.14}$$

For m = 10 (top layer):

$$\frac{dX_{sc,10}}{dt} = \frac{v_{up}\left(X_{sc,9} - X_{sc,10}\right) - J_{sc,10}}{z_{10}} \tag{1.15}$$

Where, $J_{sc,j} = \begin{Bmatrix} \min\left(v_{s,10}X_{sc,10}, v_{s,9}X_{sc,9}\right) \, if \; X_{sc,9} > X_t \\ or \\ v_{s,10}X_{sc,10} \; if \; X_{sc,9} \le X_t \end{Bmatrix}$

Hence, the threshold concentration X_t is 3000 g.m^{-3}.

Each layer is treated as an independent volume for calculating the concentrations of soluble components.

For layer m = 6:

$$\frac{\mathrm{dZ_{sc,m}}}{\mathrm{dt}} = \frac{\frac{\mathrm{Q_f Z_f}}{\mathrm{A}} - \left(\mathrm{v_{up}} + \mathrm{v_{dn}}\right)\mathrm{Z_{sc,m}}}{\mathrm{z_m}} \tag{1.16}$$

For layer's m = 1 to 5:

$$\frac{\mathrm{dZ_{sc,m}}}{\mathrm{dt}} = \frac{\mathrm{v_{dn}}\left(\mathrm{Z_{sc,m+1}} - \mathrm{Z_{sc,m}}\right)}{\mathrm{z_m}} \tag{1.17}$$

For layers' m = 7 to 10:

$$\frac{\mathrm{dZ_{sc,m}}}{\mathrm{dt}} = \frac{\mathrm{v_{up}}\left(\mathrm{Z_{sc,m-1}} - \mathrm{Z_{sc,m}}\right)}{\mathrm{z_m}} \tag{1.18}$$

Where z_m is the height of mth layer of the sedimentation tank.

1.5 SBR a modified ASP

Certainly, the Sequential Batch Reactor (SBR) represents a modified version of the traditional Activated Sludge Treatment (AST) methodology. The SBR process is a kind of wastewater treatment wherein multiple treatment phases are integrated within a solitary reactor, functioning in a batch mode. The following is an outline of the SBR procedure and its distinctions from the conventional Activated Sludge Treatment:

Batch Process: The SBR process consists of a single reactor where the treatment is conducted, with the treatment phases (aeration, settling, and decanting) executed in cycles. Activated sludge treatment involves the concurrent occurrence of aeration and sedimentation in distinct containers, as opposed to the conventional approach.

Cycle Stages: The SBR cycle generally comprises the following four stages: load, react, settle, and decant. During the load phase, the reactor is supplied with wastewater. Aeration and biological treatment occur during the react phase. In the settle phase, clarification takes place, and in the concluding phase, the clarified effluent is decanted.

Adaptability: SBR systems provide operational flexibility and are readily modifiable to accommodate fluctuations in influent flow and load. Modifications are possible in order to suit diverse treatment requirements. The adaptability of conventional activated sludge treatment systems to variations in influent characteristics may be limited.

Process Management: SBRs enable enhanced optimisation and control of processes. By exerting greater authority over each stage of the treatment cycle, operators are able to make modifications in accordance with the particular needs of the effluent. Activated sludge treatment may necessitate the implementation of more advanced control strategies in order to attain maximum efficiency.

The footprint: Differentiating themselves from conventional activated sludge systems, SBRs integrate several treatment stages within a solitary vessel, potentially resulting in a reduced physical footprint. ASP systems generally comprise distinct containers designated for aeration, sedimentation, and additional treatment procedures, which may necessitate additional spatial considerations.

In brief, SBR represents a modified iteration of the activated sludge process that functions in a bulk fashion, providing benefits such as increased adaptability, enhanced regulation, and potentially a reduced environmental impact. The SBR process's sequential configuration facilitates enhanced regulation of each treatment phase, rendering it well-suited for a wide range of wastewater treatment applications.

In the SBR process and other batch transfer processes, nitrate can be removed using one of three techniques. These include: (1) reducing nitrate by using a mixed fill period without aeration; (2) establishing aeration cycles with intermittent aeration; and (3) reducing the concentration of DO while performing operations. Enabling denitrification during periods of mixed fill that aren't aerated is the most efficient way to get rid of nitrate. This technique also stops filaments from bulking up. The SBR tank's decant volume ranges between 20 and 30 percent, so the majority of the nitrate produced during the previous aerobic cycle remains there. Following decanting, McCarty and Smith (1986) claim that residual nitrate mass can be decreased in the fill period if there is enough time and BOD. Additional aeration time might improve the reactor's ability to remove any remaining organic matter (Jung et al., 2004).

SBRs are renowned for several qualities, including the simplicity with which sludge can be handled, the high rate at which phosphorus and nitrogen are removed from wastewater, and the significant technological simplification they provide. The basic technological process parameters, such as dissolved oxygen and the concentration of organic compounds, depend on time when the fill phase starts. Wastewater is not aerated at this point (Janczukowicz et al., 2001). In addition, the anaerobic period's length should be adjusted to achieve the near-complete removal of COD that is easily biodegradable, and the aerobic period should be long enough to allow for complete nitrification, in order to successfully remove biological phosphorous and nitrogen. In order to achieve a net growth of biomass in the reactor, the total COD-loading rate must be maintained at a high level (Helness and degaard, 2001). Five common steps are shown in typical sequences in Figure 1.17.

Stage 1: Filling

The cycle starts with the fill operation, which involves dispersing the influent wastewater evenly throughout the tank, in order to promote a favourable reaction between both the substrate & the microorganisms and to promote microbial activity as the wastewater arrives the bioreactor. A number of factors can be taken into consideration when choosing the fill's duration. The procedure will resemble a continuous flow system if the time is limited (successive tanks). As a result, the biomass will be exposed to high concentrations of organic materials and other components in the wastewater.

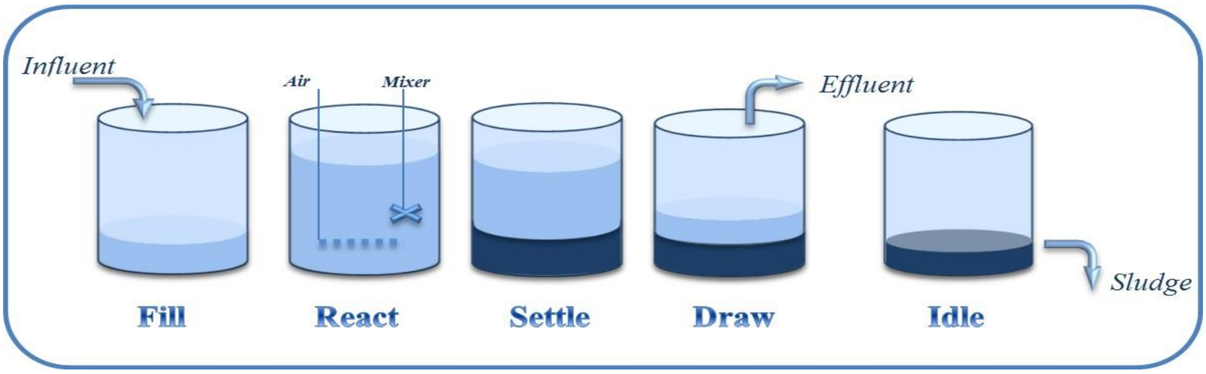


Figure 1.17: Events order in the sequencing batch reactor (SBR)

But as time passes, these concentrations will fall. On the other hand, if the fill time is prolonged, the system will operate similarly to when a continuous stream is fully mixed into the system. The biomass will be present in this instance in low concentrations, comparable to other wastewater constituents.

Stage 2: Reaction

After the fill stage is complete, the wastewater components can now begin to react during the react stage, which also allows for aeration and the consumption of biomass and substrate. Additionally, at this stage, compression or mixing can be used. Due to the impact of each on the way the process behaves, it is preferable that each phase's completion be specified separately. The fill phase can also include the reaction (aeration and mixing).

Stage 3: Settling

Following the reaction phase, there is a stage of sedimentation with the crucial requirement that all aeration and mixing be stopped. This indicates that there is solid-liquid segregation. Additionally, biomass that has been given permission to settle and clean the effluent will show up above the sludge. Due to the absence of liquids entering and exiting the tank, a discontinuous system may be able to carry out sedimentation more effectively than a continuous flow.

Stage 4: Decanting (Draw)

In order to ensure the withdrawal, treated effluent must be removed from a finite height above the sludge sedimentation once sufficient settling has taken place. The bioreactor's reserve of liquid and biomass makes up the biomass recycle for the following cycle. It is comparable to biomass recycling in a continuous process if a significant volume is held back in relation to the influent volume (to provide nitrate for an initial denitrification period).

Stage 5: Idling

Finally, each cycle typically allows for an idle period to add flexibility. In the last stage, the waste sludge can only be pumped to reduce volume in accordance with the amount of time needed to finish the cycle. The idle phase is over when the new fill opens, and a new cycle is started. Depending on the system design, the frequency range for waste sludge should be once every (60-100 days). The bioreactor's reserve of liquid and biomass makes up the biomass reprocessing for the following cycle. The improvement of poly-P occurs when there is a greater energy requirement for bacterial preservation, as found by Chen et al. (2013) when comparing the performance of two different SBR reactors for the removal of phosphorus.

Anaerobic and aerobic conditions are created sequentially in a sequencing batch reactor to build the system for biological phosphorous removal. As a result, no chemical additives are required for the system to remove the phosphorus. The system could be changed, as shown in Figure 1.18, to lead to the co-oxidation of nitrogen and carbon. After the aerobic reaction phase, this modification would involve the addition of an anoxic phase.

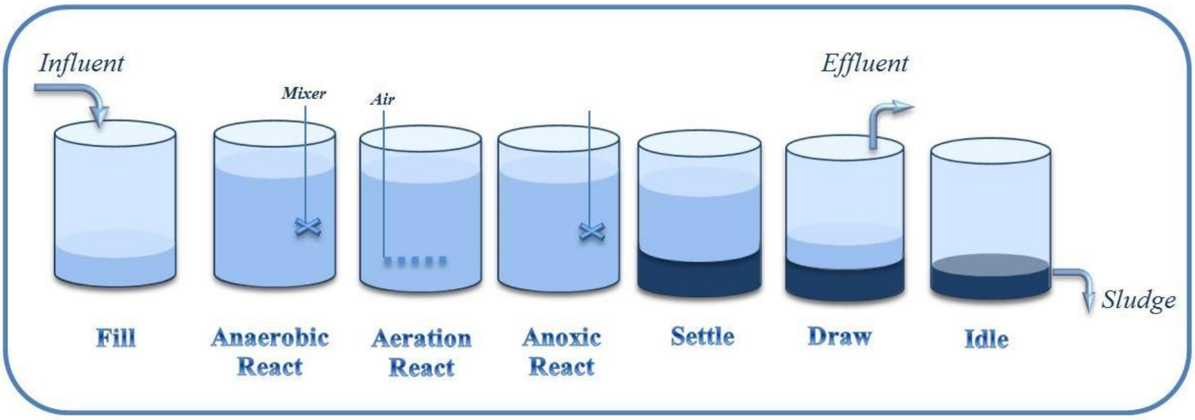


Figure 1.18: SBR for the removal of nitrogen and phosphorus

1.5.1 Modelling of SBR: Conceptual approach in ASM2d

ASM2d is a computational framework used to simulate and analyse the process of removing phosphorus from wastewater using activated sludge. ASM2d is a small-scale extension of ASM2. Two additional processes that need to be taken into account are polyphosphate storage and growth under anoxic conditions. PAOs in ASM2 have the ability to accumulate polyphosphate (poly-P) and can only thrive in aerobic conditions. ASM2d, in contrast, incorporates a simulation of denitrifying polyphosphate-accumulating organisms (PAOs) metabolism for the purpose of polyphosphate growth and storage. ASM2d shares the same constraints as ASM2. Additional details regarding the ASM2d model can be found in the literature (Henze et al., 1999). The metabolic processes that rely on Monod kinetics can be characterised by utilising kinetic and stoichiometric coefficients for all parameters and organising them in a matrix style. The stoichiometric coefficients can be easily accessed through the utilisation of matrix notation. Consequently, calculations uphold their mass balances as anticipated..

The parameters of the ASM2d model were derived based on the assumptions and correlations of the ASM2 model. The symbol X is used to denote particulate material, with a subscript indicating the acronym for the substance present in that form. Similarly, the letter S is employed to symbolise a substance that can dissolve, and its composition is indicated by a subscript. There is a belief that particle constituents are linked to activated sludge. Soluble components refer to substances that are capable of being dissolved in water.

1.5.2 Definition of soluble components in ASM2d

ASM2d model parameters for soluble components are defined as follows:

S_A [M(COD)L-3]: Acetate-like fermentation products were suspected. Fermentation products are calculated separately from other dissolved organic materials in the calculations. These biological processes use acetate as a carbon source.

S_{ALK} [mol (H_{CO3})L-3]: The alkalinity of the effluents was used to assess electrical charge conservation in biological reactions. SALK was thought to be bicarbonate H_{CO3}-only.

S_F [M(COD)L-3]: Organic substrates that are fermentable and easily biodegradable and can be obtained directly from heterotrophic organisms' transformation of the soluble COD fraction. Because these substrates were assumed to be fermentation substrates, they weren't included in fermentation products.

S_I [M(COD)L-3]: Organic material that is inert but soluble. This substance can't be changed any further. This material was thought to be present in the influent as well as in the XS hydrolysis.

S_{N2} [M(N)L-3]: N_2 stands for dinitrogen. This was presented as the only denitrification product.

S_{NH4} [M(N)L-3]: Nitrogen in the form of ammonium plus nitrogen in the form of ammonia. SNH4 was assumed to be all S_{NH4+} to balance the electrical charges.

S_{NO3} [M(N)L-3]: Nitrogen in the form of nitrate and nitrite. S_{NO3} is a nitrogen compound made up of nitrate and nitrite. Nitrite was not calculated as a separate model component. S_{NO3} was supposed to be NO_3- -N only, in contrast to all other stoichiometric calculations (COD conservation).

S_{O2} [M(O2)L-3]: Oxygen that has been dissolved. S_{O2} was thought to be susceptible to gas exchange.

SP_{O4} [M(P)L-3]: Orthophosphate is a type of inorganic soluble phosphorus. At any pH, it was presumed that SPO4 contained 50 percent H_2PO_4 and 50 percent $HP_{O4}2-$ to stabilize the electrical charges.

S_S [M(COD)L-3]: A substrate that is easily biodegradable. It was calculated as the sum of S_F + S_A

1.5.3 Definition of particulate components in ASM2d

ASM2d model parameters for particulate components are defined as follows:

X_{AUT} [M(COD)L-3]: Nitrifying organisms. Organisms that decompose nitrate. These organisms were involved in the nitrification process. It was previously assumed that autotrophs directly oxidise ammonium (S_{NH4}) to nitrate (S_{NO3}).

X_H [M(COD)L-3]: Heterotrophic organisms. These heterotrophs are thought to be able to grow aerobically as well as anoxically (during denitrification) while also fermenting anoxically. They are in charge of hydrolysis and can use any degradable organic substrate under any of the study's environmental conditions.

X_I [M(COD)L-3]: Inert particulate organic substrates. In these systems, the flocculation was not degradable. They can come from decay processes or a small percentage of the influent.

X_{PAO} [M(COD)L-3]: Organisms that accumulate phosphorus (PAOs). These organisms are thought to be capable of producing internal cell storage products. PAOs do not contain X_{PP} or X_{PHA}. According to the ASM2d model's assumptions, these organisms can grow in both anoxic and aerobic environments.

X_{PHA} [M(COD)L-3]: A phosphorus-accumulating organism's internal storage product. The primary product of X_{PHA} is poly-hydroxy-alkanoates (PHA), which can only be produced by PAOs.

X_{PP} [M(P)L-3]: Polyphosphate. PAOs store this product internally, but this is not counted as part of their mass.

X_S [M(P)L-3]: Slowly biodegradable substrate. Heterotrophic organisms can ferment these particulate organic substrates after they've been hydrolyzed.

X_{TSS} [M(TSS)L-3]: Total suspended solids. Total suspended solid materials must be taken into consideration when computing stoichiometric bio kinetic models. Phosphorus removal influences TSS prediction. The fraction of phosphorus in activated sludge grows as phosphorus removal efficiency improves.

Henze et al.'s 1999 material extensively documented and explained the ASM2d model, a commonly used ASP in wastewater treatment. It covers model preparation, biological processes, stoichiometry, and process rate equations, making it a great resource for professionals and researchers. It also methodically address biological processes, a cornerstone of wastewater treatment. The authors explain treatment system biological changes by examining microbial activity principles. The stoichiometric features of ASM2d modelling, which define the quantitative relationships between biological reactions components is clearly mentioned in this literature. Henze et al. pioneered the utilisation of ASM2d with matrix notation in 1999. The matrix notation pattern encompasses both the components and conversion operations.

Literature Review

2. LITERATURE REVIEW

This chapter reviews the literature related to WWTP models, controllers. These areas include studies that look at how to make wastewater treatment plants work better, how to model and control ASP based wastewater treatment plants, control strategies implemented in SBR based wastewater treatment, how temperature affects biological wastewater treatment processes in SBR.

To improve the efficiency of treatment plants, many control approaches have been used to optimise the production, transportation, and wastewater treatment processes, in addition to the pursuit of cleaner and more sustainable energy sources. The BSM1 model is frequently used in existing literature as a framework, with a primary emphasis on organic matter and nitrogen. The operational scenario chosen for this work is BSM1-P. Certain research focus on mitigating effluent limit violations by directly manipulating effluent factors, while others investigate the balance between operational expenses and effluent effectiveness. Management strategies vary from basic methods, such as managing the amount of dissolved oxygen in aerated reactors and the concentration of nitrate-nitrogen in anoxic tanks, to more intricate hierarchical systems, such as ammonia-based aeration management. Standardising the model is essential for efficient control because of the difficulty in assessing and linking different control approaches suggested in the literature. The temporal constants inherent to the activated sludge process and the variability of the influent load make it challenging to conduct meaningful assessments using simulations.

Temperature, a crucial determinant affecting the activity of biomass, necessitates meticulous attention to ensure the optimal functioning of biological processes. The temperature variations affect the physiochemical features of activated sludge systems, including dissolved oxygen levels and settling velocity. These changes are important for modelling and predicting the behaviour of such systems. The global setting introduces intricacy since ambient temperatures fluctuate according to regional atmospheric and environmental factors, frequently impacted by abrupt shifts in seasonal climate on a global scale.

2.1 Literature focused on BSM1-P control strategies

In a pilot wastewater treatment facility, Real-Time Expert System is used to naturally remove organic debris and nutrients. Baeza et al. (1999) introduced a remarkable demonstration of their ability to run the pilot plant of WWTP. A distributed control system (Knowledge-Based Expert System (KBES) designed with G2©) is suggested in A2/O (anaerobic-anoxic-oxic) setup in the pilot plant introduced by Baeza et al. 2002. Cho et al. (2002) devised a two-level control strategy for the pre-denitrification system. The main goal of the principal controller is to balance the S_{NO} concentration in the targeted effluent concentrations. The study conducted by Gernaey et al. (2004) examines the performance of the ASM2d model in BSM1-P, which incorporates two control loops for dissolved oxygen and nitrate levels. The model is tested using dry, rain, and storm data. A comparison is made between the results obtained from the model with PI controllers and those from an open-loop system. The study concludes that there is a trade-off between operational cost and effluent quality. Shen et al. (2008) constructed a feed-forward (FF) control system using influent and nonlinear model predictive control (MPC). They also incorporated a penalty function on BSM1. The system demonstrated a low index of effluent efficiency and acceptable energy usage for aeration and pumping. Shen et al. (2009) and Cristea et al. (2008) have devised a feedforward control system to enhance nitrogen removal in a pilot-scale A^2/O process used for municipal wastewater treatment. Their efforts resulted in a notable improvement in nitrogen removal. Implementing structured control of dissolved oxygen (DO) is crucial because to its significant impact on aeration energy consumption.

Another idea is a two-level control approach. Next, Brdys et al. (2009) show the methodical track of the DO path in the BSM1 framework. Feed-forward controllers have been utilised in wastewater treatment plants (WWTPs) to enhance the removal of biological nitrogen (N) and carbon (C) by considering the effluent quality and performance improvement. This approach is based on the research conducted by Baeza et al. in 2002 and Nopens et al. in 2010. In their study, Ostace et al. (2011) implemented model predictive control (MPC) using a reactive secondary settler model. They successfully obtained a decrease in the operational cost index (OCI) while improving the effluent quality index (EQI). Despite being widely recognised as a notable technique, EBPR still encounters challenges in achieving efficient removal of nitrogen and phosphorus in full-scale treatment plants due to the complex interactions between nitrate and phosphorus throughout the uptake process. The failures are impacted by the COD/P ratio and the organic matter in the influent. These two factors are the fundamental characteristics that need to be understood in order to comprehend the process. Guerrero and colleagues in 2011. The implementation is based on the ASM2d model. Xu and Vilanova (2013) devised various control strategies utilising BSM1-P and found that the levels of ammonia nitrogen and chemical oxygen demand (COD) in the effluent remained within the prescribed limits. However, other parameters of the effluent exceeded the imposed constraints.

The BSM1-P investigation evaluates the effectiveness of a new control application that combines cascade and override control techniques, using both metal and carbon dosages, in a carbon-limited wastewater system. Guerrero et al. (2014) discovered that the control application demonstrates superior effluent quality at an optimal cost. A fuzzy control framework was developed to decrease the concentration of phosphorus in effluent water. It was observed that fuzzy control yielded superior outcomes in eliminating P compared to the PI control loop (Xu and Vilanova, 2015 a, b). Valverde-Pérez et al. (2016) implemented control strategies to improve the removal of phosphorus using two control frameworks in a sequence batch reactor and continuous flow reactor. An activated sludge method including Enhanced Biological Phosphorus Removal (EBPR) is implemented to improve the efficiency of the Effluent Quality Index (EQI). In certain situations, the removal of nitrogen (N) and phosphorus (P) may not be feasible due to a lack of chemical oxygen demand (COD) in the wastewater. Either the inclusion of an external carbon source or the use of chemical precipitation is typically the chosen technological method for effectively removing phosphorus from wastewater with limited chemical oxygen demand (COD). The dosages mentioned in Garikiparthy et al. (2016) are costly and result in a rise in plant operating expenses. Sdeghassadi et al. (2018) created a nonlinear model predictive control (MPC) system using the BSM1 framework, which resulted in enhanced accuracy in following set-points.

The recent research by Santín et al. (2015) and Crisan et al. (2018) demonstrate the implementation of the cascade technique in the DO design. In relation to energy conservation in a wastewater treatment plant operating in real-time, hierarchical control systems are suggested to achieve the necessary DO levels for the oxidation of ammonia to nitrate. Baklouti et al. (2018) assessed the fault detection of the benchmark models. Hongyang et al. (2018) created MPC system using the BSM1-P model to ensure a sufficient level of nitrate concentration and dissolved oxygen. The study found that the control performance significantly increased by 95% in all three weather conditions (dry, rain, storm) when using MPC controller. To minimise ammonia fluctuations, a strategy combining MPC with Feedforward (FF) controllers was implemented at the base level to regulate S_{NO} and DO. Additionally, a fuzzy controller was employed at a higher level to manipulate the DO. Furthermore, the use of MPC at the supervisory level is suggested to enhance the overall efficiency of the plant, leading to cost reduction and improved effluent quality. This proposal is based on the design of Santín et al. (2016).

The artificial neural network (ANN) developed by Santin et al. (2019) is specifically built to forecast the desired value of dissolved oxygen (DO) set point. Schraa et al. (2019) have developed a control strategy called ammonia-based aeration control (ABAC) with solid retention time (SRT) management in the Activated sludge process. This approach aims to maintain a balance between SRT, DO, and ammonia levels in order to ensure both treatment efficiency and energy savings in the plant. BSM1 serves as the operational framework for conducting all of these tasks. The regulation limitations for TN concentration were achieved by implementing three control loops that rely on monitoring the concentrations of inorganic P, ammonia, and suspended particles (Luca et al., 2019). In order to forecast the DO levels, artificial neural networks are employed to account for the time delays caused by sensors and filters, ultimately achieving the desired set-point (Santin et al., 2019). The efficacy of the heuristic fuzzy controller was evaluated and it was determined that all the pollutants comply with rigorous criteria, while maintaining a high level of dissolved oxygen (Piotrowski et al., 2020). The researchers in Tejaswini et al. (2020) have established hierarchical control strategies for BSM1 and observed that these strategies lead to improved effluent quality at a reasonable cost. The outcome is a decrease in effluent ammonia nitrogen and total nitrogen, resulting in energy efficiency. An advanced method utilising sensors, residual ammonia controls, and dissolved oxygen set-points is employed in a granular sludge reactor to eliminate nutrients from wastewater. The study conducted by Bekele et al. (2020) demonstrates that maintaining a stable aerobic granular sludge is beneficial for enhancing the reactor's performance.

However, the increase in poly accumulating organisms (PAOs) is the cause of phosphorus removal in both the anaerobic and aerobic stages of the activated sludge system (AS), as stated by Rampho et al. (2005) and Ersu et al. (2010). The A^2O process, which stands for anaerobic, anoxic, and oxic, is a widely-used method in municipal wastewater treatment plants for the simultaneous removal of nitrogen (N) and phosphorus (P). This process was introduced by Oehmen et al. (2010), Zhou et al. (2015), Zhang et al. (2016), and Massara et al. (2018). Concerning phosphorus (P), the installation of enhanced biological phosphorus removal (EBPR) is a sustainable strategy to meet strict rules for wastewater discharge. However, only a few researchers have presented an effective design for improving phosphorus removal in WWTPs.

Process control is utilised in wastewater treatment facilities to optimise their performance, prolong their lifespan, and reduce both the cost per unit of product and operational expenses

(Agarwal et al., 2016; Åmand et al., 2013). Various feed-forward controllers have been utilised in BWTPs to improve the quality and efficiency of the effluent, specifically in terms of removing biological nitrogen and organic matter (Nopens et al., 2010; Tejaswini et al., 2020). The most rational strategy to achieve the required P discharge levels is by enhanced organic P removal, also known as Enhanced Biological Phosphorus Removal (EBPR) (Solon et al., 2017). BSM1 employed four distinct control schemes: C1, which utilised a DO-controller; C2, which employed both a DO-controller and a NO controller; C3, which implemented an NH-DO cascade controller; and C4, which utilised a TSS controller. Additionally, C5 employed a P controller. These control schemes were combined in various ways, and an advanced and intelligent controller was also utilised (Sheikh et al., 2021; Solís et al., 2022; Solon et al., 2017). To achieve the most efficient and environmentally sustainable operation of wastewater treatment, it is recommended to maintain a DO set-point of 2 mgO2/L. This should be done while ensuring the proper SRT and adding the necessary carbon source. By following these guidelines, the treatment process can be optimised without negatively impacting EQ, OC, or greenhouse gas (GHG) emissions. The effects of operational circumstances on EQ, OC, and GHG emissions were evaluated through the simulation of four scenarios. Two PI control loops, namely the DO-PI controller and the nitrate (NO)-PI controller, were implemented in the BSM2P model (Sheikh et al., 2021; Solís et al., 2022). The optimal arrangement of control/operational parameters (such as dissolved oxygen and solids retention time) and the management of dissolved oxygen, nitric oxide, and ammonia concentrations are essential factors that work together harmoniously.

Table 2.1: Control strategies of P in secondary BWTP

Control combinations employed in secondary treatment

S.No	**ASM**	**BSM**	**Control Algorithm**	**Control variables**	**Manipulating variables**	**Effluent quality (EQ)**	**Energy cost (EC)**	**Comment**	**Reference**
1	A^2/O (ASM2d)	BSM1P	PI, metal, carbon dosages	DO	K_La	Improved EQ	EC increases	Improved P removal	(Gernaey & Jørgensen, 2004)
2	A^2/O (ASM2d)	BSM1P	PI	Different DO, NO, NH, TSS, PO_4	K_La, H-DO, Q_w, Q_{intr}	Improved EQ	EC increases	Improved P removal	(Ingildsen et al. 2006)
3	A^2/O (ASM2d)	BSM1P	PID	DO	K_La	Improved EQ	EC reduction achieved	Improved P removal	(Shen et al. 2010)
4	A^2/O (ASM2d)	BSM1P	Cascade MPC, PI	DO, NH, NO	K_La, H-DO, Q_{intr}	Improved EQ	EC increases	Improved P removal	(Liu et al. 2012)
5	A^2/O (ASM2d)	BSM1P	PI	Different DO, TSS, NH	K_La, Q_w, Q_{intr}	Improved EQ	EC increases	Improved P removal	(Xu & Vilanova, 2013)

6	A^2/O (ASM2d)	BSM1P	PI, override control	NO, PO_4	Qintr, NO	Improved EQ	EC increases	Improved P removal	(Guerrero et al. 2014)
7	A^2/O (ASM2d	BSM1P	PI, Fuzzy	DO, NO	K_La, Q_{intr}	Improved EQ	EC increases	Improved P removal	(Xu & Vilanova, 2015)
8	A^2/O (ASM2d)	BSM1P	PI, MPC	DO, NO	K_La, Q_{intr}	Improved EQ	EC increases	Improved EQ	(Hongyang et al. 2018)
9	A^2/O (ASM2d)	BSM1P	PI	DO, TSS, $PO_{4,}$ NH, NO	K_La, H-DO, $Q_{r,}$ QW	Improved EQ	EC increases	Improved EQ	(Luca et al. 2019)
10	A2/O (ASM2d)	BSM1P	Robust optimal control, FNN	DO, NH, NO	K_La, H-DO, Q_{intr}	Improved EQ	EC decreases	Improved P removal	(Han et al. 2021)
11	A^2/O (ASM3bioP)	BSM1P	PI, Override, Fuzzy	DO, NH, PO_4, NO	$K_La_,$ H-DO, NO and Q_{intr}	Improved EQ	EC increases	Improved P removal	(Sheik et al. 2022)
12	A^2/O, R-A^2O, I-A^2O (ASM2d)	BSM1P	PI	DO-carbon and metal dosages	K_La	Improved EQ	EC increases	Improved P removal	(Sheik et al. 2022)

2.2 Literature focused on SBR control strategies

In industrial contexts, two different types of biological WWTPs are used: SBRs and WWTPs with continuous flow across the entire plant. In the SBR, the first type of plant conducts all biochemical reactions in a single tank, following a pre-set sequence, rather than using multiple tanks connected by both internal and external recirculation flows. This thesis examines the second type of biological WWTP too. The complex biological processes at the WWTP are highly dependent on the oxygen supplied by the aeration system to the SBR. The SBR's dissolved oxygen content affects phosphorus removal, nitrification, and denitrification efficiency. In addition, the scheme will have a significant financial burden due to the fact that the electricity consumed by blowers constitutes around 50% to 75% of the total operational expenses of the WWTP (Jenkins 2013).

Optimising the effectiveness of DO control has been a focal point of research endeavours for a considerable period. Prior studies have recorded many control structures and techniques for DO, including the adaptive and multivariable PID controller (Wahab et al, 2009 and Du et al, 2018), fuzzy controller (Belchior et al, 2012, and Piotrowski et al, 2020), adaptive controller (Piotrowski et al, 2016), predictive controller (Yang et al, 2014, Piotrowski, et al, 2015, Li et al, 2020), and hierarchical-nonlinear MPC (Piotrowski et al, 2021).

The second category of DO control approaches includes algorithms that measure and adjust the levels of nitrate (NO_3) (Mulas et al, 2015, Santín et al, 2015] and ammonium nitrogen (NH_4) (Vrečko et al, 2011, Åmand 2012), in addition to monitoring DO levels, to enhance the control system. The algorithms in the next category of DO control, equipped with supervisory controllers, are designed to determine the time-varying reference trajectory of DO–DO_{ref} (Houzhao et al, 2013, Grochowski et al, 2016, Piotrowski 2020). Regular updates and extensive modifications to the hardware-software structure of WWTP control are necessary to incorporate modern control methods, such as adaptive and predictive control. These approaches also require comprehensive staff training. Integrating fuzzy control systems into the current setup is a straightforward task. Furthermore, the knowledge and skills possessed by the WWTP employees contribute to the development of unclear control strategy guidelines. Therefore, it is an essential instrument when developing cutting-edge control systems for WWTPs. The different ways that fuzzy logic can be used for DO control at a WWTP have been talked about in Fan et al, 2011, Piotrowski et al, 2019 and Wu e al, 2015. In each case, the aeration system was left unturned. Fuzzy logic is used in a complicated hybrid nonlinear dynamic system that controls things. As a result, it could have a big impact on the WWTP's operations and safety steps.

2.3 Literature focused on Effect of temperature on the biological activity and treatment

Wastewater's average yearly temperature changes depending on where it's located. Like, in Latin America, the temperature is generally between 3 °C and 27 °C. In Africa, Asia, and the Middle East, on the other hand, the temperature ranges from 28°C to 45°C. It is very important to know the temperature of wastewater because it affects the reaction rates and metabolic rates of bacteria in the wastewater. No matter what the working and ambient temperatures are, strict effluent limits must be followed when treating wastewater from cities and factories. WWTP has a lot of problems because of the active biomass for nitrogen removal (N) when it comes to handling wastewater from factories and cities. The amount of nitrogen is limited by the rate of nitrification. It is known that the rate of nitrification is the rate-limiting step for getting rid of N. Taking in acetate in the anaerobic part is also a key factor in determining the amount of PAOs and, by extension, the amount of P that is removed. The impact of temperature on the moving parts in a typical WWTP has not been widely researched in the past, so this study aims to fill that gap. Hydrolysis and fermentation are not affected as much by the lower temperature. Stoichiometry and kinetic factors are affected by short-term changes in temperature. Long-term changes in temperature have an effect on plant activity.

Most of the time, temperatures between 25°C and 35°C are best for cellular processes. The nitrification process stops when the temperature reaches 50°C, and bacteria that produce methane stop working at 15°C. Based on the research by Metcalf and Eddy (2003), autotrophic nitrifying bacteria almost stop working at 5°C. Collins et al. (1973) say that the effluent quality has been a good sign, and the temperatures run from 10 to 30°C. The rate of aerobic phosphorus uptake becomes very high between 15°C and 20°C, as Baetens et al. (1999) found when they looked into how weather affected bio-P removal. Even though the solid retention time (SRT) and settling sludge compositions are different, when the temperature goes up from 25°C, nitrogen is removed at the same time as denitrification and nitrification processes, as explained by Gorgün et al. (2002).

What are the flocculants in activated sludge after it has settled? Ghanizadeh et al. (2001) looked into this when the temperature was between 3°C and 15°C. It has also been seen that as the temperature rises, the amount of suspended solids in the effluent increases while the removal of COD drops. We looked into how temperature affects things by comparing temperatures from

9°C to 30°C in an SBR that treats wastewater from a tannery to see how well it removes nitrogen. Also, it has been seen that the quality of the waste meets the standards set by Murat et al. (2004) above 20°C. Increasing the temperature from 15°C to 35°C in an up-flow micro aerobic sludge system makes a big difference in how much COD and SS are removed. Based on De Kreuk et al. (2005) and Meng et al. (2019), the reduction rates of COD and SS slow down when the temperature drops from 20oC to 8oC. In their 2002 study, Singh and Viraraghavan looked at the up-flow anaerobic sludge blanket system and changed the temperature from 6°C to 32°C to find out the bio-kinetic rates for treating sewage wastewater. The temperature is one of the most important factors that affects biomass activity, which is necessary to keep biological activity going well. Lippi et al. (2009) also talk about physical features such as dissolved oxygen, changes in settling velocity, and mixed liquor in response to temperature changes. These features help in modelling and predicting the activated sludge system. About every 10 to 15°C rise in temperature makes the rate of biological violations either double or cut in half.

If you raise the temperature by 10°C, Van't Hoff's rule says that the rate of cellular activity doubles. Different studies have come to different conclusions about how temperature affects BNR. Many studies have shown that higher temperatures (20–37°C) are better for getting rid of phosphorous (Brdjanovic et al. 1997). No matter what the carbon matter does, poly accumulating organisms (PAO) control microorganisms at low temperatures (10°C). Also, the temperature effect did not give metabolic advantages to organisms that stored glycogen over PAOs, even though López-Vázquez et al. (2008) research on aerobic metabolism was taken into account. A new study looks at how temperature affects the activated sludge model (ASM1) on the BSM1 platform, using the dynamic parameters. A difference was seen between the strict limits set by Tejaswini et al. (2019) for sewage when the temperature was less than 20°C and more than 30°C.

Alterations in temperature in WWTPs haven't gotten as much attention from the point of view of modelling and controlling the whole plant. Because biological reactions are more complicated, they needed less temperature control in WWTP processes. Most of the time, WWTPs are run at temperatures that are normal for the area. The weather has a big effect on the quality of the effluent (EQI), the cost of operations, and the general output. An up-flow micro aerobic sludge device is being used to study the effect of temperature right now. The results show that nitrogen removal works better at 17°C. These findings were published in Meng et al. (2019). According to Alsawi (2020), kinetic factors have a big effect on how productive WWTPs are, and changes in temperature have an effect on how well the process works. The fixed-bed reactor system described in the study by Hamdani et al. (2020) works better at removing nitrogen and carbon when the temperature is lowered to 10-15°C for diary effluent.

2.4 Motivation

Optimal operation of the WWTP is the primary motivation for preserving legislative regulations governing the extant WWTP. To achieve this, the possible routes are either redesign of the process or making it better with improved process control strategies. All of these things work together to control the amount of nitrogen (N), carbon (C), and phosphorus (P) in the waste while keeping the costs low. A lot of implementations and improvements have been written about, but a lot of WWTPs are still running without being upgraded because people don't know how to use modelling, control, and optimisation tools to keep an eye on the problems that come up when trying to meet strict WWTP effluent quality standards. It is very hard to control and keep an eye on the whole WWTP because different unit operations rely on chemical, biochemical, mechanical, and biological events. Also, the ecosystem around a WWTP is always changing, including the feed flow rate, temperature, nutrient concentrations, and toxic material concentration peaks. All of these changes can make biological wastewater treatment very difficult. These differences can have a big effect on how well the process works, and in some cases they can even cause the process to fail.

In order to follow strict rules: It is better to use advanced control methods to get the effluent consistency that regulations call for. The concentration of the effluent can also be kept more stable, and problems with the process that stop the treatment can be cut down. There are more complex ways to run a plant when there are more unit operations, like treatment steps that happen across the whole plant. Modern control programmes can be used to successfully regulate the quality of the effluent, making it possible to meet even the strictest environmental regulations.

Cutting down on costs: Olsson et al. (2005) say that a nutrient removal WWTP can work 10–30% better if the plants are managed well and controls are used correctly. As processes become more efficient, the space needed for new WWTPs shrinks, which lowers the cost of building them. Cutting down on the energy needed for aeration and the use of different chemicals could also help nutrient removal plants save a lot of money.

How temperature affects the WWTP: In many WWTPs, temperature is very important. The temperature is thought to be the most important factor in WWTP methods, especially for organic WWTP. No matter what the working and ambient temperatures are, strict effluent limits must be followed when treating wastewater from cities and factories. WWTP has a lot of problems because of the active biomass for nitrogen removal (N) when it comes to handling wastewater from factories and cities. The amount of nitrogen is limited by the rate of nitrification. Taking in acetate in the anaerobic part is also a key factor in determining the amount of PAOs and, by extension, the amount of P that is removed. It hasn't been studied in depth how temperature affects the kinetic processes in a normal WWTP, so that's what this thesis is all about.

Driven by these motivating factors and recognizing a literature gap, the current research is structured around the following objectives.

Ojective-1: To identify fractional-order models and control within a supervisory control framework for efficient nutrients removal in biological wastewater treatment plants

Objetive-2: To design IMC-Based Fractional Controllers within a Supervisory MPC Control Scheme for WWTPs.

Objetive-3: To design control strategies for sequencing batch reactor based biological wastewater treatment.

Objetive-4: To develop hierarchical control strategies for evaluating the DO set points by measuring Ammonia concentrations in the SBR with Fuzzy logic in higher level.

Objetive-5: To study the effect of temperature on the estimation of kinetic and stoichiometric parameters and on the water-energy nexus.

Chapter 3

Chapter 3

3. FRACTIONAL ORDER MODELS IDENTIFICATION AND CONTROL WITHIN A SUPERVISORY CONTROL FRAMEWORK FOR EFFICIENT NUTRIENTS REMOVAL

The literature study on the ASM3-bioP platform unveils diverse control strategies utilising different algorithms. However, there exist notable gaps in fractional modelling, especially in the design on a fractional controller. This aspect is crucial, given the considerable advantages demonstrated in the biological treatment of WWTPs with different ASP platforms. Consequently, this study concentrates not only on the implementation of a fractional controller but also on the development of fractional modelling for the ASM3-bioP process. The results achieved are quite beneficial, demonstrating substantial advancements in both plant and controller performance.

3.1 Combining lower-level and higher-level control methods on BSM1-P

To lower the nutrient contains and enhance the effluent quality (EQI), hierarchical control systems have been developed for biological wastewater treatment plants. The activated sludge model no. ASM3-bio-P was used to make the benchmark simulation model no. 1 (BSM1-P). This model is used to control the amount of liquid oxygen in aerobic reactors and the amount of nitrate in anoxic reactors. At the lower level, Fractional PI (FPI) controllers are made along with fractional order model of the process. At the higher level, a rule based fuzzy controller are used to improve tracking of set points. Initially, the prediction-error method is employed to construct an integer-order (IO) transfer function centred on the operating point at the lower level. Consequently, both an integer order controller (PI) and a fractional order controller (FPI) are applied to the IO model transfer function. At last, a Fractional order model of BSM1-P has been determined and an FPI controller has been integrated with it at the lower level. In order to find the higher-level model, the lower-level control loop works in a closed loop with the intended controller. After that, the controls are made based measurements of ammonia in last aeration tank at the higher level.

3.2 Introduction

Controlling a WWTP with inherent complexity and influent variations requires an effective control technique. Worldwide, wastewater treatment plants use simple PI control to complex structures like FUZZY, MPC. In all activated sludge WWTPs, the aerobic region's dissolved oxygen (DO) concentration should be high enough to meet microorganisms' oxygen needs and boost nitrification. However, an extremely high DO requires a high airflow rate, which uses more energy and may lower sludge quality. DO control is crucial for process efficiency and economic benefits.

A two-level hierarchical control architecture with FPI controllers at lower levels and advanced control methods at higher levels is created in this chapter. An FPI control scheme is constructed at the lower level and an intelligent higher-order decision-making system utilising fuzzy logic is created to enhance set-point tracking.

ASM3-BioP process model have not discussed about the development of fractional models and also the associated fractional controllers for nitrogen and phosphorus removal using the BSM1-P framework. Despite the complexity of system dynamics, fractional order systems can represent them with minimal terms. As part of the current study, a fractional model of the ASM3bioP process has been developed, based on which a fractional controller is designed for improved process performance. The novelty is establishing a systematic procedure for development of fractional order models and then design of fractional order controllers and analysis of the fractional controllers' performance. In the closed-loop, for DO & S_{NO} control, all three situations namely 1. Integer Order (IO) plant with IO controller, 2. IO plant with fractional-order (FO) controller and 3. FO plant with FO controller have been implemented. Further, ammonia-based aeration control with an adaptive Fuzzy logic control is also designed and performance is analysed.

3.3 Plant's performance Indices

Benchmark is a common assessment criterion that serves as the foundation for regionally independent assessments of globally established comparison strategies. The plant's performance is evaluated at two levels based on the evaluation criteria defined. The first level monitors the controller's implementation in a closed-loop system by eliminating the error to track the desired level, while the subsequent level investigates its impact on plant performance. Overall performance of the treatment plant is monitored by the effluent quality index (EQI), the operating cost index (OCI), obtainable effluent concentrations and violations. EQI is described by Equation 3.1, where t_0 and t_f are 7th and 14th day respectively

$$\mathrm{EQI} = \frac{1}{100(t_f - t_o)} \int_{t_o}^{t_f} \mathrm{HU}_{(t)} \mathrm{Q}_{e(t)}\, dt \tag{3.1}$$

Where $\mathrm{HU}_{(t)}$ represents the average load of pollutant levels in influent and effluent data and is described by equation 3.2

$$\mathrm{HU}_{(t)} = \mathrm{HU}_{\mathrm{TSS}(t)} + \mathrm{HU}_{\mathrm{COD}(t)} + \mathrm{HU}_{\mathrm{BOD}(t)} + \mathrm{HU}_{\mathrm{TKN}(t)} + \mathrm{HU}_{\mathrm{NO_3}(t)} + \mathrm{HU}_{\mathrm{P_{tot}}(t)} \tag{3.2}$$

The assessment of OCI is performed in order to calculate the cost of various control strategies. Equation 3.3 represents the OCI.

$$\mathrm{OCI} = (3 \times \mathrm{EC}) + \mathrm{ME} + (5 \times \mathrm{SP}) + \mathrm{AE} + \mathrm{PE} \tag{3.3}$$

Here, all energies like the aeration Energy (AE) (kW hr/day), the pumping Energy (PE) (kW hr/day), the mixing Energy (ME) (kW hr/days) respectively, are calculated to get the OCI indices. External carbon dosages (EC) are not taken into account in our approach. The relevant parameter and corresponding equations involved in calculating WWTP's performance indices are well described in the literature (Shiek et al., 2021 a,b). The equations defining the concentrations of various components, the associated energy, and the sludge production are provided in above said literature. Moreover, the effluent quality must be maintained in accordance with severe legal criteria. The effluent estimation is computed using average data. Table 3.1 displays the effluent concentration restrictions that must be satisfied by any WWTP.

Table 3.1: Effluent restrictions norms

Variable	VALUE
TN	<18 mg N/L
COD	<100 mgCOD/L
NH	<4 mg N/L
TSS	<30 mgSS/L
BOD_5	<10 mgBOD/L
TP	<2 mgP/L

3.4 Implementation of control approaches

In the lower-level control, common but popular feedback control employing the PI controller is considered for reference. Figure 3.1 shows two PI controllers in the lower level, while DO_7, whose set-point value is 2 mg O_2/L is controlled by adjusting K_{La7} in the seventh reactor and the other control loop is in charge of keeping S_{NO4} at 1 mg N/L by controlling Q_{intr}. The main focus of this study is the development of a fraction controller and replacing this PI controller at the lower level for both integer and fractional models (Figure 3.1). Figure 3.2 also depicts the hierarchical strategy with a supervisory layer. Higher-level control aims to determine DO_7 levels (lower-level set points) by manipulating S_{NH7} in the seventh reactor which reflects as a set point to the lower DO_7 loop. In terms of the lower-level controller, DO_7 and S_{NO4} are controlled by regulating KLa7 and Q_{intr} respectively. Higher DO is required for improved nitrification if S_{NH7} levels are higher. Nitrification converts ammonium to nitrate, during de-nitrification nitrate is converted to nitrogen gas. The presence of too high DO in the aeration tank will reduce ammonia but same time nitrate will increase. In the same scenario, if the DO level is too low, the ammonia level rises and the amount of existing nitrate available for de nitrification decreases. Additionally, the level of aeration affects energy use. As a consequence, the DO set point must be chosen carefully.

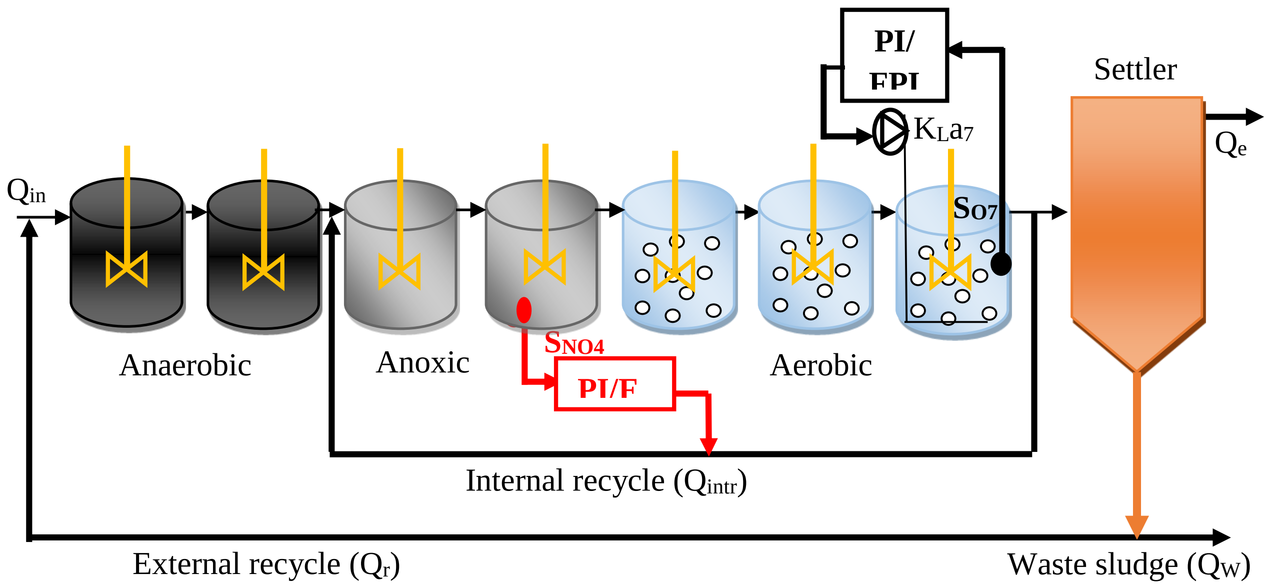


Figure 3.1: PI and FPI control approach for both DO and NO loop in lower level

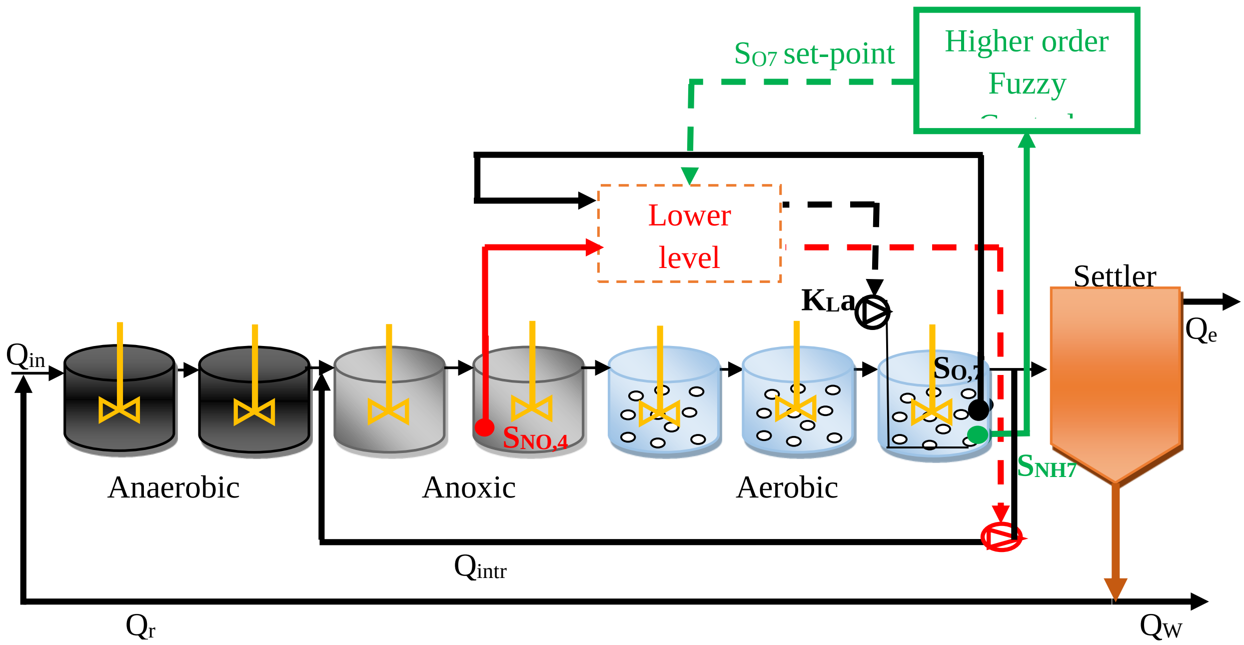


Figure 3.2: ABAC based hierarchical adaptive control strategy with lower-level PI and FPI control

3.5 Modelling of system from process Input-output data

The very first need for implementing a control structure for any type of process is to identify the right process model. In this work as discussed earlier, both IO and FO models of WWTP are identified from simulation work and hence both the IO and FO controller are implemented on it.

3.5.1 Algorithm to develop an IO Model to design controllers

The idea of identification is to derive a dynamic system model from data collected during an experiment. In general, obtaining a link between system inputs and outputs under different influences (input signals, disturbances) is required to determine and estimate system behaviour.

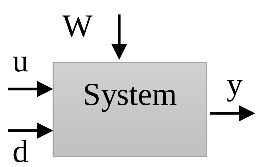


Figure 3.3: SISO system with input, output and disturbance

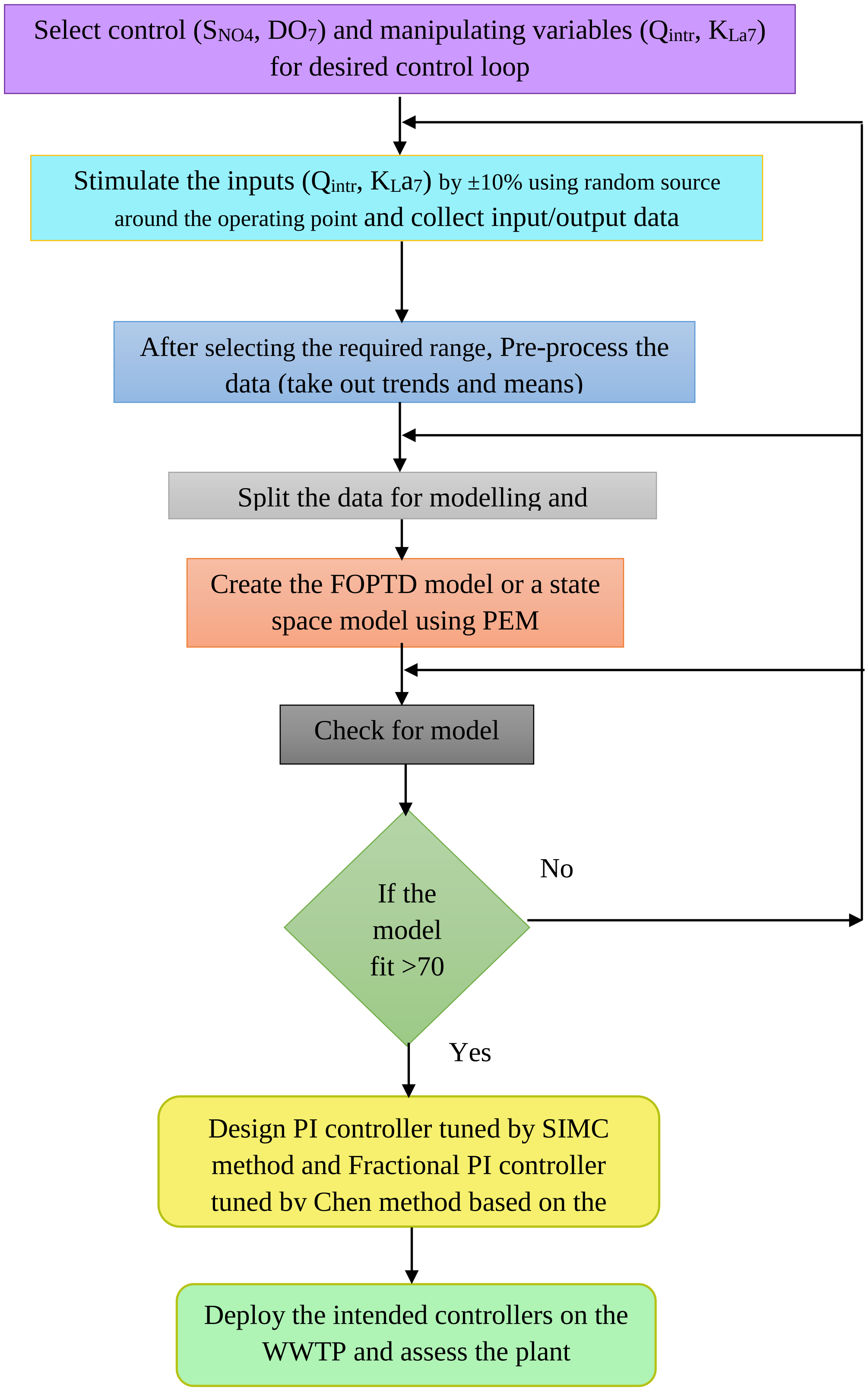


Figure 3.4: Algorithm for identifying an Integer-Order (IO) Model

Here the system is with input u, output y, measured disturbance d and unmeasured disturbance 'w'. SISO system with input, output and disturbance is depicted in Figure 3.3. Above flow diagram in Figure 3.4 describes the identification of IO First order plus time delay (FOPDT) model using system Identification toolbox.

3.5.2 Algorithm to develop an FO Model to design controllers

Figure 3.5 explain the systematic steps involved to identify a fractional order (FO) model using FOMCON toolbox in MATLAB.

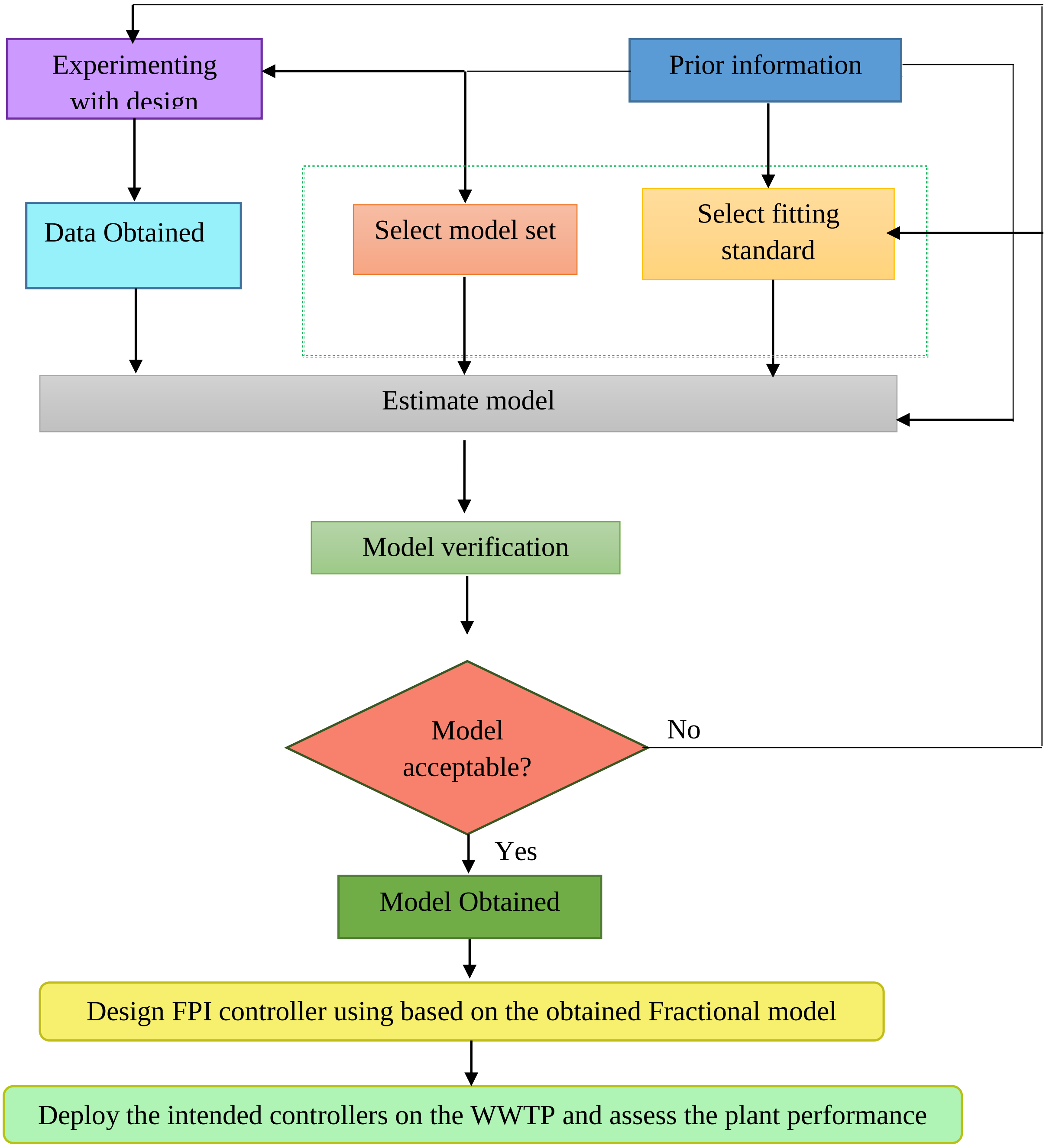


Figure 3.5: Algorithm for identifying a Fractional-order (FO) model

A critical stage of the identification is measuring the level of noise and disturbances in the acquired data and then filtering and processing the data before dealing with the identification algorithm. The FO model is identified based on the time-domain approach. The Simulation parameters window helps to select the type of system simulation we would like to use.

Among these are the following:

• Fractional derivatives being evaluated utilising Grunwald-Letnikov method.

• Approximation utilising Oustaloup filter.

• Approximation utilising Refined Oustaloup filter.

First and obviously, a 'fidata' structure must be selected. The Identified model comes with the fractional zero and pole polynomials in symbolic form. As the options available to fix either polynomial, the model is identified with fixed unity gain and fractional pole polynomial. An initial guess model is formed. To do this, polynomials can be generated independently by specifying a commensurate-order q such that $0.01 \leq q < 2$, the order of the polynomial. At the end of the identification process, a plot with a satisfactory fitting result should be displayed and also indicates the stable behaviour of the identified system. As the results are satisfactory, the model is saved to implement a controller.

3.6 Employed Control scheme

The selection of control structure is critical in developing an efficient control scheme. The elementary strategy acclaims controlling the nitrification and denitrification rates. The DO is controlled by varying the flow rate of the air supply, which ensures the necessary nitrification in the oxic reactors. In the de-nitrification process, nitrate is controlled by changing the internal recirculation flow rate based on S_{NO} in the final anoxic reactor. Considering these two default loops into account, PI, FPI controllers are constructed in this study to regulate S_{NO4} and S_{O7} by adjusting Q_{intr} in 1st anoxic reactor and K_{La7} in the 7th reactor (aerobic) (in Figure 3.1). The resultant model is only valid for balancing DO level 2 mg O_2/l and S_{NO} level 1 g/m^3 (Mulas M. 2007). For the steady-state values, the operative point for the DO loop is 2 mg O_2/l of DO when K_{La7} is 252 likewise when the internal recycling flow is 34,500 m^3/day, the operating point for S_{NO} loops is 1 mg N/l of S_{NO}. To maintain residual DO values in aeration reactors, the amount of DO supplied is usually equal to the microorganisms need. In environments with low oxygen levels, filamentous microorganisms may predominate, which results in poor sludge settlement. A high DO, on the other hand, requires more energy consumption and may lead to deterioration of sludge quality. In an aeration reactor, the DO levels are practically maintained between 1.5 and 4 mg O_2/l, with 2 mg O_2/l being the most common value. Further, if the last pre-denitrification zone does not consume more than a certain value of nitrate, excessive air consumption is not required during aeration. Anoxic reactors with the presence of internal recirculation must maintain nitrate levels between 1 and 3 mg N/l, with 1 mg N/l typically being the most desirable value. Apart from this, a Fuzzy controller at the supervisory level is presented in cascaded with the FO-PI at the lower level as shown in Figure 3.2. In order to save energy usage, estimation of S_O is important. As more 'S_O' (DO level) is essential for nitrification while S_{NH} (ammonia concentration) is high. When S_{NH} is comparatively low then, fewer S_O is essential for making less S_{NO}.

3.6.1 Proportional integral (PI) controller design

In the benchmark models, the default controller is assumed to be PI. The default loops are considered, which use PI controller to control the concentrations of nitrate (S_{NO}) and DO in the respective 4th and 7th reactors. Figure 3.1 depicts the plant arrangement with this PI controller. A wide range of methods is available in the literature for designing PI controllers. Reputable SIMC rules by Grimholt and Skogestad (2018) are deployed in this work. To develop controllers using this method, the first step is to derive a First Order Plus Time Delay (FOPTD) model (G_P) using the popular PEM method (Prediction-Error Minimization) (Ljung, 1999) discussed in algorithm to develop an IO model, presents in this form

$$\mathrm{Gp} = \frac{\mathrm{Kp}}{\mathrm{T} * \mathrm{S} + 1} e^{-\mathrm{L} * \mathrm{S}} \tag{3.4}$$

In the identified process model, K_P signifies the process gain and L is the delay time and the time constant is denoted by T. We explored the above mention original SIMC tuning rule for the first-order with delay (FOPDT) process in equation 3.4. The SIMC tunings for this FOPDT process results in a PI controller like in equation 3.5,

$$\mathrm{Kc} = \frac{1}{\mathrm{K_P}} \frac{\mathrm{T}}{(\mathrm{T_C} + \mathrm{L})} \quad \text{and} \quad \mathrm{T_i} = \min\{\mathrm{T}, 4(\mathrm{T_C} + \mathrm{L})\} \tag{3.5}$$

Here the parameter T_C, the closed-loop time constant is an adjustable tuning parameter that is used to achieve the desired trade-off between efficiency, robustness, and input utilization. T_C = L is suggested for "tight control" (good performance) alongside acceptable robustness (Grimholt et al., 2018).

3.6.2 Fractional Proportional integral (FPI) controller design

The FPI controller is also implemented for the same FOPTD model. Investigations on tuning FPI controllers demonstrate a range of tuning rules for designing FPID parameters, namely controller gain K_c, integral time constant T_i and fractional order α, are given in equations. The equivalent transfer function model of the fractional controller after doing Laplace transform, stated as,

$$G_C = K_c + \frac{K_i}{s^{\alpha}} = K_c\left(1 + \frac{1}{T_i s^{\alpha}}\right) \quad (3.6)$$

Ever since substantial work has been done to propose fractional-order PID controllers. Oustaloup et al. (2000); Podlubny (2008) conducted early research. The tuning guidelines provided by Chen et al. (2008) are used to develop the FPI controllers. According to the identified FOPDT model in equation 3.4, a very important parameter called the relative dead time (τ) of the system defined as in equations (3.7),

$$\tau = \frac{L}{L+T} \quad (3.7)$$

The 'τ' ranges between 0 and 1, and systems with L>>T are referred to as delay dominated, while systems with T>> L are referred to as lag dominated. Hence the tuning parameters come in below equations (3.8, 3.9 and 3.10).

$$\mathrm{K_c} = \frac{1}{\mathrm{Kp}}\left(\frac{0.2978}{\tau + 0.000307}\right) \quad (3.8)$$

$$\mathrm{T_i} = T\left(\frac{0.8578}{\boldsymbol{\tau}^2 - 3.402\boldsymbol{\tau} + 2.405}\right) \quad (3.9)$$

$$\alpha = \begin{cases} 1.1 & \text{if } \tau \geq 0.6 \\ 1.0 & \text{if } 0.4 \leq \tau < 0.6 \\ 0.9 & \text{if } 0.1 \leq \tau < 0.4 \\ 0.7 & \text{if } \tau < 0.1 \end{cases} \quad (3.10)$$

3.6.3 Fuzzy logic controller (FLC) design

Another combination in cascade mode structure a well-known tool, fuzzy logic is applied. Now a day's fuzzy logic is well accepted in various domains of control applications. The DO set-point in the seventh reactor is controlled at a hierarchical level with a Fuzzy logic controller to limit ammonia effluent violations in reactor 7. The membership functions (MF) of DO and ammonia (S_{NH7}) in reactor 7 were examined in the ranges of 0–4 mg O_2/l and 0–25 mg N/l, respectively. To work on these two variables, a Membership Function is chosen in a form of a Gaussian-shaped-bell curve, and they are segmented into linguistic rules of three levels, "low" "medium" and "high". The three ‘IF-THEN’ rules to regulate the DO loop are as follows:

• IF level of Ammonia is “low”, THEN set-point for DO is “low”.

• IF level of Ammonia is “medium”, THEN set-point for DO is “medium”.

• IF level of Ammonia is “high”, THEN set-point for DO is “high”.

The higher-level fuzzy control framework is developed employing these rules and attached with the lower-level Fractional PI controller.

3.7 Results and discussions

Those above-described best control schemes are designed, next applied for the Wastewater treatment system. According to the BSM criteria, an ideal sensor is utilised for all simulations. Here in closed-loop systems for DO & NO control, all three situations: 1. IO plant with IO controller, 2. IO plant with FO controller and 3. FO plant with FO controller have implemented and enhanced performance is analysed. Apart from that higher-order Fuzzy controller is also implemented and analysed in terms of plant performance.

3.7.1 Integer order (IO) plant with IO controller

An IO controller in PI (default controller) form is applied to an IO model in a FOPDT form at the lower level. The FOPDT model is identified for both the DO and NO loop as discussed in the algorithm to develop an IO model. They are given below in FOPDT format,

$$G_{DO}(s) = \frac{0.013824}{0.0015778 * s + 1} e^{-0.006021*s}$$

$$G_{NO}(s) = \frac{0.000071395}{0.013636 * s + 1} e^{-0.00025001*s}$$

The corresponding controllers for both DO and NO are tuned using original SIMC rules.

$$\text{controller Tunning}_{DO} = \left[\begin{matrix} Kc=9.47 \\ Ti=0.0015 \end{matrix}\right.$$

$$\text{controller Tunning}_{NO} = \left[\begin{matrix} Kc=3.81\times10^{4} \\ Ti=0.0136 \end{matrix}\right.$$

Finally, the controller for both DO and NO loops are

$$C_{DO}(s) = 9.47[1 + \frac{1}{0.0015s}]$$

$$C_{NO}(s) = 3.81 \times 10^4 \left[1 + \frac{1}{0.0136s}\right]$$

3.7.2 Integer order (IO) plant with Fractional Order (FO) controller

Calculating the fractional order controller for the same IO plant (IO Model with PI control) we have used the Chen Method. To tune the parameter of the fractional PI controller we need the relative dead time of the system (τ) = L/(L+T). The relative dead time for both the DO and NO loops are 0.79244 and 0.01800 respectively.

$$\text{Fractional Controller Tunning}_{\text{DO-loop}} = \begin{bmatrix} Kc = 27.1415 \\ Ti = 0.0040 \\ \alpha = 1.1 \end{bmatrix}$$

$$\text{Fractional Controller Tunning}_{\text{NO-loop}} = \begin{bmatrix} \mathrm{Kc} = 2.27 \times 10^5 \\ \mathrm{Ti} = 0.0050 \\ \alpha = 0.7 \end{bmatrix}$$

Finally, the FPI controller for DO and NO loops are

$$C_{DO}(s) = 27.1415 \left[1 + \frac{1}{0.0040s^{1.1}}\right]$$

$$C_{NO}(s) = 2.27 \times 10^5 \left[1 + \frac{1}{0.0050s^{0.7}}\right]$$

3.7.3 Fractional order (FO) plant with Fractional Order (FO) controller

Using the FOMCON toolbox a FO model plant is identified as discussed earlier (algorithm to develop an FO Model). The fractional-order (FOTF) model is identified based on the time-domain approach using ‘Oustaloup filter approximation’. The stable FOTF plant for DO and NO loops are

$$\text{FOTF system}_{\text{DO}}(s) = \frac{1}{6.4179 * s^{0.48039} - 99.996 * s^{0.21498} + 205.54 * s^{0.052764}}$$

$$\text{FOTF system}_{\text{NO}}(s) = \frac{1}{35.742 * s^{1.8253} + 34336 * s^{1.3281e-10}}$$

Finally, the Fractional-order PI controller is optimized using the ‘Nelder-Mead’ algorithm by choosing the performance metric as ISE. After selecting their minimum and maximum allowed values of all tuning parameters of the FPI controller is optimized. After selecting the minimum and maximum allowable values for all tuning parameters, the FPI controller is optimized. The tuned parameters are

$$\text{Fractional Controller Tunning}_{\text{FOTF system DO}} = \begin{bmatrix} \text{Kc} = 50.00 \\ \text{Ti} = 0.01040 \\ \alpha = 1.0519 \end{bmatrix}$$

$$\text{Fractional Controller Tunning}_{\text{FOTF system NO}} = \begin{bmatrix} \text{Kc} = 1744.8 \\ \text{Ti} = 0.003221 \\ \alpha = 0.5011 \end{bmatrix}$$

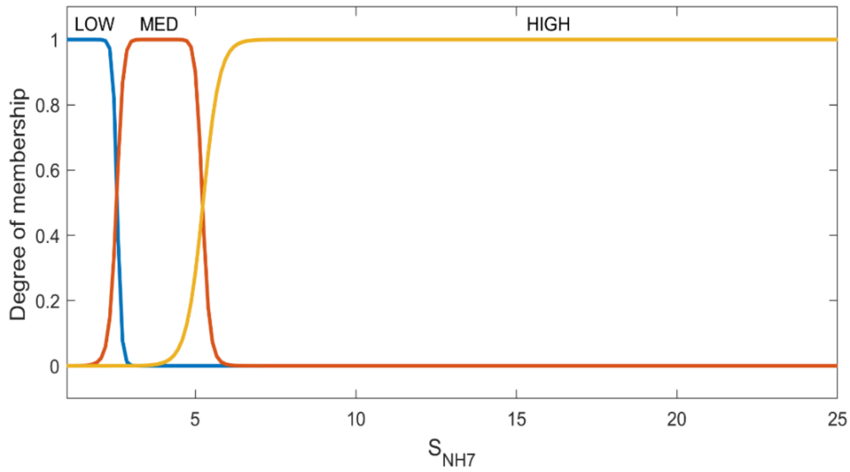
Finally, the FPI controller for DO and NO loops are

$$C_{DO}(s) = 50.00\left[1 + \frac{1}{0.01040s^{1.0519}}\right]$$

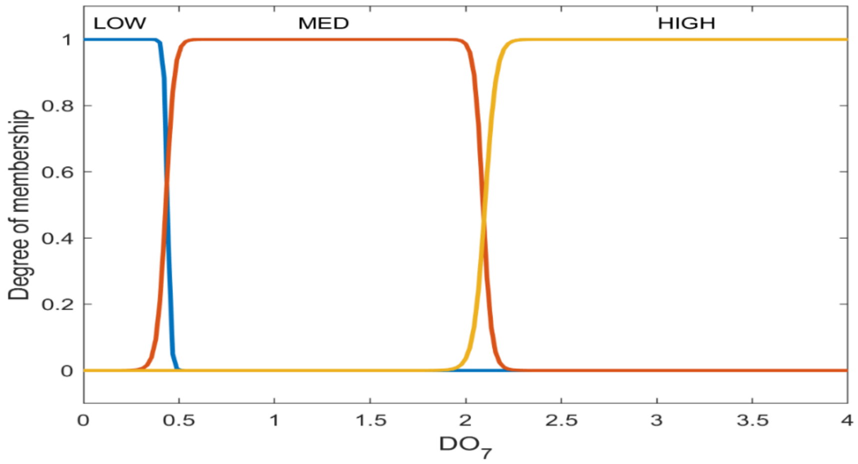
$$C_{NO}(s) = 1744.8\left[1 + \frac{1}{0.003221s^{0.5011}}\right]$$

3.7.4 Hierarchical Fuzzy controller

To achieve a strong set-point tracking, along with conventional PI and fractional PI controllers at the lower level, a cascaded advance controller such as Fuzzy control is explored at the supervisory level. The major goal of adopting this cascaded method is to change the dissolved oxygen set-point in response to changes in ammonia concentration in tank 7. This is Ammonia-based aeration control (ABAC) strategy. The control algorithms at lower level (PI and FPI) and at higher level (Fuzzy control) are distinct in nature. They are interconnected in a cascaded loop. The higher level Fuzzy control is operated for the purpose of the Ammonia-based aeration control (ABAC) strategy without affecting the lower level FPI and PI controller algorithms, but the only connection is providing the variable DO set point to the lower level PI and FPI controller from the hierarchical Fuzzy controller by manipulating the NH_7.The major goal of adopting this cascaded method is to change the dissolved oxygen set-point in response to changes in ammonia concentration in tank 7. We choose the ranges for DO and SNH7 membership functions as 0-4 mg O_2/l and 0-25 mg N/l respectively. The membership curve is considered as a Gaussian bell curve. To ensure adequate oxidation of ammonia (S_{NH7}) to nitrite (S_{NO}), the DO concentration should be kept high enough so that it does not drop before a significant quantity of nitrification occurs.



(A)



(B)

Figure 3.6: Input Membership Function for S_{NH} (A) Output Membership Function for DO (B)

As shown in Figure 3.6 (A), the distributions of membership for ammonia (S_{NH7}) concentration in tank 7 are established as 0-2 mg N/l labelled as "low", 2-4 mg N/l labelled as "medium" and values over than 4 mg N/l labelled as "high", with the fuzzy set ammonia value membership value as 1. Figure 3.6 (B) clearly shows that for DO, values less than 0.5 mg O2/l are labelled undoubtedly "low," hence the membership values for this DO are assigned as 1. Similarly, values ranging from 0.5 - 2.0 mg O2/l are labelled as "medium" in the fuzzy set. DO values more than 2.5 mg O2/l are labelled as "high". These DO_7 values are conceded to the lower DO_7 loop as set points. Figures 3.9 (A) and 3.10 (A) depict the changing DO set-point delivered by the upper level Fuzzy and it's tracking by the bottom level. Figure 3.7 (A) shows that keeping the set-point of DO at 2 mg O_2/l for the entire duration, as in the default bottom level control. Ideally, DO_7 set point is recommended as 2 mg O_2/l. However, this value may not be required all the time and that depends on the availability of ammonia concentration in the aerobic reactors. The additional contribution of this study is the creation of a two-level hierarchical approach with a supervisory layer that employs Fuzzy Logic Control. The higher-level controller's role is to compute DO_7 values (lower-level set points) by measuring NH_7 in the seventh reactor. These DO_7 values are passed to the lower DO_7 loop as set points. As a result, the higher-level control loop aids in determining the set points for the lower loop. Greater DO is required for improved nitrification when NH_7 levels are higher. Nitrification converts ammonium to nitrate, whereas denitrification converts nitrate into nitrogen gas. If the DO in the aeration tank is too high, ammonia will drop but nitrate will rise. If the DO is too low, ammonia levels rise and the amount of nitrate available for denitrification falls. Additionally, the degree of aeration affects energy use. As a result, the DO set point should be chosen smartly. At a lower level, default two PI and FPI controllers are used, and Fuzzy Logic controller is built at a higher level. The set value of DO at 2 mg O_2/l can indeed be changed to meet the requirements of the WWTP. It can be smaller if the ammonia load is low, and it can be larger if the ammonia load is high. One should note that, to have minimal operational costs, ammonia should always be kept at the lowest value to keep the effluent level below the discharge limit. Thus the simulation results showed that changing set-point using Fuzzy Logic Control improves plant performance in terms of providing better effluent quality.

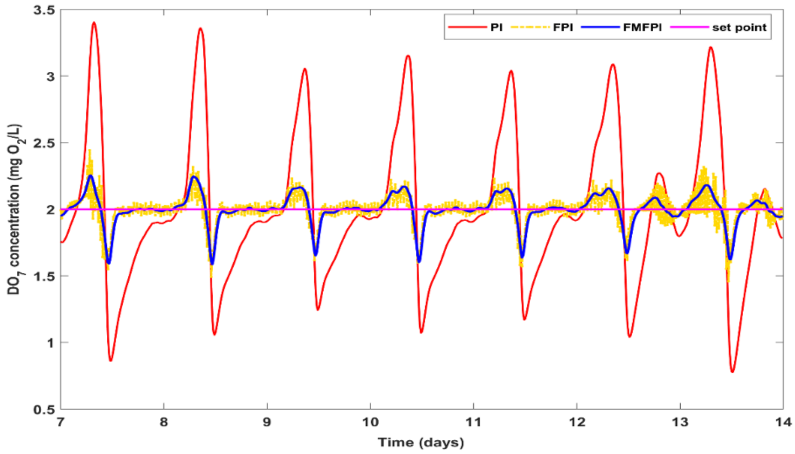
3.8 Controller Performance analysis

Set-point tracking is used to evaluate performance from a controller standpoint. In the fourth tank, a set-point is chosen as 1 mg N/l for S_{NO}, and for DO_7 in seventh tank 2 mg O_2/l is chosen as a set-point.

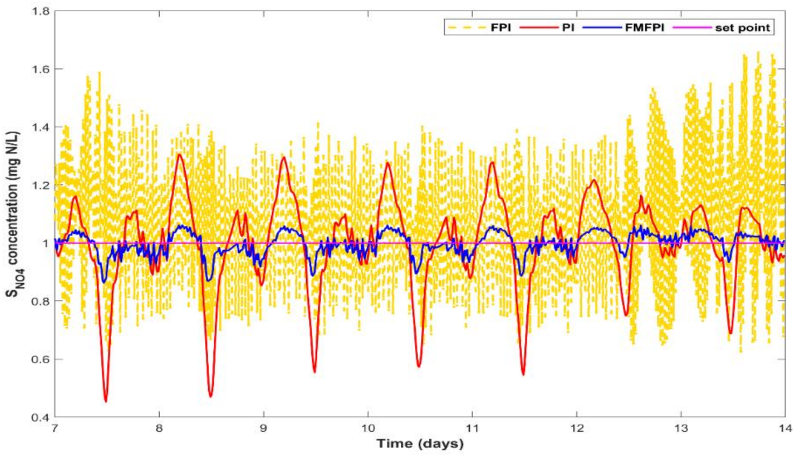
3.8.1 Lower level controller Performance Analysis

The set-point tracking of DO and nitrate (S_{NO}) by PI, FPI, and Fractional Model plant with FPI (FM-FPI) have shown in Figures 3.7 (A, B) respectively. The effective tracking ability of the FM-FPI controller is comparatively superior for both DO and NO controllers, and at the same time, the FM-FPI controller results in superior plant performance when compared to PI control and the IO model with FPI control. The FPI controller using the Chen method in lower level NO control gives oscillatory response because of high controller gain with low integral order action. The main contribution of this work is implementing fractional controller in both IO and

FO plant model for DO and NO control. The plots in Figures 3.8 (A, B) show FM-FPI impacts more on set point tracking compared to IO model FPI. The manipulated variable plots by lower-level PI, FPI and FM-FPI controller for both DO and NO loops are well tested.

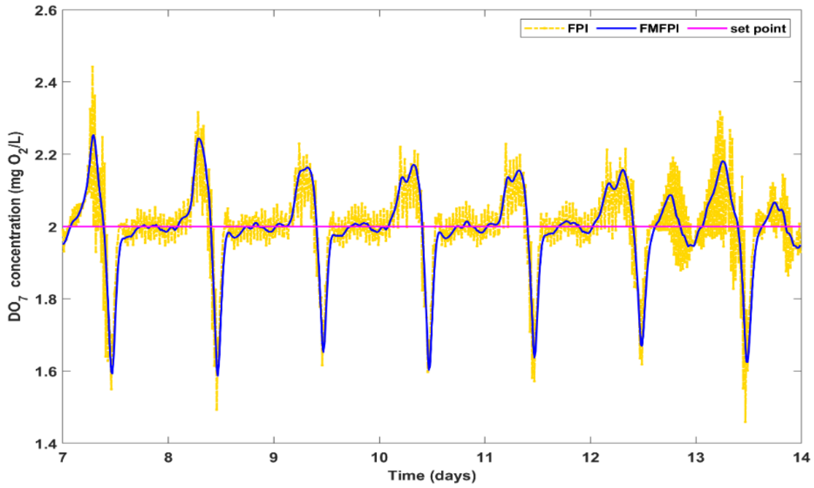


(A)

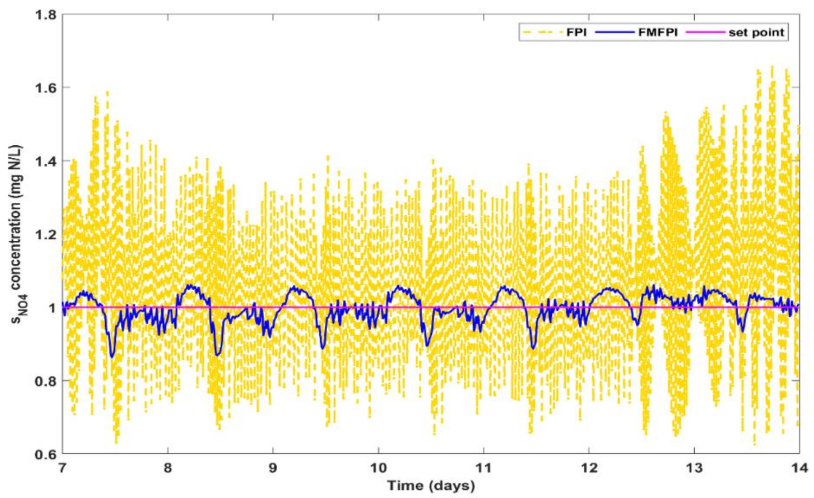


(B)

Figure 3.7: (A) DO tracking for lower-level PI FPI and FM-FPI (B) SNO tracking for lower-level PI FPI and FM-FPI



(A)



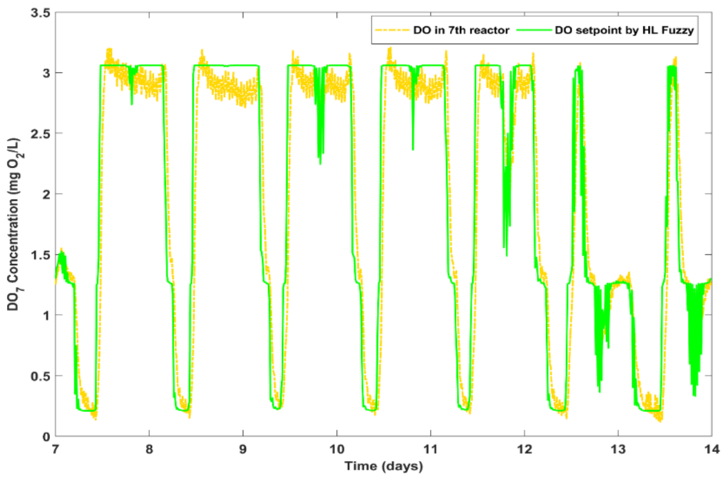
(B)

Figure 3.8: (A) DO tracking in IO FPI and FM-FPI (B) SNO tracking in IO FPI and FM-FPI

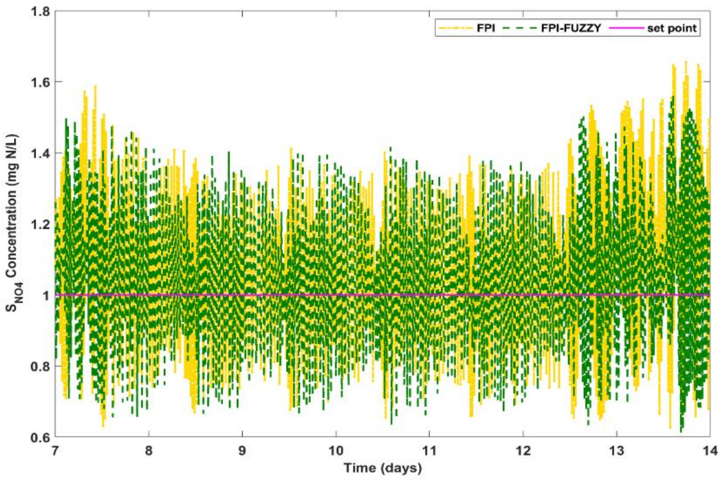
In the two considered control loops, to maintain the NO and DO levels in the anoxic and aerobic biological reactor the internal recycling flow rate and the oxygen transfer co-efficient are manipulated, respectively, removal of the organic and nutrient content from the influent is done efficiently.

3.8.2 Supervisory level controller Performance Analysis

In addition, the cascaded approach with the fuzzy controller is used to adjust the dissolved oxygen set-point in response to changes in ammonia concentration in tank 7. It has been discovered that employing a Fuzzy controller with the changing set-point increases plant performance. Figures 3.9 (A, B) shows the DOSP tracking of supervisory Fuzzy controller and nitrate tracking in the fourth reactor.



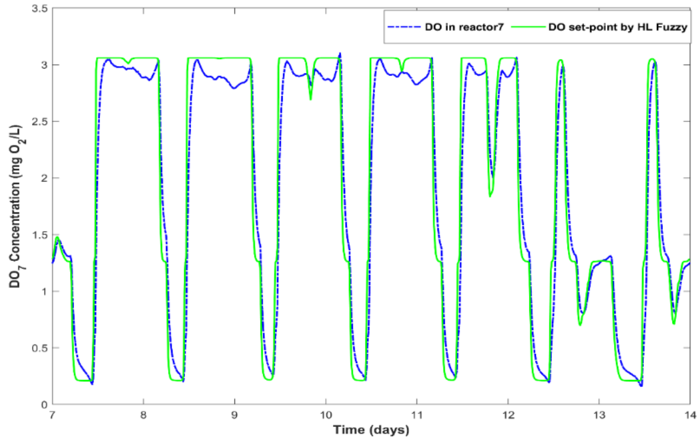
(A)



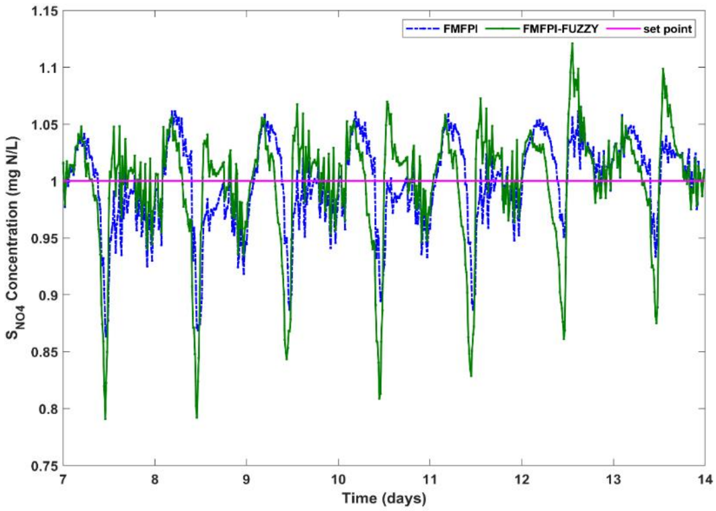
(B)

Figure 3.9: (A) DOSP tracking of supervisory Fuzzy controller with lower-level FPI controller (B) Nitrate tracking in last anoxic reactor

The Figures 3.10 (A, B) shows the dynamic set-point tracking with higher-level Fuzzy utilizing FO model FO control, as well as improved DOSP tracking and robust control action in terms of nitrate (S_{NO}) tracking.



(A)



(B)

Figure 3.10: (A) DO tracking of supervisory Fuzzy controller with lower-level FM-FPI (B) Nitrate tracking in last anoxic reactor

3.9 Plant Performance analysis

All created controllers are employed on the plant design, and their performance assessment is measured using the EQI and OCI indicators. In the nitrification process in a WWTP, ammonia oxidises into nitrates. This is done efficiently by the FL control approach, which results in lower ammonia concentrations when compared to other added control strategies, ensuring the best EQI. As stated in the plant Performance evaluation index, OCI is computed using the ME, SP, AE and PE cost indices. The current controller is selected in such a way that it has a noticeable impact on the governing processes. Figure 3.11 shows the column chart for these cost indices. The first lower loop, which manipulates Q_{intr} to control S_{NO}, has an effect on the de-nitrification process, which has a direct influence on the energy index in terms of pumping cost. Similarly, the change in the cost index of aeration energy is an outcome of the nitrification process, which is controlled by the other loop by altering K_{La7}. Results show that FL control at the higher level resulted in the highest aeration energy cost index. Table 3.2 displays the plant performance improvement in terms of EQI and OCI which shows with fractional modelling and fractional controller implementation.

Table 3.2: Impact of proposed control strategies in evaluation criteria

Average effluent concentration		**OL (Sheik et al., 2021a)**	**IO model IO control**	**IO model FO control**	**FO model FO control**	**IO model FO control higher-order Fuzzy**	**FO model FO control higher-order Fuzzy**
Components	**Limit**						
NH	4	6.08415	6.09	5.74	5.73	5.79	5.76
TSS	30	13.68	13.69	13.72	13.68	13.75	13.71
TN	18	16.5	15.92	15.80	15.77	15.53	15.57
TP	2	3.58	3.59	3.63	3.64	3.41	3.45
COD	100	44.75	44.79	44.82	44.79	44.83	44.79
BOD_5	10	1.79	1.79	1.79	1.79	1.80	1.79
NH (% of violation)		66.22	66.51	65.32	65.17	69.40	68.89
TP (% of violation)		65.77	67.41	69.64	69.49	66.6	66.81
TN (% of violation)		38.09	25.51	23.95	23.21	23.95	23.51
IQI		72152.2	72152.22	72152.22	72152.22	72152.22	72152.22
EQI		***13,411***	***13332.76***	***13265.74***	***13253.56***	***12874.25***	***12871.22***
SP		2973.45	2969.81	2958.63	2957.10	2983.72	2980.03
AE		4336.6	4254.57	4261.27	4259.72	4322.89	4321.61
PE		304.81	331.52	328.80	329.82	333.40	335.69
ME		480	480	480	480	480	480
OCI		***18,753***	***18680.72***	***18623.33***	***18619.22***	***18811.15***	***18799.30***

Table 3.3: Performance of the different control framework in terms of EQI and OCI

Plant Performance	PI (%I)	FPI (%I)	FMFPI (%I)	FPI-Fuzzy (% I)	FMFPI-Fuzzy (%I)	Improvement % with PI to FPI	Improvement % with PI to FMFPI
EQI	*0.59%*	*1.09%*	*1.18%*	*4.00%*	*4.03%*	*0.50%*	*0.59%*
OCI	*0.39%*	*0.69%*	*0.71%*	*-0.3%*	*-0.25%*	*0.31%*	*0.33%*

*%I - Improvement % with respect to OL

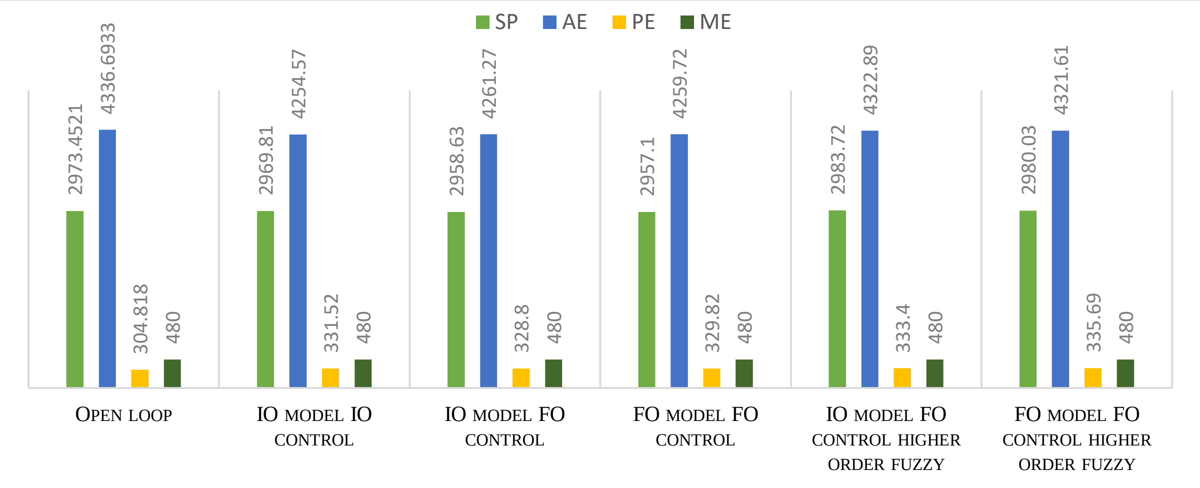
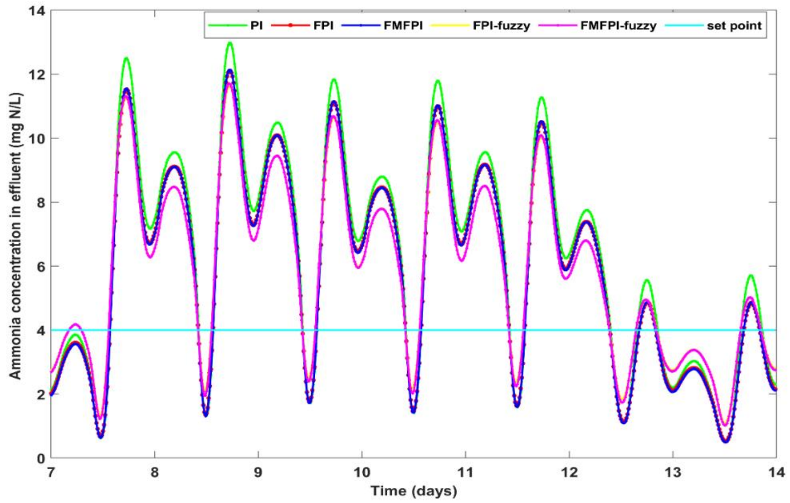
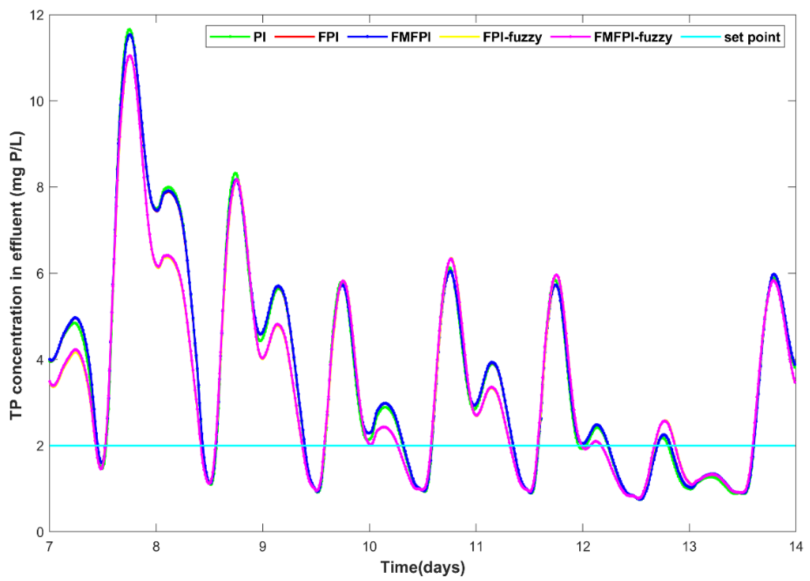


Figure 3.11: Column chart for all cost indices.

It has been noticed that the control approaches implemented have a significant impact on plant performance in terms of EQI, OCI, set-point tracking, effluent concentrations, and violations. Total nitrogen violations in the effluent are considerably decreased by the proposed control approaches, whereas ammonia violations are reduced moderately in the lower level. Figures 3.12 (A, B, C, D) shows the effluent violations percentage and their concentration in all adopted control schemes. Table 3.3 displays the increasing percentage of accepted controllers in terms of EQI and OCI. In the open-loop scenario, the EQI and OCI are 13411 and 18753, accordingly. When fractional controllers with integer models are used, EQI and OCI improve by 1.09 % and 0.69 %, respectively. When fractional controllers with fractional models are used, there is a considerable improvement of 1.18 % in EQI and 0.71 % in OCI. Again, the improvement percentage for EQI in FPI control and FMFPI control with respect to PI control is 0.50% and 0.59% respectively and for OCI it is 0.31% and 0.33%. In terms of EQI, the Fuzzy control in sequential order affecting the IO model with FPI control is improved by 4.00 %, while the FO model with FPI control improved by 4.03 % from the open-loop. However, as a result of controller cost, increases in OCI have been observed with Fuzzy control. An achievement like robust set-point tracking is also accomplished for the control loops utilising both the IO and FO model with the same FO Controller structure, but the FO model indicates that fractional control strategy implementation has a significant impact on WWTP treatment.



(A)



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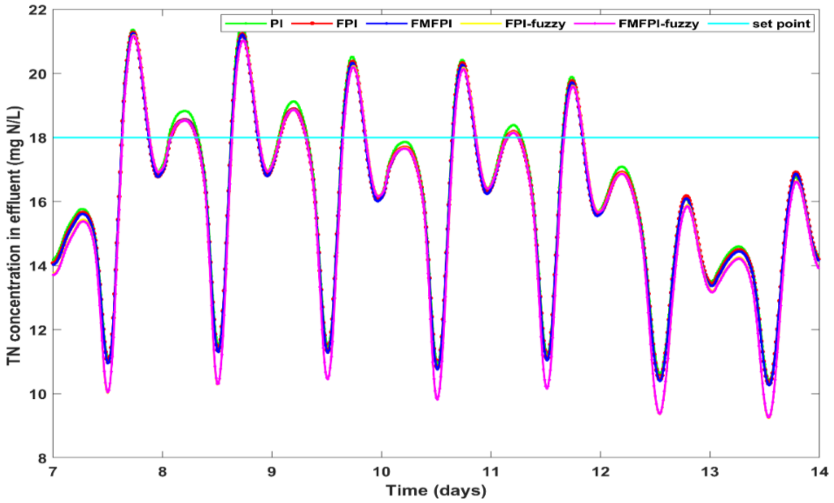

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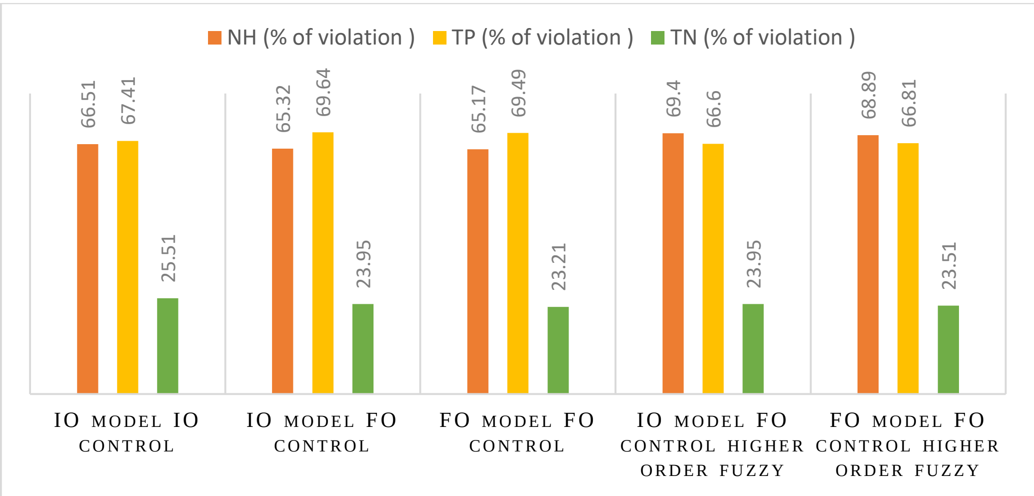


(D)

Figure 3.12: (A). Ammonia concentration (B) TP concentration (C) TN concentration and (D) Column chart shows the effluent violations percentage in all adopted control schemes

3.10 Comparative analysis of existing and current control plans

The summary of current and previous control strategies indicates that adopting these fractional control schemes in this ASM3-bioP framework has a considerable impact on plant performance in terms of EQI and OCI. In the lower level control structure, designed controllers (Shiek et al., 2021b) like PI, Fuzzy and MPC (Table 3.4) are compared with present fractional control schemes.

Table 3.4: Comparison of Performance indices in lower level control strategy

Plant Performance	FPI	FMFPI	Fuzzy	(% I) wrt FPI	(% I) wrt FMFPI	MPC	(% I) wrt FPI	(% I) wrt FMFPI
EQI	13265	13253	13381.96	0.87%	0.96%	13,243.49	-0.16%	-0.07%
OCI	18623	18619	18,739.13	0.62%	0.64%	18,619.64	-0.02%	0.00%

*%I - Improvement %

*** Fuzzy and MPC controller's performance index is presented by Shiek et al., 2020.

The plant performance in EQI and OCI is improved by 0.87% and 0.62% by FPI controller with IO plant and 0.96% and 0.64% by FPI controller with FO plant when comparing with Fuzzy control. MPC controller shows almost the same performance analysis in terms of OCI and EQI. The ammonia controller in supervisory schemes defined by (Shiek et al., 2021a) is again compared with the present heretical Fuzzy controller (Table 3.5).

Table 3.5: Comparison of Performance indices in supervisory level control strategy

Plant Performance	FPI-FUZZY	FMFPI-FUZZY	PI-Fuzzy	(% I) wrt FPI-Fuzzy	(% I) wrt FMFPI-Fuzzy	PI-MPC	(% I) wrt FPI-Fuzzy	(% I) wrt FMFPI-Fuzzy
EQI	12874	12871	12978	0.80%	0.82%	12741	-1.04%	-1.02%
OCI	18811	18799	18769	-0.22%	-0.16%	18945	0.71%	0.77%

*%I - Improvement %

*** Supervisory level PI-Fuzzy and PI-MPC controller's performance index is presented by Shiek et al., 2021.

Compared with PI-Fuzzy schemes with the current two fractional schemes the EQI is updated by 0.80% and 0.82% in FPI-Fuzzy and FM-FPI-Fuzzy schemes. However, OCI is a little more. The PI-MPC result outperforms the current fractional schemes, in terms of EQI, but OCI is improved by 0.71% and 0.77% in FPI-Fuzzy and FM-FPI-Fuzzy schemes respectively.

3.11 Conclusions

A biological WWTP is evaluated using PI, FPI, and higher-level FL control techniques based on ASM2d wastewater data (Gernaey & Jrgensen, 2004). It has been found that the three implemented control strategies (i) IO model and IO control (ii) IO model FO control and (iii) FO model FO control in lower level have a considerable impact on the plant performance in terms of EQI, OCI, set-point tracking, effluent concentrations and violations. The improvement percentages of EQI for FPI control and FMFPI control compared to PI control are 0.50% and

0.59%, respectively, while for OCI they are 0.31% and 0.33%. Whereas implementing supervisory Fuzzy logic control, EQI improved by 4.00% for the IO model with FPI control, while the FO model with FPI control improved by 4.03 % from the open-loop model. Fuzzy control, however, leads to increases in OCI due to controller costs. With the described FPI control techniques, violations of total nitrogen in the effluent are greatly diminished by 9.01% for FO model and 6.11% in IO model based strategy while comparing with PI controller. Violations of ammonia are also reduced moderately in lower-level control using FPI controller in FO model and IO model by 2.01% and 1.78% respectively, while compared with default PI. Compared with the open-loop scenario, the EQI and OCI both have improved significantly. When compared with the PI controller the results in the FO controller showed more influence on plant performance but the best result is found in the FM-FPI strategy. A Fuzzy logic controller, as a higher level ammonia controller improves the EQI significantly, however, increased OCI is observed.

Chapter 4

Chapter 4

4. DESIGN OF IMC-BASED FRACTIONAL CONTROLLERS WITHIN A SUPERVISORY MPC CONTROL.

This chapter places a heightened emphasis on the design of a fractional controller using the Internal Model Control (IMC) technique. The IMC based fractional controller design necessitates a specific structured transfer function model, which could be either integer or non-integer order, contingent upon the chosen controller (PI/FPI). Consequently this chapter centres on a systematic analytical approach to craft a fractional controller within an identified non-integer order model. The ultimate validation of this controller is conducted in a nonlinear process within the WWTP plant, applying the previous ASM3-bioP model.

4.1 Introduction

This study optimises wastewater treatment plants (WWTPs), specifically the activated sludge process (ASP) and its aeration process, a seven-reactor arrangement that removes nitrogen and phosphorus simultaneously. In recent years, the field of control theory has experienced substantial expansion in its study of fractional calculus and its practical implementations. To regulate the concentrations of dissolved oxygen (DO) and nitrate (NO) in aerobic and anoxic reactors, respectively, IMC-based fractional filter cascaded with PI and FPI controls are the two types of controllers utilised. These controllers employ models with integer and non-integer orders, respectively. The objective is to guarantee the highest level of plant efficiency, resulting in a longer plant lifespan, decreased cost per unit of production, and minimal nutrient concentration in the wastewater. The IMC fractional PI controller is designed with the maximum sensitivity (Ms) as a priority, taking into account the process's gain margin (GM) and phase margin (PM) as constraints. Conversely, advancements in the study of fractional-order calculus have allowed scientists to prove that real-time complex processes possess a dynamic nature characterised by fractional order. Systems with fractional order exhibit reduced complexity while retaining intricate system dynamics. The fractional-order PID ($PI^{\lambda}D^{\mu}$) controller is an enhanced version of the integer-order PID controller that incorporates additional integration (λ) and differentiation (μ) orders. Adjusting the parameters of this controller improves the stability of the closed-loop response. The FOMCON Toolbox is utilised to evaluate fractional model Systems based on real-time simulation data. The results of fractional model structures are also compared to those of an integer order model structure. The non-commensurate fractional model has superior performance compared to other fractional and integer model structures during simulations.

4.2 Identification of Non-integer order model with time delay (NOPDT)

We have selected the ASM3bioP model and its aeration process to study the IMC fraction filter in the non-linear processes of wastewater treatment plants (WWTPs). Our attention is specifically on an activated sludge process (ASP) that utilises a BSM1-P configuration of seven reactors, as described in section 1.4. Figure 4.1 describes the algorithm of non-integer order model identification.

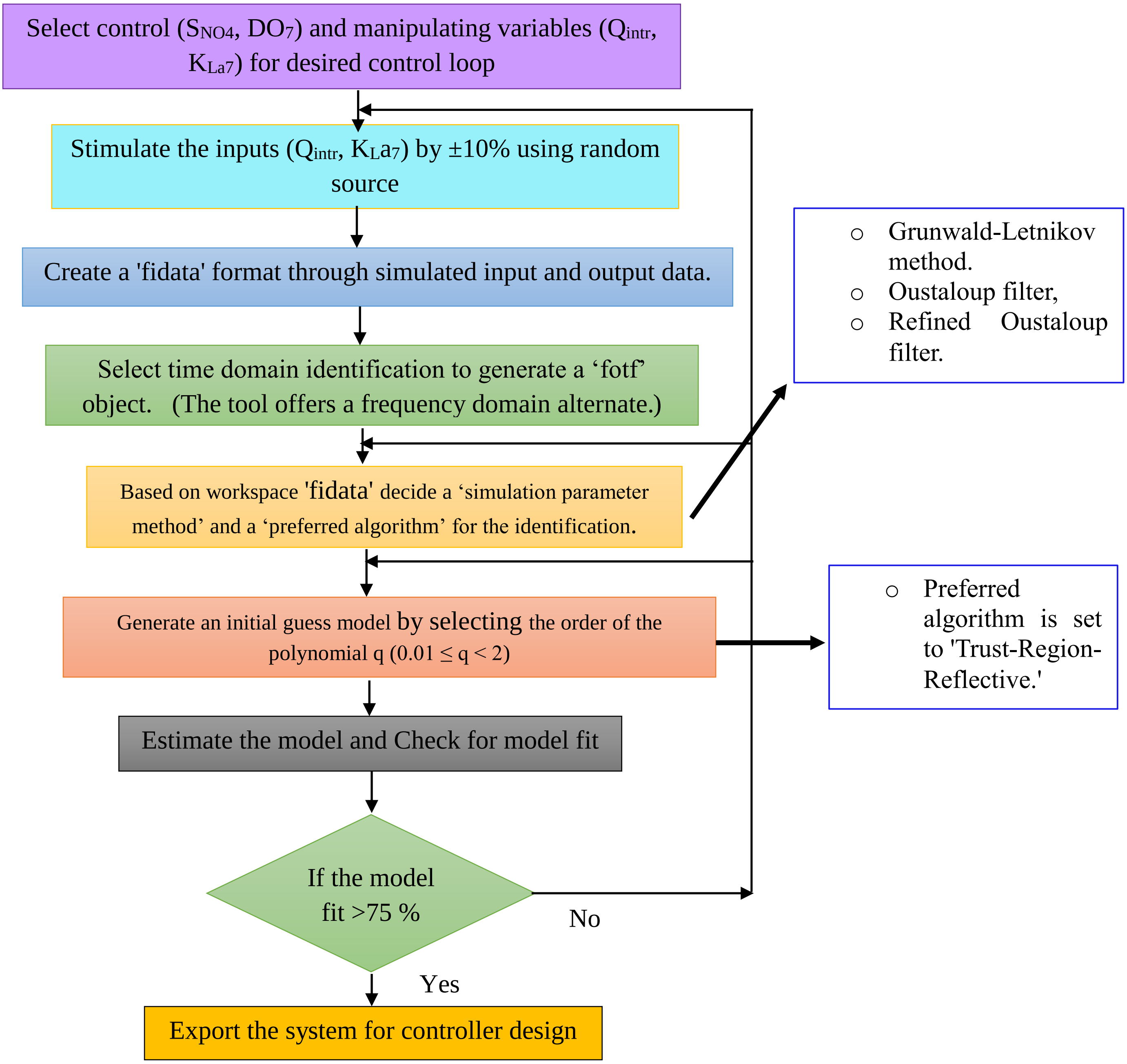


Figure 4.1: Algorithms to develop a non-integer model utilizing 'FOMCON' toolbox

Before implementing an efficient structure for any process, it is essential to determine a suitable process model. Transfer Functions (TF) explain the processes in our control system by integrating key principles of physics and bio-chemical engineering, including Newton's law, material balance, heat transfer, and fluid dynamics. Nevertheless, in practical applications, numerous industrial processes are too complex to be solely described by these fundamental concepts. The content offers an overview of the equations and modelling approach used in the process identification of the ASM3-bioP model, which helps in comprehending the intricate systems involved. In this study, we use simulation studies to identify non-integer order models with time delays in WWTP. We next develop a fractional controller by cascading GA-based IMC fractional filters onto these models. The PI controller with a fractional filter is constructed using the integer order plant model, as described in the study by Indranil et al. 2022, by applying the IMC technique.

Fractional-order calculus is a generalization of integer-order calculus which comprises arbitrary order differential and integral equations. Any derivative or integral of any order can be solved using fractional calculus theory, as can continuous versions of the fractional calculus operator, as described in (Tepljakov 2017) in Eq. (4.1).

$$
\mathrm{a}\mathcal{D}_{\mathrm{t}}^{\mathrm{p}} = \begin{cases} \frac{\mathrm{d}^{\mathrm{p}}}{\mathrm{dt}^{\mathrm{p}}} & \mathrm{Re(p)} > 0 \\ 1 & \mathrm{Re(p)} = 0 \\ \int_{\mathrm{a}}^{\mathrm{t}} (\mathrm{dt})^{-\mathrm{p}} & \mathrm{Re(p)} < 0 \end{cases} \tag{4.1}
$$

Where 'a' and ’t’ represent the calculus upper and lower limits, and is an arbitrary intricate. Many other definitions of fractional calculus have been generated by fractional order calculus theory, like the GL, RL, and Caputo theories, by Tepljakov 2017.

Based on the time-domain approach, a non-integer order time delay transfer function model is found using the MATLAB FOMCON toolbox. We can choose the kind of system simulation we want to use using the Simulation parameters window. The input and output data is generated by giving the random input to the model of ASM3-bioP model at steady sate with plant influent and relating all state variable. Steps to explain a well-fitted model identification. First and foremost, a "fidata" format has to be selected. Pick the ‘Time domain Identification’, can also choose frequency domain in the ‘Identification’ tab. Select the ‘simulation parameter methods’ in the options of Grunwald-Letnikov method or Oustaloup filter or Refined Oustaloup filter. (The next two options must allow you to choose the 'w' range and order).

4.2.1 Oustaloup filter

The Oustaloup recursive filter is commonly used in fractional calculus because it provides a fair approximation of fractional operators over a specified frequency range (Oustaloup et. al, 2000). An operator is assigned a frequency range (ω_b, ω_h) and a filter of order N, operator as s^γ $0 < \gamma < 1$, is specified by,

$$G_f(s) = K \prod_{K=-N}^{N} \frac{s + \acute{\omega}_k}{s + \omega_k} \tag{4.2}$$

Where,

$$\acute{\omega}_k = \omega_b \left(\frac{\omega_h}{\omega_b}\right)^{\frac{k+N+\frac{1}{2}(1-\gamma)}{2N+1}}$$

$$\omega_k = \omega_b \left(\frac{\omega_h}{\omega_b}\right)^{\frac{k+N+\frac{1}{2}(1+\gamma)}{2N+1}}$$

$$K = \omega_h^{\gamma} and\ N = \text{ Approximation order}$$

Figure 4.1 displays the algorithm involves in Non-integer model identification in FOMCON toolbox. Using the Oustaloup filter in the 'Identification and options' section, right 'fidata' name should be chosen and our preferred algorithm is 'Trust-Region-Reflective'. It contains a symbolic illustration of the defined model in terms of fractional pole and zero polynomials. A first-guess model is created. In order to create polynomials autonomously, a commensurate-order q that has the property that $0.01 \le q < 2$ —the order of the polynomial—can be defined. It is essential at the end of the identification process to display a plot that displays upright fitting results and shows the identified system's stable behaviour. As long as the results are satisfactory, the model is retained for use in developing a controller.

As a final step, we find a process model in the form of non-integer orders plus time delays (NOPDT), and $\boldsymbol{\beta}$ is the non-integer order.

$$\mathbf{G_P} = \frac{K}{TS^{\beta}+1} e^{-T_d S} \tag{4.3}$$

4.3 Controller Implementation

Careful consideration is essential when selecting a control structure for an effective control scheme. Controlling nitrification and denitrification rates is key in WWTPs. As discussed earlier the amount of DO that blowers add to the water in the aeration tank is a crucial indicator of the effectiveness of the biological treatment process and is directly related to the health of the microbial culture. One simple way to monitor and manage the treatment process is to monitor and control the dissolved oxygen content. Under certain conditions, high air consumption in the aeration zones is no longer necessary if the nitrate intake in the last pre-denitrification zone stays below a particular threshold. In an anoxic reactor, keeping the nitrate (NO) level within the optimal operating range of 1-3 mg N/l is critical when internal recycling takes place. Usually, 1 mg N/l is used as the desired amount.

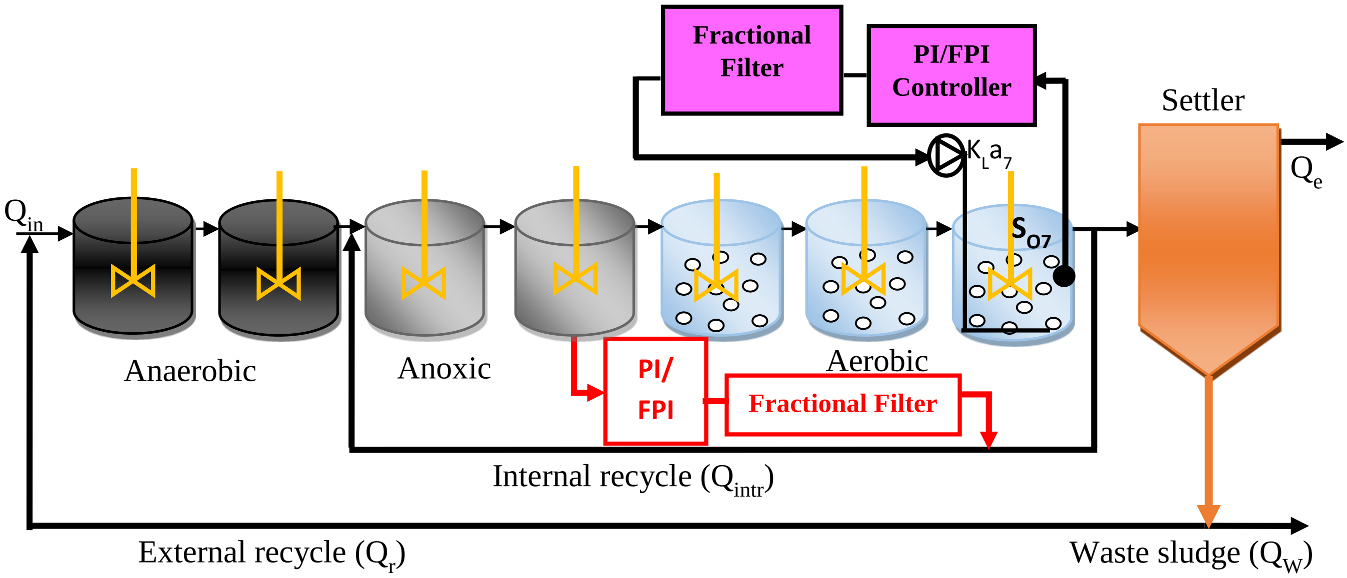


Figure 4.2: BSM-1P plant framework with IMC-based PI and FPI control approach for DO control

In this study, the fourth reactor (anoxic) controls Q_{intr} to maintain S_{NO4} at 1 mg N/l, while the seventh reactor (aerobic) modifies K_{La7} to maintain SO7 at 2 mg O^2/l. This is accomplished by cascading Fractional PI (FPI) controllers with an Internal Model Control (IMC) -based fractional filter (as illustrated in Figure 4.2). In the end, a comparison is made between the outcomes and an IMC-based fractional filter Integer Order PI that has been developed. The main focus of this study is the development of a fraction controller (FPI) for a non-integer order model system and replacing a PI controller at the lower level for both integer and fractional models.

4.3.1 IMC Fractional filter deign using Constrained GA

A popular type of feedback control system used in process control and factory automation is the IMC controller, which stands for "Internal Model Control controller." It gives you an organised way to control things that uses math models to get accurate control and make the system work well. To reach the control goals and keep the system stable, it is very important that IMC controllers are designed and tuned correctly. For IMC to work, there needs to be a mathematical model of the system or process that needs to be controlled. The IMC scheme and

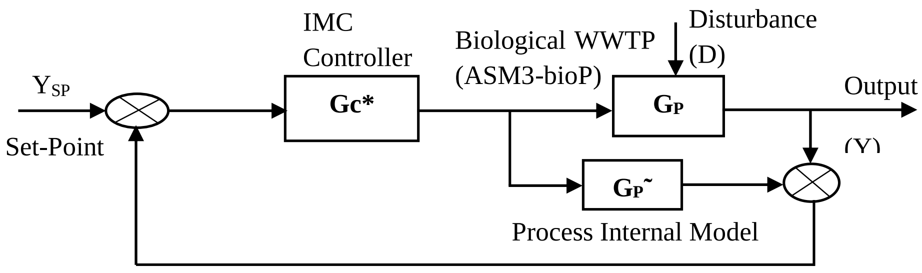


Figure 4.3: IMC-based feedback control technique

feedback loop are shown in Figure 4.3. GP, GP˛, and Gc* stand for the process, the internal model of the process, and the IMC controller, respectively. Ysp stands for the set point, Y for the managed variable as an output, and D for the disturbance.

Getting DO tracking at 2 mg O_2/l in the ASM3bioP model by changing K_{La7} is seen as a servo problem, while dealing with changing inputs is seen as a regulatory problem.

To tune an IMC controller, you have to change its parameters to get the amount of control you want. Parameters like gains, time constants, and other values tell the controller how to act. Tuning is necessary for control to work reliably and well. In this research, a Genetic Algorithm (GA) with constraints is used to find the IMC controller's filter parameter. The IMC model design is used to find the controller's wins.

The steps needed to make an IMC-PID controller are shown in Equations (4.4–4.7), which describe the controller design using the IMC method.

The final response of a classical feedback controller is described in Eq. (4.4).

$$Y = \frac{G_C G}{1 + G_C G} Y_{SP} + \frac{1}{1 + G_C G} D \qquad (4.4)$$

Step 1: Factor Process Eq. (4.5) follows the model's method.

$$G_P = G_+ G_- \tag{4.5}$$

Step 2: Derive the IMC transfer function from the IMC structures using Eq. (4.6).

$$Y = \frac{G_C^* G}{1 + G_C^*(G - G_P)} Y_{SP} + \frac{1 - G_C^* G_P}{1 + G_C^*(G - G_P)} D \tag{4.6}$$

$$G_C = \frac{G_C^*}{1 - G_C^* G_P} \quad G_C^* = \frac{1}{G_-} f$$

Here f is the filter function for the system's physical reliability $f = \frac{1}{(TS^{\propto}+1)^r}$ T = Time constant r = Positive integer.

Step 3: Obtain the model's controller from the IMC approach using Eq. (4.7).

$$G_C = \frac{G_C^*}{1 - G_C^* G_P} \tag{4.7}$$

4.3.2 Non-integer filter with integer PID controller (NOF-IOPID)

The time domain version of the generic integer order controller formula is represented by Eq. (4.8).

$$u(t) = K_P\, e(t) + K_d De(t) + K_i \int e(t) \tag{4.8}$$

Using error signal e(t) as a starting point, Kp, K_i and K_d define the proportional (P), integral (I), and derivative (D) gains. The controller's equation (4.8) is translated into equation (4.9) by performing the Laplace transform, which has zero initial conditions.

$$G_C(s) = K_P + \frac{K_i}{s} + K_d\, s \tag{4.9}$$

Eq. (4.10) represents an integer order process with a fractional filter.

$$C_{IF}(s) = \frac{1}{(\lambda s^{\alpha-1} + T_d)} \frac{T}{K} \left(1 + \frac{1}{Ts}\right) \tag{4.10}$$

Eq. (4.11) shows a fractional filter term and α is the order of filter

$$H(s) = \frac{1}{(\lambda s^{\alpha-1} + T_d)} \tag{4.11}$$

PID Controller gain values from the IMC method is $K_p = \frac{T}{K}, K_i = \frac{1}{T_i}, K_d = 0$

4.3.3 Non-integer filter cascaded with fractional order PID controller (NOF-FOPID)

Eq. (4.12) is the generic time domain variant of the fractional order controller equation.

$$u(t) = K_P\, e(t) + K_i \mathcal{D}^{-\eta} e(t) + K_d \mathcal{D}^{\Upsilon} e(t) \tag{4.12}$$

Like Integer PID, the error signal e(t) then Kp, Ki and Kd define the proportional (P), integral (I), and derivative (D) gains. Finally these η , Υ are the fractional derivate and integral co-efficient. Eq. (4.12) is changed into Eq. (4.13) through the application of the Laplace transform to the controller assuming zero initial conditions.

$$G_C(s) = K_C + \frac{K_i}{s^{\eta}} + K_d\, s^{\Upsilon} \tag{4.13}$$

Eq. (4.14) displays the fractional order system with a fractional filter CFF(s) from the IMC process.

$$C_{FF}(s) = \frac{1}{(\lambda s^{\alpha-\beta} + T_d s^{1-\beta})} \frac{T}{K}\left(1 + \frac{1}{T s^{\beta}}\right) \tag{4.14}$$

Eq. (4.15) represents the fractional filter term V(s) and α is the order.

$$V(s) = \frac{1}{(\lambda s^{\alpha-\beta} + T_d s^{1-\beta})} \tag{4.15}$$

Fractional PID Controller parameters from the IMC technique is $K_C = \frac{T}{K}, K_i = \frac{1}{T_i}, K_d = 0, \eta = \beta$

4.4 Tuning deploying MS-based GA Constrained optimization

The genetic algorithm (GA) is a way to solve optimisation problems with and without constraints. It works by using the ideas of natural selection and is similar to how living things evolve. The algorithm updates a group of individual answers over and over again. At each stage, the GA picks people at random from the present population and uses them as parents to make children for the next generation.

A fitness function is used in genetic algorithms to figure out how close a design answer is to reaching the goal value. A chromosome, which is also called a genotype, is a group of factors that together make an idea for how to solve the problem. The population includes all possible options. A genetic operator called crossover is used to change the code of one or more chromosomes from one generation to the next. To keep genetic diversity in a community, genetic algorithms are based on the way that living things cross-breed and reproduce. Mutation changes the numbers of one or more genes on a chromosome from how they were at the start.

In a genetic algorithm, the selection process includes picking out individual genomes from a population to breed with other genomes. The flowchart of the method is shown in Figure 4.1. The evaluation index used in this study was picked to minimise error. It is shown as the Integral of Absolute Magnitude of Error (IAE).

The maximum sensitivity for the gain margin and phase margin was chosen as a constraint when designing the IMC fractional P-I-D controller of the first order plus time delay structure. A constrained genetic algorithm operates to fine-tune the filter parameters (λ, α) utilising criteria such as Gain Margin (GM), Phase Margin (PM), Gain crossover frequency (Wgc), Phase crossover frequency (Wpc), and Maximum Sensitivity (M_S). Eqs. (4.16–4.17) describe the closed-loop model.

$$L(s) = G_P(s)c(s) \tag{4.16}$$

$$L(s) = \frac{1 - T_d s}{(\lambda s^{\alpha} + T_d s)} \tag{4.17}$$

While s=jw was entered into Eq. (4.17), it was transferred to Eq. (4.18).

$$L(jw) = \frac{1 - T_d jw}{(\lambda (jw)^{\alpha} + T_d jw)} \tag{4.18}$$

Based on the complex numbers, $j = \cos\left(\frac{\pi}{2}\right) + j\sin\left(\frac{\pi}{2}\right)$. The power and roots of complex numbers can be easily calculated using De Moivre's Theorem.

Eq. (4.19-4.20) represents j from De Moivre's Theorem.

$$(j)^k = \left(\cos\left(\frac{\pi}{2}\right) + j\sin\left(\frac{\pi}{2}\right)\right)^k = \cos\left(k\frac{\pi}{2}\right) + j\sin\left(k\frac{\pi}{2}\right) \text{ where } k = 1,2 \ldots .n \tag{4.19}$$

$$(j)^{\propto} = \cos\left(\propto\frac{\pi}{2}\right) + j\sin\left(\propto\frac{\pi}{2}\right) \tag{4.20}$$

In case Eq. (4.20) is substituted for Eq. (4.18), the process model is as follows. Eq. (4.21)

$$L(jw) = \frac{1 - T_d jw}{\left[\lambda(w)^\alpha \cos\left(\propto \frac{\pi}{2}\right) + j\left(T_d w + \lambda(w)^\alpha \sin\left(\propto \frac{\pi}{2}\right)\right)\right]} \tag{4.21}$$

To run the GA algorithm in a predetermined form for the closed loop model L(S), gains margin (GM), phases margin (PM), and crossover frequencies (W_{GC}, W_{PC}) are calculated.

4.4.1 Maximum Sensitivity (M_S):

We find the greatest value of the sensitivity function over a wide frequency range. Shown in in Eq. 4.22,

$$M_S|_{max(0<\omega<\infty)} = \frac{C(s)G(s)}{1+C(s)G(s)} \tag{4.22}$$

Eqs. (4.23-4.24) show the relationship involving the process models' maximum sensitivity (Ms), gain margin (GM), and phase margin (PM).

$$GM \geq \frac{M_S}{M_S - 1} \tag{4.23}$$

$$PM \geq 2\sin^{-1}\left(\frac{1}{2M_S}\right) \tag{4.24}$$

4.4.2 Performance Indices

The integral of squared error (ISE) and integral of absolute error (IAE) are frequently utilised to evaluate the performance of the controller. These are outlined by the subsequent equations (4.25-4.26).

$$ISE = \int_0^\infty e^2(t)dt \tag{4.25}$$

$$IAE = \int_0^\infty |e(t)|dt \tag{4.26}$$

4.5 Higher order filter with IMC Fractional controller deign- an analytical method

A fractional-order model generated through "Fractional order model identification" can be fine-tuned using an IMC filter. Previously described GA based IMC PID or FPID controller generates a lower order Non-integer filter. The current study also focus for a higher order non-integer filter implementation in the current application of Wastewater treatment in terms of ASM3-bioP framework. This study addresses the downsides of GA-based design and illustrates how a higher-order filter changes the current non-integer order transfer function at the same time. The Fractional Proportional-Integral-Derivative (FPID) controller's values stay the same as they were in the Internal Model Control (IMC) method. In this case, however, Li et al. (2015) explain a mathematical method that is used to find the higher-order non-integer filter. The main goal is to look into how higher-order filter factors affect the tuning of the IMC controller. A comparison study is also done between two IMC FPID controls in the complex processes of biological wastewater treatment plants (WWTPs). This method helps us understand the differences in how well the two systems work in this complicated WWTP setting. The design technique offered a simple method for setting PID parameters that consider the control system's resilience and maximise sensitivity. This method yields a fractional IMC-PID controller with a fractional-order PID structure with a Non-integer filter.

The controller design for the plant with a non-integer structure, as shown in Eq. (4.3), can be separated according to non-integer order, making it more realisable.

$$\mathrm{Gp(DO)} = \frac{0.007985}{0.00057858 * \mathrm{S}^{1.1} + 1}\mathrm{e}^{-0.0059*\mathrm{S}} \tag{4.27}$$

$$\mathrm{Gp(NO)} = \frac{0.0000291254}{0.00403027 * \mathrm{S}^{1.05} + 1}\mathrm{e}^{-0.0051*\mathrm{S}} \tag{4.28}$$

When 0 <β< 1, Eq. (4.29) gives the controller.

$$\mathrm{C(s)} = \frac{1 + 0.5\mathrm{T_d S}}{\mathrm{S}^{1-\beta}(0.5\lambda \mathrm{S} + \lambda + \mathrm{T_d})}\frac{\mathrm{T}}{\mathrm{K}}\left(1 + \frac{1}{\mathrm{TS}^{\beta}}\right) \tag{4.29}$$

And when 1 ≤β< 2, controller is given by Eq. 4.30

$$\mathrm{C(s)} = \frac{1 + 0.5\mathrm{T_d S}}{\mathrm{S}^{1-\beta}(0.5\lambda^2 \mathrm{T_d S}^2 + (\lambda \mathrm{T_d} + \lambda^2)\mathrm{S} + 2\lambda + \mathrm{T_d})}\frac{\mathrm{T}}{\mathrm{K}}\left(1 + \frac{1}{\mathrm{TS}^{\beta}}\right) \tag{4.30}$$

Where

$$\lambda \approx \mathrm{L}(-0.0667M_s^5 + 0.5314M_s^4 - 1.6861M_s^3 + 2.667M_s^2 - 2.1076M_s + 0.6679) \times 10^3 \quad (4.31)$$

Both Equations (4.29-4.30) reveal that the PI^{β} parameters are previously known. The only parameter that needs to be tuned is λ. As a result, higher control performance can be predicted if λ is correctly calibrated. In this work, the maximum sensitivity Ms for both loops is set to 1.2, likewise previously set, resulting in λ = 0.0130 for the dissolved oxygen loop and λ =

0.0112 for the nitrate loop. Furthermore, the above Eqs. (4.27-4.28) show that for both loops is $1 \leq \beta < 2$ therefore by Eq. (4.30), controllers for both loops are given in Eqs. (4.32-4.33):

$$C_{DO}(s) = \frac{1 + 0.5 \times 0.0059 \times S}{S^{(1-1.1)}\{0.5 \times 0.0130^2 \times 0.0059 \times S^2 + (0.0130 \times 0.0059 + 0.0130^2)S + (2 \times 0.0130) + 0.0059\}} \left[0.07245\left(1 + \frac{1}{0.00057858}\frac{1}{s^{1.1}}\right)\right] \quad (4.32)$$

$$C_{NO}(s) = \frac{1 + 0.5 \times 0.0051 \times S}{S^{(1-1.05)}\{0.5 \times 0.0112^2 \times 0.0051 \times S^2 + (0.0112 \times 0.0051 + 0.0112^2)S + (2 \times 0.0112) + 0.0051\}} \left[138.376\left(1 + \frac{1}{0.00403027}\frac{1}{s^{1.05}}\right)\right] \quad (4.33)$$

4.6 Hierarchical control scheme: Model Predictive Control

Lower level control controllers maintained dissolved oxygen set-point. The higher level controller adjusts DO controller set-points dependent on tank ammonia level. Different ASM3-bioP mechanisms handle S_{NH} biologically. More S_O is needed for nitrification when S_{NH} rises. As S_{NH} declines, S_O is needed less, reducing S_{NO}. Following sections propose supervisory combinations for lower and higher-level controllers. Figure 4.4 shows the two-level controller design used in this work. The higher level controller must provide appropriate set points to the lower level. Lower level DO set-point is based on tank 7 (S_{NH7}) ammonia content, which is a configurable variable at the upper level. The bottom level must follow its set-point trajectory.

MPC is a sophisticated control approach that is used in the majority of process industries. It improves performance by combining an approximation prediction model with a control method that delivers the ideal trajectory of the manipulated variable. The prediction model in this case is a linear dynamic model of the process that is used to anticipate its expected future response and then select the optimal control action available while satisfying a set of constraints. A mathematical model of the plant is used to create model predictive control systems. A state-space model is assumed to be employed in the control system design. Basically, MPC is composed of three main components: a plant model, a cost function, and an optimizer. A model simulates the behaviour of the actual process and forecasts output in the future over a predefined period (prediction horizon). Future errors are estimated based on that, and the optimizer attempts to minimise them over time (control horizon). The prediction and control horizons that are chosen can have a significant impact on the controller's functionality.

Steps to set a supervisory MPC controller

MPC utilises a process model to predict the future behaviour of a certain variable, combined with an optimisation method to address the control problem. The MPC algorithm predicts the trajectory of output variables for each control instance over a prediction horizon (p). Afterwards, it calculates a series of control actions for a control horizon (m) using the predicted output. The optimisation algorithm aims to minimise a quadratic objective function, as specified in equation (4.34).

$$J = \sum_{l=1}^{p} ||\Gamma_y(y(k+l|k) - r(k+l))||^2 + \sum_{l=1}^{m} ||\Gamma_{\Delta u}\big(\Delta u(k+l-1)\big)||^2 \qquad (4.34)$$

Where, y(k+l|k) is the controlled output at future sampling instant k+l, predicted by model at current instant k. And ΓΔu and Γy represent input rate weight and output weight respectively.

Model Predictive Control (MPC) provides set-points to lower-level fractional-order Proportional-Integral (PI) controllers at a more advanced level. The technique of determining the linear model for prediction in MPC closely resembles the identification procedure at the lower level. The Parameter Estimation Method (PEM) is used to construct the higher-level linear state-space model. The linear model is employed for prediction in Model Predictive Control (MPC) and is obtained by perturbing the set-point of the Disturbance Observer (DO) for the lower level within a range of its nominal value (±10%) and observing the resulting effect on S_{NH7}. The measured disturbance is considered to be the inlet flow rate. To add lower-level control, the PEM approach is applied using a third-order state-space model of the system, as described in equation (4.35).

$$x(k+1) = Ax(k) + Bu(k)$$

$$y(k) = Cx(k) + Du(k) \qquad (4.35)$$

Where x(k) represents the state vector and A, B, C, D represent the state space matrices.

The operating point of DO is found to be 2.2 mg O2/lfor an ammonia set-point of 3.01 mg/l. The impact on S_{NH7} is noted and the system's model obtained as per equation (4.35) is given in equation (4.36).

$$A = \begin{bmatrix} -1.5794 & -5.9788 & 0.0970 \\ 16.7419 & -22.5856 & -12.4775 \\ -1.8143 & 19.4594 & -2.5352 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.4457 \\ 4.1247 \\ -4.7635 \end{bmatrix} \tag{4.36}$$

$$C = [1.8750 \quad -0.3941 \quad -0.1303]$$

$$D = [0]$$

The tuning parameters selected to design the higher level MPC are as follows:

- Control horizon=10,
- Prediction horizon=15
- Sampling time=0.0100 days for FPI-IMC MPC

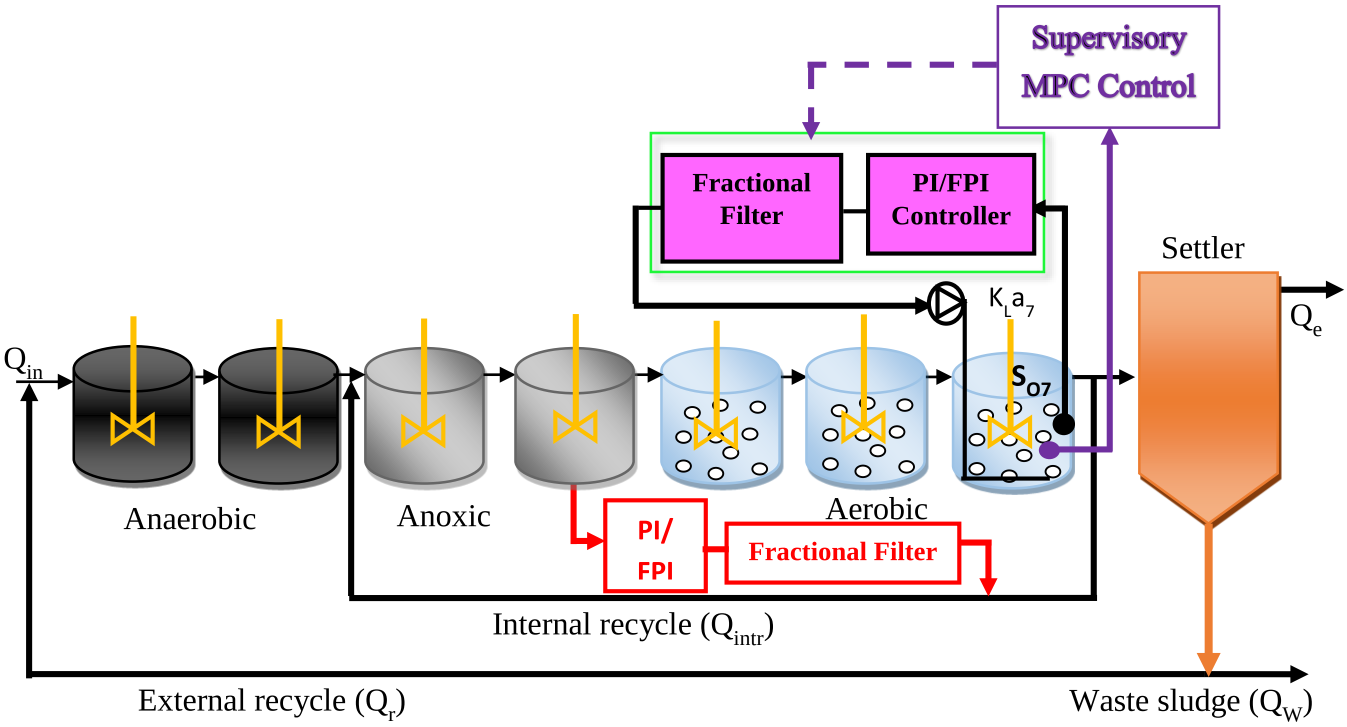


Figure 4.4: BSM-1P plant framework with IMC-based PI and FPI control approach for DO control with a supervisory MPC control

4.7 Result and Discussion

This section presents the key outcomes of the work, which include finding non-integer order models and looking at how well-tuned controllers work. In the concluding phase, the developed methodology is put to the test on the complex ASM3bioP platform model in order to assess the wastewater treatment plant's overall performance.

Non integer model

This paper's 1st focus is identifying the Non-integer model of ASM3-bioP framework and implementing a systematic IMC based controller for enhanced effluent control as well as operation cost minimization. The plant operation is done for 0-14 days. During the identification, the simulation model is made on that full range of biological processes and sampling is done by 1/96. So a total of 1345 data points are considered for process model identification. We select the Oustaloup filter as 'simulation parameter methods' and the preferred algorithm is 'Trust-Region-Reflective' for identification. Figure 4.5(a, b) presents the validation of identified non-interger order model for both DO and NO loops.

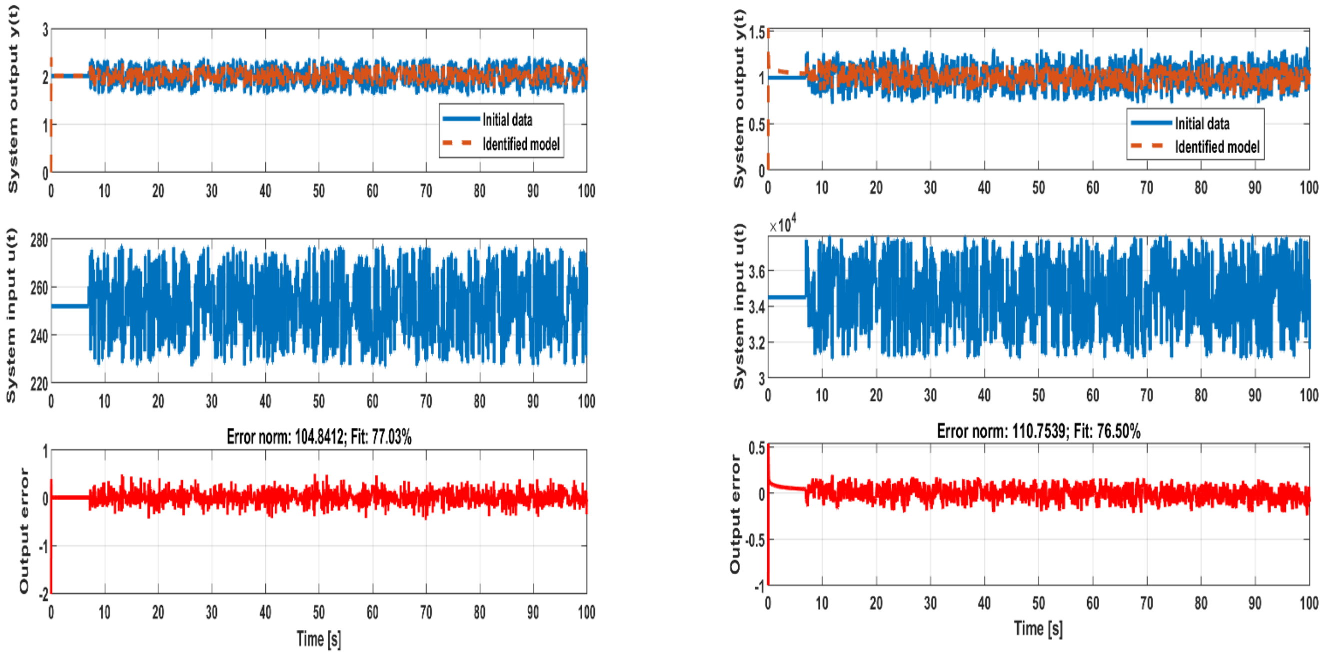


Figure a

Figure b

Figure 4.5: Validation of identified Non-integer order model with time delay; Figure a for DO loop and Figure b for NO loop

The Final process models are found in form of non-integer order with Time delay (**NOPDT**) for both DO and NO control loop, like equation 4.3. Stability analysis of the identified process model is also examined.

$$\mathrm{Gp(DO)} = \frac{0.007985}{0.00057858 * S^{1.1} + 1} e^{-0.0059*S} \tag{4.27}$$

$$\mathrm{Gp(NO)} = \frac{0.0000291254}{0.00403027 * S^{1.05} + 1} e^{-0.0051*S} \tag{4.28}$$

4.7.1 IMC based controller design using GA

The integer (Indranil et. al, 2022) and non-integer order transfer function models for DO and NO control that have been identified are presented earlier. The cascaded filter controller structure, where the filter parameters (λ, α) are tuned using GA by minimising the ISE of the closed-loop response by selecting maximum sensitivity (M_S) =1.2. The IMC structure controllers are designed in two forms: integer order and non-integer model as $C_{IF}(S)$ for NOF-IOPID and $C_{FF}(S)$ for NOF-FOPID. Table 4.1 displays the evaluated control structure for both dissolved oxygen (DO) and Nitrate (NO) loop and Table 4.2 shows the evaluated controller performance during two simulations.

Table 4.1: NOF-IOPID and NOF-FOPID control structure for dissolved oxygen (DO) and Nitrate (NO) loop control

Control loop	Transfer function	Identified model	Fractional Filter Parameters	IMC based Controller (according to Equation 10 and 14)
Dissolved Oxygen (DO) control	Integer Order $\frac{K}{TS+1}e^{-T_d S}$	$\frac{0.013824}{0.0015778*S+1}\mathrm{e}^{-0.006021*S}$	$\lambda =$ 0.1557 $\alpha =$ 0.9688	$C_{IF}(s) = \frac{1}{(0.1557\ s^{0.9688-1}+0.006021)}$ $\left[0.11413\left(1+\frac{1}{0.0015778}\frac{1}{s}\right)\right]$
	Non-Integer Order $\frac{K}{TS^{\beta}+1}e^{-T_d S}$	$\frac{0.007985}{0.00057858*S^{1.1}+1}\mathrm{e}^{-0.0059*S}$	$\lambda =$ 0.0718 $\alpha =$ 0.9998 $\beta = 1.1$	$C_{FF}(s) = \frac{1}{(0.0718\ s^{0.9998-1.1}+0.0059s^{1-1.1})}$ $\left[0.07245\left(1+\frac{1}{0.00057858}\frac{1}{s^{1.1}}\right)\right]$
Nitrate (NO) control	Integer Order $\frac{K}{TS+1}e^{-T_d S}$	$\frac{0.000071395}{0.013636*S+1}\mathrm{e}^{-0.00025001*S}$	$\lambda =$ 0.1857 $\alpha =$ 1.001	$C_{IF}(s) = \frac{1}{(0.1857\ s^{1.001-1}+0.00025001)}$ $\left[190.9937\left(1+\frac{1}{0.013636}\frac{1}{s}\right)\right]$
	Non-Integer Order $\frac{K}{TS^{\beta}+1}e^{-T_d S}$	$\frac{0.0000291254}{0.00403027*S^{1.05}+1}\mathrm{e}^{-0.0051*S}$	$\lambda =$ 0.1001 $\alpha =$ 1.0091 $\beta = 1.05$	$C_{FF}(s) = \frac{1}{(0.1001\ s^{1.0091-1.05}+0.0051s^{1-1.05})}$ $\left[138.376\left(1+\frac{1}{0.00403027}\frac{1}{s^{1.05}}\right)\right]$

Table 4.2: controller performance

Controller	**Dissolved oxygen (DO) loop**		**Nitrate (NO) loop**	
	IAE	ISE	IAE	ISE
NOF-IOPI	0.4852	0.4224	0.3719	0.1865
NOF-FOPI	0.3326	0.2759	0.2501	0.1288

The Implemented controller is tuned by IMC approach and non-integer filter parameters are optimized by constrained GA. The controller's performance is impressive for both servo and regulatory problem. Both IAE and ISE is minimized into quite good number. Based on the performance parameters and response of the controller in Figure 4.6 (a,b), can conclude FF-FOPI outperforms FF-IOPI.

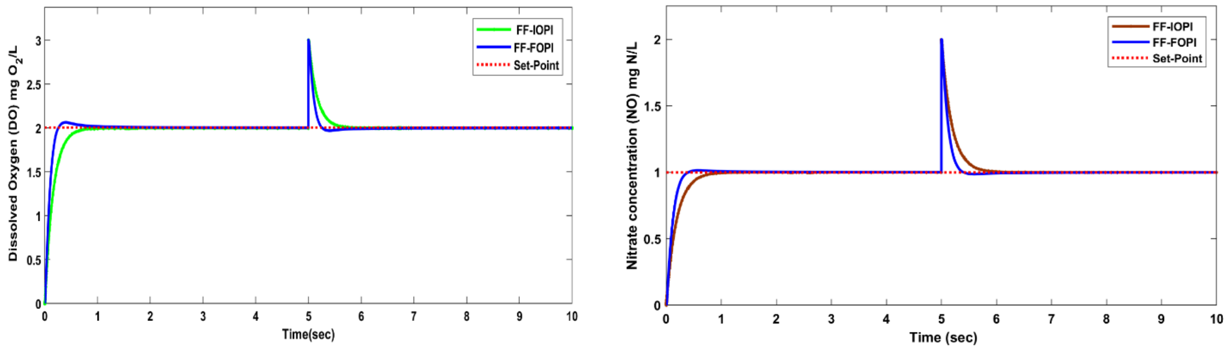


Figure a

Figure b

Figure 4.6: Set point tracking in closed loop control action with disturbance; Figure a DO tracking at 2 mg O_2/L; Figure b NO tracking at 1 mg N/L

4.7.1.1 Uncertainty analysis with perturbations in Model

One mathematical model is not enough to show how a real system works. System uncertainties can be caused by disturbance signals or changes in system variables. In this situation, a reliable control system should always work the same way. To make a strong device, maximum sensitivity (Ms) =1.2 was used. Figure 4.7 (a,b) shows controller response with perturbed model for DO loop transfer function and what happens to the controller action when the FOPTD and fractional order with delay model settings are changed. There are 20% changes in the delay parameter, 20% changes in the gain parameter, and 20% changes in the time constant parameter. Based on these results, the findings demonstrate that a well-designed optimised robust controller protects the system against unpredictable variables. We thoroughly analysed the uncertainty related to the determined model when it was subjected to closed-loop control action. We carefully evaluated the possible changes and unpredictability in the system's response. We conducted an in-depth study of closed-loop control, exploring the complexities involved and taking into account potential sources of uncertainty, such as disturbances, variations in parameters, and external effects. After an extensive evaluation, we can certainly affirm that our method successfully dealt with and reduced the uncertainties present in the identified model through closed-loop control action.

Table 4.3: Uncertainty of plant in case of DO integer order

Identified Model (DO Integer)	Perturbed Model	Perturbation	Controller Performance	
			ISE	IAE
$\frac{\mathbf{0.013824}}{\mathbf{0.0015778 * S + 1}}\mathbf{e}^{-\mathbf{0.006021*S}}$	$\frac{0.0110592}{0.00126224 * S + 1}e^{-0.0048168*S}$	-20%	0.5173	0.6064
	$\frac{0.0165888}{0.00189336 * S + 1}e^{-0.00752252*S}$	+20%	0.3582	0.4046

Table 4.3 and 4.4 summarises the performance metrics of the controller with uncertainties in the FOPTD and fractional order with delay models. For all perturbations in the models, the FF-FOPID of the Fractional order with delay model has lower values than the FF-IOPID of the FOPTD model.

Table 4.4: Uncertainty of plant in case of DO non-integer order

Identified Model (DO Non integer)	Perturbed Model	Perturbation	Controller Performance	
			ISE	IAE
$\frac{\mathbf{0.007985}}{\mathbf{0.00057858} * S^{1.1} + \mathbf{1}}\mathbf{e}^{-\mathbf{0.0059*S}}$	$\frac{0.006388}{0.000462864 * S^{1.1} + 1}e^{-0.00472*S}$	-20%	0.3282	0.4011
	$\frac{0.009582}{0.000694296 * S^{1.1} + 1}e^{-0.00708*S}$	+20%	0.2424	0.2879

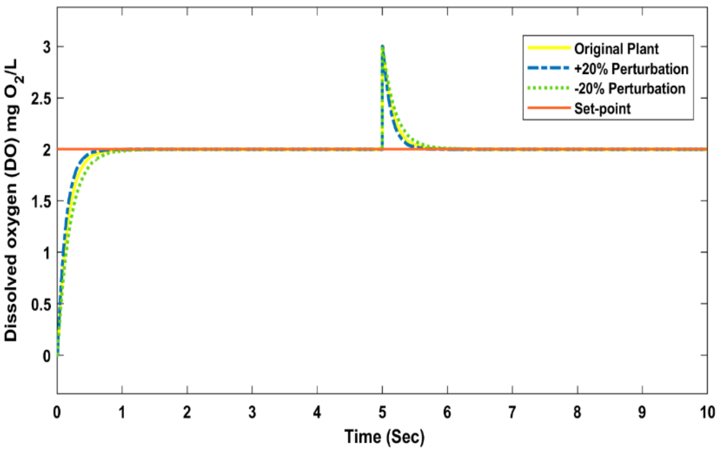


Figure a

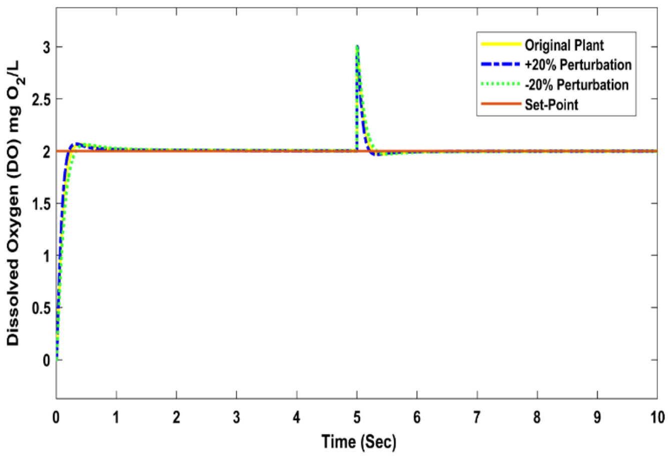


Figure b

Figure 4.7: controller response with perturbed model for DO loop transfer function; Figure a Integer Plant perturbation; Figure b Non-integer perturbation.

4.7.1.2 Fragility analysis of controller for DO fractional TF

This index checks how resilient the control loop is compared to how robust it is when the controller settings change. Find out how much the control loop's strength is lost when one or more of the nominal controller parameter values given by the equation change by up to 20%. Figures 4.8 and 4.9 depict controller and filter factor variations for the respective DO and NO loop fractional order with delay models when subjected to a 20% perturbation. Despite this notable perturbation, the system demonstrates outstanding tracking abilities in servo and regulatory responses. The controller can handle changes in parameters of up to 20%, so it is not fragile and is strong.

Table 4.5: Fragility analysis of controller for DO fractional TF

Perturbed Controller	**Perturbation**	**Controller Performance**	
		IAE	**ISE**
$\mathbf{C_{FF}(s)} = \dfrac{\mathbf{1}}{(\mathbf{0.05244\ s^{0.79984-0.88} + 0.0059s^{1-0.88}})}\left[\mathbf{0.0579664}\left(\mathbf{1} + \dfrac{\mathbf{1}}{\mathbf{0.00057858}}\dfrac{\mathbf{1}}{\boldsymbol{s}^{\mathbf{0.88}}}\right)\right]$	-20%	0.2859	0.2347
$\mathbf{C_{FF}(s)} = \dfrac{\mathbf{1}}{(\mathbf{0.08616\ s^{1.1976-1.32} + 0.0059s^{1-1.32}})}\left[\mathbf{0.0869496}\left(\mathbf{1} + \dfrac{\mathbf{1}}{\mathbf{0.00057858}}\dfrac{\mathbf{1}}{\boldsymbol{s}^{\mathbf{1.32}}}\right)\right]$	+20%	1.082	0.8529

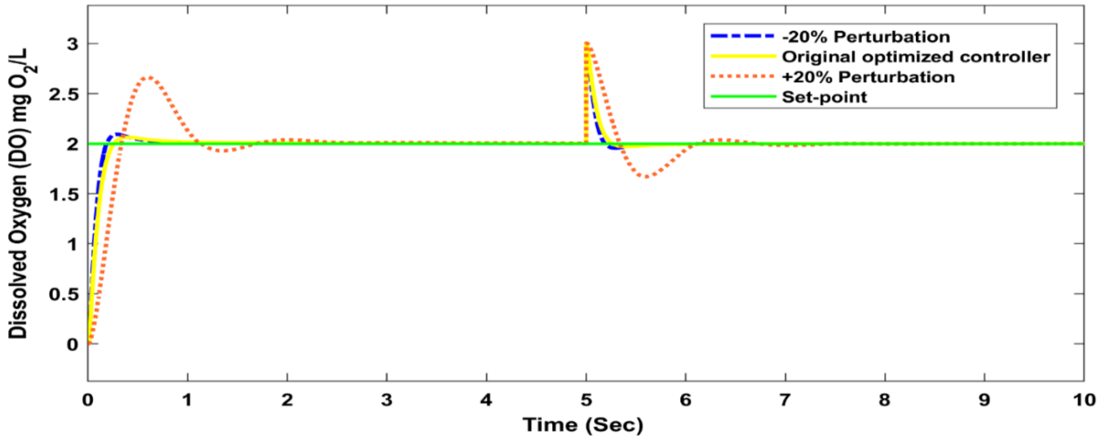


Figure 4.8: A fragile controller is successfully tested on DO loop Non-integer model

4.7.1.3 Fragility analysis of controller for NO fractional TF

Conducting fragility analysis involves assessing the susceptibility of the controller to outside influences, specifically with a 20% perturbation for a NO loop non-integer order plant. This assessment enables us to comprehend the system's sensitivity to variations and emphasises the resilience of the controller in sustaining stability and performance in such circumstances. Figure 4.9 illustrates the non-fragile closed loop control action for NO loop.

Table 4.6: Fragility analysis of controller for NO fractional TF

Perturbed Controller	Perturbation	Controller Performance	
		IAE	ISE
$\mathbf{C_{FF}(s)} = \dfrac{\mathbf{1}}{(\mathbf{0.08008\ s^{0.80728-0.84} + 0.0051 s^{1-0.84}})} \left[\mathbf{111.008}\left(\mathbf{1} + \dfrac{\mathbf{1}}{\mathbf{0.00403027}} \dfrac{\mathbf{1}}{\boldsymbol{s}^{\mathbf{0.84}}}\right)\right]$	-20%	0.2096	0.1097
$\mathbf{C_{FF}(s)} = \dfrac{\mathbf{1}}{(\mathbf{0.12012\ s^{1.21092-1.26} + 0.0051 s^{1-1.26}})} \left[\mathbf{166.512}\left(\mathbf{1} + \dfrac{\mathbf{1}}{\mathbf{0.00403027}} \dfrac{\mathbf{1}}{\boldsymbol{s}^{\mathbf{1.26}}}\right)\right]$	+20%	0.5016	0.2257

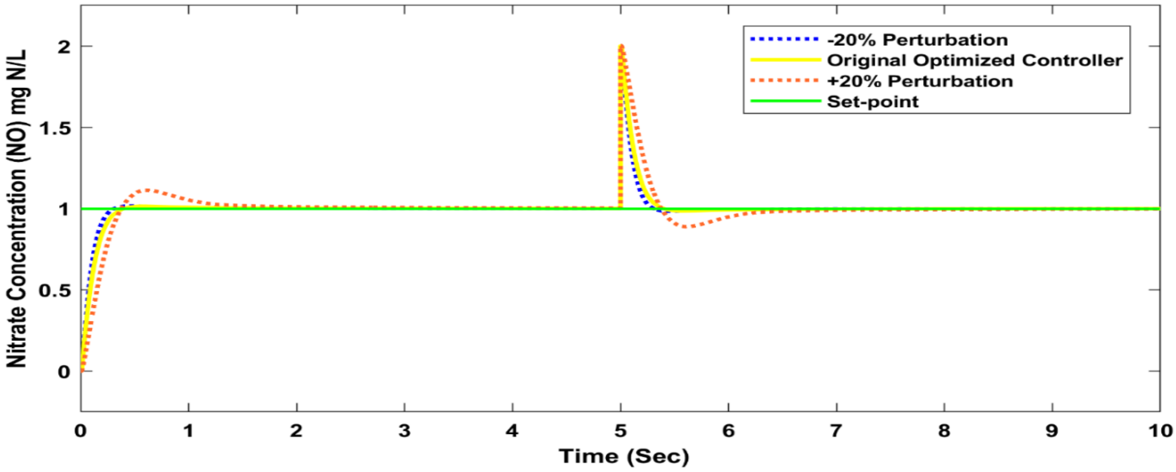
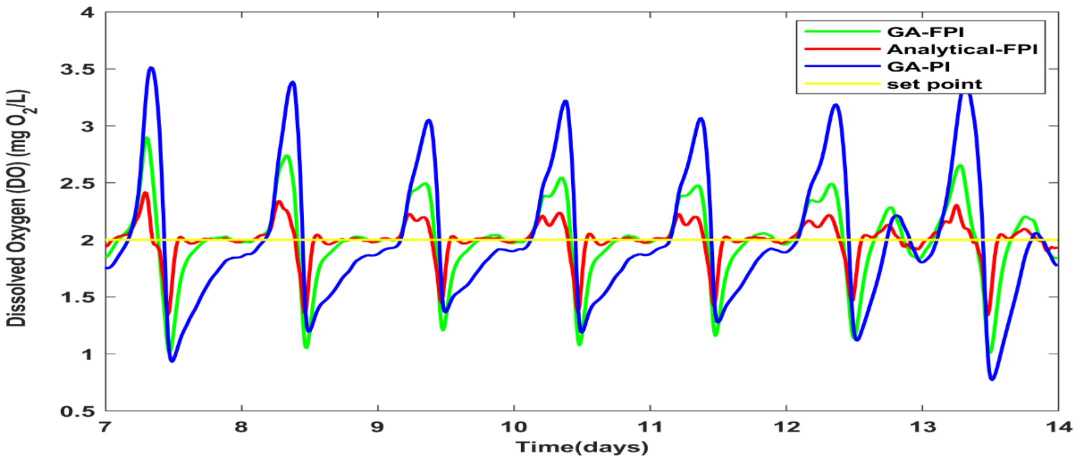


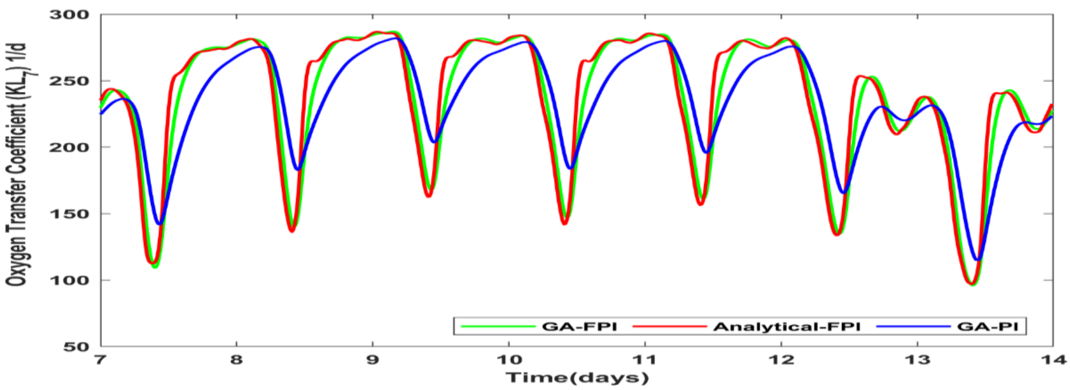
Figure 4.9: A fragile controller is successfully tested on NO loop Non-integer model

4.7.2 DO tracking in ASM3-bioP Platform with dynamic influent

Set-point tracking is a way to determine how well a controller is performing. The set-point values for S_{NO} and DO_7 are as follows:



a



b

Figure 4.10: (a)DO tracking in the seventh tank with dynamic influent; (b) manipulated variable plot in terms of oxygen transfer coefficient

1 mg N/l is selected for the fourth tank, and 2 mg O_2/l is chosen for the seventh tank. The tracking of dissolved oxygen (DO) for three different control schemes is shown in Figure 4.10 (a,b), along with their manipulated variable plots that are given in terms of the oxygen transfer coefficient (K_{La7}). The graph makes it clear that the FPI controller with a non-integer-order plant (GA-FPI) works better than the PI controller with a integer plant (GA-PI) when the same Internal Model Control (IMC) method is used. Furthermore, it is clear that the FPI controller with a higher-order filter setting (Analytical-FPI) works better than the one with a lower-order filter (GA-FPI).

4.7.3 NO tracking in ASM3-bioP Platform with dynamic influent

The set-point tracking of nitrate (S_{NO}) by GA-PI, GA-FPI, and analytical-FPI have shown in Figures 4.11 a. The effective tracking ability of the analytical-FPI controller is comparatively superior for NO controller, and at the same time, the analytical-FPI controller results in superior

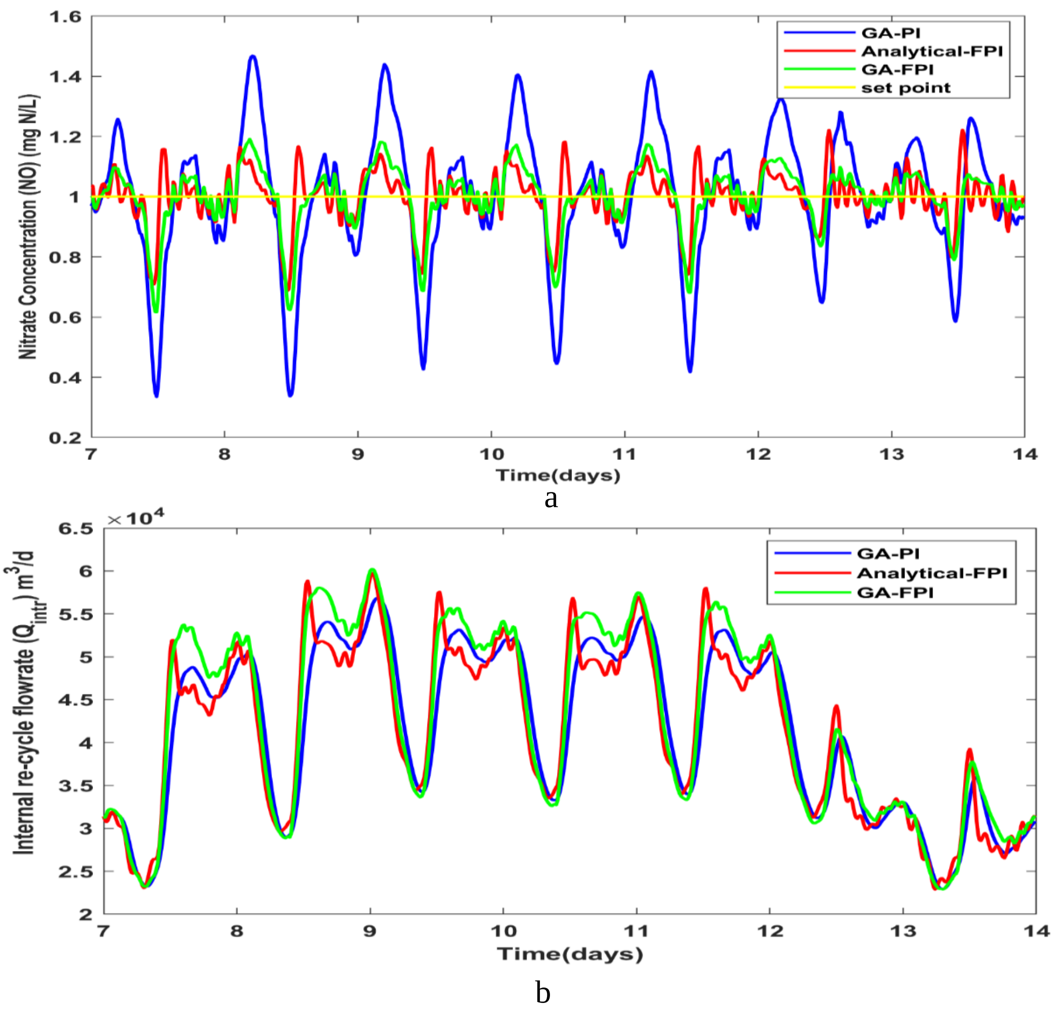


Figure 4.11: NO tracking in the fourth tank with dynamic influent; Figure Manipulated variable plot in terms of Internal recycle

performance when compared to GA-PI, GA-FPI. Figure 4.11b indicates the manipulated variable plots by lower-level PI, FPI and FM-FPI controller for NO loops in-terms of internal recycle flow rate (Q_{intr}).

4.7.4 Plant performance analysis

Comparative analysis of all three controllers is revealed as the evolution of the plant's performance is traced via the matric and effluent parameters in Table 4.7.

Table 4.7: over all plant performance analysis on lower level strategies.

Average effluent concentration		**Open loop**	**GA-IMC fractional filter +PI**	**GA-IMC fractional filter +FPI**	**Analytical-IMC higher order fractional filter + FPI**
Components	Limit				
NH	4	6.08415	6.47	6.285	6.10
TSS	30	13.68	13.68	13.6762	13.6709
TN	18	16.5	16.17	16.1479	16.03
TP	2	3.58	3.49	3.526	3.54
COD	100	44.75	44.73	44.7404	44.73
BOD_5	10	1.79	1.78	1.7869	1.785
IQI		72152.2	72152.2	72152.2	72152.2
EQI		***13,411***	***13314.72***	***13306.03***	***13255.02***
SP		2973.45	2975.73	2973.145	2970.44
AE		4336.6	4231.50	4246.96	4253.48
PE		304.81	337.25	332.112	331.98
ME		480	480	480	480
OCI		***18,753***	***18692.009***	***18689.74***	***18683.11***

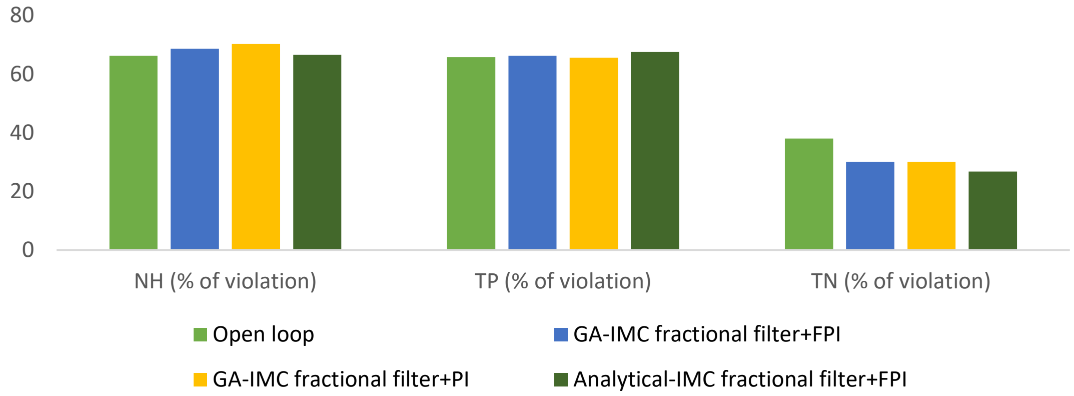


Figure 4.12: Column chart on percentage of violation in effluent

Notably, a significant improvement is shown when the higher-order fractional filter is used with the IMC FPI control technique. The highest level of efficiency is achieved, as evidenced by the lowest Effluent Quality Index (EQI) and Operational Cost Index (OCI) during the execution of the higher-order fractional filter with the IMC FPI control scheme. Upon comparing the open-loop EQI and OCI with the GA-based PI control approach, there is a noticeable improvement of 0.72% and 0.34%, respectively. When compared to the GA –FPI approach, these two metrics improve marginally by 0.06% and 0.01%, respectively. Finally, when GA-PI is compared to the higher-order filter-based FPI controller, there is a more substantial improvement, with gains of 0.44% and 0.05% in EQI and OCI, respectively. All the effluent parameters are well under the legal restrictions and lowest value of NH and TN is observed in higher-order filter-based FPI controller, however a slight increase is noted in TP. Figure 4.12 all displays the column chart on percentage of violation in effluent in terms of NH, TP and TN.

Table 4.8: plant performance comparison in best lower level controller and MPC at higher level

Performance of Plant	IMC fractional filter + FPI	IMC FF-FPI+MPC
EQI	13255.02	13203.8419
OCI	18683.11	18884.949

Furthermore, a cascaded technique implementing the MPC controller is used to dynamically adjust the dissolved oxygen set-point based on ammonia concentration changes in tank 7. This unique method resulted in a significant improvement in plant performance. Figure 4.13 depicts the dynamic interplay, highlighting the changeable dissolved oxygen (DO) set-point delivered by the supervisory MPC controller and adeptly tracked by the lower-level IMC-FPI controller.

Now implementing a supervisory MPC controller cascaded with best lower level strategy (higher order filter +FPI) shows a significant improvement in EQI but operational cost increase as a trade-off between the two.

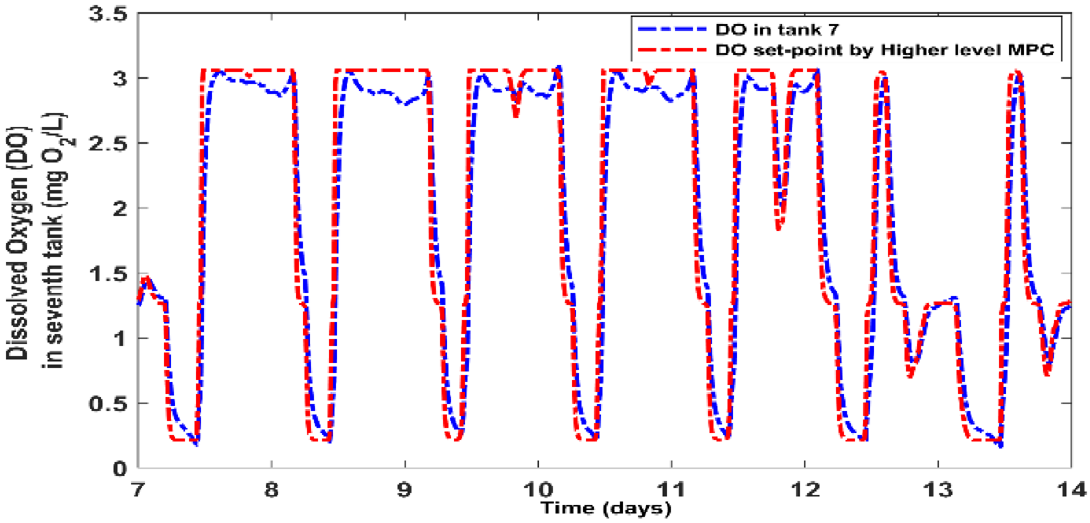


Figure 4.13: Variable DO set-point tracking of supervisory MPC controller with lower-level IMC FF-FPI

4.8 Conclusions

The non-integer order system for Biological Wastewater Treatment Plants (WWTP) is found using the ASM3bioP model and the FOMCON tools. It focuses on controlling Dissolved Oxygen (DO) and Nitrate concentration (NO). We use the Genetic Algorithm (GA) to find the best values for the Integral of Absolute Error (IAE) of the closed-loop response. This helps us figure out the fractional filter parameters (λ, α) for the Internal Model Control (IMC) controller. It is used in MATLAB Simulink to build the improved controller on the Aeration system for DO control.

Both the uncertainty of the plant and the weakness of the controller are put through a lot of tests to make sure they work well. We come up with a mathematical method that uses a higher-order fractional filter and the same IMC fractional controller for the non-integer model. The closed-loop reaction shows better tracking of the set point and rejection of disturbances. In the Fractional Filter - Fractional Order Proportional Integral (FF-FOPI) control strategy, the controller performance measures, like Integral of Squared Error (ISE) and IAE, are kept as low as possible at the same time.

When looking at how Fractional Order (FO) controllers affect plant performance, it is seen that FO controllers have a bigger effect than Proportional Integral (PI) controllers. The FF-FOPI approach, on the other hand, works the best overall. Notably, the FF-FOPI strategy works better than any other strategy when compared to the analytical higher-order filter.

Chapter 5

Chapter 5

5. DESIGN OF FRACTIONAL AND INTELLIGENT CONTROL STRATEGIES FOR SBR BASED WASTEWATER TREATMENT PROCESS FOR EFFLUENT QUALITY IMPROVEMENT

From this chapter onwards, the attention is directed towards the exploration of a batch process within the context of biological wastewater treatment. The focus will be on understanding and implementing different control strategies in a batch process and analysing the intricacies of this particular method throughout the remainder of the thesis material.

In Sequencing Batch Reactor (SBR)-based wastewater treatment plants (WWTPs), controlling dissolved oxygen (DO) is a very important part of treating wastewater. SBR technology is a flexible and effective way to treat biological wastewater. It works by putting in, reacting, settling, and decanting steps in order inside a single reactor. Managing the amounts of dissolved oxygen is very important for making sure that the biological treatment process in SBRs works at its best. Finding the right mix between giving microbes enough oxygen and keeping energy use as low as possible requires a thorough and flexible control system. This outline looks at the main things that need to be thought about, the methods, and the technologies that are used to control the amount of dissolved oxygen in SBR-based WWTPs. It emphasises how important this is for making wastewater treatment work well and be good for the environment.

5.1 Introduction

The SBR system is highly successful in removing nitrogen and phosphate (Ketchum et al., 1987; Guo et al., 2007). SBR processes are more stable than continuous processes, but they require more precise process control. This system is commonly used for smaller wastewater inputs and can be configured with a single tank or a system of many tanks in conjunction. This method employs a series of fill and draw cycles. A conventional cycle has five functional stages: filling, reactions (aerobic and anaerobic), sedimentation, decantation, and idle condition (Wilderer et al., 2001). In SBR reactor operating parameters were determined by an additional optimization layer added to the previously described two-layer hierarchical control structure. The outcome of optimization was an increase in efficiency and a decrease in energy consumption (Piotrowski et al., 2019). Piotrowski (2020) proposed a supervisory heuristic fuzzy control system which deployed to a SBR. The pollutants achieved its discharge limits with a reduced 9% operational cost. Many investigations have been attempted as automation technology (Feedback and intelligent controllers) has grown to select the proper condition for the SBR process (Yang et al., 2010).

In this research work, implementation of different controllers like simple PI to more effective FPI controller and later adaptive FUZZY controller are adopted to control dissolved oxygen (DO) in the SBR process. To run the simulation model of SBR and validate the SBR process with all control strategies in Indian climatic conditions, we need the influent. Influent data is collected from the Visakhapatnam WWTP, irrespective of the type of treatment technology (Tejaswini et al., 2021). The real plant data is used for simulations. However, the aspect that make the paper interesting is the application of control strategies to batch process in a sequential manner.

A step-feed method of filling the SBR, is also used to investigate the controller impact in the SBR process with different aeration timing. Aside from the benefits of traditional SBRs, step-feed SBRs may make effective use of influent COD as the carbon source necessary in the de-nitrification process. This indicates that a carbon supply is necessary to denitrify nitrite via step feeding and repeated aerobic/ anoxic phases. The anoxic period influent provides the nitrate generated during each aerobic period. Furthermore, the step-feed technique allows nitrification to occur during aerobic times with lower organic loading, which estimates the limitation of increased organic loading on autotrophic nitrifiers and reduces oxygen demand to oxidise these organic materials (Guo et al. 2007).

The novel aspect of this work is the development of three distinct control schemes for DO control in a batch process, SBR-based wastewater treatment plant.

This work is organised as follows: Materials and methods describe the monitoring plant and the model used, while the next segment discusses the architecture and application of the control system. The root level (DO control) PI, Fuzzy logic, and FPI controller's design processes are elucidated clearly. The subsequent portion discusses the simulation-based control findings by fixing real data records from Vizag WWTP.

5.2 Materials and Methods

5.2.1 Wastewater treatment plant description and simulation

SBRs perform biological pollutant removal in the second phase of WWTP. Unlike an ASP process, a SBR does not have any clarifier. To purify sewage sediments and minerals, mechanical pre-treatment is used. Grid, screen, grit chamber, and sand separator are used in the first step. Figure 5.1 depicts the SBR plant's process phase layout. As indicated in the introduction, a single SBR cycle consists of the following phases: filling, biological reactions (aerobic and anaerobic), sedimentation, decantation, and idling with the settler model is incorporated for better effluent quality. Double exponential settling velocity of the secondary settler model by Takas et al. (1991); is used (Sheik et al., 2021 a,b). The corresponding mathematical modelling and layout of settler (Figure 1.16) are reported in section 1.6.2. The most widely used mathematical representation of biological processes in WWTPs is Activated Sludge Models (ASM), a series established by the International Water Association. The ASM2d model (Gernaey et al., 2014; Henze et al., 2000) is used to model the biological processes of SBR in this paper, which has 21 state variables and 20 kinetic and stoichiometric parameters. The flow along with COD, TSS, and ammonia concentrations of influent are collected from Vizag plant to validate SBR process in Indian climatic conditions. The STOWA guidelines are used to compute the state variables, which contain the dynamic data needed to implement different control strategies for the treatment plant. The validation of the embraced ASM2d model is carried out in terms of the kinetic parameters of the process. BSM1 lists the kinetic and stoichiometric parameters at a temperature of 20 ºC, which is not the average ambient temperature for the Indian climate. After collecting influent data we have done kinetic parameter calculations with varying temperatures. At 20 °C (Henze et al., 2000) the values of those parameters are the same as their default values. After matching with the typical values for the kinetic rate constants of ASM2d at 20 ºC, we started executing Process Identification and controller implementation. Temperature effect on kinetic parameters given by equation as follows (Gernaey & Jeppsson (2014)):

$$\alpha_T = \alpha_{T_{20}}.\exp\left(\left(\frac{\ln\left(\frac{\alpha_{T_{20}}}{\alpha_{T_{10}}}\right)}{5}\right).(T-20)\right) \tag{5.1}$$

Where α_T the considered parameter temperature (T) value and $\alpha_{T_{20}}$, $\alpha_{T_{10}}$is the defined benchmark parameter values at 10 ºC and 20ºC (Henze et al., (2000)). Based on the equation (5.1) we have calculated the kinetic parameters at 30ºC to evaluate the Indian conditions. The table of typical values for the estimated kinetic parameters of ASM2d at 30 ºC is reported in the Table 5.4. Influent flow rate of simulated SBR - 0.033 l/min (Marsili Libelli et al., (2001)). Average influent data with state and particulate variables with symbols are reported in the Table 5.3.

WWTPs are required to meet certain strict effluent concentration restrictions which are tabulated in the Table 3.1 in section 3.2.1. The aeration system is intricate, nonlinear, and dynamic in nature. A general framework for modelling aeration systems was given (Henze et al., 1999). The aeration system used in this study consists of a blower station, collecting pipe, diffuser systems, and collector-diffuser pipes which were previously used for a variety of aeration systems reported in the literature (Piotrowski et al., 2014, 2015). Piotrowski et al., (2014) elucidate the main framework for modelling of aeration systems in SBR. The aeration system was modelled using measurement data and technical data from individual elements. Differential and algebraic equations describe the nonlinear aeration system model that was developed. Piotrowski et al., (2016) describes the model in detail, and it has been used in additional research endeavors. So DO control in SBR was tested with real data from the Visakhapatnam WWTP and implemented in a MatLab/SIMULINK environment. The data is collected from the Plant itself and is analyzed by following the STOWA guidelines.

Table 5.1: Influent load data as reported from Visakhapatnam WWTP

Influent load	Average Value
COD (mg/l)	381.99
BOD_5 (mg/L)	219.1083
TN (mg/l)	41.5992
TP (mg/l)	11.0751
TSS (mg/l)	238.92

Table 5.2: SBR operational parameters

Operation Parameters	Capacity
Working volume	5L
Influent volume	1 L
Total operation cycle	360 Mins
Solids retention time	20 days

Table 5.3: Average influent data with state and particulate variables with symbols

Components		Average
S_O	Dissolved oxygen	0
S_F	Readily biodegradable substrate)	54.21
S_A	fermentation product	36.14
S_I	inert organics	30
S_{NH}	ammonium	39.66
S_{N2}	Dinitrogen	0
S_{NO3}	nitrate	0
S_{PO4}	phosphate	8.92
S_{ALK}	bicarbonate alkalinity	7
X_I	inert organics	51.2
X_S	slowly biodegradable substrate	202.32
X_H	heterotrophic biomass	28.17
X_{PAO}	phosphorous -accumulating organisms	0
X_{PP}	stored poly-phosphate of PAO	0
X_{PHA}	Organic storage product of PHA	0
X_A	Autotrophic, nitrifying biomass	0
X_{TSS}	particulate material	215.49
X_{MeOH}	Ferric-hydroxide	0
X_{MeP}	Ferric-phosphate	0

Table 5.4: Effect of temperature on kinetic parameters (verified with Hence et al., (2000))

Kinetic Variable	10°C	15°C	20°C	30°C
K_H Hydrolysis rate constant	1.3333	2	3	6.7500
μ_H Maximum growth rate on substrate	1.50	3	6	24
q_{fe} Maximum rate for fermentation	0.75	1.50	3	12
b_H Rate constant for lysis and decay	0.1175	0.2350	0.4700	1.8800
q_{PHA}	1.3333	2	3	6.7500

Rate constant for storage of XPHA (base XPP)				
q_{PP} Rate constant for storage of XPP	0.6667	1	1.5000	3.3750
μ_{PAO} Maximum growth rate of PAO	0.4489	0.6700	1	2.2277
b_{PAO} Rate for lysis of XPAO	0.05	0.1000	0.2000	0.8000
b_{PP} Rate for lysis of XPP	0.05	0.1000	0.2000	0.8000
b_{PHA} Rate for lysis of XPHA	0.05	0.1000	0.2000	0.8000
μ_{NS} Maximum growth ratio Nitrosomonas Bacteria	0.2923	0.4700	0.7558	1.9542
μ_{NB} Maximum growth ratio Nitrobacter Bacteria	0.5807	0.7800	1.0476	1.8899
b_{NS} Constant decay ratio Nitrosomonas Bacteria	0.0496	0.0860	0.1491	0.4478
b_{NB} Constant decay ratio Nitrobacter Bacteria	0.0496	0.0860	0.1491	0.4478

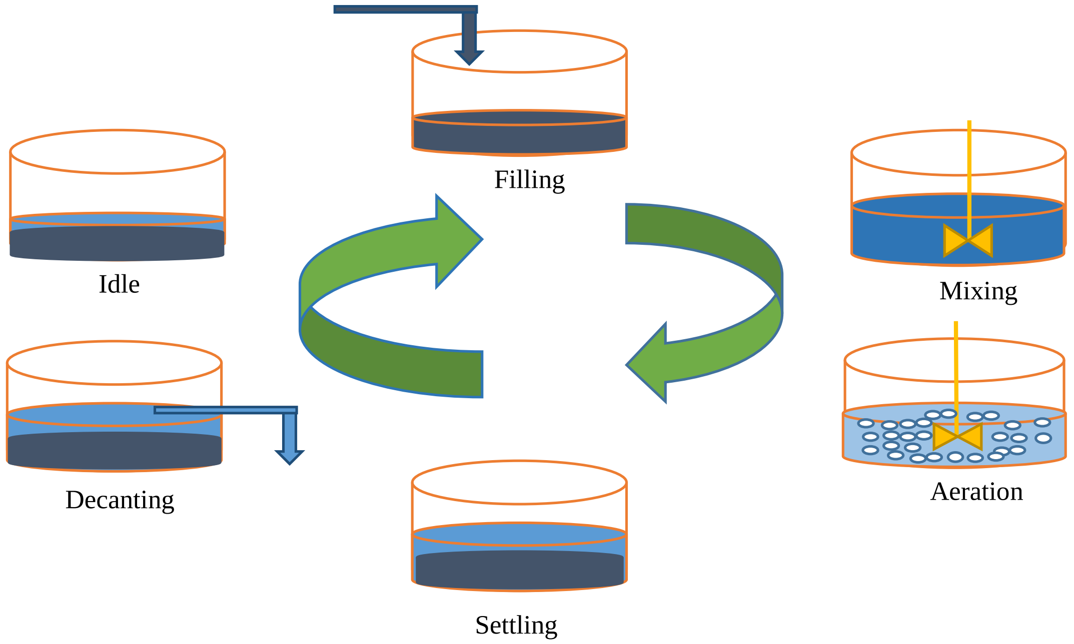


Figure 5.1: Sequential Batch Reactor phases

5.2.2 SBR plant configuration

The parameters of the Visakhapatnam WWTP are described in Table 5.1. A pilot scale Sequencing Batch Reactor (SBR) with 6-hour cycles of anoxic/anaerobic/oxic phases was employed (Marsili Libelli et al., (2001)). The operating parameters of the SBR are described in Table 5.2, and the operational cycle is depicted in Figure 5.2.

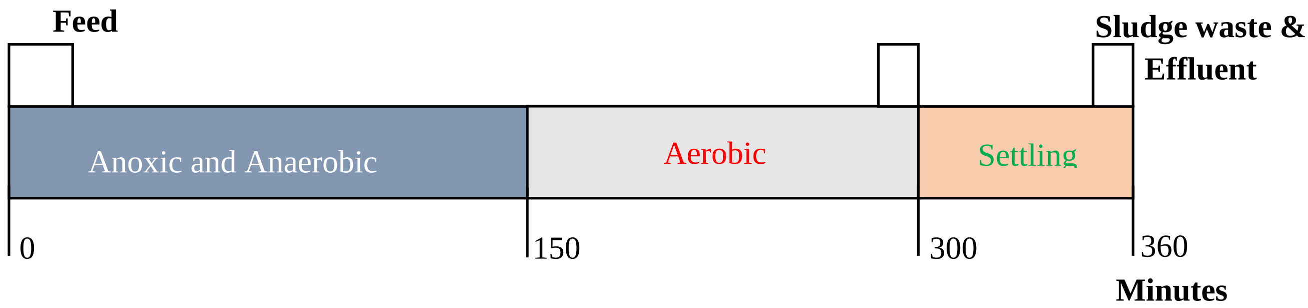


Figure 5.2: Conventional SBR Operation Phases in the current study

Modified SBR Cycle (Step-feed)

To study the step-feed mechanism in our present work SBR operation cycles are modified. As with pulse filling, there are three fill stages that are completed in a relatively short period of time. Three anoxic and anaerobic combinations are performed, with an aerobic phase in each cycle in the last. Following the sequential repeating of these stages, a setting phase with minimal decanting and sludge removal is performed in a total 6-hour cycle of SBR operation. The time duration of these phases was decided by the same method as described prior. The diagram (Figure 5.3) depicts the stages of SBR in a step feed scheme. SBR phases are Filling

(F) in 10 mins, Anoxic and Anaerobic (AN) phases of 40 mins and next Aerobic (AE) phases of 50 mins and finally 40 mins settling (S) and 10 mins Decanting (D), last 10 mins for Sludge Removal (SR).

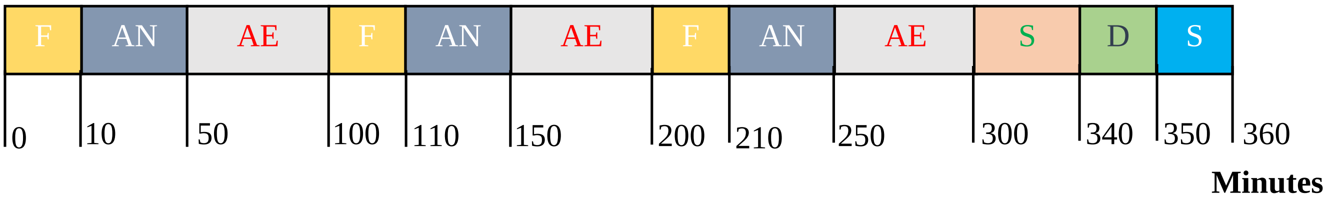


Figure 5.3: Modified SBR Operation Phases (SSBR)

5.3.1 Effluent quality index

Weighted average effluent concentration levels are used to compute the EQI. A steady state model simulation analysis is done by using the weighted average data from treatment plant. The plant performance assessment is done using the below equations (Sheik et al., 2021b; Santín et al., 2015):

$$\mathrm{EQI} = \frac{1}{100(t_f - t_0)} \int_{t_0}^{t_f} \mathrm{KU}_{(t)}\, \mathrm{Q}_{e(t)}\, dt \qquad (5.2)$$

$$\mathrm{KU}_{(t)} = \mathrm{KU}_{TSS(t)} + \mathrm{KU}_{COD(t)} + \mathrm{KU}_{BOD(t)} + \mathrm{KU}_{TKN(t)} + \mathrm{KU}_{NO_3(t)} + \mathrm{KU}_{P_{tot}(t)} \qquad (5.3)$$

In formula (5.3), the t_o and t_f imply the starting and ending times for calculating the EQI, while the KUt indicates the average of polluted combinations in the influent and effluent streams. Typically, it comprises of COD (chemical oxygen demand), BOD_5 (biological oxygen demand), TSS (total suspended solids), TKN (total Kjeldahl nitrogen), NO_3 (nitrate), S_{NH} (ammonia), TN and total phosphorous (TP) in equation (3). Thus the corresponding expression for KU_t is given in equation (5.4).

$$KU_t = \beta_t\, I_t \qquad (5.4)$$

Where β_t (g^{-1}) are weighting factors (Sheik et al., 2021b; Gernaey et al., 2014) ascribe every component of the pollution. The weighting factor values are represented below. Moreover, the concentrations of different components (G_{are} is computed by using Eq. (5.5)-(5.11).

The values of weighting factors are assigned to each effluent component, the factors are considered as follows: $\beta_{ss} = 2$, $\beta_{cod} = 1$, $\beta_{TKN} = 20$, $\beta_{NO} = 10$, $\beta_{BOD_5} = 2$, $\beta_P = 100$ Besides I_t, spontaneous concentrations of various nutrients are calculated corresponding to their state variables and particulate symbol with description is in the Table 5.3:

$$I_{TSS} = X_{TSS} \qquad (5.5)$$

$$I_{COD} = S_F + S_A + S_I + X_I + X_S + X_H + X_{PAO} + X_{PHA} + X_A \qquad (5.6)$$

$$I_{BOD} = 0.25\left(S_F + S_A + \left(1 - f_{S_i}\right)X_S + \left(1 - f_{XI_H}\right)X_H + \left(1 - f_{XI_P}\right)(X_{PAO} + X_{PHA}) + \left(1 - f_{XI_A}\right)X_A\right) \quad (5.7)$$

$$I_{TKN} = S_{NH} + i_{P,S_F}S_F + i_{P,S_A}S_A + i_{N,S_I}S_I + i_{N,X_I}X_I + i_{N,X_S}X_S + i_{N,BM}(X_H + X_{PAO} + X_A) \quad (5.8)$$

$$I_{N_{tot}} = I_{TKN} + G_{NO_3} \quad (5.9)$$

$$I_{NO_3} = S_{NO_3} \quad (5.10)$$

$$I_{P_{tot}} = S_{PO_4} + i_{P,S_F}S_F + i_{P,S_A}S_A + i_{P,X_I}X_I + i_{P,X_S}X_S + i_{P,BM}(X_H + X_{PAO} + X_A) + X_{PP} + \left(\frac{1}{4.87}\right) X_{Mep} \quad (5.11)$$

According to (Gernaey et al., 2014; Henze et al., 2000), correlated conversion factors (f_i) are selected in equations (5.6), (5.7), and (5.10).

5.3.2 Controller Performance

The standard establishes a universal assessment criterion which should serve as the basis for geographically independent reference measures for initiatives created throughout the world. The first level monitors controller installation, whereas the second is concerned with its influence on plant efficiency. The integral square error (ISE) and integral absolute error (IAE) is employed to assess controller performance. Where ‘e’ is the error between the set value and the value measured by the sensor (Piotrowski et al., (2021); Santín et al., 2015).

$$\text{ISE} = \int_{150\ mins}^{300\ mins} {e_i}^2\, dt \quad (5.12)$$

$$\text{IAE} = \int_{150\ mins}^{300\ mins} |e_i|\, dt \quad (5.13)$$

5.4 Controller Implementation

The provision of an adequate amount of dissolved oxygen (DO) is required to produce an acceptable growth of microorganisms included in activated sludge. Aeration of the wastewater is consequently required to carry out biological processes. The oxygen released into SBR by the aeration system is a crucial component of the complicated biological processes in a WWTP. The concentration of DO in SBR affects the processes like de-nitrification, nitrification, and phosphorus removal. The aeration system delivers an oxygen atmosphere in the reactor, which is intended to keep the tank in a condition of suspension. The newly generated cells combine with the old microbes and then carry out the impurity removal procedure. The aeration process is required for optimal biological responses to occur. A low dissolved oxygen content causes inadequate proliferation of microorganisms, which prevents them from decomposing nitrogen and phosphorus compounds. Excessive aeration causes over blending in the reactor, which can lead to the disintegration of flocculants.

As oxygen is required to oxidize organic material in aeration reactors and maintain residual oxygen levels, it is usually equal to the amount the microorganisms require. Microorganism growth may be limited if oxygen is low, causing filamentous microorganisms to dominate, and leading to poor settling of sludge. The opposite is true when DO is high, which requires more energy consumption and may deteriorate the sludge quality. The DO levels should typically be maintained between 1.5 and 4 mg O_2/l in an aeration reactor, with 2 mg O_2/l being the more commonly retained level. To control the DO in SBR during aeration, a common but popular feedback control employing the PI controller is considered. First of all, this is composed of the PI controller, as shown in Figure 5.4, for 'DO' control, whose set-point value is 2 mg O_2/l is controlled by adjusting the 'AIR-FLOW' in the reactor. Another contribution of this study is the development of a fraction controller (FPI) by replacing the PI controller for the DO control purpose with a developed fractional model of SBR during aeration (Figure 5.4). For both these control approaches a stable process model is required. Fuzzy Logic Control can be used for controlling many nonlinear processes around the operating point through the use of FUZZY rules and membership functions that are identical in design to human inferences.

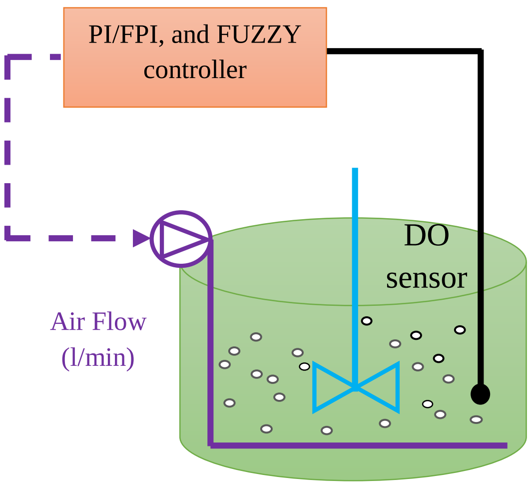


Figure 5.4: Three distinct control schemes on SBR during Aerobic Phase

As the air flow is manipulated for efficient DO level inside a reactor then net amount of air supplied to the reactor during aeration is a measure of the control cost, which is expressed as:

$$Q_{Total} = \int_{150}^{300} (Q_{air}(t))dt \tag{5.14}$$

To check the effect of control action on both SBR Cycles, all the parameters are calculated for the Indian influent data (Visakhapatnam Plant) at 30°C and finally, effluent quality index along with controller performance are measured.

5.5 Modelling of System form Process Input output Data

The selection of the appropriate process model is a prerequisite for putting a control structure in place for any kind of process. As previously discussed, this work identifies contextual integer order (IO) and fraction order (FO) modelling of SBR-based WWTPs by performing a simulation, hence both the IO and FO controllers are incorporated on it.

5.5.1 Algorithm to develop an IO Model to design PI controller

The primary objective of identification is to create a stable process model based on the data collected during an experiment. In general, determining and estimating system dynamical behavior requires establishing a link with both process inputs and outputs under various influences (input signals). The flow diagram in section 3.5.1 in Figure 3.4 describes the identification of Integer Order (IO) model using system Identification toolbox. During the process of identification the developed model G(S) of SBR comes as

$$G(s) = \frac{0.002753S + 0.0001987}{S^2 + 0.1216S + 4.662e^{-5}}$$

Later using proper model order reduction technique (Linear Feedback Control Analysis and Design with MATLAB by Dingyü Xue et al., (2007). we have developed a First order with delay time (FOPDT) process model of SBR. Finally, we have validated the reduced order model by checking both the Step Response Analysis and Bode Plot method and its stability. Results of validation is provided in Figure 5.5. Final sable FOPDT model G_R(S) of SBR comes as,

$$G_R(s) = \frac{0.0016434}{s + 0.0003856}\, e^{-0.96*s} = \frac{4.2619}{2593.36\, s + 1}\, e^{-0.96*s}$$

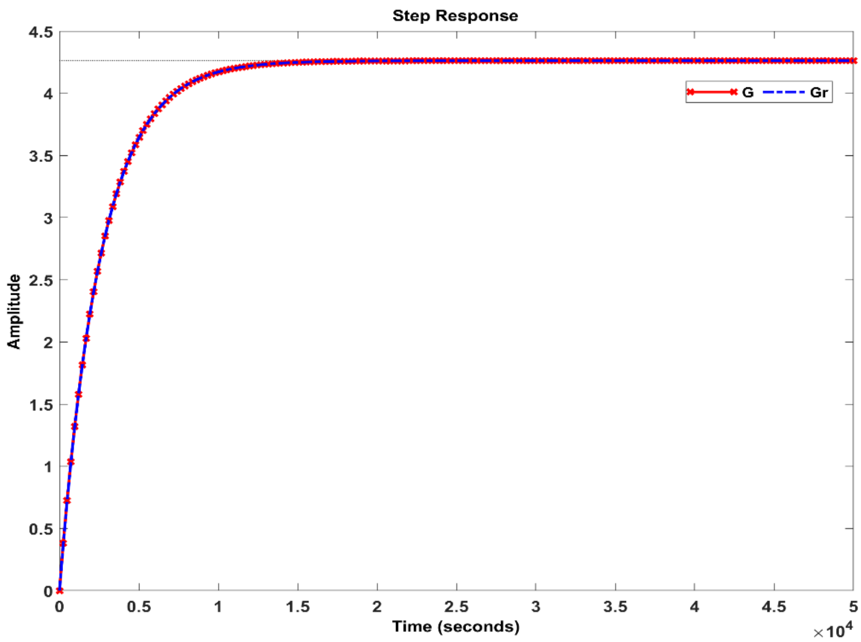


Figure 5.5: Step response plot to validate the model reduction

5.5.2 Algorithm to develop an FO Model to design FPI controller

Fractional-order calculus involves arbitrary order differential and integral equations and is a generalization of integer-order calculus. Fractional calculus theory can solve any derivative or integral of any order, as well as continuous versions of the fractional calculus operator which is defined as follows in Equation (5.15)

$$a\mathcal{D}_t^p = \begin{cases} \frac{d^p}{dt^p} \ \mathrm{Re}(p) > 0 \\ 1 \qquad \mathrm{Re}(p) = 0 \\ \int_a^t (dt)^{-p} \ \mathrm{Re}(p) < 0 \end{cases} \tag{5.15}$$

Where ‘a’ and ‘t’ are the calculus upper and bottom bounds, respectively, and is an arbitrary complex. Fractional order calculus theory has developed many different definitions of fractional calculus, including the GL, RL, and Caputo definitions (Tepljakov A et al. (2019)).

Based on the time-domain approach, a non-integer order transfer function is found using the MatLab “Fractional-Order Modelling and Control” FOMCON toolbox. We can choose the kind of system simulation we want to use using the Simulation parameters window. Indranil et al., (2022) illustrate the algorithms to identify a fractional model (FO) utilizing FOMCON toolbox.

The input and output data is generated by giving the random input to the model of ASM3-bioP model at steady sate with plant influent and relating all state variables.

Steps to identify a good fitted identified model

- A "fidata" structure must be chosen first and foremost.
- Select ‘Time domain Identification’, where options are available to choose frequency domain too.
- Choose the ‘simulation parameter methods’ in Grunwald-Letnikov method or Oustaloup filter or Refined Oustaloup filter. (Should select ‘w’ range and order for the last two options). We select the Oustaloup filter.
- In the ‘Identification and options’ section chosen ‘fidata’ name will show and the preferred algorithm is ‘Trust-Region-Reflective’.
- There is a symbolic form of identified model in terms of the fractional pole and zero polynomials. A first-guess model is created. In order to create polynomials autonomously, a commensurate-order q that has the property that $0.01 \leq q < 2$ —the order of the polynomial—can be defined.

- A plot that displays a worthy fitting result (fitness >75 %) and the identified system's stable behavior should be displayed at the conclusion of the identification process. As long as the outcomes are satisfactory, the model is saved for creating a controller.

The identified Fractional model G(S) of SBR comes as

$$G(s) = \frac{1}{0.80739s^{0.8955} - 16.77s^{0.11936} + 23.319s^{0.077491}}$$

5.5.3 Fuzzy logic Control

FUZZY logic is a widely used method in a variety of control contexts. FLCs have been employed at every level of wastewater treatment. Fuzzy control or rules (FLC) are commonly used to solve the utmost unconventional control and processing units in WWTPs, as evidenced by the literature. Fuzzy rules are used to accomplish this, much like those used when humans make inferences. In this study, FLC is employed on this SBR-based WWTP. To confine DO saturation in the SBR, the desired DO set-point is monitored by a fuzzy logic controller. In the ranges of 0–6 mg O_2/l and 0–30 l/min, respectively, the membership functions (MF) of DO and Airflow in SBR were investigated. A Gaussian-shaped-bell curve membership function is chosen for these two variables, and they are separated into three linguistic rules: "LOW," "MEDIUM," and "HIGH." The following are the three rules for governing the DO control loop:

- If the DO level is "LOW" then the Airflow set-level is "LOW"
- If the DO level is "MEDIUM" then the Airflow set-level is "MEDIUM"
- If the DO level is "HIGH" then the Airflow set-level is "HIGH"

5.6 Results and Discussion

5.6.1 Implementing Proportional and Integral (PI) control

To regulate the dissolved oxygen (DO) in SBR during the aeration phase a conventional PI controller is used inside this reflected control loop. The strategic orientation with PI controllers is depicted in Figure 5.4. Designing PI controllers can be accomplished using a variety of tuning methods. A well-accepted robust tuning rule based on Grimholt and Skogestad (2018) (SIMC rule) is deployed in this scheme. To tune a controller using this procedure, the first step involves obtaining the first-order plus time delay (FOPTD) model G(s), as previously mentioned.

$$G(s) = \frac{Kp}{\tau * S + 1} e^{-\theta * S} \tag{5.16}$$

Where K_P, the process gain, L the time delay, and T is the time constant of the identified model. On the first-order with delay (FOPDT) process in equation 5.16, the authors employed the original SIMC tuning rule. The SIMC PI tunings for this process result in a PI controller like in equation 5.17,

$$Kc = \frac{1}{K_P} \frac{\tau}{(\tau_C + \theta)} \quad \text{and} \quad T_i = \min\{\tau, 4(\tau_C + \theta)\} \tag{5.17}$$

The value τ_C, the closed loop time constant, is a tuning constraint that can be adjusted to attain the optimal trade-off among efficiency, robustness, and input allocation. $\tau_C = \theta$ is recommended for "tight control" (decent performance) as well as adequate robustness. The tuned Parameter of PI controller using SIMC, K_c =316.92, T_i=7.66, and $K_i = (K_c/T_i) = 40.32$. So, the final PI control structure for identified DO loop looks like (in Figure 5.5)

Table 5.5: PI controller settings for DO control

SBR (IO) Process Model	Controller Gain	PI controller
$G(s) = \frac{4.26193}{2593.36\, s + 1} e^{-0.96 * s}$	K_c =316.92 K_i = 40.32	$C_{DO}(s) = 316.9243 + 40.32 \frac{1}{s}$

5.6.2 Implementing Fractional Proportional integral (FPI) controller

A fractional-order (FOTF) model of the SBR plant is identified utilizing FOMCON toolbox. The "Oustaloup filter approximation" is applied in the time-domain approach to identify the model and a stable FOTF DO model is identified. Ultimately, the Fractional-order PI controller is optimized using the 'Interior -point' algorithm and the ISE as a performance metric. The maximum and minimum values for all tuning parameters should be chosen to optimize the Fractional order (FPI) controller. The final satisfactory tuned parameters of the FPI controller are K_c = 349.56, K_i = 48.95, and λ= 0.9796. As a final point, the FPI controller for SBR model is deployed and the FOTF DO loop along with controller appears to be (in Figure 5.6)

Table 5.6: FPI controller settings for DO control

SBR (FOTF) Process Model	Controller Gain	FPI Controller
$G(s) = \frac{1}{0.80739 s^{0.8955} - 16.77 s^{0.11936} + 23.319 s^{0.077491}}$	K_c =349.56 K_i = 48.95 λ= 0.9796	$C_{DO}(s) = 349.56 + 48.95 \frac{1}{s^{0.9796}}]$

5.6.3 Implementing FUZZY Logic controller (FC)

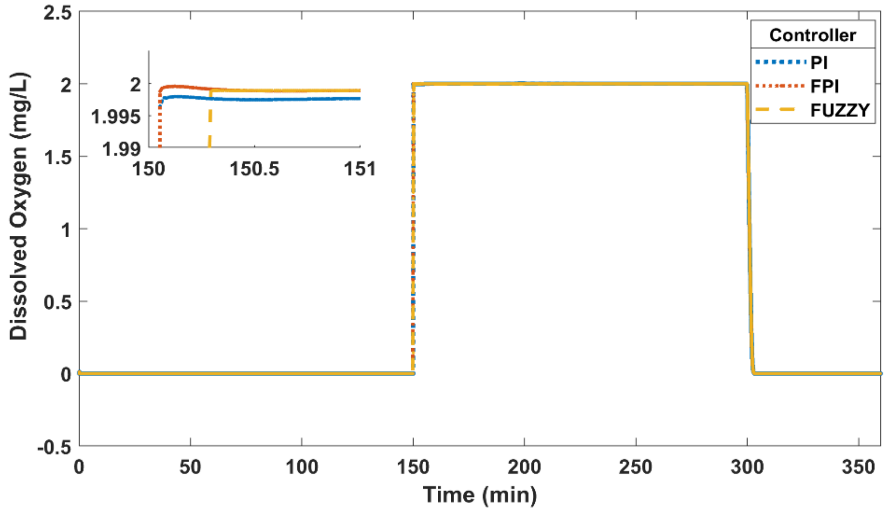
Numerous unknowable factors are involved in the Wastewater Treatment Plant's functioning. Seeing as biological mechanisms in wastewater treatment are extremely complicated, traditional approaches face significant challenges to control automatically. As a result, intelligent computing techniques, especially fuzzy logic, are an ideal choice for controlling nonlinear time-varying processes. The main objective is to conserve energy even as maintaining effluent quality. This is essentially aeration control based on DO concentration. The membership functions range explored for Dissolved oxygen (DO) and Airflow is 0-6 mg O_2/l & 0-30 l/min individually. We consider the membership curve to be a Gaussian bell curve with the degree of membership 1. The membership distributions of DO concentration in SBR are developed with 0-1 mg O_2/l as "low," 1-2 mg O_2/l as "medium," and values over 2 mg O_2/l considered to go into the "high" fuzzy set, values less than 0.05 l/min are undoubtedly regarded as "low," hence likewise, the fuzzy set values ranging from 0.05 l/min to 9.5 l/min are classified as "medium" and Airflow values of beyond 9.5 l/min are considered "high". Table 5.7 shows the rule base for fuzzy task.

Table 5.7: FUZZY rule base tabulation

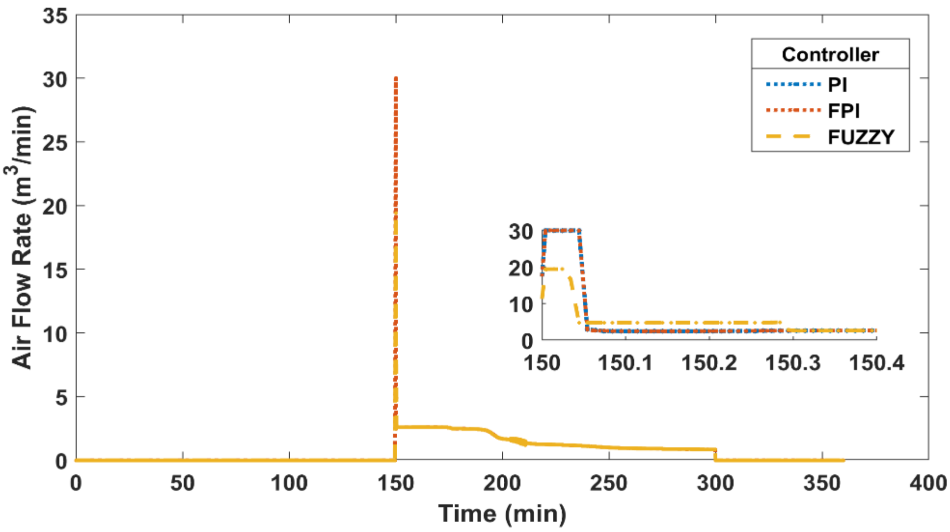
Membership Function (MF) Ranges	Parameters as member	
	Input (DO) (0-6 mg O2/l)	**Output (Airflow) (0-30 l/min)**
LOW	0-1	0- 0.05
MEDIUM	1-2	0.05-9.5
HIGH	> 2	> 9.5

5.7 DO tracking and plant performance analysis

As previously discussed, a DO set-point of 2 mg/l is selected in the reactor. The set-point tracking graphs for PI, FPI, and FUZZY are presented in Figure (5.6 A) for DO Control. From the Figure, it is observed that the tracking capability of the FPI controller is superior to that of the PI and FUZZY controllers. Figure (5.6 B), the manipulated variable plot demonstrates that, when initial aeration starts, in order to attain the DO set-point as soon as possible, the controller sends a high-value control signal in terms of airflow such that the DO reference of 2 mg O_2 /l should be tracked as soon as possible. Control performance is measured by using IAE and ISE, plant performance is measured by effluent quality. From Table 5.8, it was observed that the Total Airflow Volume (L) is approximately the same for all the control applications. For the control performance case, ISE & IAE are improved in the FPI controller on comparing with PI and FUZZY. The percentage of improvement in FPI is 17.38 %, 0.07% than PI for IAE & ISE respectively. In terms of effluent quality, the FPI controller showed optimal outputs when compared to PI & FUZZY. EQI is improved in FPI by 0.86% than PI & 1.036% than the FUZZY controller. COD, BOD5, TN, TP , NH_4 & TSS are improved by 0.53%, 1.05%,1.18%, 0.80%, 0.07% & 2.22% respectively with the FPI controller than PI controller which they provide better effluent quality.



(A)



(B)

Figure 5.6: (A) DO tracking by PI, FPI and FUZZY controller during aeration time (B) Airflow plot in terms of the manipulated variable for all adopted controller

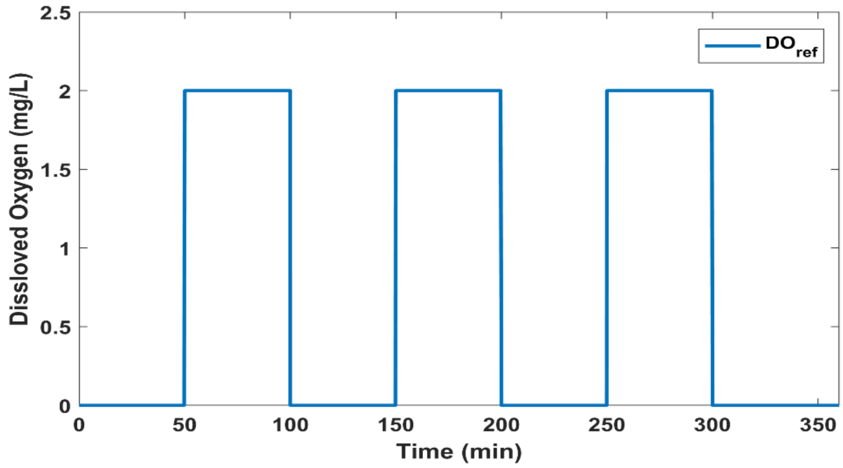
Table 5.8: Effluent quality in conventional SBR with controller performance

	PI	FPI	FUZZY
IAE	0.1057	0.08732	0.2412
ISE	0.05673	0.05669	0.1421
Total Airflow volume (l)	231.8	231.8	231.7
Effluent parameters			
COD (mg/l)	52.2850	52.0073	52.3550
BOD (mg/l)	13.1205	12.9816	13.5905
TN (mg/l)	3.0015	2.9658	3.0500
TP (mg/l)	2.2675	2.2492	2.2575
TSS (mg/l)	11.5721	11.3146	11.5921
NH_4 (mg/l)	1.8200	1.8186	1.8195
IQI (kg polls units/day)	0.7684	0.7684	0.7684
EQI (kg polls units/day)	0.0578	0.0573	0.0579

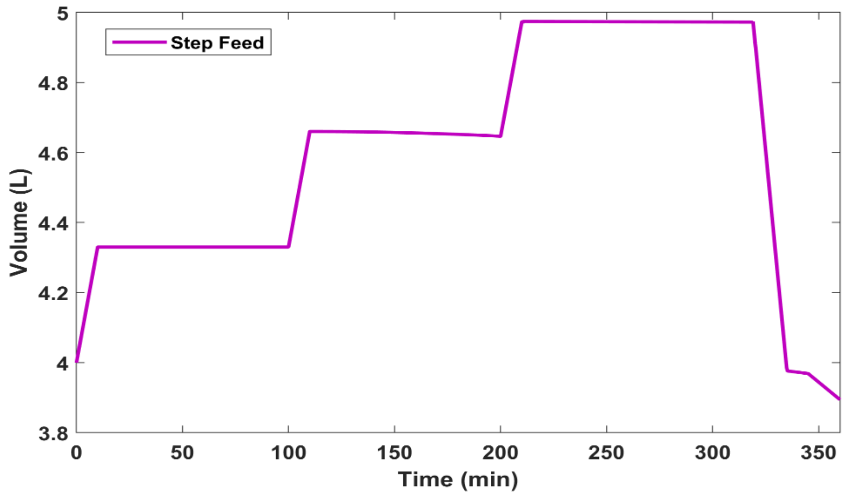
5.8 Effect of Control action on Modified SBR Cycle - Step-Feed Process (SSBR)

The primary responsibility of the DO controller is to maintain a predefined trajectory. The controller should better reflect the trajectory of any changes in DO concentration caused by changes in SBR configurations. So step feed is used to check controller performance by varying DO reference trajectory as described in Figure 5.7 A. Total volume filling during step feed. Figure 5.7 B depicts the reactor loading level with step feed over the whole operational cycle. The DO set-point of 2 mg/l is selected in the reactor for different time zones of aerobic phases as shown in Figure 5.7 A. The set-point tracking graphs for PI, FPI, and FUZZY are shown in Figure 5.7 C. It is observed that the FPI controller has a superior tracking capability than the PI and FUZZY controllers. Figure 5.7 D shows that the controller sends a high-value control signal with each change in DO trajectory, indicating that it is essential to attain DO set-value as soon as possible.

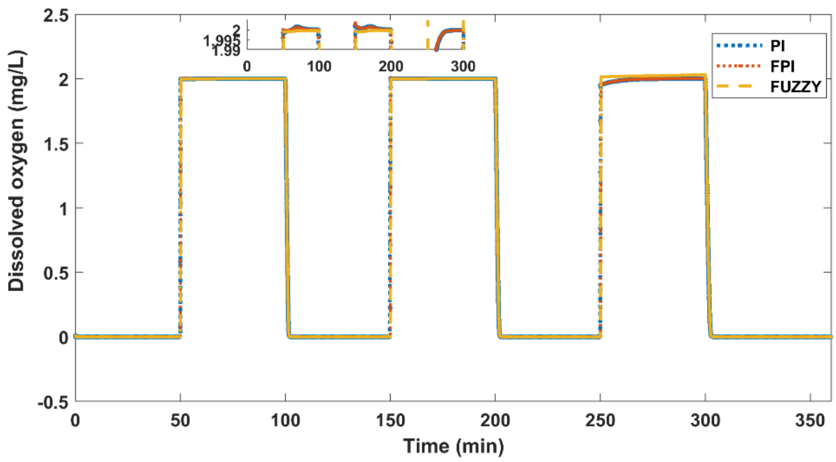
From Table 5.9, it was observed that the Total Airflow Volume (l) is approximately the same for all the control applications. For the control performance case, ISE & IAE are improved in FPI controller on comparing with PI and FUZZY. The percentage of improvement in FPI is 0.74 %, 0.14% than PI for IAE & ISE respectively. In terms of effluent quality, the FPI controller showed optimal outputs when compared to PI & FUZZY. EQI is improved in FPI by 0.34% than PI & 0.51% than FUZZY controller. COD, BOD5, TN, TP & TSS are improved by 0.17%, 0.152%, 1.69%, 0.26% & 0.08% respectively with the FPI controller than PI controller which they provide better effluent quality.


DO$_{ref}$
Dissloved Oxygen (mg/L)
Time (min)
0
0.5
1
1.5
2
2.5
50
100
150
200
250
300
350

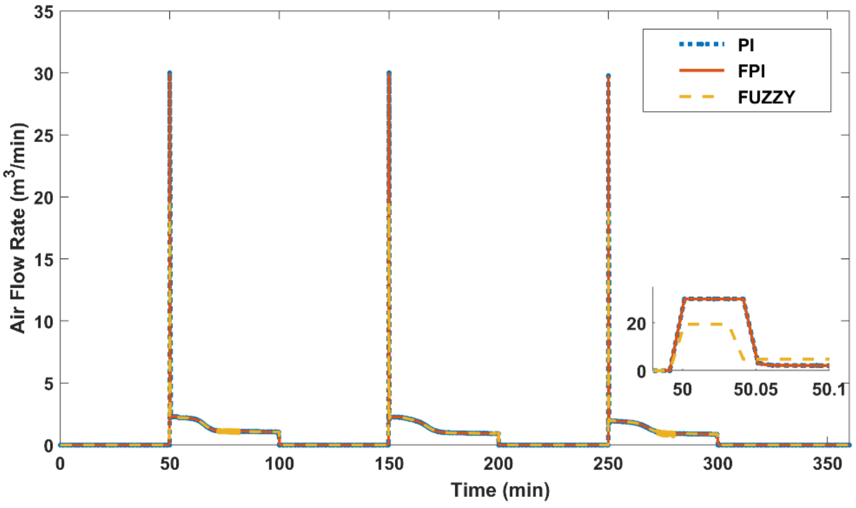
(A)


Step Feed
Volume (L)
Time (min)
3.8
4
4.2
4.4
4.6
4.8
5
0
50
100
150
200
250
300
350

(B)


PI
FPI
FUZZY
Dissolved oxygen (mg/L)
Time (min)
-0.5
0
0.5
1
1.5
2
2.5
50
100
150
200
250
300
350

(C)



(D)

Figure 5.7: (A) varying DO reference trajectory due to step feed (B) SBR total volume filling during step feed (C) DO tracking by PI, FPI and FUZZY controller during aeration time in step-feed approach (D) Airflow plot in terms of manipulated variable for all adopted controller.

Table 5.9: Effluent quality on step-feed in SBR with controller performance

	PI	FPI	Fuzzy
IAE	3.35	3.325	4.419
ISE	0.2796	0.2792	0.5252
Total airflow volume (l)	206.2	206.2	206.5
Effluent parameters			
COD (mg/l)	52.2919	52.2010	52.3520
BOD (mg/l)	13.1562	13.1362	13.1825
TN (mg/l)	3.0005	2.9496	3.0050
TP (mg/l)	2.2911	2.2850	2.2795
TSS (mg/l)	11.5912	11.5812	11.6111
NH_4 (mg/l)	1.8255	1.8259	1.8201
IQI (kg polls units/day)	0.7684	0.7684	0.7684
EQI (kg polls units/day)	0.0582	0.0580	0.0583

5.9 Conclusions

Three control frameworks such as PI, FPI, and FUZZY are attached to the SBR plant layout under the ASM2d platform. In the root level, control approaches like PI, FPI, and Fuzzy control are used to control DO during the aeration phase by manipulating the air flow rate. The ASM2d model calibrated to real plant data is used to represent the SBR-based water treatment plant. However, the aspects that make the paper interesting: control strategy applied to a discontinuous process, use of the complex ASM2d model, and calibration to real plant data. Controller performances are studied. ISE & IAE are improved in the FPI controller on comparing with PI and FUZZY. The corresponding plant performance concentration is compared with the PI controller. It was noticed that average effluent compositions of nutrients such as BOD, ammonia, COD, TN, TP, and TSS attained inside the regulatory limits. Better optimized results for nutrient removal rates and effluent quality is observed in FPI controller compared with the other two controllers. COD, BOD, TN, TP , NH_4 & TSS are improved by 0.53%, 1.05%,1.18%, 0.80%, 0.07% & 2.22% respectively with the FPI controller than PI controller. In the same control strategies (PI, FPI, and FUZZY) on modified SBR Cycle (Step-Feed Process) is implemented where they achieve even same type of improvement is observed from the resultant simulation outcomes.

Chapter 6

Chapter 6

6. DESIGN OF SUPERVISORY FUZZY CONTROL FOR ENHANCED ENERGY SAVING IN A SEQUENCING BATCH REACTOR BASED WASTEWATER TREATMENT PLANT

WWTPs need supervisory cascade control to save operational expenses. Supervisory cascade control saves time and energy by coordinating and optimising control activities across several process units. Control techniques in WWTPs ensure efficient, cost-effective, and environmentally sustainable wastewater treatment through dynamic adjustments, informed decision-making, and effective coordination.

6.1 Introduction

To ensure optimal operation and control of a wastewater treatment plant (WWTP), suitable advanced control strategies are required as they are inherently nonlinear in nature and subjected to different influent conditions. This study proposes a novel supervisory control scheme for Sequencing Batch Reactor (SBR) based WWTP. It integrates hierarchical fuzzy control, based on ammonia and nitrate observations, in the presence of lower-level Proportional Integral (PI) and Fractional-order PI (FPI) controllers, with the dual goal of aeration cost reduction and effluent quality enhancement. A modified ASM2d (Activated sludge model No. 2d) framework is used as a model for SBR. In the hierarchical control system, variable dissolved oxygen (DO) trajectories are generated by the supervisory fuzzy logic controller and passed to the lower level controller, according to ammonia and nitrate profiles within SBR. It is crucial to adjust this element properly in order to maximize wastewater treatment efficiency and reduce plant costs, especially for the aeration system. Intelligent computing techniques like MPC, RTO, particularly fuzzy logic, are indeed a good choice for controlling these types of non-linear time-varying systems. The primary objective of the controller is to save energy while maintaining the effluent quality. An intelligent fuzzy controller which combines the two distinct signals S_{NH}/S_{NO} profile and the DO concentration. Further, the desired level of DO can be attained with nominal energy consumption. In the research of Piotrowski et. al, 2019 and 2020, they came up with optimization methods that were able to optimize sequential phases in an efficient SBR operation, but to minimize aeration energy incorporating a fuzzy logic to develop a supervisory control network that generates variable DO set-points depending on the presence of the S_{NH} or S_{NO} profile inside the reactor is new and novel study. According to the author's best knowledge, an efficient aeration strategy based on nitrate or ammonia measurement has not been applied in this SBR-based treatment plant until now to reduce the amount of energy consumed inside a hierarchical control structure. The present work addresses this point and shows the benefits of having such a control architecture. A multi-level cascaded hierarchical control arrangement is considered that combines PI & FPI controllers one at a time at lower levels while advanced fuzzy control strategies are utilized at higher levels. This research work establishes different controllers like simple PI to more effective FPI controller to control DO, and a smart higher-order decision-making technique, built on fuzzy logic (Fuzzy controller) to track variable DO by measuring the ammonium nitrogen (NH_4) and nitrate (NO_3) profile in the SBR reactor. A calibrated ASM2d model based on real plant data is used to represent the wastewater treatment plant. However, the aspect that makes the paper novel and interesting is applying control strategies to a batch process in a sequential manner. The developed control strategies are tested for the influent collected from the wastewater treatment plant located in Andhra Pradesh, India.

6.2 Control approaches

The oxygen released into SBR during aeration scheme is a crucial factor in the complicated biological processes. The concentration of DO in SBR affects processes like de-nitrification, nitrification, and phosphorus removal. The aeration system delivers an oxygen atmosphere in the reactor, which is intended to keep the tank in a condition of suspension. The newly generated cells combine with the old microbes and then carry out the impurity removal procedure. Low DO content causes inadequate proliferation of microorganisms, which prevents them from decomposing nitrogen and phosphorus compounds. Too much aeration leads to over-blending in the tank of reactor, which can result in flocculants disintegration.

The aeration reactors need oxygen to oxidise organic material. Maintain residual oxygen levels, which are usually enough for microbes. Low oxygen may limit microbe growth, causing filamentous microorganisms to dominate and poor sludge settling. Conversely, high DO needs more energy and may degrade sludge.

The DO levels should typically be sustained between 1.5 and 4 mg O_2 /l in an aeration reactor, with 2 mg O_2 /l being the more commonly maintained level. To control the DO in SBR during aeration, a conventional but widespread feedback control technique, the PI controller is chosen. The PI controller at lower level controls DO by adjusting the 'AIR-FLOW' in the reactor, whose set-point is 2 mg O_2/l, as shown in Figure 6.1. In addition to PI, fractional order PI (FPI) controller is also presented as an alternative.

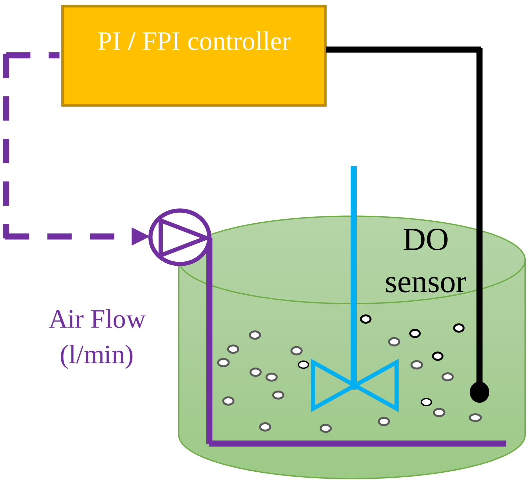


Figure 6.1: SBR at Aerobic Phase with DO control without supervisory layer

The implementation of hierarchical controllers in SBR-based WWTP is limited. Hence, in this research, different control strategies are designed and implemented by simulation. Preferably, the DO set point should be 2 mg O_2/l. However, depending on the obtainability of ammonia or nitrate present in the reactors, the above value may not be required throughout the aeration process. An important aid of this paper is the development of the two-tier hierarchical strategy with the supervisory layer that uses Fuzzy Controller (Figure 6.2). As aeration begins, S_{NH} (ammonia concentration) is more in the reactor, so nitrification requires additional S_O (DO level). The opposite occurs as S_{NH} is less, since less S_O is required to form less S_{NO}. So it is very crucial to reduce Air and energy consumption in SBR, it is necessary to determine the right DO during the aeration phase. Besides ammonia concentration-based (S_{NH}) aeration, Nitrate-based (S_{NO}) aeration control was also studied in this work. Many studies are carried out in the literature to examine how different operative circumstances (e.g. low DO concentration, selective inhibition and temperature) favour nitrite growth. So a nitrate (S_{NO}) controller at a higher level can affect low air consumption to reduce aeration energy in low DO operational conditions.

The role of the supervisory controller is to generate DO values (set points for lower-level) by determining the presence of NH or NO in the SBR. These variable DO values are used as flexible set points in the lower level DO loop. As a result, the higher-level control loop assists in deciding the lower loop's set points. Moreover, the amount of aeration impacts energy consumption. As a consequence, it is important to choose the DO set point wisely. In this work, the lower level uses the conventional PI and FPI controllers, while a higher level builds a Fuzzy Logic controller.

Thus the set point of Dissolved Oxygen at 2 mg O_2/l can be altered to ensure the WWTP's performance requirements. If the ammonia load is low, the DO set value can be lower, and higher if the ammonia level is high. The simulation result shows, that varying the set-point by Fuzzy Controller improves the plant performance by improving the effluent quality. The effect of control action on conventional SBR cycle is calculated at 30°C for all parameters.

Integral Square Error (ISE) and Integral Absolute Error (IAE) are the evolution criteria for controller performance, which we decided to minimize for controlling DO during aeration. The control action is only happening during aeration and that time interval is t= 150-300 min. Our

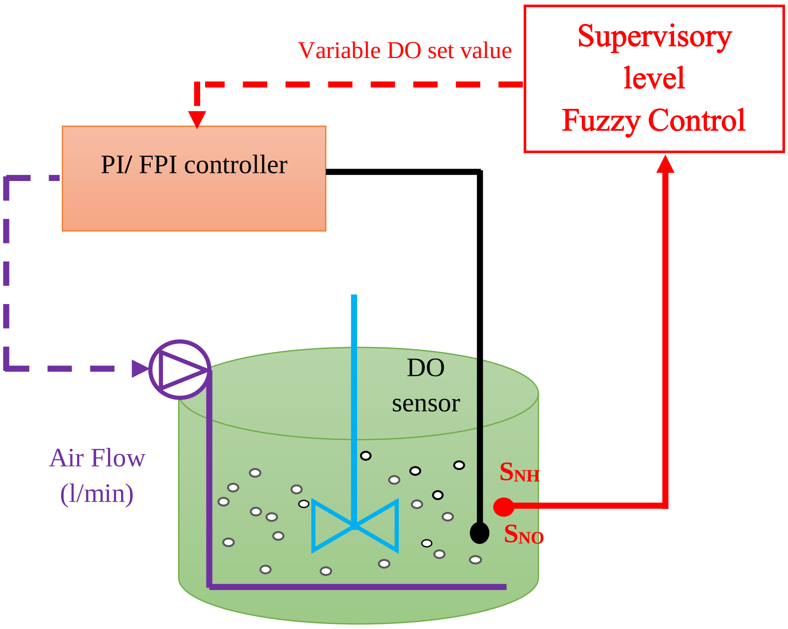


Figure 6.2: Higher Level (HL) Fuzzy control in SBR during aeration

reference for DO control is 2 mg O_2/l for lower level PI and FPI control strategy. In the hierarchical architecture, fuzzy controller is used which also considers ammonia or nitrate based aeration during the same time period i.e. t = 150-300 min. Hence, the performance of controller (ISE and IAE) is calculated in this aeration time interval only. The effluent quality index (EQI, in kg pollution units d-1), is a weighted average sum of pertinent effluent concentrations (Copp, 2002).

For SBR based biological process we are running one batch cycle from t0= 0 min to tf = 360 mins. So, the EQI should be calculated for the total operational time of single batch process of SBR operation. So EQI is defined between t0 and tf.

Table 6.1 clearly specifies the recommended control strategies (CS). Based on the control loops and using the PI control strategy as the core approach, a total of 6 control combinations are assessed in terms of how they affect and provide the assessment criteria. A total of six control frameworks are developed in this research as given below.

- CS1 is lower level PI controller for DO control in SBR.
- CS2 is lower level FPI controller for DO control in SBR.
- CS3 is lower level PI and higher level Fuzzy for ammonia-based Aeration.
- CS4 is lower level FPI and higher level Fuzzy for ammonia-based Aeration.
- CS5 is lower level PI and higher level Fuzzy for nitrate-based Aeration.
- CS6 is lower level FPI and higher level Fuzzy for nitrate-based Aeration.

The controller performance is tested by same like section 5.3.2. and total air volume (Q_{Total}) consumption is same like last lower level controller calculation.

Table 6.1: List of developed control strategies for SBR

Label	***Lower level controller***		***Ammonia (NH_4) based Supervisory controller***		***Nitrate (NO_3) based Supervisory controller***	
Characteristics	**CS1**	**CS2**	**CS3+CS4**		**CS5+CS6**	
			LL PI/FPI	**HL Fuzzy**	**LL PI/FPI**	**HL Fuzzy**
	DO (S_O) control	**DO (S_O) control**	**DO (S_O) control**	**Ammonia (S_{NH}) control**	**DO (S_O) control**	**Nitrate (S_{NO}) control**
Measuring Variable	DO in SBR	DO in SBR	S_O in SBR reactor	S_{NH} in SBR	S_O in SBR reactor	S_{NO} SBR
Set-Value	2 mg O_2 /l	2 mg O_2 /l	Variable set point	1 mg/l	Variable set point	4 mg/l
Manipulated Variable	Air-Flow	Air-Flow	Air-Flow	Set-point for DO controller	Air-Flow	Set-point for DO controller
Control Configuration	PI	FPI	PI / FPI	Fuzzy	PI / FPI	Fuzzy

The lower-level controllers are consistent with those discussed in the prior section, with the subsequent insertion of a supervisory Fuzzy controller.

6.2.1 Lower level model and controller (PI & FPI)

The dynamics around the operating point can be adequately represented by a linear model, despite the highly nonlinear nature of the process. The identified form of Integer Order (IO) model of SBR is shown in the below format,

$$\boldsymbol{G(s) = \frac{0.0016434}{s + 0.0003856}\ e^{-0.96*s}}$$

To implement a lower level controller in the form of PI and FPI structures, a FOPDT model of the SBR process is identified. This considered control loop uses a PI controller to control the DO in the SBR. Figure 6.1 depicts the plant layout with PI and FPI controllers. SIMC rules are deployed to design the controllers (Grimholt & Skogestad 2018). The tuned Parameters of PI controller using SIMC are

Kc =316.9243, Ti=7.86, and Ki = (Kc/Ti) = 40.32.

So, the final PI controller structure for DO loop is shown below,

$$\boldsymbol{C_{DO}(s) = [316.9243 + \ 40.32\frac{1}{s}]}$$

To identify a fractional model (FO), fractional derivatives are evaluated utilising the Grunwald-Letnikov method with the corresponding approximations utilising the Oustaloup filter. Fixed unity gain and a fractional pole polynomial are used to identify the model. The identified Fraction model G_{FO}(S) of SBR comes as written in below format,

$$\boldsymbol{G_{FO}(s) = \frac{1}{0.80739s^{0.8955} - 16.77s^{0.11936} + 23.319S^{0.077491}}}$$

The FPI controller is tuned by choosing the minimum and maximum values for all tuneable parameters like Kc, Ki, and λ. The tuned parameters such as

Kc = 349.99, Ki = 49.95, and λ= 0.9796.

The obtained FPI controller for DO loop is shown below,

$$\boldsymbol{C_{DO}(s) = \left[349.56 + \ 49.956\ \frac{1}{s^{0.9796}}\right]}$$

6.2.2 Higher level FUZZY Logic Control

FUZZY logic has become a popular strategy for a variety of control options. FLCs have been employed at all phases of wastewater treatment. The literature says, fuzzy control or rules (FLC) are frequently employed to solve the most modern control and processing elements in WWTPs. Fuzzy rules are used to accomplish this, much like those used when humans make inferences. In this study, FLC is employed on this SBR-based WWTP. The set-point for DO value in the SBR is controlled at a higher level with a fuzzy controller to track variable DO set point in SBR by measuring Ammonia and nitrate. Figure 6.2 depicts the plant layout with PI and FPI controllers at lower level and an intelligent fuzzy logic controller at the supervisory level.

SNH are controlled through the manipulation of DO set-points by the fuzzy control at a supervisory level. The ranges examined for the membership functions of S_O and S_{NH} / S_{NO} are 0-2 mg O2/l and 0-16 mg N/l, respectively. As a membership function for both variables, a Gaussian curve (gauss2mf) is chosen and is separated into two linguistic variables, "Low" and "High". The idea of choosing this fuzzy logic comes from the basics of ON-OFF controller, where the variation of the measured variable lies in between two states either low or high. In the batch process of SBR, the influent flow is restricted for one cycle of operation and then the presence of the measured variable is also limited in these two forms. The main principles for the DO Control loop utilising ammonia readings are as follows:

- If Ammonia content is “Low” then the DO content is also “Low”.
- If Ammonia content is “High” then the DO content is “High”.

The rules for the Dissolved Oxygen Control loop considering nitrate readings are as follows:

- If Nitrate content is “Low” then the DO content is “Low”.
- If Nitrate content is “High” then the DO content is “High”.

These rules are used to evaluate the integrated lower and higher level (PI/FPI-Fuzzy) controllers.

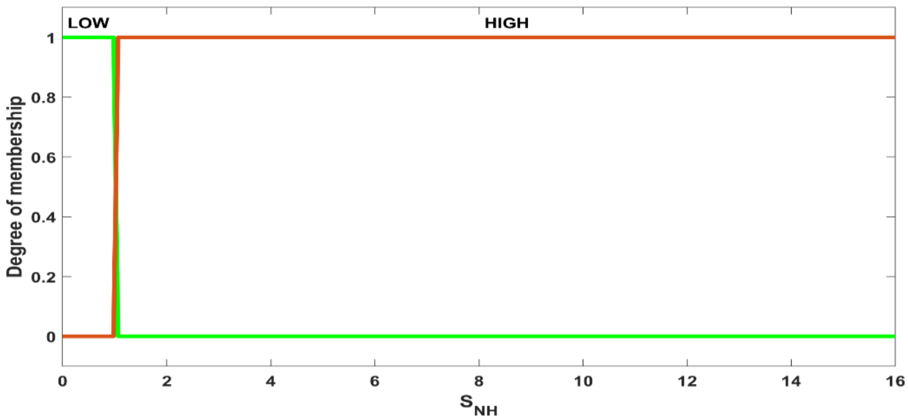
6.3 Results and discussions

For the SBR-based WWTP, the described control strategies are designed and implemented. The corresponding closed-loop performances of the WWTP with its performance indices are analysed. The lower level controller setting as described at earlier section 6.2.1

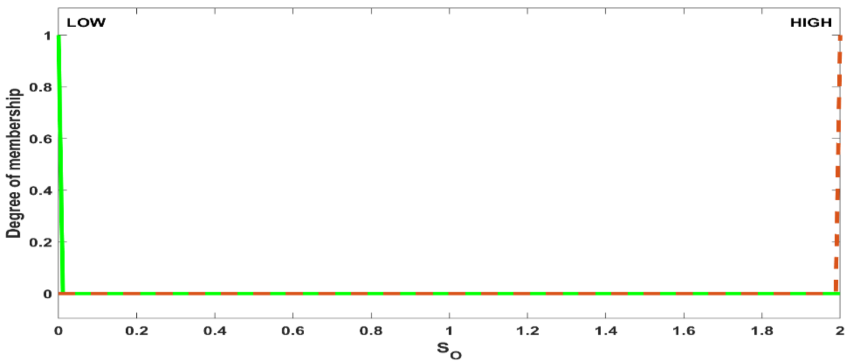
6.3.1 Higher level controller as ammonia based control (CS3 and CS4)

These CS3 and CS4 control strategies use a simple PI or FPI configuration at the lower level strategy and an intelligent Fuzzy controller at a supervisory level during this aeration phase of SBR. For supervisory control structure, intelligent computing techniques, such as fuzzy logic, are indeed a good choice (Fiter et. al, 2005). In the batch process of SBR, the influent flow is restricted for one cycle of operation. So in one operational phase, volume of influent is fixed. The idea of choosing a two membership fuzzy function originated from the foundation level where an ON-OFF controller can operate with two diverse states as Low and High. Here inside the SBR at running period the presence of NH or NO are in two possibilities, either high at initial or low after utilization. The higher level fuzzy controller computes the DO values (lower-level set points) by using the measurements of NH or NO in the SBR. These DO values are used as set points in the lower level DO loop. As a result, the higher-level control loop assists in determining the lower loop's set points. This is well established ammonia based aeration control (ABAC). In CS3, a lower level controller is PI and Fuzzy is at supervisory level. Respective Input range & output range are set to 0-2 mg O2/l and 0-16 mg N/l. Importantly, the membership curves are considered to be Gaussian bell shaped. An adequate amount of DO is necessary for optimal ammonia-to-nitrite oxidation so that it does not wash out before nitrification occurs. The ammonia set value is provided as 1 mg N/l as a lower ammonium value requires a low oxygen demand.

In SBR batch reactor, with a stagnant capacity of influent, the variation or changes in these two (NH or NO) measuring components are limited with high or low profile. So when we choose a fuzzy membership function we make it in two memberships 'HIGH' and 'LOW. Thus, the membership patterns of ammonia profile in SBR are created by treating 0-1 mg N/l as "Low" ammonia quantity, 1-16 mg N/l as "High", at membership value one, as shown in Figure 6.3 A. For the DO, values less than 0.01 mg O2/l are certainly low, hence they are allocated a membership value of 1 to the fuzzy set "low." This is congruent with the concept of membership, which defines the importance of a variable's connectedness to a fuzzy set. DO values more than 1.99 mg O2/l are measured as "High". Figure 6.3 B clearly demonstrates this. The main objective of employing this approach is to adjust the DO set-point in response to variations in the ammonia concentration within the SBR. The simulations use the original nonlinear model as a foundation. In this control method, Figure 6.4 A portrays the variable DO set-point given by the higher level and tracked by the lower level PI controller (CS3). Figure 6.4 A displays that maintaining the DO set-point at 2 mg O2/l for the whole duration, as explained in lower level DO control technique, is unnecessary. Figure 6.4 B shows the plot of manipulated variable by lower level controller. When ammonia concentrations are low, the requirement for DO is lower, hence energy may be lost in an effort to maintain the set-point. Additionally, there are situations when a greater quantity of DO is necessary; in certain cases, a shortage of DO may degrade effluent quality. As a consequence, a changeable set-point via Fuzzy Controller results in greater plant performance in terms of fewer air needs.



(A)



(B)

Figure 6.3: (A) MF of input for ammonia (S_{NH}) concentration (Lower level PI/FPI -Fuzzy); (B) MF of output for DO (S_O) concentration (Lower level PI/FPI -Fuzzy)

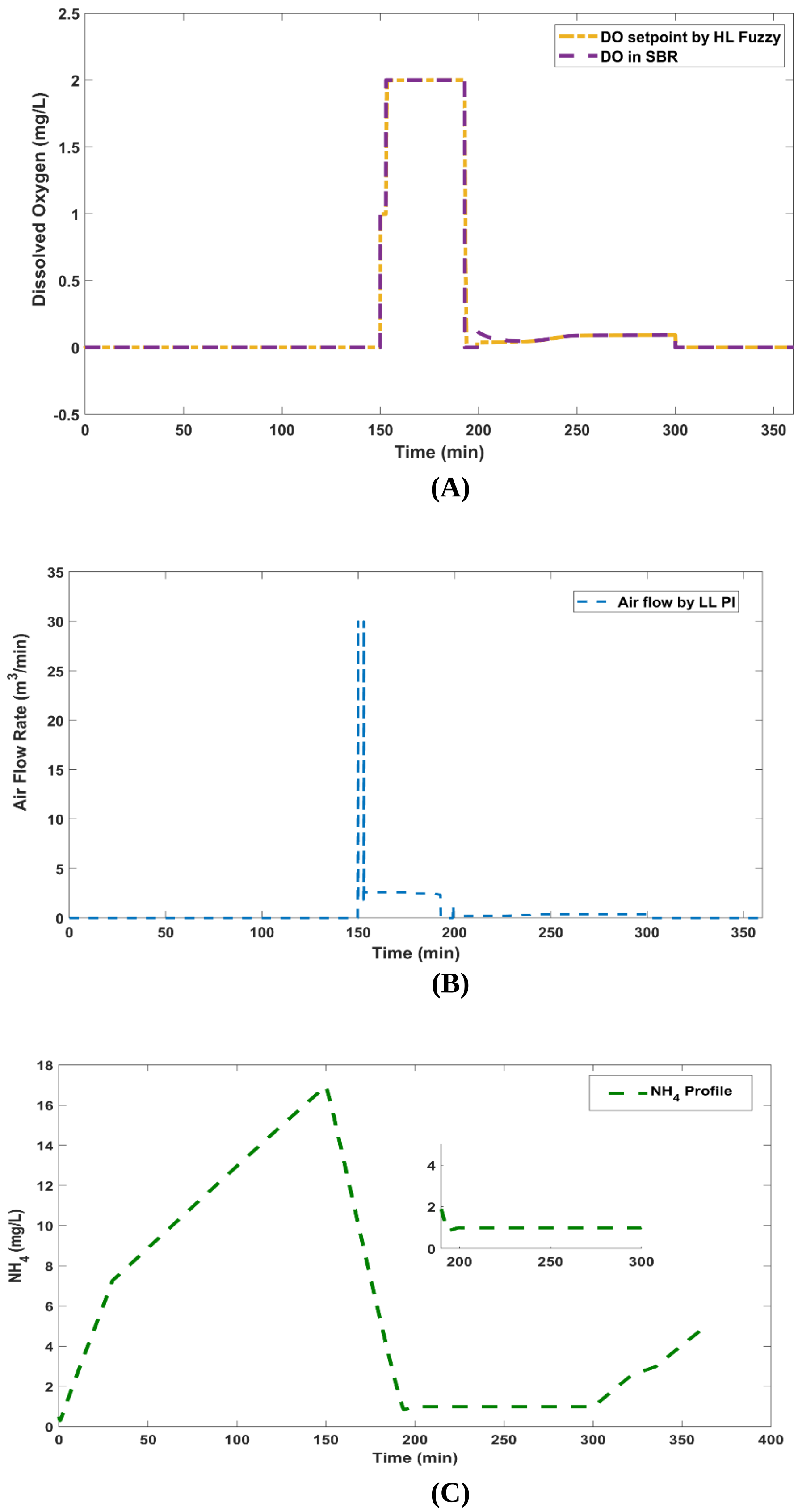
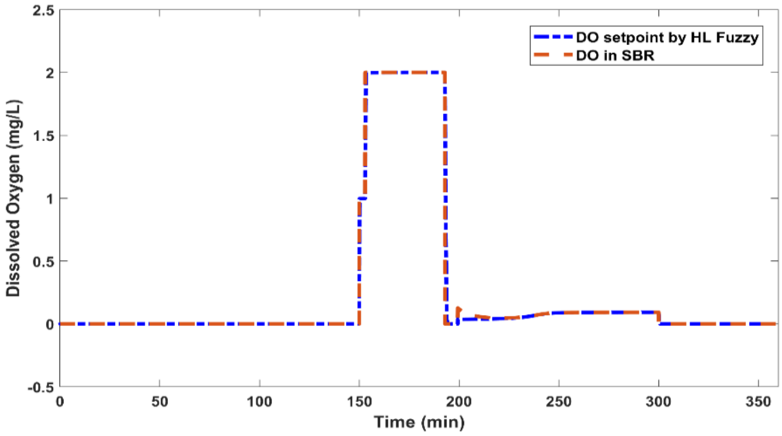
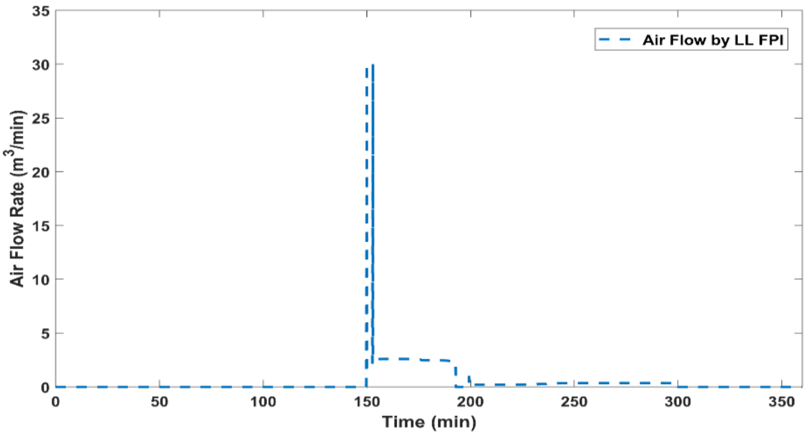


Figure 6.4: (A) variable DO set point tracking in higher level (HL) control strategy; (B) Airflow by lower level PI controller as manipulated variable; (C) NH4 profile in SBR



A



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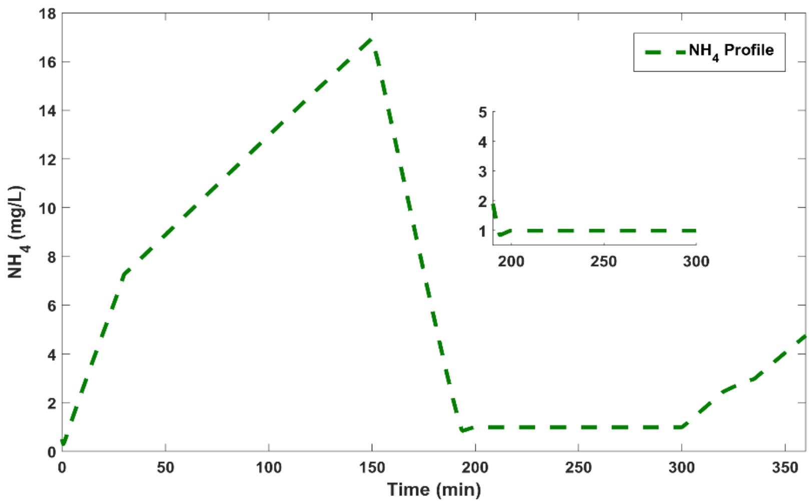


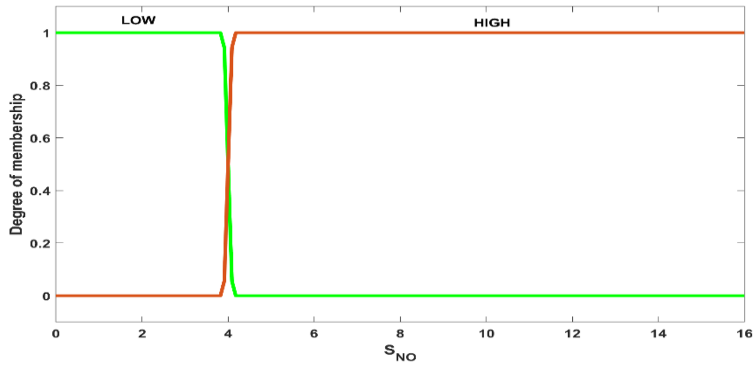
C

Figure 6.5: (A) DO set point tracking in higher level (HL) control strategy; (B) Airflow by lower level FPI controller as manipulated variable; (C) NH4 profile in SBR

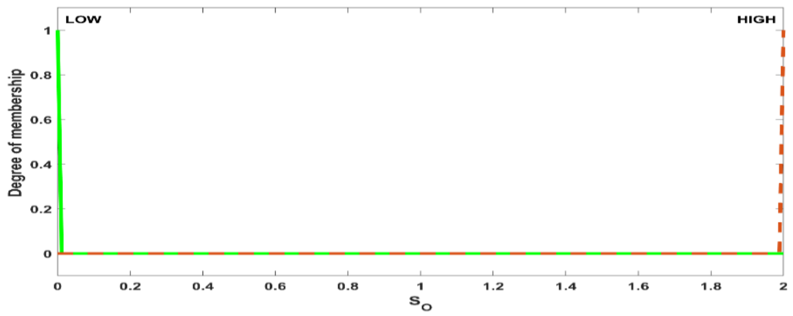
CS4's control strategy is fairly similar to that of CS3. However, in this case, the PI controller at lower level is substituted by FPI controllers. When compared to traditional PI controllers, FPI contains an additional tuning parameter, and tuning is done as described in CS2. The same fuzzy rule base is used to check the effect of this Fractional PI controller. A lower level control based on fractional PI coupled with a higher level control strategy improves tracking. The adaptable DO set-point and tracing via FPI-Fuzzy setup are shown in Figure 6.5A. Figure 6.5 A shows that the DO set-point is not a continual function and fluctuates as needed. This rises when nitrification in the aerobic time phase requires more DO, and it falls when ammonia content in the SBR tank is low. Figure 6.5B displays the manipulated variable plot in terms of AIR Flow by lower level controller. This dynamic DO set-point is very effectively traced by the lower level Fractional PI controller, and the arrangement of these two methodologies results in more effective and energy-tradeable operation in terms of aeration and concern to controller performance and EQI, as shown in Table 6.2. The plot of ammonia profile in both this control strategy is also presented in Figure 6.4 C and 6.5 C respectively.

6.3.2 Higher level controller as nitrate control (CS5 and CS6)

Similar to ammonia control, a higher-level control strategy is implemented in SBR to use Nitrate (NO_3) in order to minimize DO utilization during aeration. Both PI and FPI controllers are used in lower level in CS5 and CS6 control strategy respectively with a supervisory level fuzzy controller. The S_{NO} which is produced during nitrification can be utilised as an oxygen source to minimize the aeration cost as fresh air supply to the SBR tank can be minimized. Same time effluent quality is also improved. The set point for Nitrate in SBR is fixed at 4 mg N/l as a higher value of nitrate can be present in SBR tank to replace use of fresh oxygen. For higher level fuzzy control, each input and output range is fixed to 0-2 mg O_2/l and 0-16 mg N/l, respectively. A Gaussian bell-like curve is taken to represent the membership's shape. Thus, the membership patterns of S_{NO} concentration in SBR are created by treating 0-4 mg N/l as a "low" nitrate value, 4-16 mg N/l as a "high" with membership value 1, as shown in Figure 6.6 A. For DO, values less than 0.01 mg O2/l are certainly low, hence they are allocated a membership value of 1 to the fuzzy set "low." This is congruent with the concept of membership, which defines the value of a variable's connectedness to a fuzzy set. DO values more than 1.99 mg O_2/l are decided high. Figure 6.6 B clearly demonstrates this.



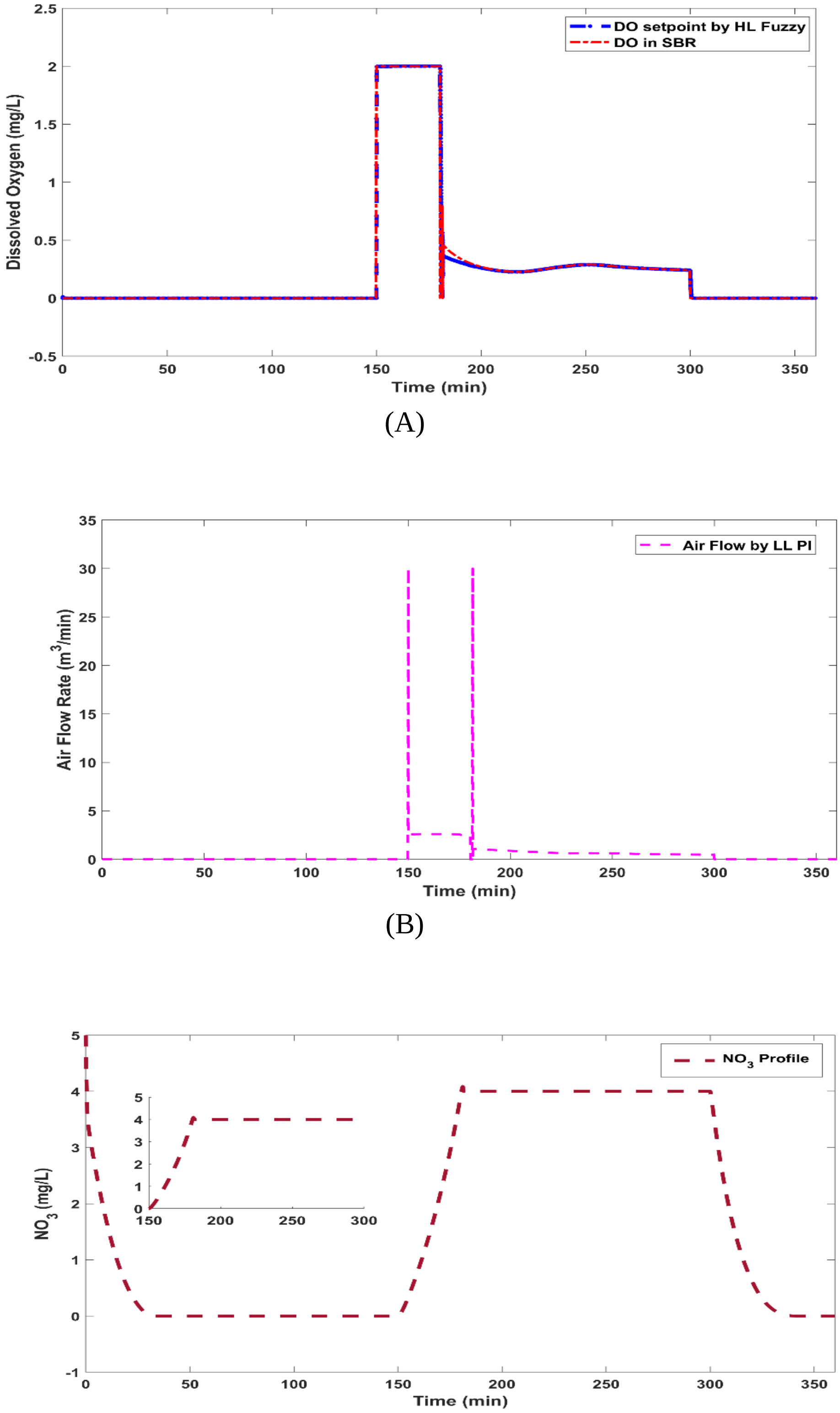
(A)



(B)

Figure 6.6: (A) MF of input for Nitrate (SNO) concentration (Lower level PI/FPI -Fuzzy); (B) MF of output for DO (S_O) concentration (Lower level PI/FPI -Fuzzy)

The main goal of implementing this scheme is to reduce the absorption of fresh oxygen because S_{NO} produced during nitrification may only be used for aeration purposes, hence minimising the aeration cost. A lower level FPI control with higher level fuzzy with same membership function is also implemented in CS6. In those control methods, Figure 6.7A and 6.8A depict flexible DO set values provided by superior level fuzzy and it's tracking in by bottom level PI (CS5) and FPI (CS6) control respectively. Both cases have noticeable improvement in controller performance criteria as well as good set-point tracking and reduced effluent quality, tabulated in Table 6.2. The Figure 6.7B and 6.8 B show the manipulated variable plots of AIR-FLOW to vary DO by lower level PI and FPI controller. The set value of Nitrate in SBR is at 4 mg N/l, nitrate profile in SBR is shown in Figures 6.7 C and 6.8 C in CS5 and CS6 respectively.



(A)

(B)

(C)

Figure 6.7: (A) DO set point tracking in higher level (HL) control strategy; (B) Airflow by lower level PI controller as manipulated variable; (C) NO3 profile in SBR

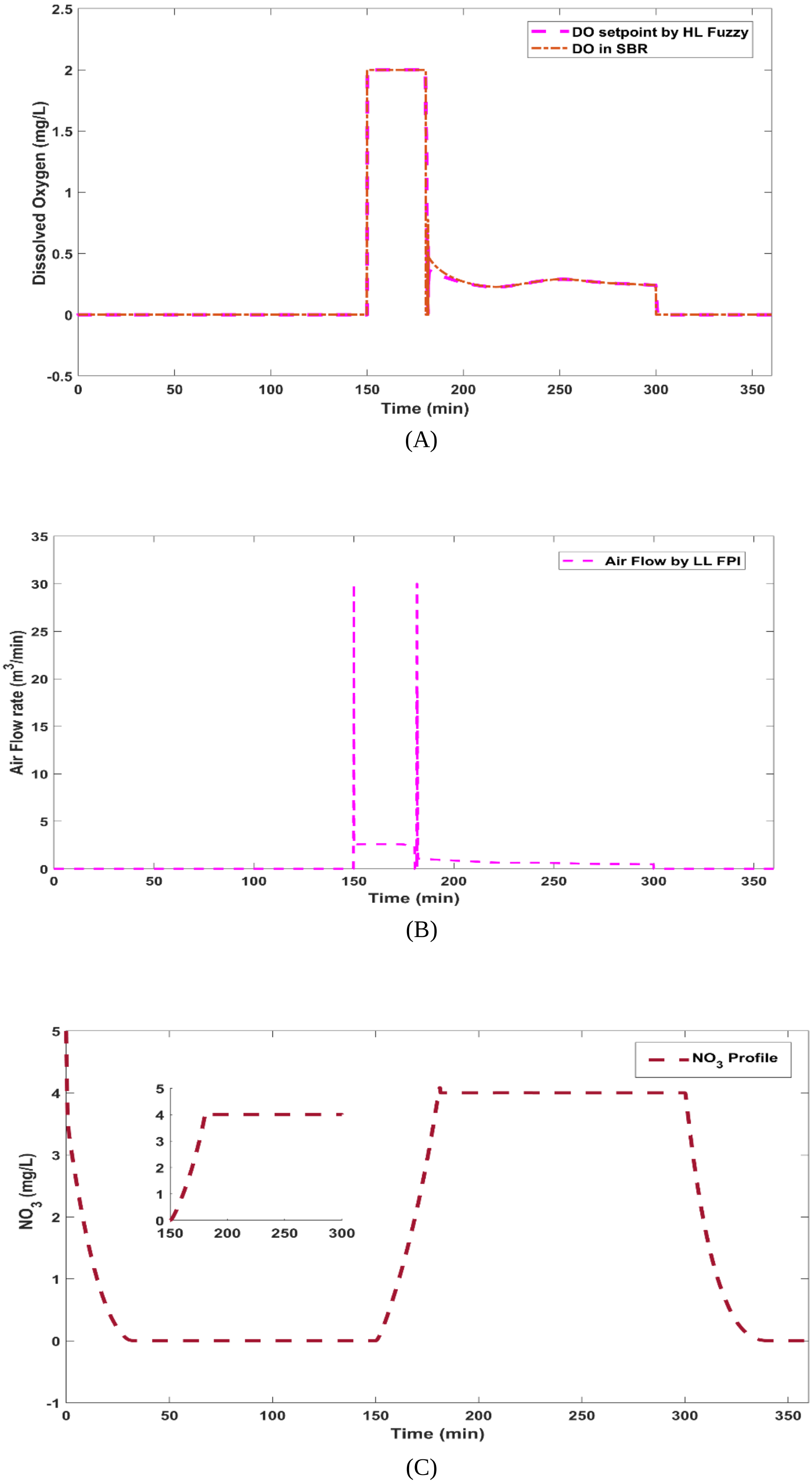


Figure 6.8: (A) DO set point tracking in higher level (HL) control strategy; (B) Airflow by lower level FPI controller as manipulated variable; (C) NO3 profile in SBR

Table 6.2: Effluent quality in SBR with controller performance

Performance Index	Lower level		Ammonia (NH_4) based Supervisory Level controller		Nitrate (NO_3) based Supervisory Level controller	
	PI (CS1)	FPI (CS2)	LL PI+HL Fuzzy (CS3)	LL FPI+HL Fuzzy (CS4)	LL PI+HL Fuzzy (CS5)	LL FPI+HL Fuzzy (CS6)
IAE	0.1057	0.08732	1.442	1.431	1.683	1.618
ISE	0.05673	0.05669	0.8446	0.8374	1.442	1.03
Total Airflow volume (l)	231.8	231.8	138.9	138.9	158.6	158.6
COD (mg/l)	52.2850	52.0073	52.1965	51.9872	52.2851	52.2975
BOD (mg/l)	13.1205	12.9816	13.1175	12.9800	13.1200	12.9776
TN (mg/l)	3.0015	2.9658	3.0012	2.9257	3.0013	2.9262
TP (mg/l)	2.2675	2.2492	2.2224	2.2109	2.2424	2.2265
TSS (mg/l)	11.5721	11.3146	11.5655	11.2855	11.5670	11.3002
NH_4 (mg/l)	1.8200	1.8186	1.8195	1.8095	1.8257	1.8157
IQI (kg polls units/day)	0.7684	0.7684	0.7684	0.7684	0.7684	0.7684
EQI (kg polls units/day)	0.0578	0.0573	0.0576	0.0570	0.0577	0.0573

As part of this HL control configuration, ammonia concentration is sustained at a predetermined level of 1 mg N/l. For improved plant performance, it calculates the level of DO essential according to the ammonia concentration and permits it down to the lower level as a set-point. Based on the two linguistic variables that describe the input & output variables, and the fuzzy controller analyses the control action. Figures 6.4A, 6.5A, 6.7A, and 6.8 A illustrate variable DO set-point tracking, whereas Figures 6.4 C, 6.5C, 6.7C, and 6.8C depict ammonia concentration set-point tracking by higher level Fuzzy in all control techniques CS3, CS4, CS5, and CS6, respectively. Observation indicates lower level controllers are adept at tracking the variability of the DO set-point pattern. SBR ammonia concentration affects the DO set-point. Variations in airflow will affect the required operational energy of plant more, so reducing the air supply will lead to a decrease in aeration cost. It is also found that all the proposed strategies yield similar results. According to Table 6.2, hierarchical control approaches are compared with lower level control strategies. In comparison to lower-level PI and FPI strategies, the proposed strategies result in better overall airflow consumption (Q_{Total}) and EQI index for SBR, while at the same time increasing controller performance. Despite maintaining set-points for NH_4 and NO_3, all supervisory control strategies produced different results. From the results in Table 6.2, at lower level control loop, the FPI controller with two extra tuning parameters can give lower IAE with 17.39% improvement and also improve EQI by 0.87% compared with PI controller.

As mentioned earlier, the main focus of this study is to minimize the aeration cost by minimizing the total air volume consumed. Less air consumption has been shown as a result of implementing the hierarchical fuzzy controller with lower level PI and FPI controller. Airflow is decreased by 40.08% as given in Table 6.2 by ammonia control strategy and 31.58% by nitrate control strategy with the addition of fuzzy controller at supervisory level. The amount of TN in effluent is also reduced by 1.19% by implementing FPI controller compared with PI controller and when the same fuzzy logic control is applied to this lower level controller FPI-Fuzzy (CS4) a reduction of 2.52% in TN is noticed compared with PI-Fuzzy (CS3) in ammonia-based control. In the case of TP, lower level FPI gives a 0.81% reduction compared with lower level PI (CS1) and with higher order Fuzzy 1.99% reduction noticed in PI-Fuzzy (CS3) when compared with CS1. Comparing lower level FPI (CS2) with higher level FPI-Fuzzy (CS4) a reduction of 1.70% has been noticed in the case of ammonia based aeration.

Now in nitrate based aeration, the main objective is to minimize fresh oxygen use and force the microbes to use compound oxygen in form of nitrate (NO3). Table 6.2 shows a good amount of reduction in total air volume, apart from that both this nitrate based higher level strategy (CS5 and CS6) also impacts on TN and TP removal and improves EQI also. Overall the ammonia control strategy is more effective in both EQI and aeration cost by minimizing air flow without affecting the effluent quality.

6.4 Conclusions

A biological WWTP based on SBR is modelled with a modified ASM2d framework and then simulated for DO control during aeration phase using real-time data from the Vizag WWTP in 30°C Indian climates. The main attention is to maintain DO in SBR during 150 to 300 minutes of one cycle of batch operation. Further, ammonia and nitrate based supervisory fuzzy control is implemented with lower level PI and FPI controller for better effluent quality and lesser aeration cost by providing precise airflow to the SBR reactor during aeration. A total of six control strategies are implemented including two DO controllers in the lower level and four hierarchically arranged nitrates and ammonia controllers employing fuzzy logic. A fractional controller with lower level DO control gives better EQI and Controller performance. Attaching an intelligent fuzzy control cascaded with PI and FPI controller greatly affects effluent quality as well as troughs air consumption which minimizes the aeration cost. With the addition of a fuzzy controller at supervision level, ammonia control strategy has less airflow of 40.08%, and nitrate control strategy has less airflow of 31.58%. In nitrate-based aeration, the main objective was to limit the use of fresh oxygen and force microbes to use compound oxygen in the form of nitrate. This nitrate-based higher level strategy (CS5 and CS6) reduces total air volume intake, helps to remove TN and TP and improves EQI. Finally, the present study concludes that by minimizing airflow without affecting the effluent quality, the ammonia control strategy with lower level FPI controller is more efficient in terms of both EQI and aeration cost. A low volume industries or domestic wastewater treatment facilities can take advantage of this low cost aeration approach incorporating a conventional SBR technologies.

Chapter 7

Chapter 7

7. INFLUENCE OF SEASONS ON THE EFFLUENT QUALITY IN SEQUENCING BATCH REACTOR BASED WASTEWATER TREATMENT PLANTS

The temperature has a significant impact on the performance of the microorganisms used in BNR. The ideal temperature for BNR is usually between 25°C and 35°C, with some variations depending on the microorganisms used. The activity of the microorganisms responsible for BNR decreases at lower temperatures, resulting in slower nutrient removal rates. This can result in a longer retention time in the treatment system and a larger treatment plant footprint. Higher temperatures increase microorganism activity, which can lead to higher nutrient removal rates but also increases the risk of operational problems such as foam formation or toxic substance accumulation. Temperature can affect the composition of the microbial community as well as the performance of the microorganisms, with different microorganisms becoming dominant at different temperatures. As a result, when selecting microorganisms for BNR, the temperature range of the wastewater to be treated should be considered. With strict discharge restrictions and a variety of treatable influents, temperature management in biological wastewater treatment processes has received minimal attention. As a result, the above processes function at ambient temperatures, and the corresponding rates reduce effectiveness due to seasonal variations. According to a study, the effluent quality showed a positive resemblance with temperature in the range of 10 to 30 °C, regardless of the sludge settling characteristics or solids retention time (SRT) (Collins et al. 1978). When nitrification and de-nitrification occur concurrently at high temperatures greater than 25 °C, nitrogen is removed from the system (Görgün et al, 2007).The effects of temperature on the flocculent settling in the activated sludge process were investigated at temperatures ranging from 15 to 35 degrees Celsius (Ghanizadeh et al, 2001). It was found that as the temperature rose, chemical oxygen demand removal percentage decreased and the concentration of suspended solids in effluent increased. The nitrogen separation efficiency of tannery wastewater analysed in an SBR over a broad range of temperatures of 9 to 30 °C was evaluated in a study (Murat et al, 2003) and the effluent limits achieved are noted for the temperatures above 20 °C. Temperature is believed to be one of the primary tangible factors impacting nutrient removal efficiency because it impacts the rate of metabolism directly (Azeez et al, 2010). The impact of temperature on wastewater and organic element treatment in wastewater is explored and rising the temperature results in a considerable improvement in the reduction of suspended solids and COD (Ahsan et al, 2005).

7.1 Materials and Methods

7.1.1 Influent Data

This section gives clarification of the working scheme of the SBR process with a modified ASM2d model. Our work is on modelling and studying the effect of temperature on biological processes and for this purpose, we have used an SBR-based biological process. After successful modelling utilizing the ASM2d model, we have validated our SBR simulation model with real plant data by giving Indian wastewater influent, collected from Visakhapatnam WWTP in India, irrespective of the type of treatment technology (Tejaswini et al, 2021). To study the seasonal temperature variation globally, we have also observed the SBR process with European influent data (Valverde-Pérez et al, 2016). State variables and particulate symbols with descriptions are in the Table 5.3 in chapter 5.

Table 7.1: Influent load data as reported from Visakhapatnam WWTP and European climate

Indian climate (Vizag WWTP)	Influent Load	European climate (Borja 2016)
381.99	**COD_i**	711.99
219.1083	**BOD_i**	420.05
41.5992	**TN_i**	79.01
11.0751	**TP_i**	16.17
27.58	**$NH4_i$**	54
238.92	**TSS_i**	430.5045

7.1.2 Treatment plant description and Simulation model

SBRs perform biological pollutant removal in the second phase of WWTP. Unlike an ASP process, an SBR does not have any clarifier. To purify sewage sediments and minerals, mechanical pre-treatment is used. The first step uses the grid, screen, grit chamber, and sand separator. Figure 7.1 A depicts the EBPR process of SBR and in Figure 7.1B its phase's layout. A single SBR cycle consists of the following phases: filling, biological reactions (aerobic, anoxic and anaerobic), sedimentation, decantation, and idling. A settler model which is incorporated for better effluent quality during settling. The double exponential settling velocity of the secondary settler model by is used (Takács et al, 1991). The corresponding mathematical modelling and layout of the settler (Figure 1.16) are reported in section 1.3.2. The most widely used mathematical representation of biological processes in WWTPs is Activated Sludge Models (ASM), a series established by the International Water Association.

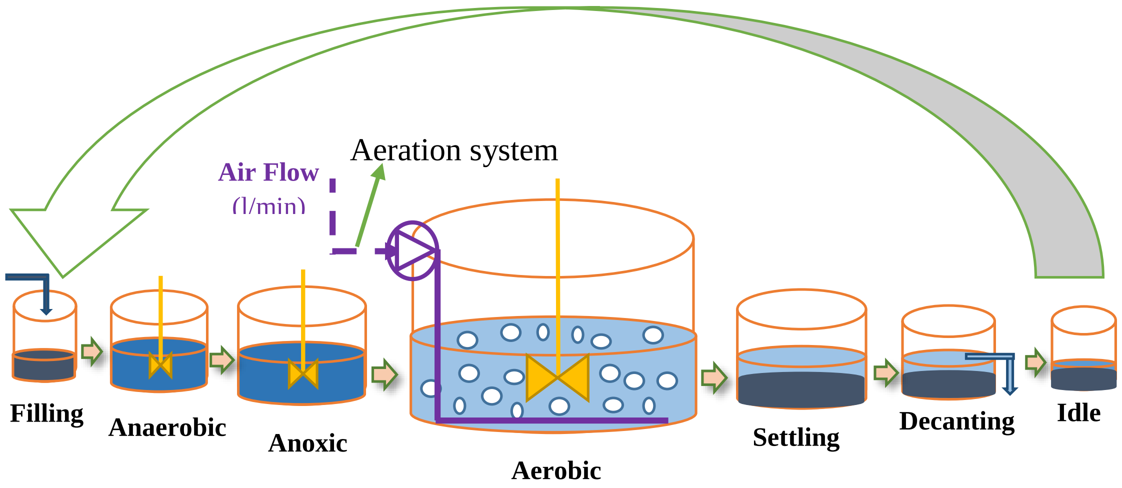


Figure 7.1: The EBPR process of SBR and its phase layout in a single cycle of the SBR phases

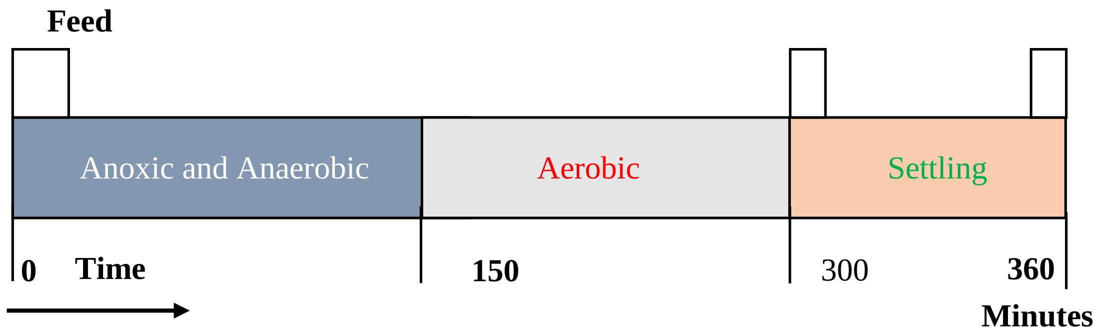


Figure 7.2: Time sequences in model SBR

The ASM2d model is used to model the biological EBPR processes of the SBR in this study, which has 21 state variables and 20 kinetic and stoichiometric parameters (Gernaey et al, 2014 and Henze et al, 1999). ASM2d is a minor ASM2 expansion. Two other processes must be considered: poly-P storage and anoxic growth. PAOs in ASM2 can store polyphosphate (poly-P) and only grow in aerobic environments. ASM2d, on the other hand, includes a denitrifying PAOs metabolism simulation for poly-P growth and storage. ASM2d suffers from the same confines as ASM2. The literature provides more information about the ASM2d model (Henze et al, 2000). By using kinetic & stoichiometric coefficients for all parameters & presenting them in matrix format, metabolic processes depending on Monod kinetics are described. The access to the stoichiometric coefficients is simple due to the use of matrix notation. As a result, calculations maintain their mass balances as intended. The method for model preparation of

ASM2d is elucidated in Henze et al, 2000. The processes involved in ASM2d are pictured in Figure 7.3.

Table 7.2: Influent in terms of state variables of two global locations

State variable	S_F	S_a	S_i	S_{NH}	S_h	S_{no}	S_{PO4}	S_{alk}	X_i	X_S	X_{bh}	X_{pao}	X_{PP}	X_{PHA}	X_A	X_{TSS}	X_A	X_{MEP}	X_{MEOH}
Indian Influent	21.10	31.9325	19.855	27.58	0	0	7.30	7	59.58	202.23	47.30	0	0	0	0	231.84	0	0	0
European Influent	87.33	15.41	34.25	54.00	0	0.25	9	7	260	260	55	0	0	0	0	439	0	0	0

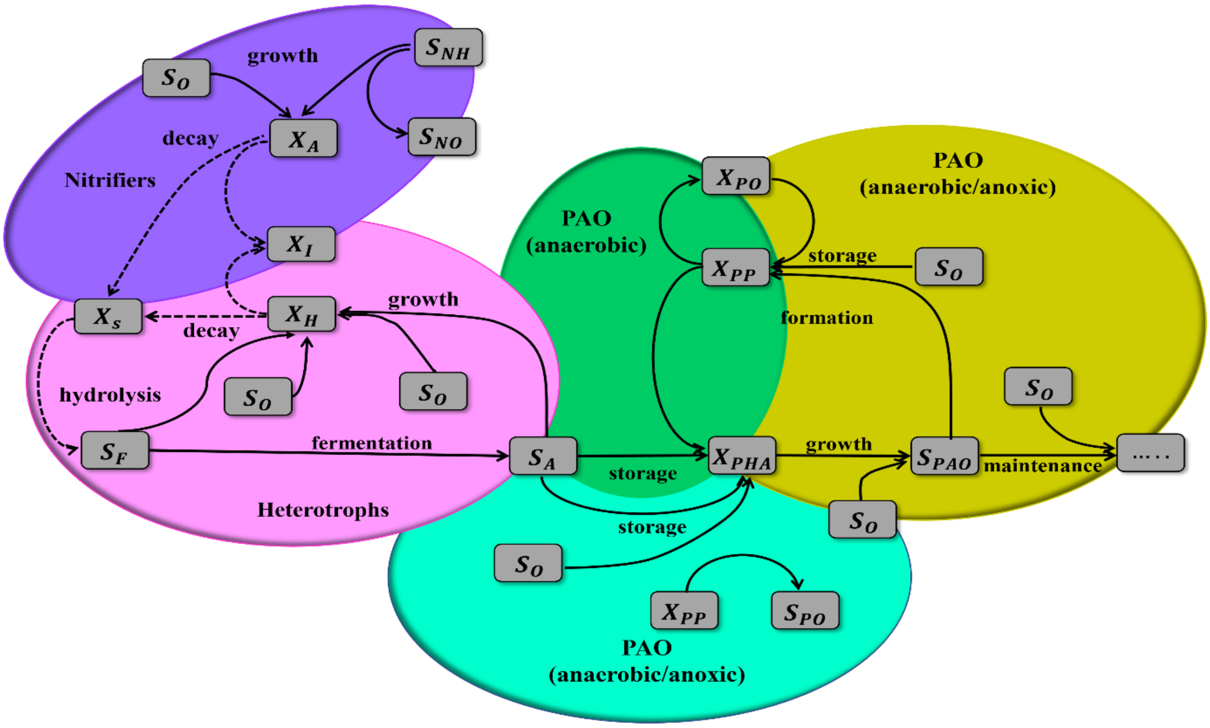


Figure 7.3: ASM2d processes have included in SBR

The model becomes rather complicated because of including EBPR and phosphorus accumulating organisms (PAO) in ASM, as shown in the Figure 7.3. The figure's left side illustrates the conversions that are done by nitrifiers and regular heterotrophs, while the other side illustrates the extension required to describe the intricate physiology of PAO. The nitrifiers and typical heterotrophs oxidise their substrate with oxygen to produce CO2, nitrate, and biomass. Their relatively straightforward physiology leads to straightforward processes. Internal storage polymers (poly-hydroxy-alkanoate: PHA, poly-P) are a part of PAO physiology, and their behaviour under anaerobic, anoxic, and aerobic conditions varies. In aerobic environment, they also react differently based on whether the substrate is available or not. The flow along with COD, TSS, and ammonia concentrations of influent is collected from the Vizag plant to validate SBR process in Indian climatic conditions (shown in Table 7.2). The average value of all state variable apart from some dummy variable of each influent is tabulated in Table 7.2. (The full form with unit is mention in Table 7.3). The STOWA guidelines are used to compute the state variables, which contain the dynamic data needed to implement different strategies for the treatment plant. The operating parameters of the SBR are described in Table 3, and sludge gets added to the initially empty 4 L of the SBR tank, it's initial sludge parameter is reported in Table 4 [6].

Table 7.3: state variables with their symbols and units.

State variable	Unit	Initial value	Range
Dissolved Oxygen (S_{O2})	[g-O2/m^3]	0.01	(0-4)
Rapidly biodegradable organic substrate (S_F)	[g-COD/ m^3]	0.1	
Fermentation products (S_A)	[g-COD/ m^3]	10	(0-10)
Ammonium nitrogen + ammonium ions (S_{NH4})	[g-N/ m^3]	0.5	
Nitrites (S_{NO2})	[g-N/ m^3]	5	
Nitrates (S_{NO3})	[g-N/ m^3]	5	(5-10)
Soluble inorganic phosphorus (S_{PO4})	[g-P/ m^3]	0.4	
Soluble inert organic material(SI)	[g-COD/ m^3]	30	(10-100)
Alkalinity (S_{ALK})	[mol HCO3-/ m^3]	20	(10-20)
Particulate inert material (X_I)	[g-COD/ m^3]	25	
Slowly biodegradable substrate (X_S)	[g-COD/ m^3]	25	
Heterotrophic biomass (X_H)	[g-COD/ m^3]	1547.17	(1000-2000)
Phosphorus-accumulating biomass (X_{PAO})	[g-COD/ m^3]	600	
Polyphosphates (X_{PP})	[g-COD/ m^3]	150	(10-20 %XPAO)
Organic compounds inside the biomass cell (X_{PHA})	[g-COD/ m^3]	100	(10-20 %XPAO)
Autotrophic biomass(Nitrosomonas) (X_{ns})	[g-COD/ m^3]	80	
Autotrophic biomass(Nitrobacter)(X_{nb})	[g-COD/ m^3]	50	
Metallic hydroxides (X_{MeOH})	[g-Fe(OH)3/ m^3]	10	
Metallic polyphosphates (X_{MeP})	[g-FePO4/ m^3]	10	
Initial volume	L	4	

* The Particulate material is represented by the symbol X, and S is used to represent the soluble substance

The influent content as a composite form are shown in the equations

$$\mathbf{COD_{in}} = [S_F + S_A + S_I + X_I + X_S + (X_H + X_N) + X_{NS} + X_{NB} + X_{PAO} + X_{PHA}] \quad (7.1)$$

$$\mathbf{BOD_{5\,in}} = [0.65*(S_F + S_A + X_I + (0.9*X_S) + 0.9*(X_H+X_N) + X_{PP} + (0.9*X_{PHA}))] \tag{7.2}$$

$$\mathbf{NH_{3in}} = [S_{NH4}] \tag{7.3}$$

$$\mathbf{TN_{in}} = [(X_I*iNX_I) + (X_S*iNX_S) + S_{NH4} + (S_F*iNS_F) + (S_I*iNS_I) + (X_H+X_N) + X_{PAO} + X_{NS} + (X_{NB}*iN_{BM})] \tag{7.4}$$

$$\mathbf{TP_{in}} = [(Xs*iPX_S+) + (X_I*iPX_I) + S_{PO4} + (S_F**iPS_F) + (S_I*iPS_I) + (X_H+X_N) + X_{PAO} + X_{NS} + (X_{NB}*iP_{BM})] \tag{7.5}$$

$$\mathbf{TSS_{in}} = [X_{MeP} + X_{MeOH} + (X_I*iTSSX_I) + (X_S*iTSSX_S) + (X_H+X_N+X_{PAO})*iTSS_{BM} + (3.23*X_{PHA}) + (0.6*X_{PP})] \tag{7.6}$$

Where, iNX_I, iNX_S, iNS_F, iNS_I, iN_{BM}, iPX_I, iPX_S, iNS_F, iPS_I, iP_{BM}, $iTSSX_I$, $iTSSX_S$, $iTSS_{BM}$ are the conversion factor according to the ASM2d [24].

7.2 Temperature assessment

Irrespective of every aspect that has been taken into account, temperature seems to be the most uncertain, especially in open environments. After collecting influent data we performed kinetic parameter calculations with varying temperatures. At 20 °C the values of those parameters are the same as their default values (Henze et al, 2000). Temperature effect on kinetic parameters given by equation as follows (Gernaey et al, 2014):

$$\alpha_T = \alpha_{T_{20}}.\exp\left(\left(\frac{\ln\left(\frac{\alpha_{T_{20}}}{\alpha_{T_{10}}}\right)}{5}\right).(T-20)\right) \tag{7.7}$$

Where α_T the considered parameter temperature (T) value and $\alpha_{T_{20}}$, $\alpha_{T_{10}}$ is the defined benchmark parameter values at 10 °C and 20° C (Henze et al, 2000). Based on the equation (7.7) we have calculated the kinetic parameters in a range of temperatures to evaluate the Indian climatic conditions. The influent flow rate of simulated SBR - 0.033 l/min (Marsili Libelli et al, 2001). Average influent data with state and particulate variables with symbols are reported in section 5.2.2. Temperature influences aeration efficiency and consequently energy utilization through airflow and S_O^{satu}. Temperature influences oxygen solubility, which rises as the temperature falls. The S_O^{satu} is valid in the range of 273.15 to 348.15 K.

$$S_O^{satu}(T) = \frac{8}{10.50237016} * 6791.5 * K(T_k) \tag{7.8}$$

$$K(T_K) = 56.12e^{-66.7354+\frac{87.4755}{T^*}+24.4526*\ln(T^*)}$$

$T^* = T_k/100$, The term 8/10.50237016 is denoted as S_O^{satu} value at 15°C is exactly 8 mg/L.

A steady state simulation is executed to analyze the effluent concentrations at a temperature range of 10– 33 °C. The foremost work of temperature analysis of the SBR Process is to measure the impact of temperature on the kinetic parameters. Table 7.4 provides a list of the kinetic parameters observed in the SBR reactor at the above-mentioned temperatures.

The aeration system is intricate, nonlinear, and dynamic in nature. A general framework for modelling aeration systems was given (Murat et al, 2003). The aeration system used in this study consists of a blower station, collecting pipe, diffuser systems, and collector-diffuser pipes which were previously used for a variety of aeration systems reported in the literature (Piotrowski et al, 2015). SBR is experienced with real data from the Visakhapatnam WWTP and implemented in a Matlab/SIMULINK environment. To check the temperature effect on European influent, a municipal WWTP of 135,000 people equivalent is chosen. The description and typical findings of each kinetic parameter for the model ASM2d are listed in Table 7.4. Additionally, although some kinetic parameters for biological phosphorus removal were approximated using data from ASM1, those for ASM2's full-scale verification studies and experience in the laboratory. It should be noted that the saturation coefficients Ki for any given molecule may differ for various organisms (for example, KO_2 may have four different values subject to the process and organism to which it is related). The investigation of the kinetic variables is conducted over a wide temperature range, and a significant increases in the kinetic variables become evident with the increase in temperature.

Table 7.4: kinetic parameters as temperature changes

Kinetic Variable/ Temp(°C)		**10**	**15**	**20**	**25**	**30**	**33**
K_H	**Hydrolysis rate constant**	1.3333	2	3	4.5000	6.7500	7.9385
μ_H	**Maximum growth rate on substrate**	1.50	3	6	12	24	31.6682
q_{fe}	**Maximum rate for fermentation**	0.75	1.50	3	6	12	15.8341
b_H	**Rate constant for lysis and decay**	0.1175	0.2350	0.4700	0.9400	1.8800	2.4807
q_{PHA}	**Rate constant for storage of X_{PHA}**	1.3333	2	3	4.5000	6.7500	7.9385
q_{PP}	**Rate constant for storage of X_{PP}**	0.6667	1	1.5000	2.2500	3.3750	3.9693
μ_{PAO}	**Maximum growth rate of PAO**	0.4489	0.6700	1	1.4925	2.2277	2.6147
b_{PAO}	**Rate for lysis of X_{PAO}**	0.05	0.1000	0.2000	0.4000	0.8000	1.0556
b_{PP}	**Rate for lysis of X_{PP}**	0.05	0.1000	0.2000	0.4000	0.8000	1.0556
b_{PHA}	**Rate for lysis of X_{PHA}**	0.05	0.1000	0.2000	0.4000	0.8000	1.0556
μ_{NS}	**Maximum growth ratio Nitrosomonas**	0.2923	0.4700	0.7558	1.2153	1.9542	2.3631
μ_{NB}	**Maximum growth ratio Nitrobacter**	0.5807	0.7800	1.0476	1.4071	1.8899	2.1266
b_{NS}	**Constant decay ratio Nitrosomonas**	0.0496	0.0860	0.1491	0.2584	0.4478	0.5580
b_{NB}	**Constant decay ratio Nitrobacter**	0.0496	0.0860	0.1491	0.2584	0.4478	0.5580

7.3 Results and discussion

The effluent concentrations are investigated using a steady-state simulation at temperatures spanning 10 and 33 °C. The parameters related to kinetics for the above-indicated temperatures are listed in Table 7.4. As the temperature rose, the hydrolysis rate constant (K_H), indicated in the table, gradually increased. In case of heterotrophic organisms (X_H), the Maximum growth rate on substrate (μ_H) and Maximum rate for fermentation (q_{fe}) have higher rate during temperature goes up. It has been shown that other values of heterotrophic rates tend to increase naturally during periods of high temperatures. In Phosphorus-accumulating organisms (X_{PAO}), the values of q_{PHA}, q_{PP}, μ_{PAO}, b_{PHA} exhibit a rising trend in their values during temperature rises.

After observing the increasing kinetic variations in parameters triggered by increased temperature, influent from various global locations is finally exposed to the SBR process. As temperature rises and biological rates climb, the effluent quality for Indian influent (Visakhapatnam plant) improves with lower values. Table 7.5 lists the changes in effluent values due to temperature change for Indian Influent .There is a noticeable drop in the effluent parameters COD, BOD, TN, and NH4 by 2.5003%, 14.927%, 5.80%, and 9.0951%, respectively. Unless a minimal rise is seen in the total amount of suspended solids and phosphorus, which are 2.0798% and 1.0745%, respectively. As temperature rises, more oxygen gets utilised by the biomass, resulting in a sharp drop in oxygen saturation (SO_2-SAT) of 33.716%. Figure 7.4 plots a chart bar aimed at the effluent values in Indian influent.

Table 7.5: Effect on Effluent due to temperature change in Indian Influent (Ref. temperature=20 °C)

Temperature (°C)	COD	BOD	TN	TP	NH_4	TSS	SO_2-SAT
10	53.3327	13.9549	3.1370	2.2406	1.9615	11.4569	8.9127
13	53.2444	13.8882	3.1294	2.2399	1.9530	11.4570	8.3420
15	53.1760	13.8368	3.1227	2.2397	1.9458	11.4638	8
17	53.0986	13.7783	3.1146	2.2396	1.9373	11.4757	7.6854
20	52.9623	13.6742	3.0989	2.2396	1.9212	11.5000	7.2596
23	52.7973	13.5447	3.0779	2.2415	1.9003	11.5248	6.8827
25	52.6693	13.4413	3.0603	2.2457	1.8831	11.5398	6.6556
27	52.5260	13.3228	3.0394	2.2522	1.8629	11.5530	6.4458
30	52.2806	13.1142	3.0011	2.2668	1.8264	11.5680	6.1608
33	51.9992	11.8718	2.9549	2.2872	1.7831	11.5800	5.9077

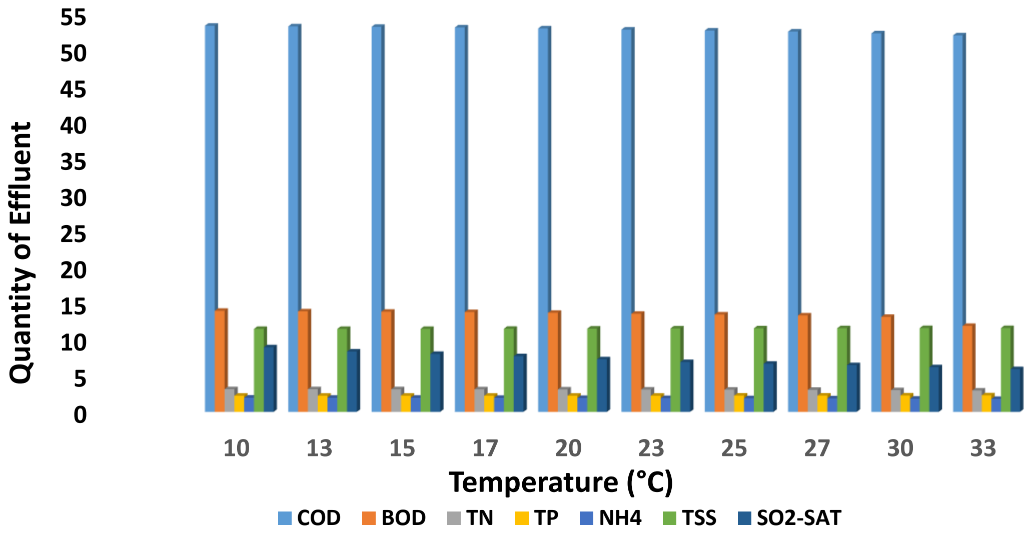


Figure 7.4: Effluent quality for Indian influent in various temperatures

In water quality metrics, dissolved oxygen (DO) is crucial for secondary treatment procedures. The amount of oxygen that is dissolved and distributed throughout a water sample is indicated by the DO level. Dissolved oxygen is used by bacteria and other microbes to break down organic matter, which drops DO concentrations. Microorganisms are released in flocs during wastewater treatment to aerobically break down and eliminate organic matter. Therefore, the concentration of dissolved oxygen are crucial for effective treatment. During the first 150 minutes, no oxygen is delivered because the process is anaerobic/anoxic (mention in Figure 7.1). After 150 minutes, oxygen is supplied with a flow of 1.85 L/min, however since there is an abundance of substrate, oxygen gets utilised by the biomass, resulting in the DO content decreasing for the initial 150 to around 200 minutes. After that, as there is not as much substrate present, less oxygen is required, but the flow remains constant at 1.85 L/min, and the DO value rises. Due to the extremely high demand for oxygen at higher temperatures, DO will be lower. The usage of oxygen by microorganisms in the reactor increases dramatically as the temperature rises, as can be observed in the Figure 7.5 A. At 10 °C it upholds at 8mg/l but drops to 2-4 mg/l above 30 °C. It implies that microbial activity increases with increasing temperature. A similar plot structure can also be identified in the context of European influent.

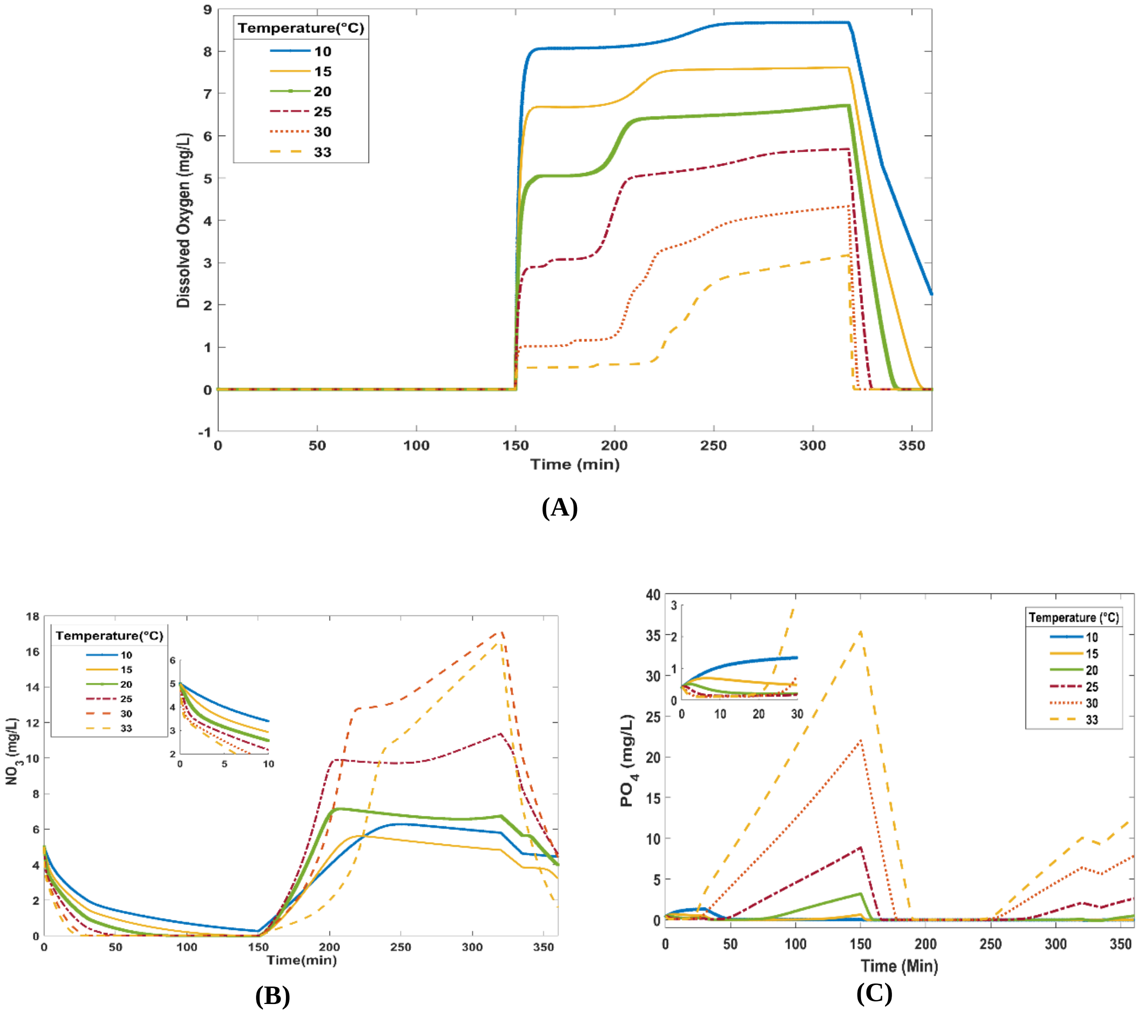
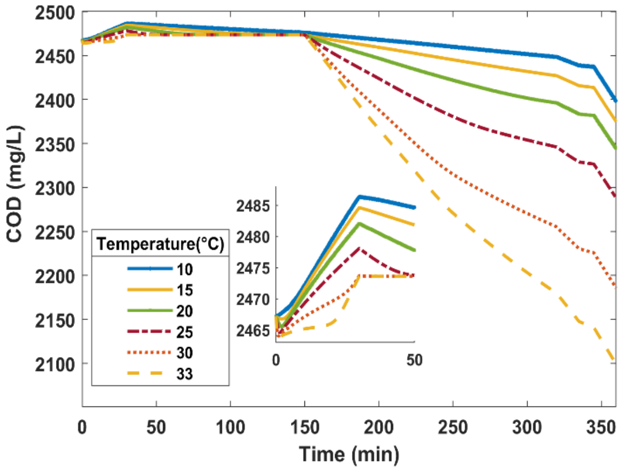


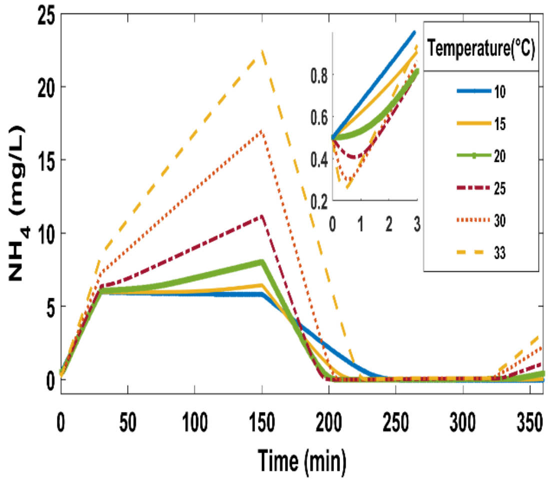
Figure 7.5: (A) DO concentration during SBR Phases; (B) Nitrate (NO_3) profile; (C) Phosphate (PO_4) profile

The NO_3 concentration in the wastewater drops during the first 150 minutes of treatment because the anoxic conditions cause the NO_3 to be consumed. The majority of the biomass will quit anoxic reactions and switch to employing aerobic reactions after 150 minutes when the oxygen supply is started. Therefore, the NO_3 content rises (in Figure 7.5B). The PO_4 plot's (in Figure 7.5C) assessment is comparable to the explanation provided for the Total P analysis.

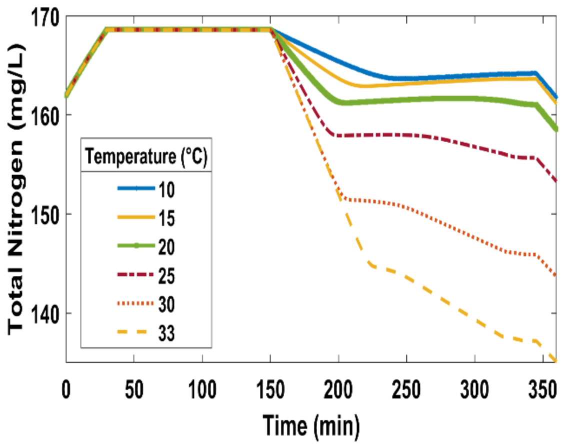
In general, the chemical oxygen demand measures how much oxygen is required to oxidise organic material. The SBR's initial 150 minutes of treatment will be both anoxic and anaerobic, thereby the batch reactor's overall COD won't fluctuate much during that period of time. From the Figure 7.6 A, Chemical oxygen demand will initially be quite high since there is a more organic and nitrogenous substrate in the wastewater. Following 150 minutes, the reactor will begin to experience an aerobic reaction, creating the amount of organic matter in the wastewater to decrease, and this in effect causes the chemical oxygen demand to drop. Because the biological activity of the biomass grows at higher temperatures, COD will be much lower after 360 minutes at higher temperatures than at lower temperatures. It follows that the COD value after treatment will be higher at lower temperatures and vice versa. Unlike the COD plot, the BOD_5 and TSS plots' conduct patterns, as well as the characteristics of the COD plot are identical.



(A)



(B)



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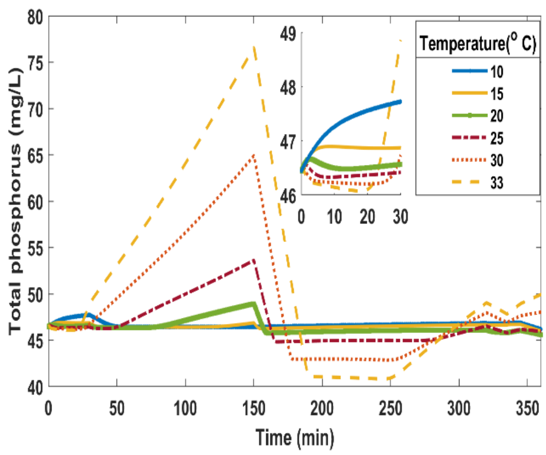


(D)

Figure 7.6: (A) COD profile; (B) NH4 profile; (C) TN profile; (D) TP profile; (Inside the SBR reactor) with Indian influent and initial sludge parameter.

In SBR, the plot for ammonia is particularly dynamic (Figure 7.5 B). Due to the ammonification of the organic nitrogen, the NH_4 content in the wastewater will dramatically rise within the first 150 minutes. Following 150 minutes, the nitrogen from the ammonia serves as both an energy source for the autotrophic nitrifying bacteria and a source of nitrogen for the heterotrophic bacteria's synthesis. Since biological activity will be strong at high temperatures, NH_4 conversion will also be high. Most of the biomass will decay and be turned into the slowly biodegradable matter between 300 and 360 minutes. Part of that slowly biodegradable substance will then be converted into NH_4, which causes the NH_4 content to increase slightly. Organic nitrogen, ammonia nitrogen, and nitrates will make up the total nitrogen content. Nitrogen oxides (NO) arrive at the reactor during the first few minutes of the treatment, increasing the total Nitrogen attention. The total nitrogen concentration stays the same even when it changes from NO_3 to N_2, as picturised in Figure 7.6 C. When the aerobic process begins 150 minutes later, nitrogenous materials are transformed into biomass. Temperature throughout the treatment process directly relates to the biomass's consumption of nitrogenous substrate.

During the first few minutes in the reactor, Phosphorous Accumulating Organisms will use the energy provided by releasing the polyphosphates in their cell store in the form of hydrophosphate to convert the fermentation products into Poly-Hydroxyl-Alkanoates. When the aerobic process begins, hydrophosphates will be transformed to polyphosphates and stored in the cell of phosphorus-accumulating organisms. Thus, the wastewater's total phosphorus level drops. According to Figure 7.6 D, temperature has a direct correlation with the rate at which phosphorus changes states.

While European influent is fed into the SBR reactor, a similar type of impact has been observed. The effluent characteristics that differ with temperature variations are listed in Table 7.6. Likewise, as the temperature increased here, the effluent reduced. At 10°C, the COD concentration of the effluent is 53.40, and it dropped by 2.50% to 52.06 at 33 °C. Similar reductions are seen in BOD, TN, and NH4 of 7.76%, 5.800%, and 9.10%, respectively. The minor increases in TP and TSS are 1.94% and 1.02%, respectively.

The utilisation of oxygen by microorganisms in the reactor is likely seen in the Figure 7.8 B, which shows how the DO concentration quickly rises as the temperature goes up. At 10 °C, the level stays at 8 mg/l, meanwhile, at temperatures exceeding 30 °C, it stays around 2-4 mg/l, indicating an increase in microbial activity as the temperature of the atmosphere climbs. According to the COD graph in Figure 7.8 A, the rate at which COD in the reactor reduces increases as temperature rises. High temperatures encourage higher rates of nitrification and denitrification, and that's why it arises.

Table 7.6: Effect on Effluent due to temperature change in European Influent

Temperature (°C)	COD	BOD	TN	TP	NH_4	TSS	SO_2-SAT
10	53.4039	13.9906	3.1392	2.2413	1.9615	11.5055	8.9127
13	53.3157	13.9242	3.1318	2.2403	1.9530	11.5077	8.3420
15	53.2467	13.8722	3.1250	2.2398	1.9457	11.5127	8
17	53.1686	13.8129	3.1170	2.2395	1.9371	11.5214	7.6854
20	53.0318	13.7079	3.1013	2.2402	1.9211	11.5437	7.2596
23	52.8667	13.5782	3.0802	2.2413	1.9001	11.5685	6.8827
25	52.7386	13.4747	3.0626	2.2455	1.8829	11.5835	6.6556
27	52.5950	13.3558	3.0410	2.2517	1.8627	11.5965	6.4458
30	52.3488	13.1465	3.0033	2.2654	1.8262	11.6111	6.1608
33	52.0673	12.9044	2.9571	2.2849	1.7829	11.6236	5.9077

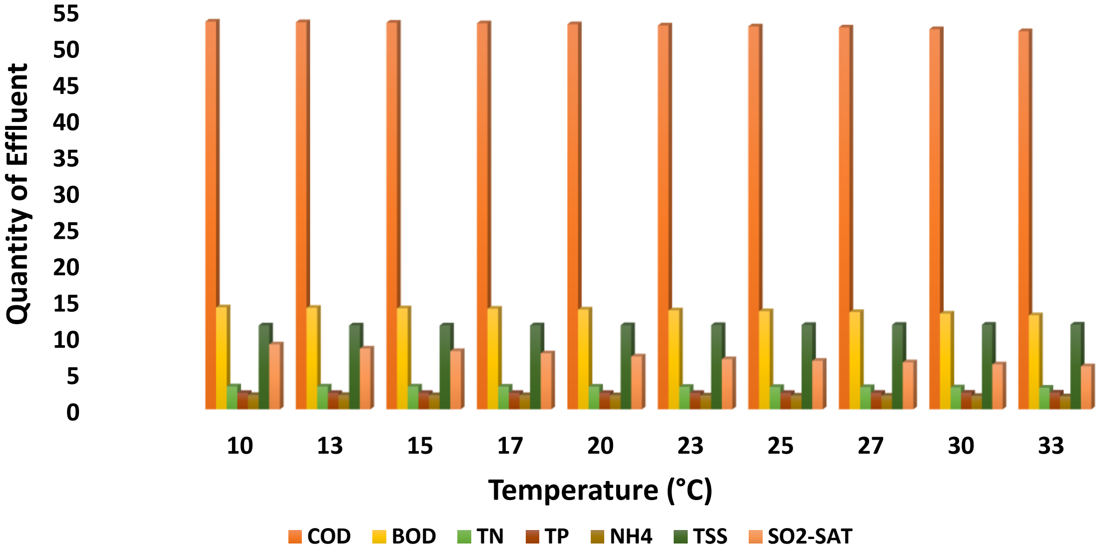
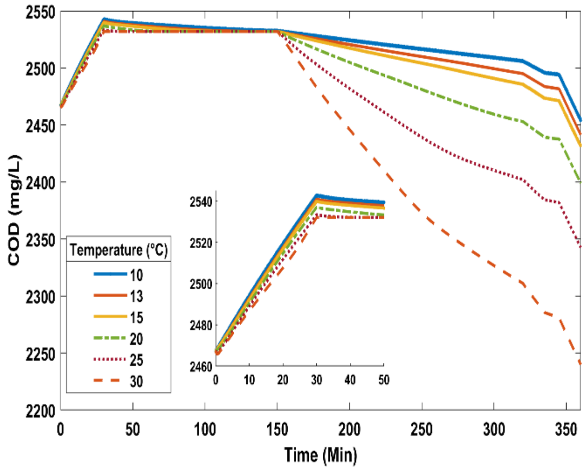
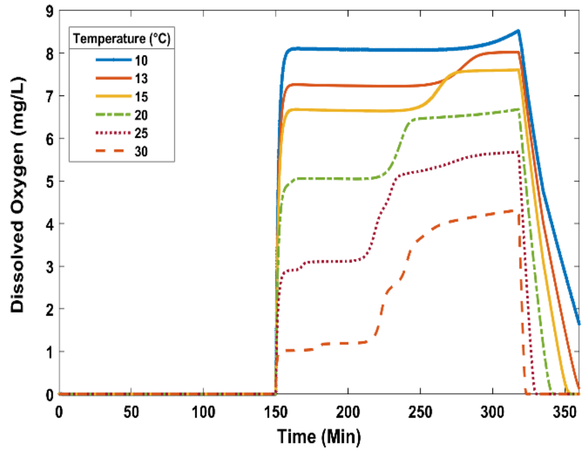


Figure 7.7: Effluent quality for European influent in various temperatures



(A)



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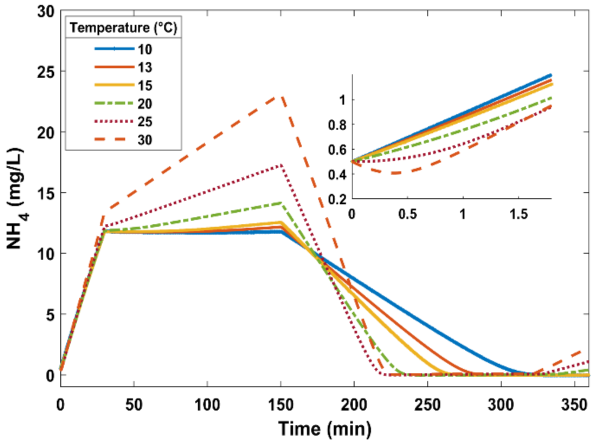

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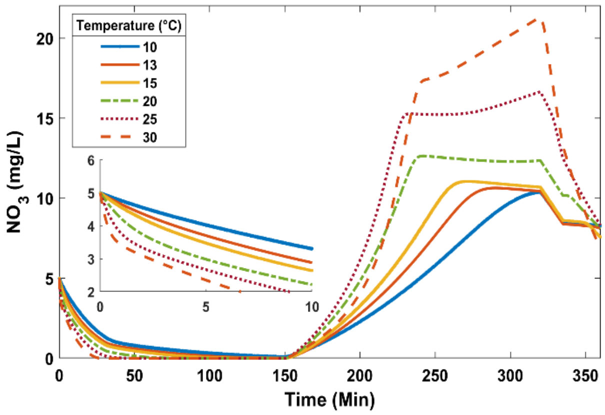

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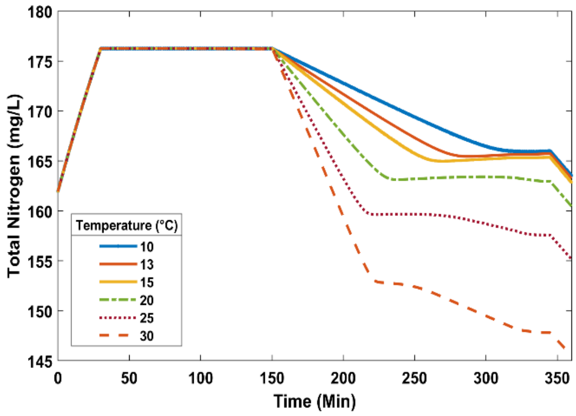
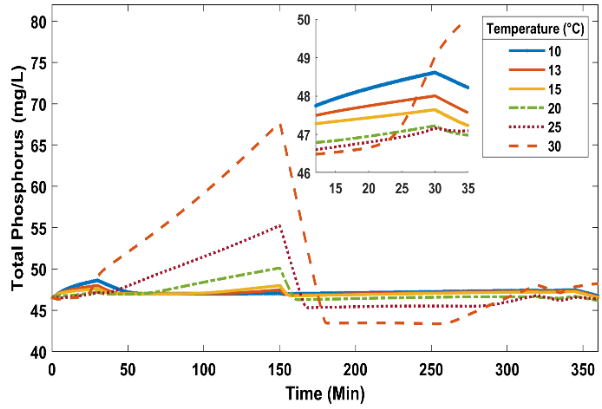


(E)



(F)

Figure 7.8: (A) COD profile; (B) DO profile; (C) NH4 profile; (D) NO3 profile; (E) TN profile; (F) TP profile; (Inside the SBR reactor) with European influent and initial sludge parameter.

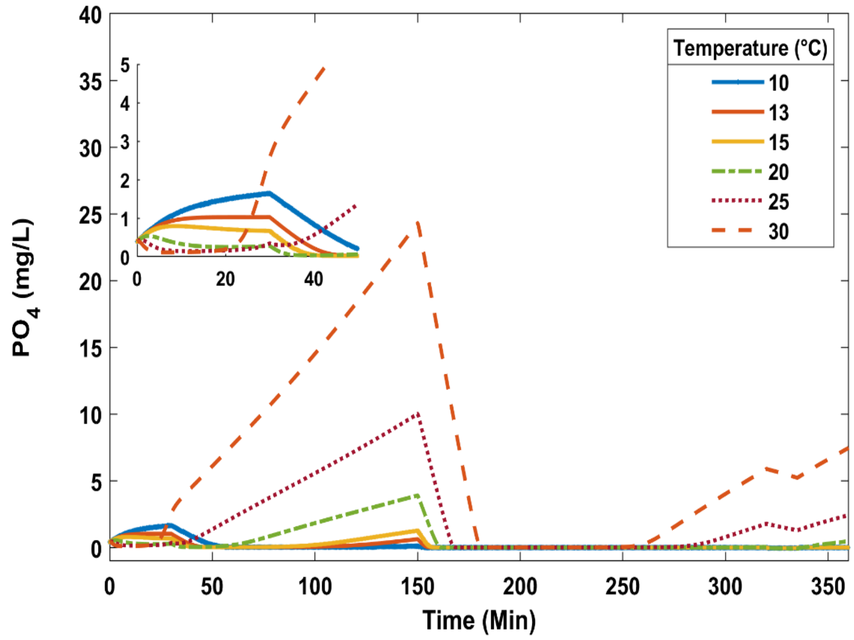


Figure 7.9: plot for PO_4 in European influent condition

Figure 7.8 D, NO_3 indicates that nitrate utilisation in the anoxic-anaerobic phase is low at lower temperatures and develops at elevated temperatures, while nitrate production in the aerobic phase increases at warmer weather. PO_4 in the Figure 7.9, it is able to see that at cold temperatures, both the anaerobic and aerobic periods PO_4 production and consumption are minimal. In the anaerobic and aerobic phases, respectively, utilisation and production climb along with heat. Total phosphorus (TP) contents in Figure 7.8 F is evident in the image to follow a similar pattern to PO_4 levels. Figures 7.8 E and 7.8 C for TN and NH_4 show that total nitrogen removal is higher at high temperatures, as are ammonia production and utilisation, respectively. Figure 7.7 illustrates the effluent parameters along with oxygen saturation in a SBR along with how these factors influence the effluent parameters when it comes to temperature dependence. Effluent plots with European inlets are quite comparable to those with Indian influent.

7.4 Conclusion

The study revealed that temperature has a substantial impact on sequential batch reactor's (SBR's) performance, which could have significant consequences for the layout and management of SBR-based wastewater treatment facilities across the globe. This might lead to the development of wastewater treatment strategies that are more effective and sustainable. Utilizing a steady-state simulation to examine effluent quantities at temperatures ranging from 10°C to 33°C, the study specifically identifies the influence of temperature on removing organic carbon and nitrogen in a sequential batch reactor. As temperature rises, the effluent quality noticeably improves. In order to reach acceptable discharge limits, it is observed that changes in kinetic parameters at various temperature ranges have a significant impact on the effluent quality. The kinetic parameter investigation is carried out at a temperature of 20 °C. In Indian influent, COD, BOD, TN, and NH_4 have decreased substantially by 2.5003%, 14.927%, 5.80%, and 9.0951%, respectively. While a slight increase in total suspended solids and phosphorus levels are noticed, which are 2.0798% and 1.0745%, respectively. As the temperature rises, the biomass consumes more oxygen, resulting in a significant decrease in oxygen saturation (SO_2-SAT) of 33.716%. As the temperature rises, the amount of oxygen consumed by microbes in the reactor notably increases, as seen in Figure 4A. It maintains about 8 mg/l levels at 10 °C but declines to 2-4 mg/l over 30 °C. It signifies that as warmer temperatures occur, microbial activity does as well. The levels of DO in wastewater treatment decrease as the microorganisms become more active. Using low DO concentrations will result in microorganisms dying off and this will lead to a loss of efficacy of treatment. The optimum control strategy requires aeration and bubbler systems to be installed in order to keep the DO levels at or below 2 mg/L as well as to evenly distribute the DO throughout the flocs containing microorganisms. Similar effects have been noted when the SBR reactor receives European influent. Furthermore, the effluent decreased when the temperature rose in this area. The effluent's COD concentration was 53.40 at 10 °C and 52.06 at 33 °C, a 2.50% decrease. BOD, TN, and NH_4 all experienced similar declines of 7.76%, 5.800%, and 9.10%, respectively. TSS and TP both experienced slight increases of 1.94% and 1.02%, respectively and all parameter are under restricted norms for effluent discharge. Finally, this study notices that temperature has considerable influence on SBR’s performance, which may have concerns for the design and operation of SBR-based wastewater treatment facilities worldwide. This could pave the way for more efficient and long-lasting wastewater treatment solutions in rationally exposed environments.

Chapter 8

8. CONCLUSIONS AND FUTURE SCOPE

8.1 Overall conclusion

In conclusion, this thesis has undertaken a comprehensive exploration of various control strategies and their impact on the performance of Biological Wastewater Treatment plants (WWTPs), particularly focusing on the performance of sequencing Batch Reactor (SBR) and aeration systems. The evaluation utilized four primary control techniques - PI, FPI, FUZZY and MPC implementing them across different levels of control hierarchy.

8.1.1 A supervisory FUZZY control framework with lower level fractional-order models on wastewater treatment plant's nutrient removal.

The performance of a biological wastewater treatment plant in ASM3bioP platform is greatly impacted by three lower-level implemented methods: IO model and IO control, IO model FO control, and FO model FO control. These strategies are evaluated using PI, FPI, and higher-level FL control approaches. The EQI improvement percentages for FPI and FMFPI relative to PI are 0.50% and 0.59%, respectively, whilst the OCI improvement percentages are 0.31% and 0.33%.

The application of FUZZY controller at the supervisory level demonstrated substantial improvements in Effluent Quality Index (EQI), supressing the outcomes achieved by lower level PI and FPI controllers. EQI is improved by 4.00% for the IO model with FPI and 4.03% for the FO model with FPI when supervisory fuzzy logic control is used. Fuzzy control lowers violations of total nitrogen by 9.01% (FO model) and 6.11% (IO model) compared to lower level PI, despite higher OCI brought on by controller costs.

Lower-level control ammonia violations are somewhat decreased in the FO model (2.01%) and IO model (1.78%) when using FPI. Plant performance is more strongly impacted by the FO controller, although the FM-FPI approach produces the greatest outcomes and greatly improves the EQI. The results underscored the importance of higher level control strategies in enhancing overall plant performance, albeit with a slight increase in overall cost (OCI).

8.1.2 Optimising wastewater treatment employing IMC-based fractional controllers in a supervisory MPC control scheme for biological treatment.

A non-integer order system for biological wastewater treatment plants (WWTP) is found for the ASM3bioP model by utilizing FOMCON toolbox, with an emphasis on regulating dissolved oxygen (DO) and nitrate content (NO). Using the Genetic Algorithm (GA) determines the fractional filter parameters (λ, α) for the Internal Model Control (IMC) controller by optimizing the Integral of Absolute Error (IAE) for closed-loop response. Using MATLAB Simulink, the IMC controller is used to improve the aeration system for the DO control. The effectiveness of the controller and the uncertainty of the plant are validated through extensive testing. For the non-integer model, a mathematical method using the same IMC fractional controller and a higher-order fractional filter is created, leading to a better closed-loop response with enhanced set point tracking and disturbance rejection. The control approach known as Fractional Filter - Fractional Order Proportional Integral (FF-FOPI) simultaneously minimises IAE and Integral of Squared Error (ISE). Fractional Order (FO) controllers have a greater effect on plant performance when compared to Proportional Integral (PI) controllers. The FF-FOPI approach with higher order filter outperformed both GA based IMC PI and FPI controllers, highlighting its potential for optimizing WWTP operations.

Moving forward, the investigation extended to the SBR plant layout, incorporating complex ASM2d modelling and calibrated real plant data.

8.1.3 Design of control strategies for biological wastewater treatment of sequential batch reactor

PI, FPI, and Fuzzy control frameworks are integrated into an SBR facility utilizing the ASM2d platform. These methods control dissolved oxygen (DO) during aeration by altering the air flow rate. The ASM2d model, calibrated with actual plant data, represents an SBR-based water treatment facility. Notably, the study investigates regulating a batch process utilizing the complicated ASM2d model and real-world plant data calibration. The controller performance is examined, and the finding showcased the superiority of FPI controllers in terms of ISE and IAE compared to PI and Fuzzy controllers. Effluent nutrient compositions remain within legal limits. FPI improves nutrient removal rates and effluent quality by 0.53%, 1.05%, 1.18%, 0.80%, 0.07%, and 2.22% over PI. A modified SBR cycle (Step-Feed Process) shows similar advantages. When FPI controller performance is examined only based on total air volume consumption, step-feed SBR shows an 11.04% reduction compared to standard SBR. The results demonstrated optimized nutrient removal rates and effluent quality with the FPI controller emphasizing its efficiency in real-world wastewater treatment scenarios.

8.1.4 Design of supervisory fuzzy control for enhanced energy saving in a sequencing batch reactor based wastewater treatment plant

This part of study models a biological WWTP based on SBR using a modified ASM2d framework and simulates DO controlling during the aeration phase using real-time data from the Vizag WWTP in 30°C Indian conditions. The goal is to keep DO levels in SBR between 150 and 300 minutes for one batch operating cycle. Supervisory fuzzy control for ammonia and nitrate, along with lower level PI and FPI controllers, attempts to improve effluent quality and cut aeration costs by optimizing airflow to the SBR reactor during aeration. Six control techniques are applied, including two DO controllers at the lowest level and four hierarchically structured nitrate and ammonia controllers based on fuzzy logic. Using an intelligent fuzzy control cascaded with PI and FPI controllers improves effluent quality and reduces air consumption, lowering aeration costs. Fuzzy control at the supervision level reduces airflow by 40.08% for ammonia control and 31.58% for nitrate control. The study concludes that an ammonia control strategy with a lower level FPI controller is more efficient in terms of both EQI and aeration cost, providing a cost-effective aeration approach suitable for small-scale industries or domestic wastewater treatment facilities that use conventional SBR technologies.

8.1.5 Influence of seasons on the effluent quality in sequencing batch reactor based wastewater treatment plants

Furthermore, the thesis delved into the impact of temperature on SBR performance, revealing temperature’s substantial influence on the efficiency of SBR based wastewater treatment facilities. As temperature increased, effluent quality improved, necessitating careful consideration in the design and operation of such facilities, particularly in varying climatic conditions.

The study demonstrates temperature's critical significance in organic carbon and nitrogen removal in SBRs using steady-state simulation at temperatures ranging from 10°C to 33°C, with higher temperatures significantly increasing effluent quality. Notably, changes in kinetic parameters throughout temperature ranges have a considerable impact on effluent quality, notably at 20°C. COD, BOD, TN, and NH_4 levels fall dramatically in Indian influent, whereas total suspended solids and phosphorus levels rise slightly. As the temperature rises, microbial activity increases, affecting dissolved oxygen (DO) levels, demanding optimal management solutions involving aeration and bubbler systems to maintain DO levels and assure treatment effectiveness. Similar trends are seen with European influent, indicating temperature's significant impact on SBR performance and the possibility for more effective and sustainable wastewater treatment options around the world.

In Summary, this thesis contributes valuable insights into realm of wastewater treatment control strategies, showcasing the efficacy of higher level control techniques, non-integer order systems, and the influence of environmental factors. The finding presented here not only expand the theoretical foundations but also offer practical implications for optimising the performance of Biological WWTP in diverse operational contexts. The journey undertaken in this thesis sets the stage for continued exploration and advancements in the field of fractional modelling and control in wastewater treatment plants, inspiring future researchers to delve deeper into the intricate dynamics of WWTP processes. A low volume industries or domicile wastewater treatment facilities can benefits from this low cost aeration techniques that incorporates standard SBR.

8.2 Plan for future work

This study sheds light on the dynamic interaction of environmental factors and wastewater treatment systems, giving important insights for future investigations. Building on these findings, future studies could look into novel approaches to improving treatment efficiency and environmental sustainability. The opportunities are

- Develop advanced control approaches to effectively eliminate phosphorus utilising a Total Suspended Solids (TSS) controller.
- Develop a fractional model and controller for a complete wastewater treatment system.
- Design machine learning models for wastewater treatment plant sensors to substitute sensor hardware with soft sensor model.
- Apply the designed control strategies to an experimental setup of a pilot plant for practical implementation.

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Appendix

10. APPENDIX

APPENDIX A

Table A3 Kinetic rate expressions for ASM3 (Henze et al. (2000))

No.	Process	Process rate equation
		Hydrolysis
P1	Hydrolysis	$k_h \frac{X_S/X_H}{K_X + X_S/X_H} X_H$
		Heterotrophic organisms
P2	Aerobic storage of COD	$k_{STO} \frac{S_O}{K_{O,H} + S_O} \frac{S_S}{K_{SS,H} + S_S} X_H$
P3	Anoxic storage of COD	$k_{STO}\eta_{NO,H} \frac{K_{O,H}}{K_{O,H} + S_O} \frac{S_{NO}}{K_{NO,H} + S_{NO}} \frac{S_S}{K_{SS,H} + S_S} X_H$
P4	Aerobic growth	$\mu_H \frac{S_O}{K_{O,H} + S_O} \frac{S_{NH}}{K_{NH,H} + S_{NH}} \frac{S_{PO4}}{K_{PO4,H} + S_{PO4}} \frac{S_{HCO}}{K_{HCO,H} + S_{HCO}} \frac{X_{STO}/X_H}{K_{STO} + X_{STO}/X_H} X_H$
P5	Anoxic growth(deni)	$\mu_H\eta_{NO,H} \frac{K_{O,H}}{K_{O,H} + S_O} \frac{S_{NO}}{K_{NO,H} + S_{NO}} \frac{S_{NH}}{K_{NH,H} + S_{NH}} \frac{S_{PO4}}{K_{PO4,H} + S_{PO4}} \frac{S_{HCO}}{K_{HCO,H} + S_{HCO}} \frac{X_{STO}/X_H}{K_{STO} + X_{STO}/X_H} X_H$
P6	Aerobic endog. Resp	$b_H \frac{S_O}{K_{O,H} + S_O} X_H$
P7	Anoxic endog. Resp	$b_H\eta_{NO,end,H} \frac{K_{O,H}}{K_{O,H} + S_O} \frac{S_{NO}}{K_{NO,H} + S_{NO}} X_H$

P8	Aerobic resp. of X_{STO}	$b_H \frac{S_O}{K_{O,H}+S_O} X_{STO}$
P9	Anoxic resp. of X_{STO}	$b_H \eta_{NO,end,H} \frac{K_{O,H}}{K_{O,H}+S_O} \frac{S_{NO}}{K_{NO,H}+S_{NO}} X_{STO}$
Autotrophic organisms		
P10	Nitrification	$\mu_A \frac{S_O}{K_{O,H}+S_O} \frac{S_{NH}}{K_{NH,H}+S_{NH}} \frac{S_{PO4}}{K_{PO4,H}+S_{PO4}} \frac{S_{HCO}}{K_{HCO,H}+S_{HCO}} X_A$
P11	Aerobic endog. resp.	$b_A \frac{S_O}{K_{O,H}+S_O} X_A$
P12	Anoxic endog. resp.	$b_A \eta_{NO,A} \frac{K_{O,H}}{K_{O,H}+S_O} \frac{S_{NO}}{K_{NO,H}+S_{NO}} X_A$

Table A4 Kinetic rate expressions for the EAWAG Bio-P module (Rieger et al. (2001))

No.	Process	Process rate equations
		Phosphorus accumulating organisms
P13	Storage of X_{PHA}	$q_{PHA}\frac{S_S}{K_{SS,PAO}+S_S}\frac{S_{HCO}}{K_{HCO,PAO}+S_{HCO}}\frac{X_{PP}/X_{PAO}}{K_{PP,PAO}+X_{PP}/X_{PAO}}X_{PAO}$
P14	Aer. storage of X_{PP}	$q_{PP}\frac{S_O}{K_{O,PAO}+S_O}\frac{S_{PO4}}{K_{PO4,PP}+S_{PO4}}\frac{S_{HCO}}{K_{HCO,PAO}+S_{HCO}}\frac{X_{PHA}/X_{PAO}}{K_{PHA}+X_{PHA}/X_{PAO}}\frac{K_{max,PAO}-(X_{PHA}/X_{PAO})}{K_{iPP,PAO}+K_{max,PAO}-(X_{PP}/X_{PAO})}X_{PAO}$
P15	Anox. storage of X_{PP}	$q_{PP}\eta_{NO,PAO}\frac{K_{O,PAO}}{K_{O,PAO}+S_O}\frac{S_{NO}}{K_{NO,PAO}+S_{NO}}\frac{S_{PO4}}{K_{PO4,PP}+S_{PO4}}\frac{S_{HCO}}{K_{HCO,PAO}+S_{HCO}}\frac{X_{PHA}/X_{PAO}}{K_{PHA}+X_{PHA}/X_{PAO}}\frac{K_{max,PAO}-(X_{PHA}}{K_{iPP,PAO}+K_{max,PAO}-}$
P16	Aer. growth of X_{PAO}	$\mu_{PAO}\frac{S_O}{K_{O,PAO}+S_O}\frac{S_{NH}}{K_{NH,PAO}+S_{NH}}\frac{S_{PO4}}{K_{PO4,PP}+S_{PO4}}\frac{S_{HCO}}{K_{HCO,PAO}+S_{HCO}}\frac{X_{PHA}/X_{PAO}}{K_{PHA}+X_{PHA}/X_{PAO}}X_{PAO}$
P17	Anox. growth of X_{PAO}	$\mu_{PAO}\eta_{NO,PAO}\frac{K_{O,PAO}}{K_{O,PAO}+S_O}\frac{S_{NO}}{K_{NO,PAO}+S_{NO}}\frac{S_{NH}}{K_{NH,PAO}+S_{NH}}\frac{S_{PO4}}{K_{PO4,PP}+S_{PO4}}\frac{S_{HCO}}{K_{HCO,PAO}+S_{HCO}}\frac{X_{PHA}/X_{PAO}}{K_{PHA}+X_{PHA}/X_{PAO}}X_{PAO}$
P18	Aerobic endog. respiration	$b_{PAO}\frac{S_O}{K_{O,PAO}+S_O}X_{PAO}$
P19	Anoxic endog. respiration	$b_{PAO}\eta_{NO,end,PAO}\frac{K_{O,PAO}}{K_{O,PAO}+S_O}\frac{S_{NO}}{K_{NO,PAO}+S_{NO}}X_{PAO}$
P20	Aerobic lysis of X_{PP}	$b_{PP}\frac{S_O}{K_{O,PAO}+S_O}X_{PP}$

P21	Anoxic lysis of X_{PP}	$b_{PAO}\eta_{NO,lysis,PP}\frac{K_{O,PAO}}{K_{O,PAO}+S_O}\frac{S_{NO}}{K_{NO,PAO}}X_{PP}$
P22	Aerobic resp. of X_{PHA}	$b_{PHA}\frac{S_O}{K_{O,PAO}+S_O}X_{PHA}$
P23	Anoxic resp. of X_{PHA}	$b_{PHA}\eta_{NO,resp,PHA}\frac{K_{O,PAO}}{K_{O,PAO}+S_O}\frac{S_{NO}}{K_{NO,PAO}}X_{PHA}$

Procedure for Identification of Different Models used in this work Identification of FOPTD Model for Lower Level

System Identification process is used to identify the plant models to be used for control of BSM1-P in FOPTD form.

Step 1. Decide the control loops and corresponding manipulated and controlled variables.

Step 2. Run the Plant simulation model to reach steady state. It may be achieved after 100- 150 days for BSM1. (Steady state should be the point around which identification is desired to be performed).

Important Tip: Make sure that steady state achieved for the controlled variable should be approximately the value near the set-points wished to be maintained in closed loop. Thus, a set of manipulated variables needed to maintain the controlled variables at their set-points with define an operating point. Here, for PI configuration the operating point used is $S_{O,7}$=2 mg (O_2)/l, $S_{NO,4}$=1 mg N/l, K_La_7=252 1/d and Q_{intr}=34500 m^3/d.

Step 3. Now run the identification file which varies all the manipulated variables (here, K_La_7 and Q_{intr}) ±10% around their operating point simultaneously and record this input. If there is a need, include the disturbance variable as an additional input (here Q_{intr}) and give only the +5% to +10% of step change to it.

Step 4. Collect the data for variations respective controlled variables (here $S_{O,7}$ and $S_{NO,4}$) due to input supplied.

Step 5. Create a "*iddata*" object with recorded controlled and manipulated variables including disturbance variable and use a proper sampling time (here, 1/96).

Step 6. Go to System Identification tool box and import the data object created in previous step.

Step 7. Use only the portion with consistent oscillations in output around operating point. (Use select range option provided in toolbox).

Step 8. Preprocess the data if needed (i.e. remove means and trends).

Step 9. Create the estimation and validation parts of data (generally 2/3 part is used for estimation and 1/3 part for validation) and import estimation data in "working data" and rest in "validation data" in toolbox.

Step 10. For estimating FOPTD model, chose the option of "Process Model" form estimation options and provide any of the initial details (like gain) if available and estimate the model.

From estimation option and specify the order and type of model (continuous or discrete) to be estimated. There are several methods available for estimation like Subspace N4SID algorithm or prediction error method but the later one is generally used.

Step 11. Check the fit to estimation data and validation data, if it is within acceptable limits (generally above 70%) then model is fit to use otherwise repeat steps 2 -10 again.

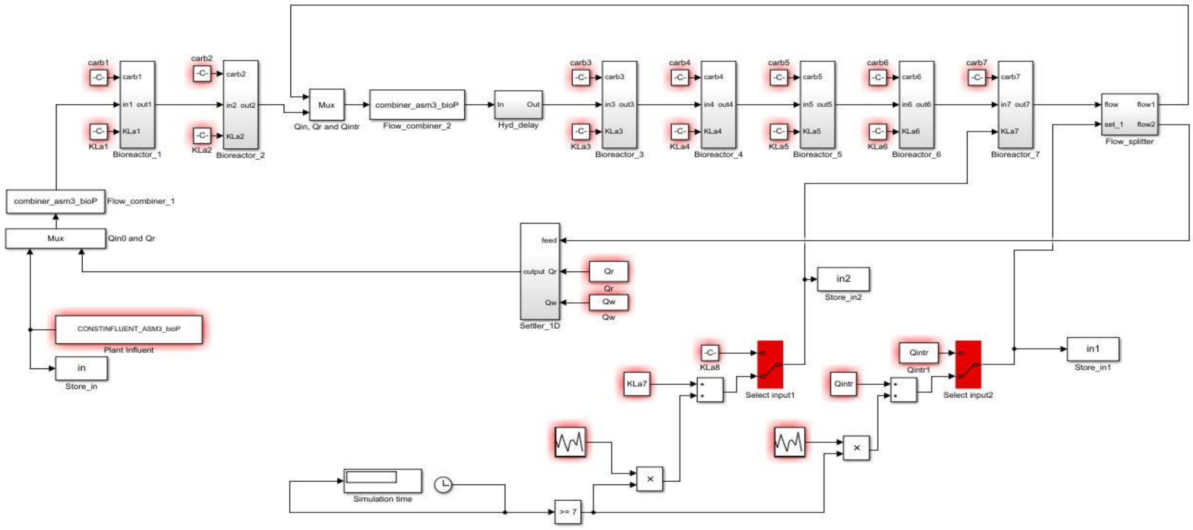

Figure A1. Lower Level Identification File

Fractional order model identification.

Based on the time-domain approach, a non-integer order time delay transfer function model is found using the MATLAB FOMCON toolbox.

Steps to identify a good fitted identified model

Step 1. A "fidata" structure must be chosen first and foremost.

Step 2. Select 'Time domain Identification', where you can choose frequency domain too.

Step 3. Choose the 'simulation parameter methods' in Grunwald-Letnikov method or Oustaloup filter or Refined Oustaloup filter. (You need to select 'w' range and order for the last two options). We select the Oustaloup filter.

Step 4. In the 'Identification and options' section chosen 'fidata' name will show and the preferred algorithm is 'Trust-Region-Reflective'.

Step 5. There is a symbolic form of identified model in terms of the fractional pole and zero polynomials. A first-guess model is created. In order to create polynomials autonomously, a commensurate-order q that has the property that $0.01 \leq q < 2$ —the order of the polynomial—can be defined.

Step 6. A plot that displays a good fitting result and shows the identified system's stable behavior should be displayed at the conclusion of the identification process. As long as the outcomes are pleasing, the model is saved for use in creating a controller.

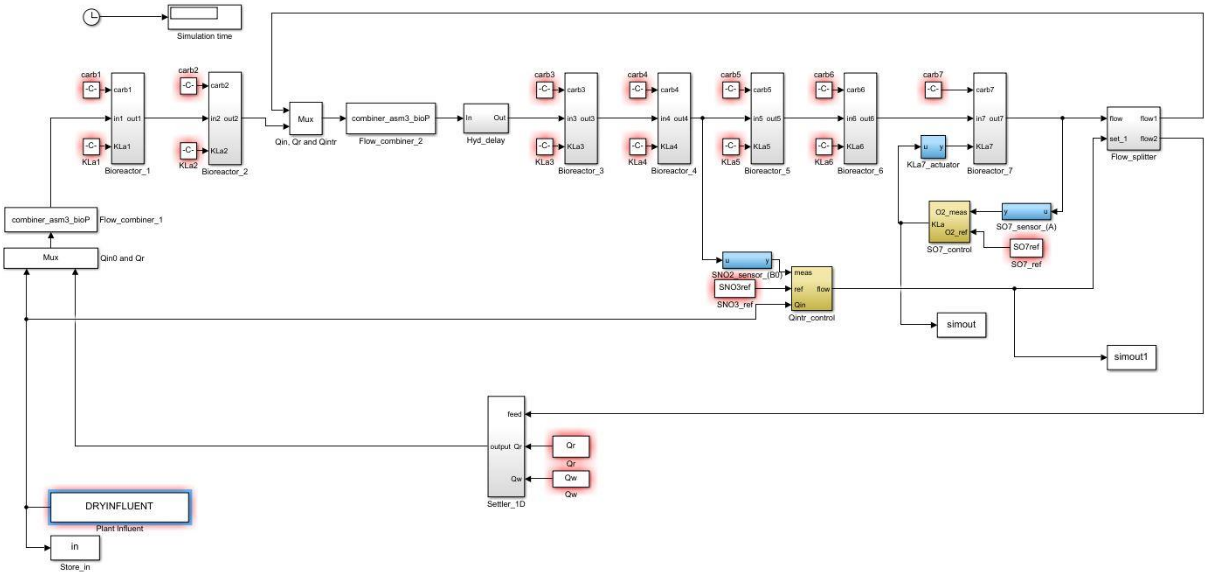

Figure A2. BSM1 Simulink Diagram with lower level PI / FPI controller.

Deciding Rules for Higher Level Fuzzy Controller

As the procedure is described for deducing the membership functions and rules for lower level fuzzy controller, similar approach is followed for higher level fuzzy controller also. Here, data is collected for ammonia concentration in tank 7 and respective DO set-point needed to be maintained by lower level control in tank 7 and a graph is generated between both variables. This graph then can be used for diving the variables into fuzzy sets.

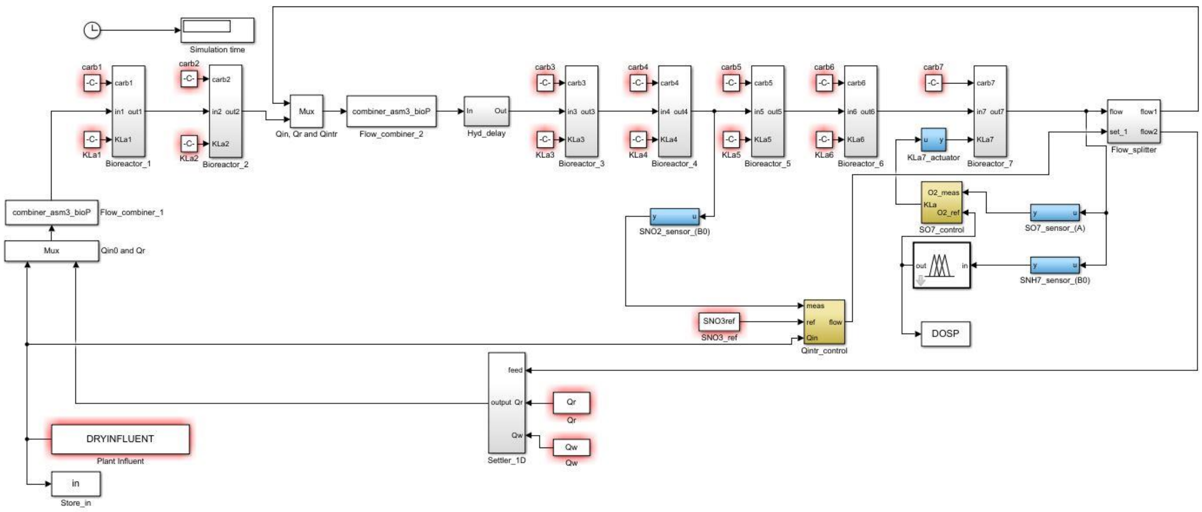

Figure B4. BSM1-P with PI or FPI with Fuzzy Configuration

APPENDIX B

Identification of State Space Model for Higher Level

Step 1. Fix the lower level controller to be used along with higher level control. Decide the control loops and corresponding manipulated and controlled variables for higher level.

Step 2. Run the Plant simulation model to reach steady state. It may be achieved after 100- 150 days for BSM1. (Steady state should be the point around which identification is desired to be performed).

Important Tip: For higher level control, the value of ammonia concentration and DO concentration in tank 7. Make sure that the steady state reached for ammonia concentration should be the value of set-point of ammonia you plan to achieve. The DO value needed to achieve the desired set-point of ammonia and the steady state value of ammonia concentration itself make a set of operating point. For example, if $S_{NH,7}$ ref =1.71 for FPI-MPC configuration then the steady state value of DO set-point needed is $S_{O,7}$ ref=2.45.

Step 3. Now run the identification file (close lower level loop and open higher level loop) which varies all the manipulated variable (here $S_{O,7}$ ref) ±10% around their operating point simultaneously and record this input.

Step 4. Collect the data for variations in respective controlled variable (here $S_{NH,7}$) due to input supplied.

Step 5. Create a “iddata” object with recorded controlled and manipulated variable and use a proper sampling time (here, 1/96).

Step 6. Go to System Identification tool box and import the data object created in previous step.

Step 7. Use only the portion with consistent oscillations in output around operating point. (Use select range option provided in toolbox).

Step 8. Preprocess the data if needed (i.e. remove means and trends).

Step 9. Create the estimation and validation parts of data (generally 2/3 part is used for estimation and 1/3 part for validation) and import estimation data in “working data” and rest in “validation data” in toolbox.

Step 10. For estimating State space model, chose the option of “State Space Models” from estimation option and specify the order and type of model (continuous or discrete) to be estimated. There are several methods available for estimation like Subspace or prediction error method but the later one is generally used. There is an option available to choose the input which have immediate effect on output (i.e. values in D matrix). Usually, matrix D=0. Chose all the desired options and estimate the model.

Step 11. Check the fit to estimation data and validation data, if it is within acceptable limits (generally above 70%) then model is fit to use otherwise repeat steps 2 -10 again.

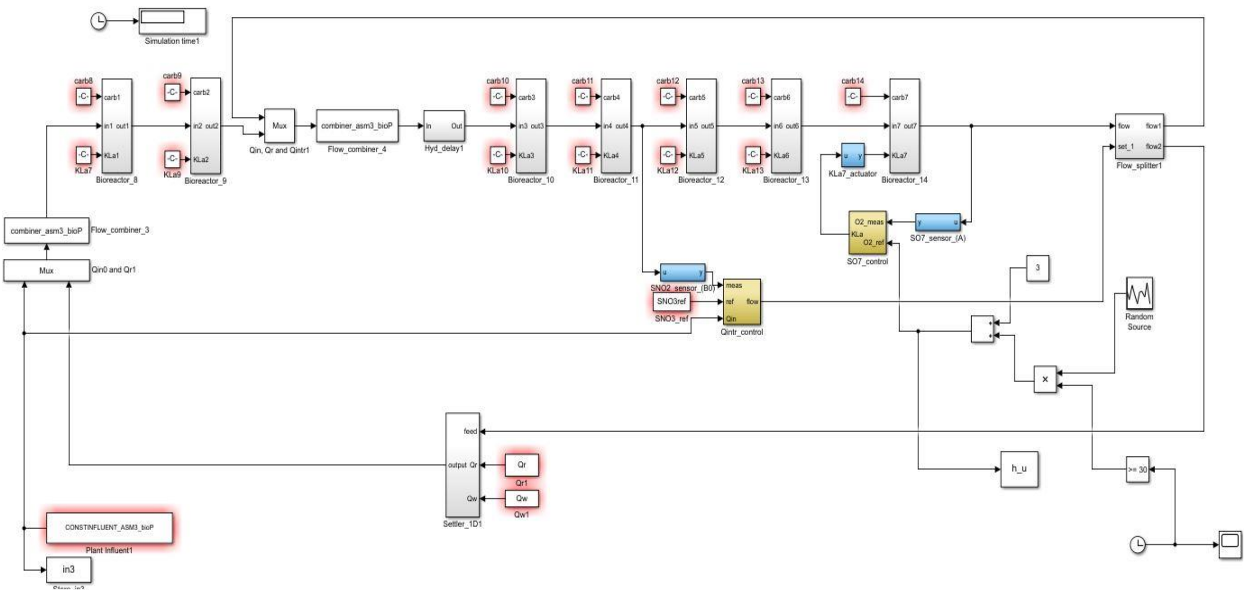

Figure B1. An Example of Higher Level State space model Identification File

Designing of MPC Controller

Step 1. Determine the state space model of the plant to be controlled with MPC controller. And save the model in workspace.

Step 2. Import the model in MPC designer app and give the nominal values for controlled and manipulated variables.

Step 3. After the model is imported, a default controller is created in controller section. Tune the controller parameters and export the designed controller to workspace.

Note: The response of the controller to test signals (step, ramp, etc) in controlled as well as manipulated variables, assuming that the model of the plant describes the exact dynamics as real plant can be checked simulating a scenario in designer app.

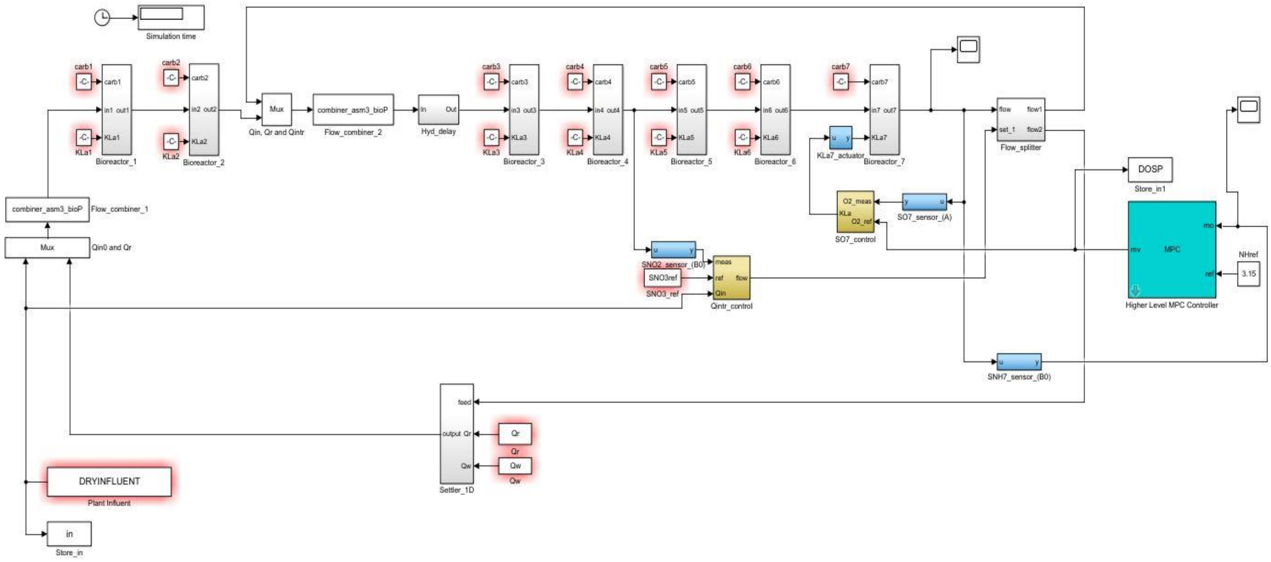

Figure B2. BSM1-P with FPI-MPC Configuration

APPENDIX C

This is the Simulink diagram to generate data to create the transfer function model for both Integer and fractional order model. The process of generating the transfer function model for both Integer and fractional order model of SBR during the Aeriation phase are same like continuous process (ASP) identification. Only we have to choose the data during the aeriation time only that is 150 to 300 minutes.

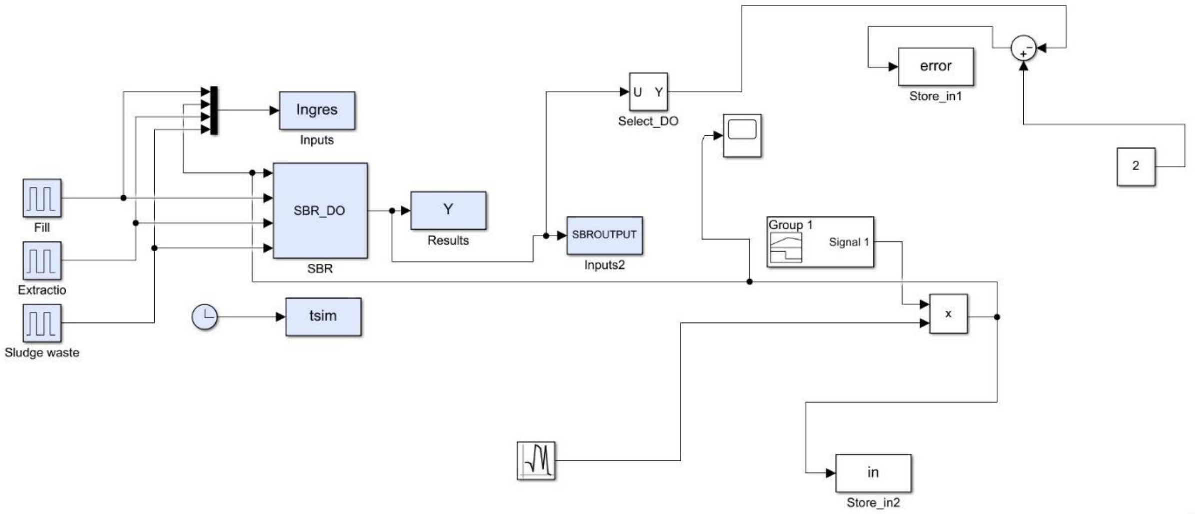

Figure C1. An Example of Lower level model Identification File in SBR

This Simulink is implementation of lower level PI controller with proper tuning (SIMC) for the SBR process. In the other two lower level control strategies the author has changed Integer controller with Fractional (FPI) and Fuzzy controller.

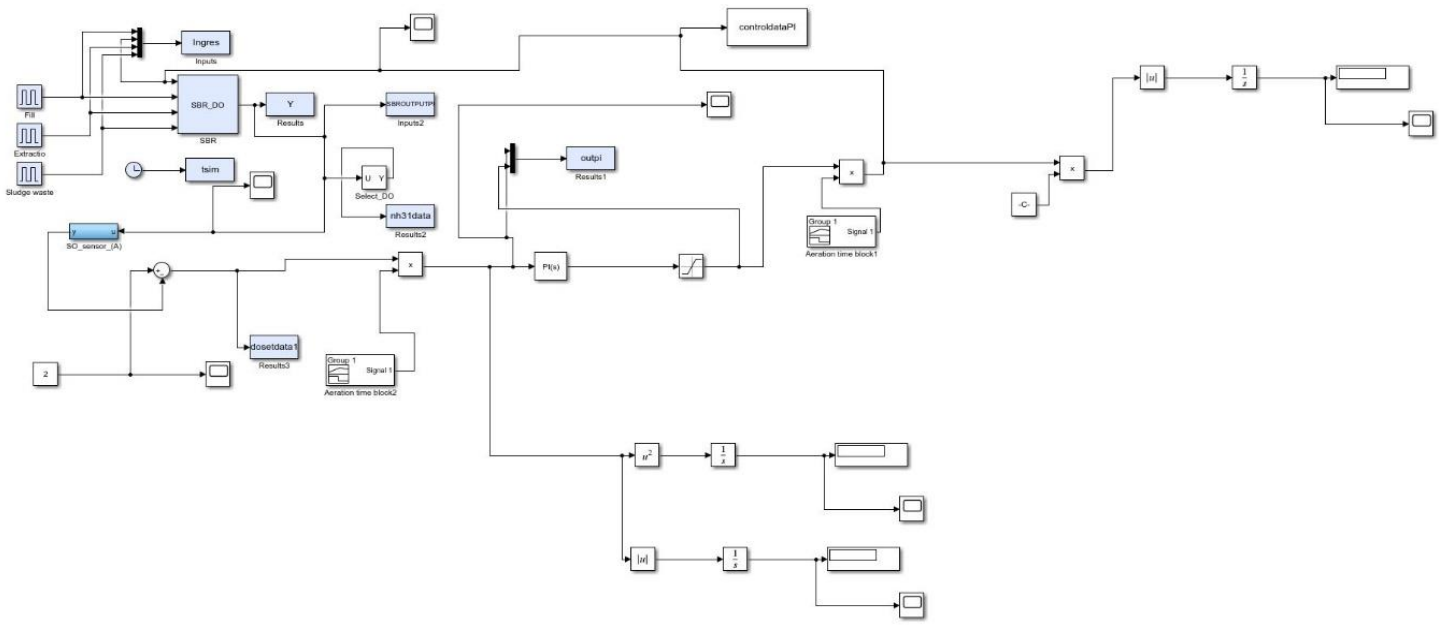

Figure C2. SBR Simulink Diagram with lower level PI controller.

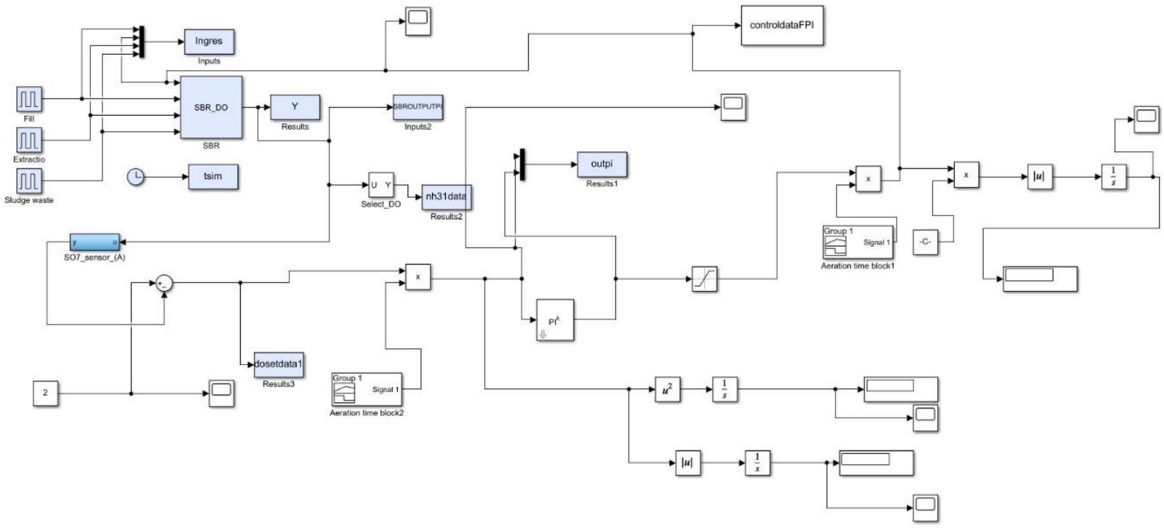

Figure C3. SBR Simulink Diagram with lower level FPI controller.

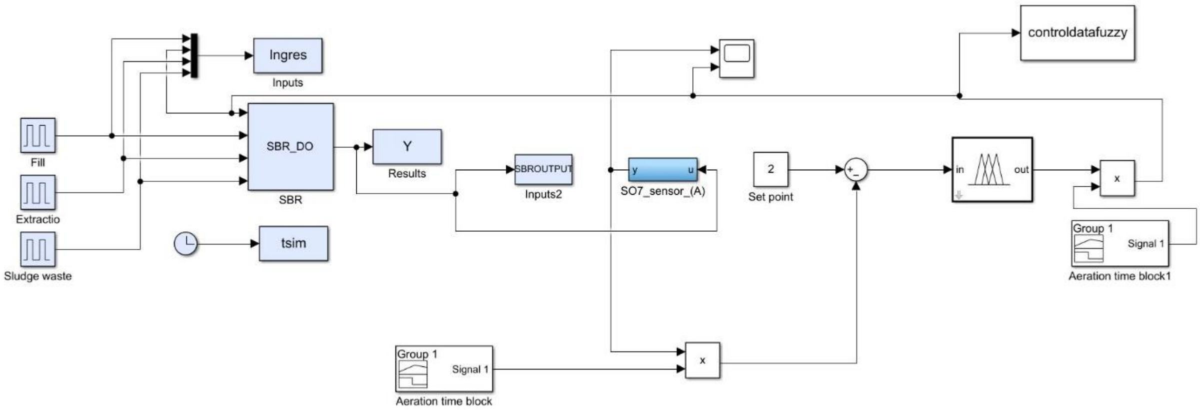

Figure C3. SBR Simulink Diagram with lower level Fuzzy controller.

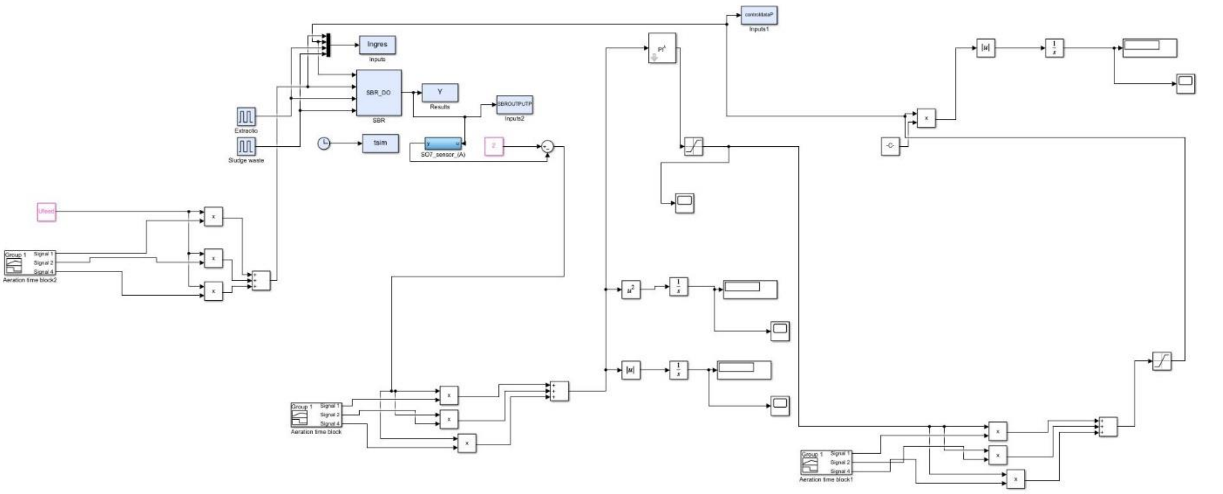

Figure C4. SBR with Stepfeed (SSBR) Simulink Diagram with lower level FPI controller.

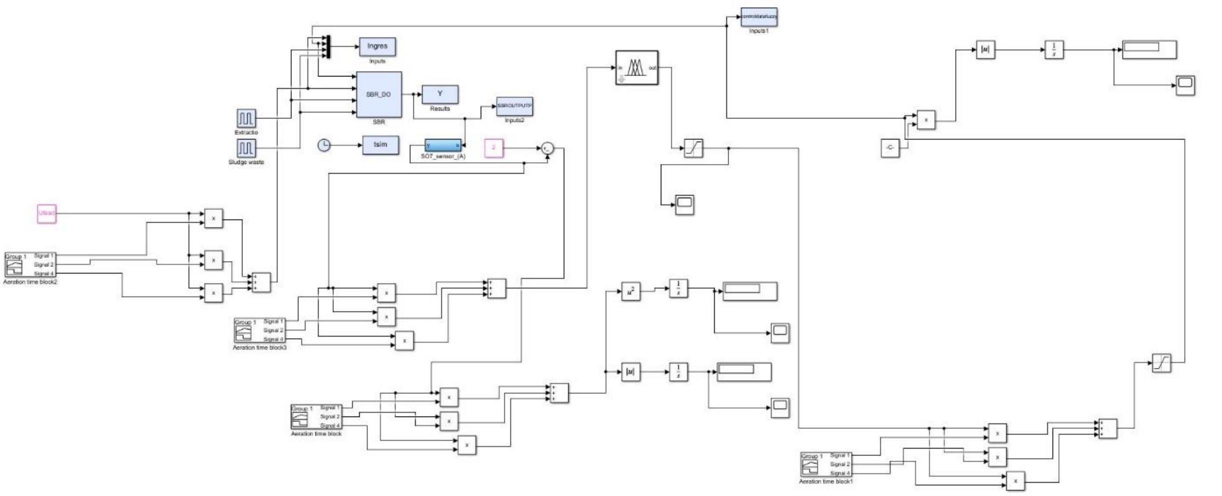

Figure C5. SBR with Stepfeed (SSBR) Simulink Diagram with lower level Fuzzy controller.

APPENDIX D

This is implementation of supervisory Fuzzy logic control to determine variable set point to lower level controller inside a cascaded scheme. For the other supervisory schemes the author changes only the sensors (NH_4/NO_3) and lower level controller (PI/FPI).

The same Simulink model is available model where PI model is replaced by FPI controller.

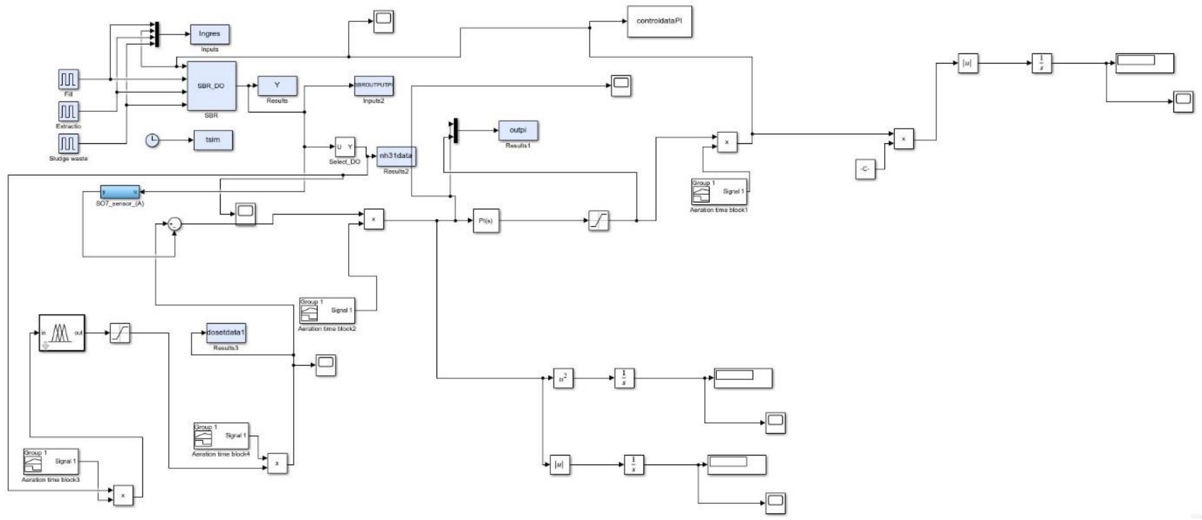

Figure D1. SBR Simulink Diagram with lower level PI with higher level fuzzy controller (NH_4/NO_3 based aeriation).

List of Publications

11. LIST OF PUBLICATIONS

Journals

- Indranil Dey, Abdul Gaffar Sheik, Seshagiri Rao Ambati*, Fractional order models identification and control within a supervisory control framework for efficient nutrients removal in biological wastewater treatment plants, ***Environmental Science and Pollution Research***, 30, 16642-16660, 2023 (SCIE, Web of Science, Impact Factor: 5.19), https://doi.org/10.1007/s11356-022-23235-x.
- Indranil Dey, P. Sridhar, Seshagiri Rao Ambati*, Design of supervisory adaptive fuzzy control for enhanced energy saving in a sequencing batch reactor based wastewater treatment plant, ***Environment, Development and Sustainability***, (SCIE, Web of Science, Impact Factor: 4.9), DOI:10.1007/s10668-023-04363-x.
- Indranil Dey, Seshagiri Rao Ambati*, Prashant Navnath Bhos, Shirish H. Sonawane, Sridhar Pilli, Design of fractional and intelligent control strategies for SBR based wastewater treatment process for effluent quality improvement, ***Water Science and Technology***, 1st revision submitted, under review, 2024.
- Indranil Dey, Prashant Navnath Bhos, Seshagiri Rao Ambati*, Sridhar Pilli, Influence of seasons on the effluent quality in sequencing batch reactor based wastewater treatment plants, ***Journal of Water Chemistry and Technology***, revision submitted, 2024.

Book Chapter

- Indranil Dey, P. Sridhar, Seshagiri Rao Ambati, GA-based IMC fractional PI controller design for Dissolved Oxygen control with a non-integer order Biological Wastewater Treatment Plant, part of book series ***Lecture Notes in Electrical Engineering*** *(LNEE, volume 1046)*, springer Nature, ICCDC 2023.

Conferences

- Indranil Dey, Seshagiri Rao Ambati, Uday Bhaskar Babu Gara, Sridhar Pilli, Optimizing the Biological Treatment in Wastewater Treatment Plants: A Focus on IMC-Based Fractional Controllers within a Supervisory MPC Control Scheme, presented at ***3rd International Conference on New Frontiers in Chemical, Energy and Environmental Engineering (INCEEE - 2023)*** 24-25 November 2023, NIT Warangal, India. (Best Paper award).
- Indranil Dey, P. Sridhar, Seshagiri Rao Ambati, GA-based IMC fractional PI controller design for Dissolved Oxygen control with a non-integer order Biological Wastewater Treatment Plant, ***4th International Conference on Communication, Devices and Computing (ICCDC 2023)*** March 1-3, 2023, HIT Haldia, India.