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SYSTEMATIC EVALUATION OF A FULL-SCALE TEXTILE WASTEWATER TREATMENT PLANT USING THE GPS-X AND ANALYTICAL MEASUREMENTS

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ABSTRACT

Extensive quantities of water and chemicals are used in the textile industry processes. Therefore, the treatment of textile wastewater is vital to protect the environment, maintain the public health, and recover resources. However, due to inadequate quality data, inexperienced plant operators, and inconsistent measurements, a prediction on the effluent quality of a textile wastewater treatment plant is difficult. Thus, the aim of this study was to comprehensively evaluate the full-scale textile wastewater treatment plant using the GPS-X software and analytical measurements to establish the operational strategies for the plant. It also aimed to develop the troubleshooting strategies in a Bahir Dar textile factory, Ethiopia. Based on the stated aim, the research had the following four specific objectives.

The first specific objective of the research was to characterize the wastewater physicochemical properties and evaluate the performance of the wastewater treatment plant in the textile factory. In the inlet and outlet of the wastewater treatment plant (WWTP), samples were collected for six months and analyzed on-site and in a laboratory for parameters including dissolved oxygen, pH, temperature, total Kjeldhal nitrogen (TKN), chemical oxygen demand (COD), biochemical oxygen demand (BOD_5), total suspended solids (TSS), total nitrogen (TN), total phosphorous (TP), nitrite, nitrate, and metallic compounds. These 22 parameters were classified into three functional groups: regulatory compliance (to assess legal discharge), nutrient dynamics (to monitor biological health), and model fractionation (to serve as specific mathematical inputs for the simulation). Statistical analyses were conducted using descriptive statistics and outlier analysis via SPSS to manage the stochastic nature of textile discharge; these methods conform to current environmental engineering trends, specifically identifying that effluent failures were operational rather than influent-driven. The results showed that the TSS, BOD_5, COD, TP, nitrite, ammonia, and total chromium contents were above the discharge limit with the values of 73.2 mg/L, 48.45 mg/L, 144.08 mg/L, 7.9 mg/L, 1.36 mg/L, 1.96 mg/L, and 0.16 mg/L, respectively.

The second objective was conducted to model, simulate, and optimize the operational process control parameters (DO setpoints, HRT, SRT, WAS, and RAS) under different scenarios. Scenario development is centered on a comparative analysis between the factory's existing as-is physical layout and an optimized should-be digital model, with the primary criteria focused on aligning operations with scientifically accepted process flows through a highly regulated Conventional Activated Sludge (CAS) framework. By transitioning to this optimized state, the research establishes a performance benchmark designed to maximize pollutant removal efficiency while simultaneously achieving significant reductions in both energy consumption and overall operational costs. GPS-X was selected over similar software like BioWin or WEST due to its superior Carbon and Energy Footprinting modules and validated accuracy in full-scale industrial modelling. Two primary scenarios were developed based on a gap analysis approach: scenario I (Existing Layout), governed by the criterion of physical fidelity, and scenario II (Modified Process Flow), governed by scientific optimization. While limited to two structural layouts for comparative feasibility, true optimality was achieved within scenario II through thousands of digital iterations via dynamic sensitivity analysis on variables such as SRT and RAS. The model was calibrated using four-months' measured data and validated and verified using two-months' measured data. The results showed that the existing process model (scenario I) compared to the modified process model (scenario II) for TSS, COD, TP, and NO_3, violated the compliance limit. However, the energy consumption and operation cost for scenario II were reduced by 52.9% and 56.98%, respectively.

The third objective was conducted to evaluate the treatment plant performance using analytical measurement and GPS-X modelling software. While GPS-X supports dynamic simulation, this study utilized steady-state analysis to establish a robust operational baseline, as the lack of online sensors would have introduced significant synthetic noise into a dynamic model. The selection of steady-state modelling was a strategic decision necessitated by the absence of high-frequency historical data and the stochastic nature of textile batch-dyeing operations. In this regard, the pollutant removal efficiency results from analytical measurement and GPS-X model were 71% and 43%, respectively. The simulation results for scenario I showed that it was energy intensive, and indicated poor effluent quality, elevated operation costs, and high sludge production.

However, scenario II was found to be the more efficient and a more effective treatment option compared to scenario I. The modelling-based performance evaluation technique was shown to be superior to the analytical measurements evaluation by identifying the parameter that violated the permissible limit, the duration of the violation, the mode of operation, and its location in the treatment plant.

The fourth objective of this research was conducted to optimize key process control parameters to the observed operational challenges of existing processes, and to suggest an operational guide to the operators and decision makers to enhance the treatment performance in the GPS-X software. According to the formulated troubleshooting and decision support strategy, the optimization results of waste activated sludge in the primary and secondary clarifiers were within the range of 15 ± 5 m^3/d and 83 ± 7 m^3/d, respectively. In line with this, the recycled activated sludge flow was optimized to 150 ± 10 m^3/d. The sludge retention time was found to be 5 ± 1d and 6.7 ± 0.5d in the secondary and primary clarifiers, respectively. In the GPS-X model, molasses addition represented as an increase in the readily biodegradable substrate fraction of the influent which contributed to save the mechanical energy for aeration by creating a layer of biochemical control instead.The addition of a carbon source, molasses resulted in a flow of 0.5 ± 0.05 m^3/d, and the variation of influent was optimized to 600 ± 50 m^3/d due to wastewater characteristics and rainfall. The optimum airflow into the aeration tank was 550 ± 5 m^3/hr, which resulted in a 91.5% saving of energy in the optimized process. The solid mass flow production was reduced from 1087 kg/d (existing process) to 760 kg/d (optimized process), while the overall pollution load in the effluent was reduced from 260 kg/d (existing process) to 20 kg/d (optimized process). Consequently, the findings disclosed that the optimized process control parameters tested under different troubleshooting strategies reduced the energy consumption, increased the effluent quality, and reduced the pollution load compared to the existing process of the plant.

DECLARATION BY STUDENT

I hereby declare that this thesis for the Degree of Doctor of Engineering in the Department of Civil Engineering at Durban University of Technology is my original work, and it has not been submitted previously to any other institution of higher education. I further declare that all the sources cited and quoted are well indicated and acknowledged in the reference section.

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Tilik Tena Wondim Date: April 06, 2026

Student Number (21855868)

DEDICATION

This achievement is dedicated to my supervisor, Bloodless Dzwairo, who supported me tirelessly and across all hours to ensure the success of this work. Her commitment to excellence and sustained mentorship represents the true spirit of an environmental guardian.

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CHAPTER ONE: BACKGROUND

1.1 Introduction

Textile industries are one of the largest consumers of water and sources of pollution due to different organic and inorganic compounds generated in the process (Bhatia *et al.* 2018; Andreides, Dolejs and Bartacek 2022). Wood fibres such as lignin, carbohydrates, extractives and chemical additives generate high volumes of concentrated wastewater (Choudri and Charabi 2019; Bidu *et al.* 2021). Furthermore, untreated wastewater with a significant amount of organic compounds and nutrients discharged into the receiving environment may severely affect the aquatic ecosystem eutrophication. This leads to water quality deterioration and the release of toxic compounds into the environment (Hamza, Iorhemen and Tay 2016; dos Santos *et al.* 2018; Durotoye *et al.* 2018).

To understand the degree and extent of the pollution, wastewater characterization and compound classification could be the first and the most crucial approach to identify the treatment options (Mhlanga and Brouckaert 2013b; Schaider, Rodgers and Rudel 2017; Pavithra *et al.* 2019). As many research findings have stated, the biological oxidation process is the main and best treatment option for textile wastewater treatment (Deng *et al.* 2020). In addition, the Activated Sludge Process (ASP) is one of the biological treatments which could be an alternative secondary treatment (Diaz-Elsayed *et al.* 2017). This treatment process uses microorganisms to speed up the degradation of waste materials in an aerobic environment (Sarayu and Sandhya 2012; Pazdzior *et al.* 2016).

ASP is a complex process that involves different biological kinetics, and stoichiometry, to transfer the conversion of contaminants to acceptable levels effluent quality and reduced sludge production (Hauduc *et al.* 2013; Holkar *et al.* 2016). For the quantitative and qualitative measurement of contaminants, performing the mathematical model and simulation are vital in optimizing the treatment process (Hauduc *et al.* 2011; Hvala, Vrecko and Bordon 2018). Modelling and simulation are powerful techniques used to understand the real-time dynamics of the treatment process and answer questions on the location of the monitoring and process control parameters (Jasim 2020; Laizer *et al.* 2022). Furthermore, biological process optimization is highly focused on minimizing operation costs and energy, increasing the effluent quality and treatment performance, reducing sludge production, and simplifying the operation burden (Van Hulle and Vanrolleghem 2004; Vera, Saez and Vidal 2013; Man *et al.* 2017; Sid *et al.* 2017).

1.2 Motivation for the research (problem statement)

Waste management is a big challenge in developing nations due to the lack of operational systems, resources, and the undefined boundary within the producer-user environment and interaction (Pattnaik, Dangayach and Bhardwaj 2018; Methneni *et al.* 2021). Decision makers should consider a combination of multiple models to improve the quality of global environmental health (Sarayu and Sandhya 2012; Puchongkawarin *et al.* 2015; Wang *et al.* 2022b). Likewise, Pavithra *et al.* (2019) stated that the global dynamic population and economic growth have complicated managing the environmental systems, and they have contributed to the production of waste directly linked to climate change. A circular economy and resource efficiency are prime concerns to achieve zero waste discharge and zero climate emission (Lotfi *et al.* 2019; Montwedi *et al.* 2021).

Moreover, some studies (Vandevivere, Bianchi and Verstraete 1998; Singh and Arora 2011) stated that waste management technology had significant negative and positive impacts on the global environment. More specifically, discharging wastewater into the environment exacerbates to climate change compared with the application of resource recovery systems from waste streams (Pang and Abdullah 2013; Patel and Bhatt 2022). Thus, identifying a waste stream's footprint and characterizing its state are two key factors, which magnify the quality of sustainable waste management (Puchongkawarin *et al.* 2015; Pattnaik, Dangayach and Bhardwaj 2018; Liwarska-Bizukojc, Andrzejczak and Solecka 2019). According to Flores-Alsina *et al.* (2021), paradigm shifts in waste treatment and sludge management are crucial to reduce the impacts on the climate by considering the process of optimization and operation life cycle. Furthermore, the modelling and simulation of a wastewater treatment plant is a potentially strategic management tool as it contributes to exploring a mitigation framework in a comprehensive way (Elawwad, Zaghloul and Abdel-Halim 2017; Elawwad *et al.* 2019; Faris *et al.* 2022).

In this research, the novelty lies in the integration of stochastic field data with deterministic GPS-X modelling to bridge the gap between empirical monitoring and operational intelligence. By shifting the focus from compliance reporting to predictive optimization, this work provides a first-of-its-kind digital troubleshooting framework for the Bahir Dar Textile Factory, Ethiopia, through optimized process control rather than expensive infrastructural expansion.

In Bahir Dar City, the wastewater management system is totally inadequate and both liquid and solid wastes are ending up in an open field which is located seven km to the south-east of the city within the Lake Tana sub-basin. Very few institutions have waste stabilization ponds to partially treat their liquid wastewater. Moreover, the textile factory had built a full-scale biological wastewater treatment plant and the effluent was discharged into the nearby surface water without any confirmed discharge limit which further polluted the water (Mehari, Gebremedhin and Ayele 2015; Wondim and Dzwairo 2018; Zhang *et al.* 2021b).

In the rainy season, flooding was likely to occur, and the health risk due to transportation of the openly flowing untreated wastewater increased periodically in the city (Mekonnen 2012; Hamza, Iorhemen and Tay 2016; Alsulaili, Al-Buloushi and Hamoda 2020). Besides this challenge, the downstream communities have intensively been using river water and abstracting the shallow ground water for drinking and irrigation. The potential sites for drinking water sources were also unsecured due to the unsafe and improper disposal of industrial and municipal wastes (Elnakar and Buchanan 2019).

Furthermore, the industries found in Bahir Dar City have been the main pollutants, and potential natural resources have been negatively influenced by the disposal of their effluents. The downstream communities have been using the polluted water for drinking and washing, and irrigating different restricted and unrestricted crops. Principally, the untreated and treated wastewater discharged into uncontrolled natural water bodies, undergoes a complex bio-chemical reaction which has polluted the global environment by releasing toxic compounds into the atmosphere (acidification, global warming, ecotoxicology, etc.) and caused water quality deterioration, soil salinity, health risks, and contributed to gully erosion (Holkar *et al.* 2016; Islam *et al.* 2023).

In this respect, due to the poor and unscientific wastewater management system, the condition was aggravated. Accordingly, it was crucial to track the potential wastewater characteristics. It was also believed that quantifying the impact on the environment using an integrated evaluation was vital to develop strategies that would assist in curbing environmental pollution by increasing the performance of the existing treatment plant.

1.3 Justification for the study

The textile treatment plant used in this case study was already in place. However, it was energy intensive and uneconomical (Islam et al., 2023). It was also observed that though the factory was investing a lot in its operations, it did not meet the compliance limits for effluent discharge, and its performance was not considered satisfactory (Bakar et al., 2020). Moreover, no wastewater treatment process optimization mechanisms were implemented in the factory (Wang et al., 2022a). Consequently, the pollution was aggravated, and the downstream inhabitants were complaining since they were using the polluted water from the receiving river without any treatment being implemented.

Therefore, the researcher was of the opinion that it was worthwhile evaluating the already existing plant to reduce the environmental pollution, running costs, and use of energy. In this study, the researcher quantified the extent of the pollution, evaluated the existing plant, examined the evaluation methods, and devised better operation strategies using the existing infrastructure (Yin et al., 2015).

1.4 Aim of the study

This study was conducted to assess the wastewater quality, evaluate the existing treatment profile, and develop a technical framework for the textile wastewater treatment plant operation of the Bahir Dar textile factory.

1.4.1 Specific Objectives

Based on the above general objective, this study aimed to:

1. Characterize the wastewater generated from Bahir Dar textile factory;
2. Model and analyse a wastewater treatment plant's unit operations and processes using the GPS-X software;
3. Evaluate the wastewater treatment plant's performance by using an analytical method and the GPS-X software, and
4. Develop a holistic operation strategy and a troubleshooting framework for the Bahir Dar textile factory wastewater treatment plant,

1.5 Scope of the study

The study focused on the evaluation of the performance of an existing wastewater treatment plant units' processes and operations, namely the Bahir Dar textile factory. The key effluent wastewater quality parameters were measured periodically. The multi-grade sand filter and guard pond were excluded from both the analytical measurement and GPS-X modelling (scenario I) to ensure the study reflected the actual operational status of the plant. Including non-functional units would have introduced significant errors in the model calibration and masked the critical failures observed in the secondary treatment stage. As a result, they were not included in the physicochemical analysis of this study. While the plant utilizes an electrolysis unit for heavy metal reduction, this component was excluded from the GPS-X model due to the absence of a corresponding electrochemical module in the software library. To ensure a comprehensive evaluation of the plant, the performance of the electrolysis unit was captured through rigorous analytical measurement and integrated into the final performance characterization.

1.6 Thesis structure

This thesis is structured in six chapters as presented below:

Chapter One presents a general description about the wastewater management systems and problems associated with the Bahir Dar Textile factory, and the objective and scope of the research.

Chapter Two provides a detailed review of the literature aligned with the four specific objectives of the study.

Chapter Three provides details about the study area.

Chapter Four explains in detail the methods and materials used in the study.

Chapter Five presents the results and discussions for the specific objectives.

Chapter Six presents the conclusions reached for each of the four specific objectives and makes overall recommendations.

CHAPTER TWO: LITRATURE REVIEW

2.1. Introduction

A textile factory is one of the economic sources that contributes significant value to the Gross Domestic Product (GDP) of developed and developing countries (Siddique *et al.* 2017; Farhana, Mahamude and Mica 2022). The textile products are circulated globally in various forms. Industries are considered common goods and are the concern of all nations (Patel and Vashi 2015). However, they have different interconnected unit processes and are very complicated (Liu *et al.* 2020a).

Industries generate large volumes of highly concentrated, and mixed wastewater, which in turn pollutes the global environment (Imtiazuddin, Mumtaz and Mallick 2012; Yaseen and Scholz 2019a). In this regard, collecting, transporting, and treating the wastewater generated from each unit's operation and process is quite challenging for municipalities and treatment plants (Latha, Partheeban and Ganesan 2017; Sharma and Malaviya 2022b).

Additionally, in textile factories the increased demand for products leads to an increase in wastewater generation and pollution pressure on the receiving environment (Bakar *et al.* 2020). In a recent study, Islam *et al.* (2023) explained that because of the mixed nature of their wastewater and water-consuming processes, textile factories tend to produce toxic contaminants like residual dye, mordants and micro-fibres that affect the health of the ecosystem. In addition, heavy metals are also produced during the dyeing process. For example, a study by Wang *et al.* (2022a) revealed that effluent identified in the study contained organic and metallic pollutants that represented a high pollution load, which could potentially affect human, aquatic, and environment health. Apparently, due to their persistent nature, heavy metals undergo biogeocycling and are bio-magnified in the food chain (Yaseen and Scholz 2019b). Hence, to reduce the energy consumption and pollutant emissions to the environment, and to increase resource recovery, the textile wastewater quality parameters need periodic monitoring and measurement (Yin *et al.* 2017).

Fortunately, there are different technological combinations to treat specific wastewater generated from the textile industry, which assist in reducing water consumption and increase the reuse potential (Mhlanga and Brouckaert 2013a; Tabassum, Khatun and Baten 2015). However, these combinations tend to be in conflict with real-time operational control of the plant due to limited data quality and adequacy, inexperienced plant operators, discrete measurement of the parameters, and a lack of cutting-edge treatment technology (Kroll *et al.* 2016a; Mihaly, Simon-Varhelyi and Cristea 2022a). In this regard, the physicochemical characterization of the wastewater is essential to devise a strategy for identifying the inefficiencies in plant operation, quantifying the impact, and optimizing the treatment process (Zhang *et al.* 2021a; Zhou *et al.* 2022).

Specifically, Bahir Dar textile factory used conventional activated sludge process treatment technology which affected the quality of the receiving aquatic environment (Mehari, Gebremedhin and Ayele 2015). Even though in biological wastewater treatment plants there are key locations where the physicochemical wastewater quality parameters are monitored, the study area had poor-operation protocols and inconsistent monitoring of wastewater quality parameters which contributed to the decline of the wastewater treatment plant's performance from time to time (Mekonnen 2012). Studies have shown that identifying the root cause of the failures, measuring the treatment performance, and quantifying the impacts on the receiving environment are big challenges (Mekonnen 2012; Mehari, Gebremedhin and Ayele 2015).

2.2. Wastewater treatment technology for the textile industry

Textile industry wastewater has been a concern of the public since the textile industry was introduced across the globe (Wang, Jiang and Gao 2022). These factories use different chemicals in the textile manufacturing process, and there are attempts to recover the chemicals as a resource (Tran *et al.* 2015; Urban 2017; Uddin 2021). A study by Puchongkawarin *et al.* (2015) showed that to meet the recovery standard and reuse effluent from the textile industry, the wastewater should be treated before being disposed of into the environment. However, there might be a release of secondary pollution from the treatment plant that should be optimized and managed in the operation (Kim, Bowen and Ozelkan 2015; Mamais *et al.* 2015).

2.2.1 Physical unit operation for textile wastewater treatment

Unit operations are the individual building blocks used to separate, move, or refine substances through mechanical means (Achillas et al., 2013). The higher wastewater flow with a complex chemical process in the industry and other emerging demands need special attention for the recovery of resources from the waste stream using physical treatment units (Deng *et al.* 2020; Adane, Adugna and Alemayehu 2021). There are different unit operation combinations to treat the specific wastewater generated from the textile industry (e.g. screen, grit chamber, clarifiers, and filter) (Arnell *et al.* 2017; Pavithra *et al.* 2019; Pazdzior, Bilinska and Ledakowicz 2019; Araujo *et al.* 2022). Calise *et al.* (2020) and Hauduc *et al.* (2011) demonstrated that unit operation in wastewater treatment is an eco-friendly method. However, it needs to be integrated with other unit processes to enhance the treatment efficiency for persistent pollutants. Furthermore, the selection of the unit operation system was highly dependent on the quality of the wastewater, the raw material used for the industrial process, and the objective of the treatment (Kanchanapiya and Tantisattayakul 2023; Khan *et al.* 2023).

2.2.2 Chemical & biological unit process for textile wastewater treatment

Van Hulle and Vanrolleghem (2004) and Wei *et al.* (2023) stated that a chemical and biological unit process in textile wastewater treatment involves a fundamental transformation of the effluent's molecular structure through specific reactions or microbial metabolism. Biological unit process like the activated sludge process, specialized bacteria consume organic dyes and nutrients (BOD_5 and COD), converting them into new cellular mass and carbon dioxide (Fu, Zhang and Wang 2011; Man *et al.* 2017; Lotfi *et al.* 2019). Simultaneously, chemical unit processes such as coagulation-flocculation use chemical additives to neutralize the electrical charges of colloidal dye particles, causing them to clump together into larger, insoluble masses. the commingled type of waste generated from different textile production units required an optimized combination of unit operations and processes. Studies by Karthikeyan *et al.* (2011) and Erkan *et al.* (2020) explained that segregation of waste at the point of generation using different unit process significantly reduces the burden on the subsequent treatment process complications although this process needs a special facility. The recent developments in the textile wastewater system showed a vast trail of electro-chemical-based treatment apart from the chemical and biological processes (Can *et al.* 2006; Bozkurt *et al.* 2016; Moussa *et al.* 2017).

2.2.3 Technological integration for the treatment of textile industry wastewater

Natural freshwater resources are depleted due to un-optimized consumption and inefficient treatment of wastewater (Sotemann *et al.* 2005; Urban 2017). Studies have indicated that integration of wastewater treatment technology reduced freshwater consumption and increased the reuse potential (Wu *et al.* 2016; Tomperi, Koivuranta and Leiviska 2017; Haddad *et al.* 2018; Zheng *et al.* 2022). A combination of the physicochemical and biological treatment processes for textile industry wastewater is more effective to remove a mix of wastes (Vera, Saez and Vidal 2013; Jegatheesan *et al.* 2016; Jafarinejad 2020). For the superior removal of pollutants from the textile industry wastewater, process optimization strategy along with technology integration was found to be effective (Dasgupta *et al.* 2015; Grandclement *et al.* 2017; Cydzik-Kwiatkowska *et al.* 2018; Ceretta, Nercessian and Wolski 2021; Wang *et al.* 2022b). On the other hand, the discharge of untreated or partially treated wastewater has become a major environmental concern which needs a zero-waste discharge strategy to curb the environmental burden (Wei *et al.* 2003; Wang 2014; Wang, Jiang and Gao 2022).

2.3. Characterization of textile industry wastewater quality parameters

The quality of wastewater varies significantly according to the type of treatment process employed, the season of the year, and the product produced in the industry (Bhatia *et al.* 2018; Dotto *et al.* 2019). Hence, to reduce energy consumption and pollutant emissions into the environment, and to increase resource recovery, the textile wastewater quality parameters need periodic monitoring and measurement.

2.3.1 Physico-chemical wastewater quality parameters

The performance of the treatment plant depends on different parameters (Tran *et al.* 2015; Yaseen and Scholz 2019b). Ogleni, Ovez and Ogleni (2010) conducted a study on the textile wastewater characterization to the major pollutant parameters for the activated sludge process. The result showed that due to the variable composition and influx characteristics, the performance of the treatment plant had declined.

Bhatia *et al.* (2018) conducted a study on the physicochemical assessment of textile industry effluent in India to evaluate the pollution load of the effluent into the receiving stream and the seasonal variation of the wastewater quality parameters. Results from the wastewater characterization analysis indicated that Chemical Oxygen Demand (COD) and Biochemical Oxygen Demand (BOD_5) were the major parameters leading to the overall poor effluent quality in all seasons. It was concluded that the effluent from the textile industry produces heavy pollution on the receiving streams. The pollution load was quantified using physicochemical characterization of the effluent (Bhatia *et al.* 2018).

In addition, Durotoye *et al.* (2018) conducted a study on the physicochemical characterization of the textile industry wastewater to quantify the pollution load. In particular, the study examined the main physicochemical parameters such as ammonia (NH_3), total nitrogen (TN), nitrite-nitrate (NO_x), volatile suspended solids (VSS), total dissolved solids (TDS), dissolved oxygen (DO), chemical oxygen demand (COD), five-day biochemical oxygen demand (BOD_5), pH, electrical conductivity (EC), chromium (Cr), iron (Fe), magnesium (Mg), potassium (K), total phosphorous (TP), Calcium (Ca), total alkalinity (TA), Zinc (Zn), total Kjeldhal nitrogen (TKN), and total suspended solids (TSS) before and after treatment. Similarly, dos Santos *et al.* (2018) stated that most of the physicochemical parameters including COD, BOD_5, total phosphorous, and iron significantly influenced the effluent quality of textile industry wastewater. The physicochemical parameters were thoroughly measured and analyzed at each step of the treatment process to enable timely action (Patel and Bhatt 2022; Wang, Jiang and Gao 2022). Similarly, characterizing wastewater quality is the primary objective of a treatment plant, as it provides the essential data needed to evaluate system performance and mitigate operational risks (Tuser and Oulehlova 2021; Uddin 2021).

2.3.1.1 Onsite wastewater quality measurement and analysis

Wastewater samples are measured both on site and at a laboratory to evaluate the nature of the waste, the treatment objectives, and the method of analysis (Young, Clesceri and Kamhawy 2005; Wang, Jiang and Gao 2022). Researchers have stated that pH, electrical conductivity, TDS, DO, residual chlorine, and temperature were measured at the site to reduce any uncertainties in the result (Mountassir *et al.* 2013; You *et al.* 2018; Bidu *et al.* 2021). Moreover, most of the chemical and biological processes in the treatment plant are highly dependent on the pH, DO, and temperature that need special attention in the operation of the plant (Turkmenler and Aslan 2017). Apparently, the parameters that are measured offsite are highly affected by atmospheric factors and lose their integrity while being transported to the laboratory (Tuser and Oulehlova 2021).

In the study by Young, Clesceri and Kamhawy (2005), the standard wastewater quality measurement techniques were reviewed and evaluated, and changes were included in the treatment protocol. The results showed that the changes in the standard method were clarified step-by-step, and the quality assurance and control protocols, and calculation procedures were discussed. The study concluded that the evaluation procedures played a critical role in determining the quantity of the final pollution load and evaluating the treatment plant's performance (Young, Clesceri and Kamhawy 2005).

The quality of the onsite analytical measurement of wastewater might result in errors during the measurement due to the different mobile kits, sample location selection, and analysis techniques (Bisschops and Spanjers 2003). To bridge the gap, Silva and Rosa (2021) recommended using repeated and consistent measurement at specific treatment plant units.

2.3.1.2 Laboratory measurement and analysis

In wastewater treatment, understanding the process begins with examining the waste. The study by Tran *et al.* (2015) showed that laboratory analysis was indispensable to classify the plant unit's process and performance. Similarly, Diaz-Elsayed *et al.* (2017) stated that the analysis of the parameters used in the laboratory was a continuous process that could not be replaced with new technology and needed a consistent setup to control the quality of the results.

Hamza, Iorhemen and Tay (2016) explained that the wastewater quality analysis process requires long analysis time, large volume of samples, complex instruments, and skilled expertise and logistics. For the purpose of high quality, data analysis quality, and control requirements, most of the textile industry physicochemical wastewater parameters were measured in the laboratory. Similarly, Uddin (2021) mentioned that before collecting samples, defining the system boundary, and planning the collection, transporting, preservation, and analysis protocols are equally important to the laboratory analysis result.

A study by Newhart *et al.* (2019) also showed that too much data might not guarantee a good quality analysis. According to Singh and Arora (2011), conducting an experiment in the laboratory is better than doing it in the treatment plant environment. To reduce uncertainties in the simulation of plant modelling, the physicochemical wastewater quality analysis should have a narrower standard deviation between measurements (Revilla, Galan and Viguri 2016; Andraka *et al.* 2018).

2.3.1.3 Performance indicator of wastewater quality parameters in the treatment plant

In textile wastewater treatment the pollution load is measured based on the dominant wastewater quality parameters, posing a significant challenge to conventional biological treatment systems (Abdalla and Khalil 2018). Textile wastewater is characterized by a complex and stochastic mixture of pollutants, ranging from high molecular weight organic dyes; such as azo, anthraquinone, and reactive compounds to inorganic constituents like salts (Na_2SO_4, NaCl) and heavy metal complexes containing total chromium, copper, or zinc. On the other hand, the degree of pollution may be classified as its potential to deteriorate the water quality and the quantity of the pollution load on the receiving environment (Aldaghi and Javanmard 2021; Islam *et al.* 2023). The selection of parameters is based on criteria that identify organic strength (COD, BOD_5), aesthetic impact (colour/dyes), and inhibitory toxicity (total chromium, TDS) to determine the biodegradability index, ensuring the treatment system can effectively manage the high-strength, stochastic loading inherent in batch dyeing operations (Bidu *et al*, 2021). Similarly, Quadros *et al.* (2010) and Erkan *et al.* (2020) identified the organic and nutrient load on the receiving environment and evaluted the treatment plant performance parameters as TSS, COD, BOD_5, NH_3, NO_2, NO_3, TN, TKN, and TP. Moreover, Abbasi, Ahmadi and Naseri (2021) consolidated the measurement of plant performance in terms of biological treatment and classified it as TSS, COD, TN, and TP which is the best way to account for the solid mass flow in the system.

2.4. Wastewater treatment process models and simulation techniques

Modelling of the wastewater treatment process started in the early 19th century to represent the real world using finite model variables (Orhon 2015). In textile wastewater there is a significant production of sludge and poor effluent quality due to inefficiencies in the treatment plant which further degrades the environment (Orhon and Cokgor 1997; Meier 2016; Apollo, Seretlo and Kabuba 2023). Research findings showed that modelling the unit's operation and the processes of the treatment plant had a vital role in unlocking the potential of optimizing the whole process (Puchongkawarin *et al.* 2015; Muoio *et al.* 2019; Zhang *et al.* 2020).

2.4.1 Wastewater treatment plant model guiding principles and protocols

In textile industry wastewater, it is difficult to measure all the kinetic process and stoichiometric process variables which are indispensable to run the model (Andraka *et al.* 2018; Li *et al.* 2020). The study by Wang, Jiang and Gao (2022) and Hakanen, Sahlstedt and Miettinen (2013) showed that by analyzing the complex treatment process with multiple attributes using only the analytical method it is very difficult to come to an integrated decision on the plant's performance. The finding by Guerrero *et al.* (2012) stated that representing reality by means of the theoretical view of mathematical definitions and structures was then the state-of-the-art approach which over simplifies the real challenge. Similarly, modelling starts from defining the real-world system boundaries and working scopes (Pons, Spanjers and Jeppsson 1999; Jeppsson *et al.* 2007; Jeppsson *et al.* 2013). The objective of operating the model might be predicting unknown outputs, understanding the process' working mechanisms, and ease of communication and action (Meier 2016; Bis *et al.* 2019; Campo *et al.* 2023).

2.4.1.1 Modell definition, data collection and analysis

In modelling the plant, special attention needs to be given to defining the operating behaviour of the system, and then making an assumption (Meier 2016; Cao *et al.* 2021). The type of data used in the model is also a main factor in selecting the model and focusing on adapting it to reality (Iacopozzi *et al.* 2007; Bachis *et al.* 2015; Benintendi 2016; Nair *et al.* 2018). The data collected from the textile wastewater treatment plant was compiled and feed the measurements into the appropriate model input (Andraka *et al.* 2018). It showed that collecting the data for prior understanding of the mathematical operation model was vital in interpreting the outputs (Schaider, Rodgers and Rudel 2017; Borzooei *et al.* 2019). Figure *1* and Figure 2 present the definition of the system boundaries, input data, sub models and model connections as follows:

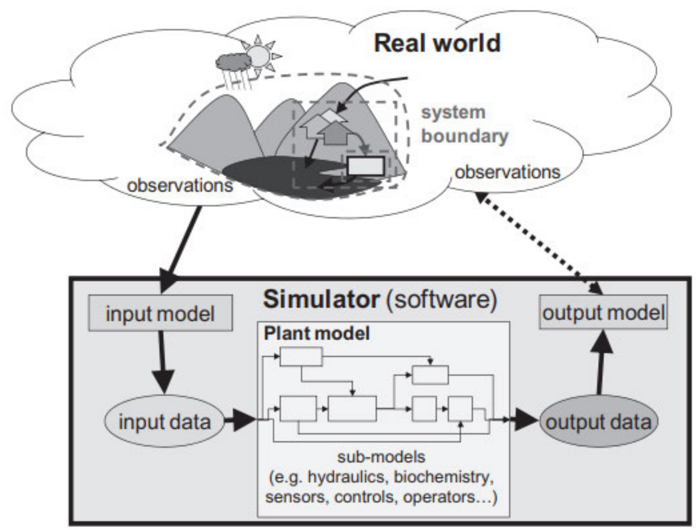


Figure 1 Representation of the real world in the model and it's connection (Hauduc *et al.* 2009; Hauduc *et al.* 2013)

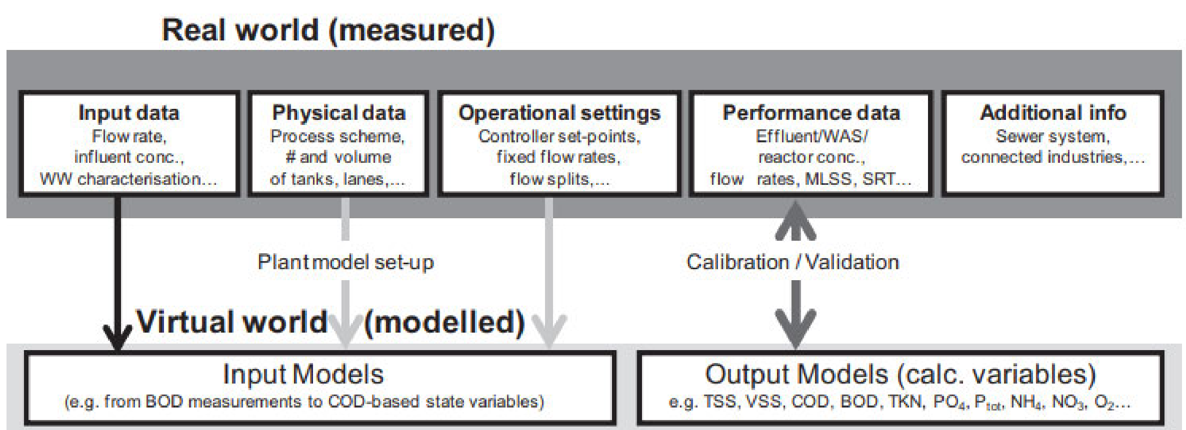


Figure 2 The input data required to set up the model (Hauduc *et al.* 2009; Hauduc *et al.* 2011)

2.4.1.2 Model set-up, sensitivity analysis, and calibration

In their study Mu'azu, Alagha and Anil (2020) described the collected and reviewed input data, and built the appropriate model on the selected platform. Due to the variation in the influent compositions and pollution loads, the operational parameters might affect the plant performance (Drewnowski *et al.* 2019; Solis *et al.* 2022). The most sensitive operational parameters should be identified and analyzed before conducting the calibration of the model (Tenore *et al.* 2020). Kim (2017) and Vivekanandan, Jeyannathann and Rao (2018) also showed that the correlation of the process control parameters over the performance indicator in the plant is a key step in simulating the process. It also indicated that a single step sensitivity analysis is indispensable for easily identifying the aggressive parameters and reducing the calibration time (Eldyasti, Nakhla and Zhu 2012; de Araujo *et al.* 2013; Hakanen, Sahlstedt and Miettinen 2013). Similarly, studies have indicated that the uncertainties of the probabilistic occurrence of multiple operational parameters were easily analyzed via Monte Carlo analysis (Diehl, Zambrano and Carlsson 2016; Kim 2017).

Multiple activated sludge process models are avilable and the GPS-X uses mantis2, which needs site-specific calibration using the measured data (Arif, Sorour and Aly 2020). A sensitivity analysis eradicates time consuming ad hoc calibration (Ludwig *et al.* 2011; Machado, Lafuente and Baeza 2014; Liwarska-Bizukojc, Andrzejczak and Solecka 2019). In addition, the model's output could be verified using a set of data prepared for validation (Gernaey *et al.* 2004; Liwarska-Bizukojc *et al.* 2011). The quality of the model prediction depends on the number of iterations of sensitivity analysis conducted, and the quality of data used for calibration and validation (Revollar *et al*. 2020; Ortiz-Martinez *et al.* 2021).

2.4.1.3 Simulation and verification of the model

The model is calibrated to generate multiple sets of outputs from the simulation run. While simulating the process, the output is verified using experimental data reserved for validation (Caligan *et al.* 2022; Nadeem *et al.* 2022). Validation tests are performed until the required quality of output with the acceptable deviation is obtained (Cao *et al.* 2021). The strengh of calibration and validation depends on the required objectives of the modelling (De Arana-Sarabia *et al.* 2018; Wang *et al.* 2022b).

2.4.1.4 Parameter optimization

The ultimate objective of modelling and simulation is to optimize the process control parameters so that the plant can be operated as efficiently, and as cost- and energy effectively as possible (Petrides, Cruz and Calandranis 1998; Zhou *et al.* 2011). The steps in setting up optimization in GPS-X (Faris *et al.* 2022) are presented as follows:

Step 1: Select one or more **target variables** for the optimization that the model predicts to minimize, maximize, or fit to the measured data.

Step 2: Select one or more **input variables** that the GPS-X model can adjust to the optimization process. In the input controller, it is crucial to specify the limit of changes controlling how far the model can adjust the input variables.

Step 3: Select the appropriate settings for optimization like target comparison, data type, objective function, and simulation stop time.

2.4.2 Wastewater treatment process modellling tools

The modellling software has become widely used and is available in different scopes and applications (Kim, Kim and Yoo 2010; Bis *et al.* 2019). Selecting the appropriate modelling tool also determines the accuracy and precision of the modelling outputs (Hvala, Vrecko and Bordon 2018). The modelling tools vary from flexible programming languages consisting of Python, C++, FORTRAN Delphi and MATLAB simulator to the commercially available software AQUASIM, BioWin, WEST, STOAT, SIMBA, GPS-X, and EFOR (Elawwad *et al.* 2019; Mu'azu, Alagha and Anil 2020; Abbasi, Ahmadi and Naseri 2021; Agarwal and Singh 2022; Akuma, Hundie and Bullo 2022) shown in Table A-2.

In this study, GPS-X was selected for its superior industrial influent fractionation and integrated operational costing modules, which are essential for simulating the complex chemical demands of textile wastewater. Unlike equation-based solvers or municipal-focused tools, it provides a high-fidelity digital twin environment that accurately predicts energy savings and operational stability. This object-oriented approach allowed for a direct, scalable comparison between existing inefficiencies and optimized process strategies. The model has six libraries which include comprehensive carbon, nitrogen, phosphorus, and pH (mantis2lib) for suspended and attached growth process. MANTIS2 model, with 56 processes, 48 state variables, and unified composite variable calculation including sludge treatments and integrated with Python (Elawwad, Zaghloul and Abdel-Halim 2017; Calise *et al.* 2020; Mu'azu, Alagha and Anil 2020; Abbasi, Ahmadi and Naseri 2021).

2.5. Integrated application of GPS-X and analytical Measurements

2.5.1 Simulation-based wastewater treatment plant performance assessment

In the activated sludge process modelling GPS-X uses the mathematical equation formulating the mass balance in the system to simulate the best representative and acceptable result (Nelson and Sidhu 2009; Meier 2016; Mihaly, Simon-Varhelyi and Cristea 2022b). Equation 1 shows the reactor mass balance.

Equation 1

$$Q_{in}C_{in} - Q_{out}C + r = \frac{d(C * V)}{dt} = V * \frac{\partial C}{\partial t} + C\frac{\partial V}{\partial t}$$

Where, Q_{in} = influent flow rate (m^3/d), Q_{out} = effluent flow rate (m^3/d), C_{in} = influent concentration (mg/L), C = effluent concentration (mg/L), r = rate of reaction (mg/L/d), V = liquid volume (m^3) and t = time (d).

In the simulation process there are state variables which are used to predict and/or calculate the composite variables for the selected models in GPS-X (Figure *A- 1*). The performance of the treatment plant is determined by running the simulation for an extended period using different treatment performance indicator parameters (Fontanier *et al.* 2005; Diehl, Zambrano and

Carlsson 2016). De Arana-Sarabia *et al.* (2018) and Chen *et al.* (2020) stated that due to the complex nature of wastewater treatment process the response is quiet dynamic, and with time the pollutants load which then means the the process need to be simplified. Measuring the performance of the plant is not a one-time task, but rather an integrated simulation of the plant under experimental scenarios (Ni, Yu and Sun 2008; Elshorbagy and Shawaqfah 2015; Diehl, Zambrano and Carlsson 2017).

2.5.2 Application of modelling and analytical analysis of wastewater quality parameters

The wastewater quality analysis is the cornerstone of the treatment plant's operation and further action (Parac-Osterman, Sutlovic and Durasevic 2010; Singh and Arora 2011; Swain *et al.* 2018). The researcher demonstrated that the analytical measurement described the immediate status of the plant's performance under specific conditions (Thamaraiselvan and Noel 2015; Tran *et al.* 2015; Tomperi, Koivuranta and Leiviska 2017). Any uncertainty about the measurement leads to a biased decision on the treatment plant's operation and compliance with the effluent standard (Newhart *et al.* 2019; Tuser and Oulehlova 2021). Similarly, the characterization of wastewater does not holistically consider the fraction of the main process kinetics and stoichiometric variables that strongly contribute to the performance of the plant (Liwarska-Bizukojc and Ledakowicz 2011; Lin and Ho 2022).

The modelling of the treatment plant is a powerful tool which represents the physical as well as the process dynamics for a better prediction of the performance (Lindblom *et al.* 2009; Cadet, Guillet and Aurousseau 2016). The inherent uncertainties due to the mathematical model's behaviour are balanced through calibration and validation of the analytical measurements (Demey *et al.* 2001; Kazadi Mbamba *et al.* 2016). Calise *et al.* (2020) and Belia *et al.* (2009) stated that the integrated application of modelling and analytical measurement is a robust approach to enhance the quality of treatment process control and reduce the carbon footprint. Furthermore, the modelling without experimental analysis wouldn't be realistic and the experimental measurement without the use of the model would lead to a less clear decision being made (Bozkurt *et al.* 2016; Castro, Bassin and Dezotti 2017; Elawwad, Zaghloul and Abdel-Halim 2017).

2.6. Wastewater treatment plant operation strategy and troubleshooting

The water consumption should be optimized to minimize the generation of wastewater, reduce the treatment cost, and promote resource recovery (Vilanova, Santin and Pedret 2017; Li, Zou and Wang 2018). However, downstream plant operation and management is a prime concern in the textile industry to bring the effluent down to an acceptable level (Ontiveros and Campanella 2013; Amanatidou *et al.* 2015). Thus, identifying the key monitoring locations and process control parameters plays a vital role in enhancing the treatment plant's performance (Jafarinejad 2020).

2.6.1 Textile wastewater treatment plant process control parameters

Kim, Kim and Yoo (2010) conducted a study to select the operational parameters in the activated sludge process to reduce the number of model process control parameters and determine the optimal solutions. The result verified that the calibrated model parameters improved the quality of prediction. Similarly, for the efficient operation of treatment plants, controlling the sensitive parameters and devising a key strategy is a key factor (Zhou *et al.* 2011; Vera, Saez and Vidal 2013).

Moreover, Bhave, Naik and Salunkhe (2020) depicted that periodic plant monitoring at a specific location guides the operator to check the performance of each unit's process. The key parameters at the specific monitoring location were identified and measured. The results indicated that the process control parameters were sludge retention time (SRT), food to microorganism ratio (F/M), sludge volume index (SVI), specific oxygen uptake rate (SOUR), sludge recycling and waste. While evaluating the plant performance, correlating the process control parameters with each other is indispensable for the operators to take an action (Smith, Elger and Mleziva 2014; Silva and Rosa 2021).

Sun *et al.* (2020) studied the influence of the operational parameters on the microbial population in the activated sludge process. The results showed that the optimum SRT significantly affected the biological activity of the aeration process by reducing the probability of developing filamentous bacteria and enhanced the removal efficiency. Thus, it can be concluded that optimizing of SRT provides good evidence that it can control the performance of the treatment plant.

2.6.2 Performance evaluation and troubleshooting of wastewater treatment plant

In relation to performance evaluation, the study by Tuser and Oulehlova (2021) demonstrated that the disruption of the treatment plant operation led to health problems and contamination of the water bodies. The study identified the potential operational challenges and associated risks. The results showed that the critical wastewater treatment infrastructures were identified, and performance parameters were evaluated. Similarly, Quadros *et al.* (2010) evaluated the wastewater treatment plant performance using the specific indicators. The sources of textile industry wastewater were quite complicated and needed treatment process operational problem records to be kept at specific locations, times, and within specific conditions; hence, the operation is not a one-off task (Zhang *et al.* 2020; Zheng *et al.* 2022).

Similarly, the objective and scope of treatment performance was indispensable in designing the troubleshooting strategy in terms of cost, time, and energy efficiency (De Ketele, Davister and Ikumi 2018). Drewnowski *et al.* (2019) and Flores-Alsina *et al.* (2014) showed that the plant's performance may change due to overloaded supernatant recycling to the upstream treatment units, shock loads, inconsistent monitoring, and poor sampling location. In addition, the internal treatment process was the key challenge in the treatment of textile waste and intrusion of toxic substances leads to deterioration of plant performance (Drewnowski 2014; dos Santos *et al.* 2018). Thus, to control plant performance better, it is necessary to employ the cascading troubleshooting model. Hence, changing one parameter at a time and then waiting for an adequate period of time until it stabilizes after the change is essential (Deepnarain *et al.* 2019).

2.7. Summary

The treatment technology used to treat the wastewater generated from the textile industry varied in type and the process is complicated. It varied from physical, chemical, and biological treatments to electro-chemistry in different spectra of treatment objectives. Among the treatment technologies, the activated sludge process is the most commonly and effectively used technology in the textile industry with different process flow layouts and integrations ensuring resources recovery.

The characterization of wastewater quality was the key for treatment plant operation and performance evaluation. The determinant pollutants of physicochemical quality parameters were the priority in experimental analysis to calculate the pollution load of the receiving environment. The analysis for the collected samples could be conducted in the laboratory and onsite.

Similarly, the modelling of the treatment was a robust technique to predict the composite parameters along with fractional variables in the treatment process. Among the different modelling tools the researchers and developers have used recently is the GPS-X modelling program due to its comprehensive library that applies to extended nutrient removal and sidestream treatments for resource recovery. The integrated approach of using the modelling tool and analytical measurement was the most preferred approach to predict a better quality result. Finally, identifying the monitoring location and corresponding process control parameters was the most critical part in the textile industry wastewater treatment plant operation. Multiple hydraulic and process performance parameters were involved in the plant operation. However, optimization and sensitivity analysis were indispensable to critically quantify and design the operational strategies. Therefore, for the purpose of plant performance evaluation, the integrated application of the modelling and analytical measurements was vital for both the decision makers and plant operators.

CAPTER THREE: STUDY AREA

3.1 Study area description

Bahir Dar textile factory is found in the north-western region of Ethiopia and on the southern coast of Lake Tana, adjacent to the Blue Nile River (Figure 3). The factory's wastewater treatment plant is established in the industry compound at a geographical position of UTM E: 37.407° and N: 11.596°. In the factory, a conventional activated sludge process (ASP) is used for treating the textile industry wastewater, and the wastewater treatment plant operates on the average and peak influent flow of 600 m^3/d and 1200 m^3/d respectively. As shown in Figure 4, the waste water is collected from all the factory process units and transported in one collection line to the treatment plant. The plant operation period highly depends on the material input supply to the production process.

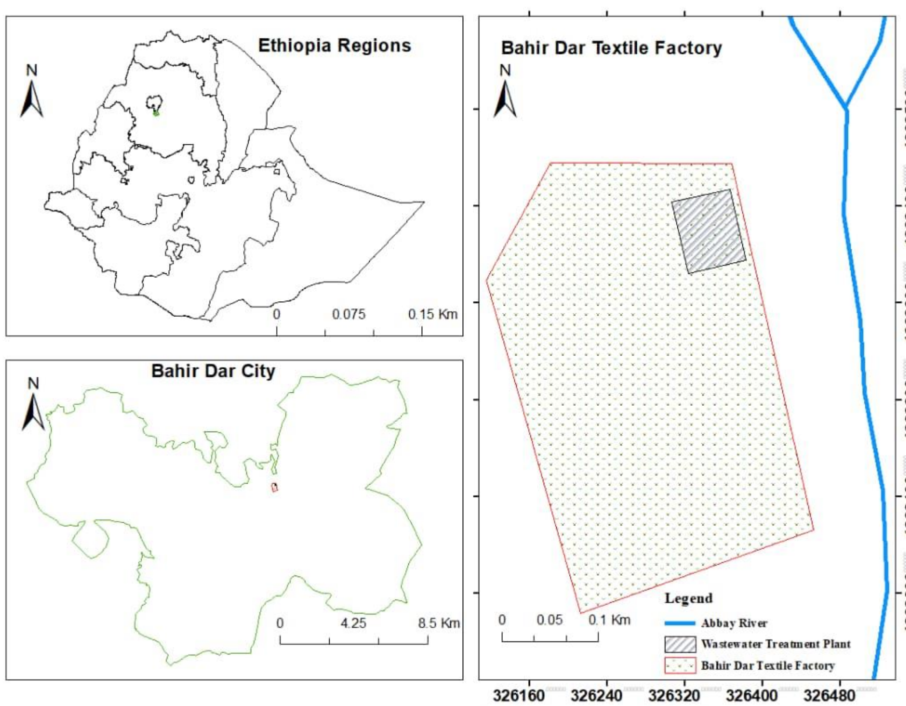


Figure 3 Map of Bahir Dar textile factory wastewater treatment plant, Ethiopia (prepared using ArcGIS)

3.2 Bahir Dar textile wastewater treatment plant process description

In this study, the Bahir Dar textile factory was selected as a case study to evaluate and use the available data. In addition, it was selected to measure the full-plant unit operations and the wastewater quality parameters process. The factory was built in 2013/14 with the conventional activated sludge process to treat an average of 600 m^3/d and peak flow of 1200 m^3/d.

During the study period the plant activated sludge with its full-scale sludge treatment configurations which include intake-grit chamber, equalization tank, electrolysis system, pumping stations, and primary clarifier (with coagulation and flocculation unit). In addition, the factory also activated a secondary clarifier, multigrade filter and guard pond before disposing wastewater into the Blue Nile river. In line with this, it had sludge treatment units including sludge thickener, dewatering filter press, and a sludge drying bed.

Thus, the primary and secondary wasted sludges were collected and pumped to the thickener after the alum was dosed in it. Moreover, there was the addition of 98% sulphuric acid into the equalization tank to balance the pH in the incoming flow which is commonly called alkaline composition. Subsequently, alum and poly aluminum chloride (PAC) coagulant were added into the primary clarifier to form the settleable flocs that could be removed easily. The configuration of the treatment units is shown in Figure 4.

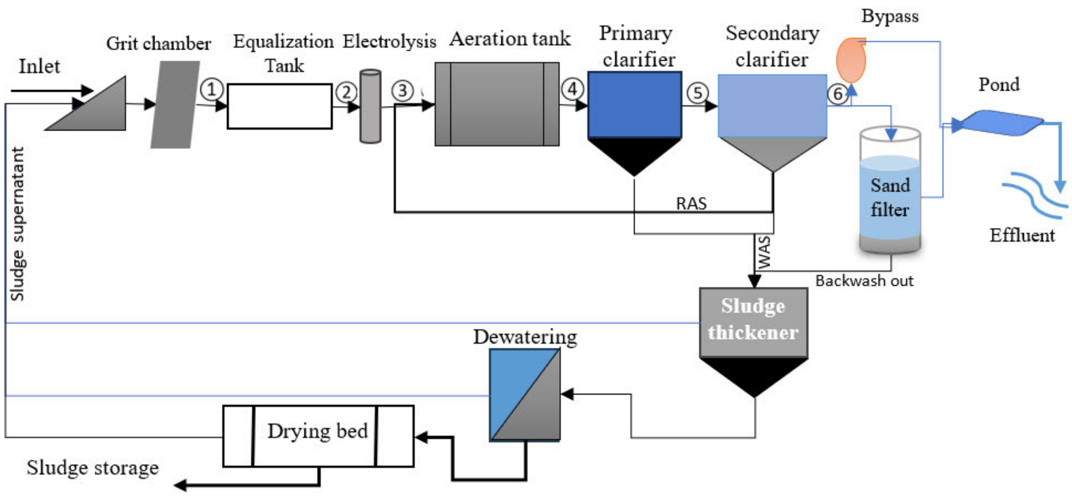


Figure 4 Existing textile wastewater treatment plant layout and corresponding sampling locations

CHAPTER FOUR: METHODS AND MATERIALS

4.1 Introduction

This chapter discusses the research design, the instruments that were used to gather data, and the process of data collection. Moreover, it also addresses the approaches that were used to accomplish the specific research objectives, the validity and reliability of the study, and the ethical considerations.

4.2 Research design

To design the research, the researcher followed the following procedures. Firstly, the data collection and reconciliation plans were developed. To understand the plant as it is operated and to identify the processes of the various operational modes, loads, sampling points, instrumentations, and its utilization for process control configuration, a field visit was conducted., The physicochemical wastewater quality and physical plant data were also used as the main input data. This was obtained by direct measurement from the treatment plant. Statistical analyses were conducted using descriptive statistics and outlier analysis via SPSS to manage the stochastic nature of textile discharge; these methods conform to current environmental engineering trends, specifically identifying that effluent failures were operational rather than influent-driven.

Secondly, the treatment plant model was set up in existing and modified scenarios. Also, the researcher defined the plant layout connections and selection of the biokinetics parameters for the sub-models. Thirdly, an iterative adjustment of model parameters was performed until the simulation results matched the observed dataset. Verification confirmed the structural integrity of the mass balances, while validation achieved through iterative calibration against a 6-month longitudinal dataset provided the statistical confidence necessary to utilize the model as a predictive tool for operational optimization and cost-reduction strategies.

Finally, the simulation and result interpretation were conducted by defining the scenarios and statistical analysis. The process control parameters were optimized taking the treatment performance into consideration. This would enable the researcher to develop the operational strategies and efficient troubleshooting of the plant.

4.3 Research instruments

In this research, both primary and secondary data gathering instruments were used. Specifically, wastewater quality data, treatment plant design documents, and previous research outputs were used as secondary data. Likewise, the researcher considered wastewater quality measured data, plant hydraulic data, and a questionnaires as primary data-gathering instruments. The GPS-X Hydromantis software version 8.5 (educational license No.9-1643), SPSS Statistics version 21 software, and MS Excel 2016 were used to compute the gathered data. The details of the instruments used in the study together with the corresponding specific objectives are described below.

4.4 Data collection

The data collection was started after careful observation of key characteristics and the behaviour of the treatment system. The data related to the history of the plant was gathered from the operators and available documents. These included the pattern of operations, failure history, data record protocols, and troubleshooting strategies. The secondary data on water quality analysis, similar study results, and design documents were collected, reviewed, and presented to the utility manager and operators to re-confirm the data quality.

On the other hand, based on the secondary information, physical measurements were conducted on the physicochemical wastewater quality analysis, the hydraulic dimensions, wastewater, and air flows in the treatment system. To ensure the quality of the data, the operators were interviewed to obtain information on any hidden components of the treatment units due to design considerations. An intensive (repeated and representative) wastewater quality analysis was also performed by taking a grab sample in the key monitoring locations. In addition, parameters were used for modelling, calibration, and validation via GPS-X software.

Therefore, the above procedures showed that the researcher followed the standard quality assurance and control techniques while collecting the data.

4.5 Data analysis

The physicochemical wastewater quality data were analyzed in the laboratory and onsite for the selected parameters. A Pearson correlation test was conducted to understand the relationships between dependent and independent parameters. Along with the Pearson correlation test, the detected outliers and irregular data sets were scientifically managed using the data transformation technique to improve the quality of the data analysis. In addition, multicollinearity and autocorrelation diagnostics were conducted to optimize uncertainties due to the variability of wastewater characteristics and model parameters by identifying the interrelationship among the independent parameters.

Upper and lower limit regression tests were performed to check the response of the data distribution pattern. Additionally, the stepwise method of multiple linear regressions was used to find the most important independent variables contributing to the dependent parameters' variance. In addition, this method was used to eliminate parameters that were not significant and could lead to over-fitting of the model. The statistical data analysis was made via *IBM SPSS Statistics version 21* software and *MS Excel 2016*. The *GPS-x Hydromantis software version 8.5 (educational license No.9-1643)* was also used for modelling the existing treatment process and modified scenarios.

4.6 Validity and reliability

The precision of the full-scale wastewater treatment plant performance evaluation depends on how, where, and when the sample is collected and the availability of sufficient data. Considering the available methods of data collection and analysis, the data calibration and validation test were conducted using statistical analysis and GPS-X. Therefore, the credibility of the data was reflected in measured data versus the predicted data.

4.7 Ethical considerations

The study was conducted by considering the ethical codes of conduct and standards as mentioned by the Durban University of Technology. Stakeholder consent was also granted by the factory to conduct the study on the wastewater treatment plant. In addition, the results obtained were shared with the factory, and they were considered confidential.

4.8 Method for specific objective 1

Characterize the wastewater generated from Bahir Dar textile factory

The first objective of this research was to characterize wastewater generated from a specific textile factory in Bahir Dar City. To achieve this objective, the wastewater sampling locations were selected based on the treatment arrangement and the current plant operation strategy. The sample size was designed by integrating a six-month temporal study with multi-point spatial sampling. This ensured a high degree of statistical confidence, minimized the impact of operational outliers, and provided the robust data density required for the precise calibration and validation of the GPS-X simulation model. Moreover, six sampling locations in the wastewater treatment plant were selected to identify and understand the removal efficiency (Figure 4).

As the figure indicates, the sample size (792)was determined based on the requirements for high-fidelity GPS-X model calibration and statistical power analysis to ensure a 95% confidence level. A stratified grab sampling method was employed across six strategic locations to capture the real-time operational volatility of the textile processes, ensuring that the subsequent troubleshooting framework was based on empirical peaks rather than smoothed averages. The samples were collected during operation days, every week, moring and evening hours at the raw wastewater inlet (1), equalization tank outlet (2), electrolytic system outlet (3), aeration tank outlet (4), primary clarifier outlet (5), and secondary clarifier outlet (6) in the active operion period from February 2021 to July 2021.

Table 1 indicates all twenty-two parameters which were analyzed from the influent to the effluent locations of the plant. The parameters were measured at each unit's operation depending on the target pollutant and the objective of the treatment unit process, and the sampling, measurement, storage, and analysis techniques were carried out by considering the quality control and assurance protocols specified in EPA (2023) as well as the standard methods presented as indicated in the table.

Table 1 The wastewater quality parameters analyzed, measurement technique, and standard methods

Parameters	units	Methodology	Standard methods (EPA 2023)	Parameter	units	Methodology	Standard methods (EPA 2023)
TSS	mg/L	Gravimetric	Gravimetric	pH	--	Electrometric	4500-H^+ B2011
VSS	mg/L	Gravimetric	Gravimetric	DO	mg/L	DO meter	4500-O G2016
BOD_5	mg/L	DO depletion	5210 B-2016	TDS	mg/L	Multi meter	2550B-2010
COD	mg/L	Digestion, photometric	5220 D-2011	EC	μS/cm	Multi meter	2550B-2010
NH_3	mg/L	Digestion, photometric	4500-NH3 C-2011	K	mg/L	Digestion, ICP	3120B-2011
NO_2	mg/L	Manual, photometric	4500-NO2 B-2011	Ca	mg/L	Digestion, ICP	3120B-2011
NO_3	mg/L	Manual, photometric	4500-NO3 B-2011	Mg	mg/L	Digestion, ICP	3120B-2011
TKN	mg/L	Digestion, photometric	4500-NH3 B-2011	Fe	mg/L	Digestion, ICP	3120B-2011
TN	mg/L	Digestion, photometric	4500-N B-2011	Zn	mg/L	Digestion, ICP	3120B-2011
TP	mg/L	Digestion, ICP	3120 B-2011	Cr	mg/L	Digestion, ICP	3120B-2011
TA	mg/L	Manual, photometric	4500- B-2011	T^o	^oC	Multi meter	2550B-2010

The physicochemical measurement and analysis of the wastewater were conducted in the laboratory and onsite. The main wastewater quality parameters that were measured in the laboratory were ammonia (NH_3), total nitrogen (TN), nitrite-nitrate (NO_x), volatile suspended solids (VSS), chemical oxygen demand (COD), five day biochemical oxygen demand (BOD_5), total chromium (Cr), iron (Fe), magnesium (Mg), potassium (K), total phosphorous (TP), Calcium (Ca), total alkalinity (TA), Zinc (Zn), total Kjeldhal nitrogen (TKN), and total suspended solids (TSS). The sensitive parameters consisted of total dissolved solids (TDS), dissolved oxygen (DO), pH, electrical conductivity (EC), temperature, and humidity were measured directly onsite using mobile test kits. The general methodological framework is shown in Figure 5.

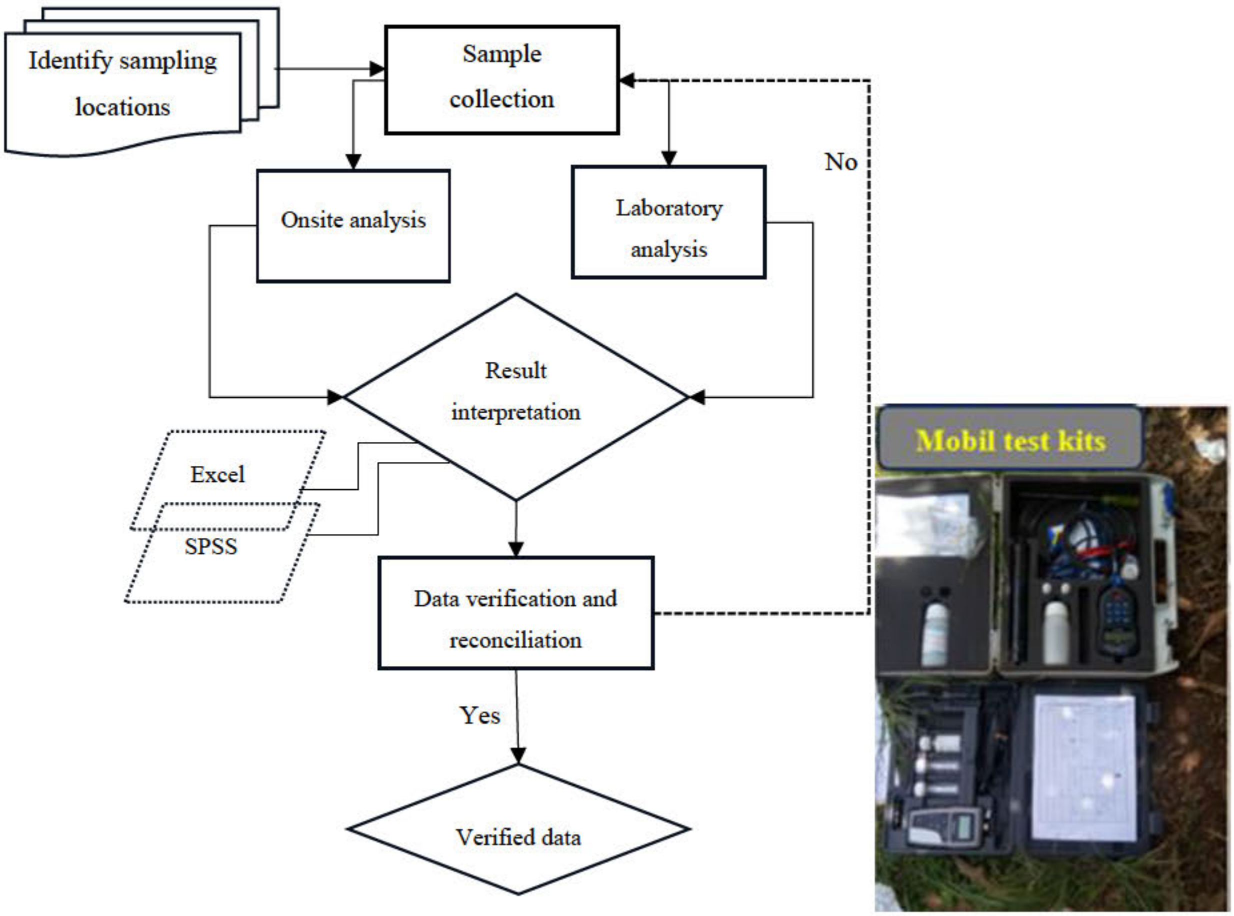


Figure 5 Methodological framework and equipment used for physicochemical characterization of wastewater

4.9 Method for specific objective 2

To model and analyse a wastewater treatment plant's unit operations and processes using GPS-X

Model layout construction

The wastewater treatment plant models were developed through the GPS-X software version 8.5 (Educational License), Hydromantis Environmental Software Solutions, Inc. for the existing and modified process layouts. As indicated in figure A-1, the wastewater treatment plant process flow diagram was built based on the plant's physical data, operational settings, performance data, and information collected from the ground and the design documents. Two models were developed including **scenario - I:** operated as an existing plant called base scenario (→***Aeration tank*** → ***Primary clarifier*** → ***Secondary clarifier***→) (Figure 6), and **scenario - II**: modified process flow diagram called modified scenario (→***Primary clarifier* → *Aeration tank* → *Secondary clarifier***→) (Figure 7).

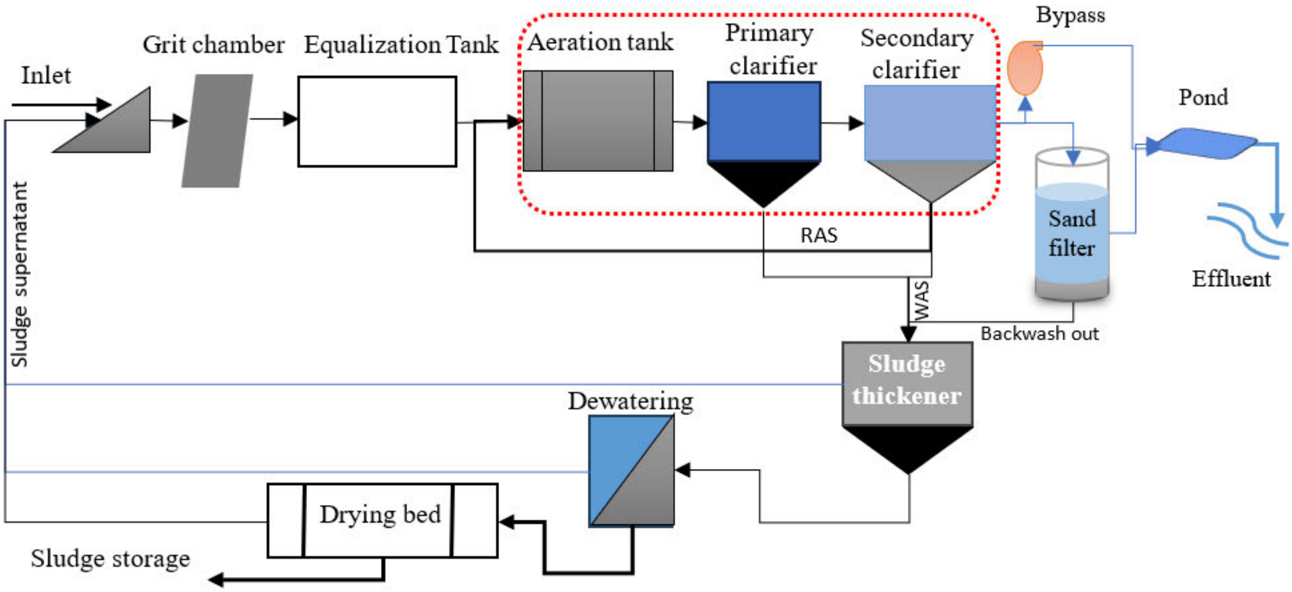


Figure 6: Existing wastewater treatment plant process flow diagram (scenario I)

As shown in Figure 6 in scenario I, the multigrade sand filter and guard pond were not functional. However, directly bypasses the effluent from the secondary clarifier to the receiving water body. However, in scenario II all the unit operations were functional, and external carbon sources in the form of molasses were added to the biological treatment (Figure 7).

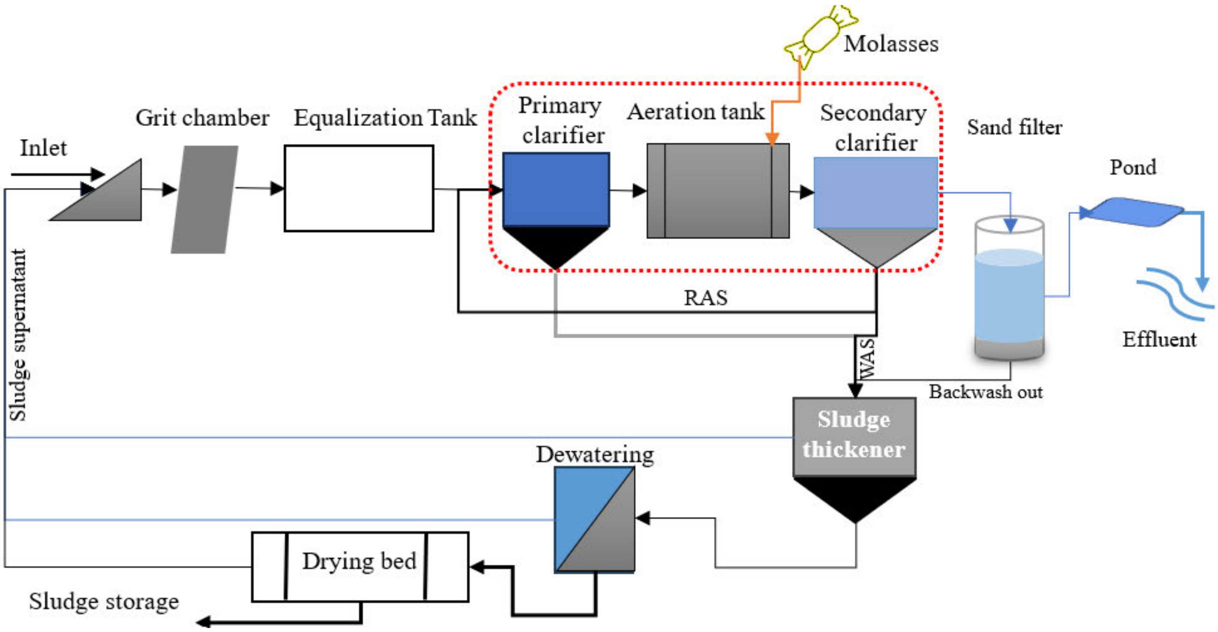


Figure 7: Modified wastewater treatment plant process flow diagram (scenario II)

Library and unit process modell selection

Among the six libraries in the GPS-X, the comprehensive, Carbon, Nitrogen, Phosphorous, and pH (Mantis2lib) were selected for this study because of the objectives of the biological treatment targeted for organic and inorganic nutrient removal. To define the set of unit process behaviours, the models were selected to calculate the state and composite variables based on the available information and data. As shown in Table 2, the models for each unit process of effluent treatment and sludge treatment were defined.

Table 2 Unit process and equivalent selected models

Unit process	Selected models	Unit process	Selected models
Influent wastewater	Codbased	Sand filter	Continuous
Primary clarifier	Simple1d	Thickener	Empiric
Aeration tank	Mantis2	Dewatering	Empiric
Secondary clarifier	Simple1d	Guard pond	Empiric

Influent characterization, model calibration, and validation

The total BOD_5 to total COD ratio was recorded as 0.31, and it was below the minimum organic demand in the biological process. Therefore, the external carbon sources in the form of molasses with 65% purity containing insignificant nitrogen and phosphorous composition were added into the aeration tank (scenario II) to obtain the optimum food to microorganism ratio in the reactor. The addition of molasses as a supplemental carbon source, is essential for mitigating the inhibitory effects of recalcitrant dye complexes and ensuring the environmental sustainability of industrial textile operations in regions with limited real-time data. Once the physical plant date was calculated and encoded for each unit's operation and process, the wastewater and the additional carbon sources (molasses) were characterized in terms of COD based model compositions and influent fractions. To characterize the influent wastewater total COD, total TKN, and total phosphorous influent composition were used for the selected influent modell. Furthermore, the influent fractions of VSS/TSS ratio, organic fractions (soluble COD/total COD, soluble BOD_5/soluble COD, and total BOD_5/total COD ratio), nitrogen and phosphorous fractions were used specifically based on the measured physicochemical wastewater quality data (as indicated in

Table 3).

Table 3 The influent compositions and fractions

[wwfinf] total COD	mgCOD/L	483.3
[wwfinf] total TKN	mgN/L	27.98
[wwfinf] total phosphorus	mgP/L	13.05
[wwfinf] VSS/TSS ratio	gVSS/gTSS	0.7
[wwfinf] soluble COD to total COD ratio	gsCOD/gtCOD	0.34
[wwfinf] soluble BOD5 to soluble COD ratio	gsBOD5/gsCOD	0.61
[wwfinf] total BOD5 to total COD ratio	gtBOD5/gtCOD	0.54
[wwfinf] ammonium fraction of soluble TKN	-	0.9

Tables 4 and 5 indicate the calibrated model using two-thirds (66.7% or four month data) of the measured data for the selected influent and effluent wastewater quality parameters. The remaining one-third (2 month) of the measured data was used for model validation (20%) and verification (13.3%). The selection of steady-state modelling was a strategic decision necessitated by the absence of high-frequency historical data and the stochastic nature of textile batch-dyeing operations. While GPS-X supports dynamic simulation, this study utilized steady-state analysis to establish a robust operational baseline, as the lack of online sensors would have introduced significant synthetic noise into a dynamic model. By lumping 792 grab samples into weekly averages, the research filtered out erratic spikes to reveal the true underlying process kinetics required for high-fidelity calibration. Ultimately, steady-state modelling provided a stabilized troubleshooting framework that the plant's current manual infrastructure can realistically manage. Moreover, a one-step sensitivity analysis was conducted to identify the most sensitive process control parameters to adjust the model parameters in the calibration and validation. Figure 8 also shows the methodological framework used for the model calibration and validation process

Table 4 The influent wastewater quality data used for model calibration and validation

	Calibration			Validation		
Month	**February**	**March**	**April**	**May**	**June**	**July**
Parameters	**Influent**	**Influent**	**Influent**	**Influent**	**Influent**	**Influent**
TSS	365.34	345.50	354.63	243.20	225.76	223.54
BOD_5	163.20	158.30	155.40	143.20	141.20	140.20
COD	522.24	490.73	500.24	467.43	456.30	462.66
NH_3-N	13.20	12.80	12.30	12.20	11.50	10.00
NO_2-N	2.50	3.10	1.87	1.35	1.67	2.10
NO_3-N	3.70	3.50	4.20	2.50	3.67	3.75
TKN	27.80	29.50	27.56	28.45	26.76	27.83
TN	35.50	38.10	34.98	33.53	33.44	35.15
TP	14.50	13.34	13.23	12.45	12.44	12.36

Table 5 The effluent wastewater quality data used for model calibration and validation

	Calibration			Validation			
Month	**February**	**March**	**April**	**May**	**June**	**July**	**Permissible limit (EPA 2023)**
Parameters	**Effluent**	**Effluent**	**Effluent**	**Effluent**	**Effluent**	**Effluent**	
TSS	79.05	92.54	91.35	69.91	56.24	50.08	35
BOD_5	45.70	63.51	65.16	43.41	37.13	35.80	40
COD	145.70	165.10	155.73	133.33	132.05	132.58	120
NH_3-N	0.48	1.39	4.62	1.30	1.85	2.12	1
NO_2-N	0.47	2.80	0.43	1.07	1.60	1.77	1
NO_3-N	5.33	0.59	0.70	4.72	4.68	4.37	10
TKN	7.62	9.76	12.80	7.83	7.31	7.08	25
TN	13.42	13.15	13.93	13.62	13.59	13.21	< 40
TP	9.09	8.96	8.91	8.00	6.52	5.89	2

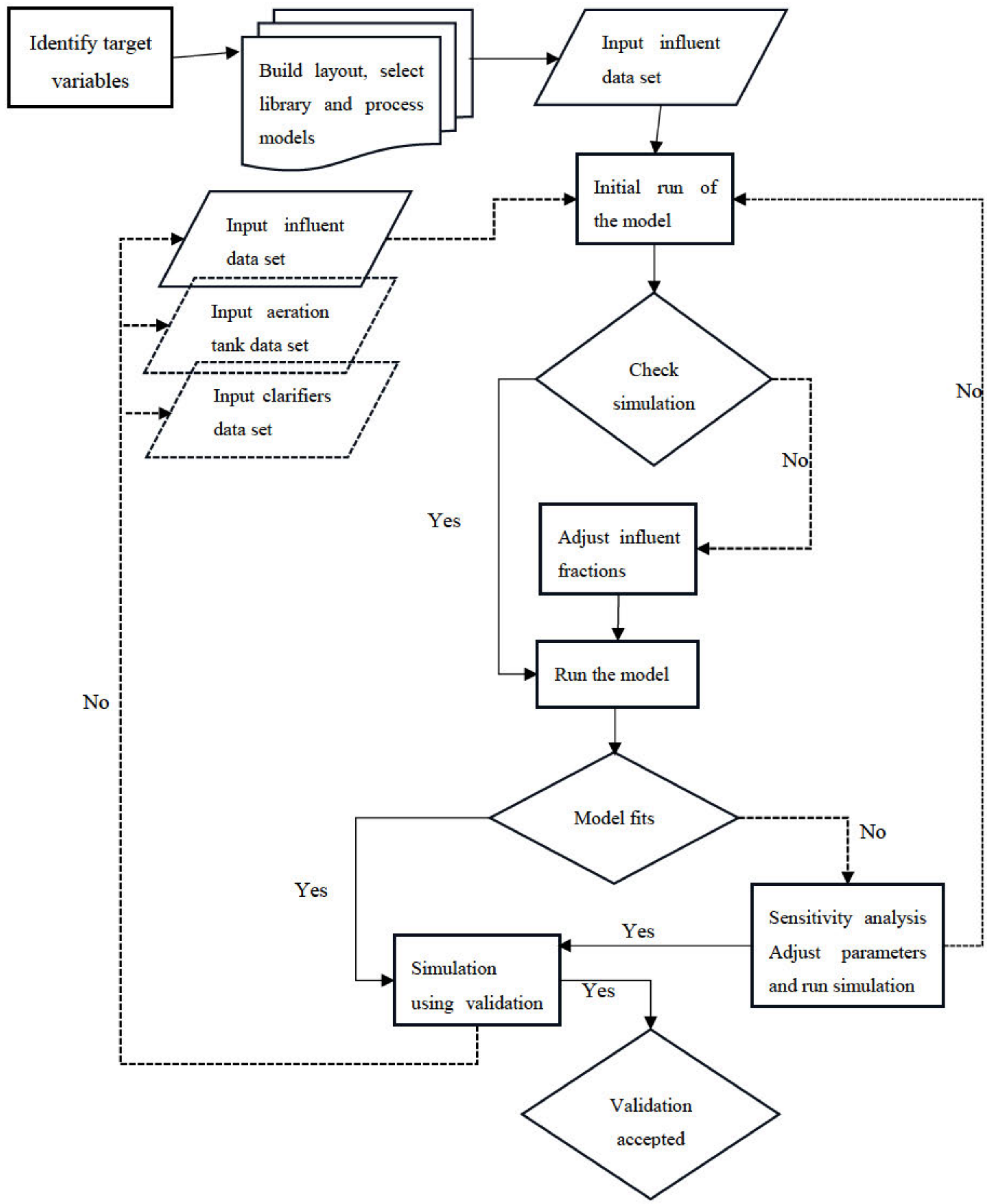


Figure 8 Calibration and validation process framework adopted from (Hauduc *et al.* 2010)

The overall mass balance and long-term performance checks, and steady-state simulation were efficient. Therefore, a 180-day simulation was run for two scenarios under steady-state conditions using the physical plant input data which are presented in Table 6.

Table 6 The physical plant input data for model simulation

Unit process	Simulation parameter		
influent	` VSS/TSS Ratio	0.75	
equalization tank	Maximum Volume	m^3	1128
	Tank Depth	m	3.5
	Air Flow	m^3/d	29780
acid dosage	H_2SO4 Concentration	%	98.0
	Density of H_2SO4	mg/L	1850000
primary clarifier	Feed Point from Bottom	m	1.0
	Surface area	m^2	100.0
	Water Depth	m	5.7
secondary clarifier	Feed Point from Bottom	m	1.0
	Surface area	m^2	113.0
	Water Depth Sidewall	m	3.0
	Water Depth at centre	m	3.24
aeration tank	Maximum Volume	m^3	1040
	Tank Depth	m	5.0
	Air Flow into aeration tank	m^3/d	156000
sand filter	Backwash Flow Fraction	-	0.02
	Backwash Solids Mass Fraction	-	0.8
thickner	Surface Area	m^3	12.56
	Depth	m	3.0
	Removal Efficiency	-	0.9
dewatering	Removal Efficiency	-	0.93
	Removal Efficiency	-	0.93
alum dose	Percent Hydrated Aluminium Sulphate	%	17.0
	Chemical Dosage, Mass Based	kg/d	1.33
PAC dose	Chloride to Aluminium Ratio in PAC	gCl/gAl	1.97
	Percent as Al2O3	%	10.0
	Chemical Dosage, Mass Based	kg/d	33.33

4.10 Method for specific objective 3

To evaluate the wastewater treatment plant's performance by using analytical methods and the GPS-X model

The efficiency of the wastewater treatment plant was evaluated using the physicochemical parameters for the selected performance indicators. The study was conducted based on the analysis of five performance parameters (as shown in Table 7) including TSS, BOD_5, COD, and TN. Figure 9 also shows TP measured at the wastewater influent, the outlet of primary clarifier, the outlet of secondary clarifier and/or final effluent. Each treatment unit operation and overall plant performance was calculated using the mathematical equation for mass flow and outflow into the treatment units (Eq. 2 and 3).

Equation 2

$$\% \, removal, R_i = \frac{[inflow\ concentration, C_{in,mg/L} - outflow\ concentration, C_{eff,\frac{mg}{L}}] \times 100\%}{inflow\ concentration, C_{in,mg/L}}$$

Equation 3

$$\text{Total plant performance, \%} = \frac{\left[Q_{in} \times \sum_{i=1}^{n} C_{in} - Q_{eff} \times \sum_{i=1}^{n} C_{eff}\right] \times 100\ \%}{Q_{in} \times \sum_{i=1}^{n} C_{in}}$$

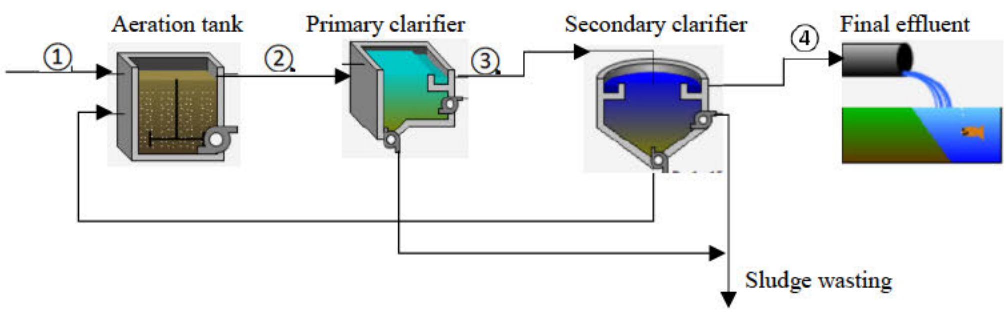


Figure 9 The sampling point for analytical measurement of plant performance

Table 7 The performance parameters indicators from analytical measurement

Unit operations	**Wastewater performance parameters, mg/L**				
	TSS	BOD_5	COD	TP	TN
Untreated wastewater	293	150.25	483.27	13.05	35.12
After aeration tank	3000	75	2400	125	140
Inflow into primary clarifier	3000	75	2400	125	140
After primary clarifier	2950	70	2300	110	135
After secondary clarifier	73.2	48.45	144.08	7.9	13.49
Permissible limit (EPA 2023)	35	40	120	2	25

Comparative time-based effluent pollution load assessments were conducted to forecast the dynamics of the receiving water ecosystem and to evaluate the plant pollutant removal efficiency. The GPS-X model was used for selected performance indicator parameters (Table 8). However, in formulating the performance indices it was difficult to investigate where and when they violated the compliance limit.

The effluent quality index (EQI) technique and mass balance were used to calculate the effluent quality considering the time duration during which the plant violated the compliance limits by computing the 180-day simulation. The Clean Water Act directive of EPA (2023) on effluent quality compliance limits was considered to assess for violation and concentration of compounds in EQI. The overall and net effluent quality indices were estimated to evaluate the plant-wide treatment plant performance of the textile factory using Equations 4 - 7, respectively.

Equation 4

$$\text{EQI (overall instantaneous)} = Q_{(t)} \sum_{i=1}^{n} w_i * S_{i(t)}$$

Equation 5

$$\text{EQI (overall T days moving average)} = \frac{1}{T * 1000} \int_{t}^{t+T} Q_{(t)} \sum_{i=1}^{n} w_i * S_{(t)} dt$$

Equation 6

$$\text{EQI (net instantaneous)} = Q_{(t)} \sum_{i=1}^{n} w_i * \max\left[0, \left(S_{i\,(t)} - S_{i,\text{limit}}\right)\right]$$

Equation 7

$$\text{EQI (net T days moving average)} = \frac{1}{T * 1000} \int_{t}^{t+T} Q_{(t)} \sum_{i=1}^{n} w_i * \max\left[0, \left(S_{i\,(t)} - S_{i,\text{limit}}\right)\right] dt$$

Where EQI = Effluent quality index [kg pollution/day]; T = Time horizon (7 days moving average) [days]; $Q_{(t)}$ = Effluent flow rate [m³/day]; $S_{i(t)}$ = The effluent concentration of the parameters at the measured time [mg/L]; $S_{i, limit}$ = the permissible discharge limit of parameters [mg/L].

Table 8 The performance parameters used in GPS-X modell

Parameters	Units	Aeration outlet	Primary clarifier outlet	Secondary clarifier outlet	Final effluent	Permissible limit
TSS	mg/L	3061	2932	197.3	197.3	35
BOD_5	mgO2/L	83.23	79.65	8.886	8.886	40
COD	mgCOD/L	2659	2541	198.2	198.2	120
Ammonia	mgN/L	0.2542	0.2542	0.2542	0.2542	1
Nitrite	mgN/L	0.2513	0.2513	0.2513	0.2513	1
Nitrate	mgN/L	17.7	17.7	17.7	17.7	10
TKN	mgN/L	137.4	131.4	10.85	10.85	25
TN	mgN/L	155.4	149.3	28.79	28.79	< 40
TP	mgP/L	127.0	121.3	9.255	9.255	2

The weighing factor for each pollutant, w_i, was assigned according to how much of an influence it had on the environment using a minimum of one-year of recorded data (Jeppsson *et al.* 2013; Liu *et al.* 2020b). However, in this study, a new approach was developed to bridge the gap of time series data scarcity and the lack of preference on the ranking of the impact by assigning a normalized equal weight for the nine effluent quality parameters which included TSS, COD, BOD_5, NH_3, TKN, TN, NO_2, NO_3, and TP (Table 8).

4.11 Method for specific objective 4

To develop holistic operation strategies and troubleshooting frameworks for [the] textile wastewater treatment plant

The operational framework was developed by conducting a sensitivity analysis for process control parameters by considering the critical monitoring locations. The physical plant control parameters including wasted activated sludge rate (WAS), recycled activated sludge rate (RAS), solid retention time (SRT), air flow into the aeration tank, and hydraulic retention time (HRT) were correlated, analyzed, and optimized under the steady-state condition to develop monitoring framework.

Furthermore, the sludge volume index (SVI), food to microorganism ratio (F/M), volumetric BOD_5 loading ratio, and cake mass flow were analyzed. One step and Monte Carlo sensitivity analysis were performed, targeting the optimized effluent quality load (EQI), operation cost, energy use, and sludge production. The methodological framework is shown in Figure 10.

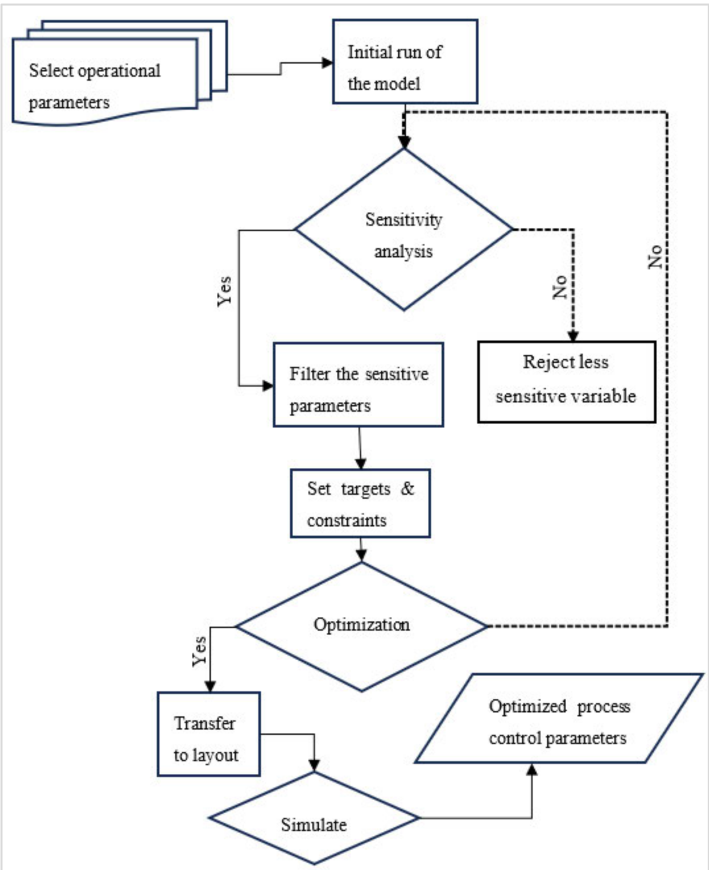


Figure 10 Plant process control parameters optimization methodology framework

CHAPTER FIVE: RESULTS AND DISCUSSIONS

5.1. Results and discussion for specific objective 1

The first objective of this research was to assess wastewater generated from a specific textile factory in Bahir Dar City.

Outliner management and normality test

As presented in Table 9, the descriptive statistics results showed that the distribution of the output for the influent quality pertaining to TSS, VSS, and EC were identified as being significantly different. However, the normality distributions, except for BOD_5, COD, NH_3, and NO_3, were symmetrically spread over the range. Table 10 also indicated the effluent quality parameters: TSS, VSS, BOD_5, NO_3, TKN, and total chromium identified minor and major outliers. These could have significantly affected the test data (Belia *et al.* 2009).

Table 9 Descriptive statistics for the measured influent wastewater

Parameters	TSS mg/L	VSS mg/L	BOD_5 mg/L	COD mg/L	NH_3 mg/L	NO_2 mg/L	NO_3 mg/L	TKN mg/L	TN mg/L	TP mg/L	TA mg/L
Min	223.54	144.49	140.20	456.30	10.00	1.35	2.50	26.76	33.44	12.36	89.65
1st quartile	230.12	154.59	141.70	463.85	11.68	1.72	3.54	27.62	33.89	12.44	92.30
Median	294.35	190.11	149.30	479.08	12.25	1.99	3.69	27.82	35.07	12.84	95.32
3rd quartile	352.35	237.01	157.58	497.86	12.68	2.40	3.74	28.30	35.41	13.31	100.59
Mean	293.00	194.76	150.25	483.27	12.00	2.10	3.55	27.98	35.12	13.05	97.71
Max	365.34	248.43	163.20	522.24	13.20	3.10	4.20	29.50	38.10	14.50	112.34
Min.Out	46.78	30.98	117.89	412.84	10.18	0.70	3.25	26.61	31.61	11.14	79.87
Majo.Out	535.69	360.62	181.39	548.88	14.18	3.42	4.03	29.31	37.69	14.62	113.03
Std. dev.	68.72	48.21	9.92	25.56	1.14	0.63	0.57	0.92	1.70	0.83	8.40

Continued

Parameters	pH	DO mg/L	TDS mg/L	EC µS/cm	K mg/L	Ca mg/L	Mg mg/L	Fe mg/L	Zn mg/L	Cr mg/L	T^o ^oC
Min	7.80	1.45	400.00	622.00	3.08	25.66	11.00	0.12	0.12	0.09	25.65
1st quartile	7.92	1.51	401.00	676.33	3.23	36.25	13.98	0.15	0.18	0.27	25.99
Median	8.00	1.57	409.50	690.15	3.33	40.83	16.17	0.17	0.27	0.29	26.50

3rd quartile	8.15	1.68	421.00	709.00	3.47	47.67	18.03	0.19	0.42	0.31	26.73
Mean	8.02	1.60	412.33	685.13	3.41	47.83	16.71	0.20	0.32	0.26	26.48
Max	8.20	1.80	432.00	721.50	4.00	95.00	25.00	0.39	0.66	0.33	27.60
Min.Out	7.58	1.26	371.00	627.31	2.86	19.13	7.89	0.09	-0.17	0.22	24.89
Majo.Out	8.49	1.92	451.00	758.01	3.83	64.79	24.12	0.24	0.77	0.35	27.84
Std. dev.	0.16	0.13	13.28	35.71	0.32	24.43	4.84	0.10	0.20	0.09	0.70

Table 10 Descriptive statistics for the measured effluent wastewater

Parameters	TSS mg/L	VSS mg/L	BOD_5 mg/L	COD mg/L	NH_3 mg/L	NO_2 mg/L	NO_3 mg/L	TKN mg/L	TN mg/L	TP mg/L	TA mg/L
Min	50.08	39.98	35.80	132.05	0.48	0.43	0.59	7.08	13.15	5.89	57.67
1st quartile	59.66	47.61	38.70	132.77	1.33	0.62	1.62	7.38	13.27	6.89	59.88
Median	74.48	59.16	44.56	139.52	1.62	1.34	4.52	7.72	13.50	8.45	66.17
3rd quartile	85.99	75.89	58.49	150.13	2.05	1.73	4.71	12.04	13.62	8.68	68.33
Mean	73.20	59.28	48.45	144.08	1.96	1.36	3.40	8.73	13.49	7.90	66.22
Max	92.54	76.62	65.16	165.10	4.62	2.80	10.00	25.00	13.93	8.96	70.33
Min.Out	20.15	5.20	9.02	106.72	0.24	-1.04	-3.03	0.40	12.73	4.21	47.19
Majo.Out	125.50	118.30	88.16	176.18	3.14	3.39	9.36	19.03	14.15	11.37	81.02
Std. dev.	17.73	15.35	12.86	13.95	1.42	0.90	2.16	2.21	0.29	1.38	7.87
Standard (EPA 2023)	35	NA	40	120	1	1	10	25	<40	2	NA

Continued

Parameters	pH	DO mg/L	TDS mg/L	EC µS/cm	K mg/L	Ca mg/L	Mg mg/L	Fe mg/L	Zn mg/L	Cr mg/L	To ºC
Min	8.14	5.25	378.00	640.19	1.91	40.96	13.97	0.21	0.15	0.11	23.80
1st quartile	8.24	5.34	393.20	648.23	2.07	41.23	14.68	0.22	0.19	0.12	25.44

Median	8.33	5.54	404.48	662.06	2.30	42.85	15.93	0.26	0.26	0.15	25.46
3rd quartile	8.36	7.74	416.82	668.81	2.90	48.38	16.84	0.41	0.39	0.21	26.27
Mean	8.29	6.22	403.70	661.69	2.38	44.56	15.82	0.29	0.27	0.16	25.37
Max	8.39	7.92	426.10	683.57	12.00	51.27	17.95	2.00	2.00	0.24	40.00
Min.Out	8.06	1.74	357.77	617.34	0.81	30.51	11.44	-0.07	-0.10	-0.02	24.19
Majo.Out	8.55	11.34	452.25	699.70	4.16	59.10	20.08	0.69	0.68	0.34	27.52
Std. dev.	0.10	1.26	17.96	17.31	0.43	4.32	1.51	0.09	0.10	0.06	0.87
Standard (EPA 2023)	5 - 9	5 - 9.5	<1500	<4000	12	<60	<60	2	2	0.05	<40

The profiles of operational control wastewater quality parameters

In wastewater treatment, there is a defined process control strategy for selecting key monitoring units and process control parameters (Bhatia *et al.* 2018). Among the wastewater qualities, pH, DO, total alkalinity, and temperature are the main process control parameters which are monitored periodically in the complete mix of biological treatment units (Andreides, Dolejs and Bartacek 2022). In this study, the mean temperature for influent wastewater varied from 25.7 ^{o}C to 27.6 ^{o}C and for the effluent wastewater from 23.8 ^{o}C to 27 ^{o}C for all treatment unit operations (Figure 11). The EPA (2023) directive also states that the maximum acceptable limit of the temperature for the treated effluent is < 40 ^{o}C. The average temperature of the effluent wastewater in the treatment plant was found to be within the standard.

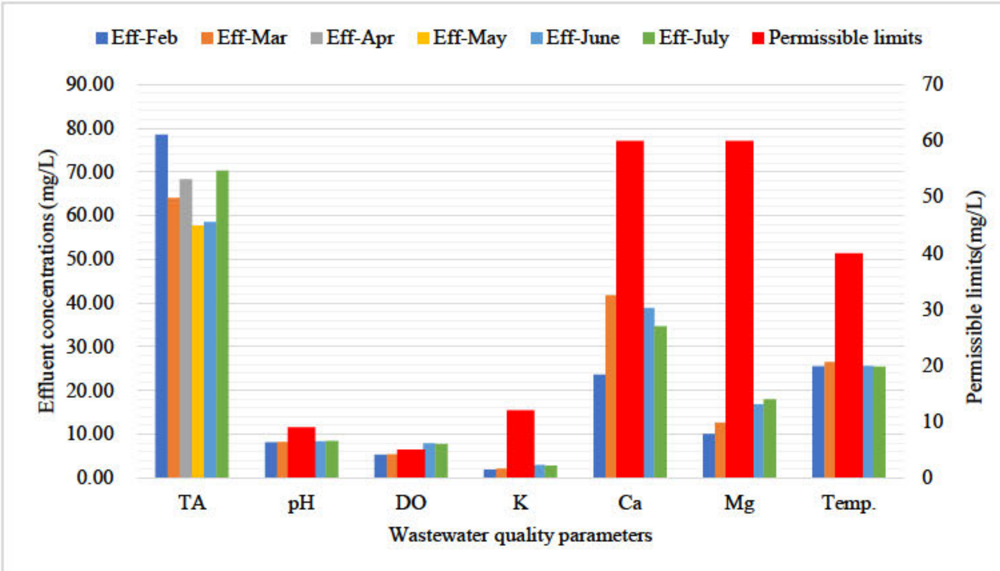


Figure 11 Operational control influent and effluent textile wastewater parameters

Figure 11 showed that there was fluctuation within the treatment unit even though the maximum temperature was detected to be in the permissible range. The activated sludge process temperature was 26.12°C, and it declined when the wastewater flowed down to the primary and secondary clarifiers to 26°C and 25.37°C respectively. Study showed that the higher temperatures increased microbial activity and chemical reactions in the treatment plant (Mhlanga and Brouckaert 2013b; Chen *et al.* 2017a). Moreover, the decomposition and removal efficiency of biodegradable organic pollutants and compounds highly depended on the temperature in the treatment plant (Bhave, Naik and Salunkhe 2020; Uddin 2021). Similarly, the increase in temperature beyond the limits could deplete the dissolved oxygen and increase the operational cost of the treatment plant (Drewnowski 2014). On the other hand, the reduction of the temperature from the aeration to the clarifier showed that the active biomass in the form of mixed liquid suspended solid was removed (Saki *et al.* 2020).

In wastewater treatment, almost all unit operations and processes hypo-statically depend on pH (Singh and Arora 2011). As shown in Figure 11, the result showed that the pH of influent and effluent fluctuated from 7.8 to 8.14 and 8.2 to 8.39 respectively. The pH was adjusted in the equalization tank to efficiently operate the subsequent treatment units and it was regulated at each process. Measuring pH is crucial to determine the solubility and availability of nutrients in wastewater (Parac-Osterman, Sutlovic and Durasevic 2010). The pH could be cross-communicated with temperature and controlled simultaneously. For most of the organic pollutants to be removed in the aeration tank, the well-being of activated sludge microorganisms is vital (Ogleni, Ovez and Ogleni 2010).

Based on a study by Cydzik-Kwiatkowska *et al.* (2018), the optimum pH level for bacterial growth ranges from 6.5 to 7.5. It was indicated that the activated sludge process may suffer as a result of the lack of heterotrophic bacteria, and it developed a nitrification process at a pH of 7.8 to 8.2 (Lin and Ho 2022). Although the pH of the treated effluent was within the standard, the results showed a maximum pH of 8.39 for all measured values. This change occured due to the metals in the wastewater, which were transported to the effluent (Islam *et al.* 2023).

In addition, Figure 11 shows that the measured average values of untreated and treated wastewater DO levels were 1.6 mg/L and 5.25 mg/L respectively. Hence, the DO concentration in the effluent of treated textile wastewater discharged to the nearby river was nearly within the minimum permissible limit range of 5 mg/L to 9 mg/L. The decline in dissolved oxygen concentration in the treatment plant indicated inefficiencies in the aeration system to oxidize the organic pollutants biologically (Lin and Ho 2022). Based on the study by Mhlanga and Brouckaert (2013b) , the levels of DO varied with wastewater temperature, characterized wastewater and mixed system, season, time of day, and rate of flow. Furthermore, releasing a low level of DO into the surface water highly affected aquatic animals, and it formed intermediate pollutants due to the presence of organics in the wastewater (Achillas *et al.* 2013).

Similarly, like DO and pH, total alkalinity, and other metallic compounds played an important role in a healthy microorganism ecosystem, which assisted with pollutant removal in the treatment plant (Chen *et al.* 2021). As shown in Figure 11**,** the average concentrations of total alkalinity, potassium, calcium, and magnesium in the effluent were recorded as 66.22 mg/L, 2.38 mg/L, 44.56 mg/L, and 15.82 mg/L respectively, which were within the effluent limit (Bhatia *et al.* 2018; Bidu *et al.* 2021). It indicated that calcium and magnesium metals were considered inert materials and contributed to the fraction of the inorganic suspended solids, which could be monitored in the treatment process (Revilla, Galan and Viguri 2016).

Heavy metals

Figure 12 also indicates that the measured parameter values for treated effluent concentrations of Fe, Zn, and total Cr, were 0.29 mg/L, 0.27 mg/L, and 0.16 mg/L respectively. Even though Fe and Zn were within the standard values, there was a slight increment in the effluent for Fe concentration, most probably due to poor performance of the electrolytic process and micro-electrolytic Fe flocs shortcircuited in the plant (Uddin 2021). On the other hand, there was a reduction of Cr from 0.26 mg/L to 0.16 mg/L. However, the effluent concentration of chromium was well over the 0.05 mg/L limit for surface water discharge. High levels of Cr lead to ecotoxicology of aquatic life and carcinogenic effects for humans through the receiving waters (Bhatia *et al.* 2018; Bidu *et al.* 2021). Moreover, the textile wastewater consisted of various high molecule compounds with minimal levels of degradation, which made it difficult to attain the discharge limit.

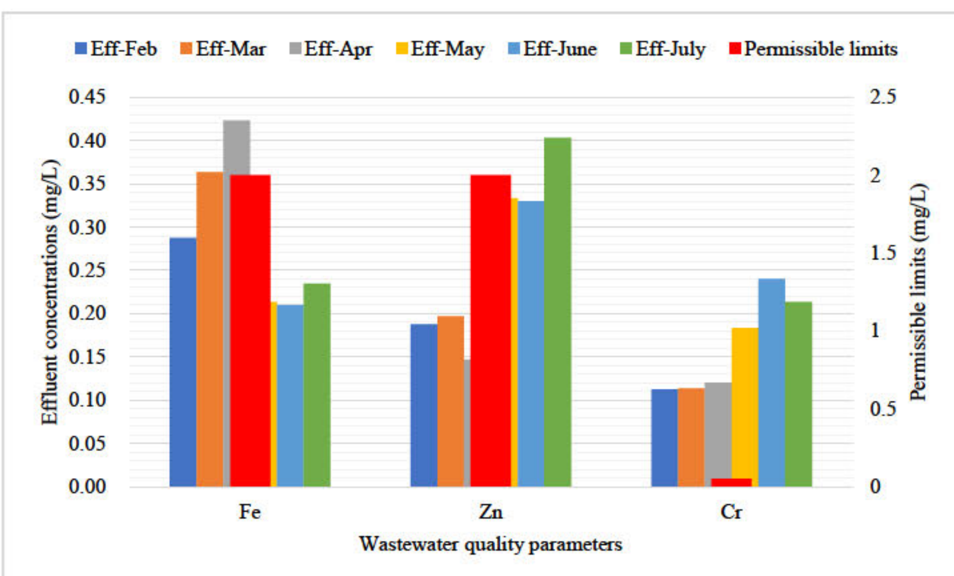


Figure 12 Measured heavy metal in textile wastewater

Primary physico-chemical wastewater quality parameters

In textile industry wastewater treatment, biological and chemical processes are the primary unit of operations to quantify the deterministic primary pollutants (Zawilski and Brzezinska 2009; Wang, Jiang and Gao 2022). The wastewater parameters BOD_5, COD, TSS, TDS, VSS, TKN, NH_3, NO_2, NO_3, and TP are the primary pollutants to model and optimize the treatment plant (Patel and Bhatt 2022; Sharma and Malaviya 2022a).

The measured average values of BOD_5 and COD at the effluent were 48.45 mg/L (± 12.86) and 148 mg/L (± 13.95) respectively (Figure 13b). However, both measured BOD_5 and COD values at different periods did not comply with the standard permissible discharge limits of 40 mg/L and 120 mg/L respectively. The increase in COD concentration indicated the presence of toxic compounds that affected the biological process in the treatment plant (Adane, Adugna and Alemayehu 2021). This toxicity could be attributed to untreated heavy metals and organic compounds generated from textile wastewater (Methneni *et al.* 2021). BOD_5 was also 17.4 % above the standard limit, which implied the depletion of DO due to the MLSS's high concentration of organic matter, which could not be effectively degraded biologically. Moreover, studies confirmed that COD and BOD_5 are interrelated parameters and are preferably degraded as organic matter in biological and chemical oxidation respectively in a treatment process (Cossu, Lai and Sandon 2012; Mhlanga and Brouckaert 2013b). Accordingly, the significant increase in COD shown in Figure 13b demonstrated the probable presence of toxicants, heavy metals, and persistent organic matter in the wastewater (Guerrero *et al.* 2012; De Ketele, Davister and Ikumi 2018).

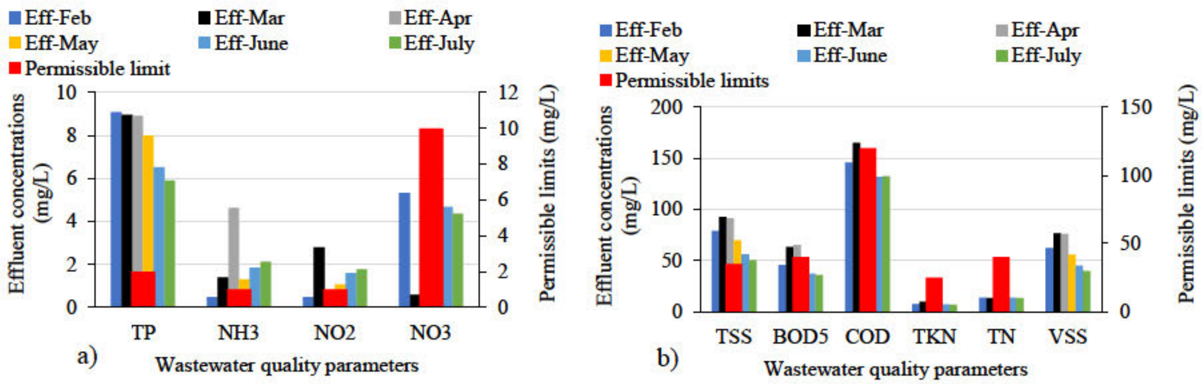


Figure 13 Physico-chemical textile wastewater parameters of primary pollutants and metals

For the effective removal of organic pollutants, (i.e., BOD_5 and COD) the oxygen uptake rate in the aeration system is vital. In addition to the carbon sources, the heterotrophic bacterium in the activated sludge requires sufficient and optimum amounts of nutrients, such as nitrogen and phosphorous (Borzooei *et al.* 2020). According to Figure 13a, the average effluent concentrations of NO_2 and TP were recorded 1.36 mg/L (± 0.9) and 7.9 mg/L (± 1.38), which were higher than the permissible limits of 1 mg/L and 2 mg/L respectively. Hence, the increased concentration of total phosphorous in the effluent was probably due to the presence of soluble inert material that remained undegradable (Bhatia *et al.* 2018).

The experimental analysis showed that TSS concentration in the samples was higher than the allowable effluent standard of 35 mg/L (Figure 13b). The increase in the level of total suspended solids in the effluent would affect the quality of the receiving water and further deplete the dissolved oxygen. Pavithra *et al.* (2019) mentioned that high concentrations of TSS most probably emanated from the colouring material used in the textile process. An increase in suspended particles could also be the result of a shock load of influent solids that are mostly inorganic chemicals not prone to degradation, which in turn could decrease the micro-organism suspended solid ratio in the aeration process (Pittoors, Guo and Van Hulle 2014). Moreover, this increment could also be due to poorly operated and unmanaged primary and secondary clarifiers of the textile treatment units (Zhou *et al.* 2011).

The average effluent TDS and EC values of 403.70 mg/L (± 17.96) and 661.69 μscm^{-1} (± 17.31) were within the standard permissible discharge limit of < 1500 mg/L and < 4000 μscm^{-1} respectively. However, on some occasions, weekly data showed high fluctuations of effluent TDS compared to the influent, which probably indicated that inorganic and organic compounds were not efficiently degraded and removed in each treatment unit's operations and processes (Lotfi *et al.* 2019) .

Volatile suspended solids (VSS) measured was 59.28 mg/L (± 15.35). VSS is a rough measure of solids concentration in a sample of activated sludge and is a good indicator of bacterial biomass in a sample (Mhlanga *et al.* 2009). Figure 13b shows that the level of VSS was high in the influent and effluent samples, with 194.76 mg/L and 59.28 mg/L, respectively. A high level of VSS depicted that the bacterial biomass in the treatment was high (Amanatidou *et al.* 2015). On the other hand, a high level of VSS in the effluent indicates that potential amounts of organic solids and/or biological floc were disposed of along with the effluent (Amanatidou *et al.* 2015).

5.2. Results and discussion for specific objective 2

To model and simulate a wastewater treatment plant's unit operations and processes using GPS-X

The existing and modified process flow of the textile wastewater treatment plant model was built on GPS-X simulation software (Orhon 2015). Figure 14 shows that in scenario I (existing operation) the model showed the raw wastewater being directly loaded into the aeration tank and then transported to the primary clarifier which is the wrong process linkage (Katheresan, Kansedo and Lau 2018). The treated effluent from the secondary clarifier was directly bypassed to the receiving water body. However, the modified scenario II presented in Figure 15 promoted nutrient and solid removal in an optimized way (Juneidi, Sorour and Aly 2022; Wang *et al.* 2022b). The pumping stations were reduced by shifting the mode of operation in the existing infrastructure. For the enhanced biological degradation and stability of the process, additional carbon sources were added in the form of molasses (Araujo *et al.* 2022). The wastewater process flow diagram follows the correct linkage, and the bypass was removed from the model. Thus, both scenarios were modelled and simulated. Finally, the operational framework was developed for the correct scenario II as indicated in objective 4.

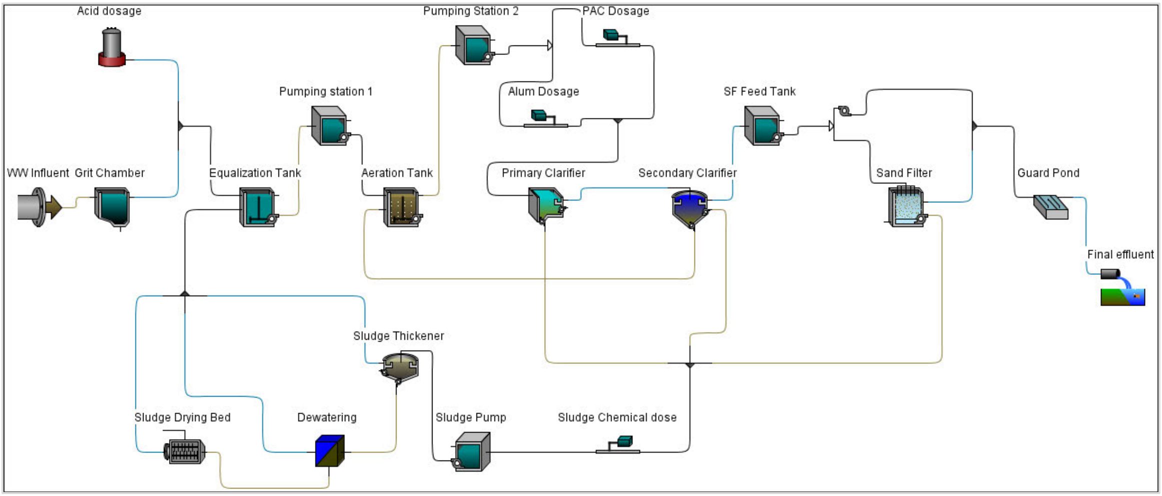


Figure 14 Existing wastewater treatment process model (scenario I)

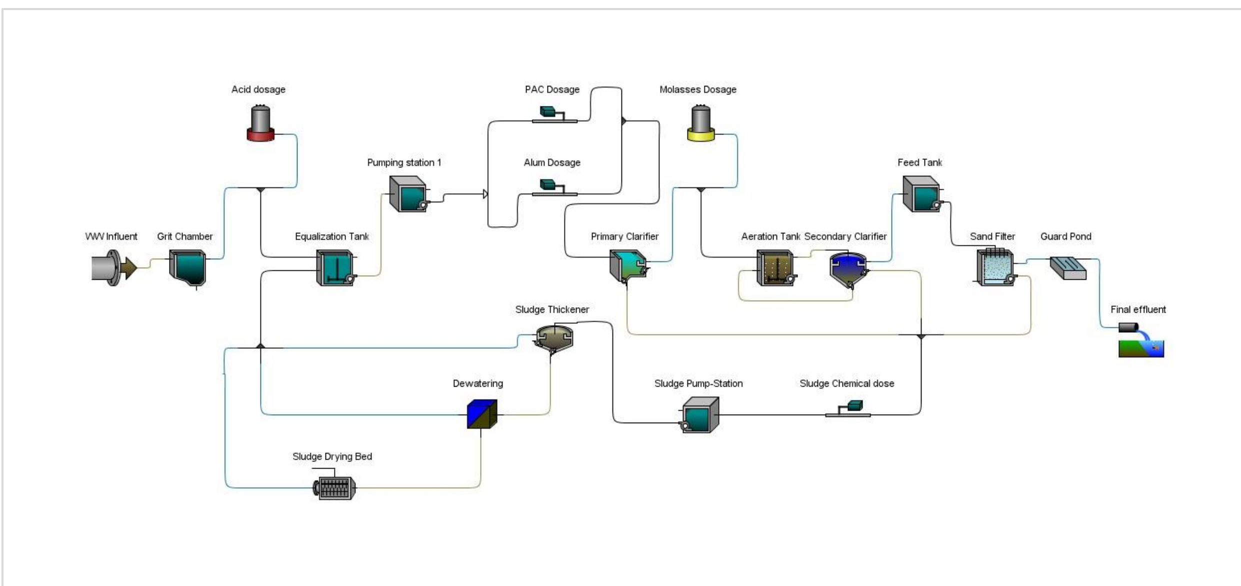


Figure 15 Modified wastewater treatment process model (scenario II)

The wastewater treatment plant for the existing scenario and the calibration were performed for the prediction of best-fitted model parameters for the measured analytical data from the case study. Due to the complexity of the process and sidestream recycling, three-step calibration tests were conducted using the first four months' data (Pittoors, Guo and Van Hulle 2014). The calibration was efficiently executed by characterizing the influent composition fractions by changing the default GPS-X values and it changed its composite variables according to its mass balance relationship (Hu *et al.* 2014; Solis *et al.* 2022). The influent fraction of VSS/TSS, total BOD_5/total COD, soluble COD/total COD, soluble BOD_5/soluble COD, and ammonium fraction of soluble TKN were changed from GPS-X default values of 0.75, 0.64, 0.34, 0.61, and 0.9 to 0.615, 0.68, 0.56, 0.63, and 0.92, respectively (Table 11). The first calibration test under the change in influent fractions shown in Figure 16a and Figure 16b for the influent wastewater parameters (almost all) was excellent and had an acceptable confidence level.

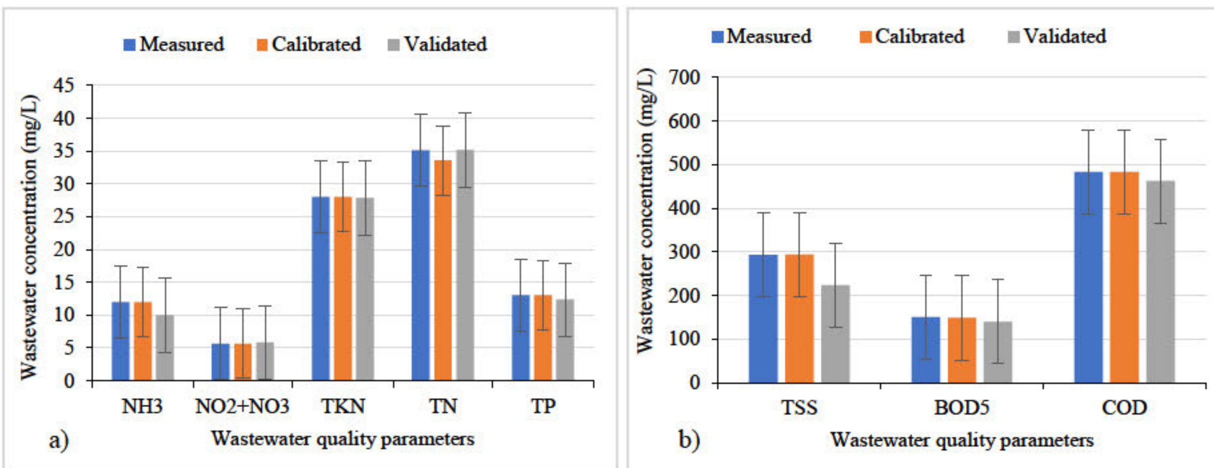


Figure 16 Influent composition model calibration and validation using influent fractions

However, the calibration test for the effluent parameters shown in Figure 17a and Figure 17b failed to take the actual measured data into account and overestimated for TSS (136 against 56.26 mg/L), TN (26.22 against 13.59 mg/L), and nitrite-nitrate (18 against 6.28 mg/L) while it underestimated for BOD_5 (5.7 against 37.13 mg/L) and ammonia (0.22 against 1.85 mg/L). Thus, the result from the calibration test of effluent wastewater quality needed an additional strategy to adjust the model parameters by identifying the most deterministic variables (Zawilski and Brzezinska 2009; Eldyasti, Nakhla and Zhu 2012; Hakanen, Sahlstedt and Miettinen 2013).

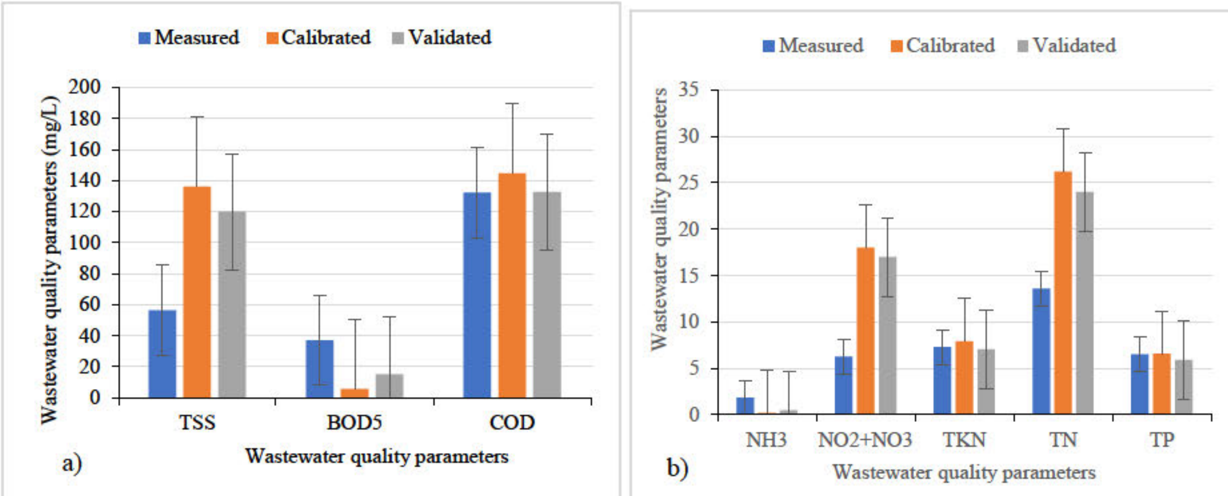


Figure 17 Effluent concentration model calibration and validation using influent fractions

The nitrogen compounds and the organic substrate are mostly controlled in the biological process while the TSS is balanced in the secondary clarifier (Liwarska-Bizukojc and Ledakowicz 2011; Liwarska-Bizukojc, Andrzejczak and Solecka 2019). In this regard, the model stoichiometric fractions, biokinetic, and operational parameters at aeration tank aerobic heterotrophic yield on soluble substrate, maximum growth rate of ammonia oxidizer, maximum growth rate for nitrite oxidizer, and alpha factor (coarse bubble) were adjusted from the default GPS-X value of 0.666, 0.9, 1, and 0.8 to 0.57, 1.00, 0.84, and 0.5, respectively (Table 11). The second calibration experiment for the effluent quality parameters is the result of the change in the aeration stoichiometric and biokinetic variables presented in Figure 18a and Figure 18b showed that the nitrogenous component fitted well with the measured data.

However, the TSS and BOD_5 were still overpredicted and underestimated, respectively, and needed additional adjustment of the influencing parameters. Based on research by Andraka (2020) and Pedrazzani *et al.* (2016) the removal of TSS from the effluent is dependent on the settling performance of the secondary clarifier and is related to the sludge volume index (SVI). Hence, the SVI (150 against 110 mL/g) in the clarifier was changed from the default GPS-X value; however, the TSS concentration in the effluent did not capture the actual measurement. In model calibration, it is recommended to use the data that is trusted more (Machado, Lafuente and Baeza 2014; Mbamba *et al.* 2019). Thus, COD, TKN, and TP were used as the main influent composition due to the impact on the receiving water body.

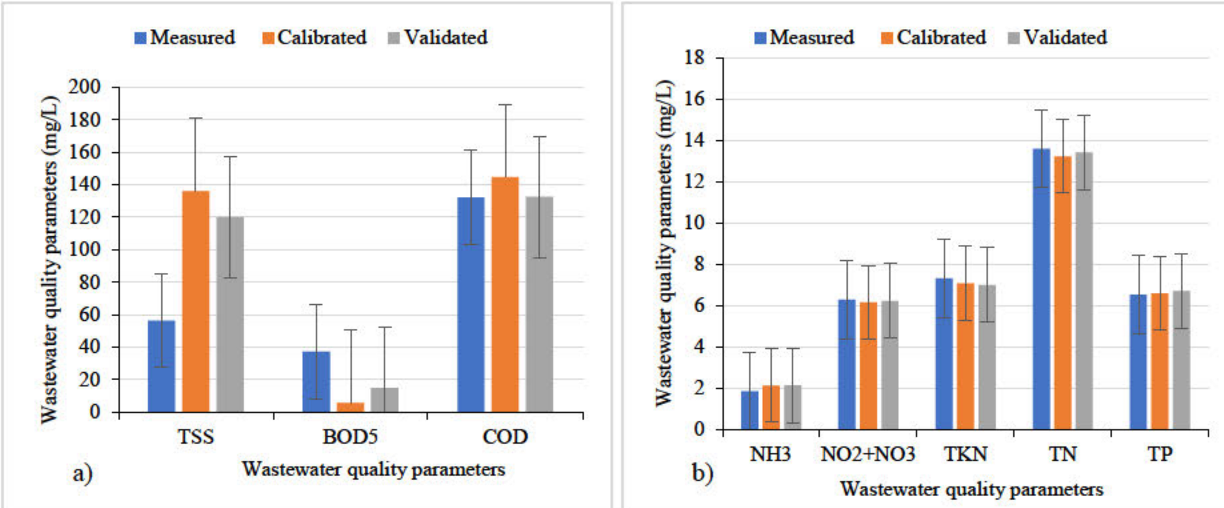


Figure 18 Effluent concentration model calibration and validation using aeration parameters

The quality of calibration was measured after the default value of GPS-X parameters was changed with the adjusted variable and the simulation test result confirmed the actual measurement (Arif, Sorour and Aly 2020). Furthermore, the calibration results for the influent and effluent parameters were within the confidence interval and the model was qualified for simulation (Liwarska-Bizukojc *et al.* 2011). The GPS-X calibration model output varied significantly with a slight change from the default value. To counterbalance this, a two-step sensitivity analysis was performed (Vivekanandan, Jeyannathann and Rao 2018).

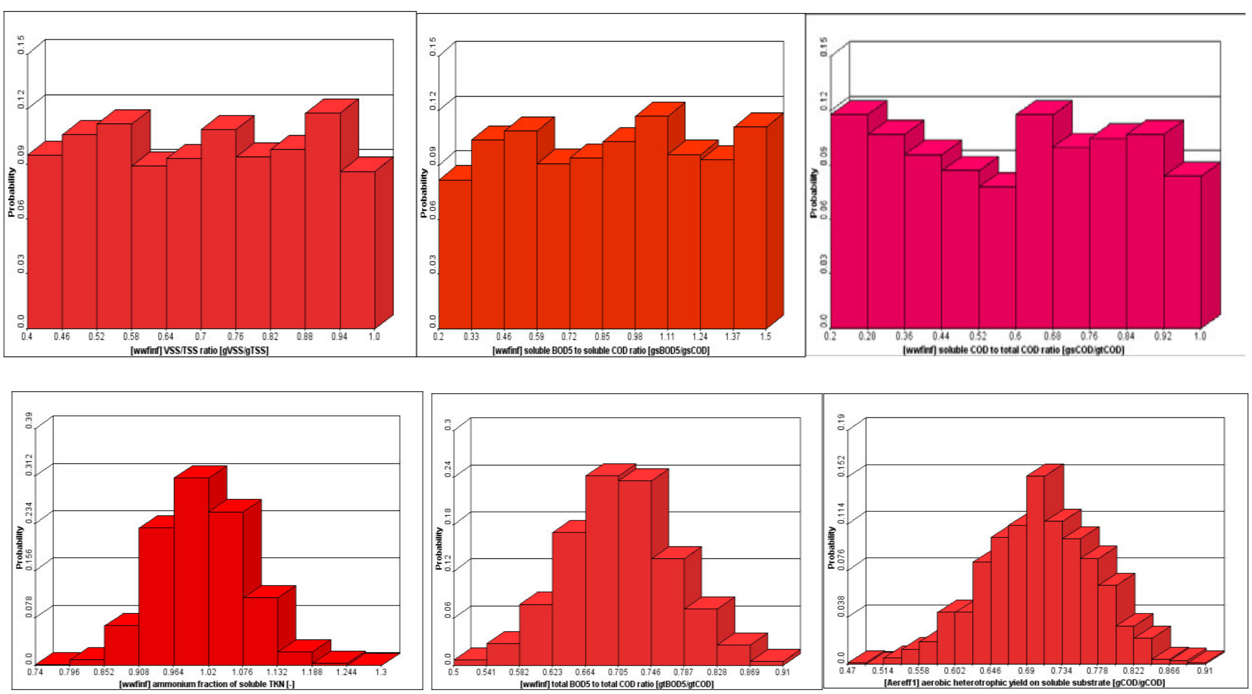
The validation of the model was performed using the two months' data that was not part of the model development. As presented in Figure 16, Figure 17, and Figure 18, the validation results matched the measured data and were within the acceptable confidence limit. For the verification of the model similar influent fraction, stoichiometric, and biokinetic variables were used as part of the calibration.

Table 11 Activated sludge influent fractions, stoichiometric and kinetic variables

Parameters	Units	GPS-X default value	Calibration	Validation
VSS/TSS ratio	gVSS/gTSS	0.75	0.615	0.615
soluble COD to total COD ratio	gsCOD/gtCOD	0.34	0.56	0.56
soluble BOD5 to soluble COD ratio	gsBOD5/gsCOD	0.61	0.63	0.63
total BOD5 to total COD ratio	gtBOD5/gtCOD	0.54	0.68	0.68
ammonium fraction of soluble TKN	-	0.9	0.92	0.92
aerobic heterotrophic yield on soluble substrate	gCOD/gCOD	0.666	0.57	0.57
maximum growth rate of ammonia oxidizer	1/d	0.9	1.00	1.00
maximum growth rate for nitrite oxidizer	1/d	1	0.84	0.84
alpha factor (coarse bubble)		0.8	0.5	0.5

Multiple step Mote Carlo sensitivity analysis

The sensitivity analysis was performed to identify the critical parameters that needed to be optimized while simulating the models (Machado, Lafuente and Baeza 2014; Mbamba *et al.* 2019). For the calibrated and validated model, the multiple-step Monte Carlo sensitivity simulation was conducted for 1000 runs to evaluate the statistical distribution of the input variables and the probability of attaining the specific target in the treatment (Mannina and Cosenza 2015; Kim 2017).



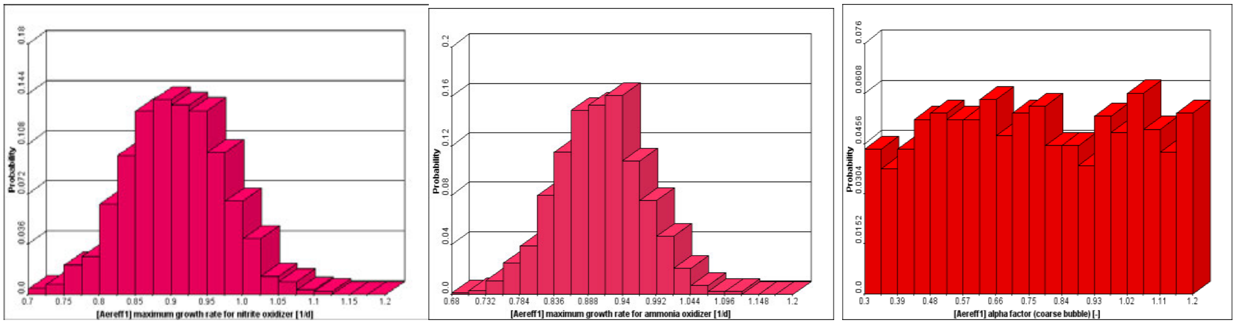


Figure 19 The probabilistic distribution of the influent fractions, stoichiometric and kinetic variables

As presented in Figure 19, the Mote Carlo sensitivity result depicted that the probabilistic distributions of VSS/TSS, soluble BOD_5/soluble COD, soluble COD/total COD, and alfa factor were uniform. However, the remaining variables were of normal distribution. The variables were changed simultaneously to critically identify the most sensitive parameters and to quantify the probability of the outputs complying with the requirement (Vivekanandan, Jeyannathann and Rao 2018). Figure 20 also showed that the sludge blanket height of the primary and secondary clarifiers was hardly above the minimum requirement, with 87.5 and 86.6%, respectively, and had the probability of violating the standard (Mannina and Cosenza 2015; Solis *et al.* 2022).

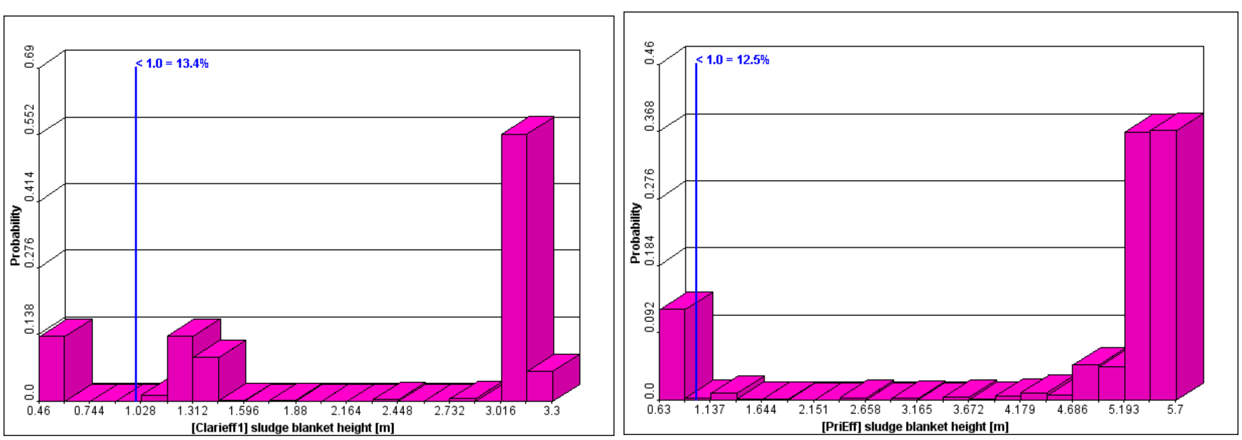


Figure 20 The probability distribution of sludge blanket height of both clarifiers

Likewise, as presented in Figure 21, the final effluent removal efficiency probability of BOD_5, NH_3-N, COD, TP, and TSS were 49.1%, 88.4%, 35.5%, 26.5%, and 38.4%, respectively. The result showed that for the slight change of the variables in GPS-X run for 1000 iterations, the probability of percentage removal of pollutants was below the permissible limit. Similarly, a

99.8% probability of DO was obtained above the required concentration of 2 to 3 mg/L (Pittoors, Guo and Van Hulle 2014; Li *et al.* 2020; Saki *et al.* 2020). The daily mass cake flow production was also high. Thus, the existing scenario I needed a strategy to be holistically optimized. For this, the one-step sensitivity analysis was performed for the same variables to find the most sensitive parameters that could be controlled (Eldyasti, Nakhla and Zhu 2012).

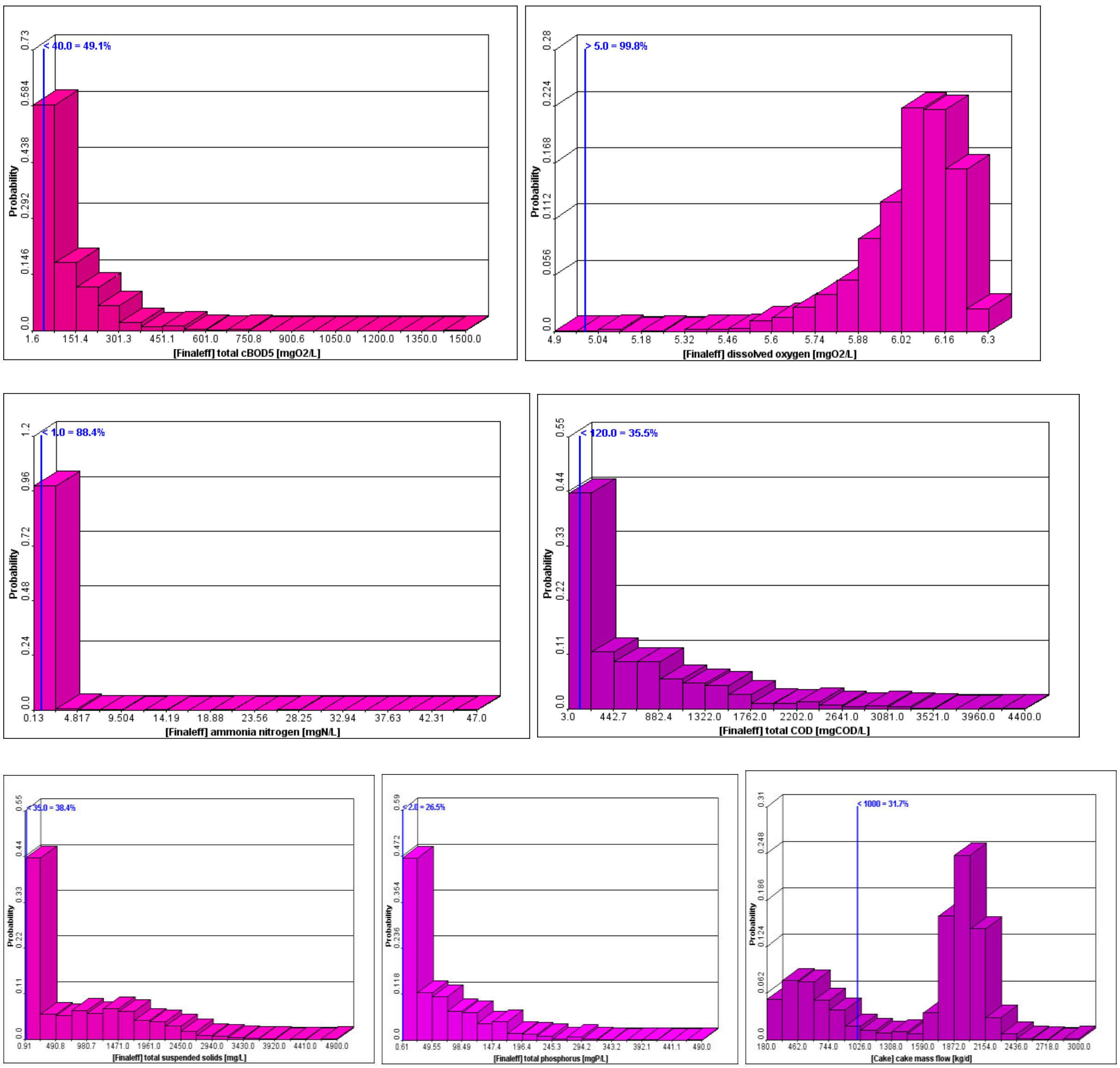
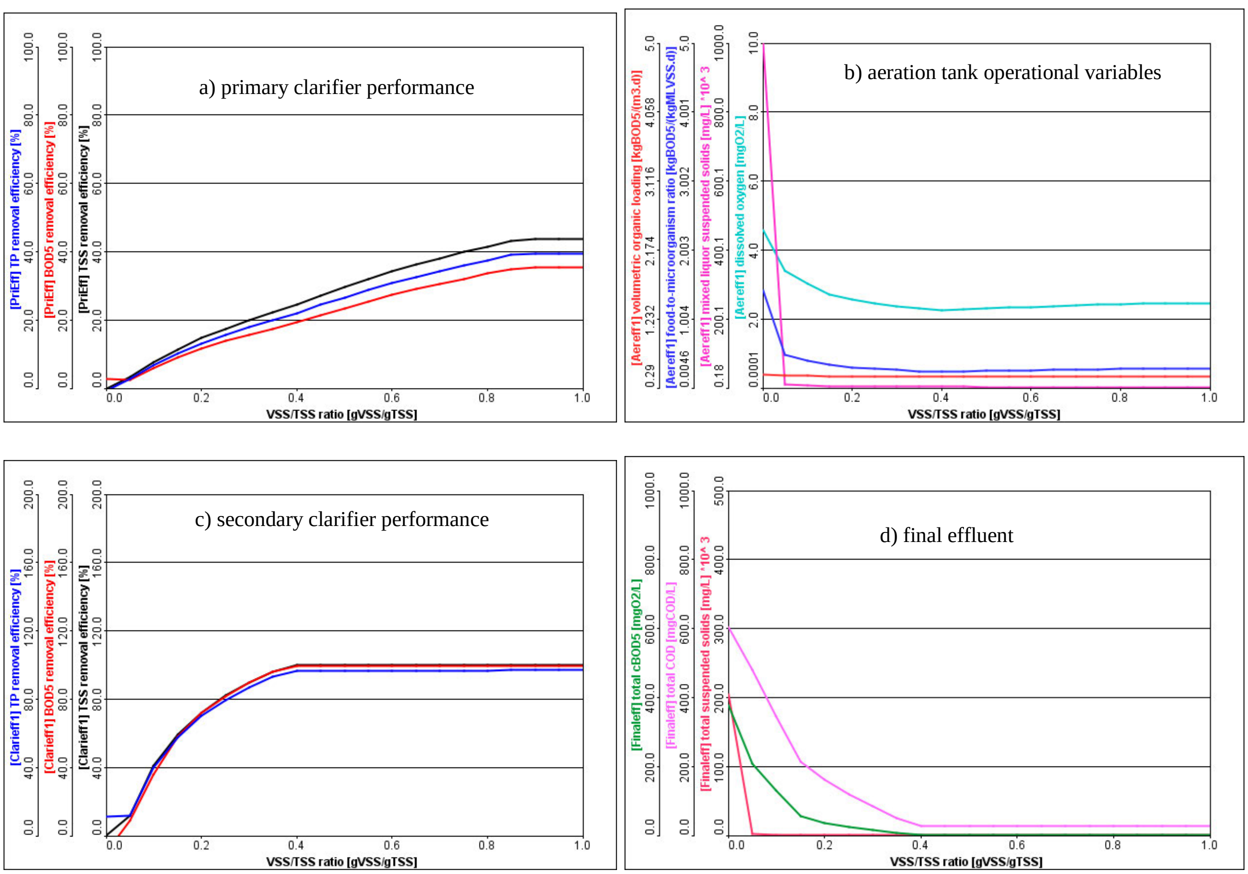


Figure 21 Monte Carlo sensitivity analysis probability distribution of effluent concentration

The one-step sensitivity analysis for VSS/TSS and BOD_5/COD ratio, the aerobic heterotrophic yield on a soluble substrate on the performance of the plant

Figure 22 and Figure 23 present the influence of the VSS/TSS and BOD_5/COD ratio on the effluent quality, clarifiers' performance, and aeration process control. The efficiency of treatment plants depends on the influent fractions in the biological process (Cossu, Lai and Sandon 2012; Xiong *et al.* 2012; Cossu *et al.* 2017; Jafar *et al.* 2022). In the model calibration and validation, the influent fractions were iterated and tested against the response in the simulation for VSS/TSS changes from 0.4 to 1.0, the performance of the primary and secondary clarifiers was increased and then remained constant (Figure 22a and c). Meanwhile the effluent quality also smoothly decreased and remained stable except for total phosphorus. Conversely, the performance parameters in the aeration tank were not significantly affected by the change in the VSS/TSS ratio (Figure 22b, d, e, and f).



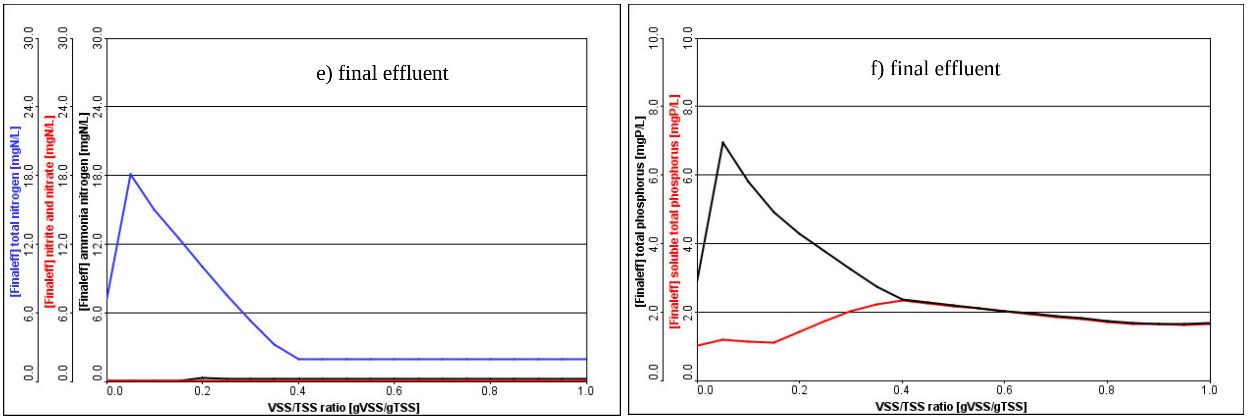
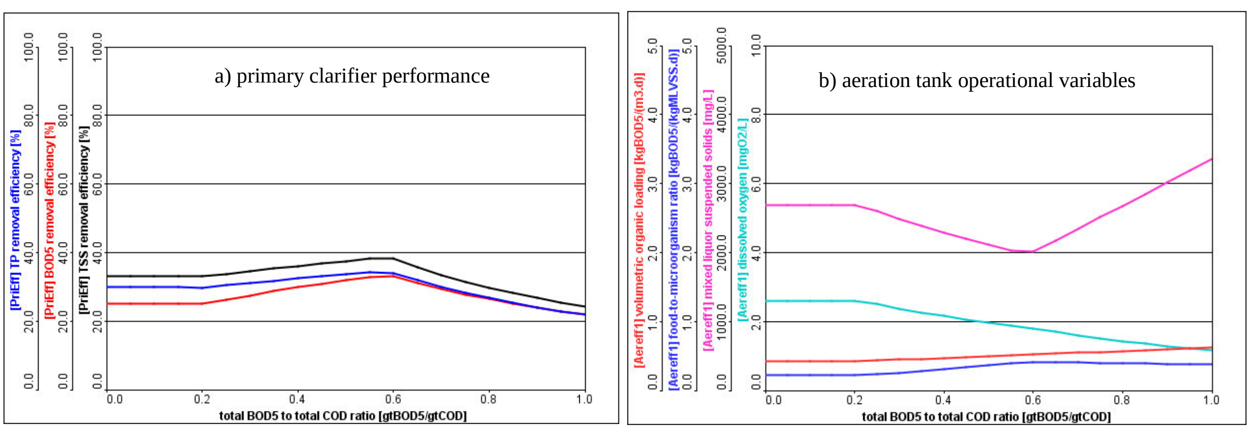


Figure 22 Influent fractions VSS/TSS ratio influence on plant performance

Similarly, compared to the VSS/TSS ratio, the change in the BOD_5/COD ratios significantly influenced the quality of effluent TP which increased from 1.7 to 2.7 mg/L (Figure 23e). Conversely, the primary and secondary clarifier performance and the effluents TSS, COD, BOD_5, and nitrogen compounds were not affected by the change in the BOD_5/COD ratio (Figure 23a, c, d, and f). Additionally, the DO (2mg/L) and MLSS (2300 mg/L) declined to the level of the optimum BOD_5/COD ratio of 0.5 (± 0.1) (Figure 23b). Therefore, from the sensitivity analysis under steady-state simulation, the ratio of VSS/TSS and BOD_5/COD were adjusted to 0.6 (± 0.1) and 0.5 (± 0.1), respectively to ensure the target effluent quality and the health of the plant operation (Cossu, Lai and Sandon 2012).



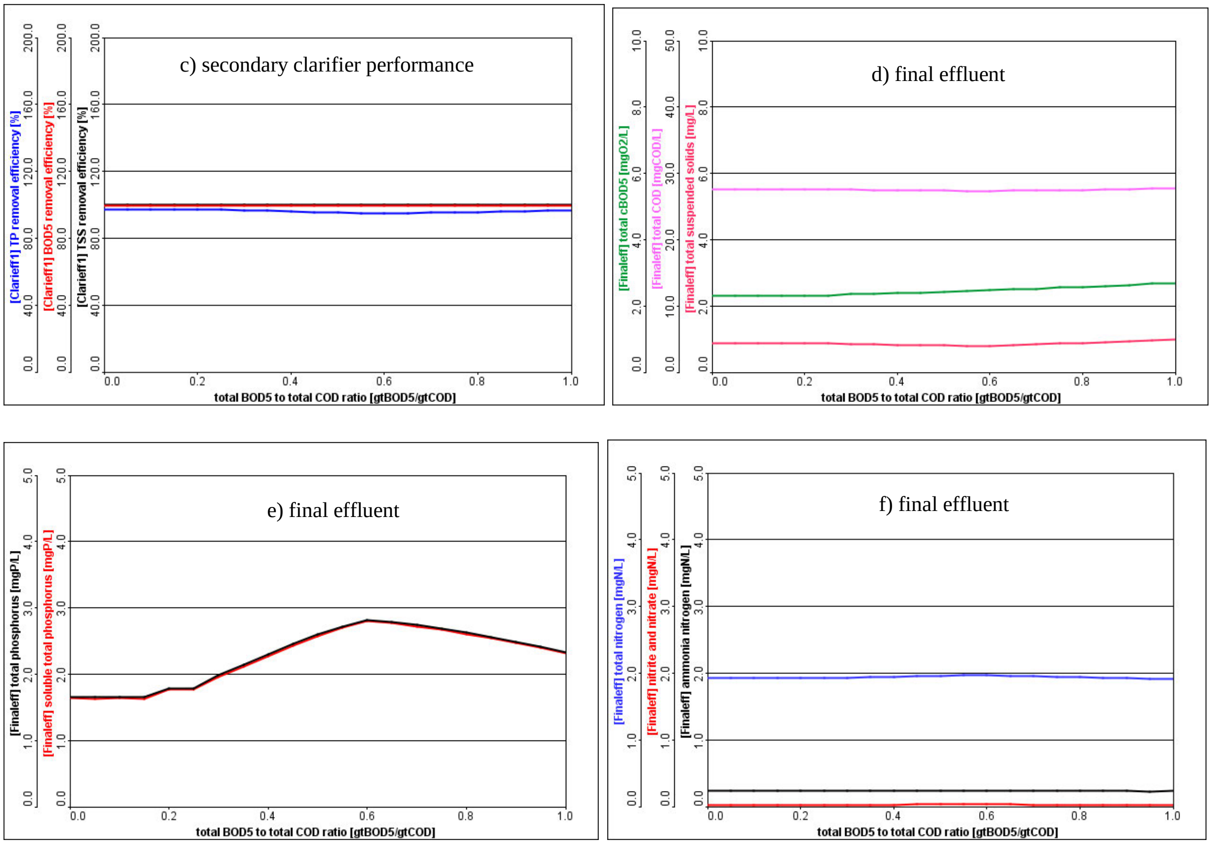


Figure 23 Influent fraction total BOD_5/total COD ratio influence on plant performance

In the activated sludge process, the aeration system in one of the predominant treatment units degraded the biomass aerobically by heterotrophic microbes (Vanrolleghem and Verstraete 1993; Ni, Yu and Sun 2008). The results in Figure 24a and c showed that the removal efficiency of the clarifiers declined in proportion to the increase in the aerobic heterotrophic yield ratio. Similarly, the effluent concentrations of BOD_5 and COD were increased significantly for the change in aerobic heterotrophic yield ratio of 0.7, while the effluent TP declined to the acceptable limit of 2 mg/L, and the nitrogen compounds remained unchanged (Figure 24d, e, and f).

The aerobic heterotrophic yield fraction is vital for biomass balance in the aeration tank by sustaining the required amount of MLSS in the system (Xie *et al.* 2012). For the slight change in the aerobic heterotrophic yield fraction shown in Figure 24b, the MLSS and DO were drastically increased from 1010 to 3650 mg/L and 0.5 to 7.4 mg/L respectively while the F/M ratio declined slightly to within the acceptable range of 0.2 to 0.5 (Vera, Saez and Vidal 2013; Jasim 2020). Thus, from the simulation result, it was deduced that 0.6 (± 0.1) aerobic heterotrophic yield on the soluble substrate was required to ensure acceptable effluent quality and effective plant operation.

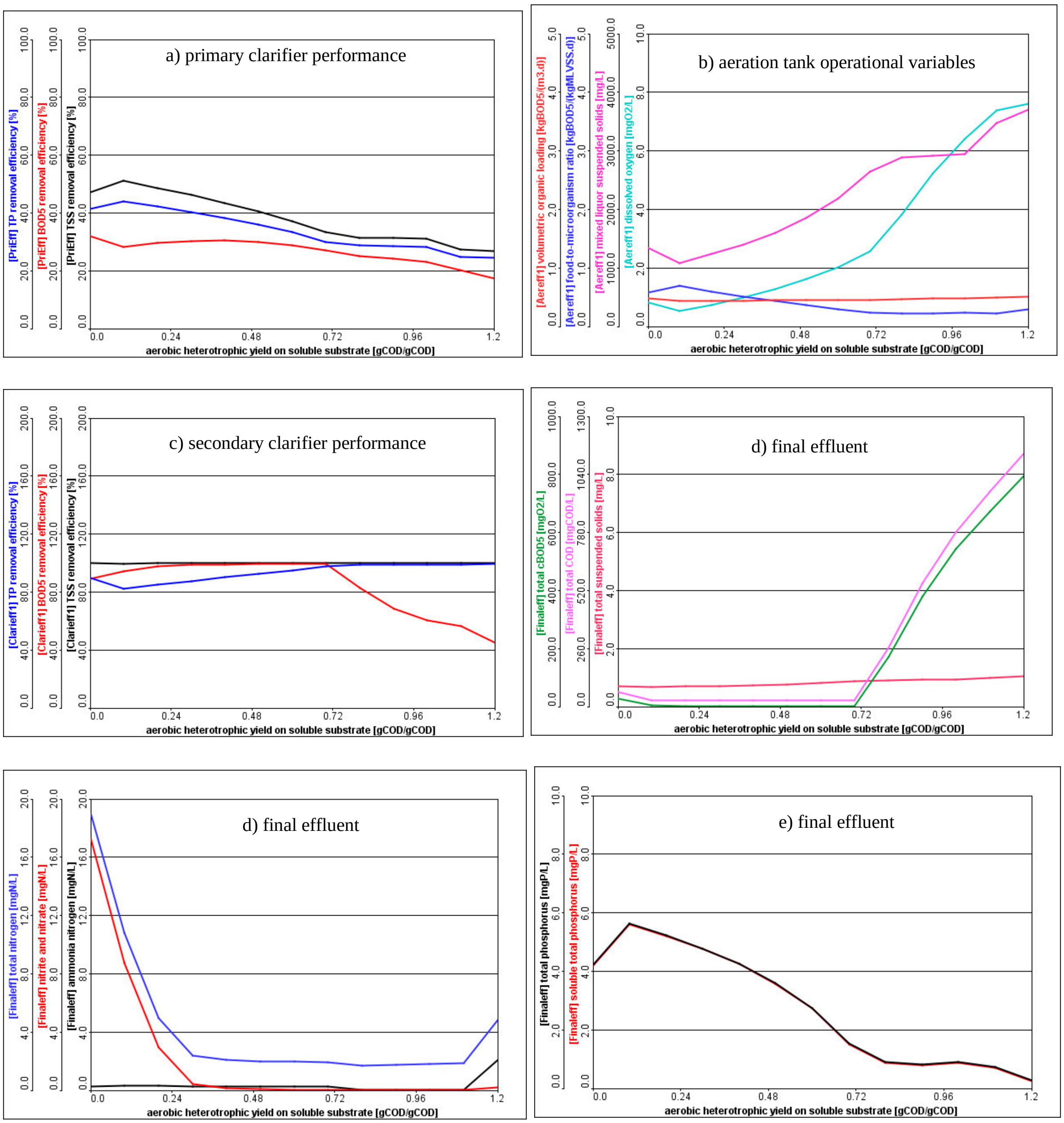


Figure 24 Aerobic heterotrophic yields on soluble substrate influence on plant performance

Simulation result of the scenarios

As presented in Figure 25a, the removal efficiency of the primary clarifier under scenario I for the parameters TSS, BOD_5, TN, and TP was simulated as 4.5%, 4.3%, 3.9%, and 4.4%, respectively. Meanwhile, the scenario II result depicted that the removal efficiency of the primary clarifier was increased to 88.96%, 29.78%, 38.86%, and 50.2% for TSS, BOD_5, TN, and TP, respectively.

Similarly, FFigure 25b showed that in scenario I, due to the very small wasting of sludge (4.2 m^3/d) from the primary clarifier, the sludge blanket height (SBH) of 5.5 m and the solid loading rate (SLR) of 22.64 kg/m^2. d were recorded higher than scenario II with the values of 15 m^3/d, 2.66 m, and 10.29 kg/m^2. d, respectively. However, the solid retention time (SRT) for scenario I was simulated as less than in scenario II with the result of 3.4 and 7.15 days, respectively. Operating the plant with the modified scenario II leveraged better removal efficiency than the existing scenario I. This implies that better integration of processes is indispensable in wastewater treatment (Kumar *et al.* 2015).

Moreover, the wasted activated sludge (WAS) and SRT had a prime role in maintaining the performance of the primary clarifier (Drewnowski *et al.* 2019). On the other hand, a short SRT and small WAS flow leads to insufficient withdrawal of sludge, which in turn increases the sludge blanket depth and reduces the performance of the primary clarifier (Xiong *et al.* 2012; Zinatizadeh, Rahimi and Younesi 2020). Thus, scenario II optimized the wasting of sludge as well as enhanced the removal efficiency of the primary clarifier.

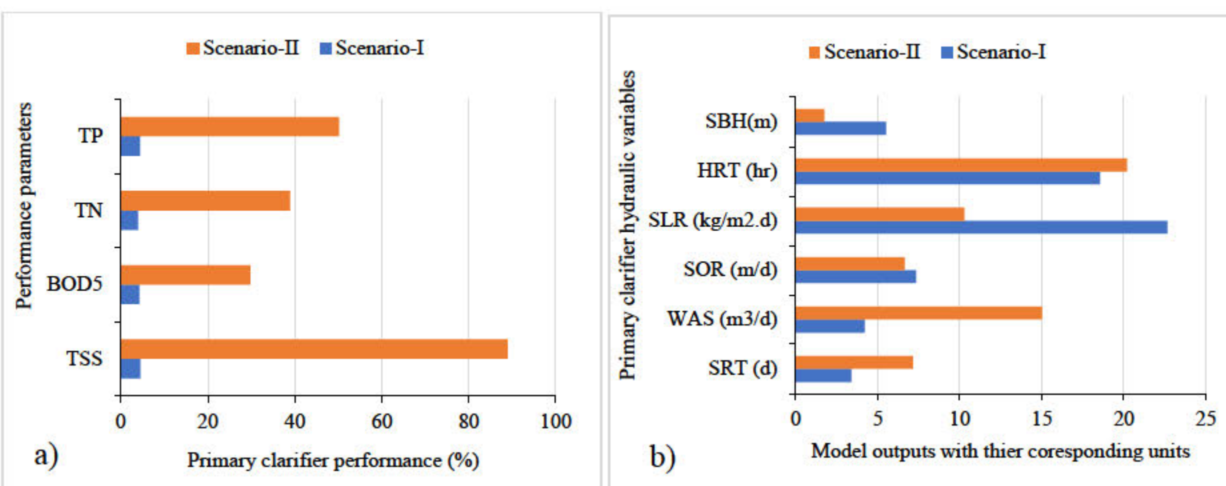


Figure 25 Primary clarifier 180-day simulation result for scenarios I and II

The performance of clarifiers is measured on the settling potential of raw sludge and biological flocs along the layers of the tank (Campo *et al.* 2023). The solid concentration at each layer of the tank is critical to control the sludge blanket height in the clarifier (Keinath 1989; Zinatizadeh, Rahimi and Younesi 2020). Figure 26 presented that the solid concentration of the primary clarifier in scenario I was 2546 mg/L, 12,367 mg/L, and 26,975 mg/L in the first layer, in the next eight layers, and in the tenth layer, respectively with the sludge blanket height of 5.5 m shown in Figure 25b. However, in scenario II the solid concentration declined layer by layer from the first layer of 967 mg/L to the bottom of 23,564 mg/L with a sludge blanket height of 2.66 m as shown in Figure 25b.

The simulation results deduced that the modified process layout and its optimized WAS, SRT, and other operational parameters played a vital role in enhancing pollutant removal efficiency (Hu *et al.* 2018; Drewnowski *et al.* 2019). In the study, the settleability control in the primary clarifier is shown to be indispensable for reducing the cost of the downstream treatment process (Sid *et al.* 2017; Turkmenler and Aslan 2017; Rajaei and Nazif 2022).

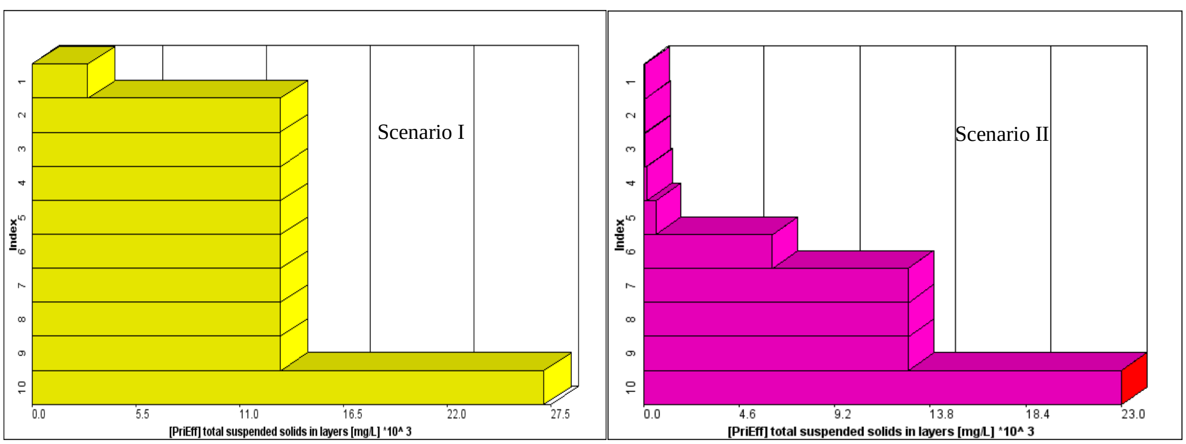


Figure 26 Primary clarifier solid profile and state point for scenarios I and II

In the activated sludge process, the secondary clarifier is an integral part of biological treatment (Zhou *et al.* 2011; Muoio *et al.* 2019). The pollutant removal efficiency of the secondary clarifier was dependent on the well-being of the microorganism and the operational parameters in the aeration tank (Xie *et al.* 2012; Pittoors, Guo and Van Hulle 2014; Revilla, Galan and Viguri

2016). Figure 27a presented that the performance of the secondary clarifier for scenario I and II for the pollutant removal of TSS, BOD_5, TN, and TP increased from 93.26%, 88.86%, 80.71%, and 92.36% to 99.53%, 99.83%, 98.74%, and 99.37%, respectively.

On the other hand, the hydraulic operation parameters were simulated for both scenarios as shown in Figure 27b. The sludge blanket depth was significantly reduced from 3.09 m to 0.4 m for scenarios I and II, respectively with a slight increase in WAS (83 m^3/d against 82 m^3/d) leading to an equivalent reduction in SRT (3.84 d against 4.9 d) in scenario II. Furthermore, the recycled activated sludge (RAS) was significantly increased from 60 m^3/d to 150 m^3/d for scenarios I and II respectively.

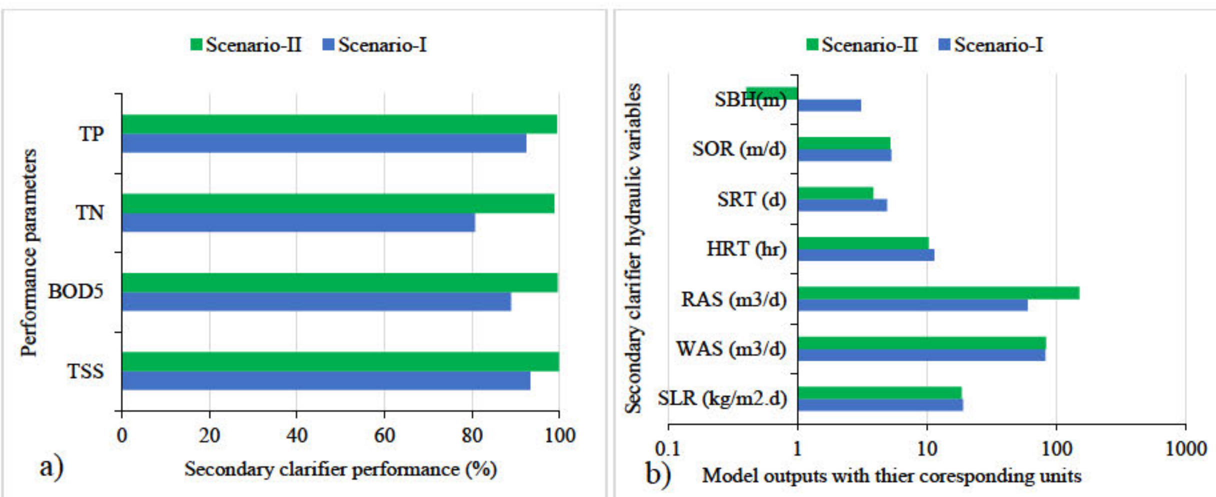


Figure 27 Secondary clarifier 180-day simulation result for scenarios I and II

Figure 28 and Figure 29 depicted that the settling characteristics of the MLSS derived from the simulation of the rate at which the solid settled in the clarifier was good for scenarios I and II. However, *Figure 28* showed that the clear water, the separation, and the sludge storage depth for the secondary clarifier in scenario I were quite small and led to an increase in the sludge blanket depth (Abou-Elela, Hamdy and El Monayeri 2016).

This contributes to the deterioration of the effluent quality (Cadet, Beteau and Hernandez 2004; Abbasi, Ahmadi and Naseri 2021). On the other hand, in Figure *29* of scenario I, even though the rate of solid settling was good and under the settling flux curve, the biological flocs were not sufficiently thickened to produce the required bottom sludge in the clarifier (Cossu, Lai and Sandon 2012). The expected RAS concentration was significantly higher (14,125 mg/L) than the required amount of maximum underflow flux of 10,000 mg/L (Klas, Mozes and Lahav 2006). The study explained that for the increased solid level in the clarifier, the control of filamentous bacteria by lowering the feed MLSS is vital (Deepnarain *et al.* 2019; Zheng *et al.* 2022).

Similarly, as presented in Figure 28 and Figure 29 of scenario II, the solid concentration profile was interestingly distributed along the depth of the tank and the sludge blanked height was within the required limit as presented in Figure 27. Furthermore, the clear water, the separation, the sludge storage, and thickening depth have a clear distinction and the simulated expected RAS concentration was 9000 mg/L which was within the range. Thus, the simulation result revealed that the performance of the primary and secondary clarifiers for scenario I did not efficiently remove the pollutant as per the requirement.

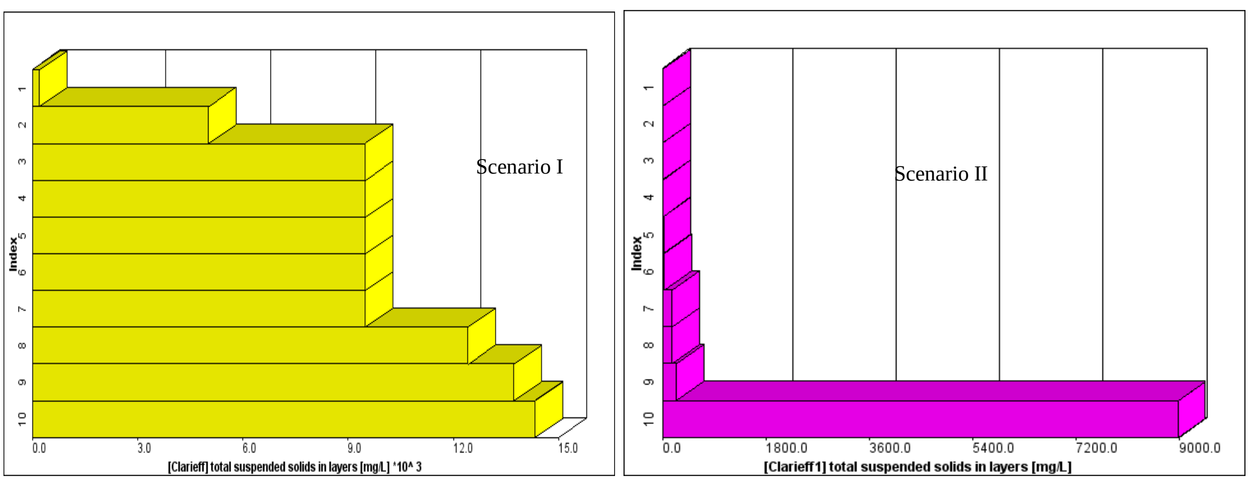


Figure 28 Secondary clarifier solid profile and state point for scenarios I and II

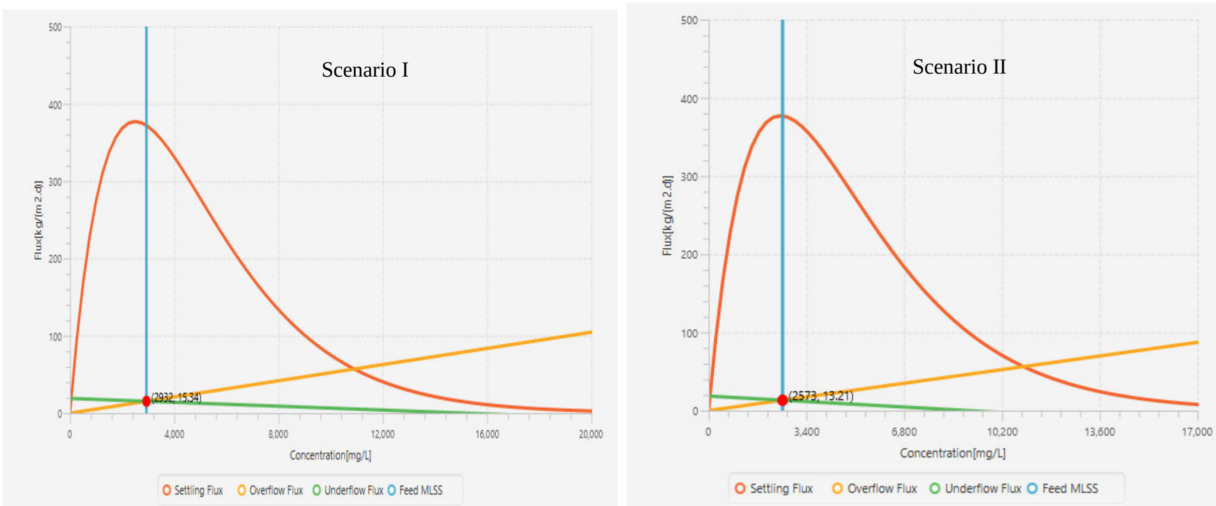


Figure 29 Secondary clarifier state point analysis for scenarios I and II

The simulation results in Figure 30b depicted that the F/M ratio and organic loading rate were increased from 0.06 and 0.09 to 0.26 and 0.45, while the DO at the outlet of the clarifier declined from 6.5 mg/L to 2.33 mg/L respectively for scenarios I and II. From the result in scenario I, the DO concentration in the aeration tank was too high above the maximum requirement of 3 mg/L, which reduced the efficiency of the treatment plant and promoted the growth of filamentous bacteria which is difficult to settle in the secondary clarifier (Mu'azu, Alagha and Anil 2020). Furthermore, due to the smaller value of the F/M ratio and volumetric loading below the minimum requirement (0.2 and 0.3, respectively), the plant operated as an extended aeration mode which unbalances the performance and causes increased secondary emission (Vera, Saez and Vidal 2013; Mamais *et al.* 2015). In line with this finding, the MLSS was moderately reduced from 2932 mg/L to 2573 mg/L while air flow into the aeration tank was significantly reduced from 6500 m^3/hr to 550 m^3/hr for scenarios I and II, respectively (Figure 30a). The SRT, WAS, and RAS optimization in scenario II for the secondary clarifier highly influenced the operational parameters in the aeration tank.

The proper control of RAS has a vital role in balancing the microorganisms in the aeration tank and maintaining the optimum F/M ratio for good performance of the plant (Vera, Saez and Vidal 2013). An optimum SRT in the secondary clarifier due to proper WAS flow protects the well-being of the microbial population and reduces the microbes being washed out, which in turn deteriorates the effluent quality (Chen *et al.* 2017b; Hu *et al.* 2018; Apollo, Seretlo and Kabuba 2023). The airflow in the aeration tank was not cost-and energy-effective in scenario I. Thus, the simulation result showed that the operational parameters in the aeration tank for scenario I were both below and above the requirement in the activated sludge process, while scenario II performed well (Revilla, Galan and Viguri 2016).

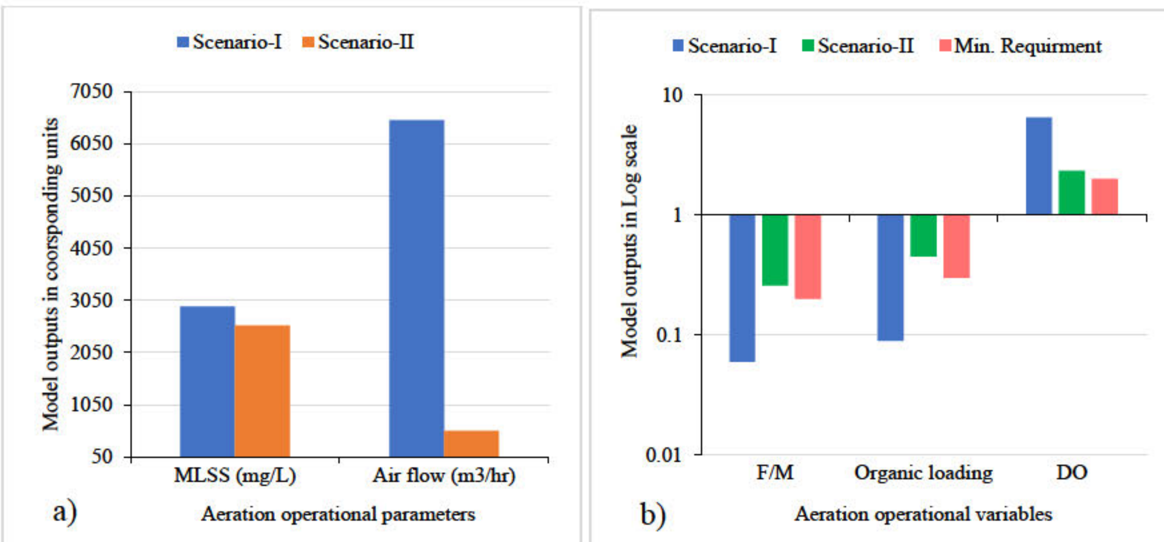


Figure 30 Aeration tank operational parameter 180-day simulation for scenarios I and II

Figure 31a shows that the effluent concentration of TSS was reduced from 134.8 mg/L to 26.11 mg/L in scenarios I and II, respectively. The result from the simulation depicted that in scenario I the TSS violated the permissible limit concentration of 35 mg/L for the effluent discharge. Similarly, the COD concentration of the effluent for scenarios I and II was simulated as 143.8 mg/L and 54.12 mg/L respectively, which was above the standard limit of 120 mg/L for scenario I (EPA 2023).

However, the BOD_5 of effluent concentration for both scenarios was below the permissible limit of 40 mg/L (Table 10). According to the study by Han *et al.* (2018) and Flores-Alsina *et al.* (2009), the increment in the effluent TSS and COD indicated that due to the formation of filamentous bacteria, the floc in the secondary clarifier might not settle easily. This proves that the sludge blanket depth was very high in both the primary and secondary clarifiers. The MLSS and DO were higher in scenario I, which might have led to an increase in the solid content in the aeration tank further reducing the performance of the clarifiers (Liwarska-Bizukojc, Andrzejczak and Solecka 2019). Furthermore, there might have been biological floc fragmentation which leads to deterioration of the effluent quality due to high solid content being washed-out (Han *et al.* 2018; Sun *et al.* 2020).

The effluent TP and NO_3 concentrations for scenario I were 9.2 mg/L and 17.69 mg/L, and both were above the permissible limit concentration of 2 mg/L and 10 mg/L, respectively (Table 10). However, the remaining effluent quality parameters simulated for scenarios I and II were within the standard limit as shown in Figure 31b. An excessive discharge of nitrate and phosphorus potentially affects the receiving aquatic ecosystem (Falas *et al.* 2016; Liwarska-Bizukojc 2022; Nadella and Sen 2022). Due to the high DO concentration in the activated sludge process for scenario I, the concentration of nitrate was elevated. The more the BOD_5/TKN ratio declines, the lower the nitrification efficiency of the biological process to produce the nitrifying bacteria (Vera, Saez and Vidal 2013; Elshorbagy and Shawaqfah 2015). In addition, the presence of adequate inorganic carbon sources in the system is also a prime factor in the nitrification process (Diaz-Elsayed *et al.* 2017; Bhattacharya and Mazumder 2023).

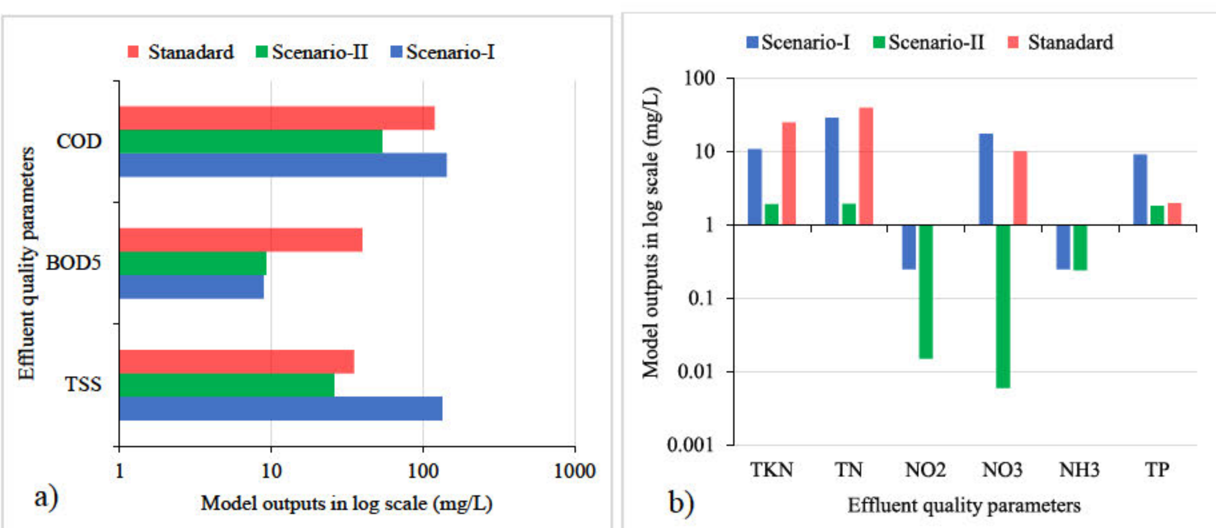


Figure 31 Final effluent concentration 180-day simulation result for scenarios I and II

The simulation of the wastewater treatment plant in the GPS-X models mainly focused on increasing the effluent quality, and reduced the cost and energy use with the ultimate reduction of sludge flow. Figure 32a showed that the quality of the effluent and treatment performance were measured using the effluent quality index in GPS-X models and the results from the simulation for scenarios I and II were 150.9 kg/d and 0 kg/d, respectively. This indicated that the increased pollution load on the receiving water body was due to the violation of the parameters TSS, COD, TP, and NO_3 (Pang and Abdullah 2013; Henriques and Catarino 2017).

However, in scenario II all the parameters were within the compliance discharge limit due to the optimization of operational parameters at different stages of the treatment unit process. Along with this, the cake mass flows were 1085 kg/d and 760 kg/d for scenarios I and II, respectively. A study by Apollo, Seretlo and Kabuba (2023) and Caligan *et al.* (2022) described that sludge production is highly affected by the sludge producing treatment units that should be properly managed. Similarly, to reduce the sludge management cost and the burden of sludge management units, the SRT of the clarifiers is vital for developing the optimum quantitative flow diagram (Flores-Alsina *et al.* 2014). The key feature of effective simulation is efficiently linking all the processes (Wu *et al.* 2016). Comparatively, scenario II produced less sludge mass flow than scenario I.

The modelling and simulation end up generating cost and energy-effective processes within a short time with a precise prediction of the system (Yan *et al.* 2017; Abbasi, Ahmadi and Naseri 2021). As presented in Figure 32b, operation cost and energy use of the process layout is predicted as 72.58 $/d and 19.89 $/d, and 40.51 kw and 12.48 kw for scenarios I and II, respectively. In scenario II the cost and energy were reduced significantly, and this reduction was due to removing unnecessary pumping stations, optimized operational parameters, reduced sludge mass flow, and reduced air flow into the aeration tank. The study by Brdjanovic *et al.* (2000) and Xie *et al.* (2022) explained that obtaining a cost-effective treatment is an aggregated outcome of the multiple attributes operating in the system.

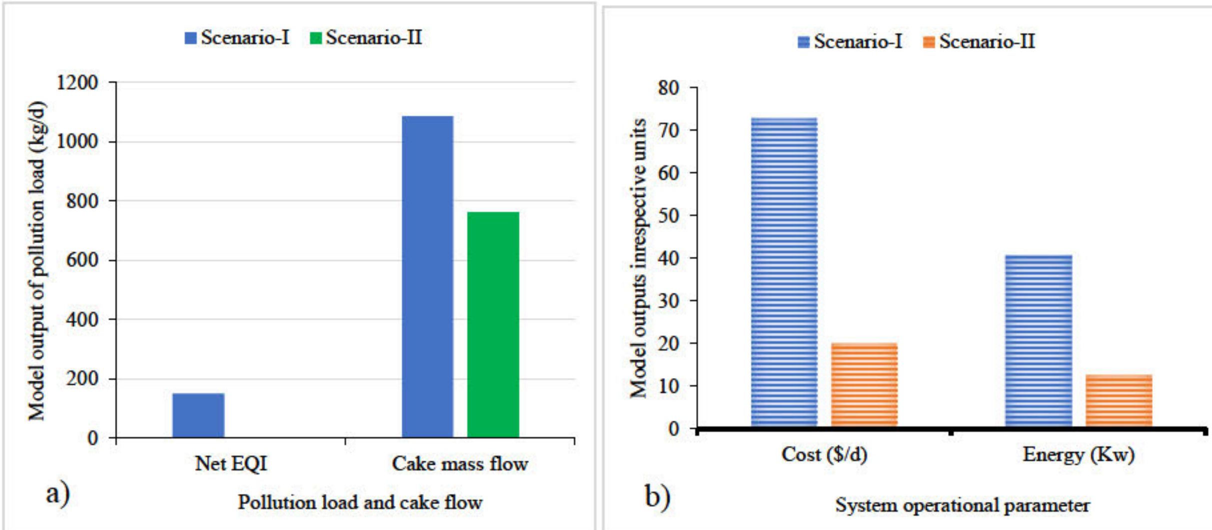


Figure 32a, b Cake mass flow, energy use, and cost simulation result for scenarios I and II

Furthermore, Figure 33 and Figure 34 presented the detailed energy consumption and operation cost of both scenarios. Figure 33 shows that most of the energy was consumed by the aeration tank for scenarios I and II with values of 64.4% and 57.7%, respectively. In Figure 34 the corresponding costs for the aeration tank were 61.5% and 19% for scenarios I and II, respectively. The result deduced that there was a significant reduction in energy and cost for the aeration tank in scenario II. This indicated that the air flow into the aeration tank was effectively optimized to enhance the treatment efficiency in a cost- and energy-effective way (Bodik and Kubaska 2013; Henriques and Catarino 2017; Calise *et al.* 2020; Abbasi, Ahmadi and Naseri 2021). The details of each unit process cost and energy are shown below in Figure B- 13, Figure B- 14, Figure B- 15, and Figure B- 16.

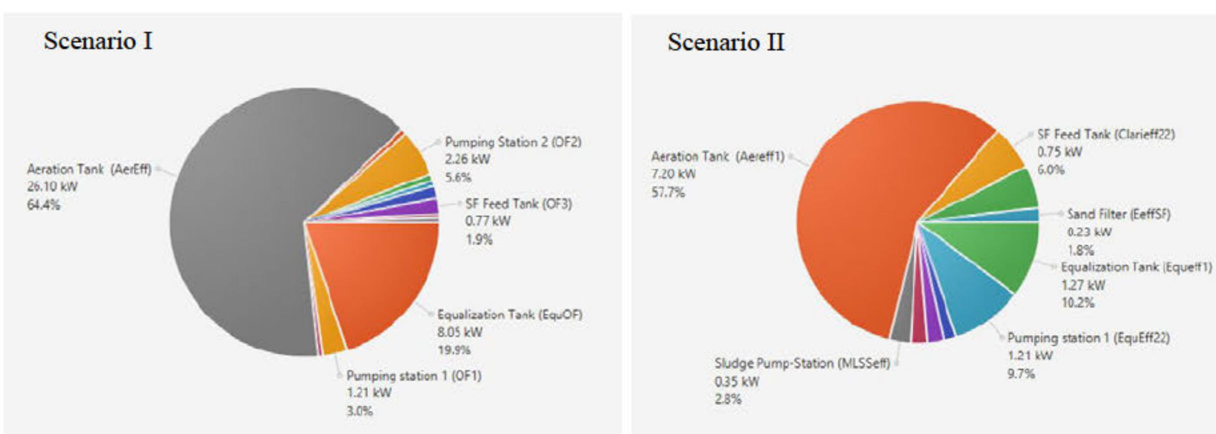


Figure 33 Energy consumption of unit operations for scenario I and II

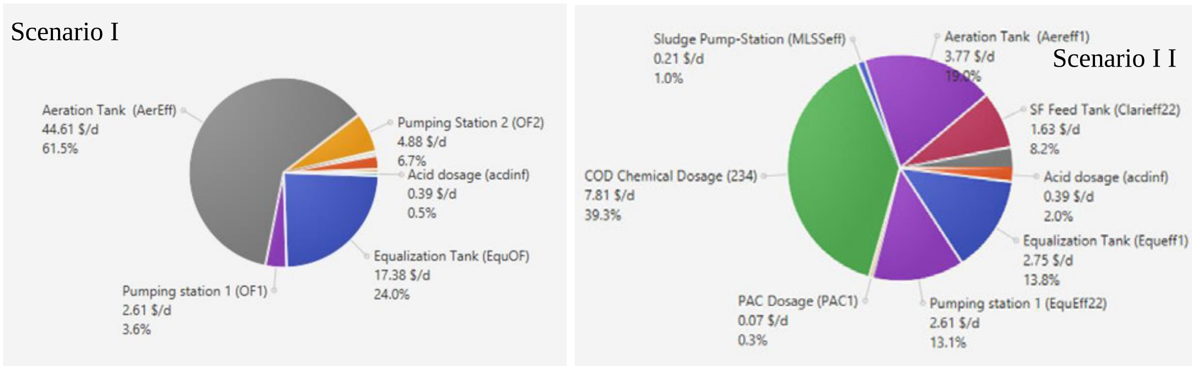


Figure 34 Operation cost expenditure of unit operations for scenario I and II

5.3. Results and discussion for specific objective 3

To evaluate the wastewater treatment plant's performance by using an analytical method and GPS-X model

Wastewater treatment plant performance by analytical measurement

The results and discussion for this objective are presented only for scenario I. All the intermediate samples were collected from the existing scenario as it was then operating. Thus, to compare and evaluate the analytical measurement and GPS-X model, the results must use similar data and process layout. The characterization of the wastewater quality is essential to devise a strategy for identifying the inefficiencies within a plant, and for technology selection, upgrading the system, and improving the operational performance of the plant (Ogleni, Ovez and Ogleni 2010; Elawwad *et al.* 2019).

In the performance of the primary clarifier unit of the existing wastewater treatment plant as operated in scenario I, the results from analytical measurements were TSS (1.7%), BOD_5 (6.7%), TN (3.6%), TP (12%), and COD (4.2%). Similarly, in the performance of the secondary clarifier, the results were TSS (97.5%), BOD_5 (30.8%), TN (90%), TP (92.8%), and COD (93.7%). Furthermore, the overall parameter removal efficiency of the plant influent quality concerning the final effluent results was TSS (75%), BOD5 (67.8%), TN (61.6%), TP (39.5%), and COD (70.2%), respectively (Figure 35a). The results showed that the primary clarifier did not function well to remove the target pollutants. Since the primary clarifier was operated after the aeration tank it could be that buildup of filamentous bacteria and sludge bulking would lead to poor performance (Deepnarain *et al.* 2019; Liwarska-Bizukojc, Andrzejczak and Solecka 2019).

Conversely, the pollution load removal efficiency of the secondary clarifier was very good for TSS, TP, and COD. However, as shown in Table 10 these parameters were still above the permissible limit. The study by Beltran *et al.* (2012) stated that the analytical physicochemical wastewater quality analysis result doesn't give a trend of data and instantaneously describes the status of pollution. On the other hand, higher removal efficiency would not be a guarantee to remove all the target pollutants (Cydzik-Kwiatkowska *et al.* 2018).

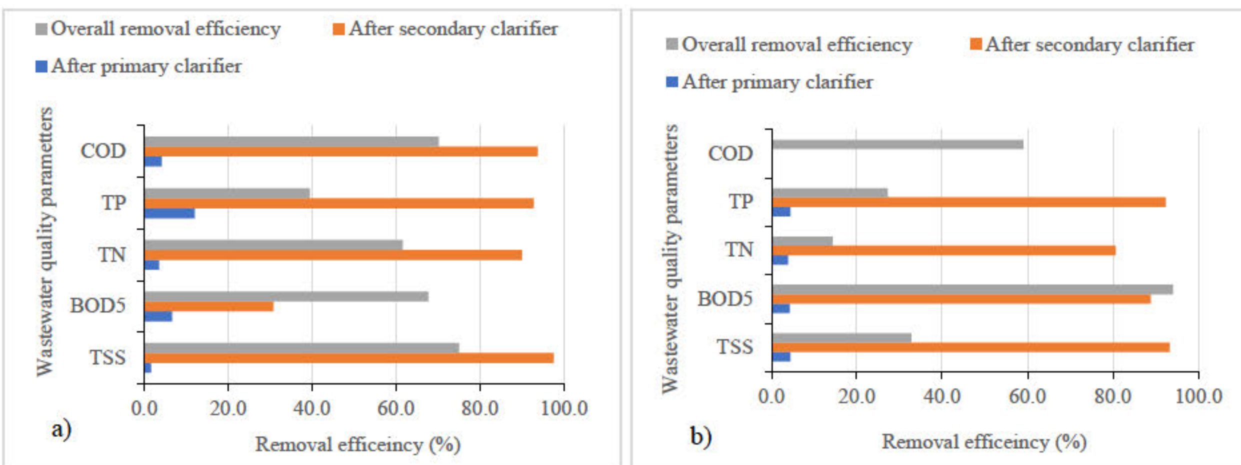


Figure 35 Pollutant removal efficiency by analytical measurement and GPS-X modell

Wastewater treatment performance assessment using effluent water quality index (EQI) of GPS-X

The results for the Bahir Dar textile factory wastewater treatment plant, which were monitored for six months consisting of a complex matrix of physicochemical parameters measured individually, did not give a reliable and timely evaluation of the effluent wastewater quality. To mitigate against time-series data availability problems, discontinuous monitoring, and discrete decision-making processes, GPS-X based models were thus developed to aggregate multiparameters in a simple output. After smoothing of the data set, the effluent pollution load was calculated using Eq. 4 and Eq. 5 because it could potentially estimate the overall instantaneous and moving average pollution load due to the concentration of each effluent wastewater quality parameter (Ayoub and El-Morsy 2021). For strategic plant management and to achieve the compliance limit, the net EQI was computed using Eq. 6 and Eq. 7 for both moving average and instantaneous data. In the net EQI model of GPS-X, the weighted pollution load over and above the violation concentration was calculated to measure the treatment efficiency (De Ketele, Davister and Ikumi 2018; Mihaly, Simon-Varhelyi and Cristea 2022b).

In the assessment of plant performance, weight elicitation is essential to identify the most sensitive effluent wastewater quality parameters (Alikhani *et al.* 2017; Adane, Adugna and Alemayehu 2021). In this study, due to the lack of a weighted priority being assigned to the pollutants discharged into the water body, an equal weight (w_i) of 1 was assigned to the nine effluent wastewater quality parameters. Since it was an equally weighted scenario, no preference for any of the parameters over the others was given where they all contributed equally to the model optimization (Wondim and Dzwairo 2018).

As was discussed for the modelling and simulation process in objective two of this study, in following the simulation protocols, the treatment performance for the primary clarifier result was obtained as TSS (4.5%), BOD_5 (4.3%), TN (3.9%), and TP (4.4%). The removal efficiency of the secondary clarifier was calculated as TSS (93.3%), BOD5 (88.8%), TN (80.7%), and TP (92.4%) in scenario I. Moreover, the overall plant performance was simulated as TSS (32.8%), BOD5 (94.1%), TN (14.4%), TP (27.2%), and COD (59%) (Figure 35b).

In the GPS-X model analysis the primary clarifier result showed that all the performance indicator parameters were not removed well. Poor performance of the primary clarifier/s might be cross-linked with larger solid retention time, inappropriate sidestreams recycling, and improper location of units (Yoshida *et al.* 2015; Nelson, Alqahtani and Hai 2018). The secondary clarifier performance result explained well that TSS and TP removal efficiency were very good. Moreover, BOD_5 and TN were within the permissible discharge limit (Table 10). A 180-day simulation result of overall plant performance for TSS (32.8%), TP (27.2%), and COD (59%)

was very poor and explicitly indicated in the model where and when the permissible limit was violated and which parameter was responsible (Figure 35b and Figure 36b).

In accordance with this, the total plant pollutant removal efficiency was recorded as 71% and 43% for analytical measurement and GPS-X model-based simulation, respectively (Figure 36). For both techniques, the final effluent result for parameters of TSS, TP, and COD were above the permissible limit while TN was within the compliance limit. However, BOD_5 for analytical measurement was above the limit and for GPS-X simulation it was below the limit with values of 48.85 mg/L and 8.9 mg/L, respectively. For the calibrated model of GPS-X the BOD_5 to COD ratio of the influent wastewater was insufficient (0.31) for the biological oxidation process which may have led to immediate degradation of the organics by the bacterial population (Karthikeyan *et al.* 2011; Ge *et al.* 2014). Conversely, the analytical measurement results described the removal efficiency at a specific location and time in the treatment plant. However, the total removal efficiency of the treatment plant for the GPS-X modell explicitly accounted for the time violation for each parameter over the simulation period. In the analytical analysis the measured parameter and the permissible limit were not mathematically linked and the mass balance was also highly dependent on the physical analysis which could have led to a wider deviation (Muoio *et al.* 2019; Calise *et al.* 2020).

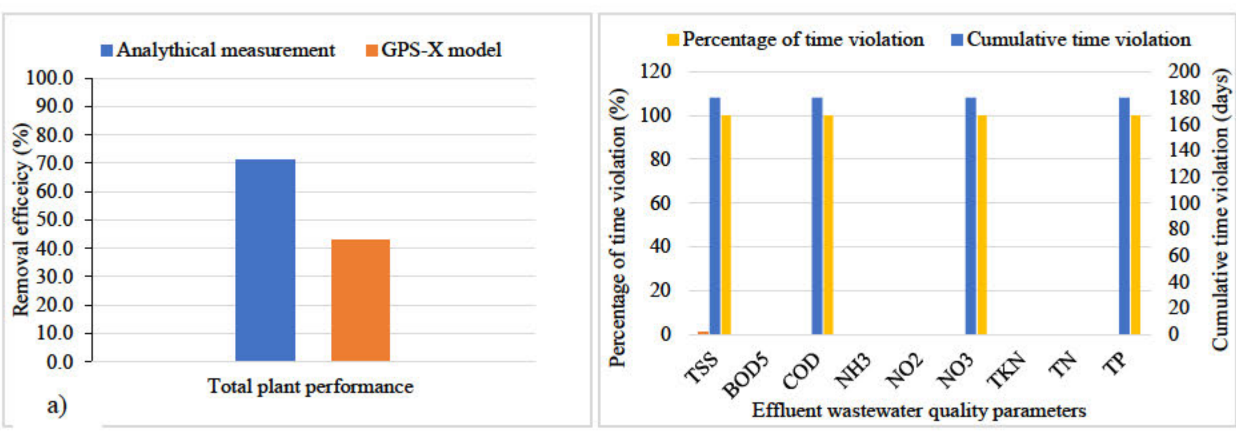


Figure 36 Comparison of a) total plant performance and b) statics of violation in GPS-X model

The effluent quality index result of the GPS-x model results defines the performance of the treatment plant for pollutant removal and guides the operators to select which parameters need special attention (de Araujo *et al.* 2013; Flores-Alsina *et al.* 2014). From the simulation result, the overall EQI was 279.9 kg/d, which indicates the total pollution load, of which the net EQI 151.2 kg/d was the net pollution due to the violation of the permissible concentration. Net EQI pollution load describes the amount of pollutant that remains untreated above the violation effluent concentration (Nelson, Alqahtani and Hai 2018; Mu'azu, Alagha and Anil 2020). However, from the analytical measurement result, it was difficult to calculate and define the net aggregated pollution load above and over the compliance concentration (de Araujo *et al.* 2013; Flores-Alsina *et al.* 2014).

Figure 36b presented the EQI percentage and cumulative time violation. The results indicated that under 180-days simulation the TSS, COD, NO_3, and TP were violated 100% throughout the operation period, while the BOD_5, TKN, NH_3, TN, and NO_2 results showed no violation (zero percent) and complied with the violation concentration limit at all times in the treatment process. Based on the analytical measurement of the six parameters, the effluent quality was above the effluent standard limit (Table 10). However, it was reported that, it was too complicated to identify the cumulative violation time and percentage contribution of the parameter from a list of time series data and multiple samples (Nelson, Alqahtani and Hai 2018; Mu'azu, Alagha and Anil 2020).

One-off data measurement and discrete analysis of a wastewater treatment plant as a continuous system cannot be used for efficient plant management (Liu *et al.* 2020b). Hence, a real-time data measurement and logging system is vital for an immediate response to any failure occurring in the treatment plant (Xie *et al.* 2022). A full setup of monitoring device facilities and personnel are indispensable for effective plant operation (Andreides, Dolejs and Bartacek 2022). However, in this study in particular and in developing nations in general, using state-of-the-art technology recording data and adopting effective utility management systems is seldom implemented (Kroll *et al.* 2016b; Andreides, Dolejs and Bartacek 2022). Therefore, a simplified mathematical model as developed for EQI calculation using the GPS-X technique is vital for performance evaluation.

5.3.1. Summary

The treatment performance result of the existing wastewater treatment plant (scenario I) showed that the primary clarifier pollutant removal efficiency was very poor and varied from 1.7% to 12% and 3.9% to 4.5% for analytical measurement and GPS-X model-based simulation respectively. The secondary clarifier performed well for GPS-X model prediction with a value of 80.7% to 93.3%, and removal efficiency for analytical measurement varied from 30.8% to 97.5%. Conversely, the overall parametric removal efficiency of the plant varied from 39.5% to 75% and 14.4% to 94.1% for analytical measurement and simulation, respectively.

In line with this, the total plant pollutant removal efficiency was recorded as 71% and 43% for analytical measurement and GPS-X model-based simulation respectively. From the simulation result, the overall EQI was 279.9 kg/d, which indicated the total pollution load of which the net EQI of 151.2 kg/d was the net pollution due to the violation of the permissible concentration. Moreover, the percentages and cumulative time violation results recorded over 180 days' simulation for TSS, COD, NO_3, and TP were violated 100% throughout the operation period, while BOD_5, TKN, NH_3, TN, and NO_2 results showed no violation (zero percent) and complied with the violation concentration limit at all times in the treatment process. However, it was reported that it was complicated to identify the pollutant removal efficiency considering the cumulative violation time and percentage contribution of the parameter from a list of time series data and multiple samples in the analytical measurements. The GPS-X model-based simulation outperformed analytical measurements because it replaced disconnected data points with a unified biological system. It accounted for the synergy between oxygen transfer, microbial growth, and hydraulic retention, proving that the treatment plant's failure was not due to a lack of infrastructure, but a lack of optimized operational intelligence.

5.4. Results and discussions for specific objective 4

To develop holistic operation strategies and troubleshooting frameworks for the textile wastewater treatment plant

The GPS-X model simulation results for the textile wastewater treatment plant performance evaluation under different steady-state scenarios were the most sensitive process control parameters with respect to the permissible limit of nine performance indicator wastewater quality parameters which included TSS, BOD_5, COD, TP, NO_2, NO_3, NH_3, TN, and TKN. Moreover, the parameters optimized for economical plant operation are also included.

The influence analysis for influent flow (Q_{inf}), primary and secondary wasted activated sludge (WAS_1^o and WAS_2^o), and recycled activated sludge (RAS) on the performance of the plant

The influent flow variations presented in *Figure 37a* and *c* showed that the practice of removing TSS, BOD_5, and TP from primary and secondary clarifiers had a negative performance on increasing Q_{inf} from 300 to 415m^3/d. This showed that the constant influent concentration of physicochemical parameters with reduced Q_{inf} increases the effluent concentration (Wu *et al.* 2010; Meier 2016). For the increased Q_{inf} from 550 to 650 m3/d the performance of both clarifiers increased. However, for the steady increase in Q_{inf} from 1200 to 2000 m^3/d the removal efficiency of both clarifiers declined except for the TSS and TP parameters in the secondary clarifier (Figure 37a and c). Accordingly, the $Q_{inf,}$ changed from 550 to 2000 m^3/d, significantly increased the aeration operational variables of food to microorganism ratio (F/M) and DO values of 0.15 to 0.93 and 1.6 to 4.2 mg/L respectively (Figure 37b). Moreover, the mixed liquor suspended solids (MLSS) and volumetric organic loading rate declined slightly with the increase in Q_{inf}.

Similarly, Q_{inf} caused a slight improvement of TSS, COD, TN, and TP within the specific range of inflow and reduced the effluent quality of nitrite and nitrate (Figure 37d, e, and f). However, the higher influent flow was greater than 650 and 1000 m^3/d, and the effluent quality of the BOD_5 and NH_3-N deteriorated. The result from the sensitivity analysis of influent flow variation showed that the flow of 600 (± 50) m^3/d was in the acceptable range for efficient plant operation to attain the desired effluent quality and control the process parameters.

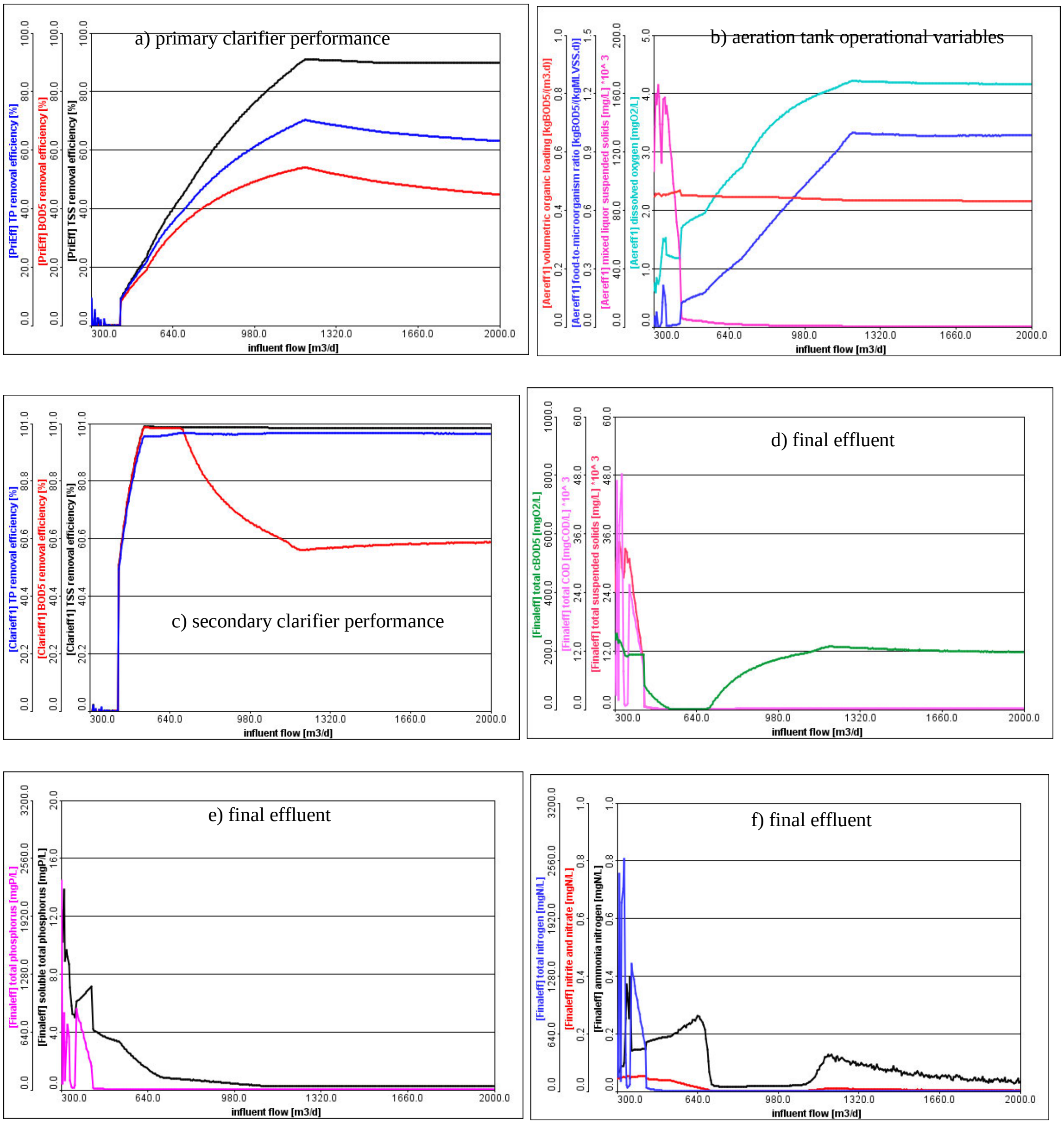
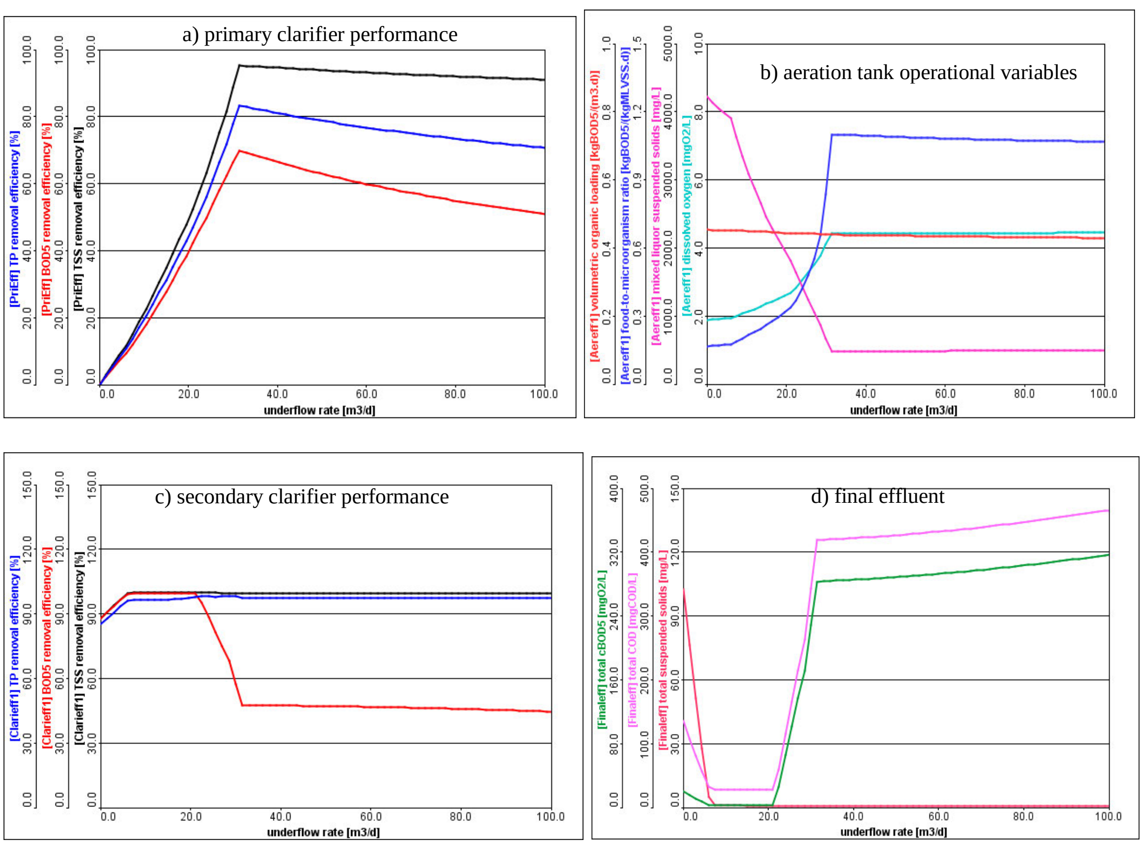


Figure 37 (a-f) Influent wastewater flow influence on plant operation and performance

The WAS_1^o is one of the process control parameters in the primary clarifier used to increase the final effluent quality by reducing the organic load (Jeppsson *et al.* 2007; Flores-Alsina *et al.* 2014). Figure 38a and c for the WAS_1^o flow of 10 to 20 m^3/d showed that the primary and secondary clarifier pollutant removal efficiency was increased for the respective TSS, TP, and BOD_5 parameters. Meanwhile, the aeration process control variables results fluctuated between 0.2 to 0.3 and 1.98 to 2.2 mg/L, and 2000 to 3800 mg/L for F/M, DO, and MLSS, respectively (Figure 38b). In addition, the final effluent concentrations of BOD_5 (10 mg/L), COD (40 mg/L), TSS (5 mg/L), and TP (1.45 to 3.5 mg/L), with an insignificant change for nitrite and nitrate were observed for WAS_1^o changed from 10 to 20 m^3/d (Figure 38d, e, and f). However, the increase of WAS_1^o to the flow of 30 m^3/d significantly affected the efficiency of the secondary clarifier for BOD_5 (from 93.41 % to 48.7%) and removed and worsened the quality of the final effluent by causing both the BOD_5 and COD to deteriorate. Moreover, the operational parameters in the aeration tank also rose over the allowable value.

However, a further change of WAS_1^o greater than 30 m^3/d remained constant. The increased wastage of raw sludge from the primary clarifier is susceptible to the subsequent treatment process (Wang 2014; Wu *et al.* 2016). Studies by e.g., Wang *et al.* (2022b); Sid *et al.* (2017) stated that the MLSS is highly dependent on the organic loading from the primary clarifier which, in turn, is maintained by controlling the wasting of raw sludge. Hence, the sensitivity analysis result stated that the primary clarifier operation was economical when it operated in the WAS_1^o flow of 15 (± 5) m^3/d.



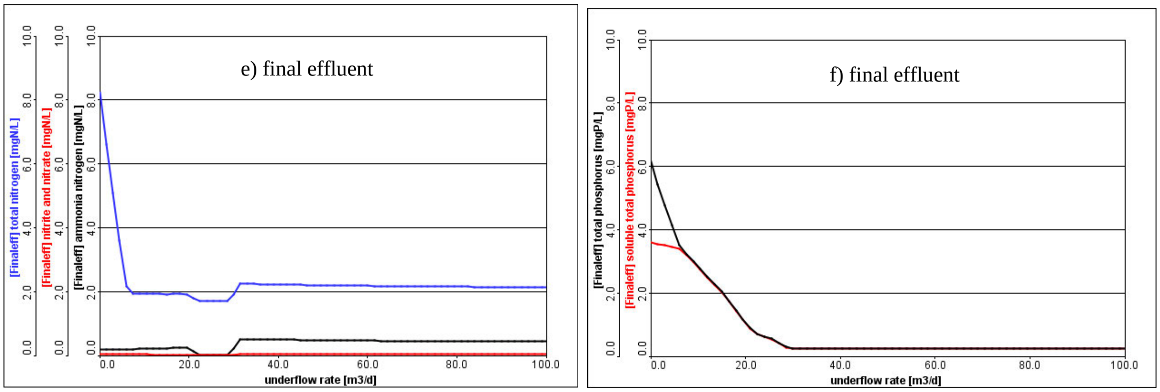


Figure 38 (a-f) Primary clarifier wasted activated sludge (WAS_1^o) flow influence on plant operation

RAS and WAS_2^o are the most critical process control parameters to maintain a proper F/M ratio for good performance operation and to prevent excessive solid buildup in the aeration tank, respectively (Elawwad *et al.* 2019; Campo *et al.* 2023). Figure 39 and Figure 40 indicated small changes in WAS_2^o which had more influence than RAS at each unit operation and process. The Figures indicated that the RAS increment from 50 to 200 m^3/d showed no significant impact on the performance of primary and secondary clarifiers. Likewise, Figures 39d, e, and f indicated that the effluent BOD_5, COD, and TSS remained unchanged while TP, TN, and NH_3-N slightly increased the concentration as a result of a change in RAS. However, there was a significant negative performance of primary and secondary clarifiers for the WAS_2^o flow of < 50 m^3/d (Figure 40a and c).

Studies by (Elawwad *et al.* (2019); and (Mu'azu, Alagha and Anil 2020)) revealed that the insufficient amount of wasted activated sludge withdrawal from the clarifier leads to the increased depth of sludge blanket and develops system instability. Conversely, the WAS_2^o flow increased from 50 to 150 m^3/d and significantly improved the removal efficiency of the primary and secondary clarifiers as well as produced effluent quality within the acceptable range (Figure 40d, e, and f). The optimum amount of secondary sludge wasting increases the treatment performance and effectively controls the biomass population (Nelson, Alqahtani and Hai 2018). Moreover, it ensures the well-being of the active microbial population in the activated sludge process (Silva and Rosa 2021).

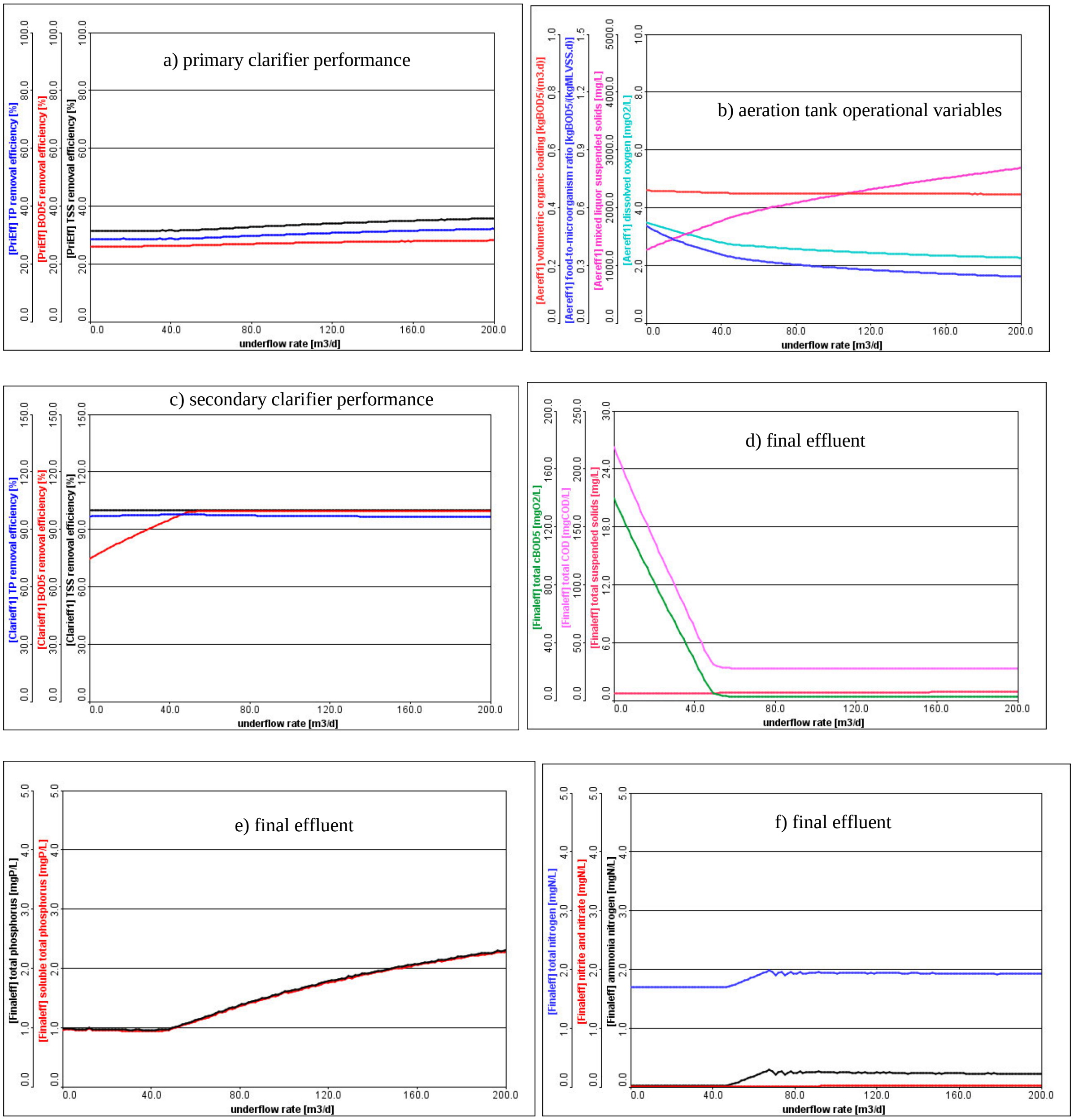
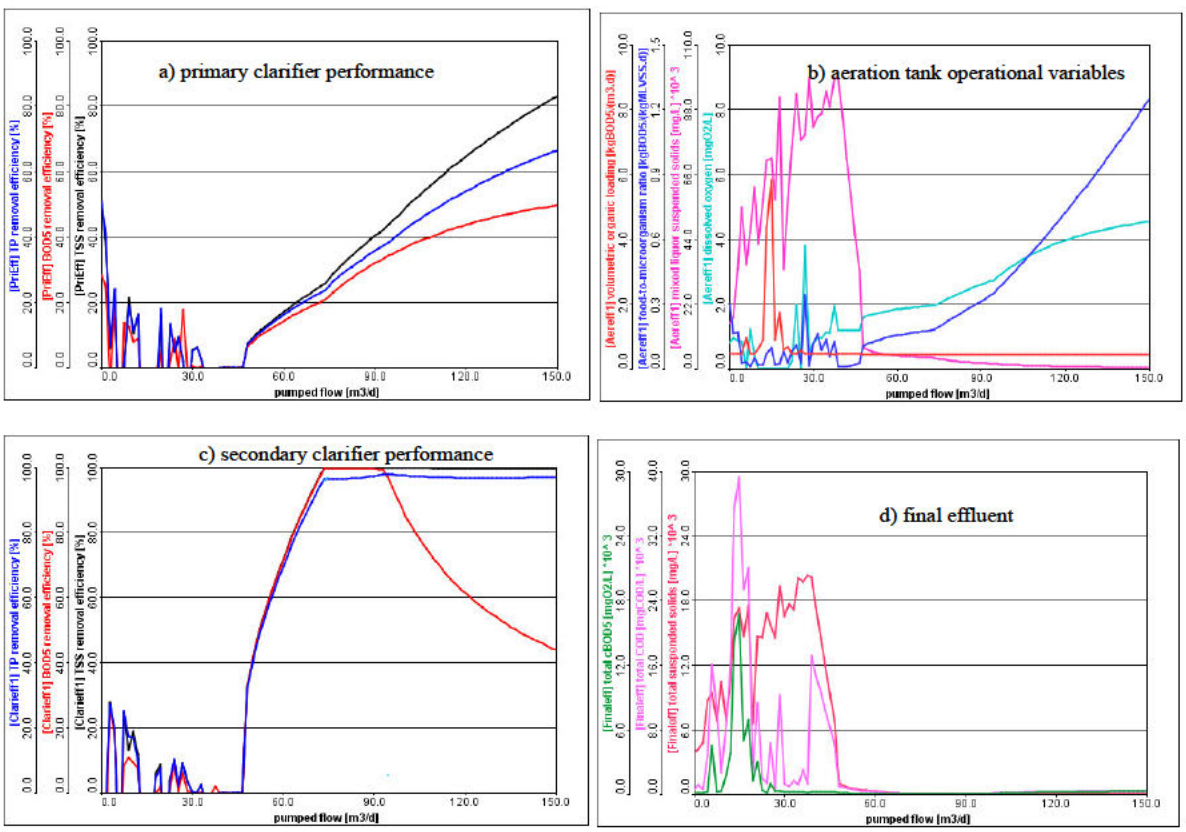


Figure 39 (a-f) Secondary clarifier recycle activated sludge (RAS) flow influence on plant operation

As shown in Figure 39*b*, for the change in RAS the aeration process control parameters varied from F/M (0.25 to 0.5), MLSS (1000 to 2800 mg/L), and DO (2.21 to 3.4 mg/L). In line with this, secondary sludge waste flow changes from 50 to 150 m^3/d impacted the F/M (0.15 to 1.2), MLSS (800 to 5000 mg/L), and DO (1.7 to 4.3 mg/L) (Figure 40b). The simulation was conducted under steady-state conditions for the RAS ratio of 0.25 to 0.33, which was the accepted range in the conventional activated sludge process. From the sensitivity analysis result the impact of RAS on the performance of the plant and process control operational parameters was insignificant compared to WAS_2^o.

Thus, to attain the required final acceptable effluent quality, the respective optimal plant operational RAS and WAS_2^o flow were used, being 150 (± 10) and 83 (± 7) m^3/d, respectively. Since the objective of RAS was to return active microorganisms to sustain the biological population in the aeration tank, WAS_2^o has a vital role in determining the overall system well-being and plant performance (Van Loosdrecht *et al.* 2015; Elawwad *et al.* 2019).



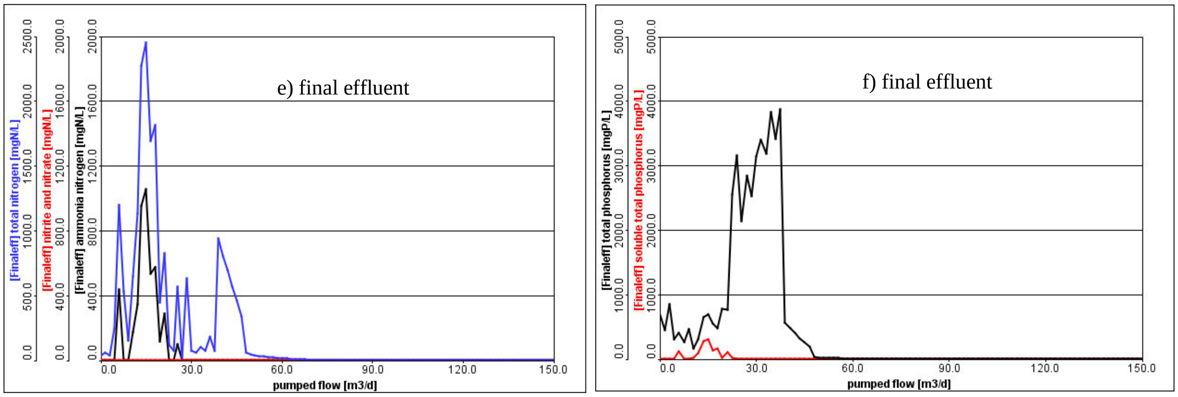


Figure 40 (a-f) Secondary clarifier wasted activated sludge (WAS_2^o) flow influence on plant operation

The sensitivity analysis for air flow into the aeration tank, sludge retention time (SRT), and molasses flow on the performance of the plant

As shown in Figure 41a and c, the airflow into the aeration tank insignificantly changed the performance of the primary and secondary clarifiers. In addition, as indicated in Figure 41d, e, and f, the effluent quality wasn't directly affected by the variation due to airflow which was greater than 200 m^3/hr. However, the dissolved oxygen concentration was increased from 0.15 to 5.67 mg/L for the air flow changes from 200 to 3000 m^3/hr. The F/M, MLSS, and volumetric organic loading remained unchanged (Figure 41b).

The air supply into the aeration tank is responsible for the mixing of biomass and incoming pollutants and for attaining a minimum DO requirement of 2–3 mg/L for biological degradation (Xiong *et al.* 2012; Smith, Elger and Mleziva 2014). For the variable nature of biological activity in the aeration tank dynamic simulation was used (Smith, Elger and Mleziva 2014; Cadet, Guillet and Aurousseau 2016). Thus, from the sensitivity analysis result, to keep the minimum required DO concentration at the outlet of the aeration tank, 550 (± 5) m^3/hr of air flow was exerted into the aeration system.

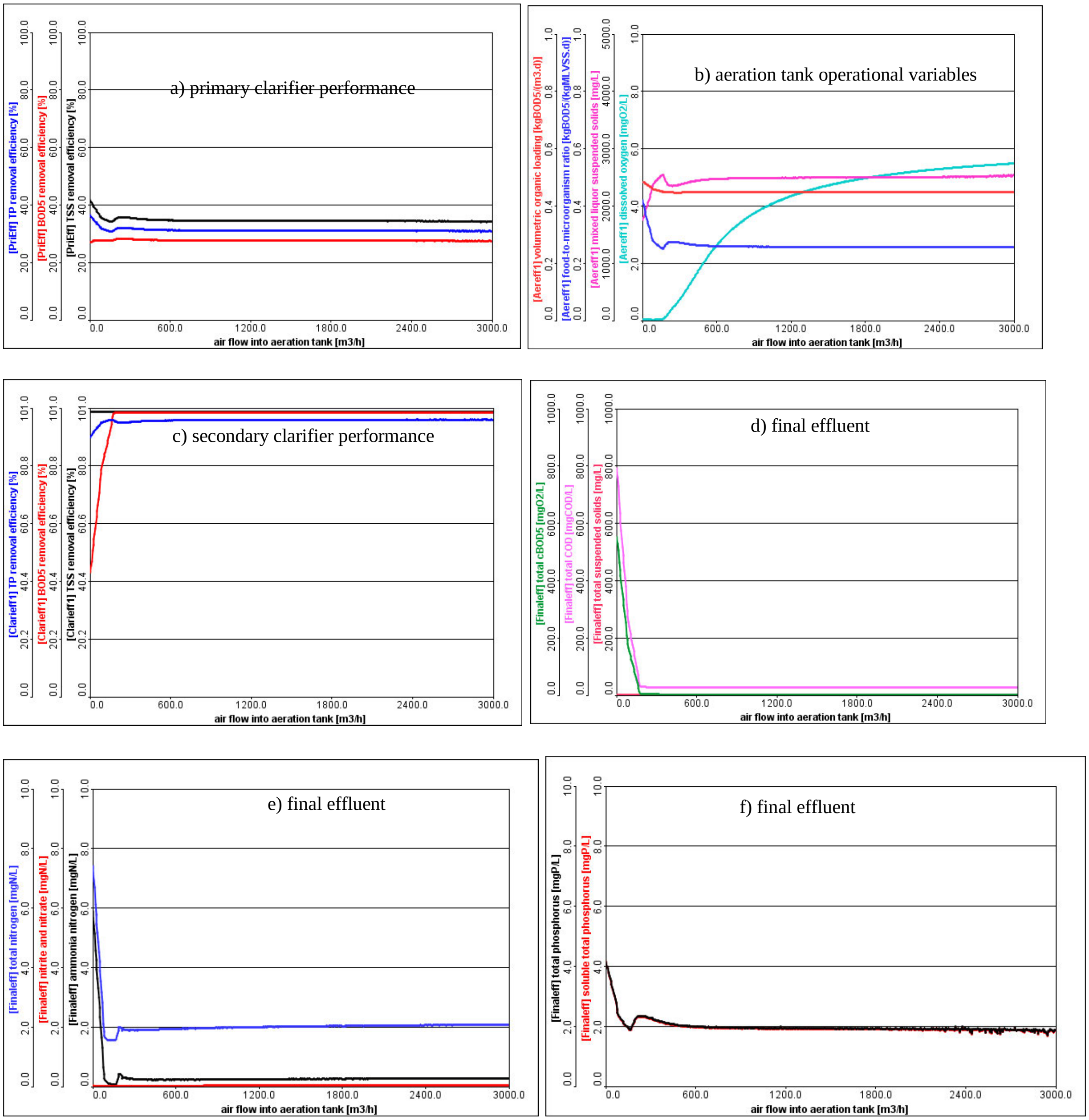
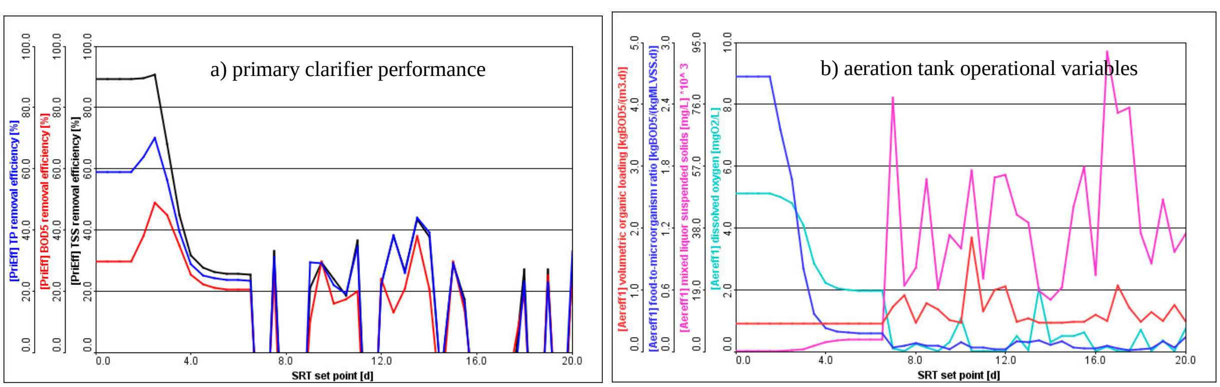


Figure 41(a-f) Influence of air flow into aeration tank on plant performance

The SRT is vital in determining the life cycle of biological organisms in the treatment system and keeping the effluent quality up to standard by considering optimized sludge production (Revilla, Galan and Viguri 2016; Muoio *et al.* 2019). The higher SRT value of > 6.2 days significantly affected the performance of the removal of pollutants from the primary and secondary clarifiers (Figure 42a and c), while at the SRT of 4 to 6.2 days, the secondary clarifier was stable and effectively removed the target contaminants with the discharge of optimum sludge flow. The production of new solids and the longer life of old sludge in the system may deteriorate the performance of the clarifiers (Ni, Yu and Sun 2008).

The MLSS, F/M, and DO were significantly changed from 2500 to 3200 mg/L, 0.25 to 0.3, and 2 to 2.3 mg/L, respectively for the SRT changes from 4 to 6.2 days. In addition, for the higher SRT, the aeration performance variable fluctuated drastically in an unstable pattern (Figure 42b). Moreover, for the optimum range of SRT, the models showed that the effluent TSS, COD, BOD_5, TN, TP, NO_2, and NO_3 were better, while the higher SRT value significantly deteriorated the effluent quality (Figure 42d, e, and f).

The modelling result suggested that to attain the minimum required values of process control parameters and for better performance of the plant the SRT was set to be 5 (± 1) days. The higher simulated value leads to instability in the whole treatment process (Figure 42). The SRT requirements in the biological treatment process determine the amount of sludge that must be removed (Muoio *et al.* 2019; Nadeem *et al.* 2022). The MLSS, WAS, and SRT are interlinked in the activated sludge process to control the plant operation economically and efficiently (Xiong *et al.* 2012; Chen *et al.* 2017a; Mu'azu, Alagha and Anil 2020).



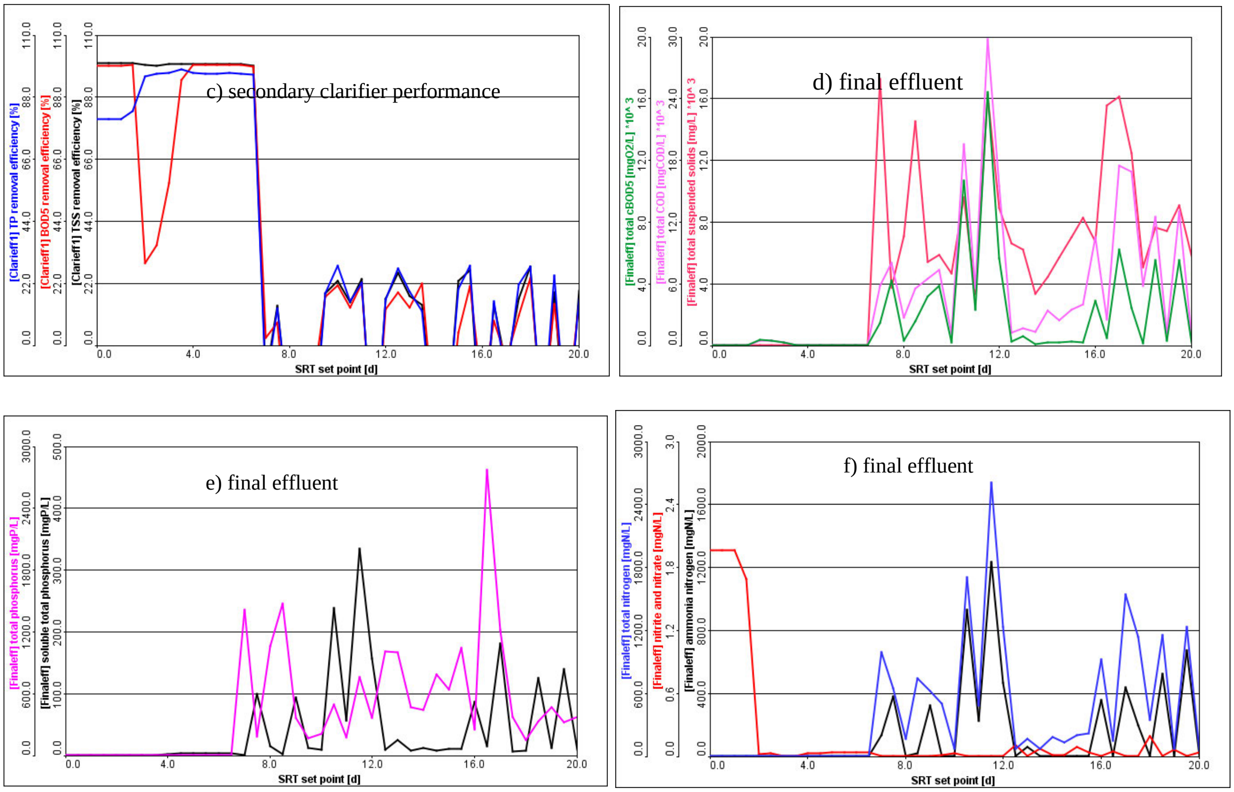


Figure 42 (a-f) Influence of secondary clarifier sludge retention time (SRT) on plant performance

Even though the exerted oxygen was sufficient to metabolize the waste, the available organic food was smaller (BOD_5/COD ratio of 0.31), and additional carbon was added into the aeration tank in the form of molasses to maintain the optimum F/M ratio (Dai, Chen and Lu 2016; Araujo *et al.* 2022). However, the change in molasses flow did not significantly alter the removal efficiency of the primary and secondary clarifiers (Figure 43a and c).

However, the variables in the aeration tank remained unchanged for the molasses flow of > 0.8 m^3/d. While the flow varied between 0.5 to 0.8 m^3/d, the result for F/M (0.23), MLSS (2500 to 2800 mg/L), DO (1.7 to 2 mg/L) and organic loading (0.45 to 0.6 kg/m^3. d), respectively were simulated in the model (Figure 43b). From the model analysis result the higher molasses flow > 0.8 m^3/d significantly deteriorated the BOD_5 and COD quality with a slight increase in the removal performance of TP, TN, and other nutrients in the final effluent (Figure 43b, e, and f). Additional organic sources improve the microbial population to gain additional food sources to degrade the particulate and inorganic waste contents (Flores-Alsina *et al.* 2010; Laizer *et al.*

2022). Thus, the simulation model sensitivity analysis result depicted that the optimum additional carbon sources in the form of molasses flow were 0.5 (± 0.05) m^3/d.

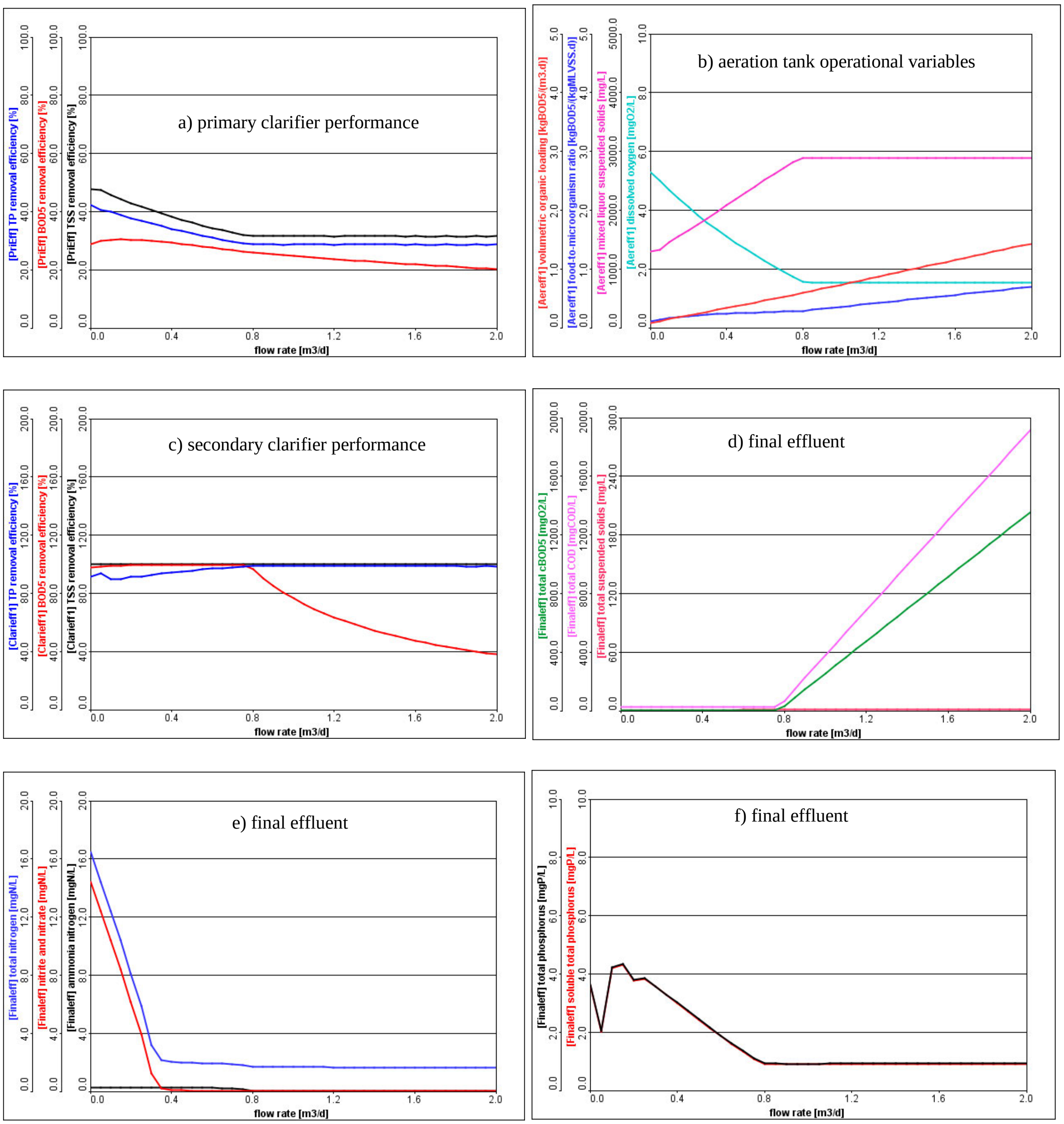


Figure 43 (a-f) Influence of additional molasses flow on plant performance

Plant troubleshooting and diagnostic strategy

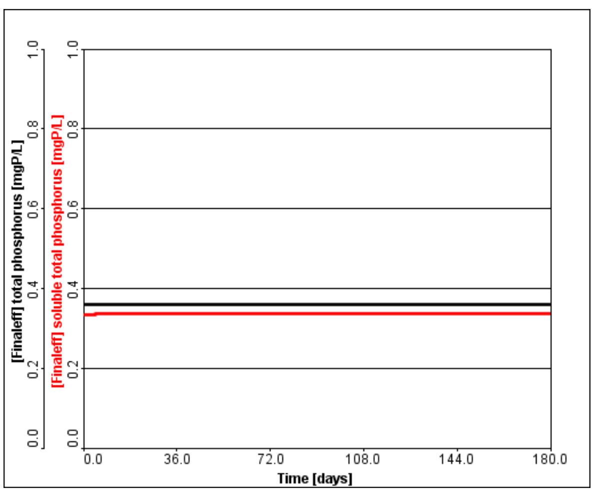
The modified scenario II simulation and optimization fully considered the existing infrastructure to reduce additional capital cost for upgrading and renovation. The findings from this study identified the main challenges and problems in the existing infrastructure as well as devised the optimized troubleshooting strategy for ease of operation (Table 12). The piping and instrumentation diagram (PID) controller is built into the GPS-X model.

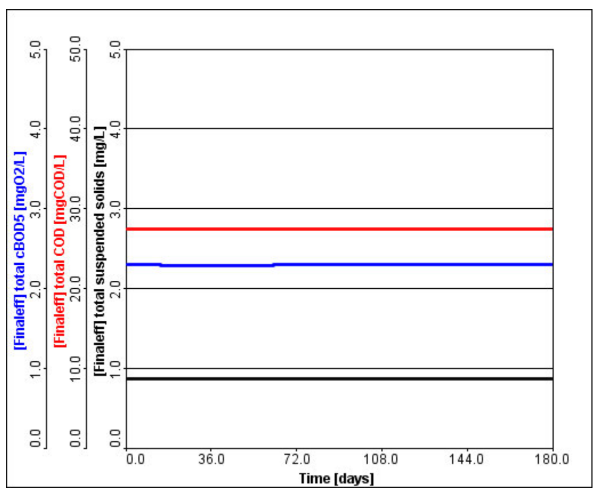
However, the existing infrastructure lacks the PID controller which is indispensable for efficient plant operation (Flores-Alsina *et al.* 2010; Beltran *et al.* 2012; Tomperi *et al.* 2016; Rajaei and Nazif 2022). In this regard, for the successful implementation of the model developed in this study, there should be at least RAS, WAS, and airflow meters and controllers, settleometer apparatus for MLSS control, and a DO meter controller (Vilanova, Santin and Pedret 2017; Li *et al.* 2020; Wei *et al.* 2023). Thus, for the observed challenges in the treatment plant, the key process control parameters were optimized and monitored, and the location and corresponding parameters were defined. The detailed troubleshooting framework is shown in Table 12.

Table 12 Process control parameters and troubleshooting strategy

No.	Observed challenges	Objectives	Process control parameters	Existing (old) process parameters	Corrective actions (optimized)	Monitoring Parameters	Monitoring locations
1	High primary sludge blanket	Optimize raw sludge wasting	WAS flow	WAS flow 4 m^3/d	Increase WAS 15 ± 5 m^3/d	SRT, effluent TSS, BOD_5	Primary clarifier
			SRT	SRT 3.4 days	Decrease SRT 6.7 ± 0.5 d		
2	High secondary sludge blanket	Optimize sludge wasting	Airflow	DO 6.5 mg/L	Increase (if DO < 2 mg/L, else reduce) airflow	DO (2 – 3), MLSS (1000-3000) mg/L, F/M (0.2 - 0.5), and volumetric loading (0.3 – 1.6)	Aeration tank
			RAS flow	RAS 43 m^3/d	Increase RAS 150 ±10 m^3/d	SVI > 100	Secondary clarifier
			SRT	SRT 4 days	Decrease SRT 5 ± 1d		Secondary clarifier
			WAS flow	WAS 84 m^3/d	Increase WAS 83 ± 7 m^3/d		Secondary clarifier

3	White foam formation	Optimize aeration control	WAS flow	WAS 84 m^3/d	Reduce WAS 83 ± 7 m^3/d	MLSS (1000-3000)	Aeration tank
	Dark foam formation		Airflow	6500 m^3/hr	Increase airflow 550 ± 5 $m^{3/}hr$	DO, NH_3, NO_2, NO_3	
5	Low recycle sludge concentration (< 8,000)	Optimize RAS solid mass	RAS flow	RAS 43 m^3/d	Reduce RAS flow 150 ±10 m^3/d	SVI, solid mass balance	Secondary clarifier
			Airflow	6500 m^3/hr	Increase Airflow 550 ± 5 $m^{3/}hr$	DO (2–3 mg/L)	Aeration tank
6	Storm flow handling	Optimize storm flow	Influent wastewater	600 m^3/d	Optimize Q_{inf} 600 ± 50 m^3/d	Influent TN, TP, TSS, NH_3	Equalization tank
7	Small BOD_5/COD ratio (< 0.5)	Optimize carbon source	Additional carbon source (molasses)	No carbon addition	Increase molasses flow 0.5 ± 0.05 m^3/d	F/M, Volumetric loading, MLSS	Aeration tank





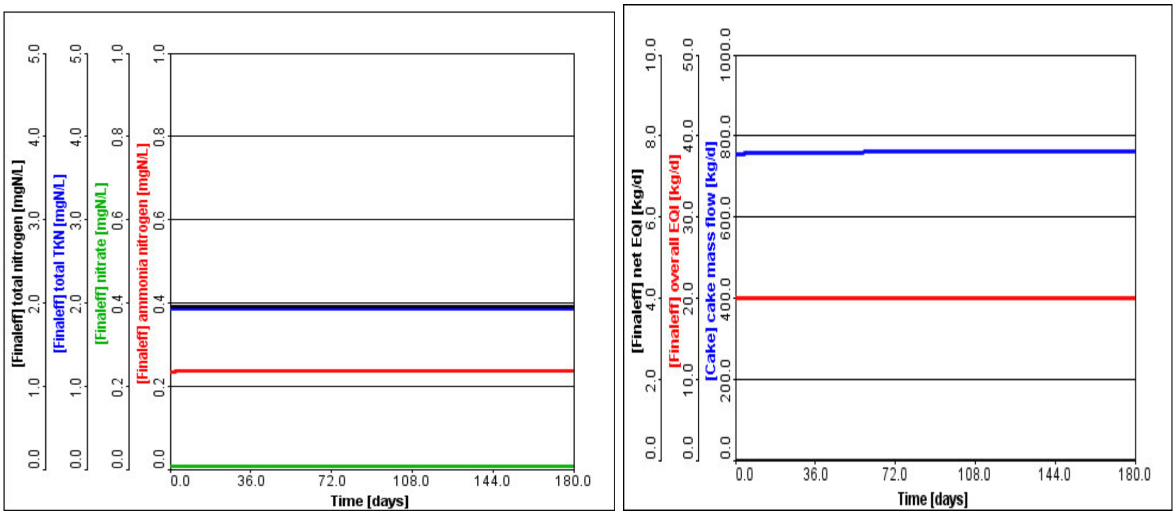


Figure 44 The simulation results of final effluent concentration for the optimized parameters

After all the optimized parameters were fed into the model the simulation result in *Figure 44* showed that the effluent concentrations of all the performance indicator parameters were within the permissible limit. This result is the diagnostic version of the existing scenario using a modified process layout. Furthermore, the simulation result depicted that the variation within the simulation period was quite stable and smooth (Odegaard and Skrovseth 1997; Diehl, Zambrano and Carlsson 2016, 2017). Thus, from the result we can conclude that shifting the existing treatment plant operation to the modified process flow layout model was the most efficient and effective option.

CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

The first aim of this research was to characterize wastewater which was generated from a specific textile factory in Bahir Dar City. To achieve this objective, the physicochemical characterization was conducted from the inlet to the outlet of the treatment plant via twenty-two wastewater quality parameters. Seventeen parameters were analyzed in the laboratory and the remaining five parameters, pH, DO, TDS, EC, and the temperature were measured onsite while collecting the samples. A total of 729 samples were collected for six months from six sampling locations in the treatment plant. Before the results were analyzed the data verification and statistical analyses on the outliners and quality of measurement were tested using SPSS. Descriptive statistics were also conducted, and corrective actions were taken as per the statistical protocol and ethics. Most of the influent measurements were normally distributed while the effluent parameters were had a minor and major outliers.

Among the analyzed physicochemical wastewater quality parameters, the TSS, BOD_5, COD, TP, nitrite, ammonia, and total chromium results were above the discharge limit with 73.2 mg/L, 48.45 mg/L, 144.08 mg/L, 7.9 mg/L, 1.36 mg/L, 1.96 mg/L, and 0.16 mg/L respectively. Based on this finding, it was concluded that the process flow layout currently operating in the textile factory was poor, and it needed special attention and intervention to enhance its performance.

The second objective of the research was to model and simulate a wastewater treatment plant's unit operations and processes using GPS-X. In order to achieve this research objective, two model scenarios were built for the existing and modified process flow diagram. The first scenario considered the process layout as currently operating in the case study, and the second scenario was modified inline with scintificaly accepted process flow via the conventional activated sludge process. All the analytical measurements were performed for the existing layout. Hence, the full-scale calibration of the model was performed for the existing process flow (scenario I) and modified process flow (scenario II).

The three-step calibration tests were conducted using the first four-month's data for an influent fraction of VSS/TSS, total BOD_5/total COD, soluble COD/total COD, soluble BOD_5/soluble COD, and ammonium fraction of soluble TKN in the GPS-X model. During this step, it was observed that the influent model output was optimally fitted with the measured data while the effluent TSS, TN, and nitrite-nitrate were overestimated. However, the BOD_5 and ammonia influent fractions were underestimated.

In the second step of calibration, the aeration tank operational parameters were used to predict the effluent model outputs, and the nutrients were captured with the actual measured data. However, BOD_5 and TSS were underestimated and predicted respectively. Lastly, the sludge volume index was adjusted from the default value. However, the TSS did not capture the actual data, hence, the most trusted and best-fitted parameters were used for the model calibration test. For all tests, the model was verified using two-month's data that were not used in modellling and calibration, and two-step sensitivity analyses were performed to identify the most influencing variables for model calibration and to optimize the parameters for plant operation.

The primary and secondary clarifiers' performance, aeration tank operation, sludge production, chemical demand, energy use, cost, and final effluent quality were simulated and optimized for scenarios I and II. The result confirmed that in scenario I the primary clarifier pollutant removal performance was less efficient than in scenario II. In line with the secondary clarifier effluent quality as well as internal operational parameters, it was also observed that scenario I was below standard and thus less efficient. However, in scenario II the main hydraulic parameters including RAS, WAS, and SRT were explicitly optimized, and the removal efficiency was significantly increased compared to scenario I. Similarly, the aeration performance parameters for scenario I were below the minimum level which violated the requirement for efficient biological process while scenario II operated effectively. Furthermore, scenario I compared to scenario II main wastewater quality parameters, violated the compliance limit, and the final effluent quality was accounted for as poor. Similarly, the energy consumption and operation cost for scenario I was significantly higher than scenario II, with high cake mass flow production and poor effluent quality. Thus, the modified model, scenario II, was highly efficient, and more cost-and energy-effective than scenario I.

To evaluate the wastewater treatment plant's performance by using analytical methods and GPS-X modelling

The comparative evaluation was conducted for analytical measurement and GPS-X modelling. The physicochemical data were measured at the inlet and outlet of the aeration tank, and the primary, and secondary clarifiers. Using the mathematical equation, the performance was calculated for each unit process and total plant pollutant removal efficiency. The primary clarifier had very weak pollutant removal efficiency, while the secondary clarifier was 'good' for TSS, COD, and TP; these parameters were above the permissible limit. The total performance of the plant from analytical measurement was 71%.

In GPS-X modelling, the simulation was performed for 180 days using the calibrated version of scenario I. The statistics of time violation and cumulative time percentage were calculated in the model. Accordingly, the results depicted that the primary clarifier's performance was poor compared to the secondary clarifier. However, the total performance of the plant was very poor and simulated as 43%. The analytical measurement and GPS-X model-based simulation results confirmed that the analytical measurement leveraged inferior results irrespective of time. However, the model result was able to identify the parameter that violated the permissible limit, the violation duration, the operation mode and its location in the treatment plant. Furthermore, the model predicted complex process units within a short time and more efficiently.

To develop holistic operation strategies and a troubleshooting framework for textile wastewater treatment plant

The influence of operational parameters in the influent, primary and secondary clarifiers, and aeration tank were analyzed for the modified scenario. Finally, the optimized operational troubleshooting framework was developed for plant operators and decision-makers.

The simulation result for WAS in the primary clarifier was operated within the optimum range of 15 ± 5 m^3/d, RAS 150 ± 10 m^3/d, WAS in secondary clarifier 83 ± 7 m^3/d, SRT in secondary clarifier 5 ± 1d, SRT in primary clarifier 6.7 ± 0.5 d, Q molasses 0.5 ± 0.05 m^3/d, Q_{inf} 600 ± 50 m^3/d, and airflow into aeration tank 550 ± 5 m^3/hr. Thus, it is possible to conclude that the critical operational parameters identified through rigorous simulation and optimization were better than the analytical measurement. The treatment plant was sensitive to a wide range of variations for each process control parameter.

According to the analytical measurement and model-based simulation experiment for both scenarios, it can be concluded that the modified process flow layout (scenario II) was viable, and it was a successful option for treating the textile wastewater for the selected case study. In addition, the modelling result predicted the performance evaluation better than analytical measurements. Comparing the results for scenario II, generated using modelling in GPS-X, it was found to be efficient in pollutant removal, and also cost- and energy-effective.

6.2 Recommendations

The purpose of this study was to evaluate the existing treatment plant's performance and to investigate the best possible remedial option by means of a simplified operational strategy. In addition, it also aimed to examine the performance evaluation techniques used by plant operators, environmental authorities, and policymakers to easily evaluate and improve the performance of a similar textile or any other industrial treatment plant.

The findings from this research were vital for the case study to be tested on real plants and optimized process control parameters. The key actionable reccomendations from the research:

- *Immediate Transition to Scenario II Layout*: The factory should restructure its current wastewater process flow to align with the Conventional Activated Sludge (CAS) process modeled in Scenario II. The simulation proves that the existing layout is fundamentally incapable of meeting discharge limits; therefore, physical piping or sequence adjustments are required to ensure scientifically accepted hydraulic flow.
- *Implementation of Precision Aeration Control:* To resolve the "below minimum" dissolved oxygen levels and high energy costs identified in scenario I, the plant must install automated blowers or VFDs (Variable Frequency Drives). Maintaining an airflow

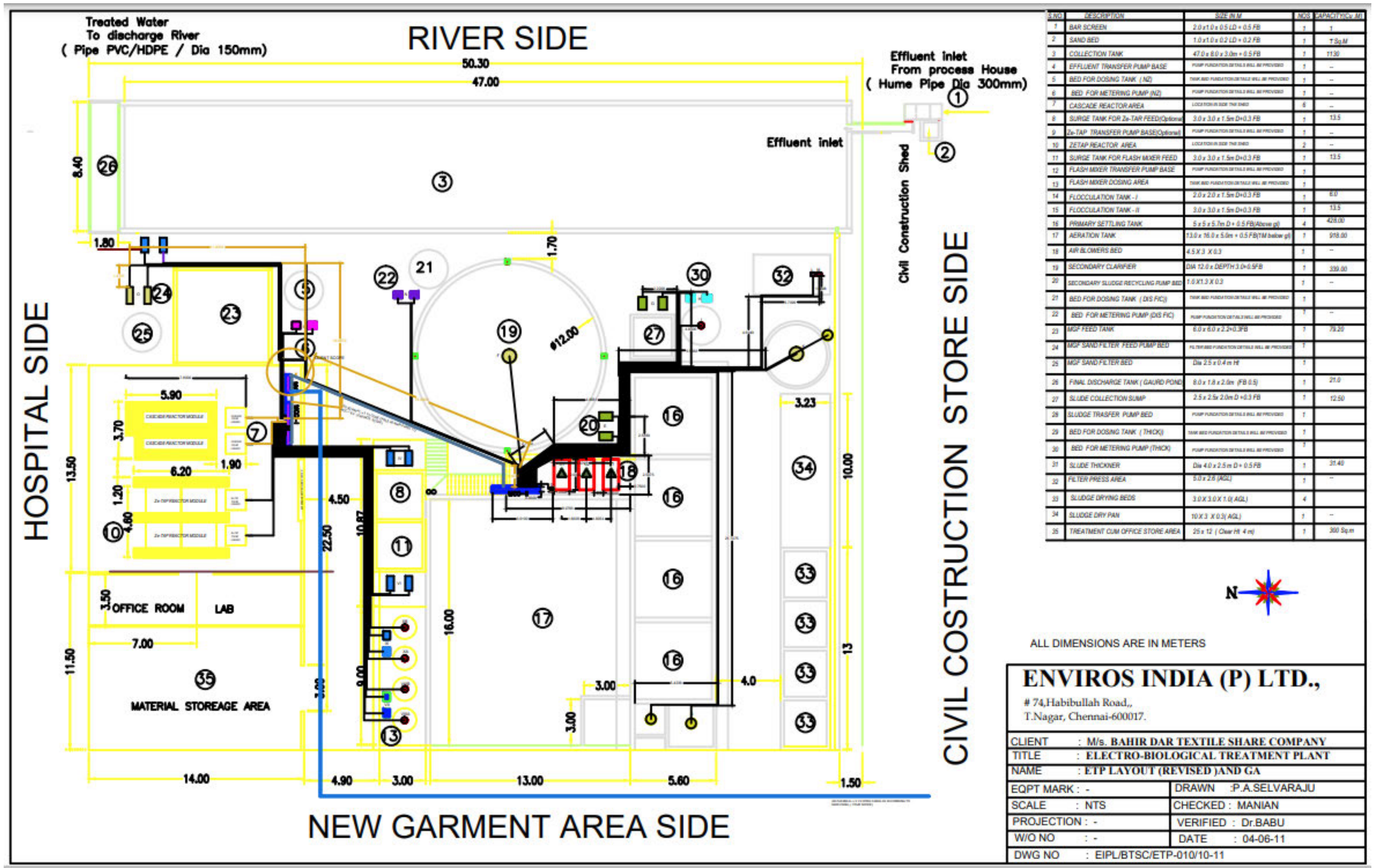
of 550 $\pm$ 5 m^3/hr is critical to sustaining the biological health of the aeration tank while preventing energy waste.

- *Standardization of Sludge Management (SRT and RAS/WAS):* Operators should move away from arbitrary sludge wasting. Based on the GPS-X optimization, the Solitary Retention Time (SRT) must be strictly maintained at 5 $\pm$ 1 days for the secondary clarifier. Furthermore, the Return Activated Sludge (RAS) should be stabilized at 150 $\pm$10 m^3/d to maintain the necessary biomass concentration for pollutant removal.
- *Adoption of a Digital Twin/Modelling Framework for Compliance:* Since analytical measurement overestimated plant performance (71% vs. the more accurate 43% from modelling), the factory should adopt GPS-X or similar software as a Digital Twin. This allows management to predict time violations and address non-compliance before the effluent actually reaches the river.
- *Targeted Remediation for Heavy Metals and Nutrients:* Specific intervention is required for Total Chromium (0.16 mg/L) and Total Phosphorus (7.9 mg/L), which currently exceed limits. While scenario II improves general efficiency, a dedicated chemical precipitation step or enhanced biological phosphorus removal (EBPR) should be integrated into the aeration phase to ensure these specific parameters reach the permissible safe zone.
- *Establishment of a Troubleshooting and Maintenance Protocol:* Using the optimized operational framework developed in the study, a formal Standard Operating Procedure (SOP) manual should be authored. This manual must include the optimum ranges identified (e.g., Q_$_{inf}$ at 600 $\pm$ 50 m^^{3}/d and provide clear troubleshooting steps for when parameters drift outside these validated boundaries.
- *Downstream Community Protection and Monitoring:* Until the transition to scenario II is fully stabilized, the factory should establish an active water quality monitoring station at the river discharge point. This serves as a "social license to operate," providing transparent data to downstream inhabitants and ensuring that the "pollution aggravation" noted in the justification is actively being mitigated.

Therefore, the study could also encourage other researchers to undertake further research incorporating life cycle assessment by incorporation other emergind pollutants. Accordingly, advanced experiments and simulation should be planned to investigate the real-time impacts of the process control parameters on plant performance.

Annex – A

A-1 Analytical measurements and existing data



S.NO	DESCRIPTION	SIZE IN M	NOS	CAPACITY(Cu. M)
1	BAR SCREEN	2.0 x1.0 x 0.5 LD + 0.5 FB	1	1
2	SAND BED	1.0 x1.0 x 0.2 LD + 0.2 FB	1	1 Sq.M
3	COLLECTION TANK	47.0 x 8.0 x 3.0m + 0.5 FB	1	1130
4	EFFLUENT TRANSFER PUMP BASE	PUMP FUNDATION DETAILS WILL BE PROVIDED	1	–
5	BED FOR DOSING TANK (NZ)	TANK BED FUNDATION DETAILS WILL BE PROVIDED	1	–
6	BED FOR METERING PUMP (NZ)	PUMP FUNDATION DETAILS WILL BE PROVIDED	1	–
7	CASCADE REACTOR AREA	LOCATION IN SIDE THE SHED	6	–
8	SURGE TANK FOR Ze-TAR FEED(Optional)	3.0 x 3.0 x 1.5m D+0.3 FB	1	13.5
9	Ze-TAP TRANSFER PUMP BASE(Optional)	PUMP FUNDATION DETAILS WILL BE PROVIDED	1	–
10	ZETAP REACTOR AREA	LOCATION IN SIDE THE SHED	2	–
11	SURGE TANK FOR FLASH MIXER FEED	3.0 x 3.0 x 1.5m D+0.3 FB	1	13.5
12	FLASH MIXER TRANSFER PUMP BASE	PUMP FUNDATION DETAILS WILL BE PROVIDED	1	
13	FLASH MIXER DOSING AREA	TANK BED FUNDATION DETAILS WILL BE PROVIDED	1	
14	FLOCCULATION TANK - I	2.0 x 2.0 x 1.5m D+0.3 FB	1	6.0
15	FLOCCULATION TANK - II	3.0 x 3.0 x 1.5m D+0.3 FB	1	13.5
16	PRIMARY SETTLING TANK	5 x 5 x 5.7m D + 0.5 FB(Above gl)	4	428.00
17	AERATION TANK	13.0 x 16.0 x 5.0m + 0.5 FB(1M below gl)	1	918.00
18	AIR BLOWERS BED	4.5 X 3 X 0.3	1	–
19	SECONDARY CLARIFIER	DIA 12.0 x DEPTH 3.0+0.5FB	1	339.00
20	SECONDARY SLUDGE RECYCLING PUMP BED	1.0 X1.3 X 0.3	1	–
21	BED FOR DOSING TANK (DIS FIC))	TANK BED FUNDATION DETAILS WILL BE PROVIDED	1	
22	BED FOR METERING PUMP (DIS FIC)	PUMP FUNDATION DETAILS WILL BE PROVIDED	1	–
23	MGF FEED TANK	6.0 x 6.0 x 2.2+0.3FB	1	79.20
24	MGF SAND FILTER FEED PUMP BED	FILTER BED FUNDATION DETAILS WILL BE PROVIDED	1	
25	MGF SAND FILTER BED	Dia 2.5 x 0.4 m Ht	1	
26	FINAL DISCHARGE TANK (GAURD POND)	8.0 x 1.8 x 2.0m (FB 0.5)	1	21.0
27	SLUDE COLLECTION SUMP	2.5 x 2.5x 2.0m D +0.3 FB	1	12.50
28	SLUDGE TRASFER PUMP BED	PUMP FUNDATION DETAILS WILL BE PROVIDED	1	
29	BED FOR DOSING TANK (THICK))	TANK BED FUNDATION DETAILS WILL BE PROVIDED	1	
30	BED FOR METERING PUMP (THICK)	PUMP FUNDATION DETAILS WILL BE PROVIDED	1	
31	SLUDE THICKNER	Dia 4.0 x 2.5 m D + 0.5 FB	1	31.40
32	FILTER PRESS AREA	5.0 x 2.6 (AGL)	1	–
33	SLUDGE DRYING BEDS	3.0 X 3.0 X 1.0(AGL)	4	
34	SLUDGE DRY PAN	10 X 3 X 0.3(AGL)	1	–
35	TREATMENT CUM OFFICE STORE AREA	25 x 12 (Clear Ht 4 m)	1	300 Sq.m

Figure A- 1 Existing textile wastewater treatment plant layout and physical data

Figure A- 2 Existing treatment plant site visit, reconnaissance, and pre-sample collection

Figure A- 3 The status of treatment units, mobile kits, and laboratory apparatus

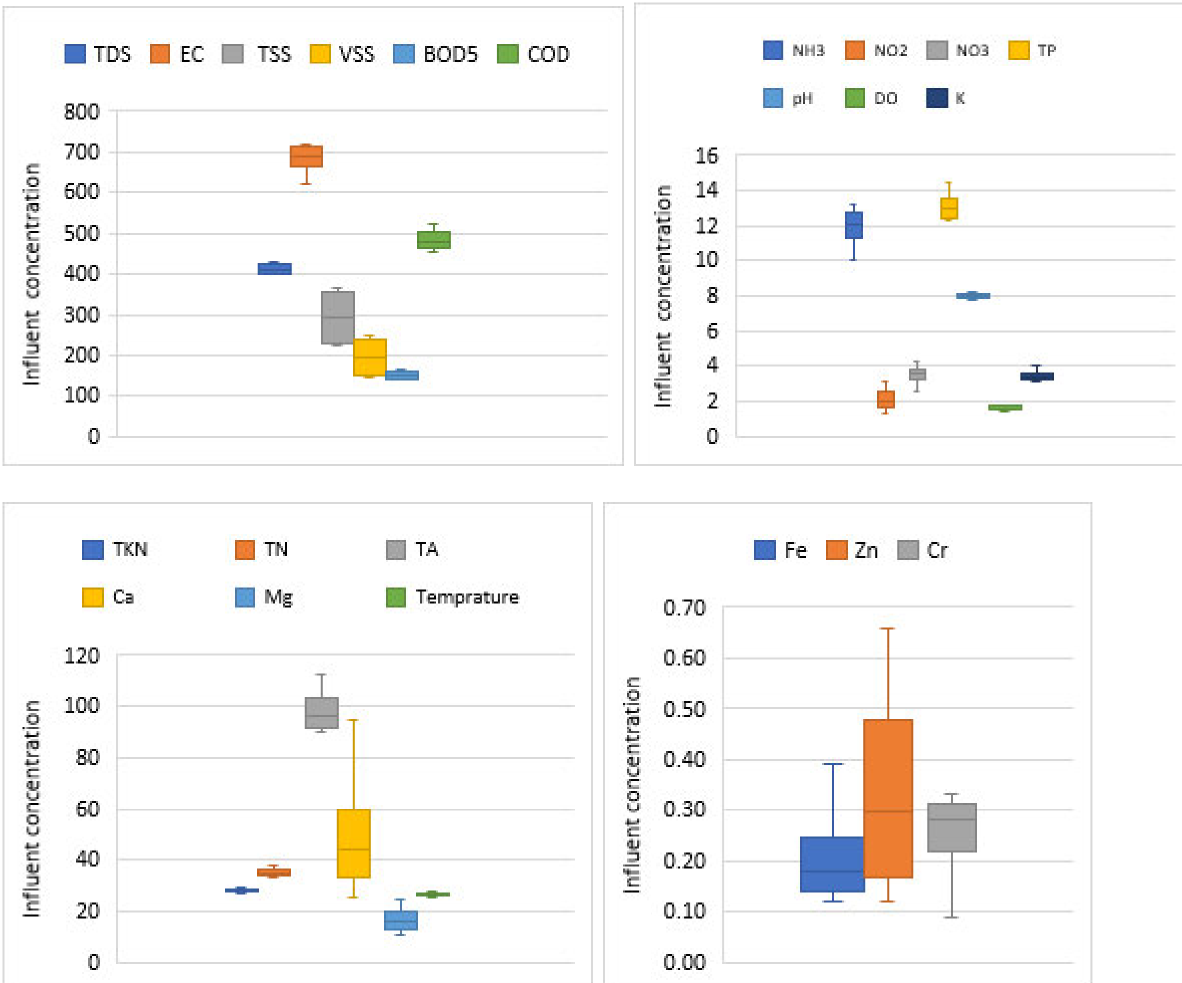
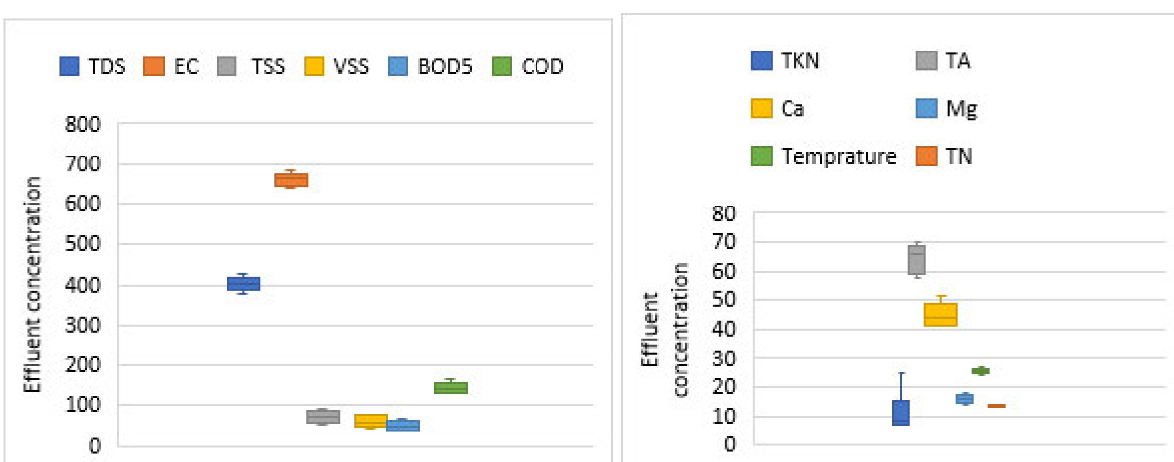
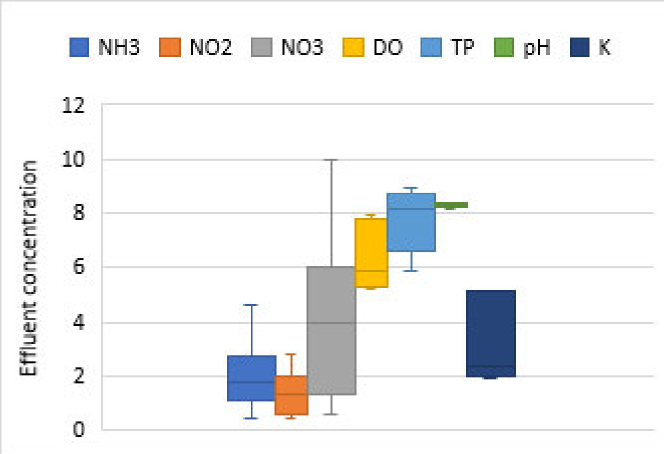


Figure A- 4 Descriptive statistics for influent concentration analytical measurement





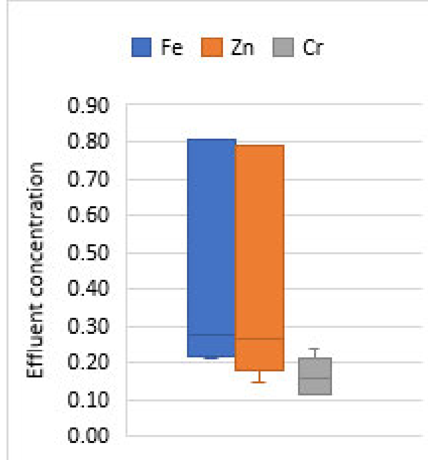


Figure A-5 Descriptive statistics - effluent concentration analytical measurement

Table A-1 Analytical measurement performance parameters correlation

Pearson Correlation										
Effluent Quality Index	EQI	TSS	BOD5	COD	Amonia-N	Nitrit-N	Nitrate-N	TKN	TN	TP
EQI	1.00	0.97	0.99	0.92	0.67	-0.83	-0.85	0.92	0.65	0.87
TSS	0.97	1.00	0.95	0.83	0.53	-0.91	-0.73	0.85	0.68	0.96
BOD5	0.99	0.95	1.00	0.85	0.75	-0.83	-0.90	0.96	0.69	0.83
COD	0.92	0.83	0.85	1.00	0.53	-0.65	-0.74	0.76	0.42	0.74
Amonia-N	0.67	0.53	0.75	0.53	1.00	-0.47	-0.94	0.89	0.67	0.29
Nitrit-N	-0.83	-0.91	-0.83	-0.65	-0.47	1.00	0.57	-0.77	-0.71	-0.91
Nitrate-N	-0.85	-0.73	-0.90	-0.74	-0.94	0.57	1.00	-0.96	-0.63	-0.51
TKN	0.92	0.85	0.96	0.76	0.89	-0.77	-0.96	1.00	0.78	0.68
TN	0.65	0.68	0.69	0.42	0.67	-0.71	-0.63	0.78	1.00	0.59
TP	0.87	0.96	0.83	0.74	0.29	-0.91	-0.51	0.68	0.59	1.00

Table A- 2 Comparative evaluation of different models

No	Software	Model Type	Country of Use	Key Influent Parameters Modeled	Strength	Limitation	Availability
1	GPS-X	Modular, Object-Oriented	North America, Africa, Asia	Ss, Xs, Si, Xi (COD Fractions), VSS/TSS, TKN Fractions	Superior Influent Advisor for industrial waste;	High computational demand	Commercial
2	BioWin	Integrated, Steady-State/Dynamic	North America, Australia	Readily vs. Slowly Biodegradable COD, Particulate vs. Soluble Organics	Gold standard for Biological Nutrient Removal (BNR) and aeration kinetics.	Less focus on integrated "visual" troubleshooting.	Commercial

3	WEST	Script-based, Open Structure	Denmark, Belgium, Germany	User-defined Fractions, ASM1-3 State Variables, pH/Alkalinity	Extremely flexible; allows researchers to code custom kinetic equations.	Requires advanced programming and math skills.	Commercial
4	AQUASIM	Equation Solver	Switzerland, Academic Labs	Biofilm thickness, Gas-liquid mass transfer coefficients	Precision modelling of Biofilm and specialized reactors.	Not intended for full-scale municipal plant layouts.	Commercial / Academic
5	SIMBA	MATLAB/ Simulink Based	Germany, Austria	Control loop variables, Sensor noise, SCADA signal data	Best for Automation and Control Strategy development.	Requires a MATLAB license and Simulink expertise.	Commercial
6	STOAT	Component-Based	United Kingdom	BOD/COD ratios, Ammonia, Settling Velocity (Vs)	Integrated Sewer-to-Plant modelling; very lightweight.	Graphical interface and libraries are dated.	Commercial
7	EFOR	Process-Oriented	Denmark, Norway, Sweden	Nitrogen/Phosphorus fractions, Sludge age, Temperature factors	Simplified for Regulatory Compliance and municipal reporting.	Limited specialized libraries for industrial waste.	Commercial

Annex – B

B-1 GPS-X model input and outputs

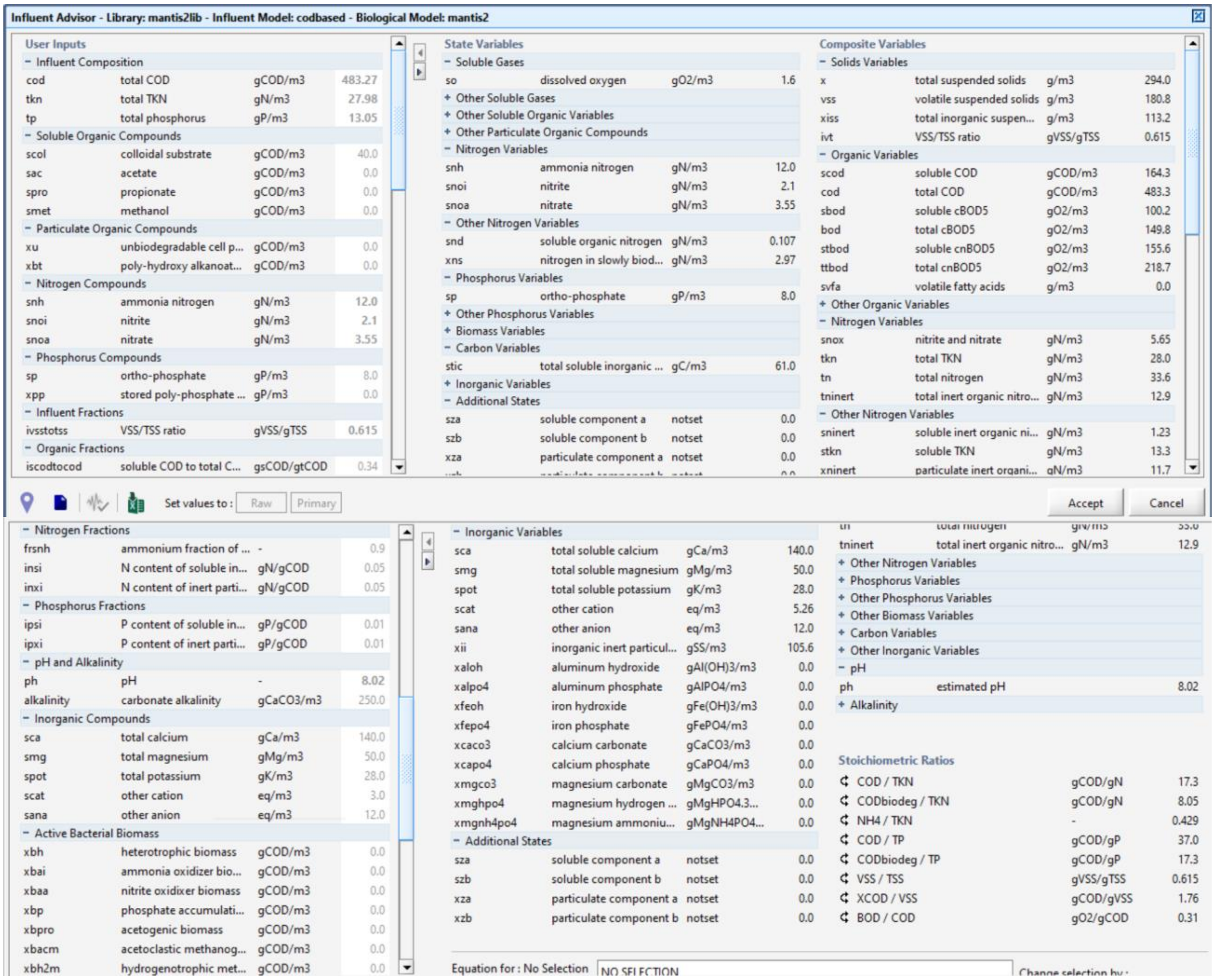


Figure B- 1 Influent composition and variables

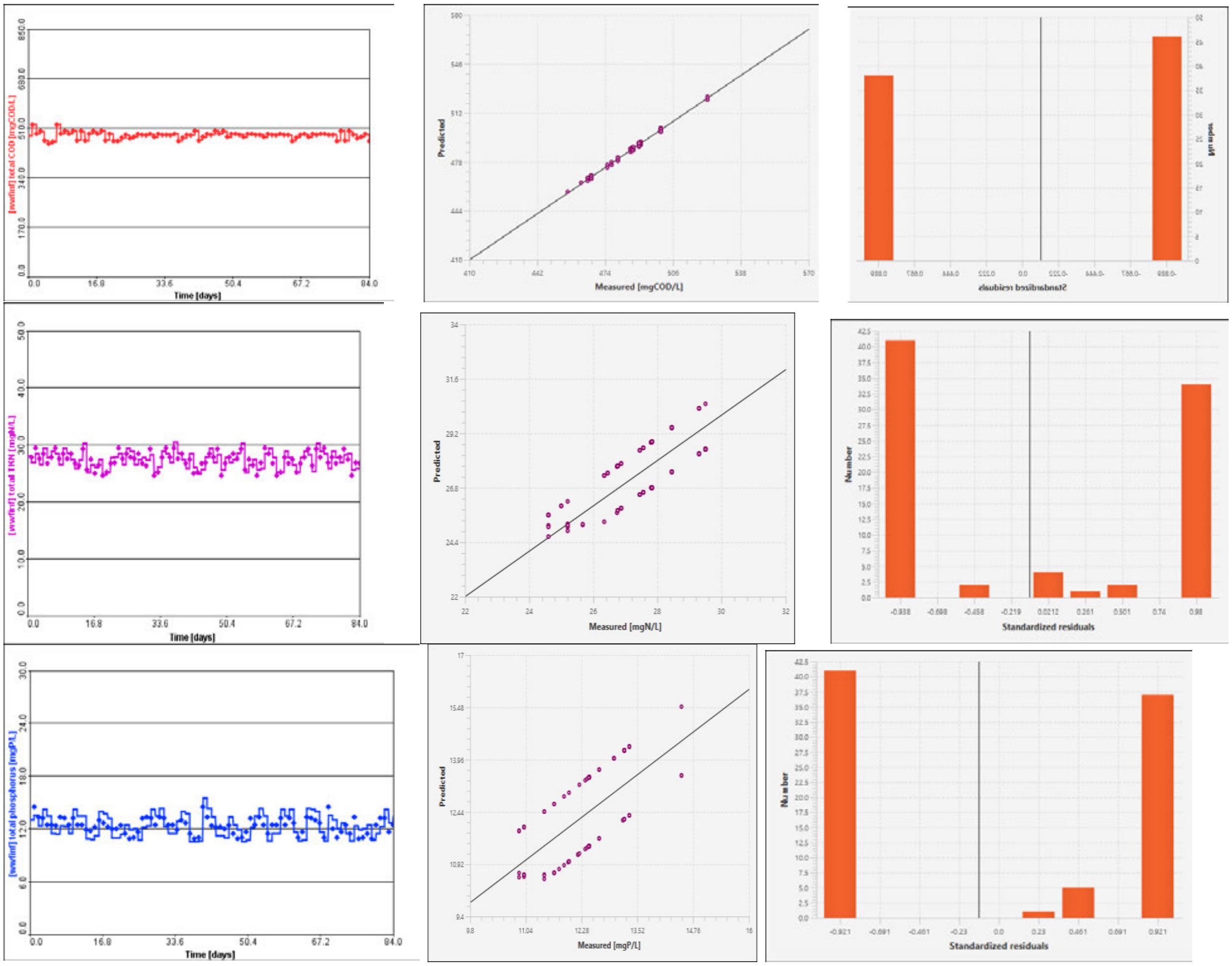
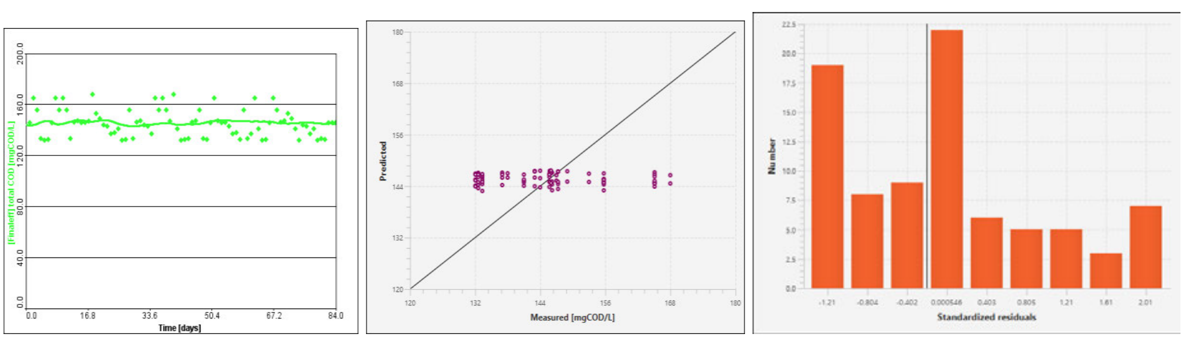


Figure B- 2 Influent calibration results for COD, TKN, and TP



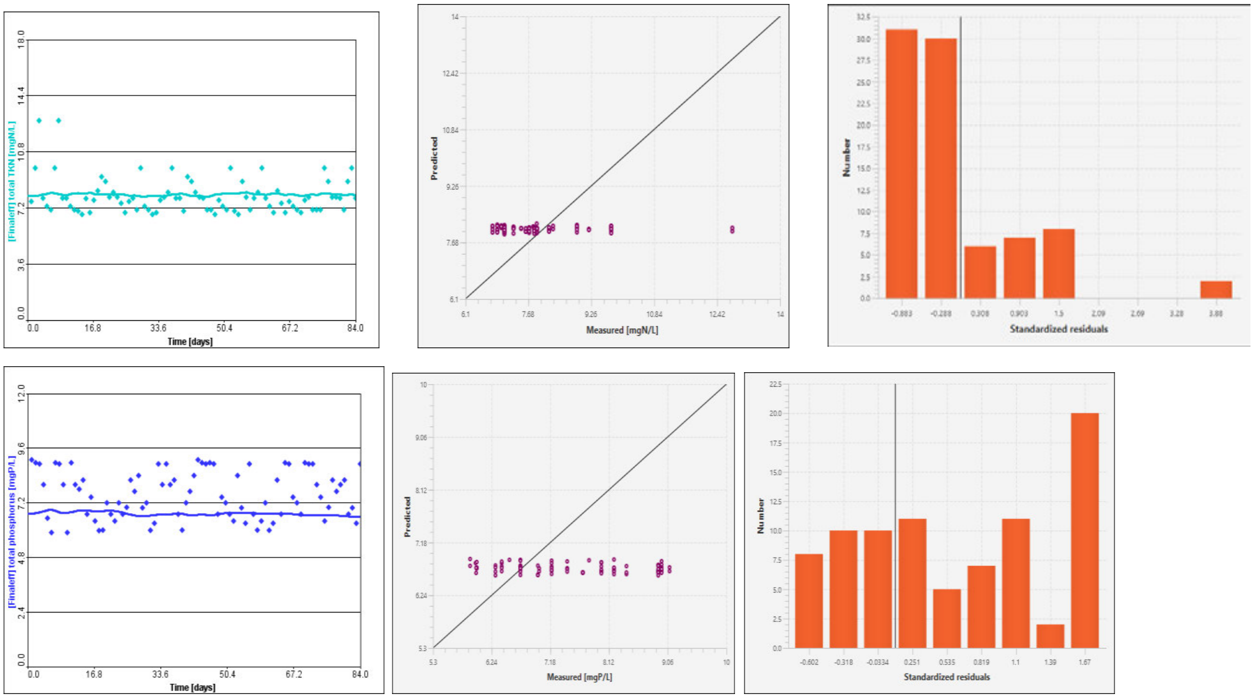


Figure B- 3 Effluent calibration result for COD, TKN, and TP

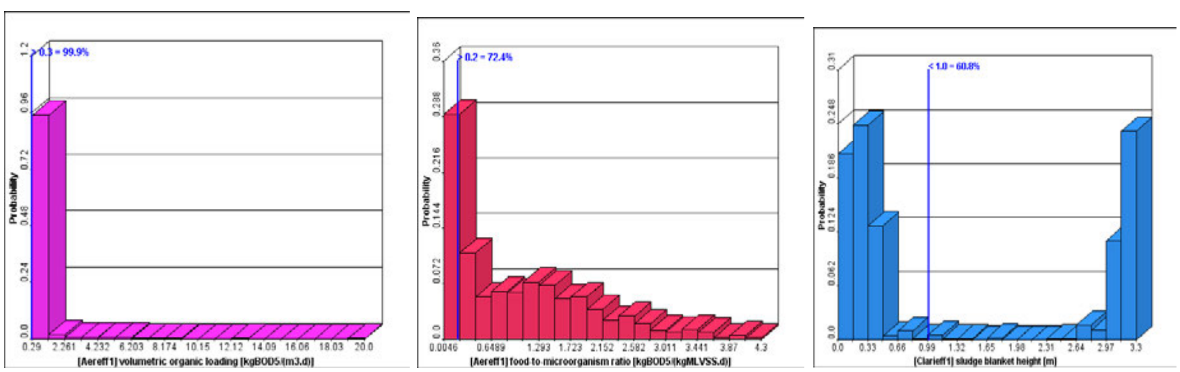
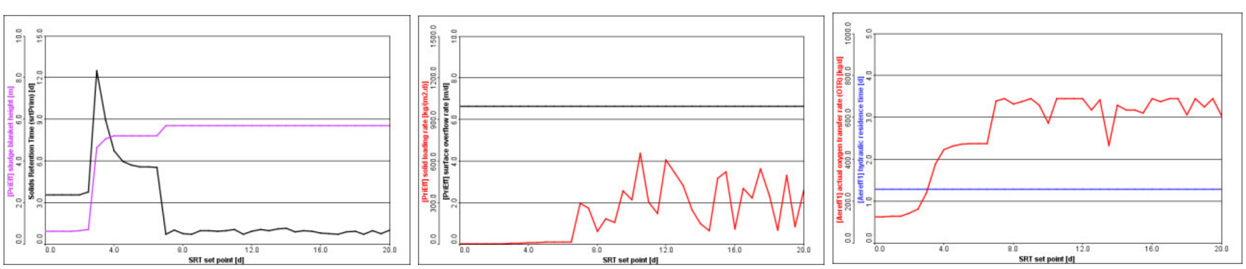


Figure B- 4 Monte Carlo sensitivity analysis for operational parameters in ASP



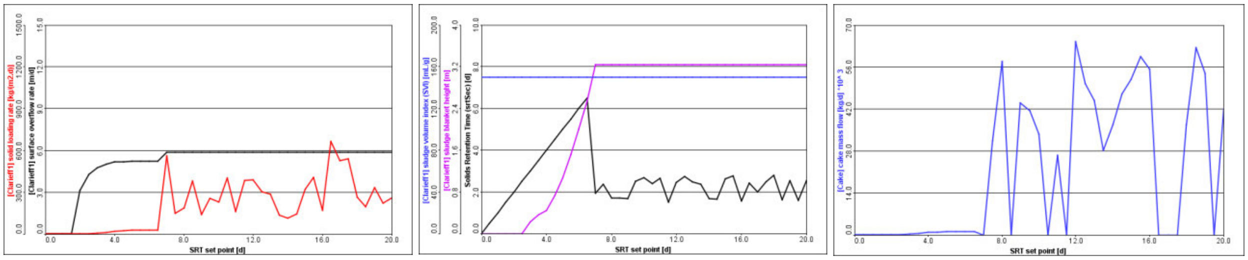


Figure B- 5 One-step sensitivity analysis of SRT against performance parameters

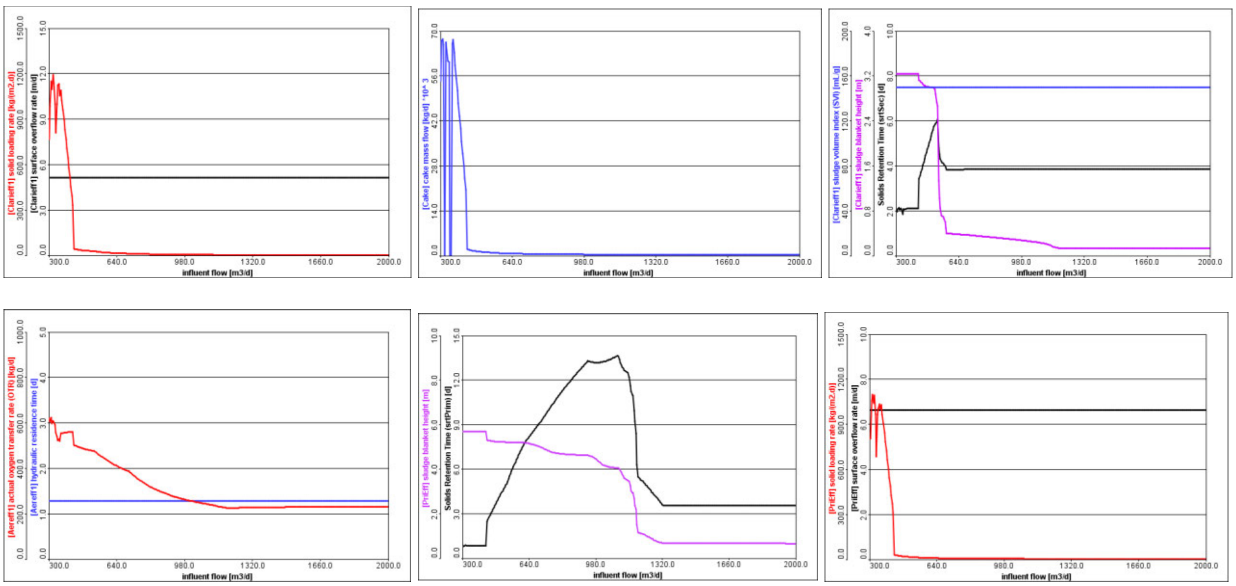
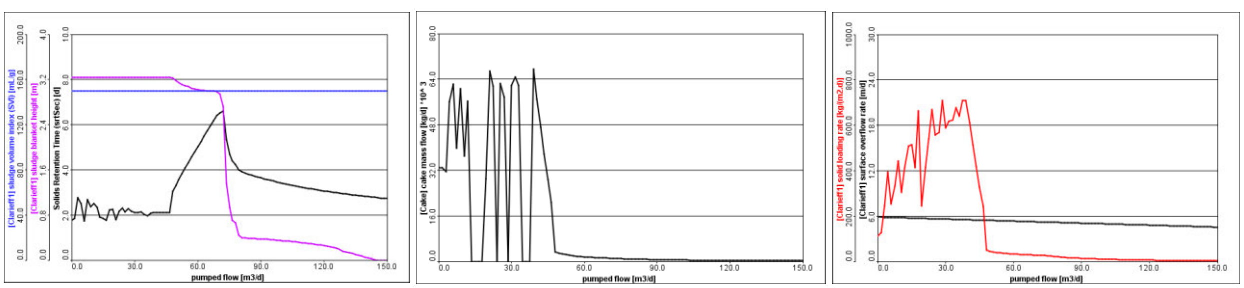


Figure B- 6 One-step sensitivity analysis of Q_{inf} against performance parameters



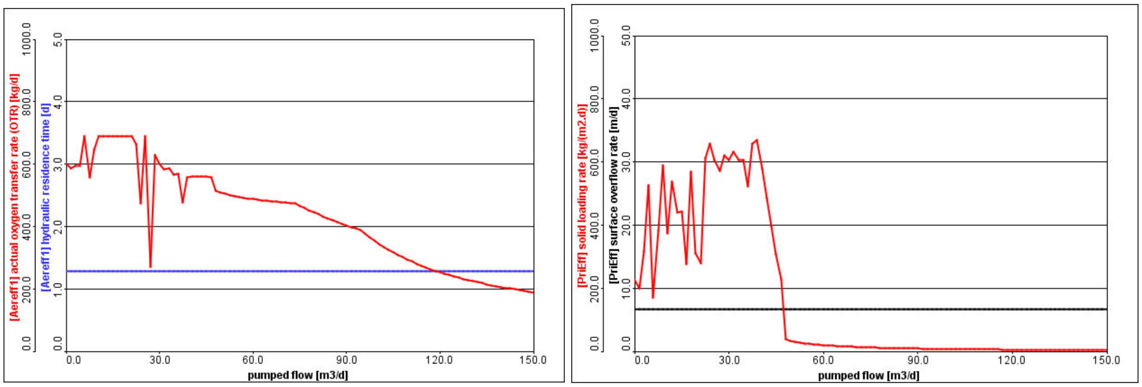


Figure B- 7 One-step sensitivity analysis of WAS against performance parameters

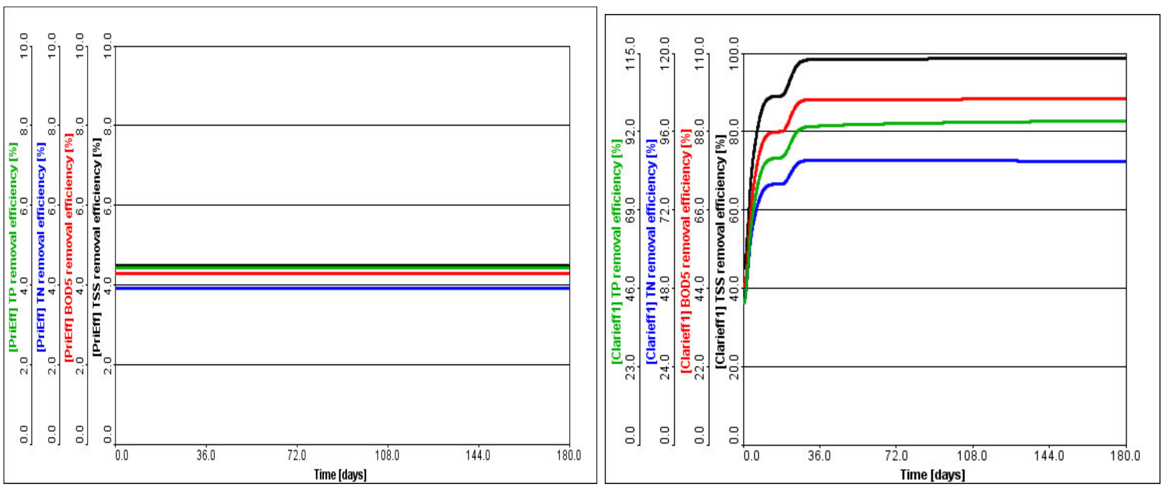


Figure B- 8 Primary and secondary clarifier performance for scenario I

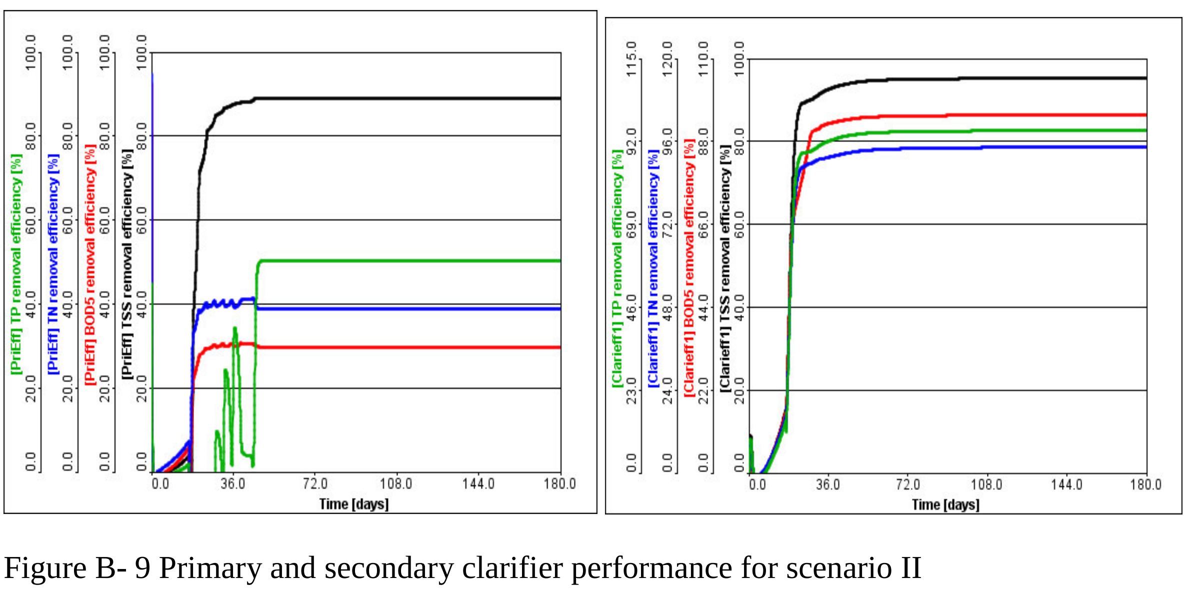


Figure B- 9 Primary and secondary clarifier performance for scenario II

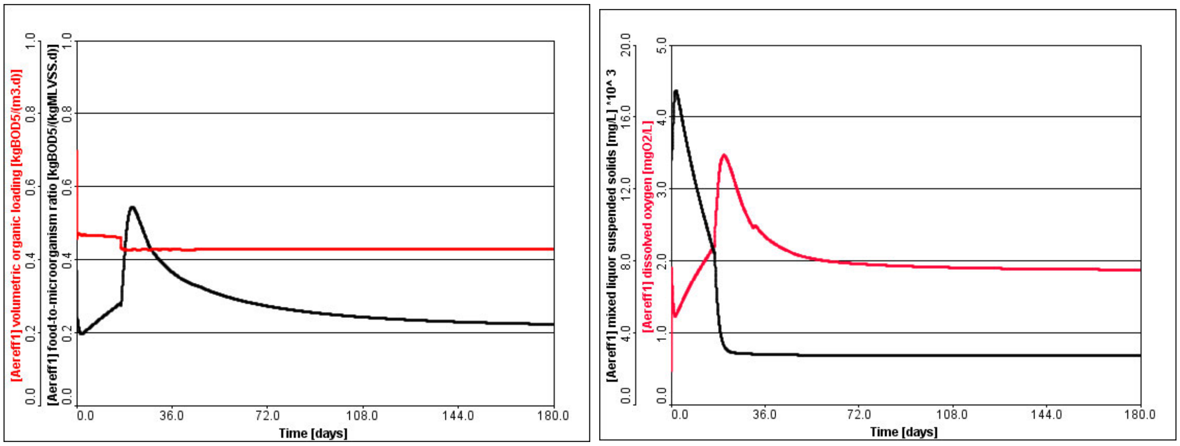


Figure B- 10 Aeration tank operational parameters for scenario-II

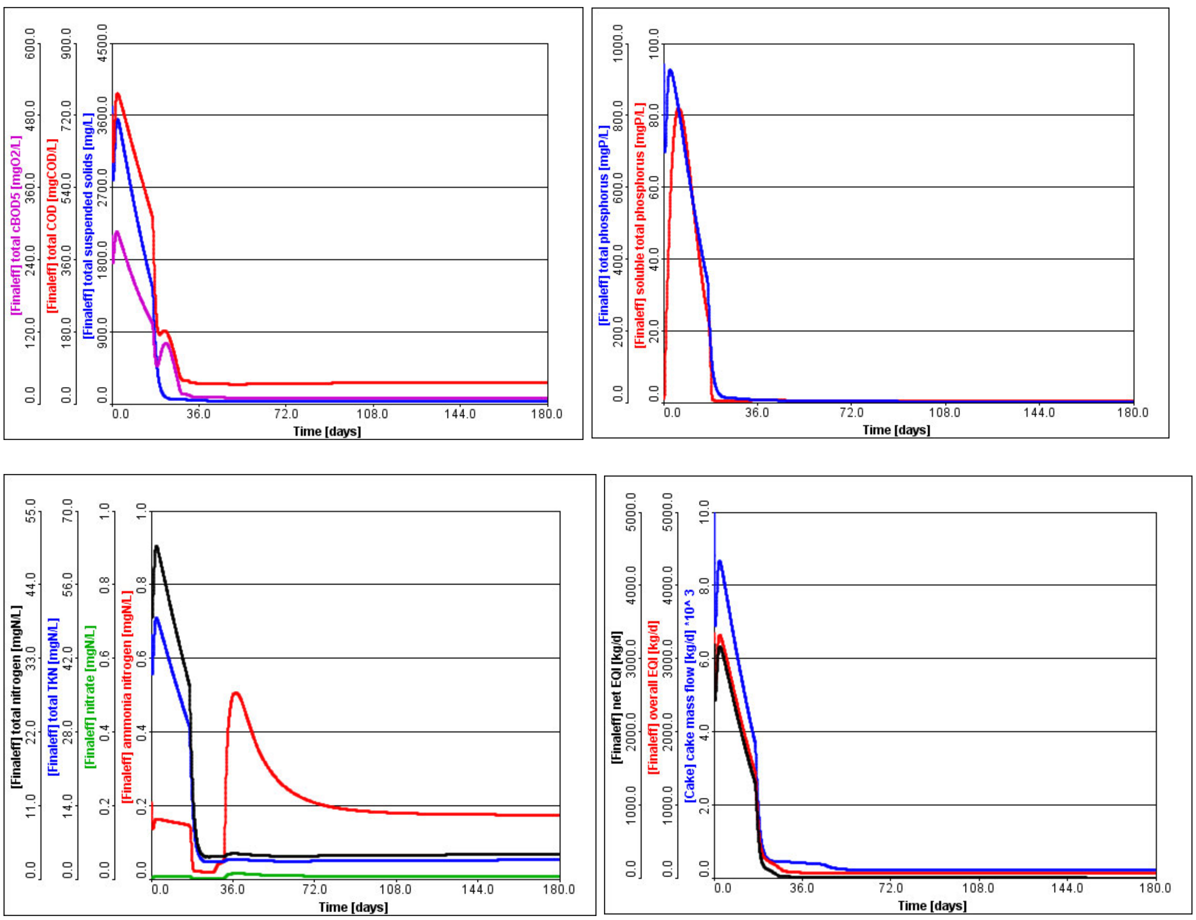


Figure B- 11 Final effluent concentration for scenario-II

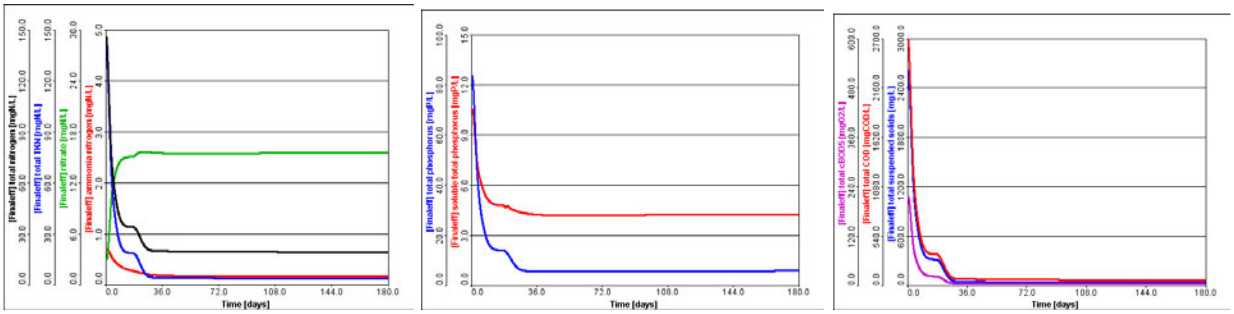


Figure B- 12 Final effluent concentration for scenario I

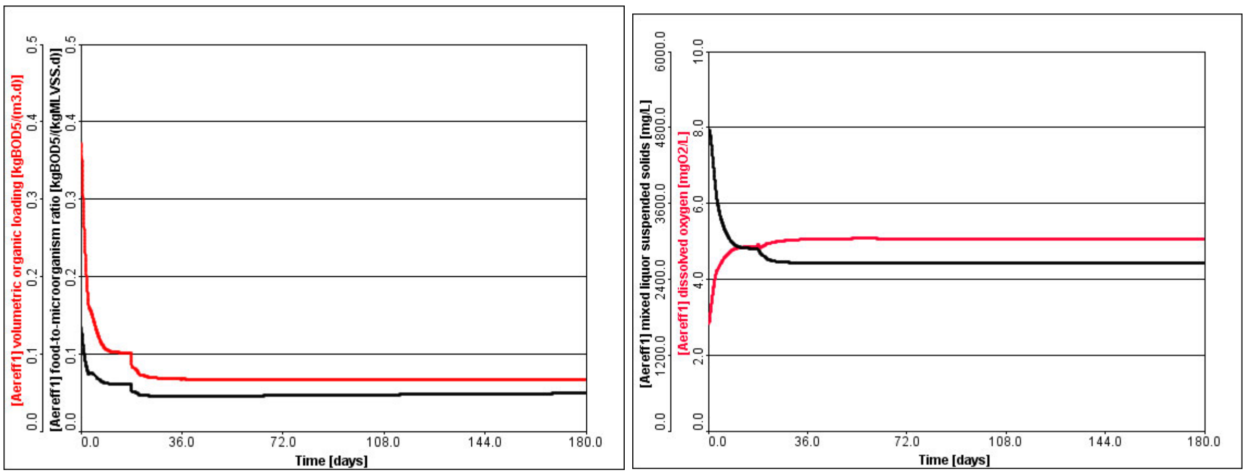
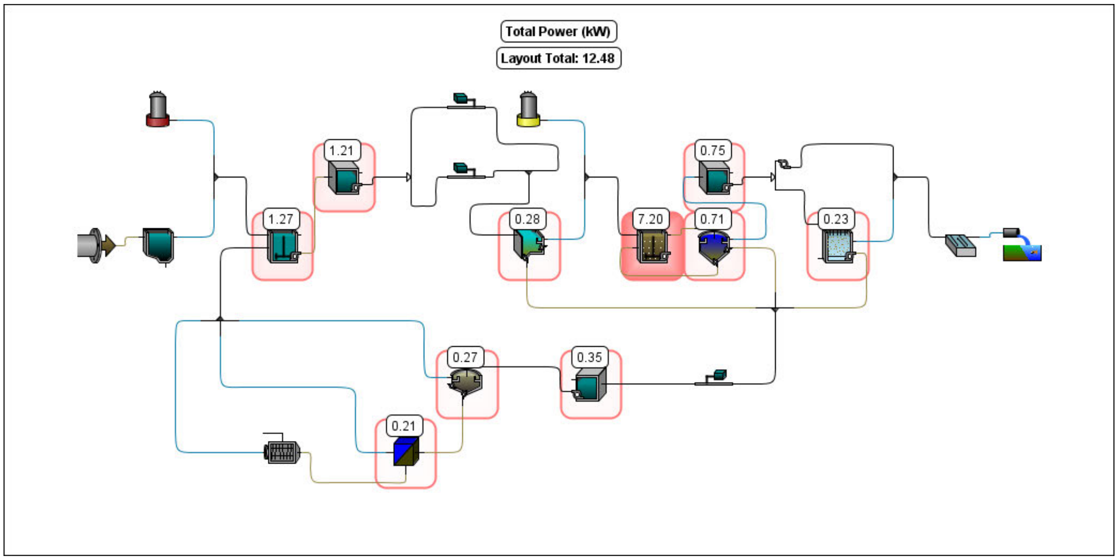


Figure B- 13 Aeration tank operational parameters for scenario I



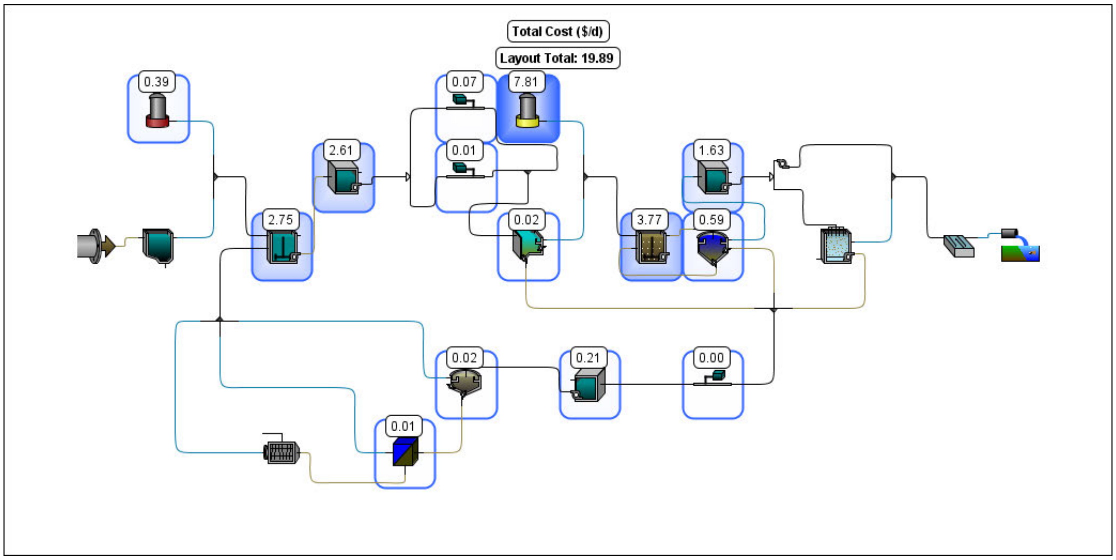


Figure B- 14 Total layout energy and cost for scenario II

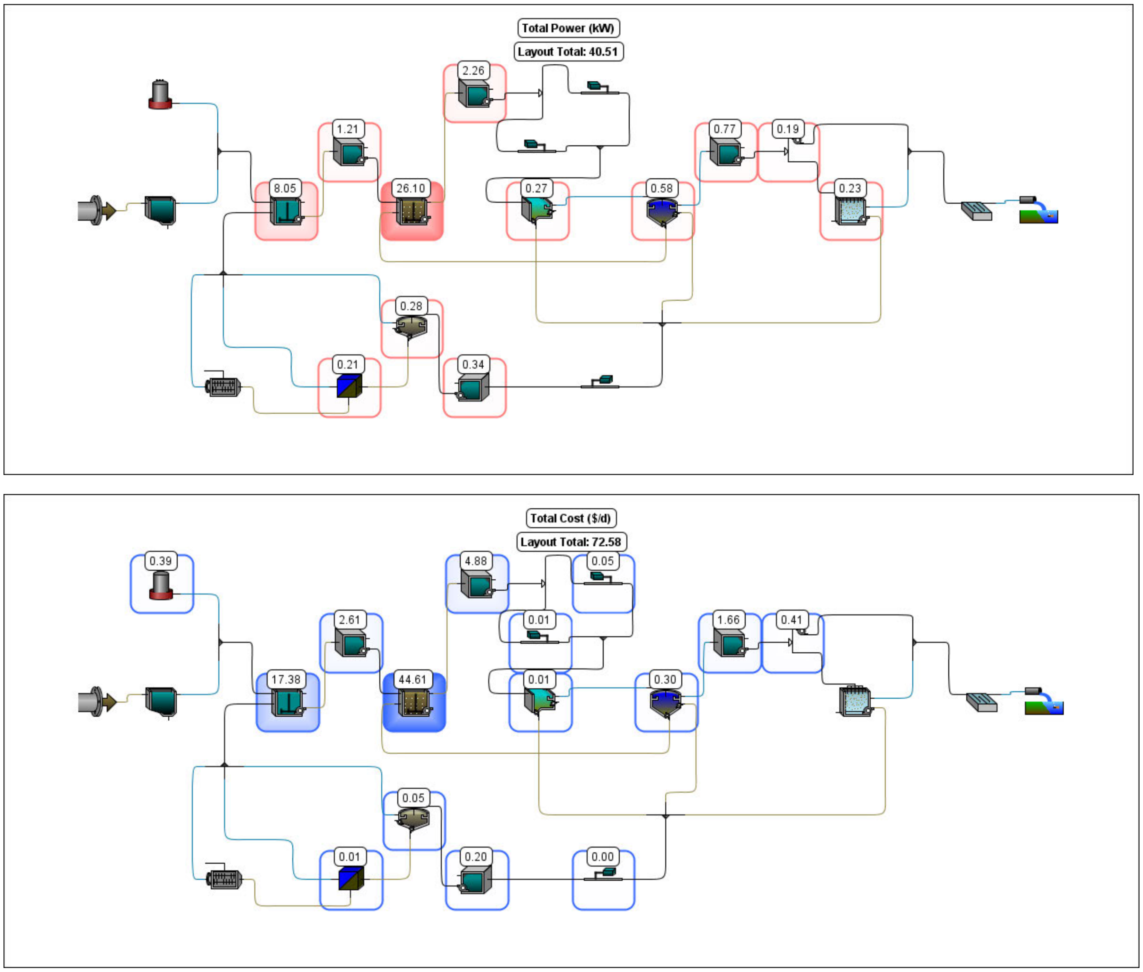
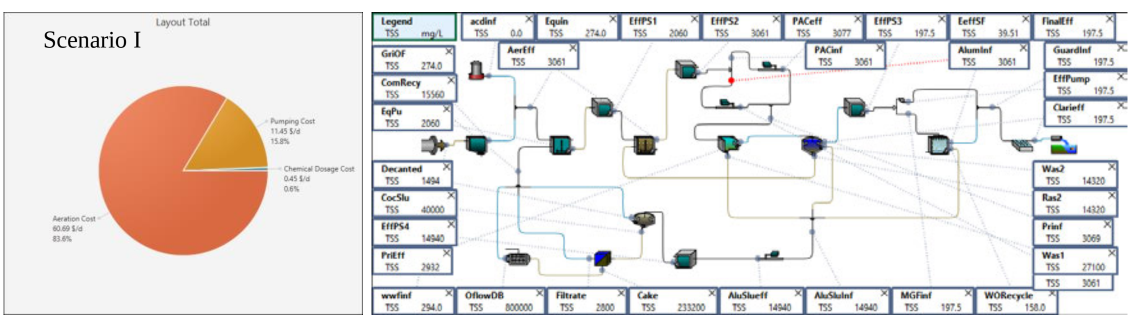


Figure B- 15 Total layout energy and cost for scenario I



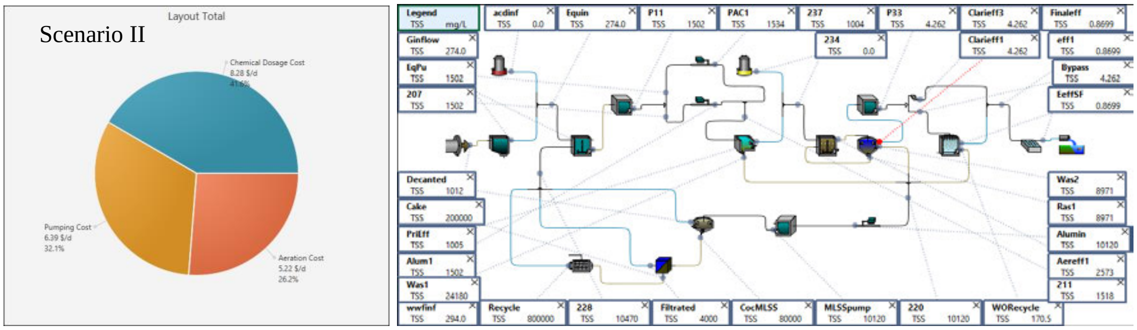


Figure B- 16 Total layout cost and mass balance for scenario I and II

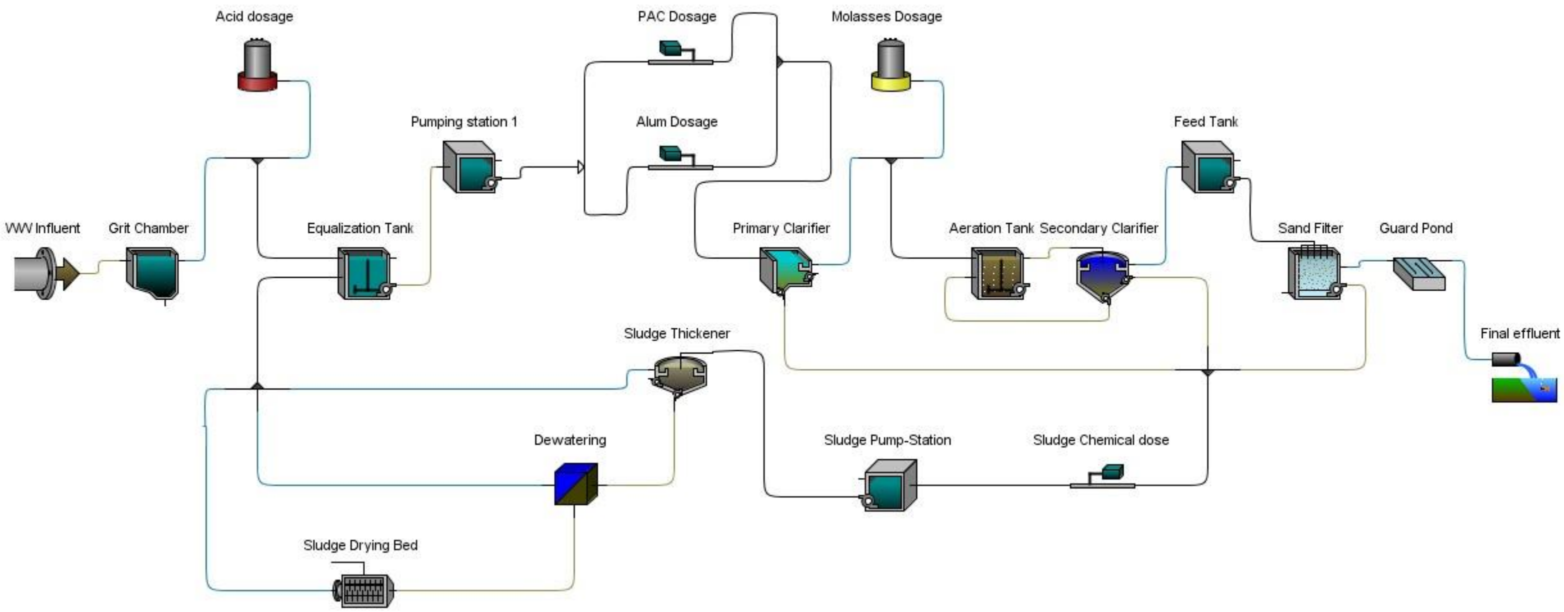


Figure B- 17 Modified wastewater treatment process flow diagram (scenario II)

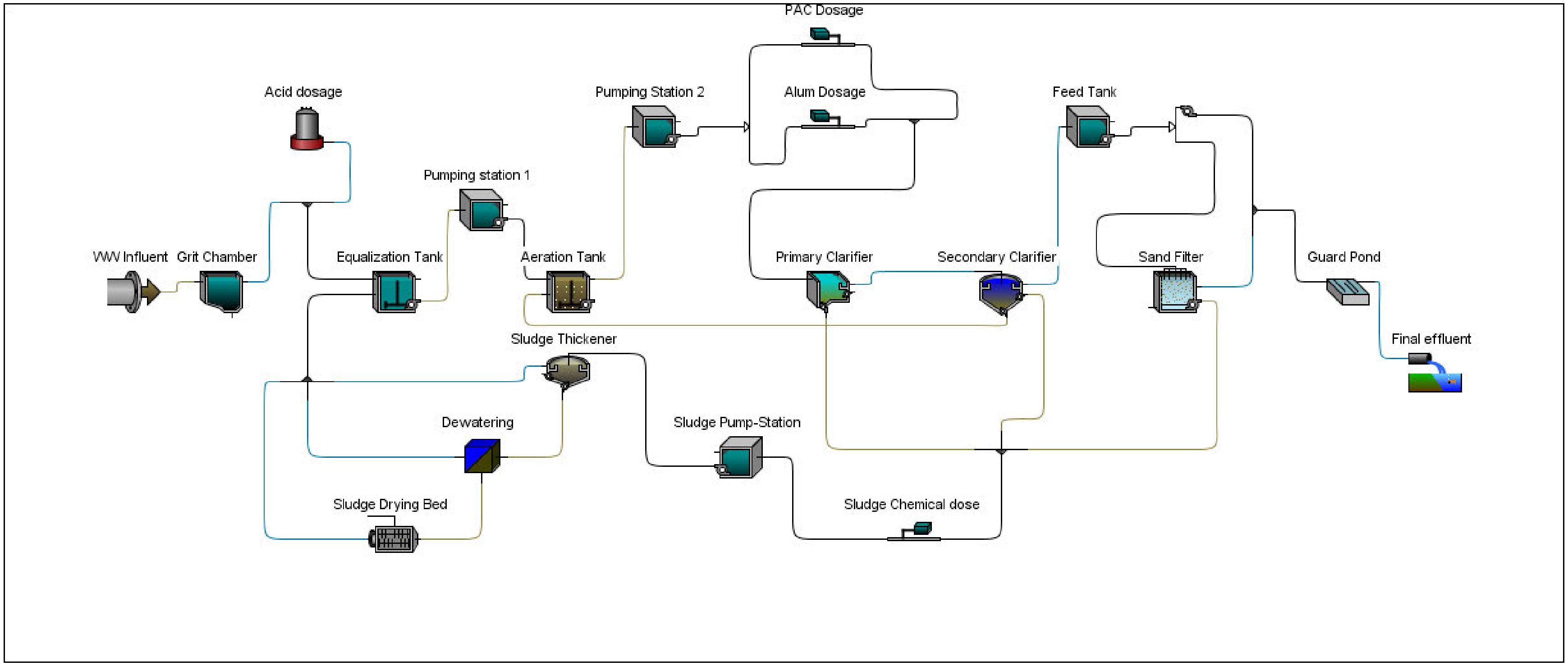


Figure B- 18 Existing wastewater treatment process flow diagram (scenario I)

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