Performance analyses of wastewater treatment plant: A case of Hazelmere water treatment plant.

By

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DECLARATION

I Nonsindiso Mkhize, hereby declare that this dissertation, except as indicated in the text, is entirely original work of mine and has not been submitted in part or whole to any other Institution.

This research is on the "Performance analyses of wastewater treatment plant: A case of Hazelmere water treatment plant" and registered at the Durban University of Technology under the supervision of Dr. Mohammed Seyam and co-supervision of Dr. Joseph Bwapwa.

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APPROVED FOR FINAL SUBMISSION

Supervisor: Dr. Mohammed Seyam

DEDICATION

I dedicate this dissertation to my parents, especially my mother, who has always loved me unconditionally and taught me to work hard for the things I aspire to achieve. I am truly thankful for having them in my life. This work is also dedicated to my sister, Anele Mkhize, who has been a constant source of support and encouragement during obstacles of research and life. I also dedicate this dissertation to my late grandfather, Mr. Simon Mkhize.

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ABSTRACT

There is still an existing gap in the assortment and treatment of domestic wastewater; where wastewater treatment plants exist, they frequently operate beneath a set of guidelines. This prompts the discharge of pollutants into natural water bodies, establishing an adverse consequence on the climate and on human wellbeing. The performance of wastewater treatment plants is a fundamental parameter to be observed and assessed. This allows for better comprehension of the plans and operating challenges in water treatment plants. The results from assessment evaluations might be used for strategic planning aimed at upgrading plant operations and promoting adjustment necessities for better plant output.

In this study, the Hazelmere Wastewater Treatment System's performance was evaluated from 1999 to 2018. The study's principal objective was to evaluate the exhibition of the treatment plant in terms of the expulsion of microbial and chemical contaminations. Secondary data from the plant's data records were used in the analysis. The study was also aimed at developing a predictive model which can be used to estimate future trends and parameters. Since long-term forecasting may produce more variations and higher errors, the forecast is only made for the next three years.

The analysis conducted by this study revealed that the Hazelmere wastewater treatment plant's performance met the predetermined criteria. The measured values of E. coli, turbidity, and iron were higher than the benchmark focus requirements established (recommended) by international standards. The expulsion of turbidity for the period under study all satisfied World Health Organization (WHO) and South African National Standards (SANS) for discharge [≤ 1 NTU]. Iron removal also satisfied the WHO/SANS standards for release at [≤2 mg/L].

From 1999 to 2018, the effluent produced by the wastewater treatment plant was pathogen-free, with a recorded annual average of 0MPN/100mL. As a result, E. coli removal efficiency was at 100% during the mentioned period.

Given the cost of running the plant, it is crucial that enhancements are made to expand the plants performance. Potential enhancements must adhere to criteria such as low speculation and upkeep costs, an increase in the plant's water-driven limit, and being simple to work with and maintain.

The findings revealed that the proposed stochastic model can accurately and consistently predict the concentrations of the plant's wastewater parameters.

Hence, if consideration is given to the nature of the input factors of the model, stochastic demonstrating can be utilized to help support wastewater plants. This will lead to a reduction in the number of experiments performed to analyze the pollutants and thus minimizing plant operating costs.

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LIST OF ABBREVIATIONS

(BOD) Biochemical Oxygen Demand

(COD) Chemical Oxygen Demand

(DO) Dissolved oxygen

(DWA) Department of Water Affairs

(E. coli) Escherichia coli

(HWTP) Hazelmere Wastewater Treatment Plant

(PAHs) Polycyclic aromatic hydrocarbons

(LCCA) Life Cycle Cost Analysis

(MAC) Maximum Acceptable Concentration

(PST) Primary Sedimentation Tank

(R.I) Random Consistency Index

(RAS) Returned Activated Sludge

(R.T) Reactor Tank

(SANS) South African National Standards

(TOC) Total Organic Carbon

(TP) Treatment Performance

(WSP)Waste stabilisation ponds

CHAPTER 1– INTRODUCTION

1.1. Background

The world is currently dealing with numerous water scarcity issues. Climate change, for example, is likely to have an impact on water availability. It is also reported that water will be available in certain areas, more difficult to find in others and some shall consider wars to access water (Barnaby, 2019).

It is estimated that about one million people die each year worldwide as a result of unsafe water-related diseases, the majority of whom are children under the age of five. This is more prevalent in developing countries where there are resource constraints pertaining to clean water supply (Supply and Programme, 2015). The current global water crisis requires immediate attention because approximately 800 million people do not have access to potable water and a further 2 billion are deprived of proper sanitation (Chan and Lake, 2012).

Apart from water, South Africa has many natural resources that are distributed unevenly throughout the country. The yearly precipitation in South Africa is below the global average and the nation encounters high dissipation rates. Occasional precipitation occurs on a regular basis, resulting in the accumulation of silt, organic and inorganic material in dams and rivers. Many streams and waterways may completely dry up outside of the stormy season, and supplies are vulnerable to significant changes in dam water level (Black, 2016). The high contamination of most water catchment areas around the country might therefore be directly attributed to this cause.

According to Emenike, Tenebe, et a. (2017), the majority of South African waterworks face challenges in providing adequate treatment; additionally, sterilisation may not be completely effective, exposing users to the risk of waterborne illnesses even after treating the water supply. The Eastern area of the Eastern Cape has various hubs where water assets connect with a well-planned network of filtration plants and mass water supply organisations. These consider the arrangement of standard water administrations in contrast to those in the territory's country regions, where the offices responsible for providing water treatment are underdeveloped.

The water industry is currently under increased pressure to produce higher-quality treated water at a lower cost. Water treatment methods that are commonly used include substance pre-treatment, coagulation, flocculation, settling, filtration, and sterilisation.

It is of vital importance that all unwanted substances from raw water are removed thoroughly to produce potable water for human consumption without any concerns that may relate to unfavourable health effects. Water quality poses a significant challenge around the world in terms of ensuring that consumable water meets the specified standards, failing which people may be exposed to various diseases such as diarrhoea, which is linked to the consumption of unsafe water. The number of diarrhoea cases documented in 2000 was 2 billion, with 2,2 million people dying that year (Tsitsifli and Tsoukalas, 2021).

Given the large number of people who are affected by the consumption of unclean and unsafe water, there is a strong need to assess the existing water sectors in order to mitigate this effect and to develop better ways to improve the effectiveness of the practices that are in place to assess the water quality efficiently.

As a result, the study intends to investigate the performance of the Hazelmere wastewater treatment plant by analysing the removal efficiencies of various parameters. The data provided in this study contains only information about iron, turbidity and E. coli. These are the main parameters tested on the inflowing and outflowing from the Hazelmere wastewater treatment plant in this study. When reflecting on the main procedure in the treatment of wastewater, it must be noted that the wastewater is first stored in the dam and thereafter sent to the treatment plant. Therefore, the treated water is stored in the reservoir before being sent to the consumers. The current challenge is to maintain the quality of the purified water provided to consumers. The Hazelmere wastewater treatment facility might be able to answer the same question. To respond, a critical aspect is to question the plant's performance through removal efficiencies.

1.2. Problem Statement

Wastewater treatment aims to eliminate contaminants that, if discharged into the aquatic ecosystem, can harm it (Laohaprapanon, 2013). As a result, the chosen alternative must meet current regulatory standards while also minimising the impact of the natural environment on the water body inlet to ensure full compliance. Additionally, both structural and operational costs need to be kept to a minimum. Particular, energy saving measures such as aeration, pumping, heating and mixing must be examined (Laohaprapanon, 2013). Among other chemicals such as metal salts, an external carbon source and the costs linked with sludge collection and disposal they all need to be considered (Laohaprapanon, 2013).

“Finally, when technical reliability is maximized several additional factors must be considered. Firstly, the plant’s adaptation to different types of perturbations, i.e., good disturbance rejection. Very few wastewater treatment plants (WWTPs) receive a constant influent either in quantity or quality but are subject to daily, weekly and annual variations. Secondly, when the plant has instrumentation, control, and automation, it is important to evaluate the performance of the controller and the degree of adaptability to different perturbations under different design” (Laohaprapanon, 2013).

The Hazelmere wastewater treatment plant has a similar establishment and is designed and optimized using a variety of techniques, such as mechanical, chemical, and aerobic/anaerobic biological treatment processes, to treat residential wastewater. However, the issue is that this treatment system is not intended to handle wastewater that has been heavily contaminated by stubborn substances generated by nearby businesses. Low volumes of highly organic wastewater can significantly impede the biological processes of water treatment facility.

According to Steinvall (2013), it is additionally common for both small and medium-sized wastewater treatment plants to experience a significant decrease in treatment efficiency as a result of industrial wastewater discharges. The same occurrence as was observed by this study. These disturbances had caused significant short-term problems, but more serious problems had occurred in the long run. In the worst-case scenario, pollutants from the Hazelmere wastewater treatment plant could be amplified in the food chain.

Another significant problem with inadequate treatment of industrial wastewater at the Hazelmere wastewater treatment plant is sludge handling, as sludge becomes hazardous as contaminants accumulate (Kiggundu, 2019).Since drinking contaminated water has serious repercussions if not properly addressed, it is urgently necessary to investigate the water sector to see how they ensure and maintain a supply of high-quality water in terms of the practices that are being used, as well as to find better ways to increase their effectiveness.

Additionally, due to the population's rapid growth, trash will be produced, resulting in pollution, which will undoubtedly lead to the development of waterborne diseases. Due to the population's desire for fresh water and the limited supply that is accessible, there is a significant problem with water shortages that have a resounding global impact. In addition to water constraints, pollution caused by population growth is detrimental to environmental degradation.

There is no question that the increased demand for water places additional pressure on wastewater treatment facilities to produce enormous volumes of effluent; nonetheless, the operation of the facility is crucial to providing high-quality water that will fulfill the criteria to prevent waterborne illness.

When treating wastewater, the main objective is to deliver an effluent that is compliant with the discharge standards. In South Africa and specifically in KwaZulu-Natal (KZN) and its surroundings (iLembe and other nearby regions), the inability to achieve this crucial goal is considered bigotry (241-2 2011).

This necessitates the development of a coordinated framework including researchers and plant staff. As much as there is a need for collective effort, the water source and the integrity of the dissemination framework should be considered similarly vital (Sebusang and Basupi, 2021). The main goal can thus be attained by adhering to a reference plan and standard guidelines. Among the various objectives of water treatment are to create water that is appealing to the buyer and arrives at the correct amount and quality (Ahuja, 2019).

As a result, in a country where water is scarce, it has become increasingly critical to ensure the optimal health and operation of our water frameworks. In this regard, the examination centers do not evaluate the water parameters but rather model them, resulting in the development of a predictive scheme that can be used to improve water parameter monitoring. The study is dealing with a large amount of data from 1999 to 2018, with the goal of analyzing and monitoring the performance of the wastewater treatment plant during that time period, as well as predicting the trend of the available parameters for the next three years.

1.3. Research objectives

The general objective of the thesis is to optimize the performance of wastewater treatment at the Hazelmere plant using influent and effluent data from physical, chemical and biological parameters generated between the years 1999-2018.

Specific Objectives:

1. Performance evaluation of iron, turbidity and E-coli for the raw wastewater from 1999 to 2018 in Hazelmere Dam reservoir in Verulam which constitutes the influent.
2. Predict the levels of chosen parameters using R package to estimate their future trends.

1.4. Research questions

The study's research questions are structured as follows:

- What are the annual and monthly averages of given parameters for iron, turbidity and E-coli for the raw wastewater from 1999 to 2018 in Hazelmere dam reservoir in Verulam which constitutes the influent?
- What the annual and monthly averages of given parameters for iron, turbidity and E-coli for the raw wastewater from 1999 to 2018 in the effluent generated by the wastewater treatment plant?
- What rehabilitative measures can be proposed for the wastewater treatment plant with poor water quality?

1.5. Scope of the study

This study focuses on the effectiveness of treatment plant of wastewater and it uses data from 1999 to 2018 generated from the operations of the plant to predict the trends of the chosen parameters. The Hazelmere wastewater treatment plant is chosen as the experimental site, it is situated at Verulam, which is in the North part of the eThekwini municipality in KwaZulu-Natal (KZN) province.

1.6. Thesis outline

This dissertation is structured as follows:

Chapter 1: Introduction

Chapter 1 introduces the study by outlining the research problem. As a result, the background of the research is presented, and the study's aims, objectives, and glossary of terms.

Chapter 2: Literature Review

This chapter outlines the theoretical framework and literature review in which the key concepts are defined and explained. The chapter begins by reviewing domestic wastewater, which is followed by a literature review on the water treatment stages, the impact control and regulations in South Africa and the various unit processes used for domestic wastewater.

Chapter 3: Research Methodology

The research methodology will be discussed in this chapter, along with the techniques used to collect primary and secondary data and conduct analysis.

Chapter 4: Research Findings, Data Analysis and Interpretation

During this study, the data collected was analyzed in this chapter, and research findings were discussed concerning the study's specific objectives. Data was further interpreted from the findings; a conclusion was then reached.

Chapter 5: Recommendations and Conclusion

The investigation is concluded in the last chapter, wich summarises the results and offers recommendations which are influenced by them. Finally, a conclusion to the study is presented in this section.

1.7. Conclusion

This chapter provides an introduction to the topic of the study, and the environment in which the actual study is conducted. The chapter also suggests the problem's history, the study's purpose, its aims, and its research questions. Along with a discussion of the suggested research issues, this chapter also clarified the importance of the study. Therefore, the following chapter examines literature relevant to the research topic, which includes a discussion of public building project performance and the effects of cost and time overruns. The chapter concluded with an examination of the thesis structure.

CHAPTER 2- LITERATURE REVIEW

2.1 Introduction

This chapter presents an analysis of wastewater; water quality parameters and a review of previous work performed to evaluate water parameters. Water quality effects: Physico-chemical and microbiological parameters to measure water quality are discussed. Wastewater treatment is the most common method way of eliminating physical, chemical, and microbiological impurities from any sort of wastewater, derived from domestic or industrial processes to deliver it in a form that is suitable for reuse or disposal.

When contrasted with other developed nations, there is a sizeable gap between untreated wastewater and treated wastewater at the South African level (Cudjoe and Acquah, 2021).

Untreated wastewater and the poor quality of treated wastewater pollute the environment. As a result, there is an urgent need to develop better, more efficient wastewater treatment plants and to work on improving existing wastewater treatment plants. Improving the quality of treated wastewater will save the environment and reduce the risk of water scarcity to a certain extent by reusing this water.

Wastewater treatment entails breaking down complex natural mixtures in wastewater into simpler mixtures that are stable and irritant-free, either physico-synthetically or potentially by utilizing miniature life forms (organic treatment). The following are the negative natural consequences of allowing untreated wastewater to be released into groundwater, surface water bodies, or potentially lands:

1. The disintegration of the natural materials contained in wastewater can prompt the creation of enormous amounts of rank gases.

2 Untreated wastewater (sewage) containing a high concentration of natural matter, when released into a waterway/stream, absorbs disintegrated oxygen to meet the Biochemical Oxygen Demand (Body) of the wastewater, lowering dissolved oxygen for aquatic life and endangering fish lives.

3. Wastewater may likewise contain supplements, which can animate the development of oceanic plants and algal blossoms, consequently prompting eutrophication of the lakes and streams.

4. Untreated wastewater typically contains a variety of pathogenic, or sickness-causing, microorganisms. Furthermore, hazardous mixtures that exist in the human digestive system or may be present in specific wastewater streams. These could contaminate the land or water body where such sewage is disposed of.

2.2 Domestic wastewater

Domestic wastewater incorporates both Blackwater (chiefly faeces and urine) and greywater (predominantly water derived from dishwashing and laundry) (Nourani, Elkiran et al. 2018). A wastewater treatment plant consists of different treatment units, which depend on various treatment levels required, these are; (i) pre-treatment, to eliminate coarse solids, for example, floatables, coarseness and oil; (ii) primary treatment, to eliminate suspended solids and particulate natural matter; (iii) secondary (or organic) treatment, to eliminate biodegradable natural matter (in arrangement or suspension) and suspended solids; lastly (iv) tertiary treatment, to eliminate explicit mixtures, like supplements, microorganisms, and so forth and these are discussed in the subsequent section 2.2.1 to 2.2.4. The whole process flow is depicted in *Figure 2.1*. The main components of domestic wastewater are shown in *Table 2.1*.

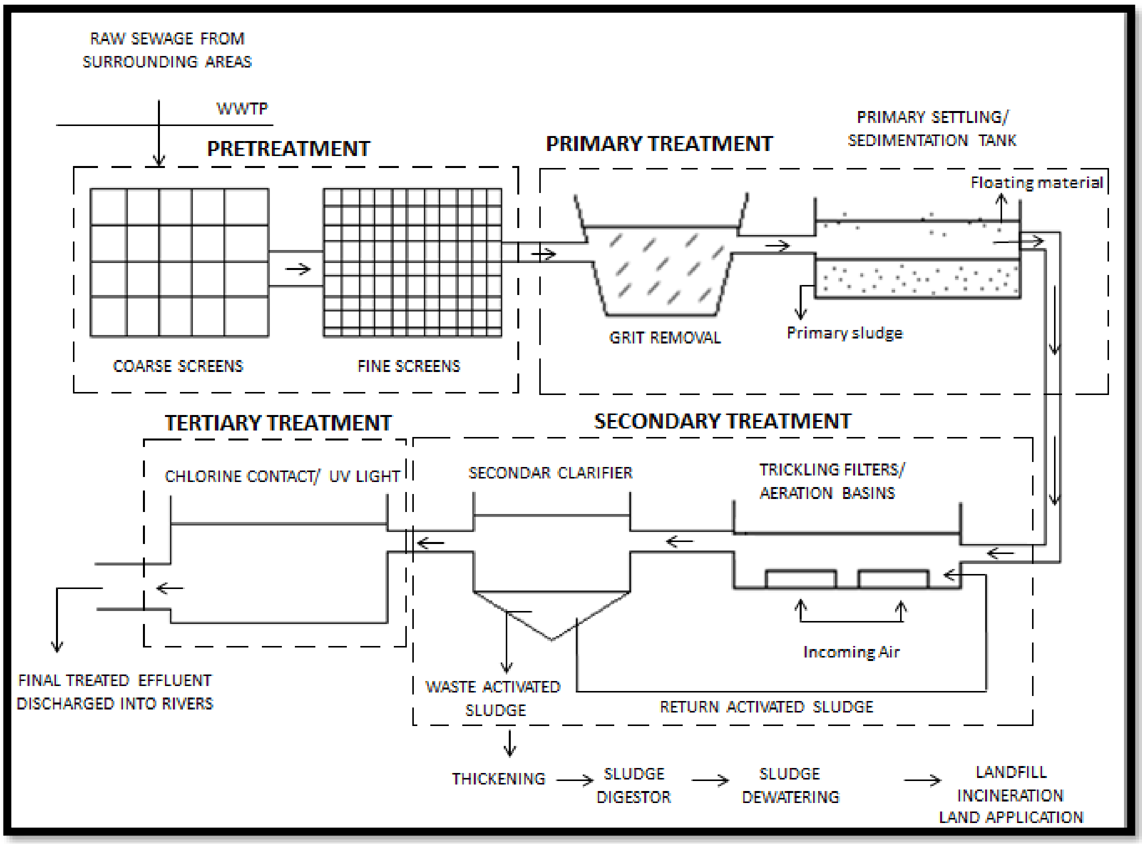

Figure 2.1: Water treatment stages (Herrera Melian, 2020)

2.2.1 Preliminary treatment

As wastewater streams into a treatment plant, it goes through a first stage referred to as the preliminary treatment. The stage is performed to eliminate debris and other objects that are untreatable and could be removed by physical means (Crini et al., 2019). This stage is vital as it enhances the protection of water treatment equipment such as pumps and reduces the clogging of valves. Protection of vital water treatment components and equipment will subsequently result in a significant reduction in plant maintenance costs and will reduce its energy consumption. This first stage utilises screens to eliminate the bigger inorganic materials like debris, paper, clothes, wood, and plastic materials, and clothes. Ozgun et al., (2021) note that the screens utilised in this stage are generally comprised of equal steel and metal bars with openings. In addition, this stage is used to enhance flow control and odour reduction. The retrieved garbage is then gathered and disposed of in landfills. Following screening, grit and sand are eliminated by use of mechanically agitated basins before the effluent can flow to the primary stage (Ozgun et al., 2021).

2.2.2 Primary Treatment stage

As the name proposes, primary treatment is performed to undertake fractional disposal of suspended solids and organic materials from wastewater. This is enhanced by utilising physical means such as screening and sedimentation methods (Ozgun et al., 2021). Primary classifiers are driven mechanically by electric motors to allow for the removal of settleable and floating solid material (Knisely et al., 2020). Oils and greases are also eliminated using the same process. The sedimentation tanks, also known as clarifiers, are shrouded and consistently kept in a vacuum to reduce odour. The odour is caused by gases produced by waste water, the most prominent of which is hydrogen gas. (Sevostianov et al., 2021). Pre-air circulation or mechanical flocculation with the guide of some extraordinary synthetics can be utilised to work with essential treatment.

The primary target of this treatment step is to eliminate the greater portion (50-70%) of the absolute suspended solids in the wastewater (Cyprowski et al., 2018).

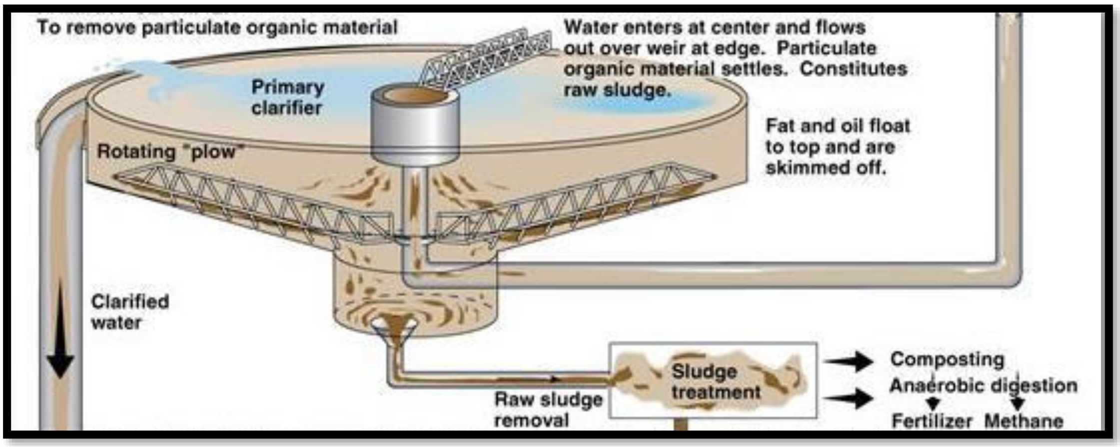

Figure 2.2: Primary sedimentation tank (Jover-Smet et al., 2017).

Primary treatment comprises of a mix of processes that advances biodegradation by microorganisms. This incorporates the usage of sedimentation tanks, trickling filters, lagoons etc. to eliminate suspended solids and floating materials. Two main steps undertaken in primary treatment are pre-air circulation and sedimentation. The water is passed on to stand so the solids can sink to the base and, oil and oil can ascend to the top (Sevostianov et al., 2021). The suspended solids are scratched off the base and the froth (rubbish) of oil and oil is washed off with water jets. Key to successful sedimentation is the retention time allowed which must be adequate to promote the settling and floating of materials (Choong et al., 2018). Optimal retention times range from 1.5 to 2 hours. Higher retention times cause material disintegration whilst lower retention periods ineffective removal of these materials. A primary sedimentation tank is rectangular or circular in shape and more often these are constructed as two separate entities to enable maintained to process without shutting the plant completely as shown in *Figure 2.2*. Significant evacuation of pathogenic organic entities does not form part of the main target of this stage.

2.2.3 Secondary treatment stage

Secondary-stage treatment involves the usage of microorganisms to oxidize and disintegrate particulate biodegradable matter into simplified form, which can be eliminated from the wastewater stream as sludge (Liu and Lipták, 2020). This process can likewise eliminate suspended and non-settleable colloidal solids partially, as they are caught in flocs or biofilm.
Varjani et al. (2020) state that other substances such as nitrogen and phosphorus could likewise be eliminated with solids content or through the process of organic decomposition. The principal objective for this treatment stage is to eliminate promptly biodegradable biological

oxygen demand (BOD) and Chemical oxygen demand (COD) that remains after the primary stage and further elimination of the remaining solid particles (Esteves et al., 2019). Secondary treatment follows biological methods which can be anaerobic or aerobic in nature. Two principal sorts of biological treatment methods utilized are activated sludge and bio-filter methods (Spinelli et al., 2018). The following illustration shows activated sludge in *Figure 2.3* below.

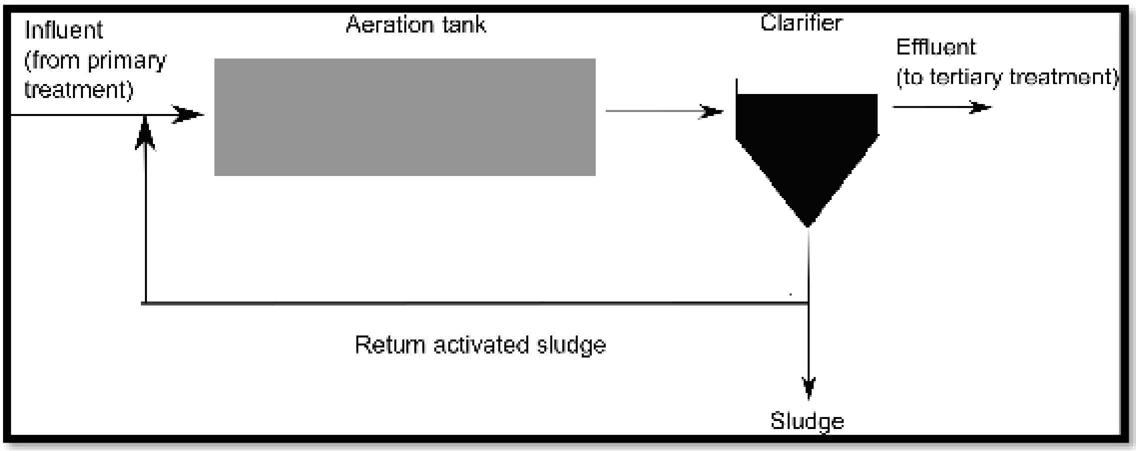

Figure 2.3: Activated Sludge process (Spinelli et al., 2018)

By removing the naturally settled particles as well as any floating components like fats and oils, this procedure enables the separation of the solids and liquids stages in the wastewater. Van Lier et al. (2015) emphasize that at this point, 90% of the wastewater's natural nitrogen, natural phosphorus, and heavy metals associated to solids are removed as they sludge up in the tank.

2.2.4 Tertiary Treatment

Sequentially, a tertiary treatment follows secondary treatment and is aimed at further eliminating those wastewater constituents and pathogenic microorganisms that cannot be eliminated by prior treatment methods (Giannakis et al., 2017). The sludge is the remaining organic matter broken down by the use of bacteria. The sludge is thereafter sent to bacteria-filled oxidation ponds where they carry on to break down the sludge before bacteria is then destroyed by ultra violet (UV) light. The final stage will involve disinfection with chlorine before releasing the harmless product into the environment.

2.2.4.1 Stabilisation

Ponds Waste stabilisation ponds are ideally planned to be 1.5m deep basins with clay walls that are typically placed in a sequence so that wastewater flows from one pond to the next under the control of gravity, improving gradually as it does so. According to Ujang and Henze (2006), the advantages of waste stabilisation ponds, which result from their special combination of physical simplicity and biological complexity, include the following:

- Low cost;
- Simplicity of construction;
- Excellent pathogen removal;
- Ability to treat a variety of wastes;
- Toleration of organic and hydraulic shock loads;
- Low maintenance requirements;
- Low sludge production;
- Reliability of operation and
- Simple land reclamation (Ujang and Henze, 2006).

2.2.4.2 Disinfection

Disinfection is a crucial component of tertiary treatment. Water intended for human consumption should ideally be free of microorganisms, but in reality, this is an unachievable aim (Gray, 1999). The objective of water disinfection is to eliminate pathogenic microbes as a result, pathogenic bacteria, viruses, and amoebic cysts that are frequently detected in wastewater are inactivated or destroyed by disinfecting the effluent of wastewater treatment plants (WEF, 1996; WISA, 2002). Another benefit of disinfection is that it enhances the water's overall microbiological quality in addition to eliminating infections (WRC, 2006). Because biological effluents from domestic wastewater treatment still contain intestinal microorganisms such helminth ova and faecal coliform bacteria like Escherichia coli, they must be cleaned before reuse (Liberti et al., 2000).

Table 2.1: Types and numbers of Microorganisms found in raw domestic sewage (Tchobanoglou et al., 2004)

Organism	**Concentration number ML^{-1}**
Total Coliform	10^5-10^6
Faecal Coliform	10^4-10^5
Faecal streptococci	10^3-10^4
Enterococci	10^2-10^3
Salmonella	10°-10^2
Pseudomonas aeruginosa	10^1-10^2
Clostridium perfringens	10^2-10^3
Mycobacterium tuberculoses	Present
Protozoan cysts	10^1-10^3
Giardia cysts	10^1-10^2
Cryptosporidium cysts	10^{-1}-10^1
Helminth ova	10^{-2}-10^1
Enteric virus	10^1-10^2

Microorganisms that are more plentiful and simple to test for are frequently utilized as substitute organisms for the pathogens' intended targets since the pathogens present in waste and polluted waters are typically limited in number and challenging to isolate and detect (Belmont et al., 2004). Escherichia coli means there is faecal contamination since it is present. Escherichia coli is enteric bacteria that can be used to determine the sanitary condition of water and wastewater due to its prevalence. A limit of 1000 faecal coliform units has been set by the World Health Organization FCU/100 mℓ for Category “A” water quality (Liberti et al., 2000).

2.2.5 Various unit processes used for domestic wastewater

Water is vital in our daily lives because it is used for a variety of purposes. It is therefore critical that it be thoroughly treated to ensure that it is safe for consumption, free of pathogens, and meets national standards. The treatment process may slightly differ depending on the type of water that requires treatment and the treatment plant operation, however, the basic principles are predominantly the same (Liberti et al., 2000).

- **Screening**

The screening process is performed to eliminate material which is not desired to enter the treatment process (Lares et al., 2018). These materials include large solid materials which are easily trapped by screens. Screens are tilted at an angle ranging from 30 to 45 degrees and spaced apart between 50 and 150 mm and they can be round or rectangular in shape. The influent sewage water goes through a bar screen to eliminate all huge particles like clothes, sticks, plastic bundles and so on conveyed in the sewage stream (Koopman and Bitton, 2019). Fine screens are situated after the coarse screens to eliminate the smaller solids like clothes and paper. Substances normally eliminated incorporate wood, cardboard, clothes, plastic, coarseness, oil and rubbish (Michielssen et al., 2016). If gross solids are not removed, they become entrained in pipes and moving parts of the treatment plant, causing significant damage and plant failure. The waste is washed, squeezed, and disposed of in a landfill. The screened wastewater is then pumped to the next stage for grit removal.

The main parameter considered in the selection of the screening method is based on screen opening size and the flow rate required (Qasim, 2017). Other contributing factors influential to the screening process section are cost and debris requirements (Qasim, 2017).

- **Clarification and flocculation**

Hubbe et al. (2016) state that the principal treatment process for physically eliminating suspended solids and debris is generally termed coagulation and flocculation. This process revolves around three stages staring with rapid mixing followed by coagulation of particles then finally flocculation. Coagulation and flocculation occur simultaneously hence they are described as a unit process (Santos et al., 2015). Ferric and aluminium salts are added to wastewater as coagulation agents. This process results in improved sludge settling and the elimination of biological contaminants. However, this process is costly due to high chemical demands and the disposal of sludge.

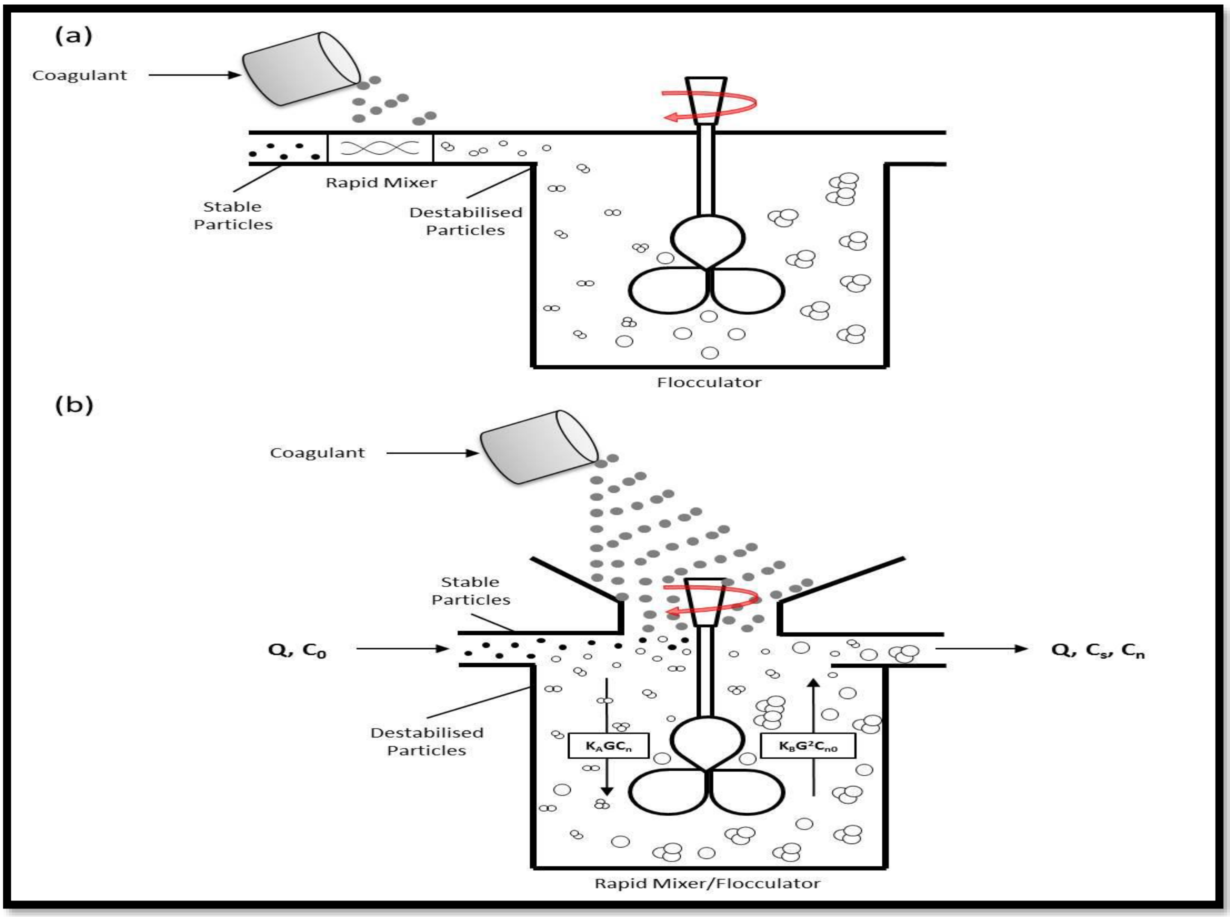

Figure 2.4: Coagulation and Flocculation process (Awang et al., 2015)

- **Filtration**

Filtration is the most common way of eliminating solids from a liquid by passing through a permeable medium. According to Hube et al. (2020), coarse, medium, and fine permeable media are utilised depending on the filtration level required. The medium for filtration are man-made membranes which can be nets, sand channels, or highly advanced filters (Wang et al., 2018). Filtration speed and cleanliness are key to portions of filtration method selection. The stream needed for filtration can be accomplished by utilising gravity or a pressure drop. In pressure filtration, one side of the channel medium is located at higher pressure whilst the other one is at lower pressure allowing the pressure drop to enhance the filtration process. Filtration membranes can be grouped into reverse osmosis, ultrafiltration, Nano hybrid membrane and Nano filtration and electro dialysis (Magni, et al., 2019).

Ultra-filtration membranes are minute membranes ranging from 10 to 100 nm that are utilised to eliminate colour, bacteria, and organic colloids. This process is preferred due to its lower energy consumption profiles. However, this process can not eliminate meta ions and heavy metal removal is not effective. Vinardell et al. (2020) confirm that reverse osmosis is most prevalent in global wastewater treatment plants. This process removes heavy metals and metal ions using hydrostatic pressure. However, reverse osmosis consumes a lot of electrical energy. In electro-dialysis an electrically driven membrane is used to eliminate heavy metals from wastewater. This process is also garnering attention since is uses fewer chemicals and results in high water recoveries. Nano filtration can eliminate pollutants below 10 nm in size. Nano filtration is used for heavy metal removal.

When a semi-permeable media is used to separate a concentrated solution from a dilute solution, particles will drift from higher to lower concentrations. This phenomenon is called osmosis (Wenten, 2016). By applying pressure in higher concentration, water molecules will move to the lower concentration region, a process called reverse osmosis. The medium in such a system must prevent the passage of solute particles.

2.2.6 Domestic wastewater quality parameters

Physical, chemical, and biological characteristics of water make up water quality parameters, which can be examined or monitored depending on particular water parameters of concern. As such, water quality parameters mostly rely on the use of water. It must be mentioned that parameters that have to do with monitoring matrices for drinking water and wastewater are notably different from one another (Magombo, 2017). Three kinds of water quality parameters can be categorised into; Physico-chemical basic parameters and nutrients, micro pollutants including metals, pesticides and pharmaceuticals, and

biological parameters with pathogens microorganisms and these include E. coli Listeria, Listeriosis, Salmonella, etc (Mentzafou et al., 2019).

Table 2.2: Selected wastewater parameters and their significance on plant design and performance (Mentzafou et al., 2019)

CHARACTERISTICS	**SIGNIFICANCE**
Temperature	To design the most suitable biological processes
Ammonia (NH_4^-) Organic nitrogen (org N) Nitrites (NO_2^-) and Nitrates (NO_3^-) Total Nitrogen (TN) Total Phosphorus (TP)	A measure of the nutrients and degree of decomposition of a wastewater
pH	A measure of the acidity or basicity of a wastewater
Biological oxygen demand (BOD) Chemical oxygen demand (COD) Total organic carbon (TOC)	Different parameters to measure the organic content of a wastewater

2.2.6.1 Escherichia coli

Escherichia coli (E. coli) has been utilised as the best bacterial indicator of faecal contamination in water and as the most precise marker of faecal coliforms (Guchi, 2015). E. coli is a member of waste coliform group and typically considered to be the most important bacterium in water monitoring projects because it serves as crucial indicator of water pollution. There may be health hazards brought on by E. coli contamination of drinking water. Therefore, pathogens which cause diseases such as diarrhoea, cholera, typhoid etc are directly linked to the occurrence of even small traces of E. coli in drinking water (Guchi, 2015).

2.2.6.2 Iron

Water naturally contains iron metal. Nevertheless, extra iron in water might result from the water treatment process since it is used as a coagulantt. Other sources of iron can be sewage, mineral processing, and the burning of coal (Silva et al., 2016). Excessive disposal of iron impacts aquatic life. Iron can be found in substantial quantities in soils and rocks, mostly in insoluble forms. Magombo (2017) states that both manganese and iron are present in most portable water supplies and are the primary causes of metallic taste and staining.

Water primarily contains two types of iron: insoluble ferric and soluble ferrous irons (Singh and Sharma, 2019). According to Marsidi et al. (2018) ferric iron deposits inside corroded pipes can escape and give rise to rusty tap water. Iron is completely dissolved in the water, making ferrous iron transparent and colorless. Marsidi et al. (2018) state that iron is innocuous element that is not harmful and is present in both public and private water supplies. However, excessive concentration of dissolved iron can cause bad, unpleasant water that stains both garments and plumbing fixtures (Marsidi et al., 2018).

Iron does not pose a health threat, however, it is viewed as a secondary contamination. At the concentration normally found in drinking water, provide a health benefit that can help the human body to transport oxygen in the blood (Marsidi et al., 2018). The Environment Protection Agency (EPA) standards on portable water consider both primary and secondary regulations. The primary standard mainly focuses on health concerns to protect people from pollutants. Whereas the secondary standards are mainly concerned with aesthetic issues, such as taste, odour, colour and corrosiveness. Iron is controlled under the secondary maximum contaminant level (SMCL) standard. The SMCL level of 0.3 mg/L is regarded as safe for drinking. There are two limits for iron in South African National Standard (SANS) for drinking water. Whereby the first is for health, and the second is for appearance. The allowable aesthetic limit for Iron is$\leq$ 0.3 mg/l and for health is$\leq$ 2mg/.

2.2.6.3 Turbidity

Turbidity is estimated by utilizing the turbid meter on a chemical substance. Then, the photometers called turbid meters measures the intensity of the dispersed light. Opaque particles disperse light, so dissipated light estimated at a right angle to a light emission light is corresponding to turbidity. Currently, formazing polymer is used as the primary measurement standard for calibrating turbid meters, and the outcomes are called Nephelometric Turbidity Units (NTU).

2.2.6.4 ***Chemical Oxygen Demand COD***

Chemical oxygen demand (COD) is a term used to illustrate the organic strength of wastewater and contamination of natural waters in waste water examination (Dai et al., 2020). COD estimates the amount of natural matter in a wastewater that can be chemically oxidized by using an oxidant. Commonly used in wastewater is Dichromate, this is due to its high oxidising capability. Bekkari and Zeddouri (2019), state that the chemical breakdown of organic and inorganic substances either broken down or suspended in a wastewater sample is what the COD test technique relies on.

The results of a COD test show how much the measure of dissolved oxygen was used up during the chemical breakdown of organic waste within and inorganic matter within specified time such as two hours. The more the COD means that the measure of impurities or toxins in the sample will increase. Therefore, we can say the COD is directly linked to the contamination level in a wastewater sample. As a result, COD is generally measures in milligrams per litre of the water (Bekkari and Zeddouri, 2019).

Chemical Oxygen Demand (COD) gives the proportion of the oxygen needed for the oxidation process. Largely, the COD of raw sewage at various locations is often estimated to be between 200 to 700 mg/L. In the COD test, the oxidation of organic matter takes two hours to complete while the biochemical oxidation of natural matter needs half a month.

2.2.6.5 Biochemical Oxygen Demand BOD

The Biochemical Oxygen Demand (BOD) of the amount of oxygen present in the sewage is required for the biochemical deterioration under aerobic circumstances, of organic material that is biodegradable (Baki et al., 2019). The oxygen burned through in the process is determined by the amount of decomposable organic matter in the process. According to Baki and Egemen (2018), the overall scope of BOD noticed for raw sewage is 100 to 400 mg/L. Qualities in the lower range are normal in regular South African urban areas.

Therefore, water that is turbid is not clear rather "filthy", meaning that it has a limited ability to transmit light. Turbidity can be caused by a wide range of materials that involve mud and other minute inorganic particles, algae, and organic matter.

2.2.6.6 Acidity levels (pH)

According to Daigavane and Gaikwad (2017), the pH of any solution is an examination of the hydrogen (H+) particles present. Afsharnia et al. (2018) state that the hydrogen particle concentration reported as pH, is a crucial indicator of how well the organic units are performing. The pH of raw sewage is a little greater than the water supplied to the local area. Nevertheless, the deterioration of organic matter may reduce the acidity levels, while the presence of industrial wastewater might deliver fluctuations (De Belen and Cruz, 2017). Mostly the pH of crude sewage lies between 5.5 and 8.0.

Table 2.2: Main components of wastewater Crini et al. (2019)

Contaminant	**Significance**	**Origin**
Settleable solids (Sand, grit)	Settleable solids may cause anaerobic conditions and sludge deposits in sewers, treatment facilities or open water	Domestic, run-off
Organic matter (BOD); Kjeldahl-nitrogen	Surface water's oxygen balance is depleted by biological decomposition; if this happens under anaerobic conditions, odor creation, fish skills, and ecological imbalance will result.	Domestic industrial
Pathogenic microorganisms	significant dangers to the public health from the spread of cholera and other water-borne diseases	Domestic
Nutrients (N and P)	High records of nitrogen and phosphorus in surface water will create extreme algal growth that lead to eutrophication. Dying algae contribute to organic matter	Domestic, rural run-off, industrial
Micro-pollutants (heavy metals, organic compounds)	Non-biodegradable compounds may be toxic, carcinogenic or mutagenic at very low concentrations. Some may bio accumulate in	Industrial, rural run-off (pesticides)

	food chains e.g chromium (VI), cadmium, lead etc.	
Total dissolved solids (salts)	High amounts may be difficult wastewater use for agricultural irrigation or aquaculture	Industrial, (salt water intrusion)

2.3 Impact control and regulations in South Africa

Various laws limit the environmental effects caused by the dumping of municipal wastewater effluent. Despite having its own laws, South Africa does not operate in isolation. Punishment for breaking these laws could include imprisonment. The following are some of the laws that must be paid in order to manage the negative environmental effects of municipal wastewater effluent disposal:

2.3.1 National Environmental Management Act 107 of 1998 (NEMA)

NEMA Act no. 107 of 1998 emphasizes the need to prevent ecosystems disruption and diversity loss. This is relevant to the discharge of wastewater into river systems, which may lead to a change in the quality of the water and the extinction of aquatic life owing to a high concentration of such toxins. The Act also emphasizes the necessity of monitoring the effluent standards and quality of household wastewater discharges on a monthly basis. Anyone who violates Schedule 3 of the NEMA Act regarding a threatened species is subject to a fine that may be up to three times the species' value. Therefore, the discharging partially treated effluents that could harm aquatic life is also included in this.

2.3.2 National Water Act (NWA Act no 36 of 1998)

For the management, protection, use, development, conservation, and control of water resources, the act offers a comprehensive legislative framework. The act's provisions must be followed, and its guidelines for handling waste effluent disposal and other matters are intended to safeguard and manage water resources. According to the Department of Water Affairs' (DWA) guidelines, water extracted for industrial use must be returned to the water source from whence it was taken. The National Water Act mandates that the wastewater effluents discharged into South Africa's river systems adhere to approved standards (see Table 2.4

below) in order to prevent ecological issues with the river systems. Similar to the NEMA Act, section 151 (2) of the National Water Act no. 36 of 1998 stipulates that anyone who violates this act is subject to a fine or imprisonment for up to five years, as well as the possibility of being responsible for the costs associated with remediation. Table 2.4: DWA aquatic environment recommendations, volume 7 (DWA waste discharge standard values applicable to discharge wastewater into the water resource).

Table 2.3: DWA waste discharge standard values

Variables and substances	**Existing SA general standards**	**Existing SA future standards**	**DWA aquatic ecosystem standards**
Chemical oxygen demand mg/l	75	65	NA
Ammonia (as N) mg/l	3	1	0.007
Nitrate (as N) mg/l	15	15	0 – 6
pH	Between 5.5 and 9.5	Between 5.5 and 7.5	6 – 9
Chlorine (as Cl) mg/l)	0.25	0.014	0.0002
Suspended solids mg/l	25	18	NA
Faecal coliforms per 100 ml	1000	1000	NA
Sulphates mg/l	NA	NA	NA
Electrical conductivity mS/m	NA	NA	NA
Sodium mg/l	NA	NA	NA
Magnesium mg/l	NA	NA	0.18
Manganese mg/l	NA	NA	NA
Iron mg/l	0.3	0.3	NA

***** *NA means the standard is not yet set*

2.4 **Performance Assessment of Wastewater Treatment Plants**

In many nations, notably the European Union, municipal water services, including wastewater management, are legally monopolized. Due to this, utilities must be able to demonstrate that their company is run successfully and efficiently (Matos et al., 2003). Utilizing performance indicators to evaluate strategic planning and management is one of the standard methods. A firm is assessed using performance indicators, a monitoring technique, which uses past data to create key indicators that are tracked over time (Matos et al., 2003). The data is often averaged to annual or monthly values, and the strategy is appropriate for utility-level strategic planning and monitoring. For assessing treatment effectiveness, energy efficiency, and costs, performance indicators are helpful. Key performance indicators (KPIs) are frequently used for company comparisons. Even while it is possible to delve deeply into the operations and engage in process benchmarking, this is a tool for steady-state monitoring of previous results with limited information regarding the treatment process itself.

A common method for evaluating a product or service's environmental impact is life cycle analysis (LCA). In LCA, the full life cycle of the process and its associated activities are assessed for their global environmental effects. Production of input commodities and waste treatment are valued related activities. LCA has previously been used to analyze wastewater treatment facilities (Corominas et al., 2013). Typically, annual averages and default values from common databases are the data sources for LCA. This shows the impact on the environment globally and is helpful for benchmarking and comparisons. It is also possible to use LCA in scenario planning. LCA, however, offers few insights into the specifics of the process and the conditions involved and neglects to address other relevant topics, such costs. Mass and energy balances provide more thorough insights for evaluating treatment processes in greater detail (Barker and Dold, 1995).

These computations can be used to assess the effectiveness of various unit processes. This is a desirable method since it uses explicit equations to determine things like fluxes, concentrations, and tank volumes. Similar steady-state analyses of factors like expenses can also be performed using this type of spreadsheet calculation. Calculations employing such straightforward steady-state models are beneficial for a variety of applications, including the planning of future operations and reconstruction as well as historical evaluation (Ekama, 2009). A simulation employing mechanistic process models is now the most thorough and effective method available to assess wastewater treatment procedures (Daigger, 2011). Unparalleled insights into the mechanics of the plant are provided by the intricate mathematical representations of the unit processes in the models. Process models permit simulations in both steady-state and dynamic modes, the latter of which captures dynamic variables such as variations in load and temperature as well as seasonal influences. Further, evaluations of therapy effectiveness are not the sole option.

2.5 The average concentrations of the main wastewater quality parameters in South Africa

Watersheds that receive waste water may experience significant changes. The harmful effects could be immediate or accumulative. Acute effects from wastewater effluents are typically caused by hazardous quantities of heavy metals and organic pollutants, large loads of oxygen-demanding compounds, high levels of ammonia and chlorine, or any combination of these. Cumulative impacts are due to the gradual buildup of pollutants in receiving surface water, which only becomes apparent when a certain threshold is exceeded. Acute effects from wastewater effluents are typically caused by hazardous quantities of heavy metals and organic pollutants, high levels of ammonia and chlorine, high loads of oxygen-demanding compounds, or any of these factors. Their reproductive cycle, growth, and life might be affected or jeopardized by rapid changes within specific ranges. Discharged effluents from wastewater treatment facilities often increase the oxygen demand level of the receiving water because of the organic load of wastewater. When surface water is exposed to improperly treated wastewater, dissolved oxygen (DO) levels in the water decrease.

The levels of DO in the effluent of various wastewater treatment plants in South Africa, according to earlier studies, are typically lower than the necessary limit of 8–10 mg/L. DO concentrations below 5 mg/L would be harmful to the aquatic ecology. According to Morrison et al. (2019), the aquatic ecosystems oxygen balance significantly determines how poorly treated wastewater affects surface water, and its existence is crucial for maintaining biological life in the system. Osuolale and Okoh (2015) and Agoro et al. (2018) showed that, between September 2012 and August 2013, the DO concentration in two WWTPs in the South African Eastern Cape province ranged from 3.9 to 9.6 mg/L and 6.9 to 9.4 mg/L, respectively.

Except for December 2012 (9.6 mg/L), the levels of DO detected in one of the WWTPs were often lower than the amounts of 8–10 mg/L, which are typical of unpolluted water. In their examination of the effects of insufficiently treated effluents from four wastewater treatment facilities in Buffalo City and Nkonkobe Municipality of the Eastern Cape Province of South Africa, Momba et al. (2020) noted DO values in the range of 3.26-4.57 mg/L. Aquatic creatures in the water resource can be harmed by concentrations lower than 5 mg/L. According to Igbinosa and Okoh (2009), DO concentrations varied from 4.15 to 6.26 mg/L in the autumn to 4.85 to 11.22 mg/L in the winter and 4.96 to 6.69 mg/L in the spring. This demonstrates that seasonal fluctuations have a big impact on surface water DO levels.

The low amounts of DO seen as compared to surface water sources are caused by the presence of degradable organics in wastewater. Low DO levels can cause some fish species to malfunction and ultimately cause fish mortality. The amount of organic contamination in water and wastewater is often estimated by BOD and COD. They are crucial indicators of wastewater quality since most wastewater treatment plants utilize them to gauge their effectiveness. To support aquatic life, surface water should have low BOD/COD concentrations. Fish in particular may be harmed by high BOD and COD levels. When BOD and COD levels are low in river systems, the water quality is good; when they are high, the water is contaminated. The BOD/COD ratios and DO concentrations are inversely correlated. When big biodegradable organics which most wastewater contains are present in the water, DO is consumed by bacteria. When this occurs, the DO level falls below a critical level, which has an adverse effect on life since it prevents them from continuing their typical life-sustaining processes including development and reproduction. Fish and other aquatic species are impacted by this decline. *Table 2.5* lists the COD levels that have been recorded for the effluent of several WWTFs in South Africa.

Table 2.4: COD levels of the effluent from wastewater treatment facilities in South Africa

WWTF's location	**COD (mg/L)**
Eastern Cape Province I	4.6–211
Eastern Cape Province II	10.33–88.33
Alice WWTP, Eastern Cape Province III	7.5–248.5
Thohoyandou WWTP, Limpopo Province	50–105
Siloam WSPs, Limpopo Province	82–200

The recommended limit for COD in wastewater in South Africa is 75 mg/L, although most of the sample months at the WWTFs showed that this amount had been surpassed (Iloms, 2020). According to Table 2.5 above, wastewater effluent is a significant source of organic pollution in South Africa's surface waters. Eutrophication can result from the introduction of nutrients like phosphate, nitrates, and nitrites into water bodies. In general, nitrogen-containing compounds are prevalent in many wastewater streams, and if they are not properly treated, they may enter the receiving watershed and cause a variety of problems. When nutrient-rich wastewater effluents are released onto water courses, eutrophication may occur. This can result in an algal overgrowth and plant developmen in the aquatic ecosystem. This results in an increase in water turbidity, an increase in plant and animal biomass, an increase in sedimentation rate, and a decrease in species diversity. Additionally, this implies that anoxic conditions may arise, which could result in modifications to dominant species of the aquatic biota. Several publications have identified nitrate nitrogen and phosphorus concentrations in South African wastewater effluents that can cause eutrophication.

2.6 Reviews of previous work on the topic “wastewater treatment plant performance’’

Ibrahim and El Sayed (2019) performed an investigation to assess the effectiveness of pollutant removal at the Suez Bay wastewater treatment plant (SWTP) at the Ataqa to meet Egyptian Legal 1994 requirements. Pro-fluent water and sewage muck from this plant is proposed for horticultural utilization. Eighteen (18) samples were collected in 2018. The main findings in this study revealed that removal efficiency of TSS, turbidity, NH3, COD, BOD, oil and grease, were found to be 87%, 67%, 93%, 89%, 92% respectively, separately. The study proposed further investigation on heavy metals to ascertain if the treated water qualified for reuse.

Al-Shandah (2021), carried out a performance analysis on four WWT plants in Jordan. Total dissolved solids, biological oxygen, chemical oxygen demand, and total dissolved solids were all analyzed and compared to the country's national standard norms by the researcher. The results showed that the TSS of the WTTP was higher on average than the country's national standards of 60 mg/L. BOD levels were also found to be higher than the national average of 150 mg/L. The researcher used his findings to recommend that the plant's sludge be avoided for agricultural use.

Nethravathi (2018), performed an efficiency evaluation of a WTTP at the Anjana treatment plant in Hong Kong. The parameters that were analyzed by the researcher were TDS, COD, and BOD. Samples of treated and untreated wastewater were collected two days per week for one month. Samples were collected on Thursdays and Mondays weekly for both the summer and winter seasons. The removal efficiency was evaluated and compared with the country's standard norms. An analysis of the results showed that removal efficiency for BOD and TSS were 94 and 93 % respectively in winter. BOD and TSS were found to be 93 and 87 % respectively in summer. When these values were evaluated against the country's national standards it was found that the plant was operating efficiently.

Kibambe, Momba et al. (2020) compared removal efficiencies of three (WWTP) with respect to perfluoroalkyl substances. Collected samples from three sites were analysed using solid phase extraction followed by liquid chromatography-tandem mass spectrometry. From the analysis of the results it was revealed that all three WWTP were unable to remove all perfluoroalkyl substances. This revealed that the removal efficiencies of seven perfluoroalkyl substances varied from plant to plant.

Bhave, Naik et al. (2020) evaluated the treatment efficiency of a plant that utilised bioreactors. Wastewater samples were collected for a period of 17 weeks. analysed parameters were COD, BOD and TSS. From the analysis of the result, it was revealed that a was a reduction in treatment efficiency from the plant.

2.7 Summary

This chapter reviewed the literature on water treatment quality. It looked at the various steps involved in water treatment as well as the overall treatment process. It also examined the various water quality parameters in order to gain a thorough understanding of them. Finally, it examines how South African laws and legislation affect water quality. The chapter also assessed research on the physical aspects of water quality.

CHAPTER 3- METHODOLOGICAL APPROACH

3.1. Introduction

This chapter focuses on the methodology that will be used to evaluate the performance of the wastewater treatment plant based on the removal efficiencies of parameters such as iron, turbidity, and E. coli.
Among the methods are data collection from Hazelmere Dam, data sorting, data analysis, and modeling future trends for monitoring water quality using the R programming language.

The R program is a statistical computing and graphics language and environment that will be used to analyze the variance in water quality between South African national standards and WHO guideline values. The researcher will also assess the concentration of each of the three parameters in the input and output to determine the efficacy of the Hazelmere water treatment plant in effectively removing each parameter from the water.

3.2. Autoregressive Integrated Moving Average (ARIMA) model

An autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model in statistics and econometrics, and is particularly useful for time series analysis. Both of these models are used to time series data in order to forecast future points in the series or to better comprehend the data. When data demonstrate evidence of mean non-stationarity (but not variance or auto covariance), ARIMA models may be used. In these situations, an initial differencing step (corresponding to the "integrated" part of the model) may be applied once or more times to eliminate the non-stationarity of the mean function (i.e., the trend). When a time series exhibits seasonality, seasonal differencing may be used to remove the seasonal component.

We are motivated to transform a stationary time series into a non-stationary time series, for example by using differencing, before we can use the ARIMA model because, according to the world's decomposition theorem, the ARIMA model is theoretically sufficient to describe a regular (also known as purely nondeterministic) wide-sense stationary time series. Note that under the ARIMA framework, the predictable component is handled as a non-zero-mean but periodic (i.e., seasonal) component so that it is eliminated by the seasonal differencing if the time series contains a predictable sub-process (also known as pure sine or complex-valued exponential process) (Hausler-Cozma et al., 2019).

The evolving variable of interest is regressed on its own lagged (i.e., prior) values, according to the AR component of ARIMA. The MA component shows that the regression error is actually a linear combination of error terms with values that happened simultaneously and at different points in the past in the past. The I (for "integrated") denotes that the differences between the new values and the old values have taken the place of the data values. Each of these qualities serves to maximize the model's ability to match the data. Non-seasonal ARIMA models are Non-seasonal ARIMA models are typically referred to as ARIMA "p,d,q" models, where "p" denotes the order of the autoregressive model (the number of time lags), "d" denotes the degree of differencing (the number of times the past values have been subtracted from the data), and "q" denotes the order of the moving-average model. The standard notation for seasonal ARIMA models is ARIMA "p,d,q" "P, D, Q" "m," where "m" stands for the number of periods in each season and the capital "P, D, Q" letters stand for the moving average, autoregressive, and differencing terms for the seasonal portion of the ARIMA model (Hausler-Cozma et al., 2019).

Unit Root Tests

Numerous financial and economic time series display non-stationarity in the mean or trending behavior. Leading instances include asset prices, currency exchange rates, and macroeconomic variables like real GDP levels. Choosing the most appropriate form of the data's trend is a crucial econometric assignment. For instance, before analysis in the ARMA modeling described above, the data must be changed to stationary form. If the data are trending, trend removal of some sort is necessary.

First differencing and time-trend regression are two methods for trend removal or de-trending. For *I (1)* time series, first differencing is appropriate, and for trend stationary *I (0)* time series, time-trend regression is appropriate. When deciding whether to first difference or regress trending data on deterministic functions of time in order to make the data stable, unit root tests can be utilized. Furthermore, non-stationary time series variables may have long-run equilibrium relationships, according to economic and financial theory. Cointegration methods can be utilized to represent these long-run relations if these variables are I (1).

Consider the stylized trend-cycle decomposition of a time series yt to comprehend the econometric concerns with unit root and stationarity tests:

2 yt = TDt + zt

3 T Dt = κ + δt

4 zt = φzt−1 + εt, εt∼WN(0, σ2)

Where TDt is a deterministic linear trend and zt is an AR(1) process. If |φ| < 1 then yt is I(0) about the deterministic trend TDt. If φ = 1, then zt = zt−1 + εt = z0 + Pt j=1 εj , a stochastic trend and yt is I(1) with drift. Simulated *I*(1) and I(0) data with κ = 5 and δ = 0.1. The *I*(0) data with trend follows the trend TDt = 5+0.

1t extremely carefully and demonstrates trend reversion. The I(1) data, however, drifts upward but does not always return to TDt. Testing the null hypothesis that = 1 (difference stationary) against the alternative hypothesis that 1 (trend stationary) is the foundation of autoregressive unit root tests. Because the null hypothesis states that the autoregressive polynomial of zt, (z) = (1 z) = 0, has a root equal to unity, they are known as unit root tests.

3.3. Methodology

As previously stated, removal efficiencies of various parameters. The information provided for research is limited to iron, turbidity, and E. coli.

To reach the study's objectives the methodological approach to be used involves the detailed analyses of removal efficiencies of given parameters which are iron, turbidity and e-coli. This will be done on the raw water and the effluent between 1999 to 2018 from the Hazelmere wastewater treatment plant. To achieve this, the following approach can be undertaken:

1. Assessing the variation of turbidity from inlet to outlet.
2. Assessing the variation, Iron (Fe) from inlet to outlet.
3. Assessing the variation of E. coli from inlet to outlet.
4. Estimating the future trend of these parameters.

The following chart summarises the steps used for the methodological approach.

3.3.1. Sample collection

Water samples were taken in previous years in duplicate monthly from each point to accommodate seasonal representatives. Prior to sampling, the sample bottles were washed thoroughly with de-ionized water and thereafter thoroughly rinsed with water on site before use. Samples were collected by inserting the cleaned 1-litre plastic bottles into the water at a point that was reflective of the river's flow regime until the bottle was filled with the sample. Immediately after each sample was taken, the sample bottles were capped and sealed. Due to dense riparian vegetation, the collection of samples had to be conducted off the bridge at these respective sites. These samples were collected by lowering a bucket into the water from the bridge, suspended by a rope, thereafter the water sample so retrieved would then be placed into one of the sample bottles which were pre-washed with de-ionized water and rinsed as previously indicated. The samples collected from the site under study were appropriately handled to ensure integrity and were appropriately labelled. Each bottle was tagged to record its location; date and time of sampling and unique site name. Thereafter samples were carefully packed and transported, in a cooler box to prevent possible physical, chemical or biological changes to the samples, to the laboratory for analyses.

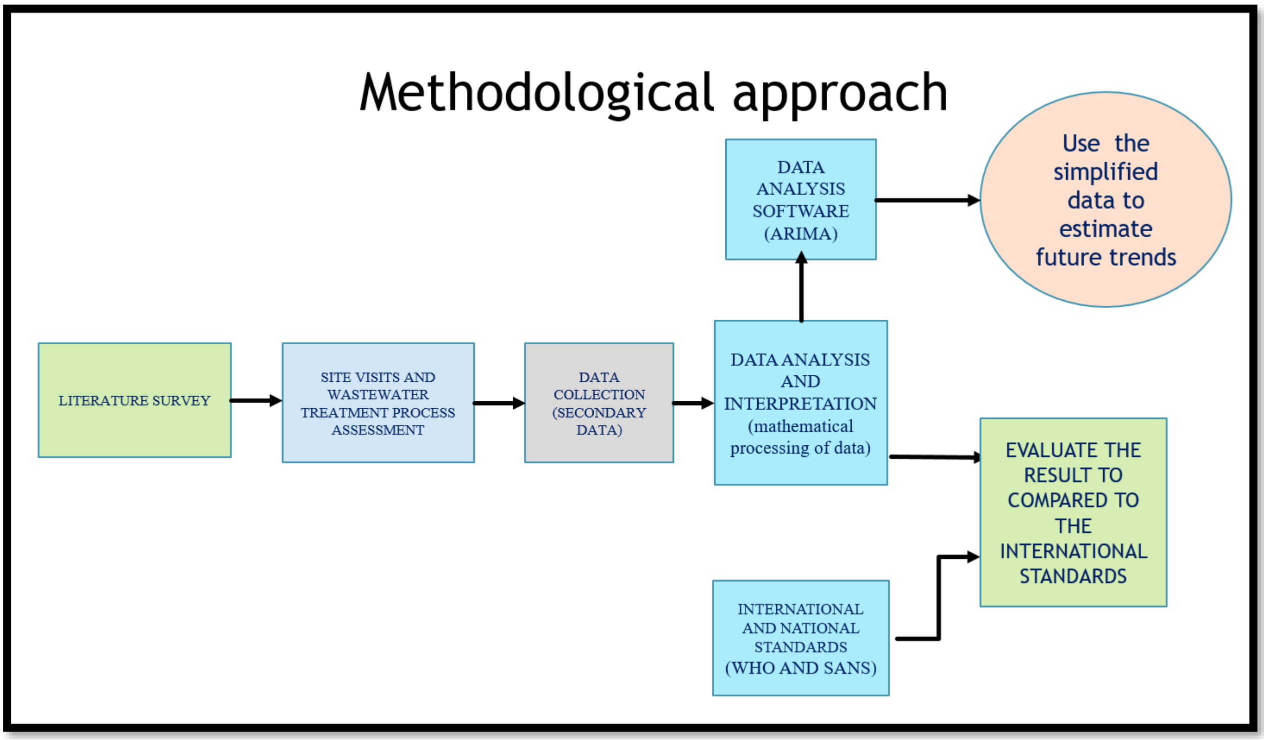

Figure 3.1: Methodological approach chart

3.3.2. Data collection

The raw water data was acquired from the Hazelmere wastewater treatment plant data records for the period from 1999 to 2018.

3.3.3. Data analysis

All the analyses were done using Microsoft excel. This analysis used minimum and maximum averages. Furthermore, removal efficiencies for each parameter were calculated for the chosen parameters, diagrams were plotted for a detailed analysis of the patterns or trends for each parameter. This was done to have more information that will support the forecasting or prediction of the chosen parameters beyond 2018 using R studio programming.

3.3.4. Forecasting of parameters beyond 2018

R programming is a computer language utilized in arithmetic computing and diagrams. The programme is normally used when analyzing data. There is not much difference when comparing it to Matrix laboratory (MATLAB) or Automatic Programming Language (APL) programs since it also makes use of vectors, arrays and data frames. Lemenkova (2019), mentions that R features are attained from the programme, with S-expression showing both data and code. Furthermore, S-expression is the core base for the programme. According to Hafner (2019), both S and R functions are essential for calculations. However, Hausler-Cozma et al. (2019) state that R and S differ significantly when it comes to their ability to sustain information within a function. Both R and S offer a succeeding assignment operator. This type of result takes place in R once the search has taken place, beginning with the parent environment and being diagonal up between the parent environments up until the universal environment is gained.

3.4. Study Area and source of influent water

Hazelmere dam is situated in uMgeni River in the North part of Kwa-Zulu Natal province in South Africa. The dam has a catchment area of 376 km^2, 44 m in height and with a surface area of 189, 9 ha. Areas that are within the surrounding of the dam include Verulam which is 4, 5 km away, Tongaat which is 12, 28 km and Umdloti beach which is 11, 84 km away. uMgeni area receives raw water mainly from the Hazelmere Dam The water provided by the dam is primarily river water and possibly rainwater. When rain falls, the water must be treated before it can be used, which the Umgeni Hazelmere wastewater treatment plant does. After being treated, the water is used as potable water, and the end users are the people of Verulam, Ballito, and Stanger. The uMdloti region gets its raw water primarily from Hazelmere Dam. The uMdloti region is depicted in *Figure 3.2* below.

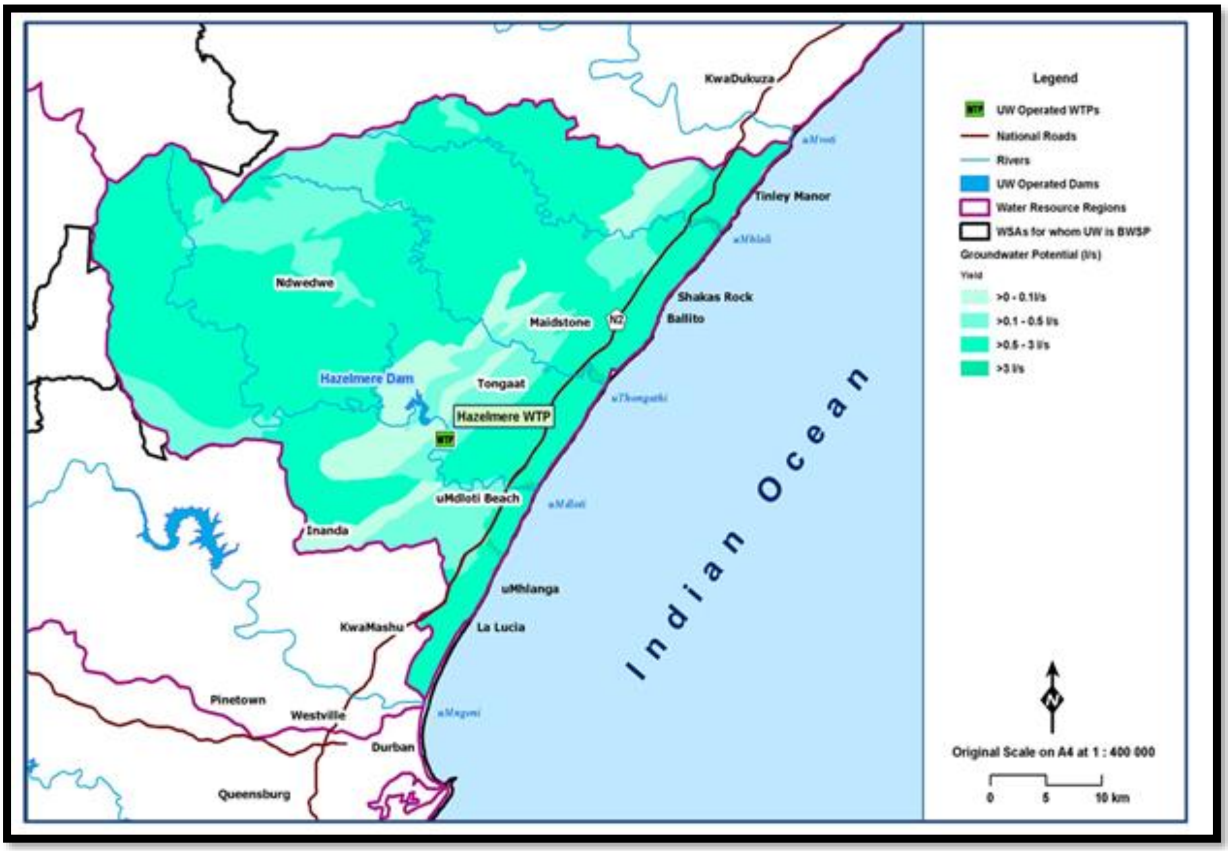

Figure 3.2: uMdloti region (Hausler-Cozma et al., 2019)

The dam, situated on the uMdloti river approximately 5 km North of Verulam, was constructed in 1976. While the present full supply level (FSL) of the dam is 86 m above sea level (msl), provision was made during the construction for raising the FSL to 93 msl. The Raising of Hazelmere Dam Feasibility Study is currently being undertaken to analyze the performance of the wastewater treatment plant. The primary objective of the study is to assess the performance of wastewater treatment from Hazelmere using the influent and effluent data from physical, chemical and biological parameters generated from 1999 to 2018. The data provided by the wastewater treatment plant include turbidity, iron and E. coli. To meet this objective, the study will need to address several issues, including establishing the optimal parameters for iron, turbidity and E. coli, as well as identifying any possible technical and environmental constraints to raising the dam. This study, therefore, presents the findings of the Water Quality and Environmental Impact Assessment, a specialist component of the Raising of Hazelmere Dam Feasibility Study.

3.5. Water Quality from the Hazelmere dam

It is shown in *Figure 3.3* that the 2017 and 2018 water quality results for the Hazelmere system have demonstrated a significant improvement when compared to the two preceding years (2015 and 2016). The deteriorating water quality status observed in 2015 and 2016 was largely due to the drought conditions. The change in weather conditions curtailed the drought conditions. The increased water quantity and rising of the dam wall have increased the storage capacity and the assimilative capacity of the dam. However, due to elevated erosion and nutrient inputs recorded within the catchment area in 2019 water quality deterioration has occurred. The impoundment has consequently experienced a greater level of eutrophication.

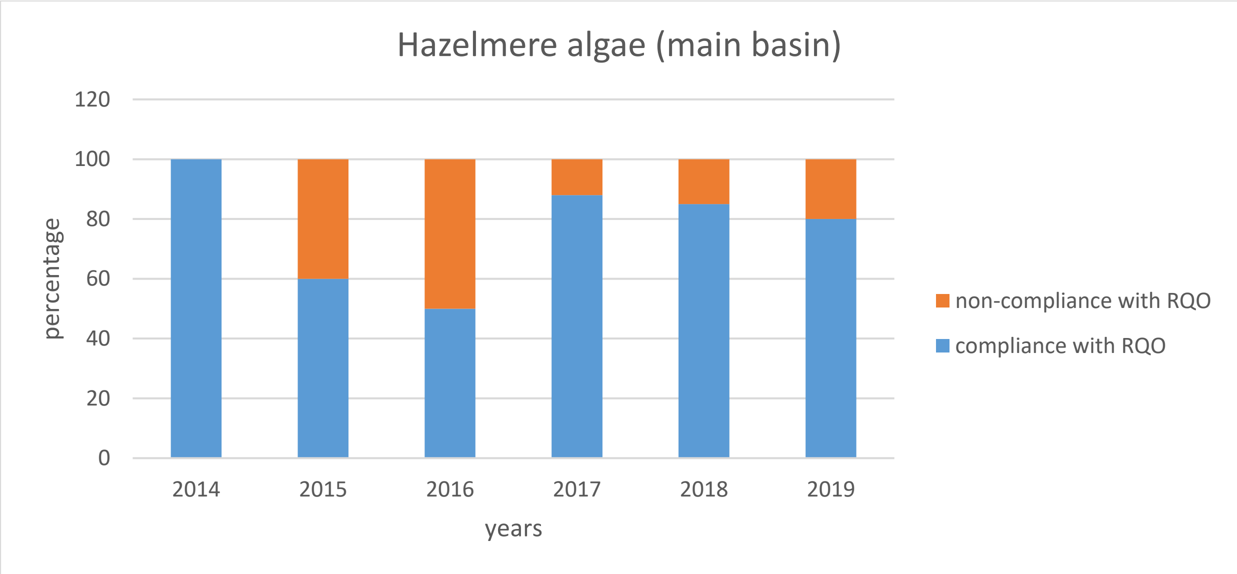

Figure 3.3A: Percentage compliance vs. non-compliance with the Resource Quality Objective for the HWTP

Since algal growth is constrained by dam turbidity, which results in poor water clarity and insufficient light penetration, algal counts in the Hazelmere dam are typically low to moderate (median 1 000 cells/ml). However, during periods of drought and dam drawdown, algal populations can drastically rise and become a nuisance. This circumstance occurred in the 2015–2016 drought (*Figure above*) when a lack of rainfall led to decreased dam turbidity and decreased inflows to the dam. Severe algal issues and associated water treatment issues were caused by a lack of spillage and an increase in retention time in the dam.

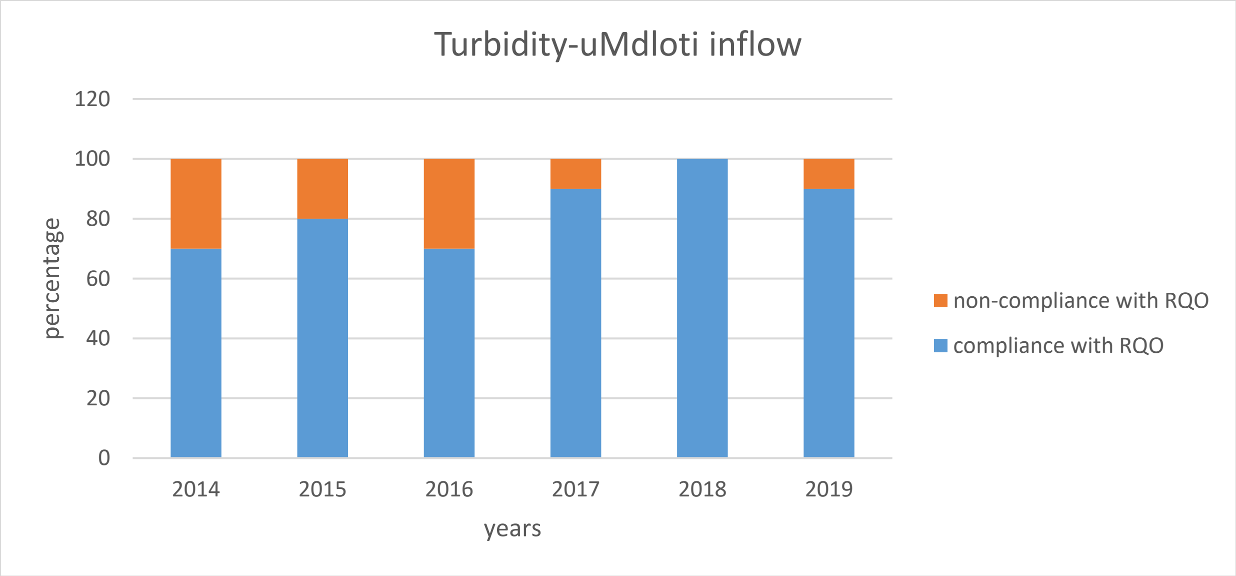

Figure 3.3B: Percentage compliance vs. non-compliance with the Resource Quality Objective for the HWTP

Erosion resulting from human activities is by far the most significant water quality-related problem in the uMdloti catchment. Median suspended solids concentrations for the dam inflow and surface sites respectively. These high concentrations are caused by the erodible sandy soils exacerbated by human activities resulting in significant gully and sheet erosion in the catchment. Most transport into the dam occurs during times of heavy rainfall/inflow. The fine clay suspended in the water in the dam is colloidal in nature and does not flocculate naturally or sediment easily.

Consequently, water abstracted from the Hazelmere dam is difficult and expensive to treat. In terms of aquatic life, the DWAF Aquatic Ecosystems Water Quality Guidelines (2016) recommend that any increase in suspended solids concentrations must be limited to < 10% of the background concentrations at a specific site and time. To compare compliance versus non-compliance in the preceding *figure*, it is shown that the dam may be a large sink for suspended solids.

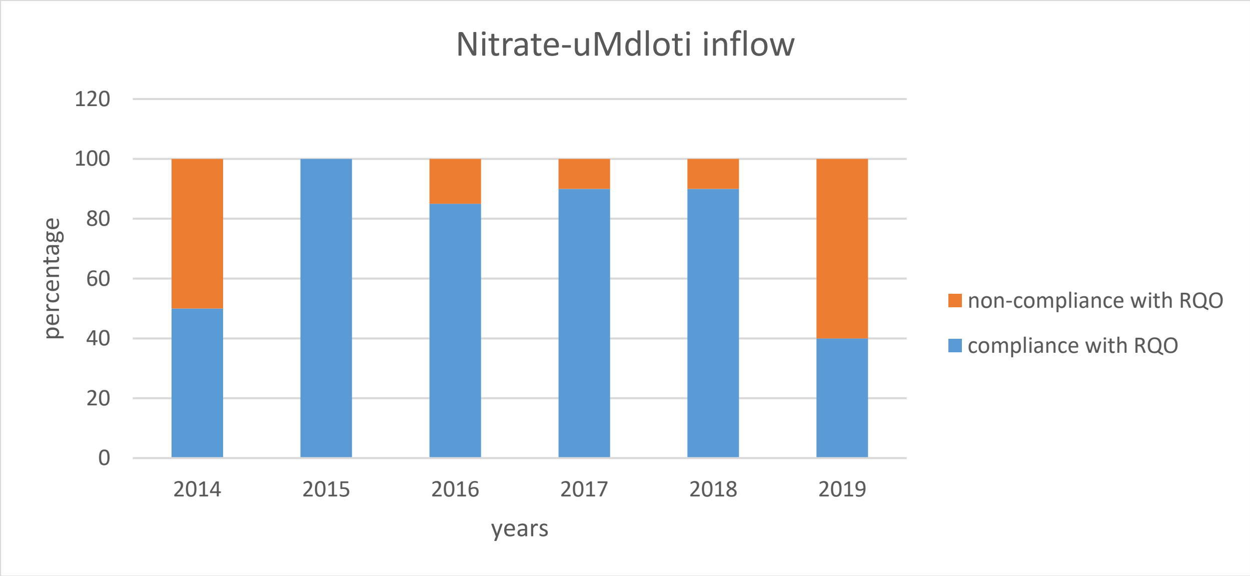

Figure 3.3C: Percentage compliance vs. non-compliance with the Resource Quality Objective for the HWTP

The DWAF Aquatic Ecosystems Guidelines (2016) state that an average summer soluble reactive phosphorus concentration is indicative of mesotrophic conditions. The average summer soluble reactive phosphorus concentrations were calculated to be between 8.0 and 8.5 µg/l for the uMdloti Hazelmere inflow and the dam surface. Hence, the upper uMdloti-Hazelmere system can be classified as a mesotrophic system, which means that it is likely to have high levels of biodiversity and low to moderate algal growth. Median total phosphorus concentrations were measured from 2014 to 2019.

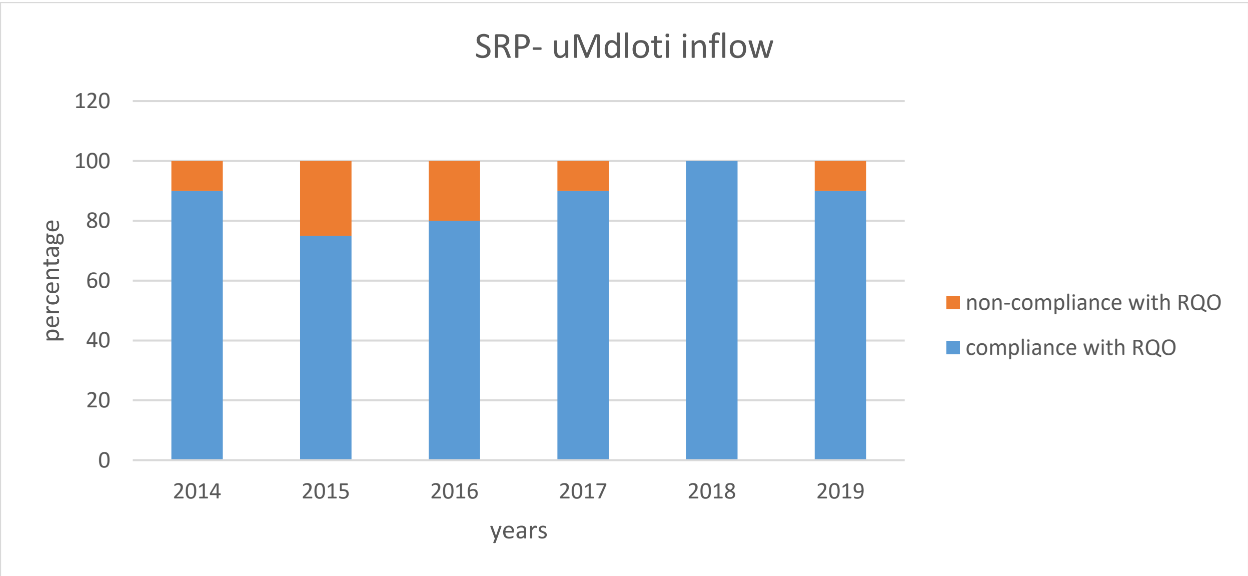

Figure 3.3D: Percentage compliance vs. non-compliance with the Resource Quality Objective for the HWTP

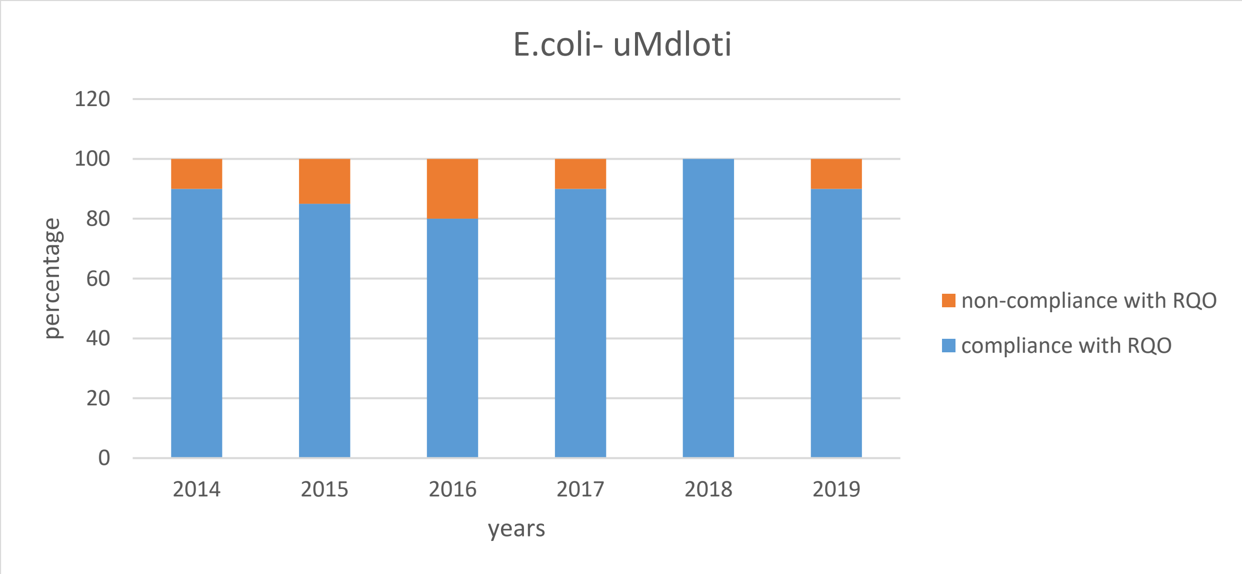

Figure 3.3E: Percentage compliance vs. non-compliance with the Resource Quality Objective for the HWTP

E. coli non-compliance with RQO at the uMdloti Hazelmere inflow between 2014 and 2019 is moderate. Since the compliance with E. coli values was close to 80 and 100 per cent respectively, the faecal contamination does not appear to be due to rainfall-related runoff during the summer high rainfall months. Rather, the microbiological contamination is likely to be due to sporadic faecal contamination from human and animal sources that enter the river. As shown in the *Figure* above, the data indicate a significant reduction in the E. coli counts between the Hazelmere inflow and the dam main basin. This is associated with bacteriological removal in the dam due to predation and die-off caused by ultra-violet light disinfection.

3.6. Hazelmere Wastewater Treatment Plant

Hazelmere Dam shown in *Figure 3.4* below is the source of raw water for the Hazelmere WTP (*Figure 3.5, Table 3.1*). The current yield of the dam, at a 98% assurance of supply, is 76 Ml/day. The WTP has a capacity of 75 Ml/day and receives raw water through a 600 mm diameter Asbestos Cement (AC) gravity pipeline and an 800 mm diameter steel pipeline (*Table 2*). The treatment process at Hazelmere WTP consists of chemical dosing, clarification, filtration and disinfection. Sludge treatment employs a gravity settling and a Centrifuge Sludge Dewatering System. The characteristics of the Hazelmere WTP are shown in *Table 3.2.* There are 25 Ml of clear water storage available on the site at the water treatment plant although one of the two 12.5 Ml is being upgraded from a floating roof reservoir to a concrete reservoir.

Table 3.1: Characteristics of the Hazelmere Wastewater treatment plant (Infrastructure master plan 2018/2019 volume 5: north coast system)

Wastewater treatment plant name	Hazelmere	
System	North coast supply system	
Maximum design capacity	75 Ml/day	
Current utilization (October 2018)	56,5 Ml/day	
Raw water supply capacity	90,6 Ml/day	
Pre-oxidation type	Pre-chlorination	
Primary water pre-treatment chemical	Polymeric coagulant	
Total coagulant dosing capacity	800 kg/day	
Rapid mixing method	Hydraulic jump	
Clarifier type	Clari-flocculator	Pulsator-clarifier
Number of clarifiers	7	4
Total area of all clarifiers	1469 m^2	800 m^2
Total capacity of clarifiers	45 Ml/day	60 Ml/day
Filter type	Constant rate rapid gravity filters	
Number of filters	17	6
Filter floor type	Lateral without nozzles	Precast with nozzles
Total filtration area of all filters	540 m^2	294 m^2
Total capacity of backwash water tanks	300 m^3	200 m^3
Total capacity of sludge treatment plant		
Capacity of used wash water system	0,98 Ml/day	
Primary post disinfection type	Chlorine	
Disinfection dosing capacity	450 kg/day	
Disinfection storage capacity	5 tonne	
Total treated water storage	25 Ml	

Figure 3.4: Hazelmere Dam

Figure 3.5: Hazelmere Water treatment plant

Table 3.2: characteristics of Hazelmere dam (Infrastructure master plan 2018/2019 volume 5: north coast system)

Catchment details	
Incremental catchment area	377 km^2
Total annual area	377 km^2
Mean annual precipitation	967 mm
Mean annual runoff	70,7 million m^3
Annual evaporation	1 200 mm
Dam characteristics	
Gauge plate zero	61,0 mASL
Full supply level	85,98 mASL
Spillway height	24.98 m
Net full supply capacity	17,855 million m^3
Dead storage	0,893 million m^3(5% -July 2015)
Total capacity	18,481 million m^3(October 1992)
Surface area of dam at full supply level	1,81 km^2
Original measured dam capacity	22,338 million m^3(October 1979)
Dam type	Concrete gravity wall with central spillway
Crest length	Spillway section: 91 m Non-spillway section: 372 m
Type of spillway	uncontrolled
Capacity of spillway	950 m^3/s
Date of completion	1975

3.7. Parameters to be analyzed in this study

There are only three parameters in this study: turbidity, iron, and E. coli. These parameters were selected because they were the only ones available at the time of the study.

3.8. Validity and Reliability

According to Peat (2001), reliability usually describes the consistency of a research method, while validity describes the suitability of the instrument used. The research instrument should measure what it is designed to measure and should perform as it is signed to perform. Cook (2015) defined this as the best available approximation of the truthfulness of a given proposition.

3.8.1. Validity

This research study considered two forms of validity, content validity and criterion-related validity.

• **Content validity** measures the extent to which the research instrument used is appropriate to answer the research questions. Content validity mainly depends on judgement. To ensure content validity for this research study, the research topic was fully defined and the objectives of the study were laid out. In addition to consulting experts in the fields of operation and management of water treatment plants, the researcher conducted an extensive background study on the area. The combination of the consultations and the literature review on the use of genetic algorithms in modelling helped to determine the usefulness of the research and its instrument.

• **Criterion-related validity** usually describes the relevance of a certain measure. Pennington (2003) described it as a measure of how well a variable or set of variables can predict an outcome. Trochim and Donnelly (2005) observed that, in using criterion validity, predictions are made based on the research construct or theory. To assess the quality of a criterion measure, relevance, freedom from bias, reliability and availability should be considered. This can be achieved by using statistical analysis such as correlation. In this study, the model results were statistically analyzed and compared to the actual observed data as presented in Chapter 4. Data cleaning and interpolation will be performed to identify and fixing incorrect data.

3.8.2. Reliability

To ascertain reliability, the researcher had to be aware of the sampling and testing methods at the wastewater treatment plant. In conjunction with validity, reliability can help to assess the integrity of the historical data collected. In the event of errors in the datasets, it is easier for a researcher to make decisions on missing values, censored values and the presence of outliers. These errors are common in water quality datasets but the treatment method greatly depends on the reliability of the method employed to do the sampling and tests.

3.9. Conclusion

The research methodology was the focus of this chapter, which described the research sample and sampling techniques used in the research reported in this thesis. The goal of this chapter was to provide literature related to the research background. The underlying philosophical paradigm and assumptions of the research, approach, research design, and methodology used in the research were discussed in this manner. Essentially, the methodology used in this study was a significant step toward finding solutions to the water waste plant issues. The next chapter will contain a detailed discussion of the study's findings and their interpretation.

CHAPTER 4- RESULTS AND DISCUSSION

4.1. Introduction

This chapter presents and discusses the findings of the study in alignment with the objectives outlined in Chapter 1. The work focused on three available parameters, which were Iron, Turbidity and Escherichia coli (E. coli). For E. coli, there were no variations because the pathogen load was less significant.

4.2. Monthly average removal efficiency for turbidity, iron and E. coli from 1999 to 2018

4.2.1. Annual removal efficiencies for Turbidity, iron and E. coli for the year 1999

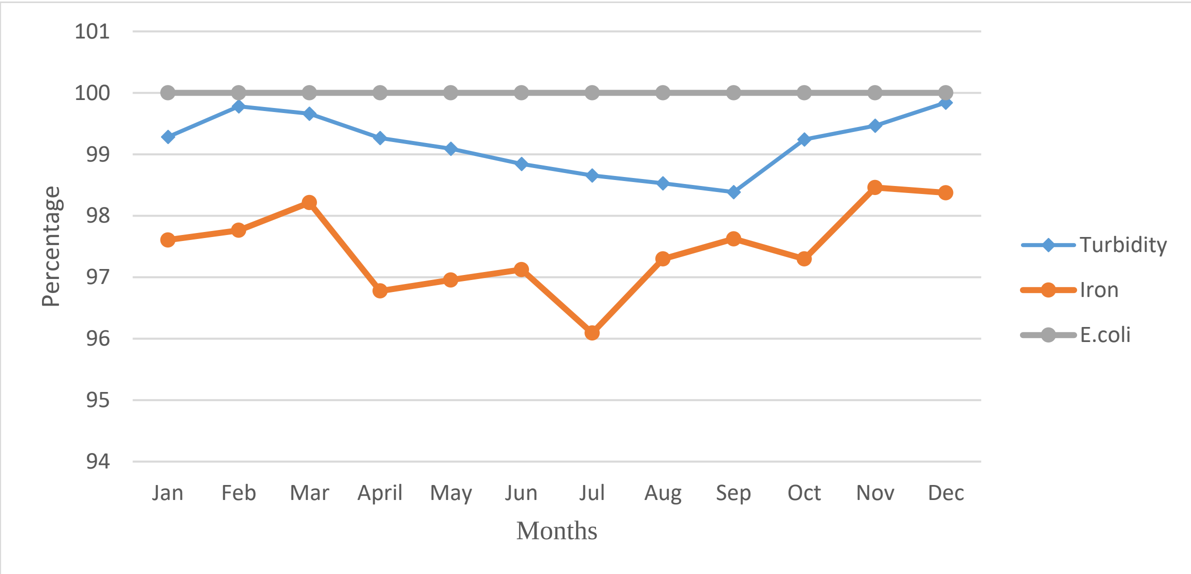

Figure 4.1: Removal efficiency data for turbidity, iron and E. coli for the year 1999

Table 4.1: Yearly average for influent and effluent for the year 1999

Turbidity (NTU) WHO/SANS 241:2011 standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS 241:2011 standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS 241:2011 standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
62.94463	0.329206	1.072645	0.026587	22.09167	0

From the analysis of *Figure 4.1*, it is observed that the removal efficiency of E. coli from the treatment plant is 100% as indicated in *Figure 4.1* this implies that the effluent produced by the treatment plant is free of pathogens as indicated in *Table 4.1*. Concerning other parameters, there is a variation in removal efficiency that shows a few fluctuations though it is not significant. The removal efficiency for iron varied between 96, 09 and 98, 45% while for turbidity 98, 38 and 99, 84%. From the data presented in *Table 4.1* related to the yearly averages for influent and effluent, it can be concluded that the effluent complied with the relevant quality standards for the 2015 SANS blue drop limits or WHO standard limits for the year 1999 in terms of iron, turbidity and E. coli. Overall, the variations of these parameters from the influent to the effluent are linked to the variability of the composition of the raw water fed to the plant.

This variability in river water composition, which is the influent water, could be complex depending on the level of pollution in the river water. It is important to stress the fact that pollution of the river water is not easy to control due to the high amount of illegal discharges in South African rivers. The nature and the composition or type influence the removal process. The nature of the influent relates to physical-chemical characteristics such as pH, colour and odour and many other inherent features. The composition relates to the content or molecules that can be organic or inorganic. The type of influent depends on the source or origin.

4.2.2. Annual removal efficiencies for Turbidity, iron and E. coli for the year 2000

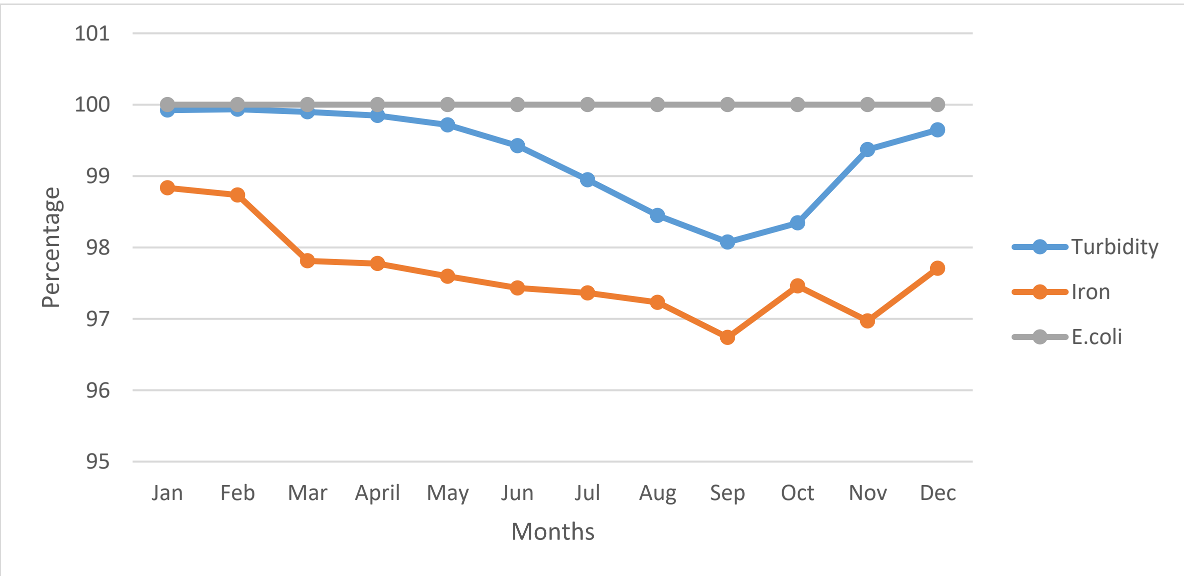

Figure 4.2: Removal efficiency data for turbidity, iron and E. coli for the year 2000

Table 4.2: Yearly average for influent and effluent for the year 2000

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
138.8615	0.313078	1.183567	0.025894	577.0917	0

When analyzing *Figure 4.2,* the removal efficiency of E. coli from the treatment plant has remained the same compared to the previous year, which is 100%. This indicates that the effluent produced by the treatment plant is still free of pathogens as shown in *Table 4.2.* Concerning the turbidity, the removal efficiency has ranged from 98,07 to 99,94 %. A drastic decrease is observed from May until September when it reaches its lowest and it starts increasing for the remaining part of the year. This could be due to the increase of influent turbidity during the course of the year 2000. By comparing the average influent turbidity for the year 1999 presented in *Table 4.1* (62.94463 NTU) to the average influent for the year 2000 presented in *Table 4.2* (138.8615 NTU), it is observed that the influent turbidity has doubled from 1999 to 2000. It is possible that the plant was fed with an influent containing more solids making it a challenge for the plant to adapt to the increase of solids. Therefore, this could be one of the causes for the decrease in removal efficiency from May to September 2000. The increase from September can be due to less turbidity from influent to effluent as presented in the raw data attached in *Appendix 1*. However, the average effluent turbidity presented in *Table 4.2* complied with the 2015 SANS blue drop limits and WHO standard limits for the year 2000. Iron has also followed almost the same trend as turbidity. Iron occurs naturally in wastewater or water; its occurrence can also have an industrial origin or domestic waste with some levels of iron. The monthly average removal efficiencies for iron have ranged from 96, 73 to 98, 83 % as shown in *Figure 4.2*. The yearly average for effluent iron complies with the 2015 SANS blue drop limits and WHO standards limit as shown in *Table 4.2*. Briefly as mentioned before the variability of removal efficiency and the level of parameters is dictated by the variability of the composition for the influent.

4.2.3. Annual removal efficiencies for Turbidity, iron and E. coli for the year 2001

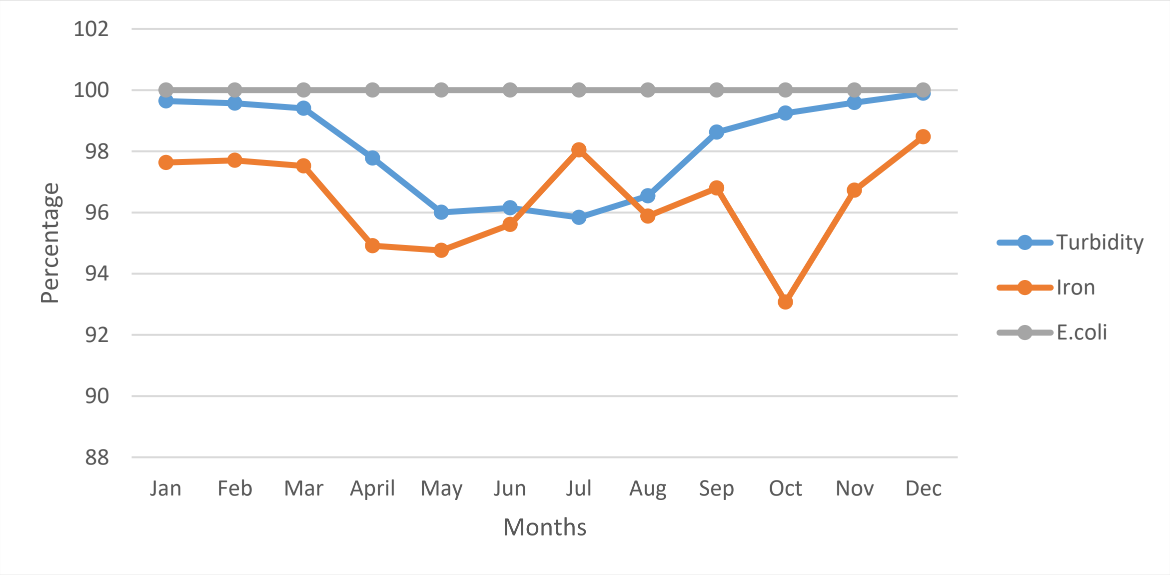

Figure 4.3: Removal efficiency data for turbidity, iron and E. coli for the year 2001

Table 4.3: Yearly average for influent and effluent for the year 2001

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
54.68827	0.269895	0.730118	0.024496	25.1375	0

From the analysis of *Figure 4.3*, the removal efficiency of E. coli from the treatment plant is 100% this implies that the effluent produced by the treatment plant is free of pathogens as shown in *Table 4.3*. The remaining parameters reveal that there is a variation in removal efficiency with some fluctuations. It is observed that the turbidity removal efficiency decreased from March to September and began increasing for the rest of the year. The removal efficiency for turbidity varied between 95, 83 and 98, 89% as shown in *Figure 4.3*. *Table 4.3* shows that the effluent turbidity complies with the relevant quality standards for SANS blue drop limits and WHO limits.

For iron, the average annual removal efficiency varies from 93, 07 and 98, 47%. From the data presented in *Table 4.3* related to the yearly averages for influent and effluent, it can be concluded that the effluent for the year 2001 has complied with the relevant quality standards for the 2015 SANS blue drop limits and WHO standard limits. In conclusion, the variations recorded for removal efficiencies and levels of parameters are linked to the variability of the composition of the influent daily.

4.2.4. Annual removal efficiencies for Turbidity, iron and E. coli for the year 2002

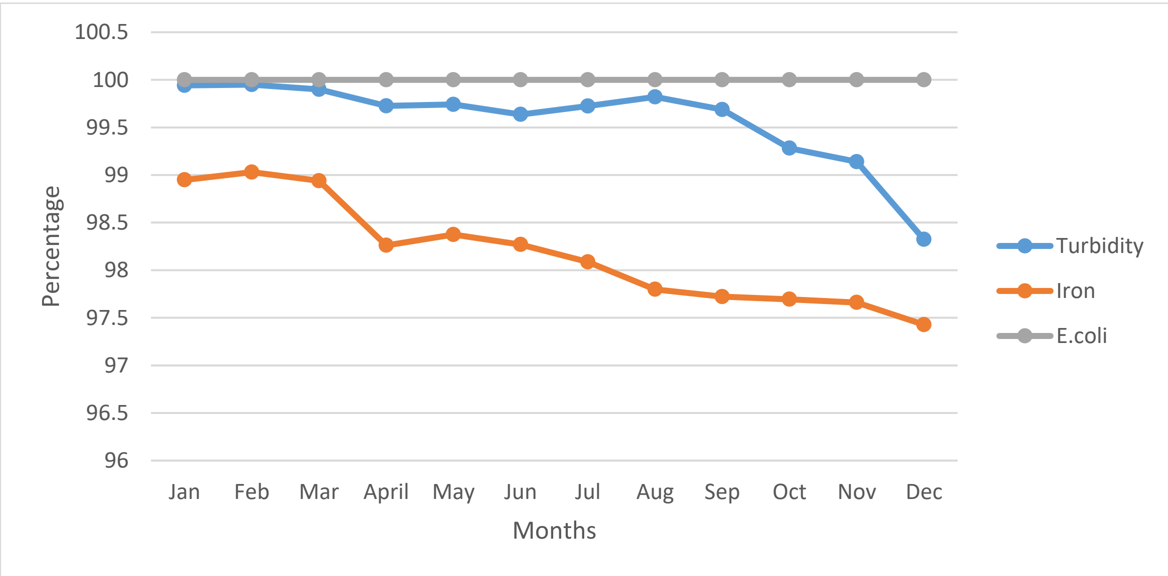

Figure 4.4: Removal efficiency data for turbidity, iron and E. coli for the year 2002

Table 4.4: Yearly average for influent and effluent for the year 2002

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
149.2325	0.262214	1.251957	0.02164	103.9889	0

Figure 4.4 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the treatment plant was pathogen-free for the year 2002 as shown in *Table 4.4.* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.4* shows that the general trend for both turbidity and iron is decreasing from March to December 2002. This could be due to the nature and the composition of influent coming from uMdloti river which is fed to the treatment plant. This treatment plant is not adjusting easily to the change in the composition of the influent which could subsequently affect the wastewater plant performance. The average annual removal efficiency for turbidity has ranged from 98, 32 to 99,94% while for iron it is between 97, 42 to 99,03%. From *Table 4.4* it is observed that the effluent complies with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2002.

4.2.5 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2003

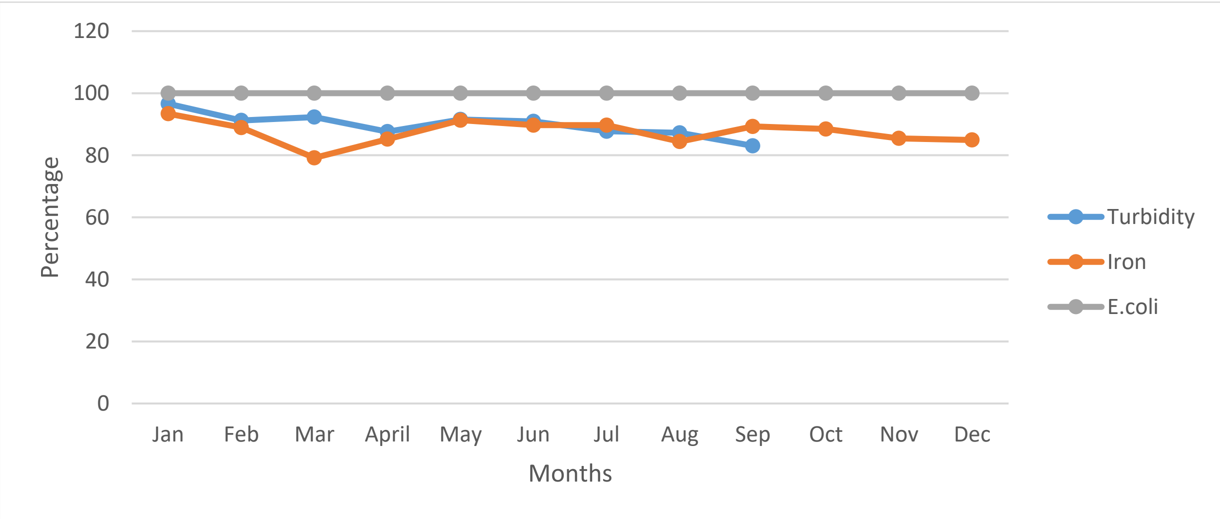

Figure 4.5: Removal efficiency data for turbidity, iron and E. coli for the year 2003

Table 4.5: Yearly average for influent and effluent for the year 2003

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
7.727955	0.333649	0.276569	0.02175	3.458333	0

Figure 4.5 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the treatment plant is pathogen free for the year 2003 as shown in *Table 4.5.* With the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.5* shows fluctuations for both turbidity and iron. This is in spite of the fact that some data for turbidity from October to December 2003 was not available. These fluctuations in terms of turbidity and iron data are again linked to the nature and the composition of the influent fed to the wastewater treatment plant which is varied. The annual average removal efficiencies for turbidity have ranged 83, from 03 to 96,58% while for iron it ranged from 84,41 to 93, 38% as shown *in Figure 4.5.* From *Table 4.5* it is observed that the effluent complies with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2003.

4.2.6 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2004

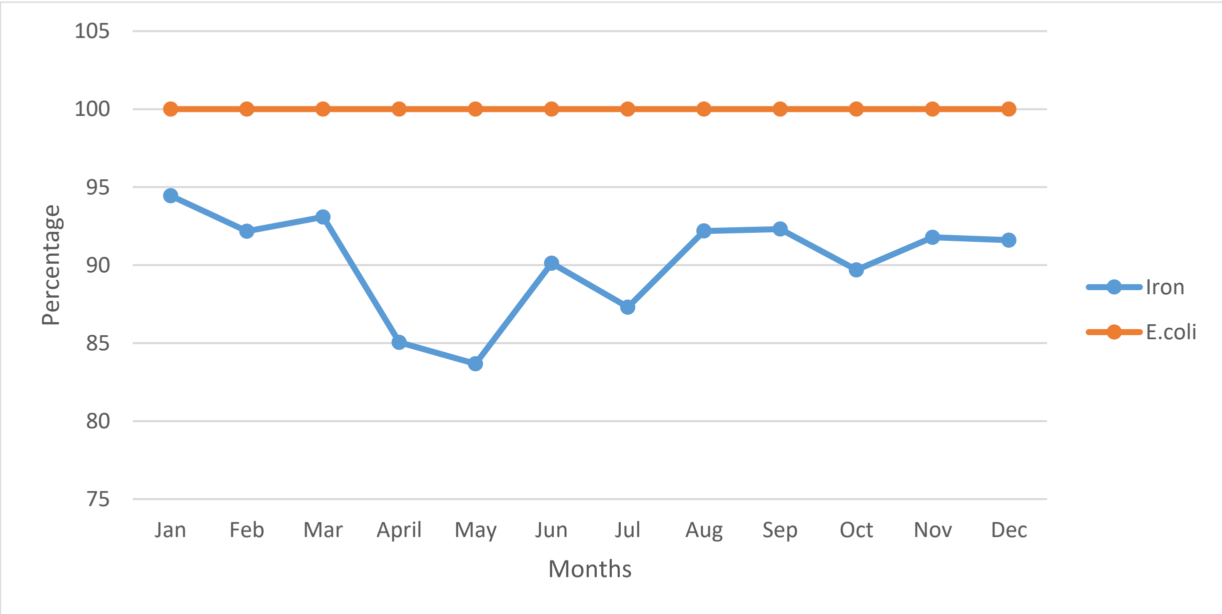

Figure 4.6: Removal efficiency data for iron and E. coli for the year 2004

Table 4.6: Yearly average for influent and effluent for the year 2004

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
92.30998	0.346902	0.26625	0.024875	5.95	0

Figure 4.6 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the treatment plant is pathogen free for the year 2004 as shown in *Table 4.6.* with the recorded annual average equal to 0MPN/100mL. For this year the data for turbidity was not available. The analysis of *Figure 4.6* shows variations for iron. The possible reason for these variations in iron data could be due to the nature of the type and the composition of the influent fed to the wastewater treatment plant which is never the same daily. The annual average removal efficiencies for iron have ranged between 83, 67 to 94, 44% as shown in *Figure 4.6.* The iron effluent produced by the wastewater treatment plant for the year 2004 complied with the 2015 SANS blue drop limits and WHO standard limits as shown in *Table 4.6.*

4.2.7 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2005

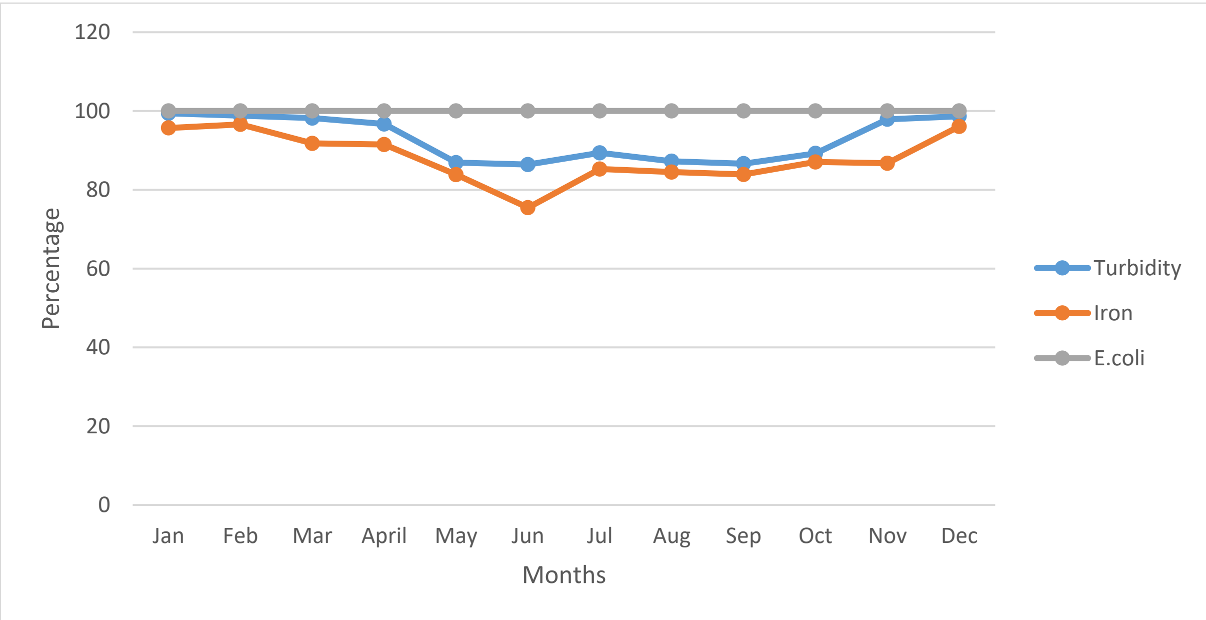

Figure 4.7: Removal efficiency data for turbidity, iron and E. coli for the year 2005

Table 4.7: *Yearly average for influent and effluent for the year 2005*

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
15.10646	0.410616	0.463625	0.042833	8.983333	0

Figure 4.7 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the treatment plant is free of pathogens for the year 2005. This is presented in *Table 4.7* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.7* shows the average annual removal efficiencies for turbidity are almost the same from January to April 2005. It decreases from April to May 2005 and then remains almost constant from May to October 2005, this could be because the influent fed to the wastewater treatment plant might have had the same nature and composition during that period. Furthermore, it increased from October to November 2005; then stabilises between November and December 2005. This implies that there could have been a change in the composition or the nature of the influent fed to the wastewater treatment plant affecting its performance. The annual average removal efficiencies for turbidity have ranged from 86, 40 to 99,39% while for iron; it ranged from 83,83 to 96, 58%, as shown in *Figure 4.7*. In *Table 4.7* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2005.

4.2.8 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2006

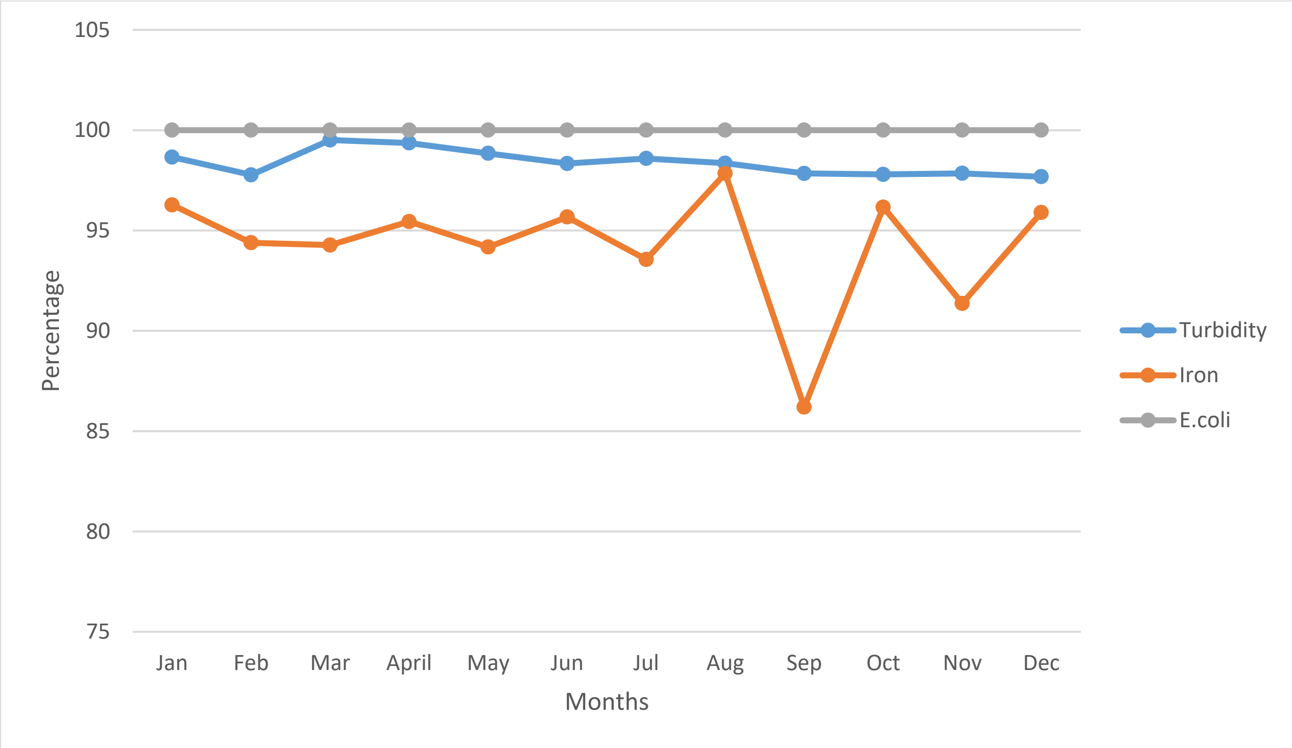

Figure 4.8: Removal efficiency data for turbidity, iron and E. coli for the year 2006

Table 4.8: Yearly average for influent and effluent for the year 2006

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
31.975	0.389356	1.010261	0.158298	19.1	0

Figure 4.8 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is pathogen-free for the year 2006 as presented in *Table 4.8* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.8* shows a slight change in removal efficiencies for turbidity from January to March 2006. It is observed that from April to December 2006, the removal efficiencies for turbidity are almost constant.

This is an indication that the influent composition in terms of turbidity has remained almost the same from April to December 2006. However, fluctuations in iron have been recorded throughout the year 2006, this is possibly due to the variability of the composition of the influent in terms of iron. The annual average removal efficiencies for turbidity have ranged from 97, 67 to 99, and 50%. Iron, however, was recorded at between 86, 19 to 97, and 84% as shown in *Figure 4.8*. In *Table 4.8* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2006.

4.2.9 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2007

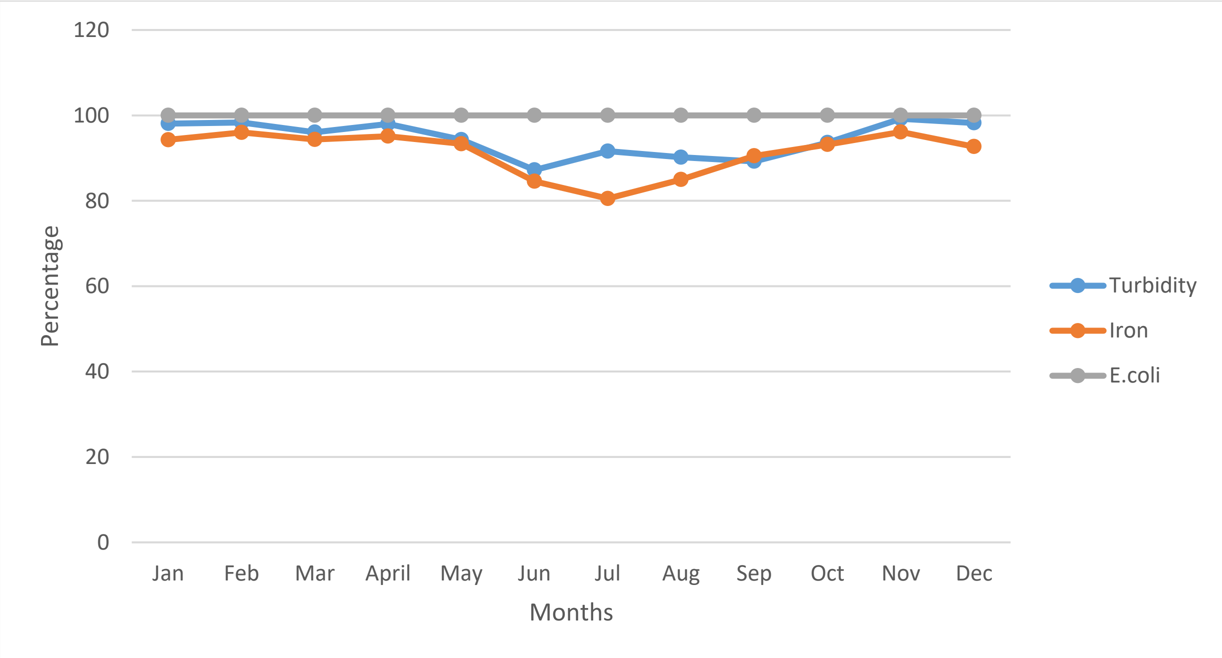

Figure 4.9: Removal efficiency data for turbidity, iron and E. coli for the year 2007

Table 4.9: Yearly average for influent and effluent for the year 2007

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E.coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
18.41352	0.507497	0.701827	0.048708	24.44167	0

Figure 4.9 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2007 as presented in *Table 4.9* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.9* shows almost the same trends for both turbidity and iron removal efficiencies from January to June 2007. After June 2007 the trends differ. This could be due to the change in influent composition, nature or type which are not always the same throughout the year. The annual average removal efficiencies for turbidity have ranged from 87, 21 to 99, 20% while for iron it is between 80, 52 to 96, 12% as shown in *Figure 4.9.* From Table 4.9 it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2007.

4.2.10 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2008

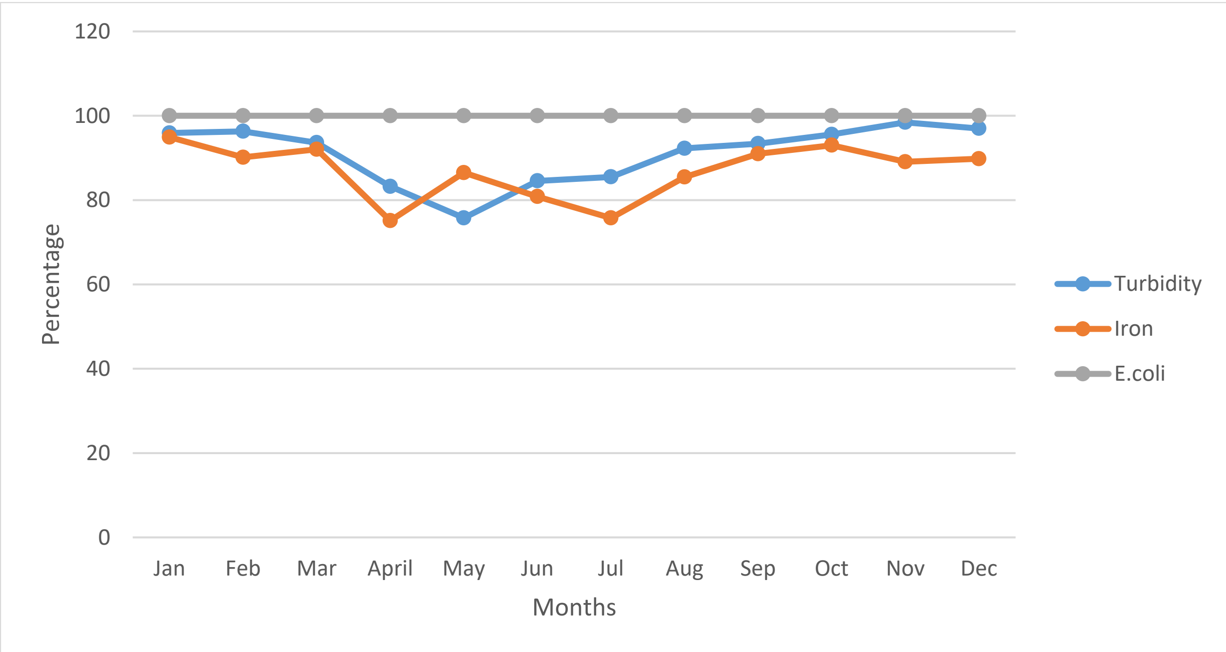

Figure 4.10: Removal efficiency data for turbidity, iron and E. coli for the year 2008

Table 4.10: Yearly average for influent and effluent for the year 2008.

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E.coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
9.316426	0.539792	0.700481	0.079292	32.40833	0

Figure 4.10 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2008 as presented in *Table 4.10* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.10* shows almost the same trends for both turbidity and iron removal efficiencies throughout the year except for May to July 2008. This could be because the influent composition, nature, or type remained nearly constant throughout the year.The annual average removal efficiencies for turbidity have ranged from 75, 76 to 98, 42% while for iron it ranges from 80, 82 to 94, 91% as shown in *Figure 4.10*. From *Table 4.10* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2008.

4.2.11 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2009

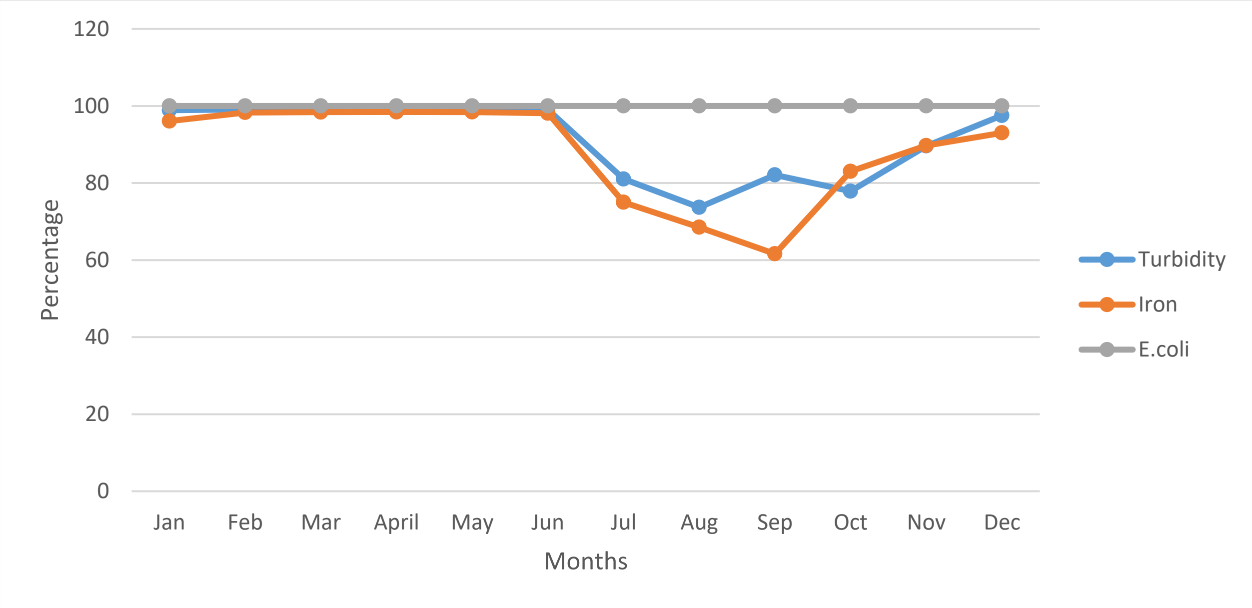

Figure 4.11: Removal efficiency data for turbidity, iron and E. coli for the year 2009

Table 4.11: Yearly average for influent and effluent for the year 2009

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E.coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
33.70871	0.73182	2.142278	0.059958	18.73333	0

Figure 4.11 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is pathogen-free for the year 2009 as presented in *Table 4.11* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.11* shows a constant trend for all three parameters from February to June 2009. This could be due to the fact that the nature or the composition of the influent was almost the same during that period. From June to December 2009 all three parameters recorded different trends. This could be due to the variation in the composition of the influent which can cause the change in the removal efficiencies. The annual average removal efficiencies for turbidity have ranged from 82, 08 to

99, 07% while for iron it is between 75, 00 to 98, 43% as shown in Figure 4.11. From Table 4.11 it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2009.

4.2.12 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2010

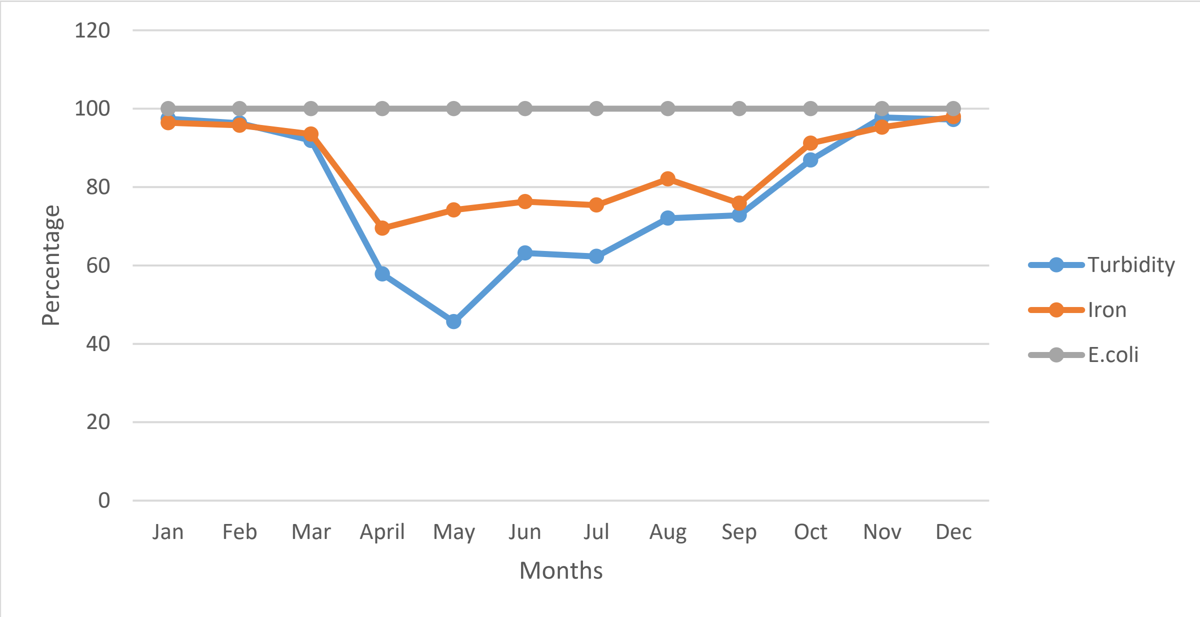

Figure 4.12: Removal efficiency data for Turbidity, iron and E. coli for the year 2010

Table 4.12: Yearly average for influent and effluent for the year 2010

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E.coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
17.28274	1.31091	1.168452	0.094833	8.516667	0

Figure 4.12 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2010 as presented in Table 4.12 with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.12*

shows that turbidity and iron follow almost the same trend regarding the removal efficiencies. Turbidity recorded the lowest removal efficiency from 1999 to 2018 which was 45,61 % this could be probably due to the presence of more solids in the influent which the plant was not capable of removing them effectively. Consequently, the turbidity removal efficiency capacity declined due to an ineffective clarification process. For iron there is a drastic decrease from March to April 2010, thereafter an increase is observed following a short decrease from August to September 2010. This variation is linked to the nature and composition of the influent which changed throughout the year. The annual average removal efficiencies for turbidity have ranged from 45, 61 to 97, 92% while for iron it is between 74, 13 to 97, 92% as shown in *Figure 4.12*. *Table 4.12* shows that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2010.

4.2.13 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2011

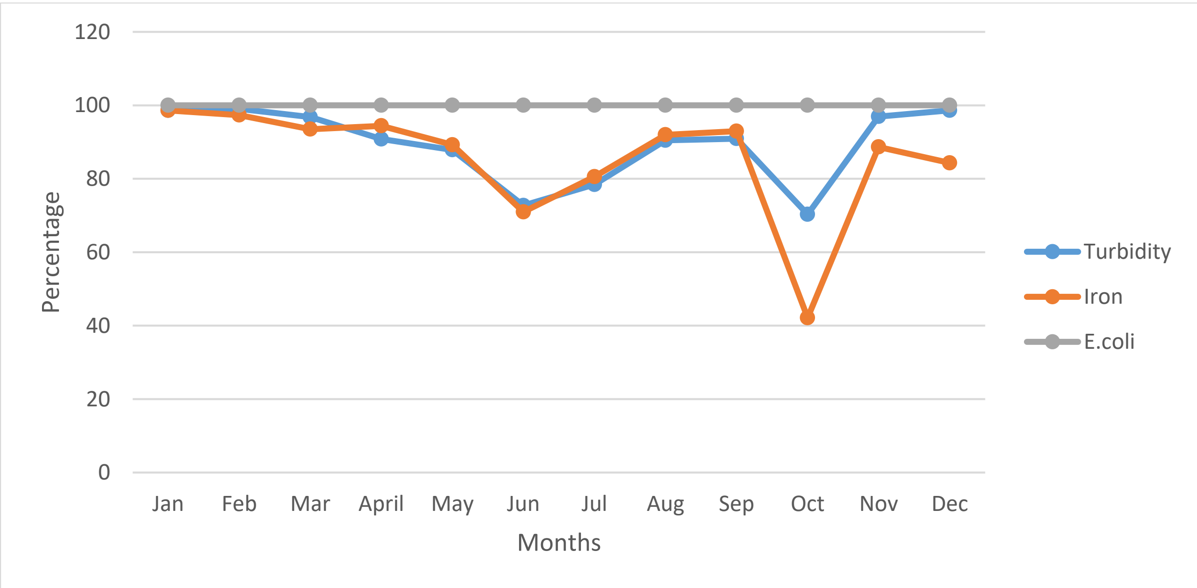

Figure 4.13: Removal efficiency data for turbidity, iron and E. coli for the year 2011

Table 4.13: Yearly average for influent and effluent for the year 2011

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
17.8283	0.570544	0.738825	0.065517	6.483333	0

Figure 4.13 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2011 as presented in *Table 4.13* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.13* shows that iron and turbidity removal efficiency have exactly a similar trend from January to November 2011. However, it was observed that iron has reached its lowest level from 1999 to 2018 which is 42,14 %. This could be due to the nature or composition of the influent during that period. The annual average removal efficiencies for turbidity have ranged from 70, 30 to 99, 02% while for iron it ranges from 43, 14 to 97, 32% as shown in *Figure 4.13*. From *Table 4.13* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2011.

4.2.14 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2012

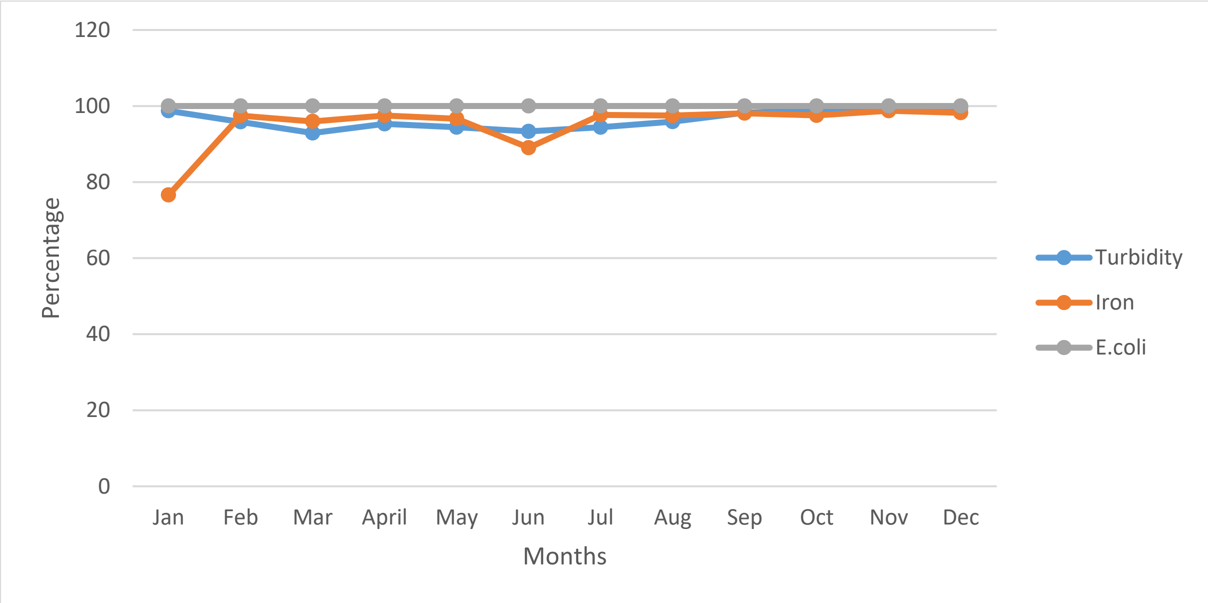

Figure 4.14: Removal efficiency data for turbidity, iron and E. coli for the year 2012

Table 4.14: Yearly average for influent and effluent for the year 2012.

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E.coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
29.84112	0.449084	1.055595	0.049135	20.79087	0

Figure 4.14 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2012 as presented in *Table 4.14* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.14* shows that the trend for removal efficiencies is almost the same for all three parameters except for iron which has recorded variations from January to February 2012 and from June to July 2012. This situation is linked to the fact that the composition of the influent has remained almost constant for that year and the wastewater treatment plant was able to keep the removal efficiency trend almost constant. The annual average removal efficiencies for turbidity have ranged from 93, 32 to 99, 67% while for iron it is between 76, 61 to 98, 75% as shown in

Figure 4.14. From *Table 4.14* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2012.

4.2.15 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2013

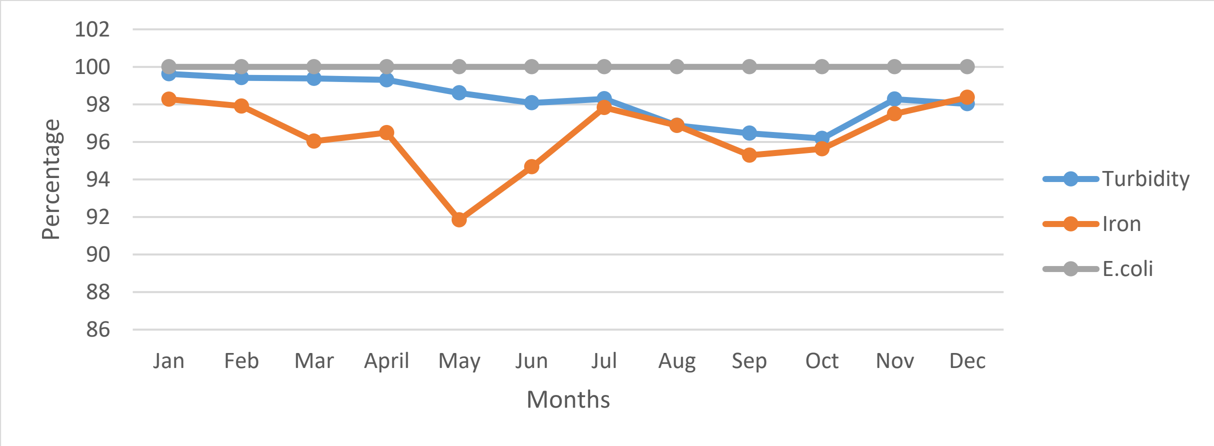

Figure 4.15: Removal efficiency data for turbidity, iron and E. coli for the year 2013

Table 4.15: Yearly average for influent and effluent for the year 2013

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E.coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
38.84479	0.432448	1.616303	0.08452	5.91964	0

Figure 4.15 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2013 as presented in *Table 4.15* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.15* shows that E. coli, turbidity and iron removal efficiency trends are different; this implies that the composition of the influent fluctuates more often or else the nature and type of influent fed to the wastewater plant change more often. The annual average removal efficiencies for turbidity have ranged from 96, 18 to 99, 62% while for iron it is between 91, 84 to 98, 36% as

shown in *Figure 4.15*. From *Table 4.15* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2013.

4.2.16 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2014

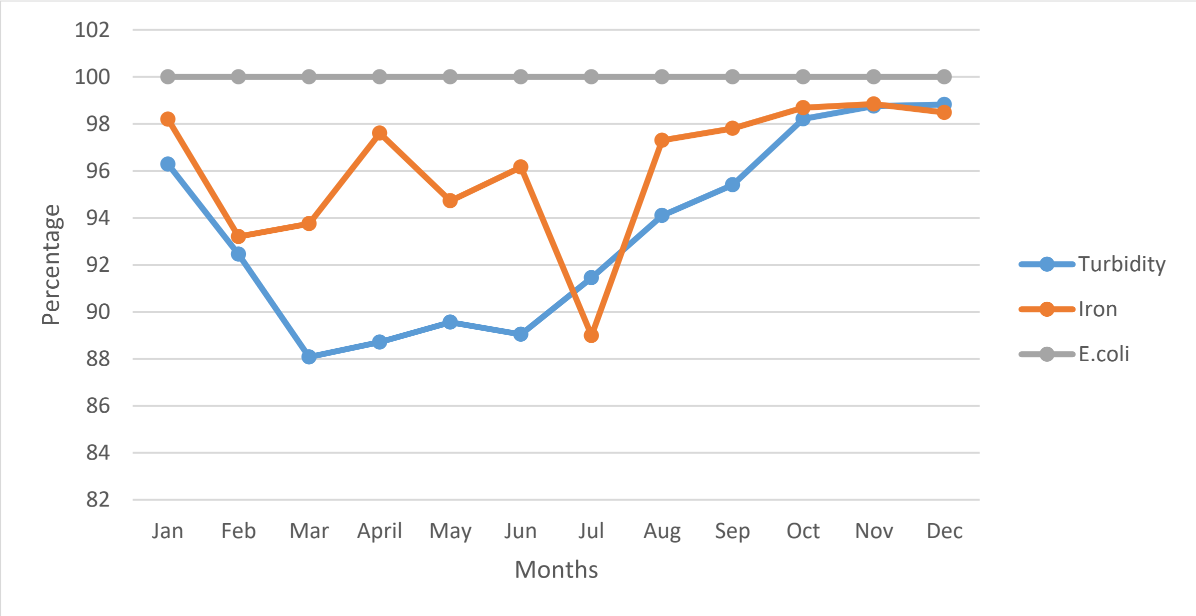

Figure 4.16: Removal efficiency data for turbidity, iron and E. coli for the year 2014

Table 4.16: Yearly average for influent and effluent for the year 2014

<table>
<tr><td colspan="2">Turbidity (NTU)

WHO/SANS standards for discharge
[≤ 1 NTU]</td><td colspan="2">Iron (mg/L)

WHO/SANS standards for discharge
[≤2 mg/L]</td><td colspan="2">E.coli (MPN/100mL)

WHO/SANS standards for discharge
[Not determined]</td></tr>
<tr><td>Influent</td><td>Effluent</td><td>Influent</td><td>Effluent</td><td>Influent</td><td>Effluent</td></tr>
<tr><td>14.69185</td><td>0.588042</td><td>1.042492</td><td>0.071875</td><td>3.384482</td><td>0</td></tr>
</table>

Figure 4.16 shows that E. coli removal efficiency is 100%. This means that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2014 as presented in *Table 4.16* with the recorded annual average equal to 0MPN/100mL. It is observed from *Figure 4.16* that all three parameters are trending differently in terms of removal efficiencies; this implies that the composition of the influent fluctuates more often or else the nature and

type of influent fed to the wastewater treatment plant change more often as it has been the case for the previous year. The annual average removal efficiencies for turbidity have ranged from 88, 07 to 98, 82% while for iron it is between 88, 98 to 98, 84% as shown in *Figure 4.16.* From *Table 4.16* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2014.

4.2.17 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2015

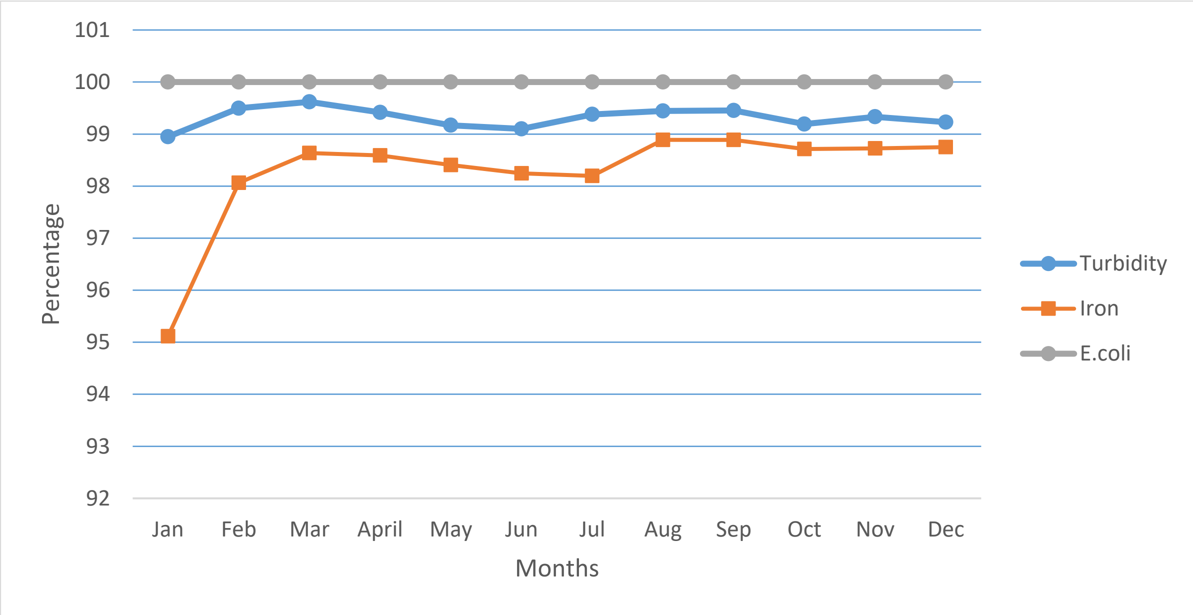

Figure 4.17: Removal efficiency data for turbidity, iron and E. coli for the year 2015

Table 4.17: Yearly average for influent and effluent for the year 2015

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E.coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
47.21489	0.300789	1.821322	0.030004	16.76785	0

Figure 4.17 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2015 as presented in *Table*

4.17 with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.17* shows that the trend for removal efficiencies is almost the same for all three parameters except for iron which has recorded variations from July to August 2015. This situation is linked to the fact that the composition of the influent has remained almost constant for that year and the wastewater treatment plant was able to keep the removal efficiency trend almost constant. The annual average removal efficiencies for turbidity have ranged from 98, 94 to 99, 61% while for iron it is between 95, 11 to 98, 88% as shown in *Figure 4.17*. From *Table 4.17* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2015.

4.2.18 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2016

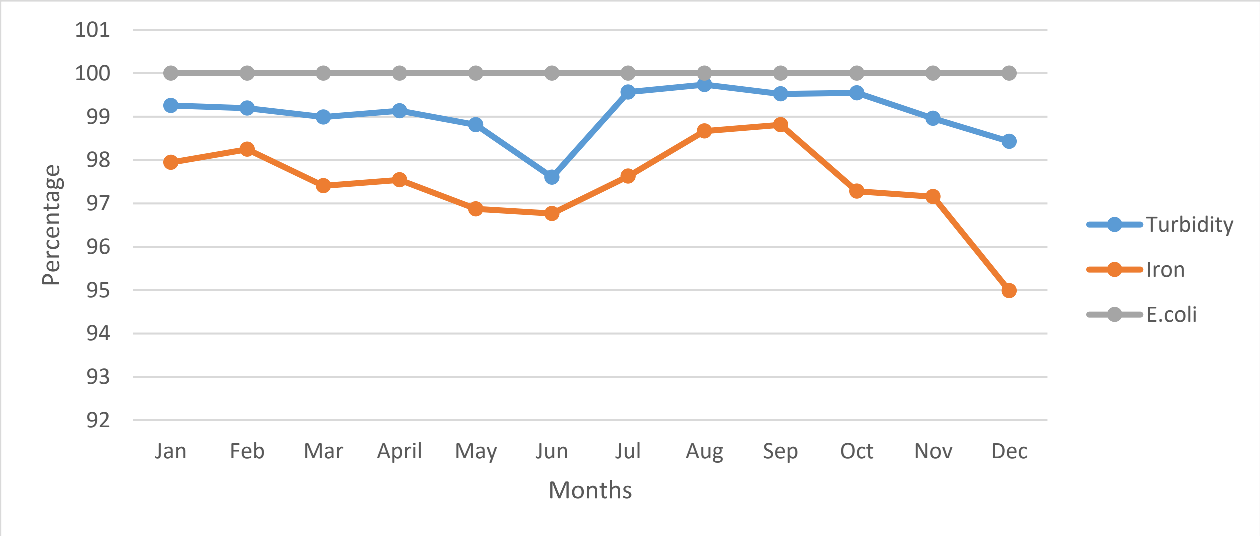

Figure 4.18: Removal efficiency data for turbidity, iron and E. coli for the year 2016

Table 4.18: Yearly average for influent and effluent for the year 2016

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E.coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
37.32893	0.240646	1.224903	0.023958	27.74314	0

Figure 4.18 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2016 as presented in *Table 4.18* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.18* shows that turbidity and iron almost follow the same trend with some fluctuations recorded during the course of the year. However, this trend shows that there is no significant variation in terms of the composition and the nature or type of the influent. The annual average removal efficiencies for turbidity have ranged from 97, 60 to 99, 73% while for iron it is between 94, 98 to 98, 81% as shown in *Figure 4.18*. From *Table 4.18* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2016.

4.2.19 Annual removal efficiencies for Turbidity, iron and E. coli for the year 2017

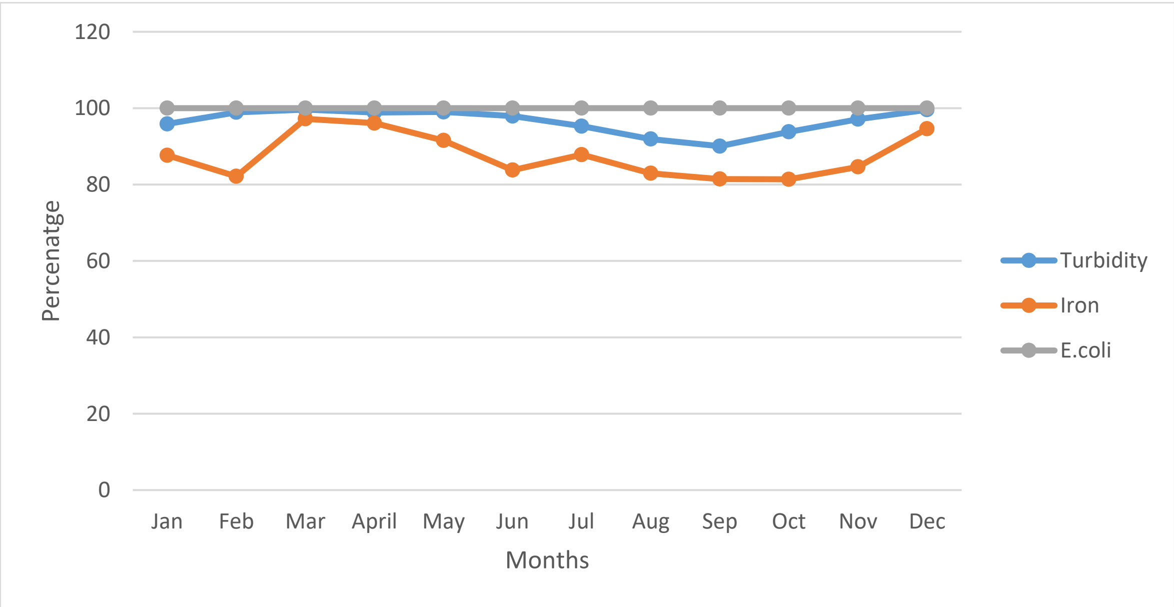

Figure 4.19: Removal efficiency data for turbidity, iron and E. coli for the year 2017

Table 4.19: Yearly average for influent and effluent for the year 2017

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
15.27409	0.209425	0.572981	0.038417	6.943357	0

Figure 4.19 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2017 as presented *in Table 4.19* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.19* shows that the overall trend for turbidity and E. coli removal efficiency is almost the same from January to June 2017. From July to December 2017 turbidity and iron have the same removal efficiency trend. This could be caused by the variations in the composition of the influent, especially in terms of iron. Throughout the year iron, removal efficiency has been the lowest compared to the other parameters. The annual average removal efficiencies for turbidity have ranged from 90, 04 to 99, 62% while for iron it is between 82, 14 to 97, 19% as shown in *Figure 4.19.* From *Table 4.19* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2017.

4.2.20 Annual removal efficiencies for Turbidity, iron, and E. coli for the year 2018.

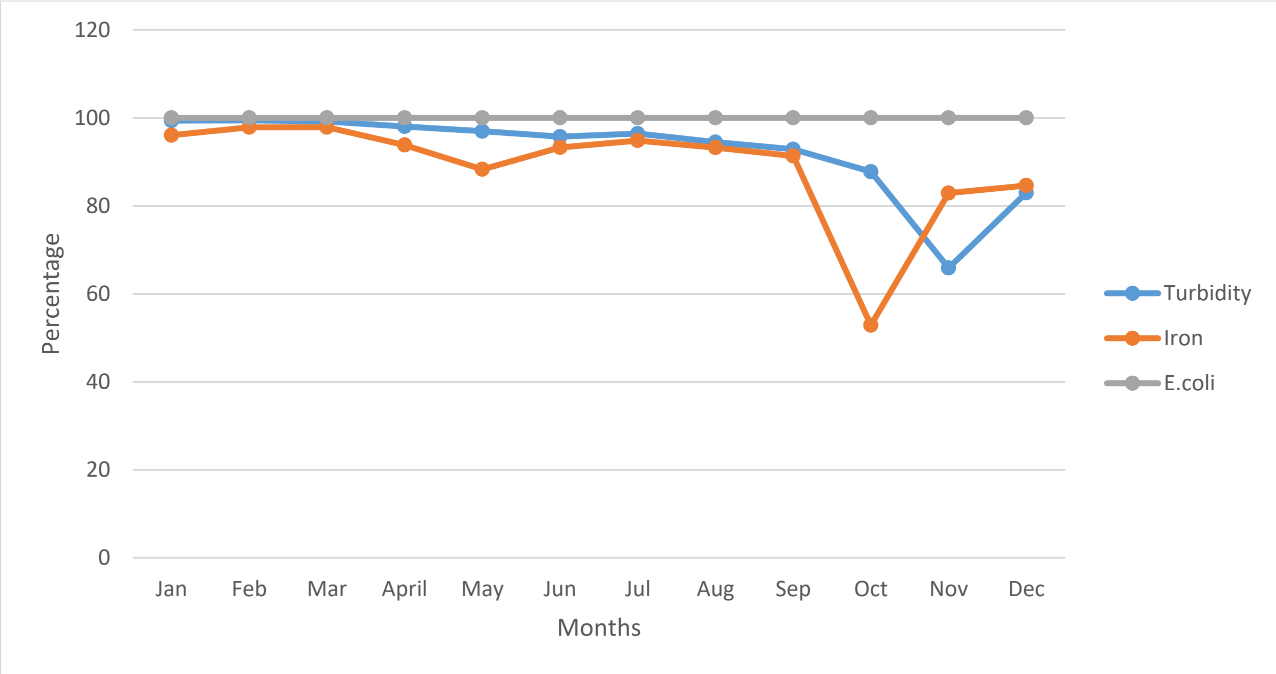

Figure 4.20: Removal efficiency data for turbidity, iron and E. coli for the year 2018

Table 4.20: Yearly average for influent and effluent for the year 2018

Turbidity (NTU) WHO/SANS standards for discharge [≤ 1 NTU]		**Iron (mg/L)** WHO/SANS standards for discharge [≤2 mg/L]		**E. coli (MPN/100mL)** WHO/SANS standards for discharge [Not determined]	
Influent	Effluent	Influent	Effluent	Influent	Effluent
12.06589	0.232067	0.562345	0.041808	2.230284	0

Figure 4.20 shows that E. coli removal efficiency is 100% meaning that the effluent produced by the wastewater treatment plant is free of pathogens for the year 2018 as presented in *Table 4.20* with the recorded annual average equal to 0MPN/100mL. The analysis of *Figure 4.20* shows that turbidity and E. coli removal efficiency trends were almost the same up to May 2018 and thereafter the overall trend for turbidity shows a decrease up to the end of the year. Iron removal efficiency differs from the two other parameters. It fluctuates more often by increasing and decreasing throughout the year. Again, this is a reflection in the composition

and nature or type of the influent. The annual average removal efficiencies for turbidity have ranged from 65, 88 to 99, 42% while for iron it is between 82, 89 to 97, 87% as shown in *Figure 4.20.* From *Table 4.20* it is observed that the effluent complied with the 2015 SANS blue drop limits and WHO standard limits for both turbidity and iron for the year 2018.

4.3. Statistical analyses and forecasting of parameters

This section aims to develop an Auto-Regressive Integrated Moving Average (ARIMA) model to perform a short-term prediction. ARIMA models are simply a combination of an autoregressive (AR) model and a moving averages (MA) model. The AR part captures the correlation of the consecutive data points, while the MA is the trend. In this section statistical interpretation is done to support the analysis of the trend for Turbidity, Iron and plant performance for both parameters.

Types of ARIMA:

(a) ARIMA with non-seasonality ARIMA (p,d,q) where p is AR order, d is degree of differencing, and q is MA order.

(b) ARIMA with seasonality ARIMA (p,d,q)(P, D, Q)[S] where the first part (p,d,q) is the non-seasonality explained in (a), and (P, D, Q) is the seasonality part with frequency S.

Temporal analysis of water quality parameters

The present analysis and modelling are performed from Hazelmere wastewater treatment data from 1999 to 2018. The raw data are constituted of 9 variables and 242 points. Only nine variables are considered in this analysis.

4.3.1 Turbidity removal

4.3.1.1 Data plots

The temporal data is plotted in scatter plot and box plot as *Figure 4.21* for an exploratory data analysis (EDA). This allows for performing a quick view of the data and noticing any anomaly in it.

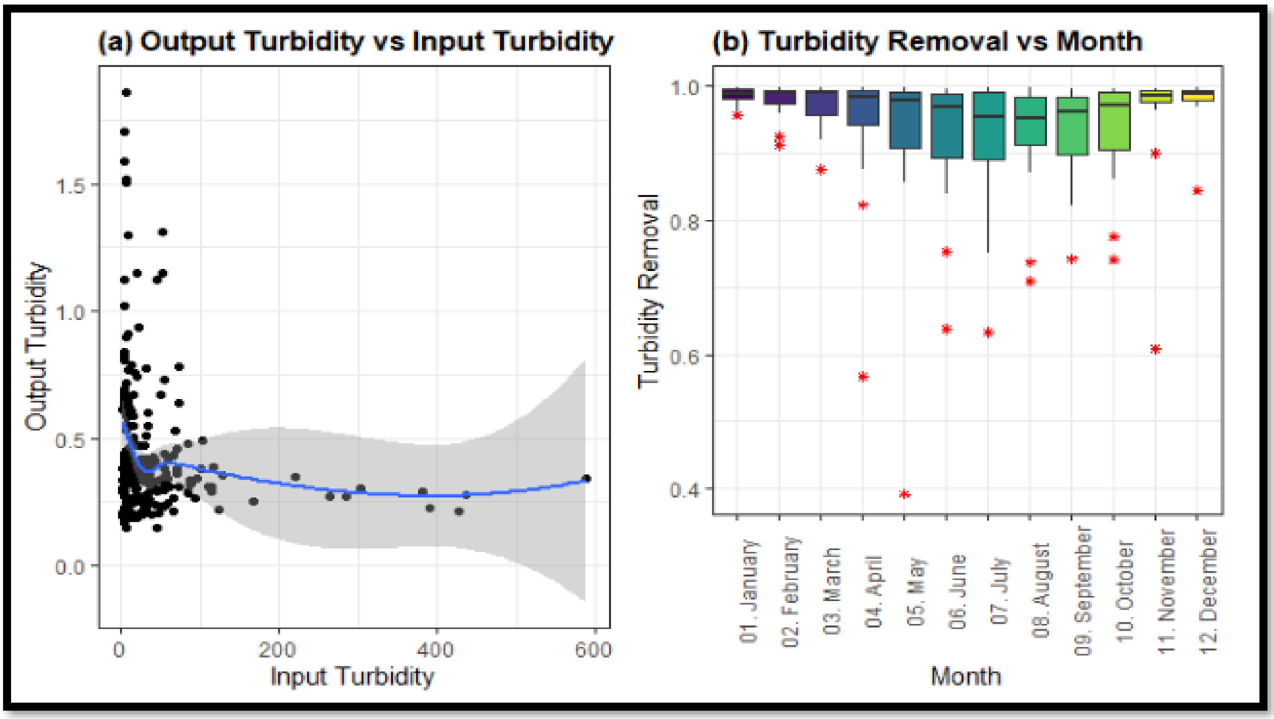

Figure 4.21: Temporal analysis turbidity scatter plot and turbidity removal boxplot

It is noticed data most of the data are concentrated below 200 input turbidity as shown in Figure 4.21(a). The input turbidity above 200 are outliers and contributed to low turbidity removal represented in Figure 4.21(b) by the red stars in the function of the months of the year. For these points, more products have been used compared to the normal.

4.3.1.2 Time series data plots

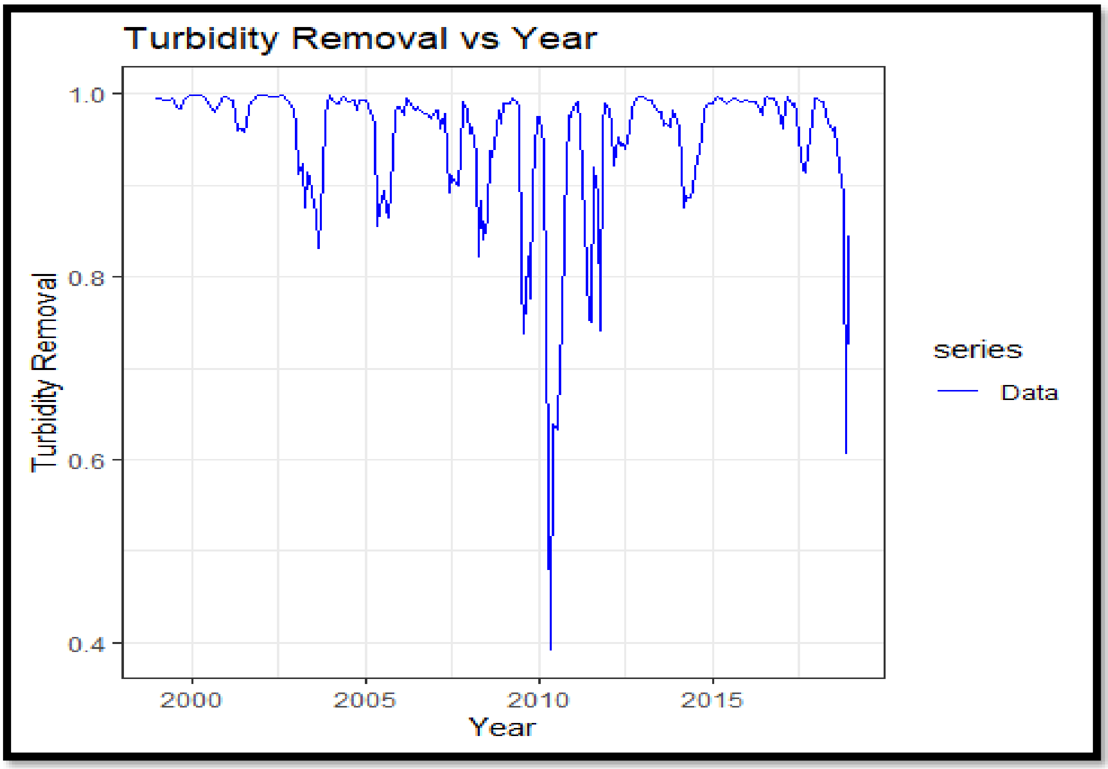

Figure 4.22: Turbidity removal time series plot

Table 4.21: Summary of turbidity removal dataset

Minimum	**1st Quartile**	**Median**	**Mean**	**3rd Quartile**	**Maximum**
0.3916	0.9372	0.9826	0.9494	0.9929	0.9995

By plotting the time series turbidity removal plot in *Figure 4.22*, time is in the x-axis and turbidity removal is on the y-axis. There is a constant pattern without seasonality. Due to the variability not being constant, the time series is non-stationary. A time series is non-stationary if the average or mean, or variability of covariance is not constant. To convert a non-stationary TS into stationary TS, differencing is performed.

From *Figure 4.22*, we notice that turbidity removal is low between 2009 to 2013, and 2018. This means that more wastewater is fed to the plant. The summary of the turbidity removal data is given in *Table 4.21*. The values of the median and the mean are closed, which is a good indication for modelling. The minimum turbidity removal is 0.3916. This value corresponds to the month of May 2010 as seen in *Figure 4.21*(b) and *Figure 4.22*.

4.3.1.3 Time series data decomposition

As the goal is to predict the turbidity removal of the plan, the turbidity removal of the TS data is split into trend, temporal seasonal and remainder or residuals components as seen in *Figure 4.23* and *Table 4.22*. This decomposition allows for more precise insight into turbidity removal behaviour during the 1999–2018 periods to develop an ARIMA model for the dataset and perform the prediction of the turbidity removal of the plan. The decomposition allows us to properly understand the data.

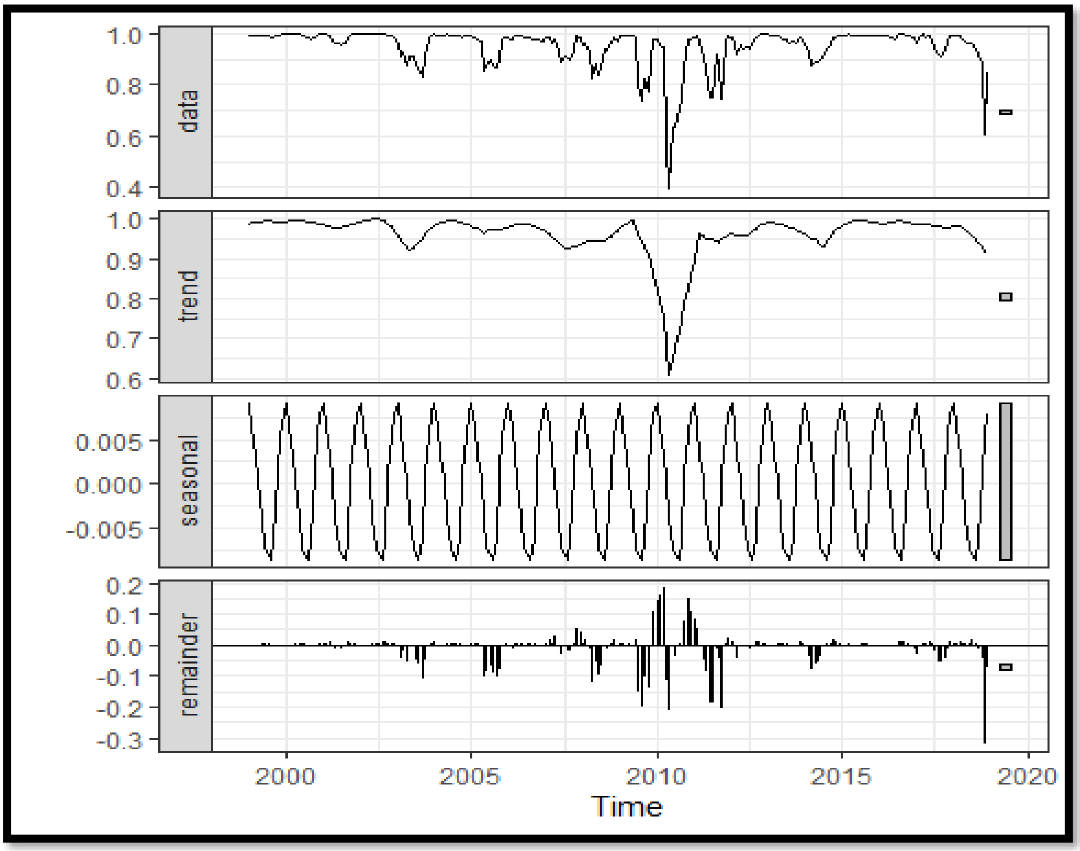

Figure 4.13: *Temporal analysis turbidity removal time series decomposition*

No seasonal differences are suggested if seasonal strength < 0.64, otherwise one seasonal difference is suggested. For the present case, the seasonal strength is 0.1< 0.64. This means no seasonal difference is performed.

Table 4.52: Temporal analysis of turbidity removal trend and seasonal strengths

Trend Strength	Seasonal Strength
0.6	0.1

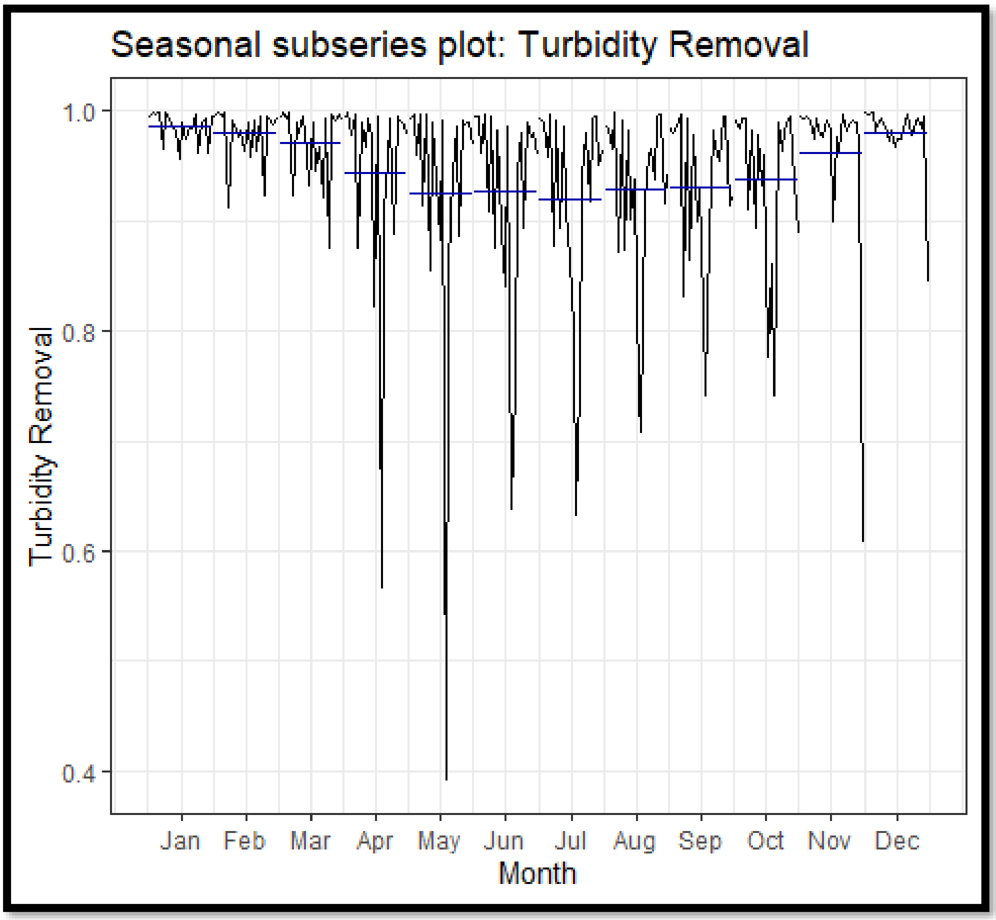

Figure 4.24: Turbidity removal seasonal subseries plot

Figure 4.24 represents a temporal analysis of the turbidity removal seasonal subseries plot. It is noticed that the data has a trend with non-seasonality, and the lower values of the turbidity removal are obtained between May and September while higher values are in January and December because there was a change in the nature or composition of the influent fed to the wastewater treatment plant. The values of strength of trend and seasonality are given in *Table 4.22* above. It can be said that from these results we are dealing with an ARIMA with non-seasonality.

4.3.1.4 Split train and test Sets

To develop the ARIMA model, the turbidity removal data are split into two groups of 70% and 30 % datasets allocated to the training and the testing, respectively.

4.3.1.5 Training data and transformation analyze

Verification of differencing

The training dataset is verified for any differencing and seasonality for a possible transformation. By verifying the first difference, the seasonal difference and the first seasonally differenced data, we obtain results in *Table 4.23.*

Table 4.26: Results of turbidity removal differencing checking

First difference	**Seasonally difference**	**First seasonally differenced**
1	0	0

Transformation analyses

Unit root tests

Training set data are checked for stationary before starting to build the ARIMA model. For that, the unit root test statistic is performed to verify the null hypothesis assumption. In this test, the null hypothesis is that the data are stationary, and we look for evidence that the null hypothesis is false. Consequently, small p-values (less than 0.05) suggest that differencing is required. In this study, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is used. In this test, if the test statistic is much bigger than the 0.01 critical value, the null hypothesis is rejected. That is, the data are not stationary. We can differentiate the data and apply the test again.

The result of KPSS Unit Root Test obtained using urca package in R is that the test statistic is 0.9138 which is much higher than the 0.01 critical value and indicates that the null hypothesis is rejected. That is, the data are not stationary. We can differentiate the data and apply the test again. We perform the first differences of the data and each time we check for unit root test until the data are stationary. This time, the test statistic is equal to 0.0222, and well within the range, we would expect for stationary data. Therefore, we can conclude that the differenced data are stationary.

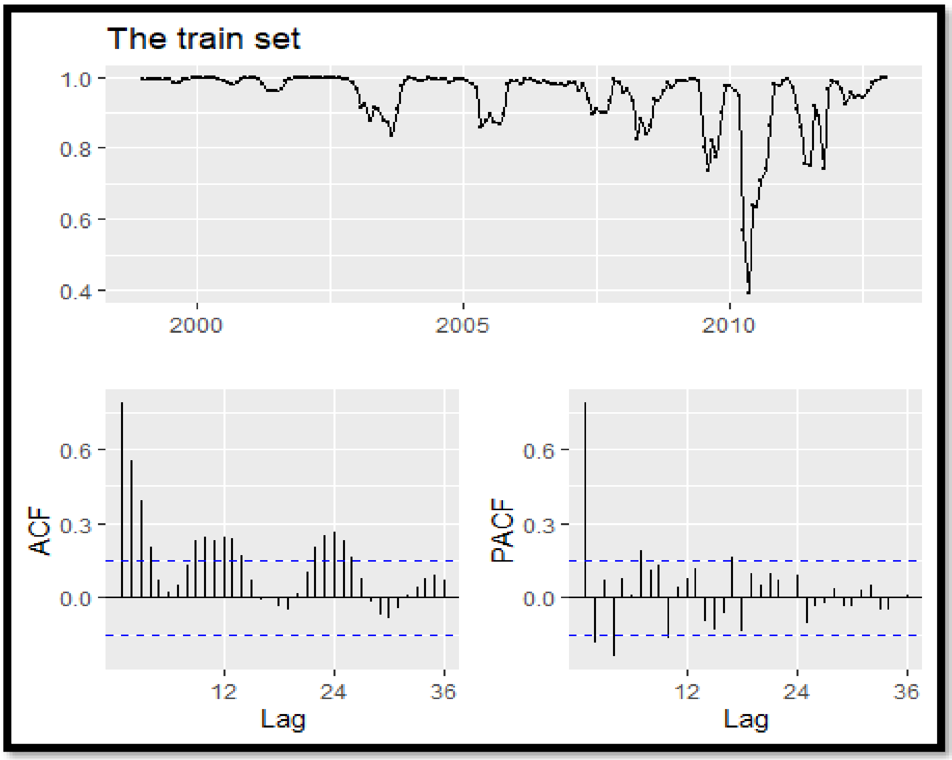

Figure 4.25: Temporal analysis turbidity removal training set analysis plots.

Figure 4.25 presents the turbidity train set with its ACF and PACF plots. The ACF of most lags and PACF of few lags are out of limit boundaries as seen in Figure 4.25 shows the temporal analysis. The first differencing is performed to stationary the turbidity removal TS as seen in Figure 4.25.

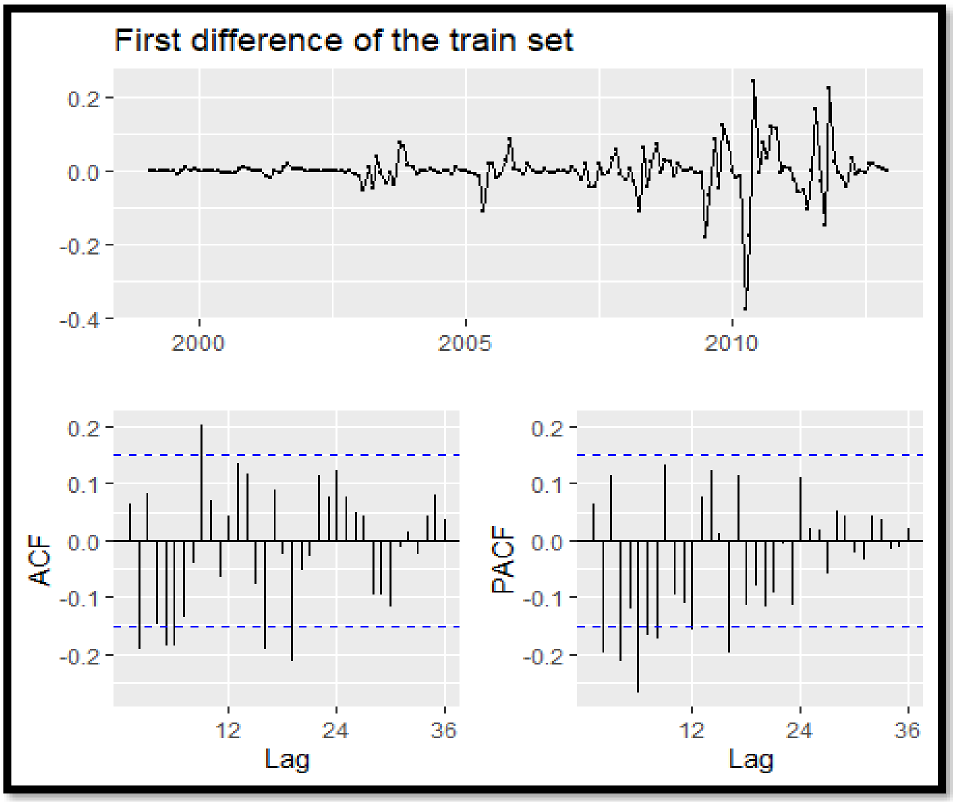

Figure 4.26: Temporal analysis turbidity removal training set first difference analysis plots

In *Figure 4.26*, most of ACF and PACF values for lags are in the limit boundaries and correlations between points are not significant except for a few lags. This allows for determining the appropriate ARIMA model and performing its residuals Box-Ljung test to be sure that residuals are white noise.

4.3.1.6 ARIMA - Autoregressive Integrated Moving Average

The obtained ARIMA is ARIMA (2,1,2) with 2 is AR order, 1 is the degree of differencing, and 2 is MA order. The parameters of the obtained ARIMA (2,1,2) are given in *Table 4.24.*

Table 4.247: Parameters of the ARIMA (2,1,2) model for turbidity removal.

Parameter	**ar1**	**ar2**	**ma1**	**ma2**	**AIC**	**BIC**
Model	0.1218	0.4191	-0.0899	-0.8627	-508.06	-492.47
s.e.	0.0957	0.0938	0.0528	0.0521	-	-

The R function ARIMA will fit a regression model of ARIMA errors if the argument xreg is used. The order argument specifies the order of ARIMA error model. If differencing is specified, the differencing is applied to all variables in the regression model before the model is estimated. Where ARIMA is (2,1,2) error the constant term disappears due to the differencing.

Residual's plot

To be sure that almost all the information is collected from the data, let's perform the ARIMA (2,1,2) residuals checking.re 4.20.1: Turbidity removal training set first difference residuals analysis plots.

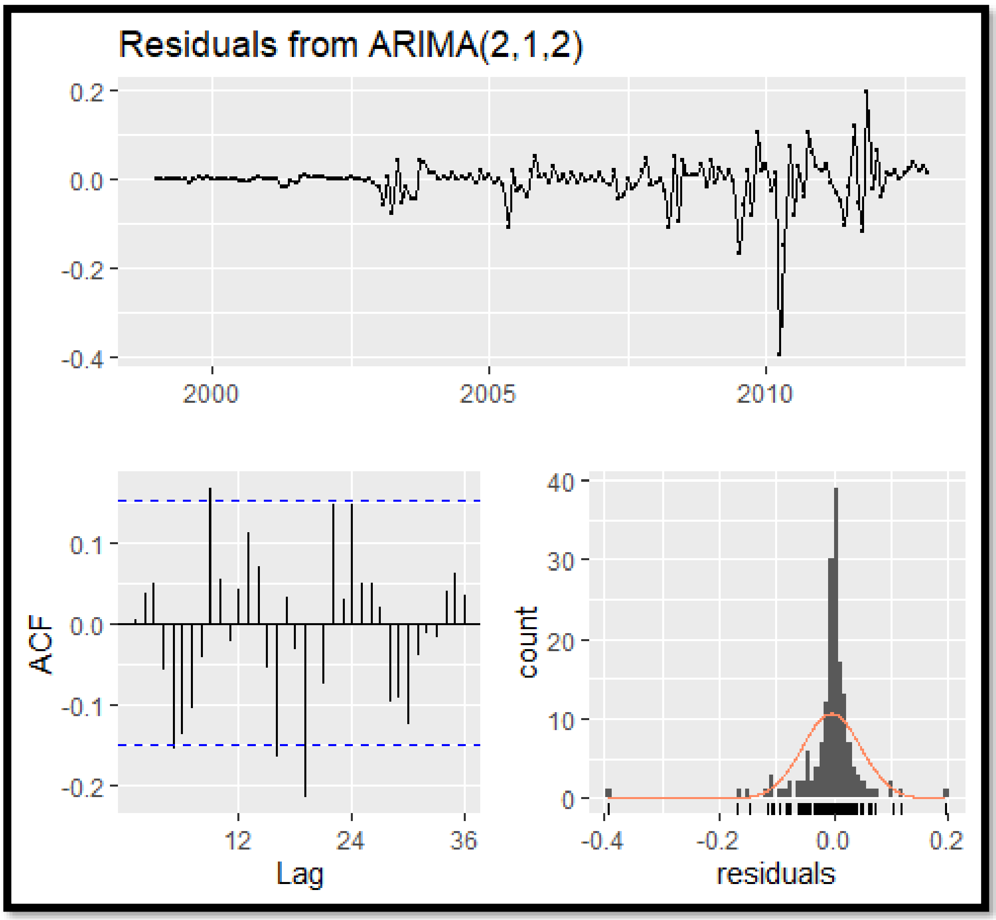

Figure 4.27: Temporal analysis of turbidity removal training set first difference residuals analysis plots

Plots of residuals of the ARIMA (2,1,2) are presented in the temporal analysis in *Figure 4.27*. The ACF plot of residuals of the model does not fall in the limited band for the lags 5, 9, 16, 18, 22 and 24, while the distribution of residuals is normal as seen in *Figure 4.27*, this means that the residuals may not be white noise. The ARIMA (2,1,2) model may not be considered for forecasting the turbidity removal of the plan. To be sure of the model, the Box-Ljung test is performed.

The null hypothesis of the Box Ljung Test is that the model does not show a lack of fit. A significant p-value > 0.05 in this test rejects the null hypothesis that the time series is not auto-correlated. The value of the p-value of 0.01682 is obtained by performing the Box-Ljung test. This means that the model does not fit the data.

Model accuracy.

The ARIMA (2,1,2) model is checked for accuracy by comparing the RMSE, MAE and MAPE values of the train and test datasets. The results are given in *Table 4.25.*

Table 4.258: Turbidity model accuracy checking

Parameter	**RMSE**	**MAE**	**MAPE**
Training set	0.1218	0.4191	-0.0899
Test set.	0.0957	0.0938	0.0528

We can notice that the obtained values for the training dataset and testing dataset are closed. This model can still be used for forecasting even though it did not pass all the tests.

4.3.1.7 Forecasting

The forecast is done over three years. The choice of short-term prediction is motivated by the fact that the long-term prediction is accompanied by an increase in the variance of the predicted parameter that can lead to a higher probability of error in the prediction.

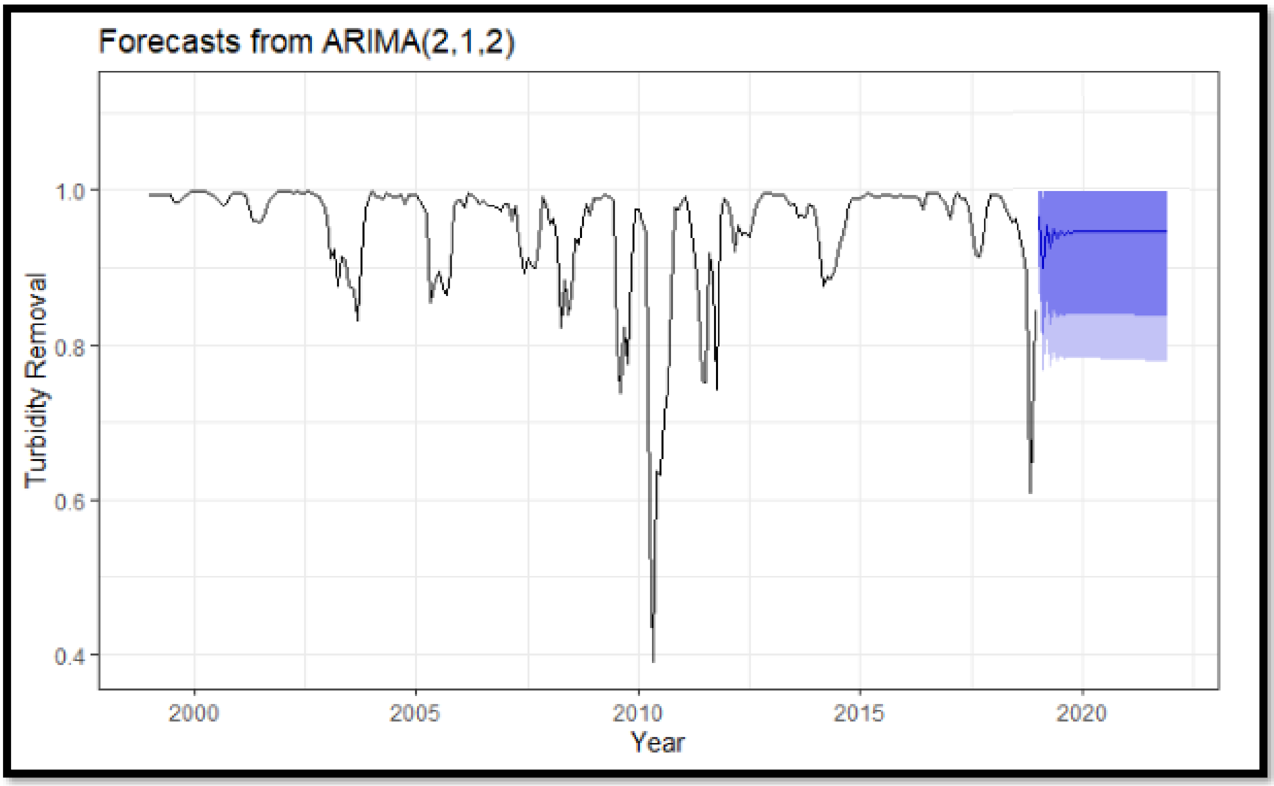

Figure 4.28: Temporal analysis of a three-year turbidity removal forecasting using an ARIMA (2,1,2)

The forecasting of the turbidity removal is represented in Figure 4:28 above. We can notice to values of the interval of tolerance. Dark blue represents 80 % interval tolerance, while light blue represents 95 % interval tolerance. In addition, there is no symmetric distribution as the upper limit of the interval is 1 because the value of turbidity removal cannot be above 1.

4.3.2 Iron removal

4.3.2.1 Data plots

To perform a review of the data and notice any anomaly in it, the iron removal data are plotted in a scatter plot and boxplot for an exploratory data analysis (EDA) as presented in *Figure 4.29.*

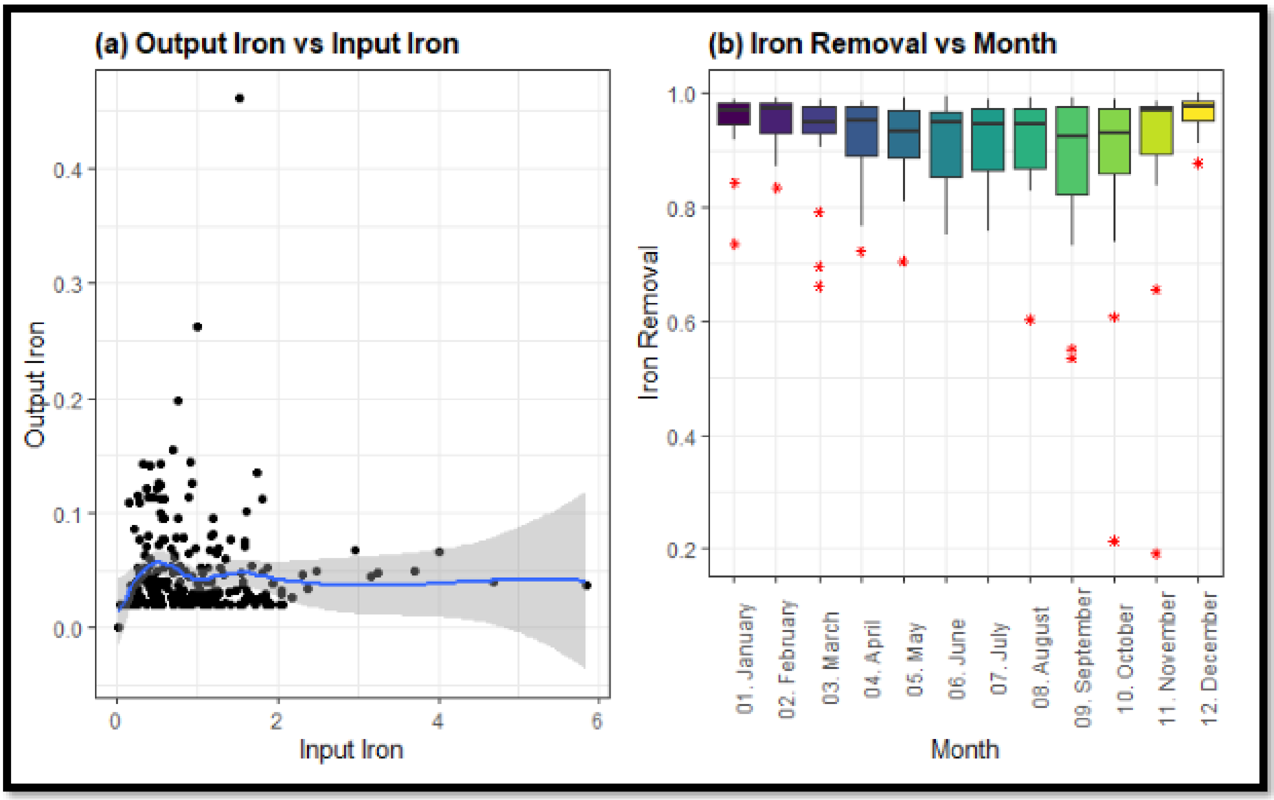

Figure 4.29: Iron scatter plot and iron removal boxplot

It is observed that most of the data are concentrated below the value of 2.5 input iron as shown in *Figure 4.29(a).* The input iron above the value of 2.5 are considered outliers and are represented in *Figure 4.29(b)* by the red stars in the function of the months of the year. For these points, more products have been used compared to the normal.

4.3.2.2 Time series data plots

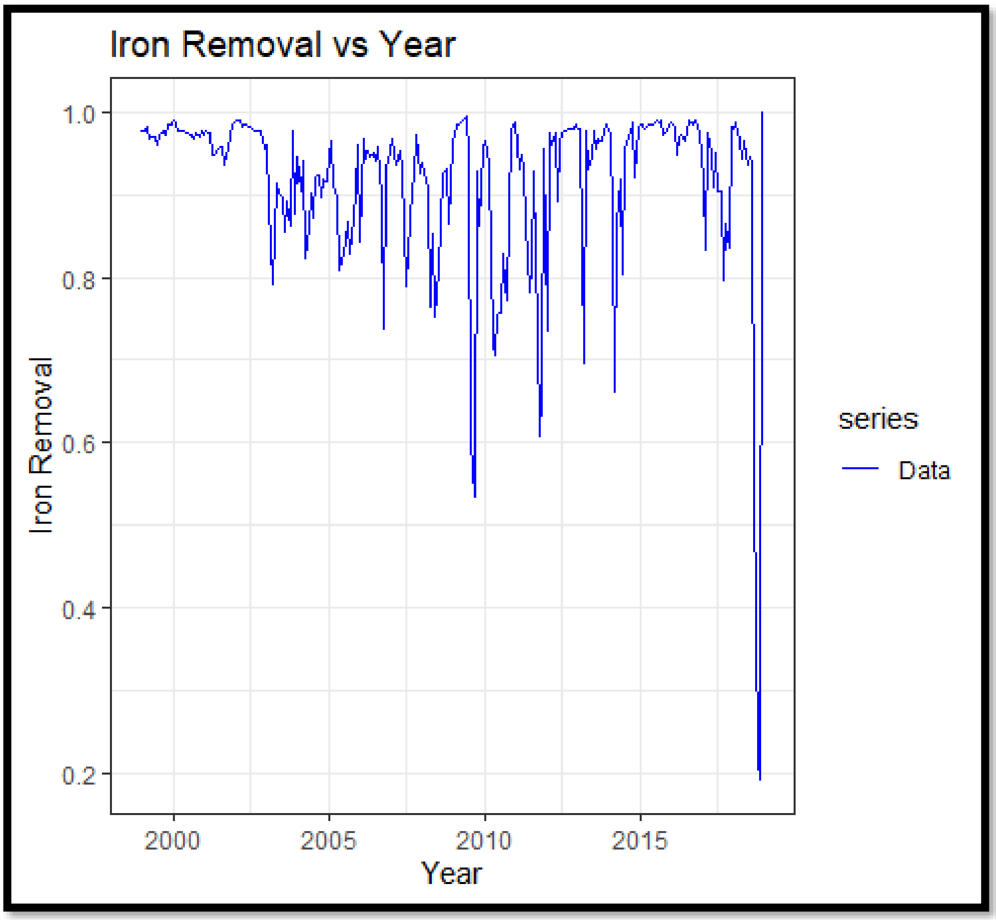

Figure 4.30: Temporal analysis of iron removal time series plots

Table 4.269: Summary of iron removal dataset

Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
0.1920	0.8975	0.9545	0.9159	0.9768	1

By plotting the time series iron removal plot from the temporal analysis in *Figure 4.30*, time is on the x-axis and iron on the y-axis. There is a constant pattern without seasonality. Because the variability is not constant, the time series is non-stationary. A time series is non-stationary if the average or mean, or variability of covariance is not constant. To convert a non-stationary TS into stationary TS the differencing is performed. In addition, we notice from *Figure 10* that iron removal is low in certain months between 2009 and 2011, and very low in 2018 this could be due to the nature or composition of the influent during that period. This means that more wastewater is fed to the plant. The summary of the iron removal data is given in *Table 4.26.* The values of the median and the mean are close, which is a good indication. The minimum of iron removal is 0.1920. This value corresponds to the month of November 2018 as seen in *Figure 4.29(b)* and *Figure 4.30.*

4.3.2.3 Time series data decomposition

As the aim is to predict the iron removal of the plan, the iron removal TS data are split into a trend, seasonal and remainder or residuals components as seen in *Figure 4.31*. This decomposition allows us to gain more precise insight into iron removal behaviour during the 1999–2018 periods to develop an ARIMA model for this dataset and perform the prediction of the iron removal of the plan. The decomposition allows us to properly understand the data.

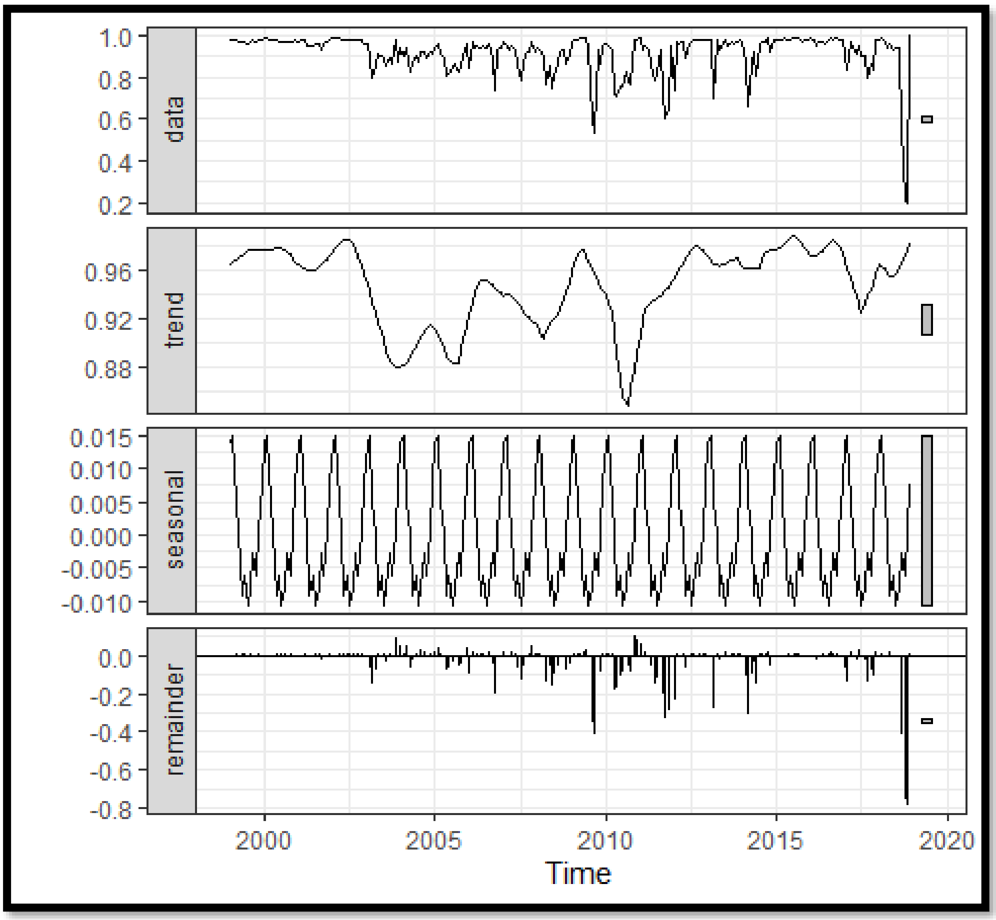

Figure 4. 31: Iron removal time series decomposition

Table 4.2710: Iron removal trend and seasonal strengths

Trend Strength	Seasonal Strength
0.1	0

The values of strength of trend and seasonality are given in Table 4.27. From the results obtained, no seasonal differences are suggested as a trend strength of 0.1 < 0.64 and the seasonal strength is 0. We can conclude from these results that we are dealing with an ARIMA with non-seasonality.

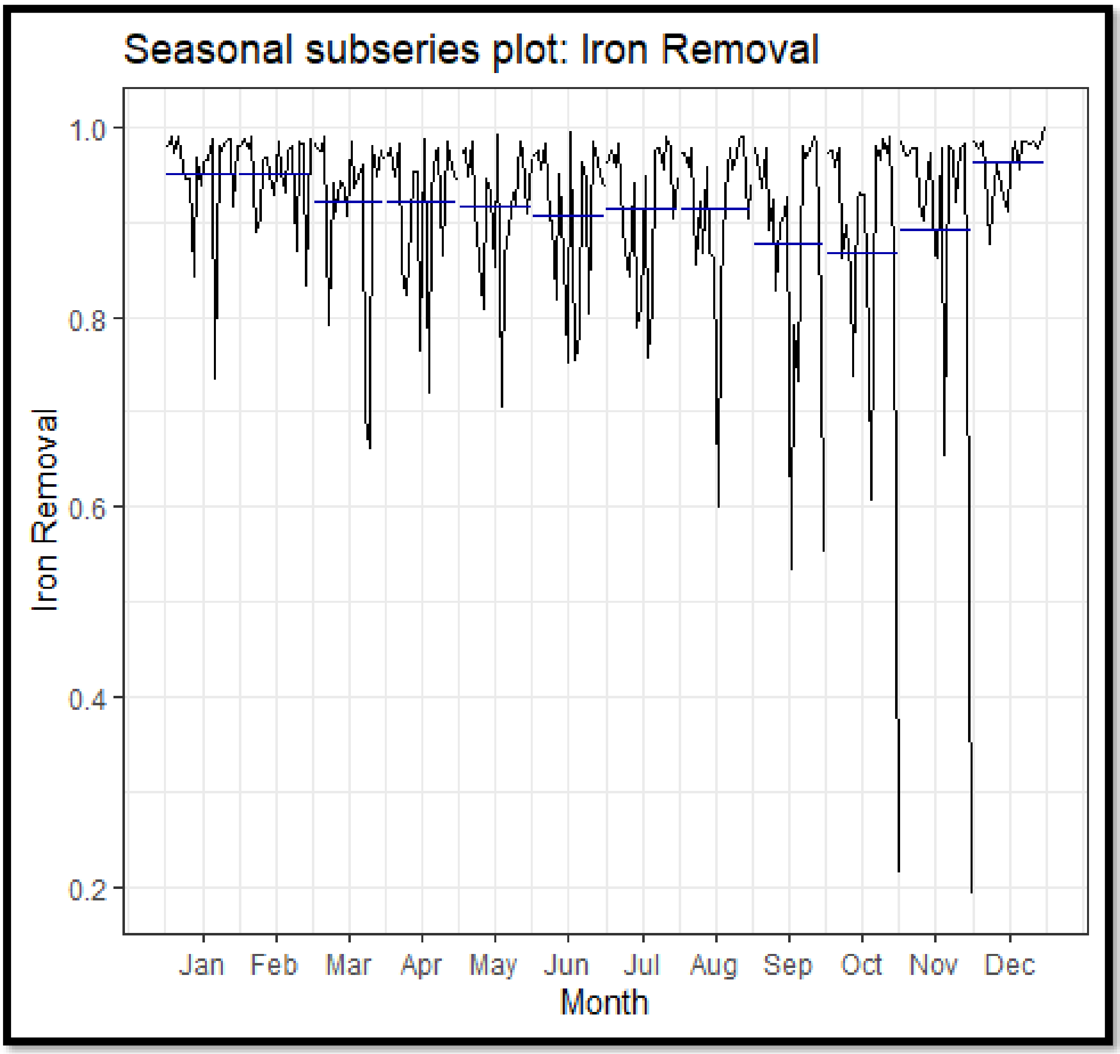

Figure 4. 32: Temporal analysis of iron removal seasonal subseries plot

From seasonal subseries plot of iron removal shows the temporal analysis in *Figure 4.32* and the descriptive statistics are shown in *Table 4.28*, it can also notice that the data has a trend with non-seasonality with the lower values of the iron removal obtained in October, while high values in December caused by the inconsistency of the nature or composition of the influent fed to the wastewater treatment plant.

4.3.2.4 Split train and test Sets

To develop the ARIMA model, the iron removal data are split into two groups of 70% and 30 % datasets allocated to the training and the testing, respectively.

4.3.2.5 Training data and transformation analysis

Verification of differencing

The training dataset is verified for any differencing and seasonality for a possible transformation. The first difference, the seasonal difference and the first seasonally differenced data are given in *Table 4.28.*

Table 4.2811: Results of iron removal differencing checking.

First difference	Seasonally difference	First seasonally differenced
1	0	0

Transformation analyses

Unit root tests

Train set data are checked about its stationary before starting to build the ARIMA model. The result is that the test statistic is 1.0181 and is almost equal to the critical value of 1, indicating that the null hypothesis is rejected. That is, the data are not stationary. We can differentiate the data and apply the test again. We perform the first differences of the data and each time we check for unit root test until the data are stationary. The plots of the iron removal training dataset and the first differencing of the train set are given in *Figure 4.33* and *Figure 4.34,* respectively.

After performing the first differencing, the test statistic is equal to 0.0257, and well within the range, we would expect for stationary data. Therefore, we can conclude that the differenced data are stationary.

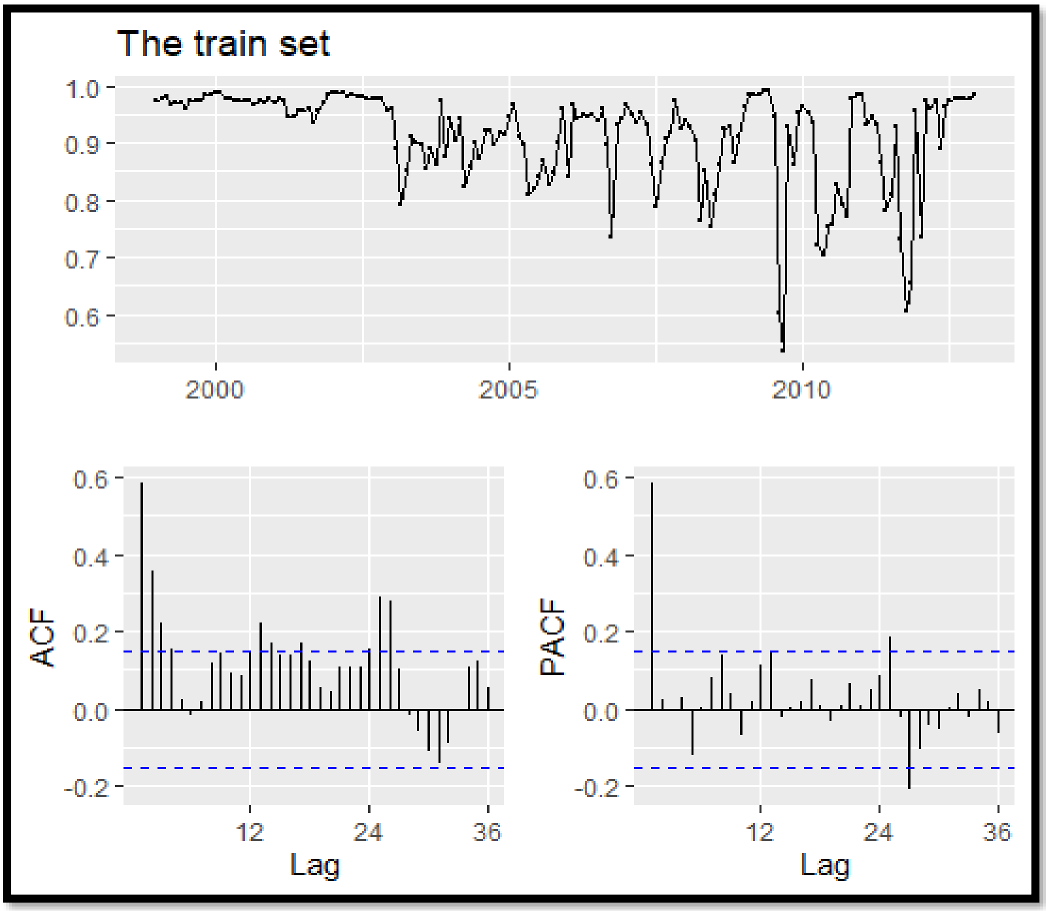

Figure 4.33: Iron removal training set analysis plots

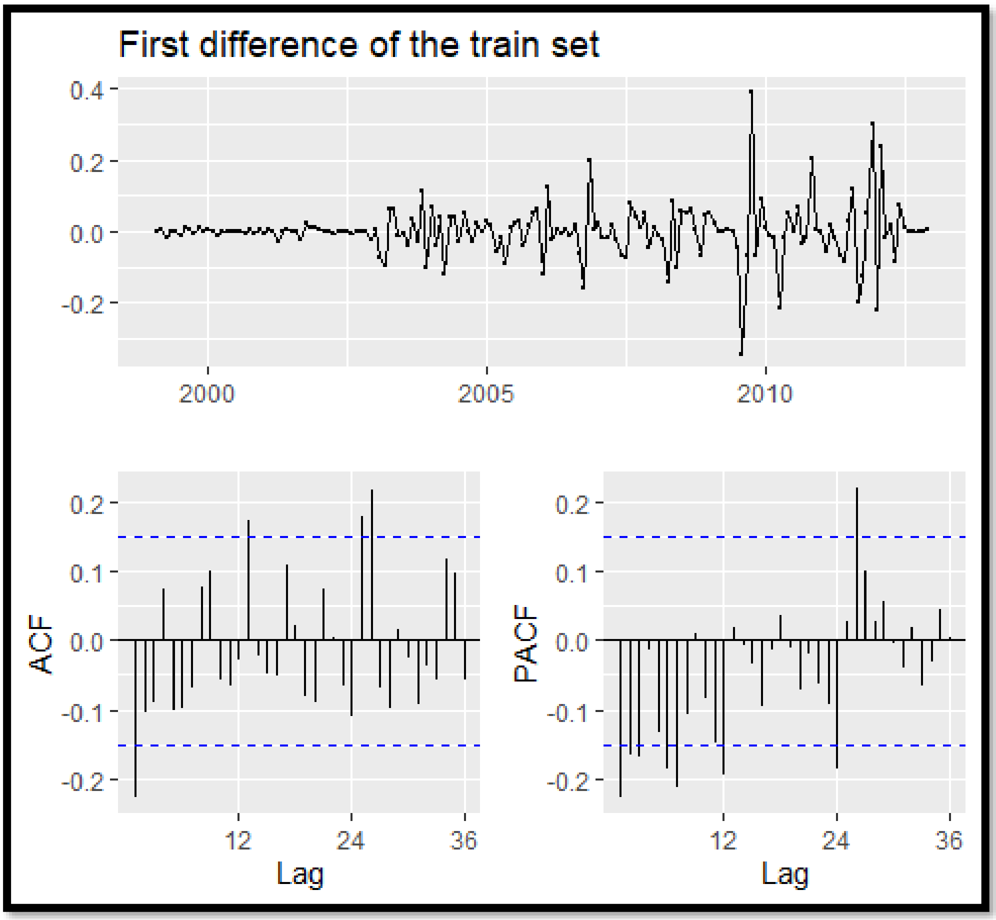

Figure 4.34: Temporal analysis of iron removal training set first difference analysis plots

We notice that correlations between most points are significant. There is a need to perform the Box-Ljung test for the residuals to be sure that residuals are white noise.

4.3.2.6 ARIMA - Autoregressive Integrated Moving Average

From the differencing, the obtained ARIMA is ARIMA (1,1,1) with 1 is AR order, 1 is the degree of differencing, and 1 is the MA order. The parameters of the obtained ARIMA (1,1,1) are given in *Table 4.29.*

Table 4.2912: Parameters of the ARIMA (1,1,1) model for iron removal

Parameter	**ar1**	**ma1**	**AIC**	**BIC**
Model	0.5266	-0.9625	-417.02	-407.67
s.e.	0.0725	0.0227	-	-

By implementing the s.e model as an ARIM model, one gains some flexibility. The estimated MA (1) coefficient is allowed to be negative as seen in the table above: this corresponds to a smoothing factor larger than 1.

Residual's plot

To be sure that almost all the information is collected from the data, let's perform the residuals checking as presented in *Figure 4.35*.

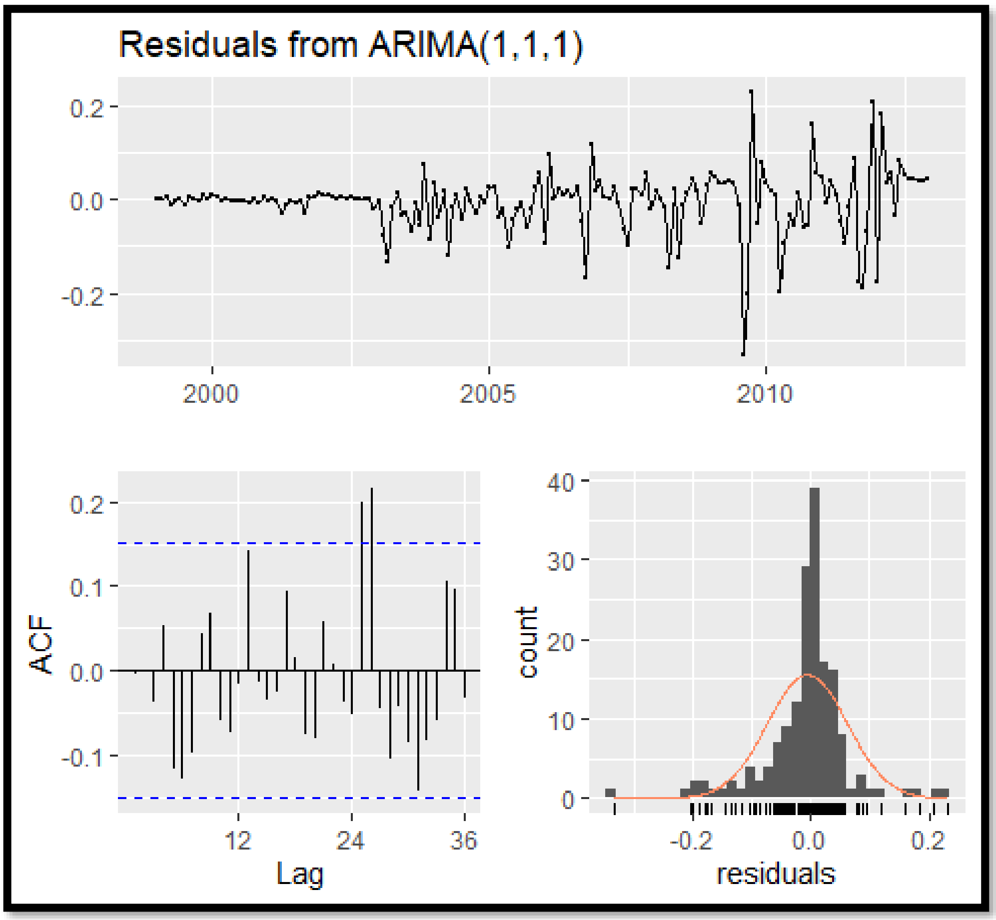

Figure 4.35: Temporal analysis of iron removal training set first difference residuals analysis plots

We notice the ACF plot of residuals of the model do not fall in the limited band for the lags 25 and 26, while the distribution of residuals is normal as seen in *Figure 4.35*, this means that the residuals may not be white noise. The ARIMA (1, 1, 1) model may not be considered for forecasting of the iron removal of the plan. To be sure of the model, the Box-Ljung test is performed. The value of p-value of 0.5361 is obtained by performing the Box-Ljung test. It means that the model does fit the data and can be used for forecasting

Model accuracy

The parameters of the obtained ARIMA (1, 1, 1) are determined, and the model checked for accuracy by comparing the RMSE, MAE and MAPE values of the train and test datasets. The results are given in *Table 4.30* as a temporal analysis.

Table 4.30: Iron model accuracy checking

Parameter	**RMSE**	**MAE**	**MAPE**
Training set	0.06767669	0.04153252	5.024661
Test set.	0.08668823	0.07360811	8.318429

We can notice the obtained values for the training dataset and testing dataset are closed. Consequently, this model can be used for forecasting even if it did not pass all the tests.

4.3.2.7 Forecasting

The forecasting of the iron removal for three consecutive years is represented in *Figure 4.36.*

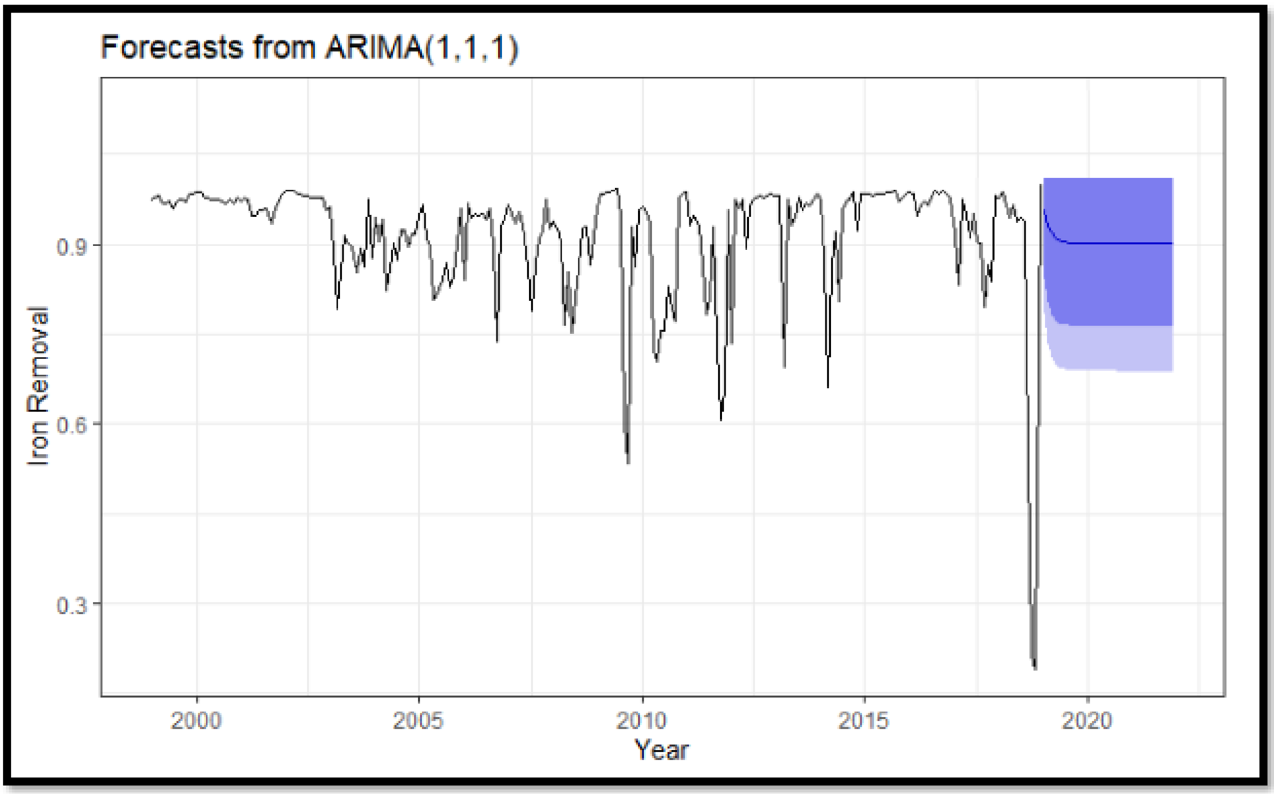

Figure 0.2.36: Three years 'iron removal forecasting using an ARIMA (1,1,1)

We can notice to values of the interval of tolerance. Dark blue represents 80 % interval tolerance, while light blue represents 95 % interval tolerance. In addition, there is no symmetric distribution as the upper limit of the interval is 1 because the iron removal cannot be above 1.

4.3.3 Plant Performance

4.3.3.1 Data plots

The plant performance data are plotted in scatter plot and boxplot as seen in *Figure 4.37*. This is done to perform a quick view of the data and notice any anomaly in it.

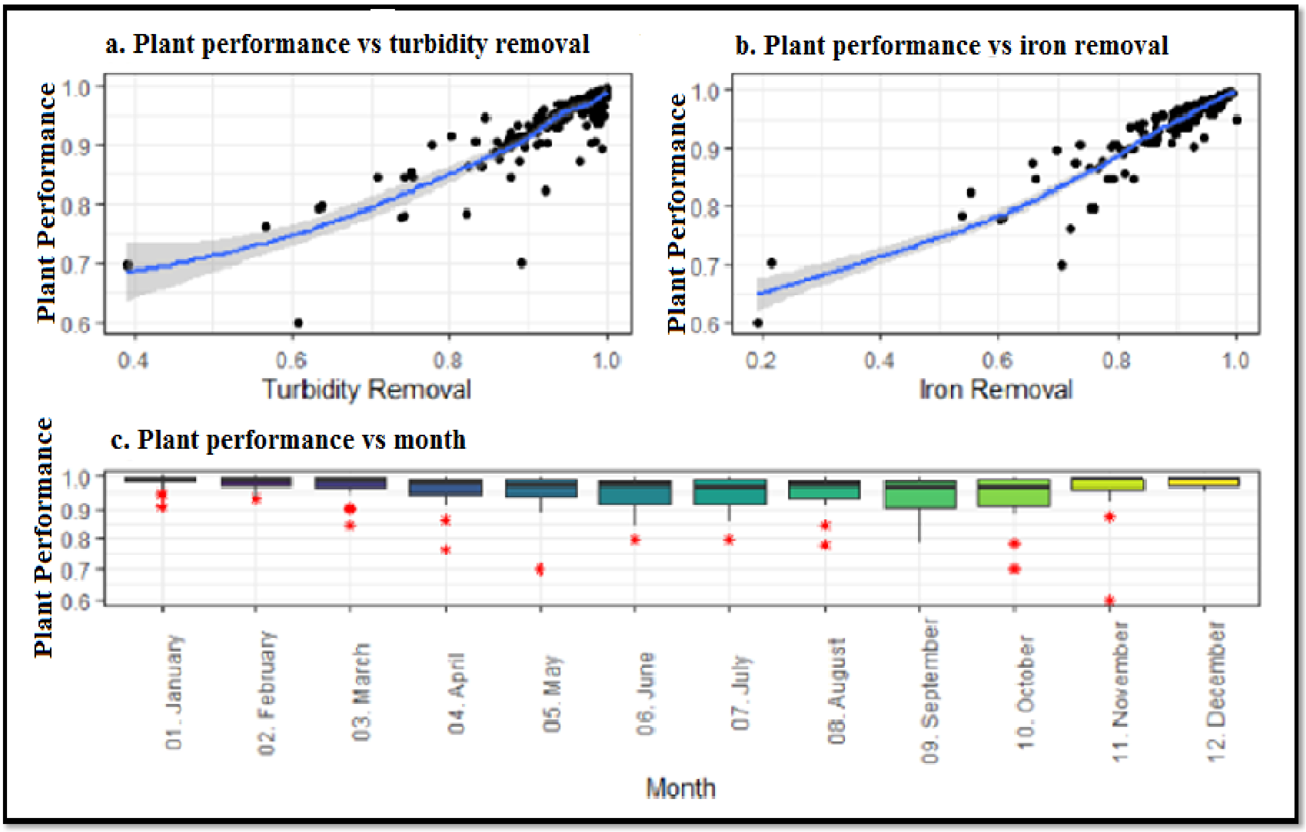

Figure 4.37: Plant performance vs turbidity removal, plant performance vs iron removal, and plant performance scatter plot

There is a strong correlation between the plant performance and the turbidity removal, and the plant performance and the iron removal as seen in Figure 4.37(a) and Figure 4.37(b), respectively. This is justified by the fact that the plan performance is define by its ability to extract products or impurities from water. For this case, only turbidity and iron were considered. In most case, the performance of the plan to remove turbidity and iron were above 90 % as seen in Figure 4.37(a)-(b). The outliers are well presented in the boxplot in Figure 4.37(c) by the red stars in function of the months of the year. These points indicate the low performance of the plan, which means more wastewater with more contaminants has been fed to the plant compared to the normal.

4.3.3.2 Time series data plots

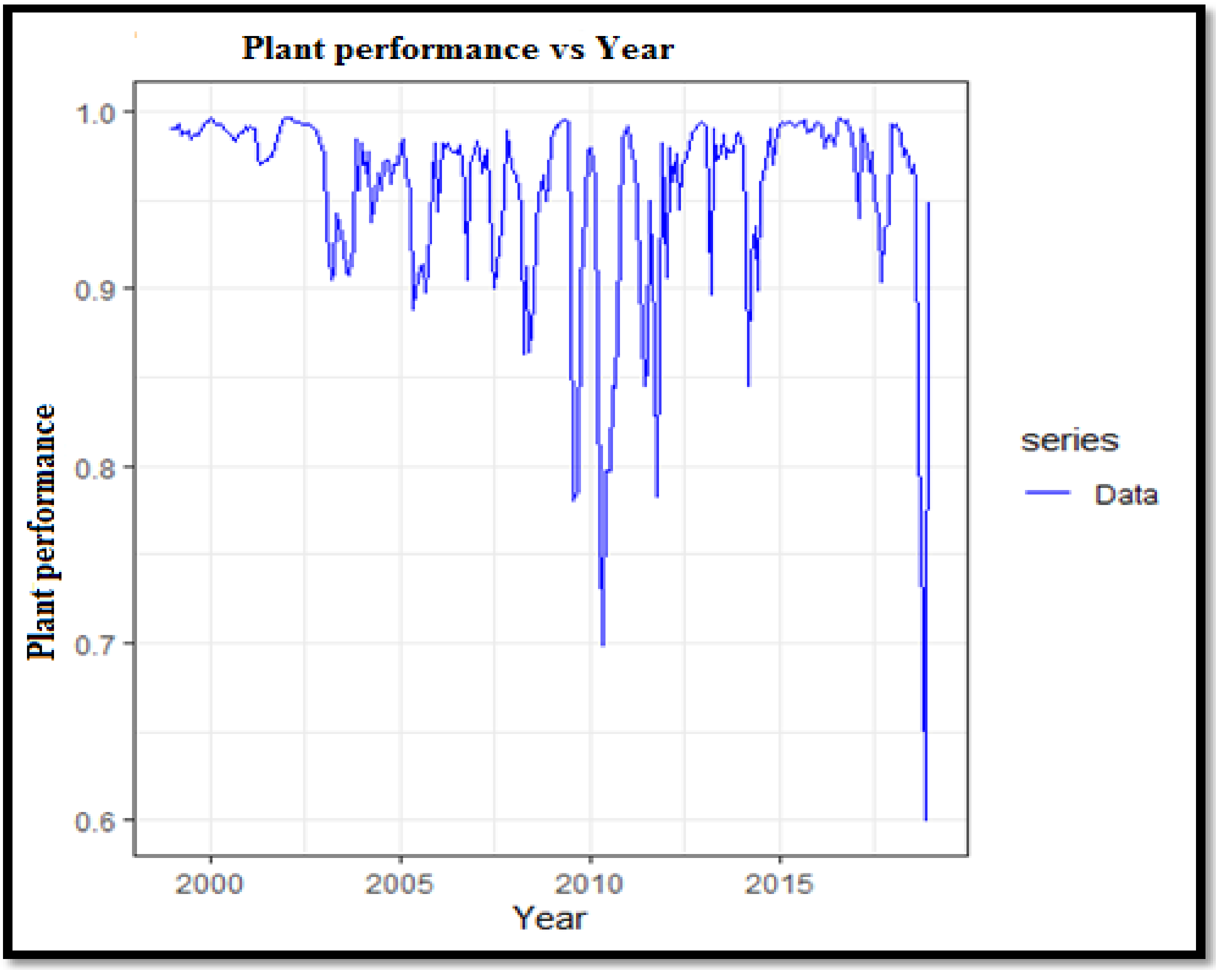

Figure 4.38: Temporal analysis of plant performance time series plots

Table 4.31: Summary of plant performance dataset

Minimum	**1st Quartile**	**Median**	**Mean**	**3rd Quartile**	**Maximum**
0.5999	0.9444	0.9764	0.9551	0.9894	0.9966

By plotting the time series plant performance plot in Figure 4.38, time is on the x-axis and plant performance in the y-axis. There is a constant pattern without seasonality. Because the variability is not constant, the time series is non-stationary. In addition, we notice low plant performance months between 2009 and 2011, and very low in 2018. This means that more wastewater is fed to the plant. The summary of the performance data is given in *Table 4.31*. The values of the median and the mean are closed, which is a good indication. The minimum value of the plan performance is 0.5999. This value corresponds to the month of November 2018 as seen in *Figure 4.37(c)* and *Figure 4.38.*

4.3.3.3 **Time series data decomposition**

As the aim is to predict the performance of the plant, the plant performance TS data are split into trend, seasonal and remainder or residuals components as seen in *Figure 4.39* and *Table 4.32* which shows the temporal analysis. This decomposition allows us to gain precise insight into plant performance behaviour during the 1999–2018 periods to develop an ARIMA model for this dataset and perform the prediction of the performance of the plant.

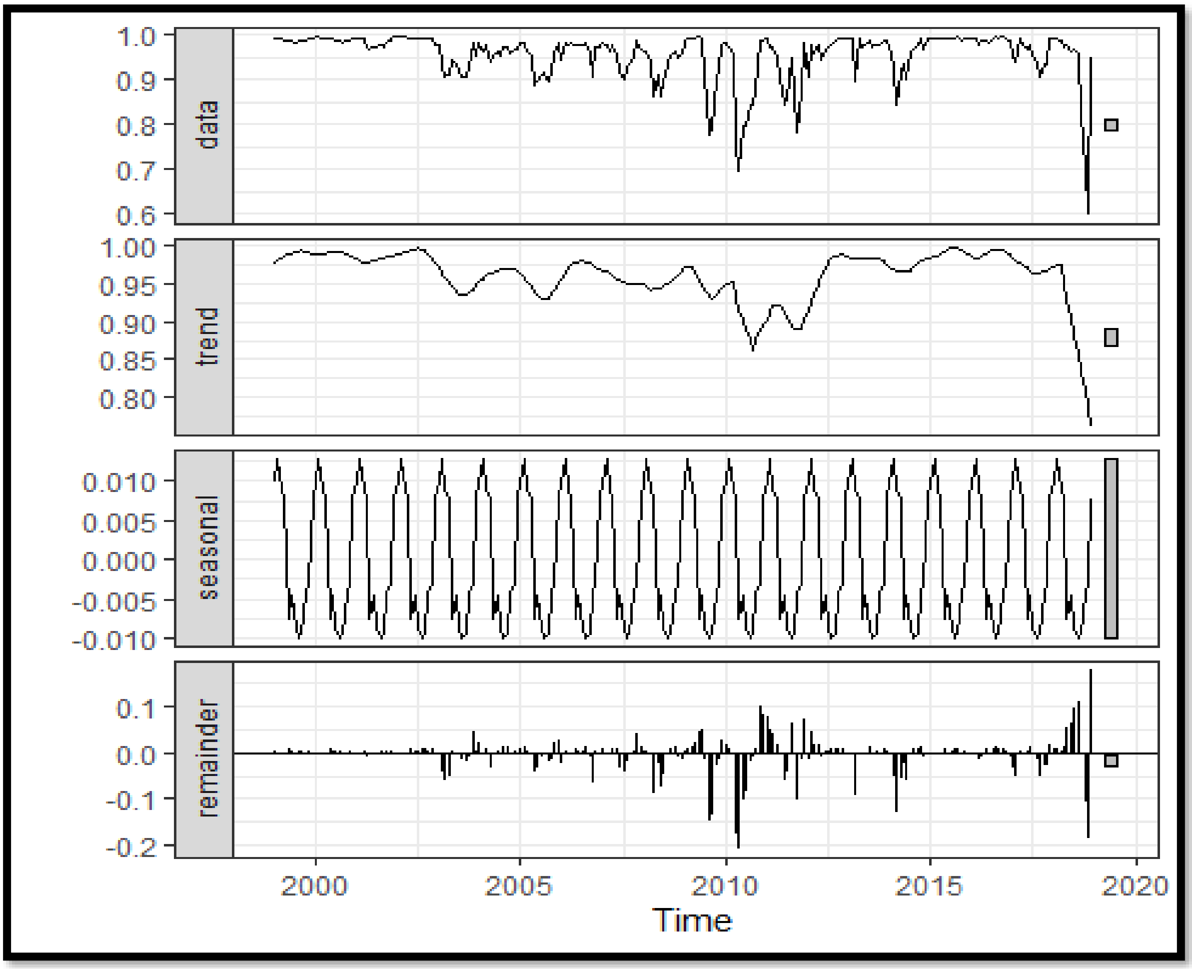

Figure 4.39: Temporal analysis of plant performance time series decomposition

Table 4.32: Plant performance trend and seasonal strengths

Trend Strength	**Seasonal Strength**
0.5	0.1

The values of strength of trend and seasonality are given in *Table 4.32*. From the values obtained in *Table 4.32*, no seasonal differences are suggested as the seasonal strength of 0.5 < 0.64 is obtained. We can conclude from these results that we are dealing with an ARIMA with non-seasonality.

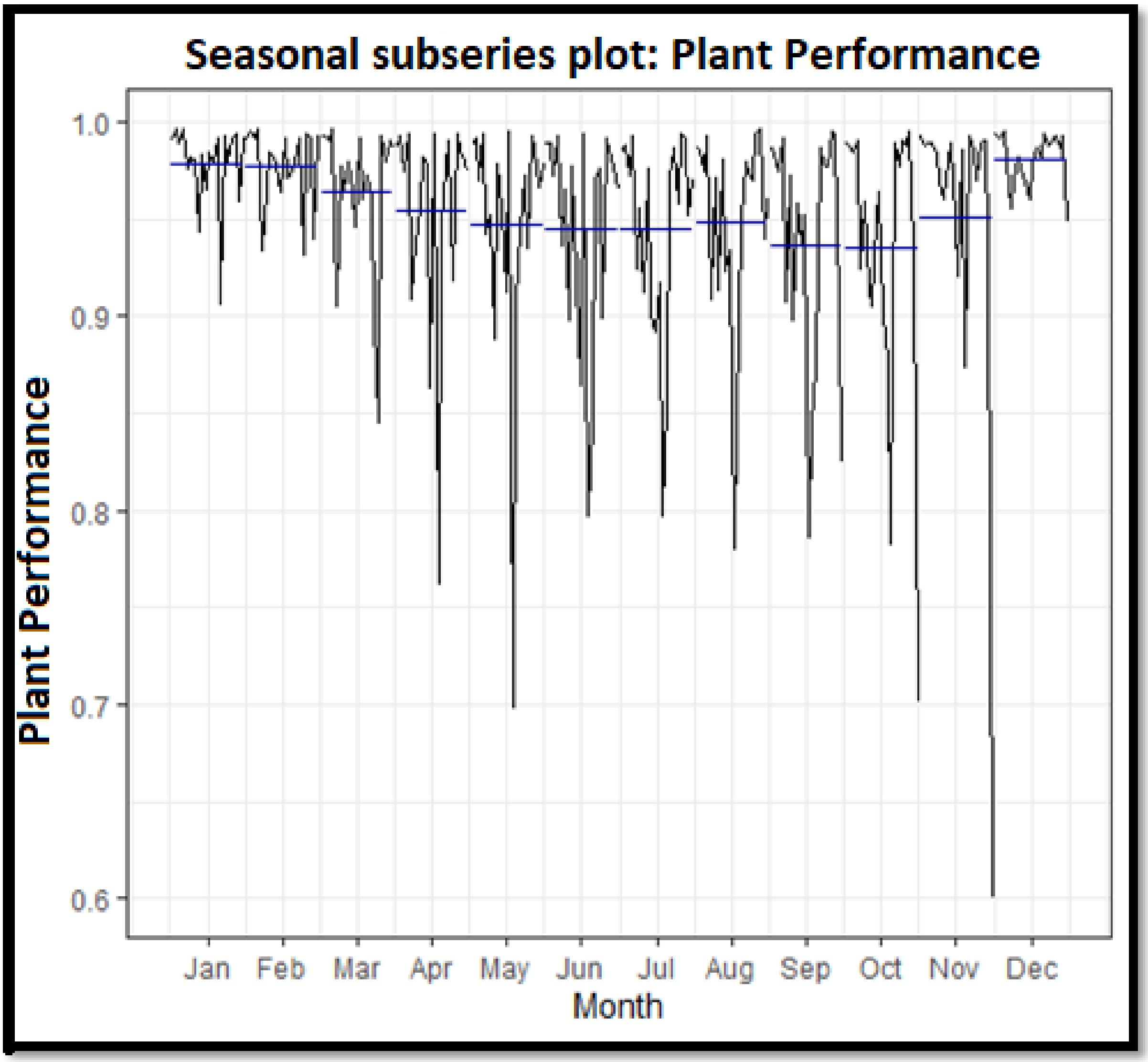

Figure 4.40: Plant performance seasonal subseries plot

Figure 4.40 represents the plant performance seasonal subseries plot; it is noticed that the data has a trend with non-seasonality. The lower values of the plant performance are obtained in September and October, while high values are in January, February, and December.

4.3.3.4 Split train and test Sets

To develop the ARIMA model, the plant performance data are split into two groups of 70% and 30 % datasets allocated to the training and the testing, respectively.

4.3.3.5 Training data and transformation analyses

Verification of differencing

The training dataset are verified for any differencing and seasonality for a possible transformation. The first difference, the seasonally difference and the first seasonally differenced of the plant performance training dataset are given in *Table 4.33.* We can notice that the data transformation can be performing by first differencing.

Table 4.33: Results of plant performance differencing checking

First difference	**Seasonally difference**	**First seasonally differenced**
1	0	0

Transformation analyses

Unit root tests

The result of the test statistic is 1.0511 and is almost equal to the critical value of 1, indicating that the null hypothesis is rejected. That is, the data are not stationary. We can differentiate the data and apply the test again. After the first differencing, the test statistic is equal to 0.0256, and well within the range, we would expect for stationary data. So, we can conclude that the differenced data are stationary.

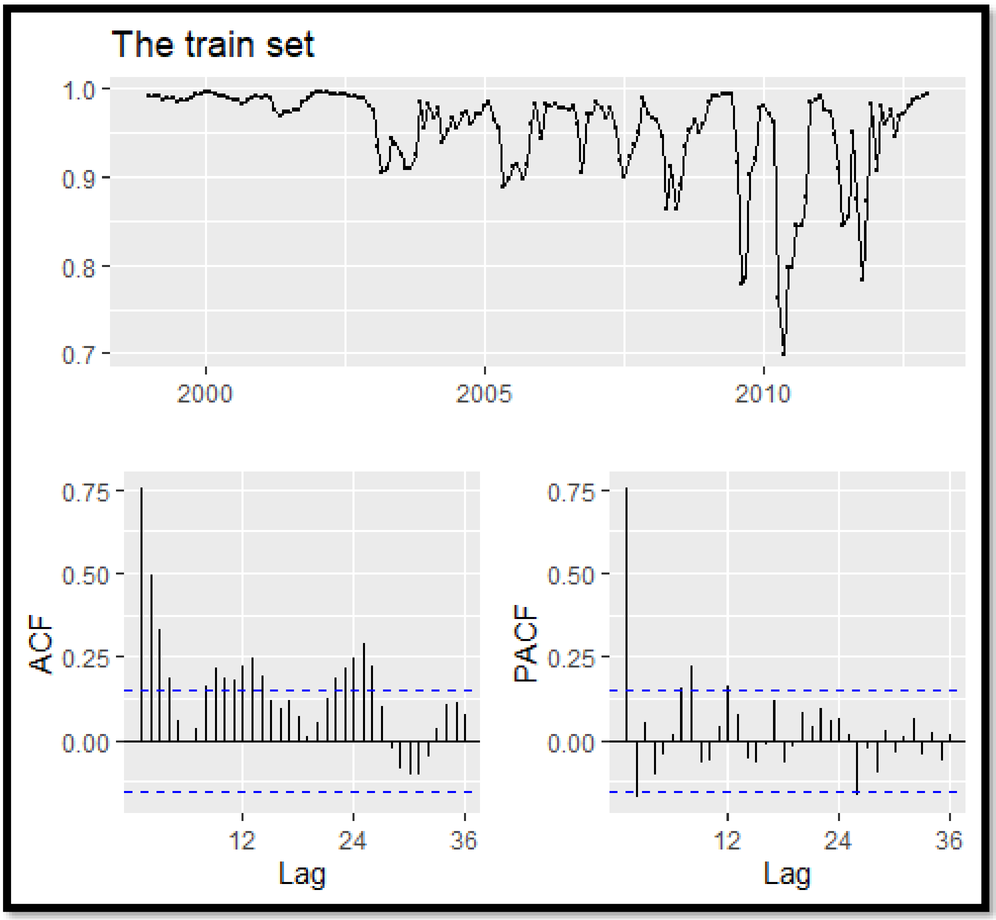

Figure 4.41: Plant performance training set analysis plots

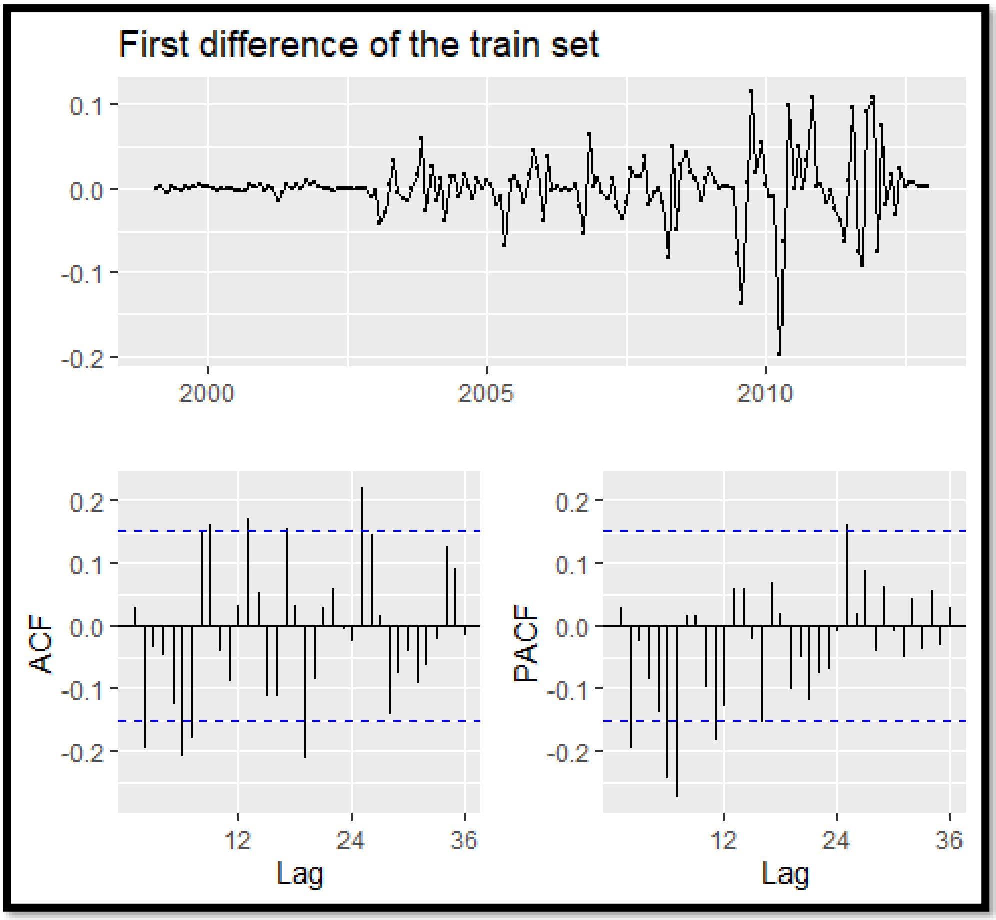

Figure 4.42: Temporal analysis of plant performance training set first difference analysis plots

Figure 4.41 and *Figure 4.42* represent the dataset, the ACF and the PACF of the training dataset and the first differencing, respectively. We notice the correlations between most points are significant. There is a need to perform the Box-Ljung test of the residuals to be sure that residuals are white noise.

4.3.3.6 ARIMA - Autoregressive Integrated Moving Average

The model of the plant performance obtained from the first differencing is an ARIMA (0,1,0). This model does not have an autoregressive (AR) part nor a moving averages (MA) part, and its parameters are given in *Table 4.34.*

Table 13.34: Parameters of the ARIMA (0,1,0) model for plant performance

Parameter	**AIC**	**BIC**
Model	-627.15	-624.04

Where the constant term is the average period-to-period changes. This model could be fitted as a no-intercept regression model in which the first difference of Y is a dependent variable. Since it includes only a non-seasonal difference and constant, thus the classification of ARIMA (0, 1, 0) model with constant.

Residual's plot

To be sure that almost all the information's are collected from the data, let perform the residuals checking.

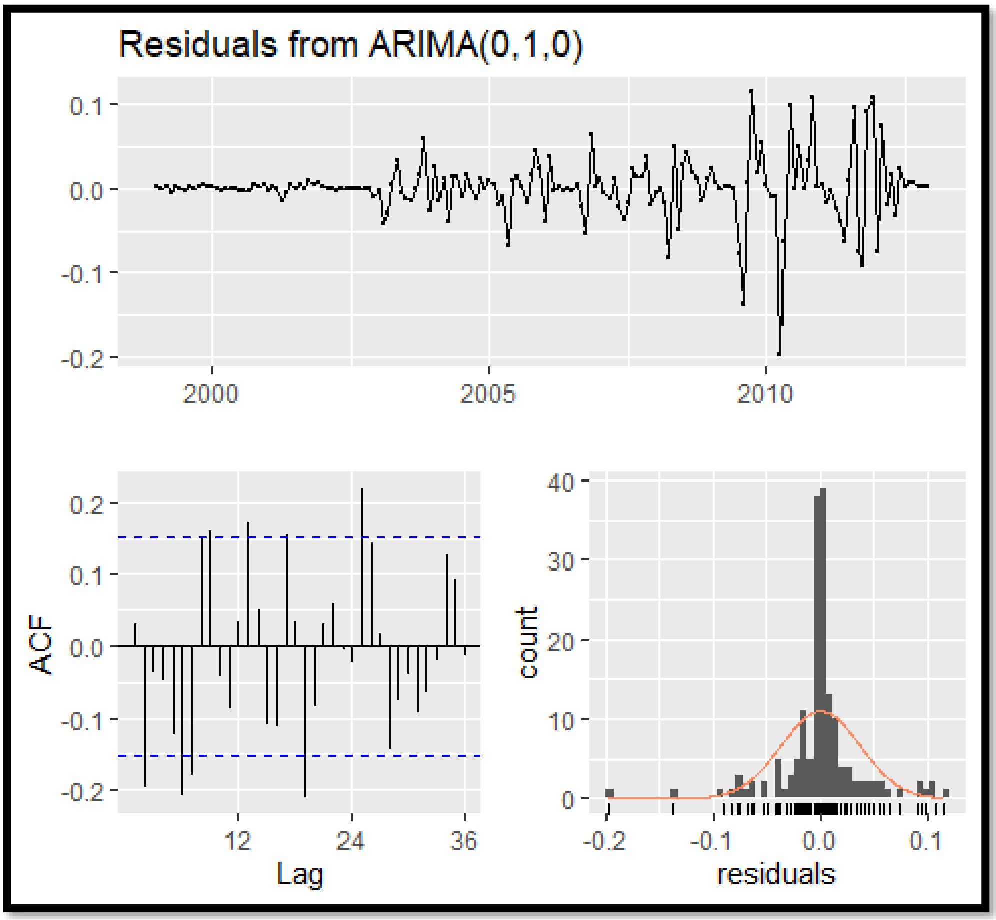

Figure 4.43: Temporal analysis of plant performance training set first difference residuals analysis plots

The ACF plot of residuals of the model do not fall in the limited band for most of lags while the distribution of residuals is normal as seen in *Figure 4.43* in the temporal analysis and *Table 4.35*, this means that the residuals may not be white noise. The ARIMA (0,1,0) model may not be considered for forecasting of the plant performance. To be sure of the model, the Box-Ljung test is performed.

Box-Ljung test

The value of the p-value of 9.276×10^{-06} is obtained by performing the Box-Ljung test. It means that the model does fit the data and cannot be used for forecasting. More verification is needed; this is done by verifying the model's accuracy.

Model accuracy

The parameters of the obtained ARIMA (0,1,0) are determined, and the model is checked for accuracy by comparing the RMSE, MAE and MAPE values of the train and test datasets. The results are given in *Table 4.35.*

Table 14.35: Plant performance model accuracy checking

Parameter	**RMSE**	**MAE**	**MAPE**
Training set	0.03667658	0.02069438	2.298387
Test set.	0.03088699	0.01844756	1.961572

We can notice the obtained values of RMSE, MAE and MAPE values for the training dataset and testing dataset are close. This means that this model can be used for forecasting even if it did not pass all the tests.

4.3.3.7 Forecasting

The forecast of the plant performance is done over three years and is represented in *Figure 4.44*

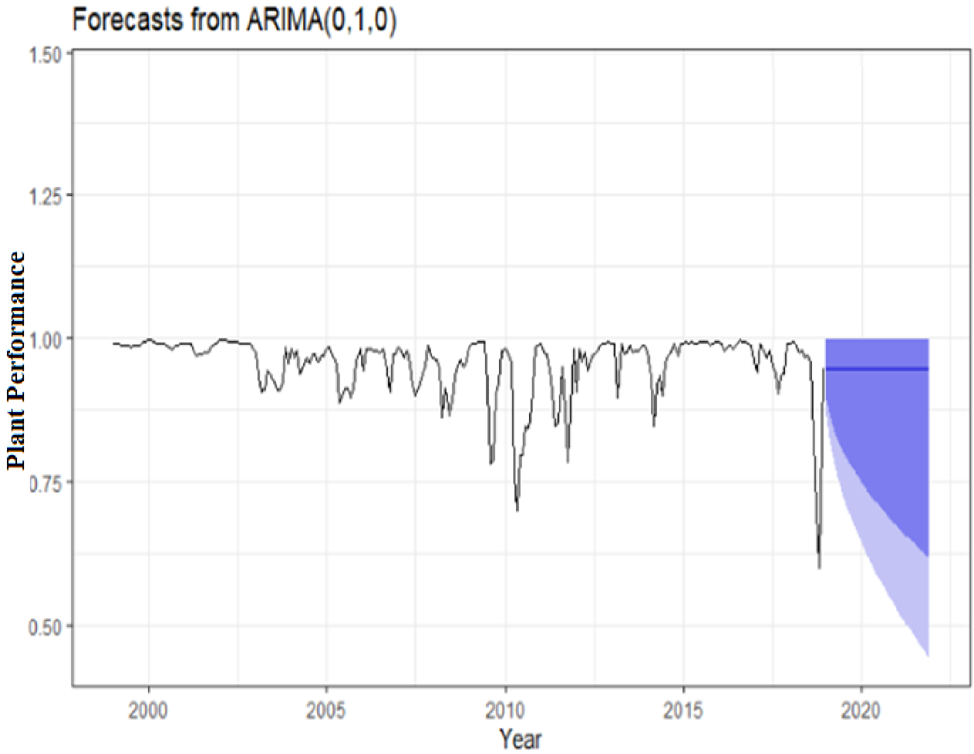

Figure 4.44: Three years plant performance forecasting using an ARIMA (0,1,0)

One can notice to values of the interval of tolerance. Dark blue represents 80 % interval tolerance, while light blue represents 95 % interval tolerance. In addition, there is no symmetric distribution as the upper limit of the interval is 1 and the performance of the plant can be above 1.

4.4 Conclusion

Demand forecasting is an important function in analyzing the performance of the wastewater treatment plant. In this context, an ARIMA model was developed to model demand forecasting by using Box– Jenkins time series approach. The historical demand data was used to develop several models and the adequate one was selected according to the performance criteria. The model that we selected, and which minimises the four previous criteria is ARIMA (2,1,2) (1,1,1) and (0,1,0). The results obtained prove that this model can be used for modelling and forecasting; these results will provide to managers with reliable guidelines for making decisions. In future work, the researcher will further need to develop other models by using a combination of qualitative and quantitative techniques to generate reliable forecasts and increase forecast accuracy. The researcher can also try a neural network approach to compare it with ARIMA’s results to confirm the ANN’s strength in the performance of the wastewater plant. Furthermore, one can also make an ARIMA-radial basis function (RBF) combination to achieve the same goal: high accuracy.

CHAPTER 5- CONCLUSION AND RECOMMENDATIONS

5.1. Background

The current study was undertaken on the Hazelmere water treatment plant. It aimed to analyze the performance of the water treatment plant for the period of 1999 to 2018. This plant treats water that is discharged into the Hazelmere dam.

Drinking water frameworks are planned and designed to meet local area water needs. Recognizing the best adjustments also, changes for the existing drinking water foundation are difficult. Water quality depends on the source-water treatment, but also on the capacity to keep up with high water quality all through the circulation framework. The demonstrating approach portrayed in the present work assesses a huge choice space and recognizes treatment or water supply arrangements for existing frameworks and assesses the execution of different arrangements given the chosen objective.

Each phase of the structure gives extra data and knowledge into how the water quality execution of a drinking water framework is identified with treatment area and limit choices. The discussion of each objective is as follows:

- From the analysis found in the previous section, it is observed that the removal efficiency of E. coli from the treatment plant is 100%. This implies that the effluent produced by the treatment plant is free of pathogens. Concerning other parameters, there is a variation in removal efficiency that shows a few fluctuations though it not significant. The data also indicated that the removal efficiency for iron varied between 96, 09 and 98, 45% while for turbidity 98, 38 and 99, 84%. The data presented indicates that the yearly averages for influent and effluent can be concluded that the effluent complied with the relevant quality standards for the 2015 SANS blue drop limits or WHO standard limits for the years 1999 to 2018 in terms of iron, turbidity and E. coli. Overall, the variations of these parameters from the influent to the effluent are linked to the variability of the composition of the raw water fed to the plant. This variability in river water composition, which is the influent water, could be complex depending on the level of pollution in the river water. Thus, the pollution of the river water is not easy to control due to the high amount of illegal discharges in South African rivers. The nature and the composition or type influence the removal process. The nature of the influent relates to physical-chemical characteristics such as pH, colour and odour and many other inherent features. The composition relates to the content or molecules that can be organic or inorganic.

- The data in the previous section also indicates that by plotting the time series turbidity removal plot in form, time is in the x-axis and turbidity removal in the y-axis. There is a constant pattern without seasonality. Because the variability is not constant, the time series is non-stationary. A time series is non-stationary if the average or mean, or the variability of covariance are not constant. To convert a non-stationary TS into stationary TS, differencing is performed. The data also indicates that turbidity removal is low between 2009 to 2013, and 2018. This means that more wastewater is fed to the plant. The values of the median and the mean are closed, which is a good indication for modelling. The minimum of turbidity removal is 0.3916. This value corresponds to the month of May 2010.

As the goal is to predict the turbidity removal of the plan, the turbidity removal of the TS data is split into a trend, temporal seasonal and remainder or residuals components, this decomposition allows us to gain more precise insight into turbidity removal behavior during 1999–2018 periods to develop an ARIMA model for the dataset and perform the prediction of the turbidity removal of the plan. The decomposition allowed the researcher to properly understand the data.

- The data in the previous section indicated that raw water quality parameters for the separate supplies are measured before they reach the balancing tank, and this is used to calculate the dosage of chemicals in the balancing tank. This is prone to error as the supply from the two abstraction points can vary. The study further indicated that there is a need to test the quality of the mixed water before the chemicals are dosed. This means that the treatment plant needs to add a buffer tank to monitor the combined raw water quality. This will also address the problems observed during modellings such as the lack of correlation between lime and pH or lime and alkalinity. The analysis showed that real losses were a major challenge in the water treatment plant's distribution system. Thus, there is a need to develop a maintenance program to cater for issues found. Communities also need to be educated on the importance of reporting any issues seen in the network. It was further recommended the development of chemical dosage models to automate drinking water treatment plants and water distribution systems.

5.2. Findings

This study has addressed the problem of critical decisions that arise during the conceptual design of wastewater treatment plants when several design objectives (e.g., environmental, legal, economic and technical) must be taken into account. It has contributed to the solution of this problem by proposing a systematic procedure to support the management of the close interplay between, and the apparent ambiguity emerging from, the multi-criteria evaluation of competing design alternatives. The preliminary multi-objective optimization allows comparisons to be made between two or more alternatives when each is close to the optimum design conditions.

- January through April are the most significant months where bacteria may be expected to become sufficiently abundant and therefore cause treatment problems and performance issues. Factors associated with elevated temperatures and inflows are closely associated with these summer highs of bacteria.
- Classical multiple regression modelling of important algae against environmental variables was unsuccessful with the predictive ability of all multiple regression models poor (Ra 2 < 0.5).
- The semi-quantitative empirical models developed in ordination analyses were the best available predictive models.
- The semi-quantitative empirical models developed in ordination analyses were the best available predictive models.
- The model derived for the Hazelmere WW explains 79% of the variation in chemical treatment performance.
- Physico-chemical water quality factors have a particularly significant impact on treatment costs and performance at the Hazelmere WW. Treatment costs increase when turbidity, total aluminium, manganese, suspended solids, potassium, sulphate, and total organic carbon concentrations in Lake Hazelmere water increase. Likewise, costs rise and performance worsens with lower water pH and alkalinity levels. Algae have a relatively minor impact on treatment costs at Hazelmere WW.
- Hazelmere is the only system analyzed that appeared to suffer from problems associated with manganese (necessitating the use of a powerful oxidant such as chlorine dioxide).
- Management strategy that reduces the turbidity of Lake Hazelmere would reduce water treatment costs at the Hazelmere WW. During periods of lake turnover (when the stratification of the water column breaks down) manganese (in the reduced form)

should be very carefully monitored to reduce its potential impact on water treatment (and hence costs).

- The model estimated for the Durban Heights WW explains some 64% of the variation in chemical treatment costs. The mode! predicts actual costs well (except during occasional peak cost periods) and can be easily applied in simulation exercises. Treatment costs increased when levels of turbidity, suspended solids, total organic carbon, conductivity, total water hardness, potassium, nitrates and coliform bacteria rise in the raw water. Treatment costs rise with a fall in raw water pH and alkalinity (more acidic conditions, requiring greater lime dosages).

5.3. Recommendations

As this chapter demonstrates, performance of the wastewater treatment plant. An ARIMA model was developed to model the demand forecasting by using Box– Jenkins time series approach. The results obtained in the previous section further proved that the ARIMA model can be used for modeling and forecasting; the above recommendation can also provide managers with reliable guidelines in making decisions. As future work, researcher will further need to develop other models by using a combination of qualitative and quantitative techniques to generate reliable forecasts and increase the forecast accuracy.

The following recommendations for future research and management strategies were highlighted in the preceding work.

- Water treatment costs are principally driven by abiotic water-quality variables e.g. turbidity, except during periods of intense taste and odour formation which appears to be principally related to the blue-green alga Anabaena. Manganese in the reduced form will also cause treatment problems and increase costs. Therefore, management actions to reduce the concentration of these variables in the raw water quality arriving at WW will reduce treatment costs.
- More parameters maybe analyzed to have a broader understanding
- **Innovating technologies:** Typical applicable technologies for water and wastewater treatment in include cost-effective measures to control algae, low energy consumption treatment, affordable on-site sanitation construction, a combination of pond system with biological treatment, and constructed wetland system, proper disinfection for wastewater, groundwater purification, water reuse and desalination, and rainwater treatment. For example, metals and sulfates can be recovered from acid mine drainage.

Struvite (magnesium ammonium phosphate hexahydrate, $MgNH_4PO_4 \cdot 6\ H_2O$), which contains phosphorus and nitrogen can also be recovered from domestic wastewater. The constructed wetlands, which are useful systems for wastewater treatment, have been proposed for tertiary wastewater treatment to prevent eutrophication and protect the ecosystem.

- **Improving operation and maintenance:** It is important to provide training and to enhance the expertise for the operation and maintenance of the facilities for water and wastewater treatment. Otherwise, the facilities in waterworks and wastewater treatment plants cannot work effectively. Capacity building is needed to improve the knowledge of the workers in this sector. Only qualified and efficient operators and managers can ensure the smooth operation of these treatment facilities. In addition, those who construct water and wastewater treatment facilities should establish necessary maintenance mechanisms so that these facilities can run sustainably.
- **Harvesting energy:** Energy is of vital importance for water and wastewater treatment systems. However, many countries are lack reliable energy supply systems. One possible solution is the utilization of solar energy. The other possibility is to recover energy from wastewater or waste sludge. For example, up-flow anaerobic sludge blanket reactor makes it feasible to harvest biogas from wastewater, and a microbial fuel cell pit latrine is supposed to be used to harvest electricity and to prevent groundwater pollution.
- **Improving governance and management:** The low priority accorded to the water sector leads to poor water quality. The governments usually do not have the political will to emphasize water and wastewater treatment because this is not considered “vote-winning”. It was suggested that local planning processes need to be reformed so that local politicians commit more strongly to improving the water supply. To establish good governance with a better mechanism and institutional framework is a key to avoiding the lack of political will and commitment for water and wastewater treatment. The management of drinking water quality, wastewater discharge, and solid waste disposal should be enhanced. The regulatory authorities should put up legislations and rules to require industries to establish on-site pre-treatment facilities.

5.4. Conclusion

Recognizing wastewater as a resource reduces water pollution by preventing the disposal of contaminated wastewater into water bodies. Reusing wastewater has therefore two main advantages: it improves the living conditions of the local population through the generation of economic opportunities, better food production and reduction of water pollution in these areas. Wastewater treatment can help alleviate the widespread problem of eutrophication due to nutrient loading from agriculture and industry. The deterioration in water quality is estimated to have already reduced biodiversity in rivers, lakes and wetlands by about one-third globally, with the largest losses in Southern Africa. The quality of surface water is therefore projected to deteriorate further in the coming decades as a result of nutrient flows from agriculture and poor/non-existent wastewater treatment, with the number of lakes at risk of harmful algal blooms expected to increase by 20% in the first half of the century (OECD, 2012).

From this study, it can be concluded that:

The effluent from the water treatment under study is highly loaded with degradable organics and other pollutants that pose an environmental risk to the receiving River. The existing septic tank is no longer sufficient to achieve any meaningful treatment, thus allowing high loads of pollutants to enter the river. Significant pollution of the river was observed for COD, BOD5, nutrients, chloride, calcium, total coliforms and TSS. The inter-relationship between some parameters monitored could be used to predict the levels of others through regression equations, as derived in this study. This could greatly reduce the costs for analysis if the concentration of one of the regressed parameters is known. There are opportunities for improving the operations and processes at the Hazelmere wastewater treatment plant, thereby reducing environmental impacts and saving on costs. The application of cleaner production concepts: good housekeeping practices, processes optimization and efficient use of resources, by-products recovery and rendering, together with the establishment of appropriate treatment systems, would greatly improve the environmental performance of the Hazelmere wastewater treatment plant.

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