Addis Ababa University
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School of Graduates Studies
School of Civil and Environmental Engineering

Optimum Coagulant Dose Prediction for Water Treatment using Artificial Neural Network

(Case of Legedadi Water Treatment Plant)

A Thesis Submitted to the School of Graduate Studies in Partial Fulfillment of the Requirements for the Degree of Master of Science in Civil and Environmental Engineering
(Water Supply and Environmental Engineering)

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This is to certify that the thesis prepared by Eyerusalem Alemayehu, entitled: Optimum Coagulant Dose Prediction for Water Treatment using Artificial Neural Network (Case of Legedadi Water Treatment Plant) submitted in partial fulfilment of the requirements for the degree of masters of science in Civil Engineering (Water Supply and Environmental Engineering) that complies with the regulations of the university to meets the accepted standards concerning originality and quality.

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I hereby declare that this thesis is my original work and has not previously been submitted for a degree or master's program at this or any other University.

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Abstract

Water obtained from surface or subsurface sources is crucial for life. But direct use of raw water has serious health risks. Different water treatment processes can be used to make the raw water safe for domestic purposes. Coagulation and Flocculation is one of the treatment stages used to remove colloidal particles through the use of chemicals (coagulants) that enable the formation of larger flocs that can be easily removed by sedimentation and filtration. Determination of the optimum coagulant dosage is important to meet the required water quality. For instance, a high coagulant dosage may lead to high residual chemical in the treated water, high sludge volume, and increased load on the filter units. All these can result in poor water treatment performances, high operational costs, and process complications. Jar test has been used widely to determine the optimal coagulant dosage for a given water quality. However, this practice has some drawbacks such as it is time-consuming, the probability of making errors is high and it is impractical for highly variable raw water turbidity. Consequently, the need to develop new tools and techniques to determine optimum coagulant dosage becomes important. However, quantifying the relationship between the process inputs and output in the water treatment unit process is very difficult with the existing process model. Thus, Artificial Neural Network was used to develop the models in this research as it is a robust technique that allows the development of a multi-variable and complex non-linear relationship. ANN Multi-Linear Perceptron type with one hidden layer was used to simulate the jar test for the optimum coagulant dosage forecasting. Two models were developed and their performances were evaluated based on Root mean squared error (RMSE) and coefficient of determination (R^2). The first model which enables prediction of turbidity for a given coagulant dosage and other factors was the process model. The second model which allows determination of optimum coagulant dosage to attain the desired turbidity level is the Inverse Process Model. The RMSE and R^2 values were found to be 0.0748 NTU and 0.6121, respectively for the Process model. For the Inverse Process model the RMSE and R^2 values were found to be 0.225mg/l and, 0.9823, respectively. These indicate that a good performance of the ANN-based model to simulate the jar test could be obtained. The models can be used to optimize the coagulation process within the available raw water turbidity range of Legedadi Water Treatment Plant. ***Key term: Artificial Neural Network, Optimum coagulant, prediction, process, and inverse process model.***

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Acronyms

ANN:- Artificial Neural Network

AAWSA:- Addis Ababa Water and Sewerage Authority

Alk:- Alkalinity

EDWQS:-Ethiopian drinking water quality standard

GUI:- Graphical User interface

LTP: - Legedadi Water Treatment Plant

MLP:- Multi-Layer Perceptron

NTU:- Nfelo metric Turbidity Unit

PACL:-Poly Aluminum Chloride

PolyDADMAC: - Polydiallyldimethylammoniumchloride

R^2:- Coefficient of determination

Rpm: - Revolution per minute

RMSE: - Root mean square error

RSF- Rapid sand filter

Std- Standard deviation

WTP:- Water Treatment Plant

UTM:-Universal Transverse Mercator

UI: - User interface

ZP:- Zeta potential

^{o}C:- Degree Celsius

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1 Introduction and Background

1.1. Introduction

Water treatment operation is the treatment of drinking water with a little cost by achieving an optimum combination of efficiency and effectiveness *(Ng et al., 2016*). Water treatment is a complex process that involves a series of physical and chemical phenomena (*Baxter et al., 2002b*). Water turbidity is one of the important parameters that the treatment plant operators should deal with curiously especially when the water source is river or lake (*Nahvi et al., 2018*). Coagulation and flocculation are the basic treatment steps to decrease the turbidity in the treated water, remove the color and odor of the water. The chemical which is used for the process of Coagulation and flocculation is called coagulant which decreases the turbidity in the raw water with the desired water quality by considering the characteristics of water such as water pH, temperature, type, and amount of turbidity (*Nordmark et al., 2016*).

The addition of chemicals to the coagulation/flocculation process destabilizes particles in the solution by neutralizing their surface charge (*Maier, Morgan and Chow 2004*). Then the particles aggregate themselves to be large and the addition of coagulant aid helps the particles to undergo this process quickly. In the sedimentation process, the large floc settles by gravitational settlement. Numerous chemicals have been used in the coagulation process. Currently, polyelectrolyte is widely used as a primary coagulant since it has different advantages than the most commonly used coagulants like aluminum sulfate and ferric sulfate. Working with a wide range of pH and little arrangement of pH are the main advantages of Polyelectrolyte (*Bratby, 2016*).

Legedadi water treatment plant has been using Polyelectrolyte since 1990 E.C. The required amount of chemical coagulant is determined through an experiment called Jar test. Even if the jar test is the only approach to determine the required amount of chemical, it takes a long time to conduct. As a result, it is carried out periodically and cannot respond to rapid water quality changes (*Joo et al. 2000 &Yu et.al 2000*). Besides, it doesn't provide the correct estimation of the optimum coagulant dosage most of the time as it is processed by human beings.

The determination of the coagulant dosage using the Jar-test and the determination of injected-coagulant type based on the operator's knowledge is becoming a sever barrier for the automation of the water treatment process. In Legedadi treatment plant as well as in most of the treatment plants found in the world, the operators are in charge to control the treatment plant and the water quality changes based on their limited knowledge and experience. Depending on the water entering and exiting the plant and the water quality, they adjust the process control variable (chemical dosage) (*Zhang and Stanley, 1999*). However, it does not consider the water quality changes that are not detected by necked eyes.

Modeling the process can overcome the limitation that the treatment plant encounter through jar test. Modeling is math-based tool, performed through numeric and Data-driven methods. In fact; the process that occurs during the coagulation process is very complex; as a result, the development of a physical-based model is difficult (*Joo et al., 2000*). Nowadays researchers are turning their attention to data-driven models as they are easy to implement and the structures are simpler than numeric.

ANN is a data-driven model and machine learning method. Application of ANN in water treatment process modeling is becoming very common as ANN is ideal to model a complex nonlinear relationship that doesn't have a clear mathematical formula (*Rodriguez and Sérodes 2004*). Moreover, the techniques do not require a pre-determined algorithm as the relation between input and output parameters are automatically set by the utilized algorithm. When the new variations occur in the water quality, ANN model can be updated continually in response to the new data. During ANN model development, there are some structures which are consist of three layers. These layers are the input layer which is used to send the data signal to the system, the hidden layer that is used to process the data, and the last layer is the output layer which is used to extract the data as per input scale.

In this research two models were developed using ANN that are capable of assisting treatment plant operators to determine the optimum chemical dosage at Legedadi Water Treatment Plant. The first one is the process model. For this model development, the input parameters for both the model and the real process are raw water turbidity, temperature, pH and the process control parameter (chemical dosage). The output is also an output for the actual process (treated water turbidity). As a result, the optimum chemical dosage is found by trial and error procedure. This helps the new operators to get better understanding of the relationship between the process control parameters (*Baxter et al., 2001b*).

The second one is an inverse process model. For this model development, the inputs include all the process input parameters except the process control parameter chemical dosage. The desired water quality value in the process model is also considered as an input parameter. The model output is the optimum value of the process control parameter (Chemical Dosage). As a result, the optimum chemical dosage in this model can be directly obtained for measured raw water turbidity to get the desired treated water turbidity. Finally, the model implementation application was prepared for both models by using Matlab App designer.

1.2. Statement of the problem

Legedadi Water Treatment plant was built to provide safe drinking water for the residents of Addis Ababa city. It treats surface water sources impounded by Legedadi and Dire dams using conventional treatment processes. The Legedadi-Dire catchment is characterized by intensively cultivated agricultural lands and expanding urban centers like Sendafa and Becha towns. Changes in the land use characteristics of the catchment together with the intense rainfall are increasing and changing raw water turbidity which has become a major issue of concern for the treatment plant operators.

Coagulation and flocculation using aluminum sulphate has been practiced for long at Legedadi Water Treatment Plant. But the increasing raw water turbidity resulted in the use of high amount of aluminum sulphate and production of large amount of sludge. This has forced AAWSA to replace aluminum sulphate coagulant by Polyelectrolyte which results in a good performance with reduced coagulant dosage, less volume of sludge and minimal operational problems. However, the polyelectrolyte chemical is imported from foreign countries with hard currency which is limited in Ethiopia.

The jar test is a procedure to determine the necessary amount of chemical dosage (polyelectrolyte) for the available turbidity. The jar test, which is the procedure used to determine the optimum amount of polyelectrolyte, is time consuming in addition to being costly and exposed to human errors during operation. The test is not proactive to analyze rapid water quality changes as it is carried out periodically. As a result, it is not suitable for real time control (*Yu et al.,2000*). Besides, the process control parameter (polyelectrolyte dosage) is adjusted by operators who are familiar with the process. But coagulant dosage determination based on experience is yet another cause for the inaccurate determination of the optimum parameter value.

Using the chemical beyond or below the optimum point for the water treatment has negative effect. A higher dosage causes a chemical residual to accumulate in the treated water in addition to increasing the cost to purchase the chemical, sediment accumulation in the filter and increases sludge volume. Besides, the use of coagulant dosage beyond the optimum value changes the pH of the water which impedes the coagulant's efficiency for formation of flocs. Usage of coagulant below the optimal dosage can result in a treated water that does not meet the desired quality level.

Development and application of mathematical models that can determine optimal coagulant dosage under different conditions is, therefore, required. Modeling a jar test has different advantages such as it saves time and minimizes cost. In this study the Artificial Neural Network model (ANN) was developed and used to simulate and optimize the coagulation-flocculation process.

1.3. Objective

1.3.1. General objective

The main objective of this research is to develop the artificial neural network model to determine the optimal coagulant dosage for different turbidity during the coagulation process in water treatment.

1.3.2. Specific objectives

The specific objectives of the study are the following:

- To assess the existing coagulation practice at Legedadi Water Treatment plant
- To develop an ANN model that is capable of predicting optimum coagulant dosage and predicting the treated water turbidity
- To develop model implementation software.

1.4. Research questions

- What is the trend of raw water turbidity at Legdadi Reservoir?
- How is the coagulation and flocculation process operated at Legedadi Water Treatment Plant?
- How efficient is the process at Legedadi Water Treatment Plant?
- What are the critical challenges faced in undertaking coagulation operations at Legedadi WTP?
- Which ANN architecture is best for modeling the coagulation process at Legedadi Water Treatment Plant?
- Which parameters are considered critical during coagulation and flocculation process at Legedadi Water Treatment plant?

1.5. Scope of the study

To meet the research objectives, different works were completed. First, the coagulation practices at Legedadi Water Treatment Plant were studied by conducting experiments, interviews, and questionnaires. The pilot-scale tests were conducted to measure the treated water turbidity twice at different periods. Jar tests were conducted to identify the coagulant efficiency at the treatment plant, the relation between the input and the output parameter for ANN model development, and to validate the collected experimental data. The coagulant efficiency study was based on the measured turbidity and efficiency of the chemical to get the desired water quality with a little amount of chemical. However, the study was not expanded to examine coagulant efficacy at various pH levels and turbidity levels. Because some coagulants are efficient with low pH and some need high pH. In addition, a coagulant which is more efficient at higher turbidity levels may not work well at lower turbidity levels.

As part of model development, data was collected from the treatment plant and AAWSA. The data collection and model development did not consider the full-scale plant to make the findings of the study practical. However, the jar test was assumed to fully represent the treatment plant coagulation and flocculation process. In addition to that, there are data limitations in secondary data in situations beyond the optimum point. Thus, the models were developed under this condition. The scope of this research was further advanced by developing a standalone application for the operator.

1.6. Content and structure of the research

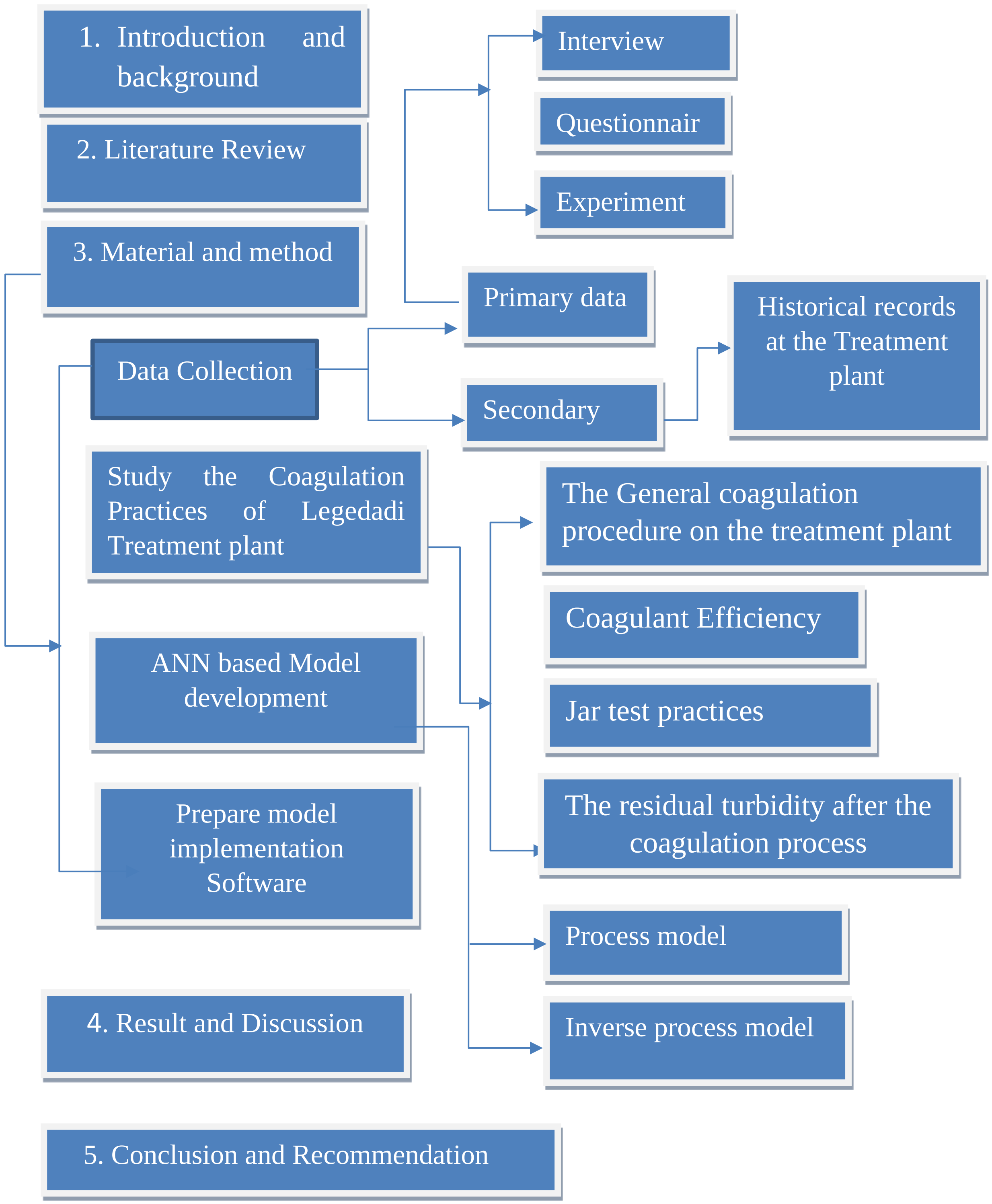


Figure 1: Content and structure of the Research

2. Literature Review

2.1. Water treatment

Water treatment is the process of ensuring that consumers have access to clean drinking water. Aside from drinking, water can be treated for a variety of applications, including industrial water supply, irrigation, recreation, and many others. The water treatment procedure can simply eliminate or reduce pollution and pollutant concentrations in the water. The water becomes desirable to the end-user if the treatment facility is effectively exploited. Human health depends on this process, which allows humans to benefit from both drinking and irrigation.

Treatment for drinking water production involves the removal of contaminants and inactivation of any potentially harmful microbes from raw water to produce water that is pure enough for human consumption without any short-term or long-term risk of any adverse health effect. Even though; waste and water treatments are designed to provide qualified water and wastewater, the raw water quality and quantity that comes to the treatment plant variance can cause change to the quality of water (*Tom, 2009).*

2.2. Water Quality parameters

Parameters that affect the water quality are distinguished into three types physical, chemical, and biological. They are summarized in Table.

Table 1:Water Quality Parameters: Source (Nayla, 2019)

Type of water quality parameters			
NO.	**Physical parameters**	**Chemical Parameters**	**Biological parameters**
1	Turbidity	pH	Bacteria
2	Temperature	Acidity	Algae
3	Color	Alkalinity	Virus
4	Taste and odor	Chloride	Protozoa
5	Solids	Chlorine residual	
6	Electrical Conductivity	Sulfate	

2.2.1. Turbidity

The row water turbidity is the significant parameter that is dealt with very curiously by water refiners when the water natural source is from a lake or river. Turbidity is a measure of how much water loos its transparency due to the particles available, which means it measures the light refractive ness of the water when light passes through it (*Lenntech ,2021*). In addition to that, water turbidity routinely means of identification of the water quality. The turbidity level commonly varies with microbiological contamination; however other factors like suspended matter including silt bacteria, algae, viruses, macromolecules and material derived from organic soil matter, mineral substances, many industrial pollutants, and so on have some sort of impact on the turbidity level of the water entering into the treatment plant. Thus, Removal of turbidity from the water is the removal of a wide variety of matters (*Environment Canada, 2021*). A specific measurement for turbidity parameter is difficult and tedious so it could be used to provide an estimation of the TSS concentration (*Lenntech, 2021*). However, Turbidity is not a direct measurement of the amount of suspended material in the given water but rather an arbitrary optical measurement based on interference of light passing through the water *(Environment Canada, 2021*). Nephelometer or turbidimeter is the instrument used to measure the amounts of turbidity, which measures the intensity of light scattered at 90 degrees as a beam of light passes through a water sample. According to EDWQS establishment, the maximum allowable turbidity is 5NTU and should be below 1NTU (*Lenntech, 2021*). Providing water with low turbidity is an indication of pathogen removal and a witness of drinking water safety (*Mann et.al, 2007*). Turbidity may be identified as the lack of clarity of the water but it is not fully related to color, there could be a chance drink water with color but not turbid.

- **What is the risk of turbidity?**

Sudden increments of turbidity in water have been associated with several outbreak diseases (*Mann et.al, 2007*). If the particles are not removed properly, they may serve as a shield for harmful microorganisms from disinfectant (*Edzwald 2010*). In addition to that, Suspended particles use as an adsorption media for heavy metals including mercury, chromium, lead, cadmium, and many hazardous organic pollutants such as PCBs, PAHs, and many pesticides

(*Cole et.al 1999*). If the water is esthetically unacceptable due to the turbidity, it makes the water unappetizing to drink *(Nayla 2019*).

2.2.2. Test and odor

The natural domestic and agricultural sources may change the tests and odors of the pure water. The causing matters are organic materials, inorganic compounds, or dissolved gasses (*DeZuane, 1997*). The numerical value of odor and test is quantitative determined by diluting a pure distilled odor-free water with the sample water. From the resulting in a mixture, it is detected and the unit is in terms of a threshold.

2.2.3. Color

The color of the water may change due to material decay from organic matter such as soil, stones, and rocks impart color to the water, which is objectionable for esthetic reasons, not for health reasons (*APHA 2005*, *Tomar 1999*). The color of the water can be determined by comparing it with the standard watercolor or color glass disk. Pure water is colorless which mean 0 unit (*APHA 2005*).

2.2.4. Solid and Electric conductivity

Solid occur in the water either in the form of suspension or dissolved solution, and it can be identified by using a glass fiber filter. The suspended solids stay on the top of the material and the dissolved solids pass through the material with the water (*APHA 2005*). Total solid (TS) is the summation of TDS and TSS.

The electric conductivity of the water reveals that how much the water carries and conducts electric current. The quantity of ions or charged particles in water determines electric conductivity, which is measured by sending a current between two electrodes placed in a sample of water at a specified distance apart (*Tchobanoglous, et.al*). Since it measures conductivity, it is an important parameter for the coagulation process. Pure water is not a good conductor of electricity. Micro Siemens per centimeter and milli Siemens per centimeter are the units of measurement for electrical conductivity.

2.2.5. Potential of hydrogen (pH)

pH is the negative logarithm of hydrogen ion concentration. It is a dimensionless number that indicates the acidic or basic strength of a solution. The pH of water, in fact, is a measure of how acidic or basic the water is (*Edzwald, 2010*). Additional hydrogen ions are present in acidic water, while extra hydroxyl ions are present in basic water.

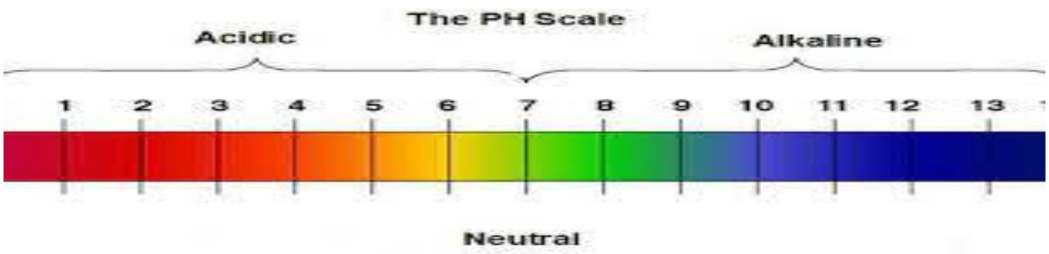


Figure 2: pH scale: Source (*Edzwald, 2010*)

pH ranges from 0 to 14, with 7 being neutral, as shown in Figure 1. Acidity is indicated by a pH less than 7, whereas a pH greater than 7 indicates a base solution. At 25°C, pure water has a pH of approximately 7.0. Because of the carbon dioxide in the atmosphere, normal rain has a pH of around 5.6 (slightly acidic). For home usage, a pH range of 6.5 to 8.5 is considered safe, while live organisms require a pH range of 6.5 to 8.5. The electrometric and colorimetric is the instrument for pH measurement (*WHO, 2011).*

2.2.6. Temperature

Chemical reaction, solubility, palatability, viscosity, and odor are influenced by temperature (*APHA 2005*). As a result, the sedimentation and chlorination processes, as well as biological oxygen requirement are affected. The effect of temperature on flocculation and filter effectiveness is well established and is shown in the study that was carried out about the temperature effects on flocculation, using different coagulants. The effects of temperature on floc formation, breakage, and reformation were assessed in the laboratory by Jar test using a photometric dispersion analyser Alum, ferric sulfate, and three poly aluminum chloride coagulants were tested for a suspension of kaolin clay in London tap water at temperatures ranging from 6 to 29°C.All coagulants' floc generation is slower at lower temperatures, according to the findings (*Fitzpatrick, 2004*).

2.3. What is Coagulation?

Coagulation is a process of removing suspended and colloidal particles from the water, which causes turbidity and color of the water. The process also assists in the removal of organic contaminate which causes different tastes and odors including bacteria and alga (*Zheng et.al, 2014*). In general, the coagulation process is an addition of chemical coagulants and hydrolysis of it to make the collide electrical neutralize in water to destabilize it, by means of this, the particle becomes fine and this help to flocculated into large and dense silk flowers and absorbed by bridge or network. It means, the coagulant added is conditioning the particles for subsequent processing by flocculation or to create conditions that will allow for the subsequent removal of particulate and dissolved. The material called coagulators is a form of a chemical that is used to decrease water turbidity. The amount of coagulator required is different with the nature of the water and the environmental condition like temperature and pH (*Zheng et.al 2014, Kerry et. al, 2012).*

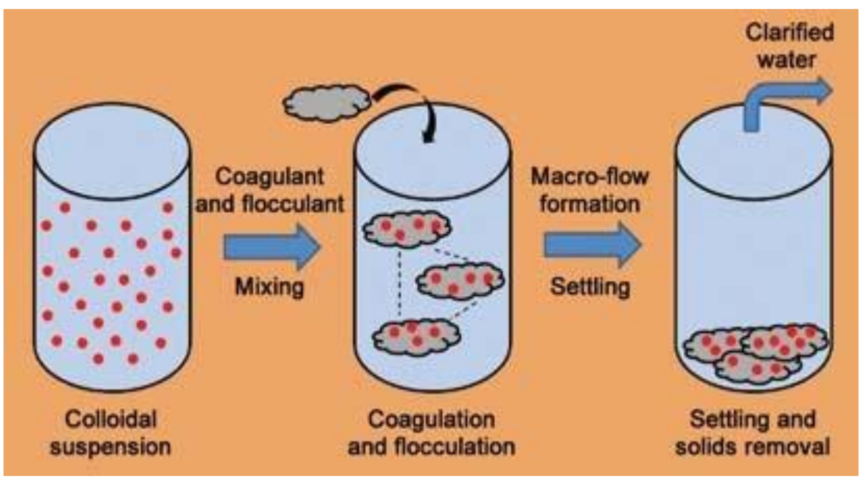


Figure 3: Coagulation and flocculation process: Source (Lee D,2014)

2.3.1. Coagulation mechanism

The coagulation mechanism is the way to destabilize collide particles to form floc. The coagulation can be accomplished through different mechanism such as double-layer compression, adsorption and charge neutralization, enmeshment by a precipitate (sweep-flocs coagulation), and adsorption and inter-particle bridging.

1. **Double-Layer Compression:** Double-layer compression works by compressing the diffuse layer that surrounds a colloid. A simple electrolyte such as NaCl is added to the suspension to cause double-layer compression. The addition of an indifferent electrolyte raises the ionic strength of the solution, compressing the EDL. Ions with the sign opposite to the net charge on the particle's surface enter the diffuse layer that surrounds it. The diffuse layer is compressed when enough counterions are injected, lowering the energy required to bring two particles with similar surface charges into close contact.
2. **Adsorption and charge neutralization:** If charged (+) counter-ions have a specific affinity for the surface of the colloid (not merely electrostatic attraction) then adsorption of the counter-ion will reduce the primary charge of the colloid. This will reduce the net potential, at any particular r thus making the attraction forces more effective. ZP is likely to be reduced also. Counter-ions can be adsorbed by ion exchange, coordination bonding, van der Waals forces, repulsion of the coagulant by the aqueous phase (surface-active).
3. **Enmeshment by a precipitate (sweep-floc coagulation**): If metal salts, e.g., $Al_2(SO4)^3$, $FeCl_3$ are added in sufficient quantities to exceed the solubility products of the metal hydroxide, oxide, or sometimes carbonates a “sweep floc” will form. Colloids will become enmeshed in the settling sweep floc and be removed from the suspension. Because colloids can serve as a nucleation site for precipitating Al or Fe oxides the relationship between optimum coagulant dose (Al or Fe) and colloid concentration is often inverse.
4. **Adsorption by Interparticle Bridging:** Inter-particle destabilization Interred particle bridging is the final step in the coagulation process. When the particle's surface charge approaches 0, bridging occurs. This is accomplished using polymers with medium to high molecular weights and the ability to gather and hold charge-neutralized flocs together. Bridges are generated when two particles reject one other. A floc is a network of bridges and coagulated particles. The creation of this floc is crucial for the subsequent flocculation process.

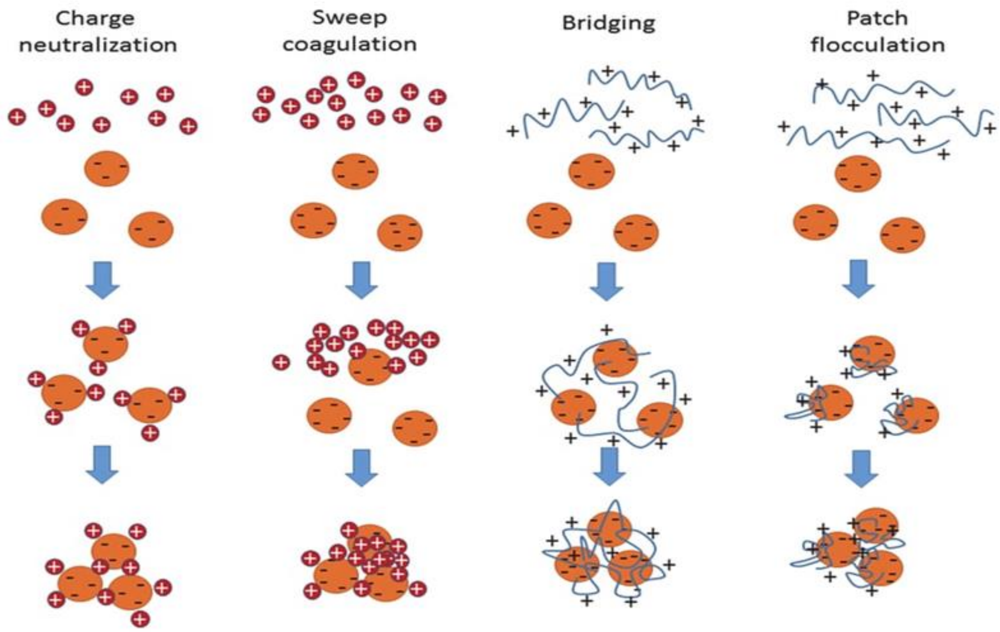


Figure 4: Coagulation Mechanism: Source from (Terhi, 2015).

2.3.2. Type of coagulant

Type of suspended solid to be removed, raw water conditions, facility design, required effluent quality, the effect upon downstream treatment process performance, cost, method and cost of sludge handling and disposal, and cost of the dose required for effective treatment are the main aspects for the selection of types of coagulant chemical. However, it must be done with jar testing and plant scale evaluation (*EPA, 2021*). The type of chemical generally failed into two categories *inorganic* and *organic*. Aluminum and iron salt are the most common type of inorganic coagulants and is known as metallic coagulant (*Bratby, 2016*). Inorganic coagulants are particularly effective on raw water with low turbidity and will often treat this type of water when organic coagulants cannot. Inorganic coagulants may alter the pH of the water since they consume alkalinity. When applied in a lime soda ash softening process, alum and iron salts generate demand for lime and soda ash. They also require corrosion-resistant storage and feed equipment (*EPA, 2021*). other chemicals used as coagulants include hydrated lime and magnesium carbonate (*Bratby, 2016*). PolyAMINEs and PolyDADMACs – The most widely used organic coagulants, which are cationic in nature and function by charge neutralization alone.

2.3.2.1. Aluminum coagulant

The aluminum coagulants include aluminum sulfate, aluminum chloride, poly aluminum chloride, sodium aluminate, aluminum chlorohydrate, poly aluminum sulfate chloride, poly aluminum silicate chloride, and forms of poly aluminum chloride with organic polymers. The most common water treatment coagulant is aluminum sulfate, or ‘‘alum’’. chemical formula of Alum is $Al_2(SO4)^3 \cdot 14H_2O$ with aluminum content ranging from 7.4% to 9.5% (usually close to 9% as Al) by mass as sold in a hydrated form (*Kerry et.al 2012 & JOHN 2016).* It is manufactured by digestion of bauxite ores with sulfuric acid (*Bratby, 2016*). Aluminum hydroxide precipitates when alum is added to the water, the overall reaction is

$$Al_2(SO4)_3 \cdot 14H_2O \rightarrow 2Al(OH)_3(s) + 6H+ + 3SO_2^{-4} + 8H_2O \quad (2.1)$$

After all, the species SO_2 left on the water is the same as if H_2SO4 had been added to the water. As a result, adding alum is like adding a strong acid in the water. Even though, the change in pH depends on the initial alkalinity, definitely a strong acid will lower the pH and consume alkalinity. Alkalinity can be added in the form of caustic soda (NaOH), lime [$Ca(OH)_2$], or soda ash (Na_2CO_3). A typical dosage of alum ranges from 10 to 150 mg/L, depending on raw-water quality and turbidity (*Kerry et. al 2012).* Then, the reaction is

$$Al_2 (SO4)_3 \cdot 14H_2O + 6NaOH \rightarrow 2Al (OH)_3 (s) + 3Na_2SO_4 + 14H_2O \quad (2,2)$$

Aluminum chloride is another type of aluminum coagulant that has been described as a good sludge conditioner and has been used widely for this purpose. Because of hydrochloric acid (HCl) released on hydrolysis, solutions need to be stored under controllable conditions (Bratby , *2016*).

2.3.2.2. Iron Coagulant

The iron coagulants include ferric sulfate, ferrous sulfate, ferric chloride, ferric chloride sulfate, polyferric sulfate, and ferric salts with organic polymers (*Brat5by, 2016*).

Ferric sulfate

Ferric sulfate is particularly used for color removal with low and high pH ranges, where it is used for iron and manganese removal and in the softening process.

All ferric sulfate coagulants are used over a wide range of pH from 4.0 to 11.0. For the latter uses the insolubility of the ferric hydroxides over wide pH ranges makes the iron coagulants in general preferable than aluminum sulfate (*Kerry et. al 2012*). The overall reaction

$$Fe_2(SO_4)_3 \cdot 9H_2O \rightarrow 2Fe(OH)_3(s) + 6H^+ + 3SO_2^{-4} + 3H_2O \quad (2.3)$$

Typical dosages of ferric sulfate and ferric chloride ($FeCl_3 \cdot 6H_2O$) range from 10 to 250 mg/L and 5 to 150 mg/L, respectively, depending on the water quality (*Kerry et. Al*, *2012*).

Ferrous sulfate

It is obtainable either as crystals or granules containing 20% of Fe, which are readily soluble in water. Ferrous sulfate reacts either with natural alkalinity or added alkalinity to form ferrous hydroxide, $Fe(OH)_2$, but since ferrous hydroxide is relatively soluble, it must be oxidized to ferric hydroxide to be useful. At pH values above 8.5 oxidation may be accomplished by aeration, by the dissolved oxygen in the water, or by adding chlorine. Except chlorine, lime must be added to obtain sufficient alkalinity (*Bratby, 2016).*

2.3.2.3. Poly Aluminum Chloride (PACl)

Controlling the formation of Al and Fe metal species is difficult especially in low dosage, thus, the use of prehydrolyzed metal salts becomes preferable. It is prepared by reacting alum or ferric with various salts (e.g., chloride, sulfate) and water and hydroxide under controlled mixing conditions (Kerry et. al, 2012). The efficacy of fast mixing, the pH, and the coagulant dosage all have a role in determining which hydrolysis species is best for treatment. The ability to act well over a wide range of pH and raw water temperatures is one of the key advantages of pre-polymerized inorganic coagulants. By slowing the hydrolysis processes of the metal coagulant after it is applied to water, pre-polymerization efficiently improves charge interactions between the coagulant and colloids. In general, these coagulants are less sensitive to low water temperatures; lower dosages are required to achieve water treatment goals; fewer chemical residuals are produced; fewer chloride or sulfate residuals are produced, resulting in lower final TDS; and they produce lower metal residuals *(Bratby, 2016).* The commercial prehydrolyzed alum salts, commonly known as PACl, have the following overall formula: $Al_a(OH)_b(Cl)_c(SO4)_d$ (*Kerry et. al , 2012*).

2.3.2.4. Polymers coagulant

Polymer is a substance or material which is found in natural and synthetic form. Polymers are water-soluble, long-chained, high-molecular-weight, organic chemicals and consisting of the macromolecular compound. Due to these characters, it can destabilize or enhance the flocculation of the constituents in a body of water (*Bratby, 2016*). The chemical units commonly have an ionic functional group that gives the polymer chain and electrical charge (*Kerry et. al 2012*). In addition to inorganic coagulants, polymers can be employed as coagulant aids. Metal coagulants frequently use anionic (negatively charged) polymers. To attract suspended materials and neutralize their surface charge, low-to-medium weight cationic (positively charged) polymers can be employed alone or in conjunction with alum or ferric coagulants to attract suspended solids and neutralize their surface charge (EPA, 2021). The special class of organic polymer is known as polyelectrolyte.

Polyelectrolyte

It is effectively replaced metallic coagulant with a lot of advantages. Such as, metal ion species that are carry-over from sedimentation basins is prevented, there is no need for pH adjustment or subsequent readjustment because the floc weight is lighter than alum, the volumes of the sludge are reduced, improved sludge thickening and dewatering characteristics reduction in the number of soluble anions. Polyelectrolyte has two of which synthetic organic compounds, one anionic and the other cationic. However, it has also its disadvantage. It is very specific for a particular type of water, being low resistivity ability of oxidizing agent and relatively it has short storage life. The maximum turbidity removed by polyelectrolyte is around 5000NTU (*Bratby, 2016).*

2.4. Flocculation

The flocculation theory evolved from the following information. 1. Due to collisions with fluid molecules, tiny particles undergo random Brownian motion, resulting in particle–particle collisions. 2. Particle collisions are caused by velocity gradients created by stirring water containing particles. These interactions are known as microscale (perikinetic) and macroscale (orthokinetic) flocculation respectively. Another form of flocculation occurs due to differential settling in which large particles settling in a quiescent basin overtake small particles to form larger particles. Flocculation is the agglomeration of destabilized particles into micro floccules, which can eventually be formed into bulky floccules and finally macro floccules. Slow and gentle mixing, rather than the quick mixing required for coagulation, is used to keep particles in suspension long enough for collisions to occur.

1. Per kinetic flocculation: - Because there is a limiting floc size beyond which Brownian motion has no or little influence, in this stage flocculation begins immediately after instability and is complete within seconds. Moreover, the thermal kinetic energy of Brownian movement can overcome the existing potential energy barrier between colloidal particles (*Bratby, 2016*).
2. Orthokinetic flocculation: - The principal parameter governing the rate of orthokinetic flocculation is the velocity gradient applied. Both applied velocity gradients and flocculation time determine the degree or extent of flocculation. Set the liquid in motion with (a) passage around baffles or mechanical agitation within a flocculation reactor; (b) the tortuous path through interstices of a granular filter bed; (c) differential settlement velocities within a settling basin, and so on to create velocity gradients. The impact of velocity gradients within a liquid body is to establish relative velocities between particles, allowing for interaction *(Bratby, 2006).*

2.5. Factor affecting the coagulation and flocculation process

The factors that influence on coagulation and flocculation are, among others, temperature, pH, influent quality, dosage, and coagulant type or Coagulant dose. The pH will not only affect the surface charge of coagulants but also affects the stabilization of the suspension. In the coagulation process, rapid mixing is used to spread out the coagulant throughout the turbid water. In the flocculation process, slow mixing is a key part to get the most favorable performance. Adequate time must be provided to allow the production of particles of sufficiently large size to permit their efficient removal in the sedimentation process (*Wang, Hung & Shammas 2005).*

2.6. Method of determination the amount of coagulant dosage

2.6.1. Jar test

Jar test provides full information for operators in the water treatment plant about the chemical that uses for operation how it behaves and acts when it is added in the water. Thus, it is a method of determining the dosage of chemical needs to minimize the turbidity amount in the raw water. Taking jar tests is not only used to know the amount of chemical, but it is also useful to determine which type of chemical type is best for the raw water environment (*Zane, 2009*). In general, it mimics full-scale plant operation and is an ideal way of optimizing the operation of coagulation and flocculation (Bratby, *2016*). A jar test is proceeded by adjusting the chemical with different amounts and adding it to the same type of raw water with the same amount held in jar beakers. When the jar tester is started working, the stirrer moves circularly with rapid movement. At the time, the slow movement follow the floc formation and development are shown, then when the stirrer stops the settling process are taken. The operator performs different coagulant aid effects in the floc formation size to get the best size for that environment. Afterward, the amounts of turbidity in each jar baker are measured to determine the best match (*Zane, 2009*). A jar test is manual and performed by trial and error.

2.6.2. Mathematical and Numerical methods

Response Surface Methodology

One of the mathematical and statistical methodologies for modeling an experimental procedure in which the response is influenced by a variety of circumstances is response surface methodology *(Alev 2018).*

This model assesses the effect of various factors on the target output and identifies the optimum condition to reduce the number of experiments. RSM was introduced by Box and Wilson in 1950. As a solution to the jar test drawback, statistical RSM was also proposed to determine the coagulant dosage by demonstrating the factor of individuals and their influence. Different researcher uses this method to optimize the coagulation practices; it was applied to optimize the coagulation and flocculation process to minimize turbidity and sludge volume index by confirming experiment that was carried out through jar test

(*Madhukar & Yogesh 2013*). However, some studies have indicated that RSM is inferior to ANN in terms of water treatment technology. *(Ezemagu et.al ,2021 and Yingyi et .al 2020).*

Genetic programing

A genetic algorithm is a search heuristic that is inspired by Charles Darwin's theory of natural evolution. In artificial intelligence, genetic programming (GP) is a technique of evolving programs, starting from a population of unfit (usually random) programs, fit for a particular task by applying operations analogous to natural genetic processes to the population of programs. The GP, which was suggested by Koza, is used for the development of the model to optimize the process coagulation and flocculation and it can be coded by using Visual Studio C++. (*Sooyee, Hyeon and Changwon, 2008*)

2.7. ANN model

2.7.1. Introduction

ANN is the type of Artificial intelligence technique, due to their interconnected structure network they are functioning by mimicking the human brain's way of storing information (*Haykin, 2009*). The neural network was first proposed by McCulloch and Pitts in 1943 (*Baxter et.al, 2002b*). It is working by adjusting the weight value of the synapse that connects the node or neurons of the network. A neural network has a learning ability from historical data that is how it has the potential of providing a map to the complex relationship between input and output.

On the contrary of mathematical modeling, to develop ANN model there is no need predetermined formula and have a linear relationship between input and the output because the relationship is set by utilized algorism automatically (*Baxter, Smith and Stanley, 2004*). So, using ANN have an advanced statistical method able to anticipate non-linear and complex relationships between inputs and outputs and it uses as a replacement of a multilinear regression model (*Baxter et.al, 2002b*).

ANN has been applied to different problems including prediction, forecasting, and process control from simultaneous and independent variations of multiple inputs and the variables can be not known, or describing them would be difficult. That is the reason behind led to naming statistical (black box) model (*Daniel & Eelco, 2017*). Additionally, ANNs have the capacity to generalize when they are displayed with novel input designs that were not included within the preparing information set (*Hunt et.al, 1992*). Generalization is the capacity of organizing to reply to never-before-seen input, comparative to the capacity of the human brain to induce arrangement through inductive thinking.

2.7.2. Basic structure and component of ANN

ANN has several key components including Perceptron or neurons (processing unit), connection weight between the neuron, transfer function, propagation rule, and learning rule (*Baxter .et al, 2002b*).

2.7.2.1. Layer and neurons

A neuron is the main building block of the neural network. The input signal Xi multiplied by the assigned specific weight value Wi and its sum; the resulting value is the input of the activation function of a non-linear neuron. Wi, Summation, and activation function are the key component (*Balakrishnan and Weil, 1986*).

$$Z=\sum W_i X_i \tag{2.4}$$

$$y=f(z) \tag{2.5}$$

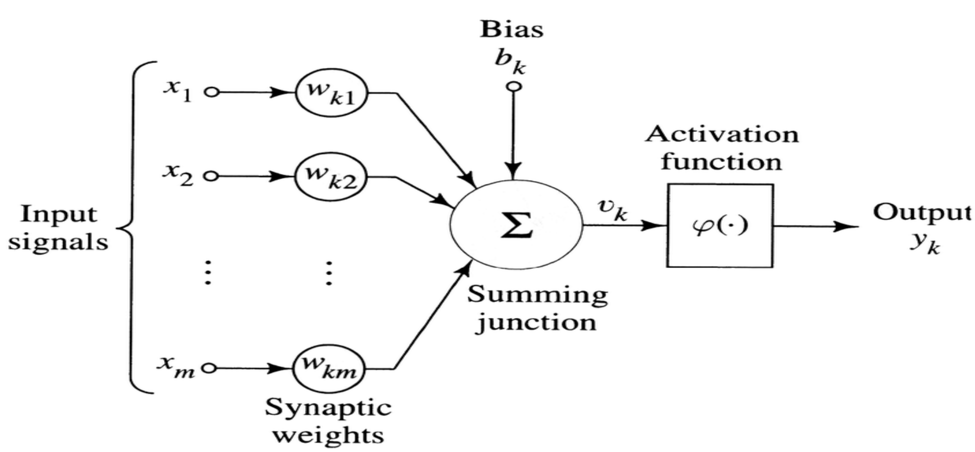


Figure 5: Non-linear neuron model: Source (Piyabute, 2014)

In a multilayer perceptron, the neurons are organized into three layers. The first layer is an input layer consist nodes that receive a signal from the external source, the neurons in the input layer are not true processing units. It is just performed to transform the input value with ranges of either [0,1] or [-1,1] that is for the network can deal efficiently (*Baxter .et al, 2002b*). The middle layer is referred to as the hidden layer because not seen by the user and its function is to possess information from the input layer or the previously hidden layer and pass it to the output to the next adjacent layer. It is possible to use more than one hidden layer to decrease the rigidity of the network and allow to increase the convergent ability with fewer connection weights (*Maier and Dandy 2000*). the output layer consists of a node that receives signals from the hidden layer and sends into a predicted value of the output to the user (*Daniel & Eelco, 2017*). The ANN models give more accurate predictions when the output variable is one, however, it is possible to model more than one output variable (*Baxter .et al, 2002b*).

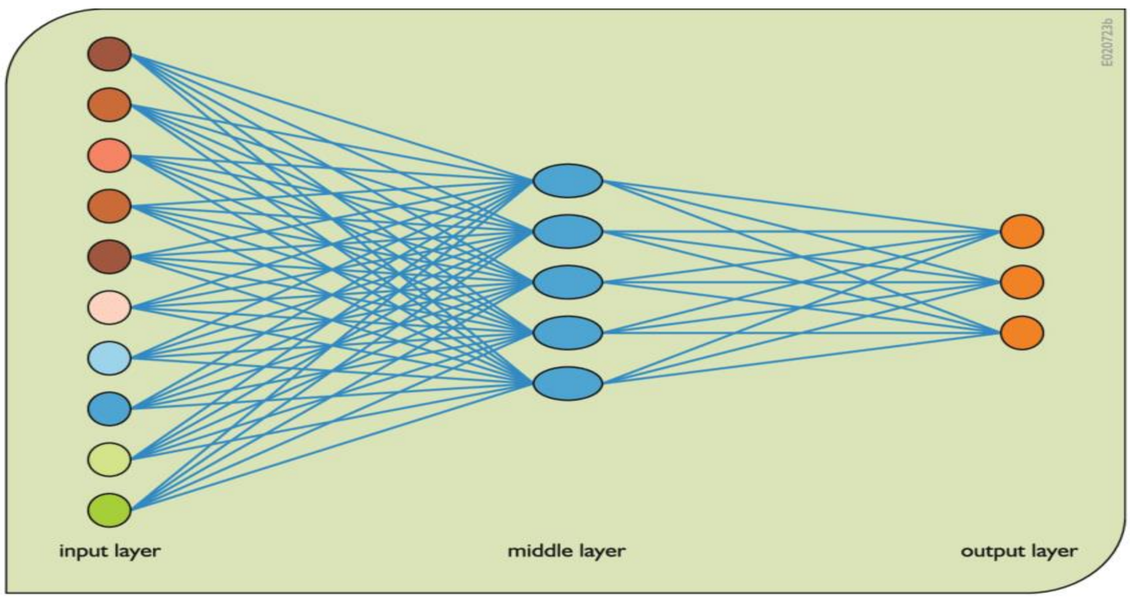


Figure 6: A typical multilayer artificial neural network showing the input layer for ten different inputs the hidden layer (s), and the output layer having three outputs. Source: (Daniel & Eelco ,2017)

2.7.2.2. Weights

In the neural network, each neuron is connected to the next neuron and these connections are characterized by weight or strength. It is always set randomly to begin with and adjusted through time during the learning process according to the learning rule until the error between the actual output and the desired output is minimized (*Daniel & Eelco, 2017*). For instance, in Matlab the weight value is set randomly by the software. However, the programmer can assign the nearest looks value. The value of the weight value reflects the virtual influence of input into the output variable. If the value is positive, the connection will be excitatory and if the value is negative, the connection will be inhibitory. If the two cases do not happen, there is no correlation between the network and the connection weight will be set to zero and the input variable can be removed from the network (*Krose and Smagt , 1996*).

2.7.2.3. Activation function

Activation functions are functions in the neural network to compute the weighted sum of input and bias. There are several types of activation function and can be used in neural network design, from bias axon to the more complicated one such as binary–transfer function, logistic-transfer function, hyperbolic tangent-transfer function, and Gaussian-transfer function those are recommended for regression problems (*Nørgaard, 2000 and Haykin, 2009*). The main use of transfer function is to limit the output value within a limited range of [0-1] and [-1,1]. Inputs of the data automatically scaled from -0.9 to 0.9 (Haykin, 2009). The linear activation functions are just a polynomial of one degree, and it is considered a single-layer ANN model. It is not popular because of its limited power to simulate complicated data. It takes the input then multiplied by the weight for each neuron and creates an output signal proportional to the input (*Mohri, Afshin & Ameet 2013*). The most used transfer function in neural nets is non-linear functions like the sigmoid function, which includes the logistic-transfer function and the hyperbolic tangent-transfer function (*Maier and Dandy 2000*). Sigmoid transfer function is mostly used in feed-forward neural networks and can reduce the computational burden the network experienced during back propagation. It increases from 0 to 1in a smooth manner (*Mohri, Afshin & Ameet 2013*). The hyperbolic function has the same shape as sigmoidal function; however, it is bounded by -1 to 1. It is known as tan function and zero-centered function. Allowing the boundary negative to the positive helps the network to train fast due to the asymmetric function.

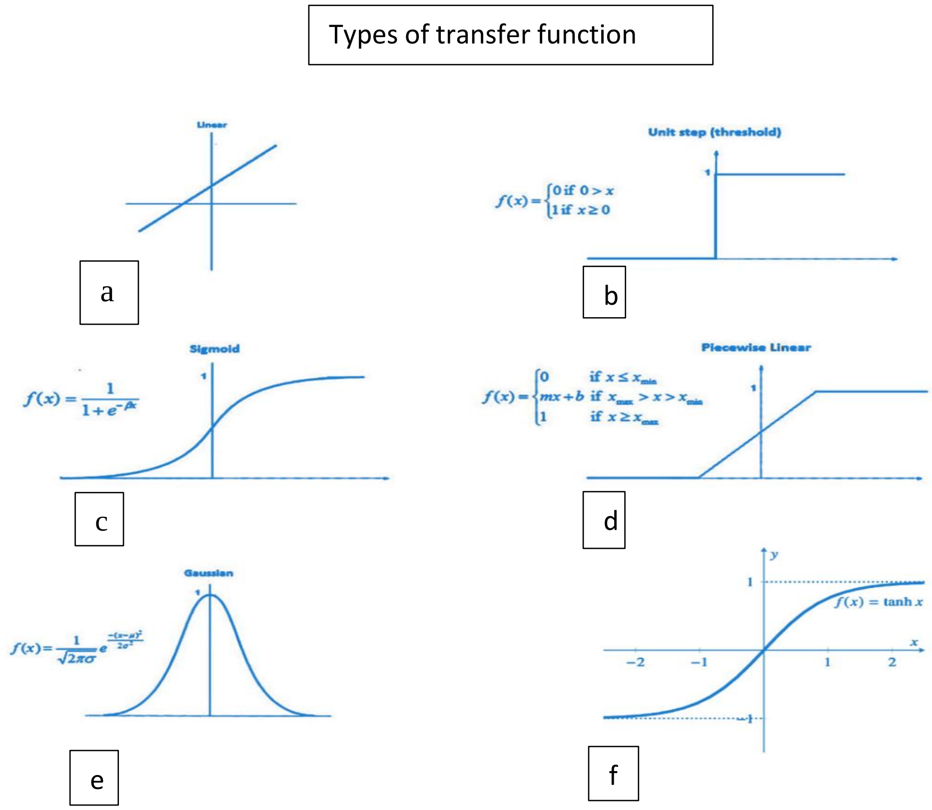


Figure 7: Activation functions: a) linear b) threshold c) sigmoid d) piecewise linear e) Gaussian f) tangential (Designed via Adobe photo shop)

2.7.2.4. Learning rule

It refers to how the weights are adjusted during training for the model best fits. Four types of learning rules are known in the neural network Error correction, Boltzmann, Hebbian, and competitive learning rules (*Basheer & Hajmeer 2000*).

Error correction

Error correction learning used the difference between the desired output and actual output to adjust the weight at that time the error is gradually reduced in overall the network (*Basheer and Hajmeer*, *2000*). In the Process model the backpropagation algorism, ECL is the most common type of learning applied in multi perceptron (*Maier and Dandy*, *2000*).

$$\Delta w_j k(n) = \eta E k(n) X_j(n) \quad (2.6)$$

Where:

$\Delta W_j k(n)$ =is the change made to weight connecting neuron j to neuron k at time

nEk(n)= difference between actual output and desired output at time ‘n’ for neuron ‘k’

ɳ= positive constant of proportionality that represents the learning rate

$X_j(n)$= input ‘j’ at time ‘ n‘ for neuron ‘k’

Boltzmann

It is a random learning method, derived from information theory and thermodynamic principles. It is the same with ECl but it is based on boltzzmann distribution function (*Hinton and Sejnowski 1986*).

$$\Delta w_{jk}(n)=\eta(\rho^{+}_{jk-}\ \rho^{-}_{jk}) \qquad (2.7)$$

Where:

ρ^{+}_{jk} = conditional correlation between the states of the neurons ‘j’ and ‘k’

ρ^{-}_{jk} = unconditional correlation between the states of the neurons ‘j’ and ‘k’

Hebbian

The strength among the node or neuron is increased when the two neurons are activated and have the same output with the same input. Connections between neurons will eventually represent the correlation between their outputs (*Mehrotra, Mohan and Ranka, 1996*).

$$\Delta w_{jk}(n)=\eta Y_j(n)Y_k(n) \qquad (2.8)$$

Y_j = output at neuron ‘j’

Y_k = output at neuron ‘k’

Competitive learning

Two different neurons are computed to win, only one of them is activated. The connection is strong between the winner neuron and the input.

$$\Delta w_j k(n)= \eta(x_j-w_j k) \text{ if neueron ‘j’ wins} \qquad (2.9)$$

$$0 \quad \text{if neuron ‘j’ loses}$$

2.7.2.5. Training function

The training function is the general algorithm used to train the neural network to recognize and map a specific input to an output. The training algorithm carries out the learning process in a neural network. Training a neural network is the process of finding the values for the weights and biases and it is accomplished by the training algorism.

Table 2: The training functions of ANN: Source (Hesam et.al 2018)

Training Algorithm	Training Function	Description
Gradient Descent	GD	Gradient descent Back-propagation
	GDM	Gradient descent with momentum back-propagation
	RP	Resilient back-propagation (Rprop)
	SCG	Scaled conjugate gradient back-propagation
Conjugated Gradient	CGP	Conjugate Gradient back-propagation with polak-Rieber Update
	CGF	Fletcher-Powell conjugate gradient back-propagation
Quasi-Network	BFG	BFGS quasi-Newton back-propagation
	LM	Levenberg-Marquardt back-propagation

2.7.3. Option of ANN configuration

There are two basic types of MLP when in the building of ANN such as process model or an inverse-process model (*Nørgaard et.al 2000)*. In the normal process model, the inputs parameters should know to predict the output. It allows indirect processes and is useful for a complex process problem type like prediction, forecasting, categorization, and image classification. To optimize the output, the trial and error method is must be used by manipulating one of the inputs. In the reverse, the inverse process model allows direct process and the target output specified by the user. In this process, the input can be directed, if the other inputs are known (*Maier, Morgan and Chow , 2004*). To optimize the process the network automatically produced control input to produce the desired output (Baxter et.al, 2002b). It is possible to create a hybrid system by using both process models and real-time control of a process can be accomplished (*Zhang and Stanley, 1999*).

The arrangements of the network divided into two categories Feed-forward and Feed backward. In the feed-forward network, the output of the network serves as the input of the next to adjust layer sequentially and it can skip the layer and feed the next following layer. The input signal is processed in the network independently (*Graupe 2007*). In the feedback ward network known as recurrent network, there is at least one lope present in the network which goes back to the previous layer to use the output of the iteration as an input to retain some memory with associated time delay (*Haykin, 2009)*. Feed-backwards neural networks are useful for time series forecasting applications, such as in the case of raw-water color forecasting, where the raw-water color value of the present day is closely related to the color values of the previous days (*Zhang and Stanley, 1999*).

The learning process can be supervised or unsupervised. A supervised learning system is undertaken by facilitating a user who is assigning the desired output that is expected from the network. In this learning process, the method is studying a task that maps input data into output data based on sample input-output pairs. The desired output is cross-checked with the actual output then if the error is large the weight is adjusted to minimize the error for the achievement of the desired output (*Haykin 2009*). The network follows successive iteration until the global minimum is reached then ECL method is used to check it (*Wesam & Abdul, 2020).* After sufficient training, the network weight is fixed then it serves the environment in unsupervised manner (*Haykin, 2009*). Unsupervised learning doesn't follow any specified target output like supervised; it trails the input data pattern of the underlying model (*Wesam & Abdul , 2020*). In this type of learning process, no external influence to adjust the weight or without any outer support, instead, there is Internal monitoring performance.

2.8. ANN Model development

To develop an artificial neural network model either in MatLab toolbox, Matlab coding, or any neuro solution softwares; there are basic steps, in general, the user should proceed step by step. Data collection and statistical analysis, selection of input and output parameters, selection of architecture, training, fine-tuning of network parameters, and evaluation of network stability and performance are the basic ones (*Baxter et.al, 2002b*). However, selecting parameters might be followed after the training by identifying the sensitive or important parameters for the model. Depending on the method that is used, it is not clear to identify which are important parameters as an input, redundant or not necessary until the end time. Whatever, steps kind of collecting data or analyzing the data are must be considered before thinking about input, output, and important parameters. The trial and error approach is the common method that is adopted to find the best value and arrangement of neurons, transfer function, learning rule, weight initialization, learning rate, and momentum (*Maier, Morgan and Chow , 2004*).

2.8.1. Raw data analysis

It means checking the data if it has an outlier or not, measuring the central tendency, and characterizing each parameter (*Baxter et.al, 2002b*). The raw data inputs are normalized with a method of normalization to improve the network performance. The collected data are divided into three parts for training, validation, and testing purpose. During modeling the Neural network training, 5:3:2 or 3:1:1are the division ratio in most literature recommended (*Baxter et.al, 2002b , Rodriguez & Serodes , 2004*). If the two-input data are similar in function, one of the two is taken as input.

2.8.2. Selection of input parameters

The selection of an appropriate set of inputs parameters from the potentially available inputs variable to include as inputs to the model is needed an investigation and crucial step in the model development. Particularly it is important in the data-driven model such as ANNS and fuzzy system because of the reason the model performance mostly depends on the inputs variable (*Holger et.al, 2005*). Most of the time the input parameter selection is not done properly and it exposes the model to not converge the optimal value easily or not at all. So, it is important to evaluate which parameters of inputs are appropriate.

The parameters that are correlated to each other to minimize the redundancy or to determine which is not properly related with the output at all that should not be included (*Bowden, Dandy & Maier, 2005*). It is done by running the model with all parameters and while remover through the process without sensitivity analysis (*Lewin et.al, 2004*). Primarily the input parameters are selected based on the relationship of the output and the availability of data.

2.8.3. Network training

Once the network structures are prepared for application the network is ready to be trained. Training of the network can be done through different computer programmed software like neuro solution. The network is trained enough to learn the trends in the relationships to be modeled without memorizing the noise in the training data set, which is known as overtraining or over fitting (*Dreyfus, 2005*). When the network becomes overtrained, the validation data errors increase, and the connecting weights revert to the values that produced the least error. Training is complete when the error reaches a predetermined minimum) or a predetermined maximum number of training epochs (presenting the entire available training data set) has been completed. Analysis result and performance evaluation after training, the network should be validated and tested by the data which is not seen by the network. In addition to that, the network stability can be checked by randomly dividing the data into training, validating, and testing set (*Baxter et.al, 2001b*). After the network become stable, the performance is not changed even if it is trained with the new data. The performance evaluation systems used in most neural network models based on R^2 indicate the close correlation between the actual and predicted value, MAE and MSE

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|Xi-Xpi| \quad (2.10)$$

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(Xi-Xpi)\text{^}2 \quad (2.11)$$

Where X_i and X_{pi} are the actual and predicted output value, n refer to the number of data used to train the model.

The low value of r^2 refers to the model performance being poor and the linear relation between the target and the actual output has a little correlation. A low value MAE and MSE indicate the model has a good performance.

2.9. ANN in water treatment.

Because the water treatment process is complex and difficult to identify the exact factors on the unit process to get the desired water quality; it is very difficult to develop a mathematical model (*Zhang and Stanley, 1999*). So, the most common methods to control this problem are the general heuristic method and operator skill and experience which is not trustworthy and slow during the experiment and trial and error execution. The ability of artificial neural networks to learn complex processes has gained much interest for optimization attempts in the drinking water treatment industry (*Baxter et.al 2002b*). There are several studies which are adopted ANN in water treatment. Researchers have discovered many advantages to using neural networks in water treatment process control. Using these predictive Models helps to eliminate the time-delay inherent in traditional monitor feedback control, chemical savings, less frequent filter backwash, improved remote monitoring, and greater overall efficiency (*Rodriguez & Sérodes 2004*, *Zhang et.al 2007*). Some studies are focused on the development of ANNs for the prediction of factors that impact water quality including optimum coagulant dosages, filter performance including particle counts, raw water forecasts, and DBP.

The performance of the network is depending on the network type and certain practices. For example, inverse process model is more accurate and provides noise reduction because it does not only control the forward process *(Zhang and Stanley*, *1999*). Instead of preparing a single neural network for the whole treatment plant, dividing the network into a different season and preparing another neural network if any changes in the treatment process such as changing a coagulant type are increased by 40% network quality (*Zhang et.al*, *2007*). In addition to that, neural network models are site-specific because the data used to model the process at one treatment plant are not the same as the other. The variations in water quality, treatment steps, and operating conditions, each plant must have a model developed using measurements taken on-site if it is possible otherwise Jar test data of that specific plant (*Lewin et.al*, *2004*).

Peterborough pilot plant

The researcher used the bench-scale data collected from the Peterborough pilot plant to train the artificial neural network to predict THM and HAA formation. The corresponding input parameters are pH, TOC, UV254, temperature, and chlorine dosage. They were randomized using the random number generator in Microsoft Excel. This randomized data are divided into the three-parts training set, validation set, and testing set in respectively 60%, 20%, and

20% of it. Neurosolution is the software used to train the model. The correlation coefficients for TTHM model is r^2 = 0.85 and it is performed somewhat better than the HAA9 model r^2 = 0.77. The MAE and MSE are for the TTHM model (MAE = 7.0, MSE = 89.3 respectively) and for the HAA9 model (MAE = 5.8, MSE = 64.0) (Wassink, 2011).

The water treatment plant in Ardabil province

The researcher used two years of recorded data from the treatment plant 112 in number. Two models are developed, the first is to predict the final turbidity after coagulation and the input parameters are temperature, pH, the degree of alkalinity, the turbidity, and coagulant dosage and the output parameters are final pH, final temperature, final Alkalinity, and final turbidity. The second model is to predict the amount of coagulant needed for the treatment plant and the input parameters are temperature, pH, the degree of alkalinity, the turbidity, final pH, final temperature, and final turbidity and the outputs parameter is chemical dosage. By using SOM the data are divided into three-sets (training 80%, validation 10%, and testing 10%). The MATLAB ANN toolbox was used to train ANN. before the training, all the data were normalized by using the normal distribution method of normalization. The final architecture of the first model, as well as the second, was found by trial and error method. To determine the end time of the training period and compare the generalization capability of different models, parallel validation, a method often used in ANN models, is used. R^2 and MSE are used to check the model performance (*Amin, 2018*).

A lot of researchers have been done to improve drinking water treatment and wastewater treatment systems using neural networks. These show the capability of neural networks and the need for further research, development, and implementation (*Wassink, 2011*).

3. Research Methodology

3.1. Description of the study area

3.1.1. Location

The Legedadi-Dire dams and the treatment plant are located 30 km to the east of Addis Ababa in Oromia Regional State. The dams have single purpose of providing drinking water for the city of Addis Ababa. They collect runoff from the surrounding catchments of Legedadi (207.3 Km^2) and Dire (77.5 Km^2). Geographically, the Legedadi catchment is located between 9.03-9.22 N latitude and 38.94-39.07 E longitude, whereas the Dire catchment lies between 9.14-9.22 N latitude and 38.83-38.96 E longitude (*Andualem and Yonas, 2008*). Both are upstream sub-catchments of the big Akaki River, which flows from northeast to southwest and constitutes the Awash River basin.

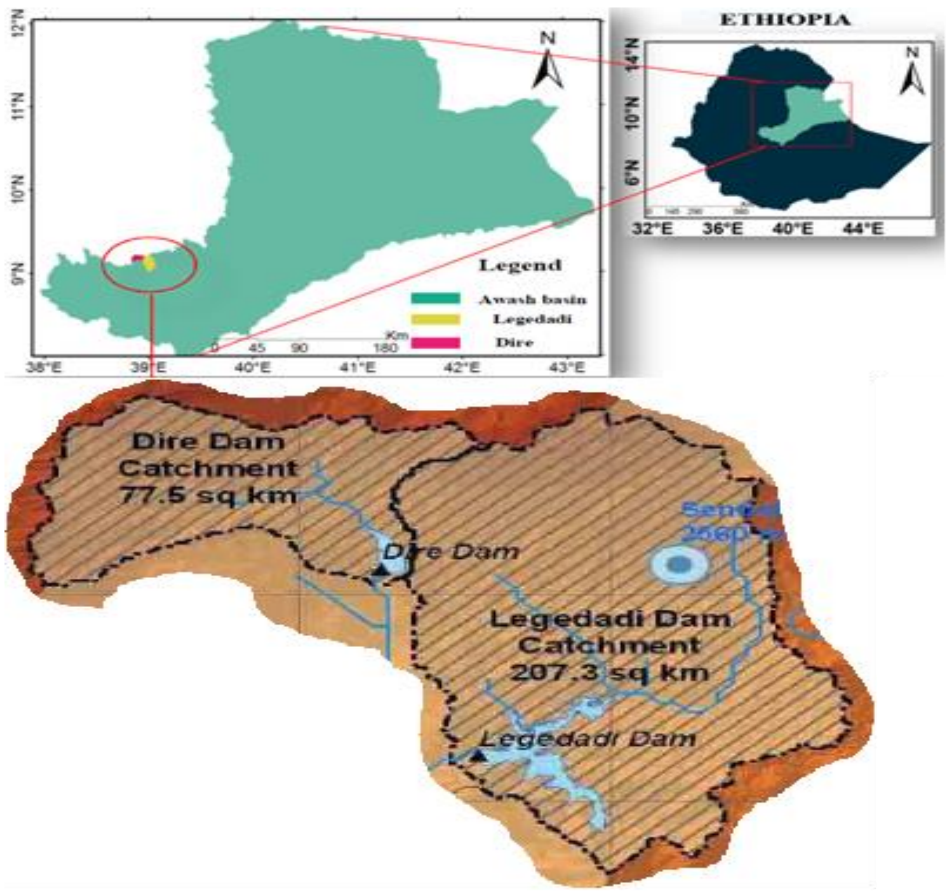


Figure 8:Catchment Map of the study area: Source (AAWSA, 2011)

3.1.2. Climate

The study area is located in the upper northwestern part of the Awash basin. There are meteorological stations near the catchment area, which are located in Sendefa and Addis Ababa. The mean monthly temperature is between 16^{o}C and 19^{o}C throughout the year. The minimum monthly average temperature recorded is 16.1^{o} C in July in the Addis Ababa Station and the maximum monthly average temperature is 25.5^{o} C in February in the Sendafa Station (*Andualem and Yonas, 2008*). The hottest season extends from December to late March. The mean annual precipitation in the catchments is between 1000 and 1300mm (*Tahal, 1999*).

3.1.3. Land use land cover

Land use in the Legedadi catchment consists of cultivated land, grassland, shrubs, eucalyptus wood plots, natural vegetation, water body, barren land, and built-up areas (paved roads, dam, and concrete buildings in Sendafa town). Grazing land for cattle is provided by the grasses that cover the undulating valley and plains (*TAHAL and Metaferia, 1999*). The towns of Sendafa and Beka, which are located in the Legedadi watershed, are developing over time (*Tahal and Metaferia, 2000*). As reported in the AAWSA 2011 master plan, the bare land, cultivated land, and planted forest land have all increased (Dar Al-Omran, 2011). The amounts of cultivated land and plantation forest have increased by 20%. While the settlement area rose by roughly 20 times and the other land covers diminished. For instance, the open grass areas have shrunk to an eighth of their prior size.

3.1.4. The capacity of the Legedadi Reservoir

Legedadi dam was built in 1971 EC and its total volume in 1977 was 45.9*10^{6} m^{3} having a surface area of 4.8*10^{6}m^{2}, mean depth nine meter, and a maximum depth of thirty-four meter. At the mentioned elevation, the water volume reduced to 4.38*10^{6}m^{3} according to the survey performed in 1998. Bathymetric Survey conducted by SEURECA in 2010 shows that the total reservoir volume is 42.17*10^{6} m^{3}. The total reduction was 3.7*10^{6}m^{3} from 1979 to 2011 due to the gradual increment of the rate siltation of Legedadi reservoir. According to the 1998 survey, the catchment sedimentation yield was 762t/km2/yr, however, the survey conducted in 2010 shows that the yield has increased to 845t/km2/yr during a period of twelve years (AAWSA,2011).

The Dire dam was built in 1999 EC to overcome the lack of capacity to supply water from the Legedadi reservoir with an initial volume of $17*10^6$ m^3. After performing some improvement, the dire Dam's capacity of storage has been increased to $23*10^6$m3.

3.1.5. Raw water quality of Legedadi Reservoir

The raw water which comes to Legedadi reservoir is characterized by high turbidity and color, low alkalinity, and hardness. The suspended solids are very fine and of colloidal nature. Raw water turbidity increased within a period of ten years from averages of 80-150 NTU to 260 NTU during the dry season and to 600 NTU during the rainy season (*Tahal, 1999*). Recently, according to AAWSA lap report in July 2011, the maximum turbidity value is reached 2666 NTU. After beginning the treatment of the raw water from the dire-dam, the water turbidity has decreased and reached the maximum turbidity level of around 1200NTU. However, the maximum amount of turbidity measured in the last year Aug/2021 was 650NTU.

3.1.6. Legedadi Water Treatment Plant

As the catchment is used intensively for agricultural farming practice which produces water that is loaded with turbidity, it automatically becomes unusable for any other household services. As a result, the household drinking water is treated at LTP before being supplied directly.

The Legedadi treatment plant located next to the Legedadi dam was built 1971. It is used for the treatment of the surface water supplied from Legedadi and Dire water reservoir. The plant was designed with a maximum production rate of 150,000m^3/day through two stages. The first stage was planned to produce 50,000m3/day while the second stage was to produce 100,000m3/day. The treated water is delivered to the city through an 18km lengthy pipe by a natural gravitational force (*TAHAL, 1999*). However, 5 years ago, the treatment plant was expanded to treat additional 30,000m^3 water to fulfill the needs of the town. The overall treatment plant was designed to produce 180,000 m^3 of water, However, the production capacity has been reduced by 10,000m3/day due to some technical issues.

3.1.7. Operation system of Legedadi Water Treatment Plant

Raw water intake

The raw water reservoir provides water by a gravity flow system. The level of the water inside the reservoir varies seasonally. The water is delivered from the reservoir to the treatment plant using the intake which has three ports at different vertical locations. The treatment plant has different conventional unit processes as shown in the Figure 9.

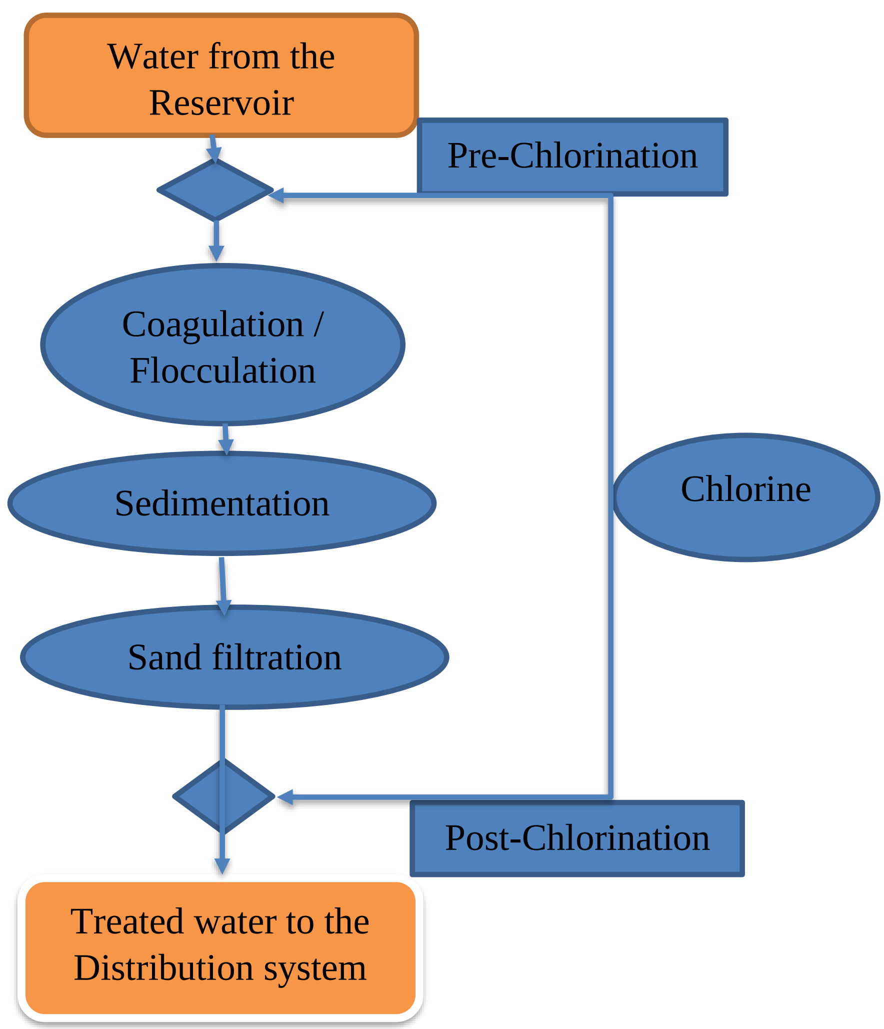


Figure 9:Schematic of the Legedadi Water Treatment Plant operation

1. Pre-chlorination

The treatment process starts with a pre-chlorination operation of the raw water as it enters the treatment plant at the mixing/distribution structure in the mixing chamber. This operation has the main purpose of destroying disease-causing organisms, bacteria's and pathogens that are likely to grow in various units of the plant. At the Legedadi treatment plant, the usual pre-chlorination dosage is between 0.8 and 1.0 g/m^3.

2. Coagulation and flocculation

There are different types of coagulants available for the process of coagulation and flocculation. The raw water characteristic in the Legedadi reservoir has led to the usage of polyelectrolyte (PolyDADMAC) as primary coagulant and as a coagulant aid. The raw water enters into the mixing chamber portion of the structure at which the coagulant chemical (polyelectrolyte) is added and the agitator thoroughly mixes the chemical. Then it moves through a series of baffles to the distribution chamber where Polydiallyldimethylammoniumchloride (PolyDADMAC) is injected. The main function of the primary coagulant is to neutralize the electrical charged suspended particle in the raw water, whereas the coagulant aid functions as an aid for the formation of a denser floc. Finally, the raw water passes over three 91cm feed wires (vacuum chamber) which are evenly distributed into three clarifiers. Then, the heavy particles easily settle to the bottom of the sedimentation compartment.

The chemicals are prepared in the chemical mixing and storage building that is constructed in front of the mixing chamber and clarification basin. The room is constructed at a higher elevation for the convenience of an easier transmission as most of the coagulant chemicals are jelly type including polyelectrolyte. In the mixing section, three different $40m^3$ containers are used to mix the polyelectrolyte whereas the coagulant aid is mixed with an additional two $32m^3$ containers found separately. The coagulant is placed in the feeder, and it dispenses the pre-set amount of chemical into these mixing tanks which are located below. Then the mixing solution is pumped by chemical feed pump to the mixing chamber by plastic pipe. The coagulant aid is diluted with water for workability purposes while its amount in one container cannot be exceeded than 13kg because of its viscous nature.

3. Sedimentation

Once the raw water is mixed with the chemical; it runs over the weirs into the clarifier vacuum chamber. The sedimentation basin used at Legedadi treatment plant is a pulsator type clarifier. The three stages of the treatment plant each have two clarifier basins. When the water rises, the valve automatically opens and lets the atmospheric pressure enter the vacuum chamber. Inside the vacuum chamber, the water is evenly distributed across the bottom of the clarifier basin by the distribution channel. The sludge blankets are moved up and down. It rises during the water released and falls during air suction. The sludge volume slowly increases; when it reaches the appropriate level, the sludge is spilled into the sludge collector (concentrator) with each vacuum chamber from the sludge bed. As the sludge concentrator becomes full, the valve opens automatically whereas it closes when the collector is void of any sludge material. Clarified water is collected at the top of the pulsator by laterals, holes and sent to the rapid sand filters. Coagulation, Flocculation, and sedimentation are all performed in one single tank.

4. Filtration

Filtration is a process used for the removal of very fine suspended particles such as mud, minute particles of floc, and clay. These particles cannot be removed through the clarification process but they can be removed by passing through different sized sand filters. In this treatment plant, the RSF method of filtration is used. The sand bed is covered on the concrete raised floor fitted with a regular spaced nozzle for the collection of filtered water. Two wastes are produced in the treatment plant which is sludge drawn off from the clarifiers and wasted filter backwash water. The filters are back washed by the use of treated water and compressed air.

5. Post Chlorination

Post chlorination is a final step in the Legedadi treatment plant which is applied to retain residual chlorine through the distribution system which prevents the growth of micro-organism. In the chlorination of water supply, it is very important that the residual chlorine is presented as free available chlorine rather than less active combined chlorine. The normal dosage for post-chlorination normally is 0.6 to 0.7g/m^3.

3.1.8. Method of chemical determination and frequency

The amount of chemical that is used to remove the turbidity is determined by using the Jar test. However, the test is not taken frequently. During the summer season, the operators take the test weekly and during the winter season, the test might be taken once in two weeks or more. The major factor that impedes frequent measurement is the distance between the treatment plant and AAWSA office. Even though there is a mini lab in the treatment plant, the operators have to travel from the head office to evaluate the optimum coagulant dose. Nevertheless, this only happens when the workers at the treatment plant observes and report some water quality changes. There is a perception that the raw water turbidity does not vary frequently especially in the winter season. The operators used to apply a coagulant aid of without changing the concentration with the raw water characteristics.

3.2. Data collection

The data related to the coagulation process at the Legedadi Water Treatment plant were collected from both primary and secondary sources. A total of one hundred nine observed data were used to train the model. From these, nineteen data were *primary data* collected by the researcher during May-November 2021 in AAWSA Laboratory and Legedadi Water Treatment Plant. The remaining data were taken from the operational records of the treatment plant. Moreover, relevant information about the general coagulation practices of the treatment plant was obtained from **four** AWSSA workers who have been closely following the coagulation and flocculation process through **interviews and questionnaires**. The complete questionnaire used for the data collection is shown in Appendix 6. The catchment's land use and land cover maps from two years (2011 and 2021 E.C) were used to demonstrate how the catchment land use has Changed, affecting water quality and quantity. The following parameters were used to develop coagulation-flocculation process ANN models for the Legedadi Water Treatment Plant; raw water turbidity, temperature of the water, pH, coagulant dosage and treated water turbidity.

Table 3: Statistics of input and output data to be used for model development

Parameters	Max	Min	Average	Standard deviation
Raw water turbidity (NTU)	681	152	377.44	144.395
Temperature (°C)	25.5	15.09	20.33	2.661
pH	7.42	6.9	7.13	0.096
Coagulant dosage (mg/l)	9	3	5.78	1.694
Treated water turbidity (NTU)	3.85	3.04	3.52	0.139

3.3. Experimental Protocols

Two types of experiments were conducted in this research namely bench and pilot-scale tests. Their main purpose was to collect primary data to validate the experimental secondary data and increase the number of data available for model development. The experiments were also used to study the efficiency of different coagulants and check the remaining turbidity of the treated water. Emphasis was given to obtaining reliable experimental data through use of appropriate quality assurance and quality control protocols.

3.3.1. Bench scale

The Jar test is a bench-scale laboratory test that simulates coagulation and flocculation processes. It is the main experiment that is conducted periodically at Addis Ababa Water and Sewerage Authority Laboratory and at Legedadi Water Treatment Plant mini-laboratory. Although, Legedadi Water Treatment Plant has a min lab, most of the samples were tested at AAWSA Laboratory. The raw water samples were collected and transported from the Legedadi treatment plant to AAWSA Lab with twenty liters container. The jar test was conducted following the standard procedures. The raw water, treated water turbidity, pH of the water, and the temperature are the parameters that were considered during the jar test. The test was carried out to identify the relationship between the initial turbidity, temperature, pH, and chemical dosage required to obtain the desired water turbidity and to validate the experimental secondary data with different ranges of turbidity. It was also conducted to evaluate the effectiveness of the coagulant used at Legedadi Water Treatment Plant. As the pH values of the water samples were not found in the secondary data set, they were collected from the treatment plant operation records for other processes.

The efficiency of the currently used coagulant in comparison with other commonly employed coagulants including aluminum sulfate, polyaluminum chloride, and iron sulfate was studied through jar tests. The first test comparison was made among Aluminum Sulfate, PACL and Polyelectrolyte. The second comparison was conducted among Aluminum Sulfate, Ferric sulfate, and Polyelectrolyte.

The jar tests were conducted using two Phipps & Bird jar test apparatus. The apparatus which is found in AAWSA lab allows, simple automatic control once it is set to perform actions starting from a rapid mix up to floc settlement. The other one which is found at the treatment plant is semi-automatic and needs an operator to control its operation.

Jar test Procedure

The following jar test procedure was followed to determine the polyelectrolyte coagulant dosage for the water sample collected from Legedadi Water Treatment Plant.

- The turbidity, temperature and pH of the sample water were measured before beginning the process.
- 1000ml distilled water was filled in a volumetric flask to dilute the chemical.
- 1000 ml of raw water was added in each of the 6 jar beakers labeled from1 to 6.
- A stock solution was prepared by dissolving 1g of polyelectrolyte with 1000ml of distilled water, in which 1ml of the solution is equal to 10mg/l (ppm).
- The prepared polyelectrolyte solution was pipetted into 6 mini jars having 50ml size by increasing the amount of the solution.
- The polyelectrolyte solution was dosed into the large jar beakers which were filled with raw water.
- The stirrers were agitated at 120RPM for two minutes to simulate rapid mixing then this was automatically followed by slow mixing at 40RPM for the next 20 min to allow creation of large-sized flocs.
- As the set time was reached, the Jar tester turned off automatically, and floc settling occurred for 20 minutes.
- The residual turbidity in each jar was then measured

- The minimum coagulant dose that resulted in the acceptable residual turbidity was taken as optimum dosage.

The Jar test apparatus and log sheet which was used to recorded the result are obtained in the Appendix 2

Figure 10:Jar tester

3.3.2. Pilot -scale test

Pilot scale test means representative engineering scale model or prototype system which is well beyond the lab scale and tested in a relevant environment. Pilot scale testing includes on-site portable equipment temporarily installed at the treatment plant. Usually it is on-site at the eventual place where full scale is built and operated.

These tests were carried out to measure the remaining turbidity in the treated water after coagulation and flocculation at the treatment plant and check whether it meets the Ethiopian Drinking Water Quality Standard. The treated water samples were collected at the end of the clarification stage and before post chlorination of the treatment plant. The turbidity was measured with the HACH 2100AN Turbidimeter. Prior to reading the turbidity, the cuvette was washed once with distilled water. The treated water was filled in the test tube and inserted in the instrument then the result was recorded. The instrument uses the light that passes through the sample to detect the angle of the light scattered at which time the amount is displayed in NTU.

3.4. ANN model Development

3.4.1. Modeling software

The Matlab version 2016a software was used to develop ANN model, which enables to write the code and modify it within a single environment. Matlab Neural Network toolbox (NNtoolbox) can be used to develop ANN, however, it does not allow the user to modify some of the Architectural features such as the number of hidden layers and transfer functions as it uses the default program. Thus, in this research Matlab codes were programmed to develop the models. However, there are architectural features that can be modified by NNtoolbox such as the number of nodes in the hidden layer and training function (learning algorithm) even though the choices are limited. Because the 2016 version has some limitations, the model implementation application was created with the 2019 version. Another program used to assess the models' outputs is Microsoft Excel.

3.4.2. Data Division and preprocessing

Data division has a significant impact on the process of ANN development and for obtaining the best minimal convergence error. If the amount of data taken for the training and testing does not split properly, the model performance would be decreased. However, no written code could aid the decision (*Quang et.al 2021*). Some researchers recommend the usage of 2/3 of the data for calibration and the rest for validation. The most recommended data division is 70/30 for training and testing, however in this research 80, 10, and 10 were used for the first model and 75, 15, and 10 for the second model for training, validation, and testing respectively. The optimum data division was found by trial and error method after proceeding through different data division ranges.

The training set was used to adjust the weight between the neuron, the validation set was used to check the generalization capability of the model once the training set is stopped under the data range used for calibration. The test set was used to check the performance of the network during learning and optimize the network architectures and it stops the training while the error in the testing set increases.

The collected data from the treatment plant booklet and experienced operators are not time series as a result the data were organized in ascending order in Excel and sorted according to the value of the raw water turbidity. However, this arrangement cannot fully represent the three data division sets as the highest turbidity ranges are placed on the top row while the middle and bottom row has a medium and less turbidity range. ANN best performs when the available data patterns are better represented in the calibration process. Besides, the training set data pattern should be represented in the validation and test set to perform the network well. The training, testing, and validation data are not indicative of each other, thus, can bring about large incongruities in the model performance. Thus, to overcome this problem, the available data were randomly distributed throughout the pattern according to the ratio set for division and this method can be an assurance to have similarity in statics (mean and variance) measurement between each data pattern set. The data used as validation and test were not similar to the data used for developing the model. Another use of data splitting into these three sets is to control overfitting but, in this case, due to the limited data, the probability of overfitting was less.

Table 4: Mean and Standard deviation between the data pattern of each set

Data set	Mean	Std
Training	5.77mg/l	1.63mg//l
validation	5.82mg/l	1.86mg/l
testing	5.7mg/l	1.88mg/l

3.4.3. Choice of model inputs

In this research, two kinds of models were developed namely *process model* and *inverse process* model. As a result, the output of one model was the input of the second and one of the input parameters for the first model was the output of the second. Even though numerous parameters have an impact on the coagulation and flocculation process, the model input was selected by considering the available data and prior knowledge of the system with the researches done for the prediction of optimal chemical coagulant. The following were followed to predict the treated water quality and coagulant dosage.

- To predict the treated water quality (Process model)

A process model can predict the value of one or more outputs if all the input variables are known. Determining the treated water turbidity by varying the process control parameter (in our case polyelectrolyte) is the process model in the coagulation process. The raw water turbidity, pH of the water, temperature, and chemical dosage are used as inputs and the treated water is an output for the model resembling the actual coagulation process.

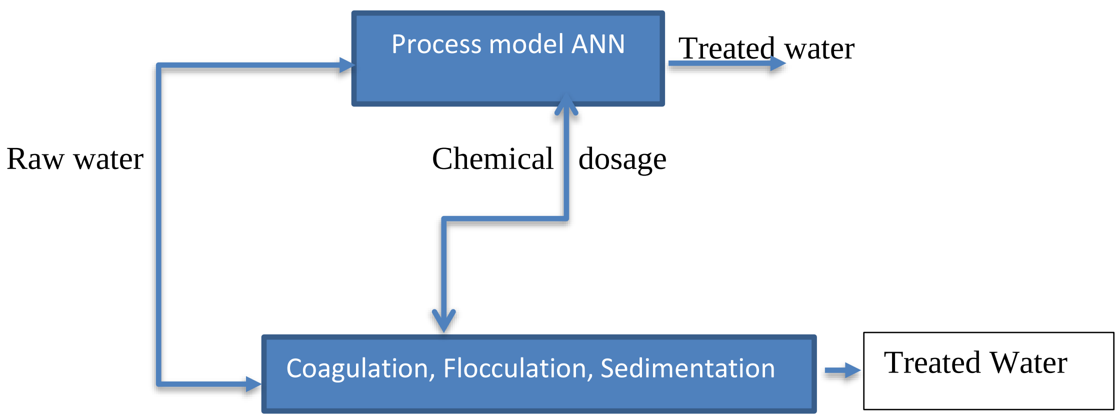


Figure 11:Schematic diagram of the process model

- To predict the chemical dosage (process inverse model)

An inverse-process model can predict the value of input if all other input variables are known and target values have been chosen for the output. In this type of model, the chemical dosage is output or predicted by the model by assigning the amount of turbidity of the treated water according to the interest of the user. The raw water turbidity, pH of the water, temperature, and treated water turbidity (on the contrary of the actual coagulation process) are the inputs of this model.

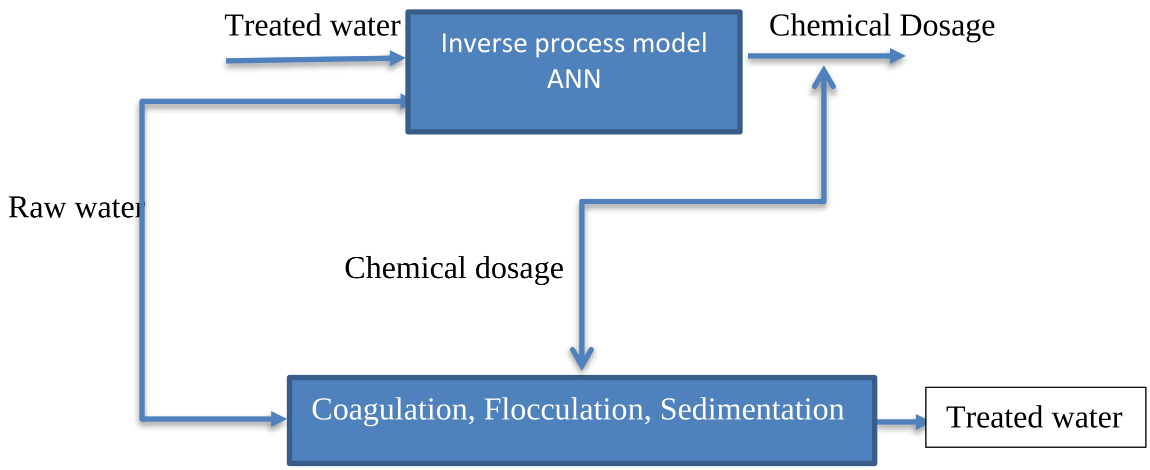


Figure 12:Schematic diagram of the inverse process model

3.4.4. The Models Architecture

The model Architecture tells how the model is built. There are different kinds of network architecture revealed recently. MLP feed-forward has been used successfully for optimum coagulant forecasting (*Amin, 2018*).

In this research MLP feed-forward with one hidden layer is used to develop both models. After the Selection of the input and output parameters based on basic factors that affect the coagulation and flocculation process in the treatment plant of the actual process and the available data, other key components of the neural network applied to develop the model were decided through trial and error method by considering the type of problem. The number of hidden layers, the neurons in the hidden layer, transfer function, momentum, and learning rate were the basic key components.

The number of hidden layer is one and the decision was taken after trying to adopt two hidden layers and noticing the error optimization ability. Despite the fact researchers have demonstrated that many functions are difficult to estimate with one hidden layer in practice, however, there is a fact that a network with one hidden layer that may approximate any continuous function given enough degrees of freedom (*Maier, Morgan & Chow 2004*).

The hidden layer consists of nodes (neurons), and its general function in NN is to transform information as a weighted value that has been received from the input layer and send it to the output layer or the next hidden layer if the network has more than one hidden layer.

Recently researchers employ numerous hidden nodes to get the global minimum convergence, however, earlier researchers recommend the maximum no of hidden neuron to be 2I+1. I is the number of inputs in the model. since it has been demonstrated that for networks with one hidden layer, this is the upper limit necessary to simulate any continuous function (*Hecht-Nielsen, 1987*).

In this research, the optimum number of hidden neurons used for the first and second model is 7 and 5 respectively, which was found by trial and error procedure by experimenting from 2 up to 10 numbers of hidden nodes and the choice was taken based on the error in the test set. Figures 13 and 14 show the basic construction of the two models.

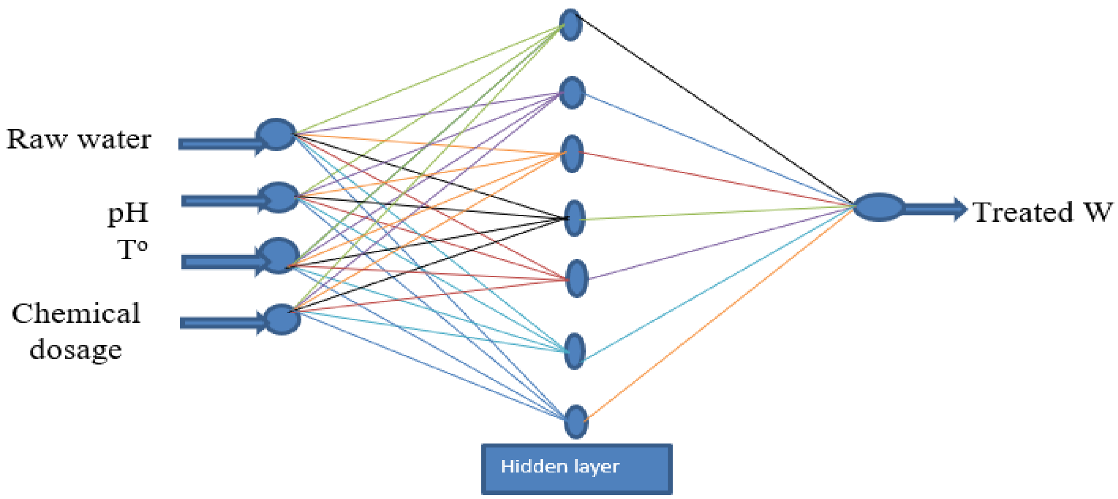


Figure 13:Architectures of model 1(process model)

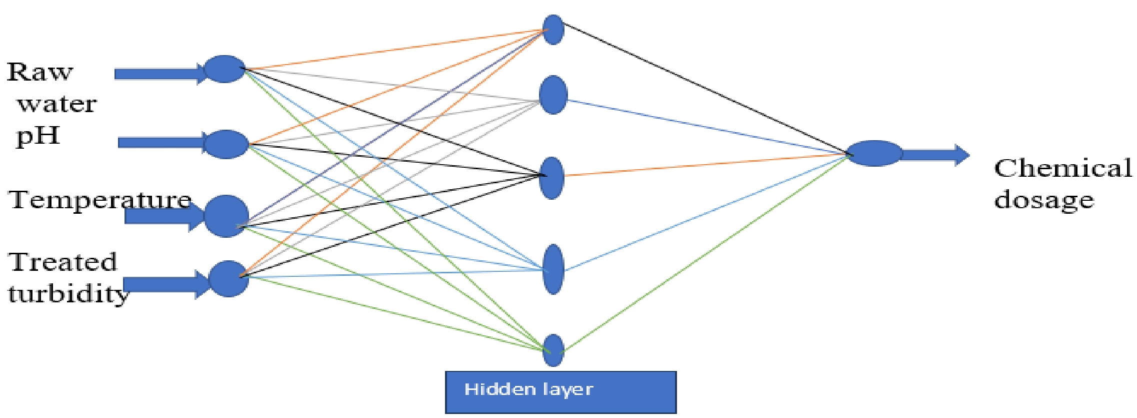


Figure 14: Architectures of model 2 (inverse process model)

The inputs neurons are four and the output neurons are one for both models as it seen in the above picture. However, the numbers of hidden neurons are different. Seven for the first and five for the second model were used and it was found to be the optimum through trial and error.

Transfer function is used to compute the weighted sum of inputs and biased value and limits the output value within the range of the transfer function. The hyperbolic tangent sigmoid ('*tansig*') transfer function performs better than log sigmoid transfer function in complex and nonlinear relations (*Jude,Deepak & Valentian 2019*). As the hyperbolic tangent limits, the output value between -1 and 1, its value is symmetry about the origin. However, the trial and error procedure were the main reference to select the Transfer function. In this research pair of hyperbolic tangent sigmoid (tansig) and linear (purline) transfer function were used for both models development. The algorithms of the transfer functions are

tansig' $f(x)=\frac{2}{(1+e-2n))-1}$ (3.1)

'Purlin' $f(x)=x$ (3.2)

3.4.5. Model calibration (Training) and Validation

To train the model within the given data and architecture, the data column matrix was changed to row matrix. MLP feed forward with the most popular backpropagation algorithm Levenberg-Marquardt backpropagation was used to calibrate the data for both models. 'Tranlim' is a training function (algorithm) used in ANN according to Levenberg-Marquardt optimization algorithm to update the weight value during training of ANN model. Levenberg-Marquardt algorithm is designed to work with loss function which is taken as the sum of squared error. Loss means the prediction error of the neural network. Even if it is difficult to know the fastest training function, 'Tranlim' has high convergence ability than the others.

Learning rate is one of the hyper parameters in neural network which is used to control the change of the model in response to the estimated error when the model weight is updated and the momentum is used to accelerate the learning rate schedule. The optimal value for back propagation was obtained using learning rate and momentum. The ranges of learning rates and momentum values considered were 0.1 to 0.8 for both parameters. The optimum value was found by trial and error by checking the error on the error of the test set.

Training in the system was continued until the best value was found which occurs when the errors in the monitoring data group become less or the training was completed at a predetermined maximum number of training epochs has been completed. The technique called stop training algorithm is used to hamper the training when errors arise in validation set at the beginning of the training. When the validation data errors increase, the connecting weights revert to the values that produced the least error.

In the process model eleven samples were selected for each validation and testing from the total data. Where as in the inverse process model seventeen samples were selected for validation and eleven samples were selected for testing. The whole data was loaded into the software which was then randomly assigned or divided for training, validation, and test set with an amount of given percentage.

3.4.6. Neural Network testing

The testing process involved several different trials of training and validation with different network architectures for the proposed models. For each combination of architectures, a specific trial was retrained and revalidated to identify the optimal selection of the model architecture. Each trial was tested by a parallel cross-validation technique that displays the model performance result in Matlab. The error statics provided by an ANN offers the following performance measurements: the mean squared error, the correlation coefficient, and the percent error. In addition to that, several different approaches including the scatter line plot of the actual and the predicted values were employed to test the performances of different architectures. R^2 tells the goodness fit of the model which describes how well the regression from the model output approximates the real data and its value varies between 0 and 1. If the R^2 value is greater than 0.5, it indicates good performance. RMSE tells how much the model output fits the real data showing its closeness to the actual data. The value of R^2 was determined in excel using a trendline through the scatter plot of the data.

RMSE was calculated in Matlab using the following code

x_rms=sqrt(1/N.*(sum((y-ynet).^2))) y refers the actual value, ynet for model output, and N number of samples.

3.5. Model implementation Application

A user-friendly platform was prepared after the optimum neural network architecture was found. This was accomplished by using app designer tools. App designer is an instrument (tools) that is used to create professional apps in MATLAB software. It is a drag and drops interactive development environment with a user-friendly GUI. Drag and drop visual components were used to design the layout of the GUI and to integrate the behavior of input and output parameters.

To design the Application, drag a component from the Component Library and drop it on the canvas. The edit field enables us to customize the components. After the components are designed, the appropriate function is called back, and then assigned for each component accordingly. Write this call back function as a helper function. After the ANN understands the relationship between the input and output parameters, the code is generated. This code is used as a function to call back in the application designer and it is declared in the form of app@name of the component.

Application Model 1: Process Model

The first model is the *process model*, which simulates the jar test and the output is the treated water turbidity. The inputs are raw water turbidity, pH of the water, the temperature of the water, and the chemical dosage. Five numeric edit field components were dragged to the canvas that allowed writing numerical values. One Execute command push button was dragged to evaluate the output when pressed. Each water parameter was assigned accordingly in the numerical edit field and the code that was generated from ANN network was called back for the push button to enable formulation of the relationship among the input and output parameters.

Application Model 2:- Inverse Process Model

The second model is called *inverse process model* and its main purpose is to determine the optimum coagulant dosage. Thus, the output is the chemical dosage that the operators need to apply for the coagulation and flocculation process to obtain the desired water turbidity. The inputs for this application are raw water turbidity, pH of the water, temperature, and the desired water turbidity. The process to design this app is the same as first model. However, in this application, the UI has an additional push-button feature to get the process model as both models were finally compiled in one form.

A general summary of the ANN model development

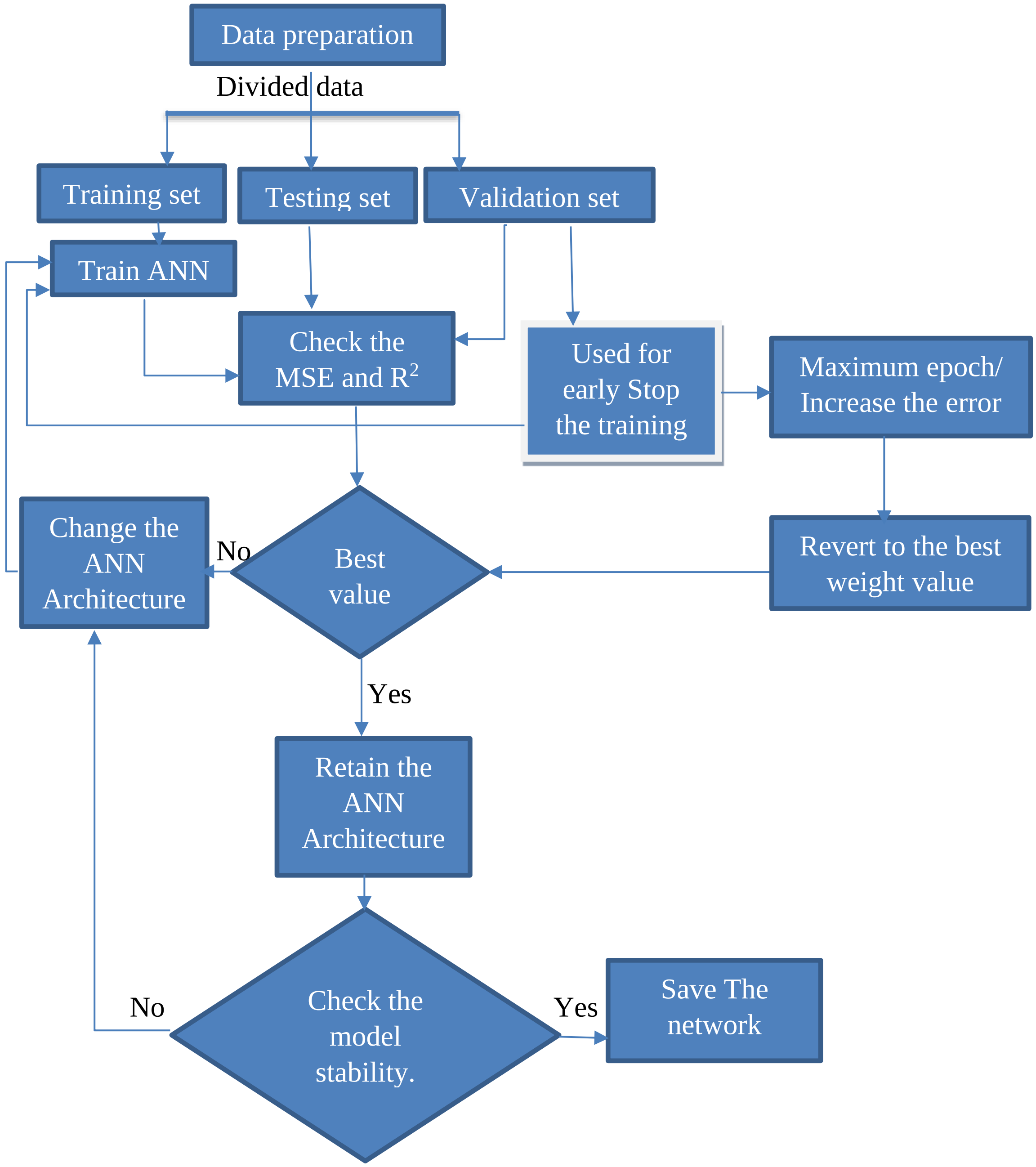


Figure 15: Summary of ANN model development

4. Results and Discussions

The study tried to *identify the main problem* of Legedadi Water Treatment Plant, particularly in the coagulation and flocculation process, and propose a solution to the existing problem. To find the major problems, first the existing coagulation and flocculation practices were studied. Second, the catchment's land use and land cover change were studied which is affecting the water quality and quantity.

4.1. Coagulation and Flocculation Practices

Analysis and evaluation of the existing practices of coagulation and flocculation processes at Legedadi Water Treatment Plant as obtained from experiments, interviews, and questionnaires are presented. It included investigation of the practices of Jar test to get the optimum coagulant dosage, efficiency of the currently used coagulant, and the treated water quality in terms of residual turbidity.

4.1.1. Experimental result

The pilot-scale tests that were conducted to measure the residual turbidity in the treated water showed that the turbidity requirement was met. According to the Ethiopian drinking water quality standard the maximum allowable turbidity level in drinking water is 5 NTU. The laboratory test result is summarized in Table 5.

Table 5: Result of the remaining water turbidity in the treated water

Data	Turbidity after clarification, (NTU)	Turbidity after filtration, (NTU)	Remark
1	3.51	3.18	acceptable
2	3.9	3.4	acceptable

The bench-scale tests that were taken to evaluate the relative efficiency of the currently used coagulant at Legedadi Water Treatment plant showed very good performance following PACL. Although in this research, the coagulant efficiency is measured only in terms of its turbidity removal capacity, other factors such as the ability of the coagulant work under high pH and the sludge dewatering characteristics should be considered.

The details of each test result are presented below

Test one: Comparison among PACL, Aluminum sulfate, and polyelectrolyte

Table 6: Jar test results of Polyelectrolyte, PACL, and Aluminum sulfate

	Jar NO					
	1	2	3	4	5	6
Row water turbidity (NTU)	305					
T° of the water (°C)	22.2					
pH of the water	7.7					
Rapid mix (rpm)	120					
Duration (sec)	90					
Flocculation (rpm)	40					
duration (min)	20					
Settling time (min)	20					
Coagulant type	Polyelectrolyte					
Coagulant concentration (mg/l)	3	4	5	6	7	8
Final pH	7.7	7.67	7.6	7.5	7.47	7.4
Final turbidity (NTU)	8.9	4.41	3.9	3.61	3.5	3.9
Floc formation	Very fine	Fine	Moderate	Course	Very coarse	Moderately fine
Coagulant type	PACL					
Coagulant concentration (mg/l)	30	40	50	60	70	80
final pH	7.69	7.5	7.46	7.27	7.23	7.16
Final turbidity (NTU)	12.8	7.04	3.6	3.04	2.78	3.31
Floc formation	Very fine	Fine	Moderate	Course	Very coarse	Moderately fine
Coagulant type	Aluminum Sulfate					
Coagulant concentration (mg/l)	70	80	90	100	110	120
Lime	3.5	4	4.5	5	5.5	6
Final pH	7.26	7.26	7.24	7.27	7.35	7.39
Final turbidity (NTU)	7.42	5.34	5.22	4.16	2.13	4
Floc formation	Very fine	Fine	Moderate	Course	Very coarse	Moderately fine

In general, the optimum point corresponds to the minimum coagulant dosage that results in the desired treated water turbidity. Even though the treated water turbidity can be reduced even more than the optimum, the chemical concentration should remain at the optimum point to minimize the residual chemical in the treated water. Use of a coagulant concentration that gives the smallest final turbidity has the disadvantage of leaving a chemical residual in the drinking water in addition to increasing the cost of chemicals. According to the Ethiopian Drinking Water Quality Standard, the allowable maximum turbidity in the treated water is 5 NTU. While the jar test is performed the residual turbidity should be between 3-4 NTU so that the treated water turbidity would not be more than 5 NTU during large scale application.

Polyelectrolyte

As shown in Table 6, the treated water turbidity was between 3 and 5 NTU when the polyelectrolyte concentration varied from 5 mg/l (Jar 3) to 8 mg/l (Jar 6). The polyelectrolyte has not resulted in a large turbidity variation after the optimum value was found. In fact, the treated water turbidity increased slightly after the optimal coagulant dosage. The reasoning is, if the chemical dosage added in the raw water is greater than the optimum dose, there could be charge reversal and destabilization of colloidal particles. The optimal polyelectrolyte dose that resulted in acceptable turbidity was 6 mg/l (Jar 4). Although a lesser polyelectrolyte dose of 5 mg/l (Jar 3) resulted in a turbidity in the range of 3-4 NTU, it was not taken as optimum because there could be a risk of poor performance at full-scale treatment plant.

Poly Aluminum chloride

The optimum coagulant was found at 50mg/l PACL concentration (Jar 3) and the final turbidity at this point was 3.6.

Aluminum Sulfate

For aluminum sulfate coagulant, the optimum dosage was found to be 110mg/l (Jar 5). This concentration was higher than that used for polyelectrolyte and PACL coagulants. In addition, Aluminum Sulfate and any of in organic coagulant requires a supplementary chemical to neutralize the pH alteration during coagulation. Thus, lime dose that was half the amount of coagulant was added to keep the pH of the water under neutral condition. Use of alum beyond the optimum dose resulted in poor performance as demonstrated by the higher treated water turbidity.

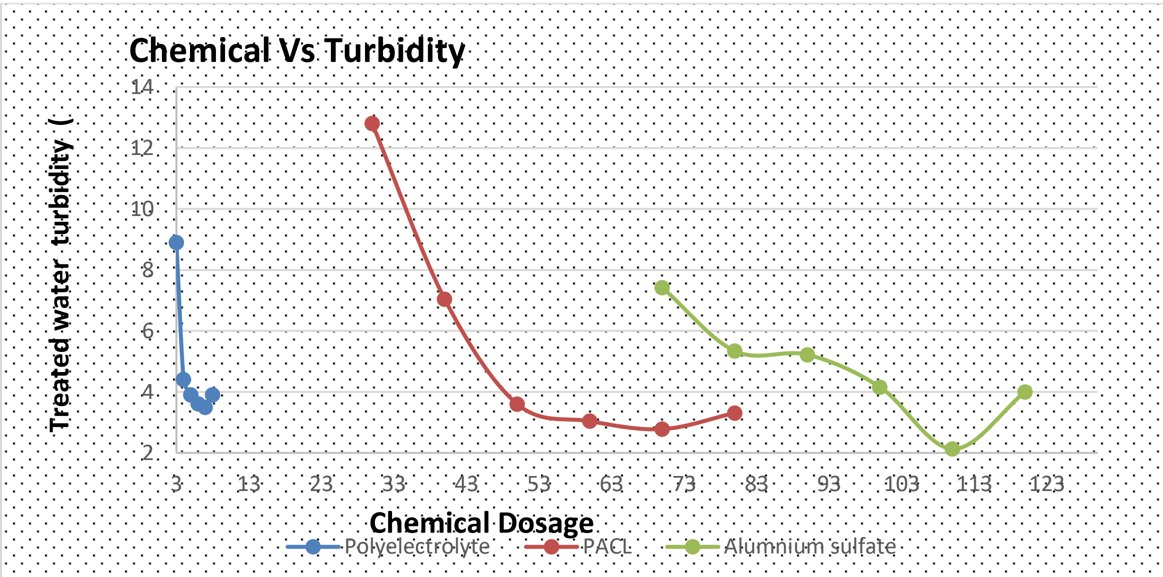


Figure 16: Residual turbidity verses Chemical dosage - Polyelectrolyte, PACL, Alum

From the conducted Jar experiments Polyelectrolyte was found to be the best chemical coagulant to produce an optimum value with a small chemical concentration. The next best coagulant was PACL and Aluminum sulfate was not a good coagulant for a higher turbidity range.

Test two was conducted to study the efficiency of the following chemicals Polyelectrolyte, Aluminum sulfate, and Ferric sulfate. As shown in *Figure 17*and *table 7* polyelectrolytes is better than aluminum sulfate and ferric chloride in terms of turbidity reduction and the coagulant dose used. Both aluminum sulfate and ferric sulfate are not good coagulants for high raw water large turbidity. Figure 17 clearly shows that these two coagulants are not even meet the required water turbidity at any point, thus, in order to remove the turbidity to the point of the allowable, the chemical should be greater than the dosage used for the test.

For this test, lime was not used with aluminum sulfate and ferric chloride to investigate their effect on the water pH during the coagulation process. Increase in ferric sulfate increased the water pH whereas the pH decreased with increase in Aluminum sulfate. However, the change in pH with polyelectrolyte was relatively smaller.

Table 7: Jar test results of Aluminum sulfate, ferric sulfate and polyelectrolyte

	Jar NO					
	1	2	3	4	5	6
Row water turbidity (NTU)	359					
T° of the water (°C)	17.7					
pH of the water	7.23					
Rapid mix (rpm)	120					
duration (sec)	90					
Flocculation (rpm)	40					
duration (min)	19					
Settling time (min)	20					
coagulant Type	Polyelectrolyte					
coagulant concentration (mg/l)	3	4	5	6	7	8
final pH	7.19	7.09	7.01	6.89	6.81	6.7
Final turbidity (NTU)	6.48	4.61	4.09	3.66	3.7	3.9
floc formation	Very fine	Fine	Moderate	Course	Very coarse	Moderately fine
coagulant Type	Aluminum sulfate(alum)					
coagulant concentration (mg/l)	3	4	5	6	7	8
final pH	5.35	4.06	3.6	3.25	3.22	3.01
Final turbidity (NTU)	56.3	37.1	13.9	17.7	19.57	20.4
floc formation	Very fine	Fine	Moderate	Course	Very coarse	Moderately fine
coagulant Type	Ferric Sulfate					
coagulant concentration (mg/l)	3	4	5	6	7	8
final pH	7.51	8.22	8.85	9.6	10.1	11.35
Final turbidity (NTU)	44.3	21	11.9	15.3	17.4	23.8
floc formation	Very Fine	Fine	Moderate	Course	Very coarse	Moderately fine

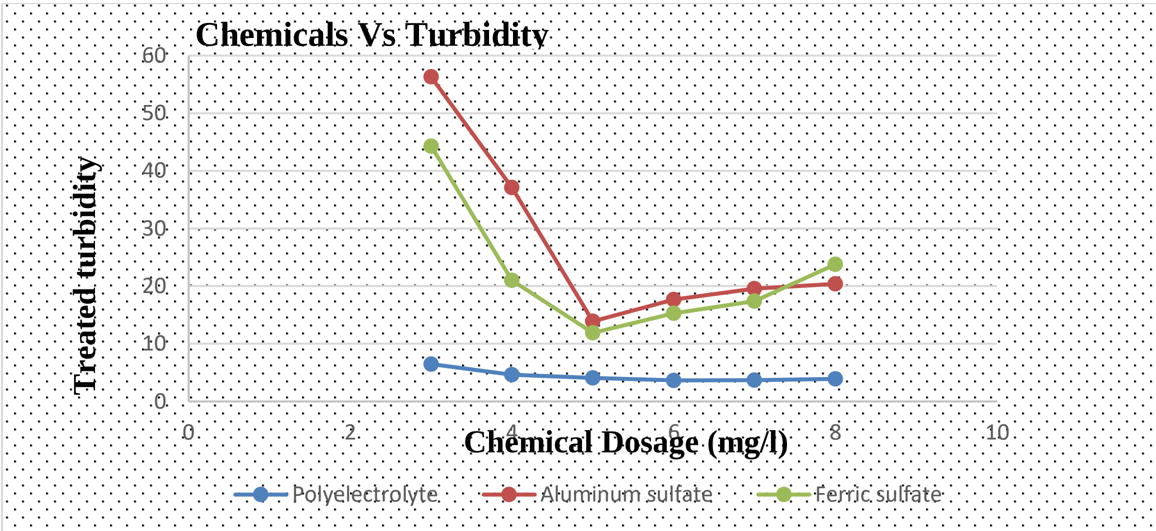


Figure 17: Residual turbidity verses Chemical dosage - Polyelectrolyte, Alum, Ferric Sulfate

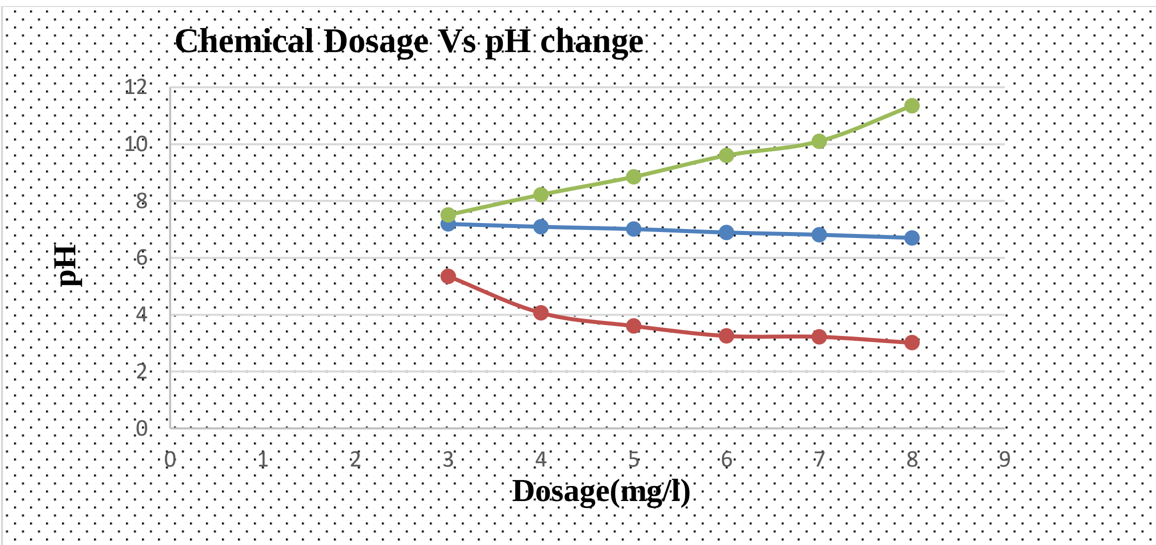


Figure 18: pH versus the chemical dosage

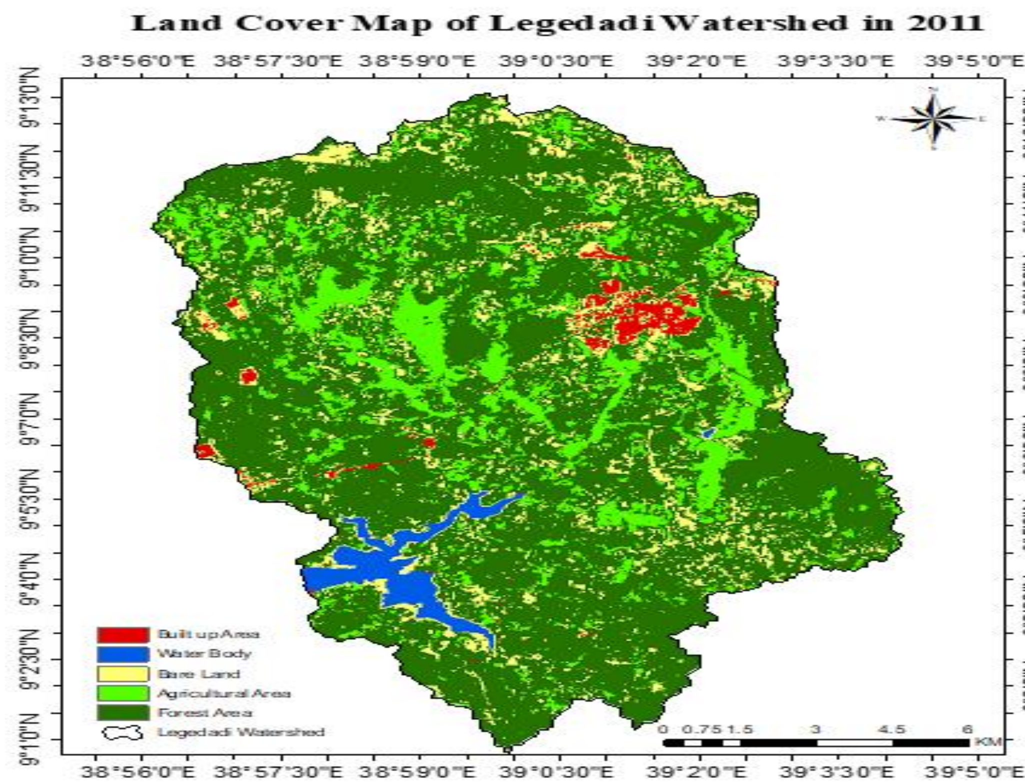
The result from the chemical comparison shows the chemical type that is being used at Legedadi Water Treatment Plant has no quality and efficiency issues when it comes to removing turbidity. Polyelectrolyte has numerous advantages such as its capability to work in high pH range minimize pH adjustment, reduced sludge volume with improved sludge thickening and dewatering characteristics. In addition, the cost of polyelectrolyte is less than that of the two commonly used coagulants, i.e., PACL and aluminum sulfate. However, the coagulant Aid, which is an effective coagulant aid, has also been used at fixed concentration of 0.2mg/l for different turbidities. However, it must vary with different coagulant amounts as its purpose is to make the floc formed denser.

4.3.2. Jar test Practices

The response from the AAWSA experts shows that the practice of conducting jar tests frequently has been weak due to some constraints such as the distance between the treatment plant and the AAWSA office, the high time and cost incurred in doing the test, and the operators' preconceived notions about the water quality status. There may be a drastic change in the water quality in daily basis, especially in the rainy seasons due to flooding. For instance, on July 25, 2021 G.C the measured turbidity was 258 NTU and after 4 days on July 29,2021 G.C, it was found to be 390 NTU. However, the operators applied the same amount of coagulant to treat the water on both days as they failed to conduct the jar test frequently. The optimum amount of chemical coagulant applied on the treatment plant must vary along with different turbidity values. The large difference in the measured turbidity shows the need for frequent jar tests to determine the optimum amount of coagulant dosage, particularly during the rainy season. Because, use of coagulant dose above or below the optimum value causes problems. Coagulant dose above the optimum value results in a large volume of sludge and high residual turbidity, particularly if the coagulant used is not polymer type. These problems have adverse economic and health impacts. On the contrary, using coagulant below the optimum dose would compromise the desired water quality.

4.2. Developments on the Catchment area and their risks

As the location of the Legedadi catchment is close to the metropolitan city of Addis Ababa and other regional towns, the risk for its surrounding to be converted into a residential area is very high. For instance, Senedfa and Beke are towns that are developing in the Legedadi catchment. Construction of different infrastructures such as buildings, roads, and sanitary systems that have impacts on water quality have occurred. According to the utility operator's statement, water quality change due to pollution is their main concern as a result of catchment development. For instance, there has been change in the land use and land cover of the catchment between the year 2011 and 2021 as shown in Figure 19.



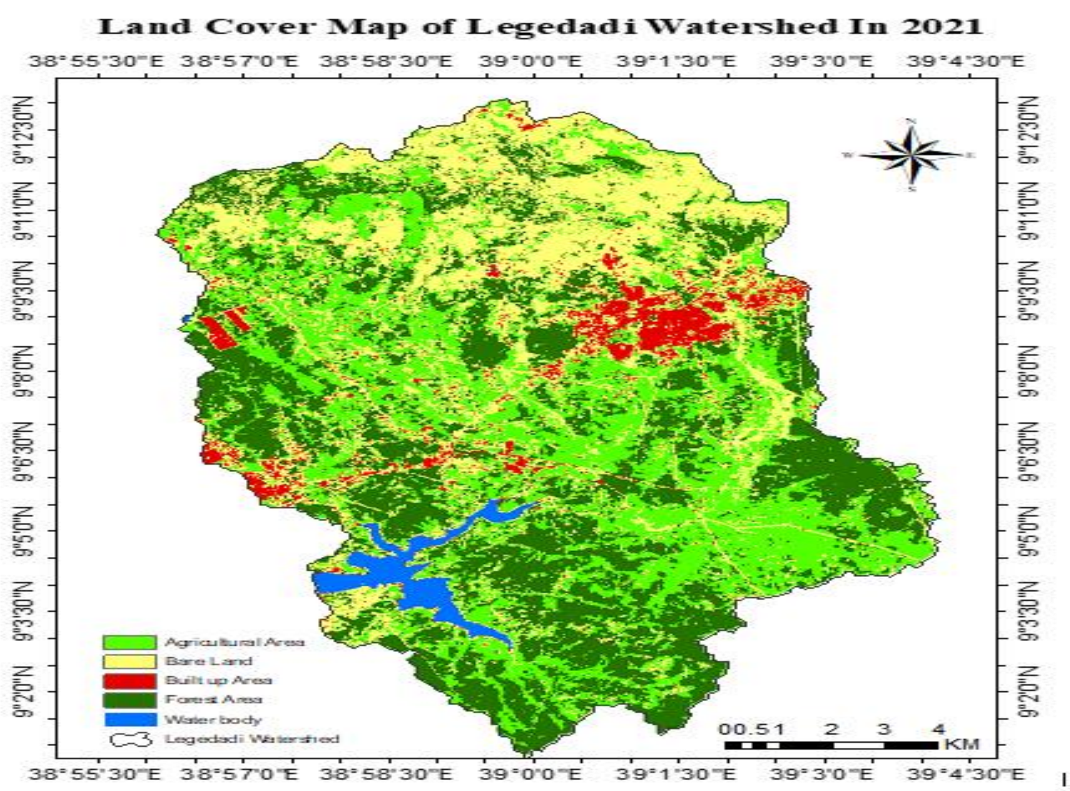


Figure 19:Change in land use and land cover of Legedadi Catchment

From the land use land cover maps, the Legedadi catchment land use difference in one decade are summarized as follow in the table which are obtained from GIS analysis.

Table 8: Summery of Land usage in the Legedadi catchment

Type of Land Use Land Cover	Area (Sq Km)		% Change
	2011 E.C	2021 E.C	
Agricultural Area	29.5	62.67	112%
Bare Land	21.95	60.05	174%
Built Up Area	3.26	9	176%
Forest Area	145.56	69.18	-52%
Water body	4.98	4.35	-13%

The result shows that the area is characterized by intensive agriculture, and the forest area has been greatly converted into another land use in a decade period. This might have increased the turbidity of the water and caused other water quality problems including change in the pH of the water. This has an effect on the operation and efficiency of the Legedadi Water Treatment Plant. Climate change may also have an impact on water quantity and quality through a combination of higher temperatures and reduced freshwater flows (*Cullis et al. 2015*). When the raw water temperature changes, the coagulant amount applied should vary as floc formation and settlement are temperature dependent. It is important for the operators to know the various factors that influence the water quality and treatment processes.

In general, the results show that the raw water that enters the Legedadi reservoir is susceptible to fluctuations in quality. This indicates the need for dynamic and frequent water quality measurement and treatment process optimization. However, the major problem at the Legedadi Water Treatment Plant is that the operators do not conduct the jar test frequently. Even though doing the jar test on a regular basis is vital, it has a number of drawbacks. Thus, development and use of alternative means like model is highly recommended.

4.3. Model result and discussion

The main objective of the model development is to incorporate the model into a control system for the optimization of the coagulation and flocculation process in terms of the process control variable. Numerous different trials were conducted to determine the optimal network architecture (i.e. in terms of the γ, μ, and hidden neurons). The optimum ANN Architectures for both models (process and inverse process model) are summarized in table 8 and table 9.

Table 9: Final Architecture selected for model 1(Process model) and Model 2(Inverse Process model

	Model 1	Model 2
Input neurons	4	4
Hidden layers	1	1
Hidden neurons	7	5
Hidden transfer function	'Tansig'	''Tansig'
Output transfer function	'Purelin'	'purelin'
Learning rate	0.6	0.6
Momentum coefficient	0.4	0.4
Output neurons	1	1
Epochs	1000	1000
Stopping Criteria	1000 epochs or increase in cross-validation error at above 25max Gradient fail	

4.3.1. Process model

The result produced by the process model is shown in Figures 20 and 21 with the respective values of RMSE and R^2. The plots were created using Predicted and Actual turbidity values, and it is used to investigate the performance of model. The correlation is shown in Figure 20, with a 45-degree line to illustrate the ideal performance (slope = 1, y-intercept of zero, r2 = 1). The regression line between the Actual turbidity and predicted has slope of 1 y-intercept of 0, and r2 value of 0.6121. It shows that the value of R^2 slightly deviated from the ideal value. However, R^2 value is not the most appropriate performance measure for turbidity prediction as most of the treated water turbidity values are very small and similar (*Maier,2004*). Moreover, the RMSE value of the model prediction was very acceptable as the value is approximate to 0. Thus, the model has reasonable accuracy to predict the treated water turbidity with R^2 value 0.6121 and RMSE value 0.0748 NTU.

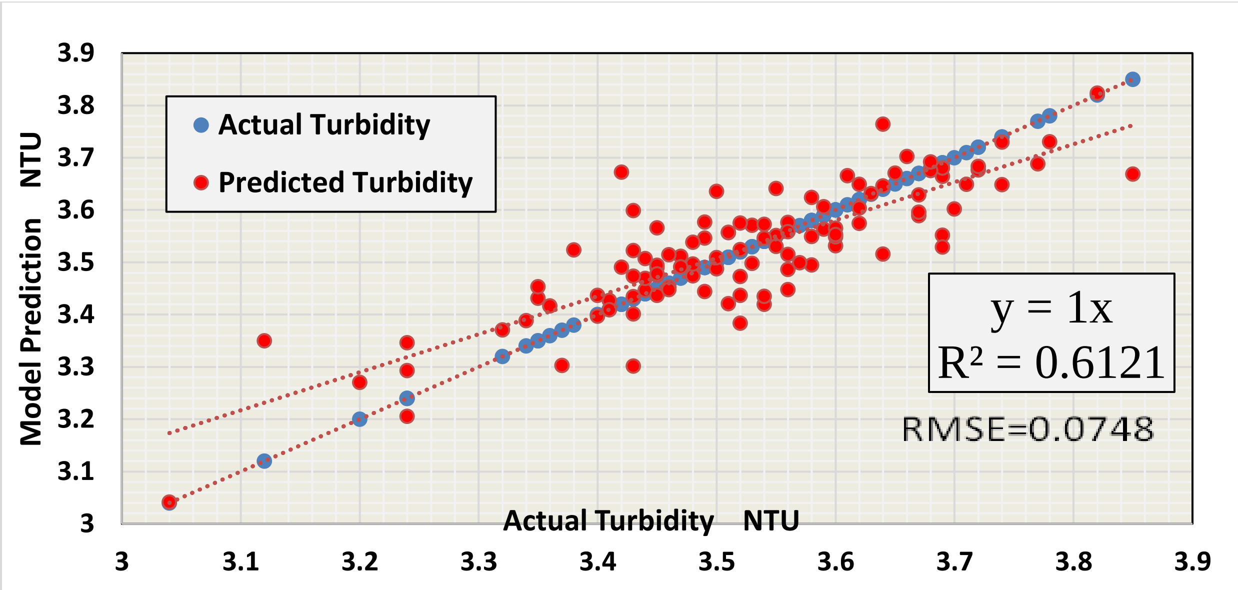


Figure 20: Scatter plot of the actual Vs predicted turbidities of a process model with the respective values of R^2 and RMSE

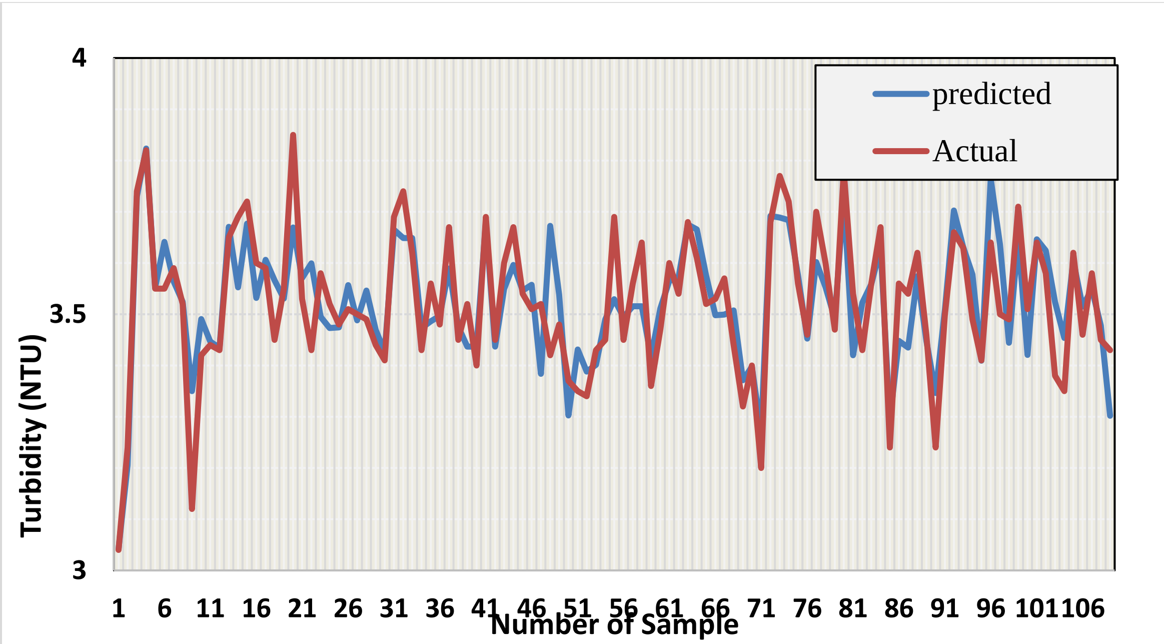


Figure 21:Line plot of the actual and model output

The line scatter graph was plotted using actual and model prediction value Vs the number of samples. This graph is used to compare how the model predicted value was close enough to the actual value, and it shows how much the lines are overlaid one into another.

In general, this model will help the operators to acquire experience in the coagulation process and assist them to determine the coagulant dosage by manipulating it. The system can be controlled by varying the chemical dosage, as a result, the operator can easily understand the chemical variation and treated water turbidity relationship including consideration of other factors. For example, temperature has a great impact on the amount of chemicals applied for the process to get the desired water quality. However, there are some limitations in model when it is applied in situations beyond the optimum dosage. This is due to secondary data used which correspond to the optimum dose that resulted in the desired turbidity. Thus, to show the model's capability in simulating the jar test, another model was developed by using only primary data even though this data is very limited in number. The treated water turbidity in each of the six jars together with the corresponding coagulant doses were recorded. The result produced by the second process model is shown in Figures 22 and 23 with the respective values of RMSE and R^2.

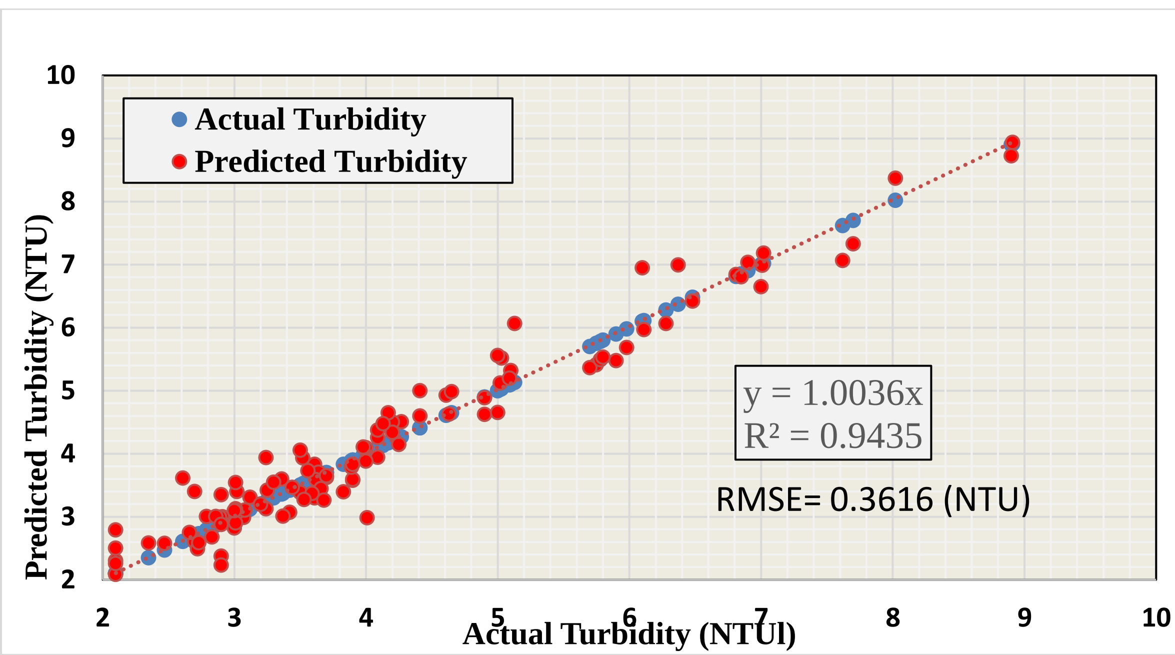


Figure 22:Scatter plot of the actual Vs predicted turbidities of a process model with the respective values of R^2 and RMSE

R^2 value for this model can be an appropriate performance measurement as most of the treated water turbidity values are scattered comparing with the above. The RMSE value is not perfect as the above model, because the data that was used to develop this model is very limited. The R^2 value of the model prediction was very acceptable. Thus, the model has reasonable accuracy to show the capability of ANN to simulate jar test with R^2 value 0.9435 and RMSE value 0.3616NTU.

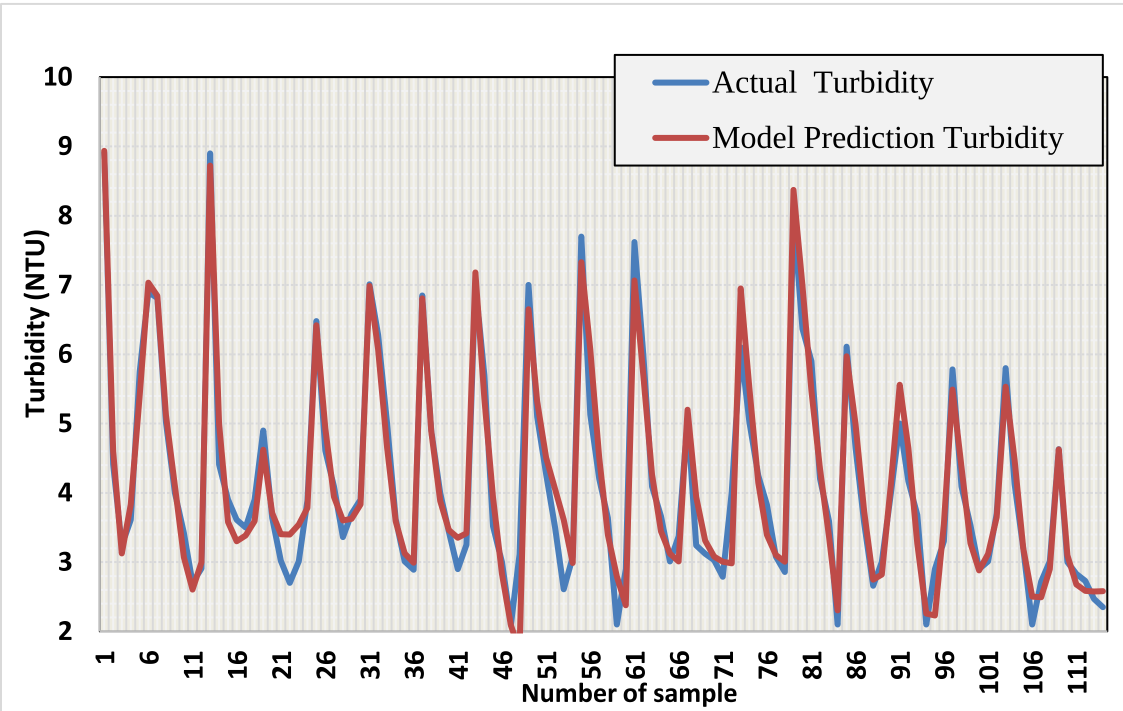


Figure 23: A line plot of actual Vs model output

The line scatter graph was plotted using actual and model prediction value Vs the number of samples. This graph is used to compare how the model predicted value closed enough to the actual value.

4.3.2. Inverse process model

The results of the inverse process model, Model-2 are shown in Figures 24 and 25 with the corresponding RMSE and R^2 values. The model has reasonable accuracy to predict the optimum chemical dosage for the measured turbidity with R^2 value 0.9797 and RMSE value 0.225mg/l. The minimum increment of the chemical during the jar test was 1mg/l so the expected error would be below this point (the level of tolerance).

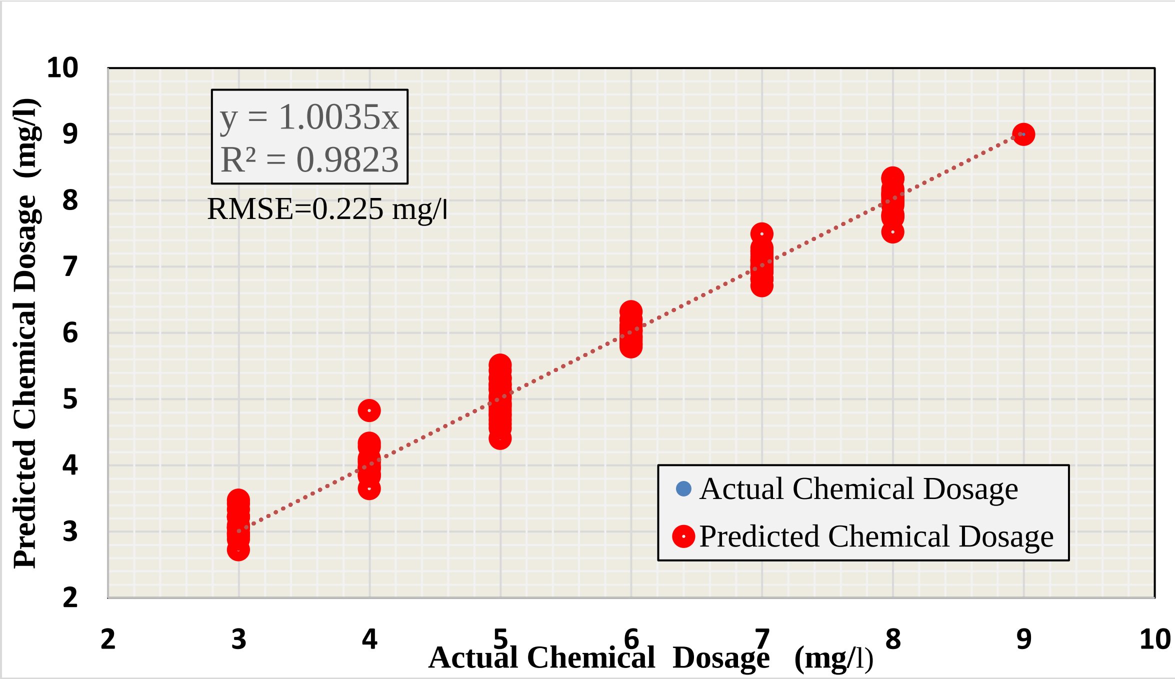


Figure 24: Scatter plot of the actual Vs predicted Chemical dosage of the inverse process model with the respective values of R^2 and RMSE

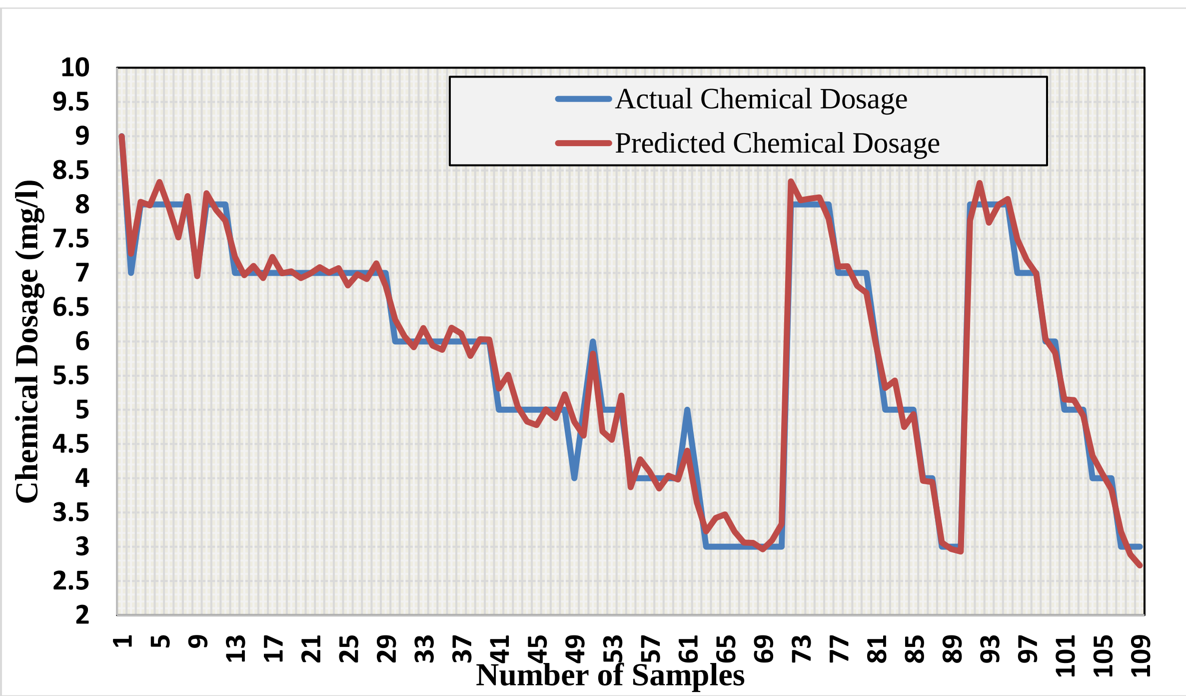
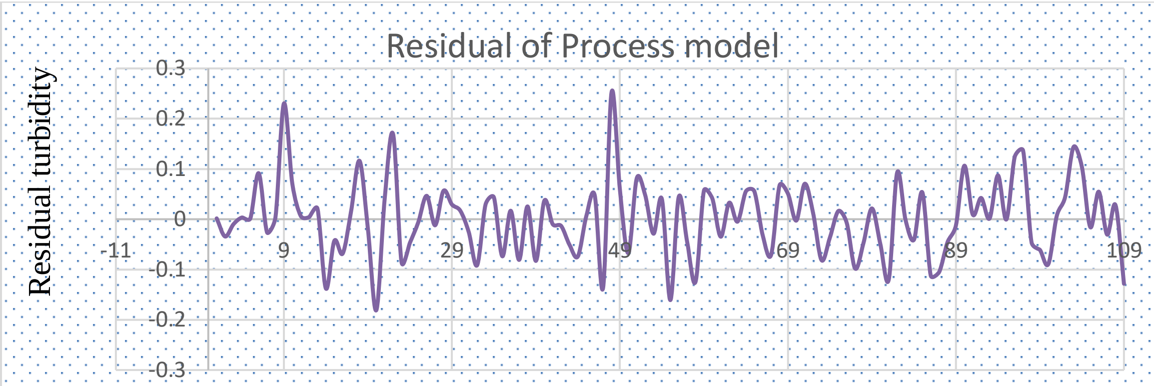
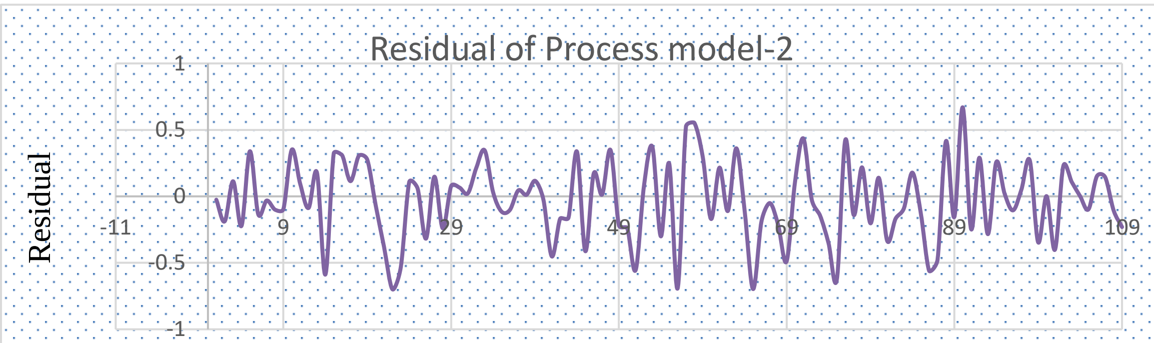


Figure 25: A line plot of actual model output

The Advantage of this model over the process model, the optimum coagulant amount can be found directly without any trial and error.

The residual values of each model are shown in the following three figures.





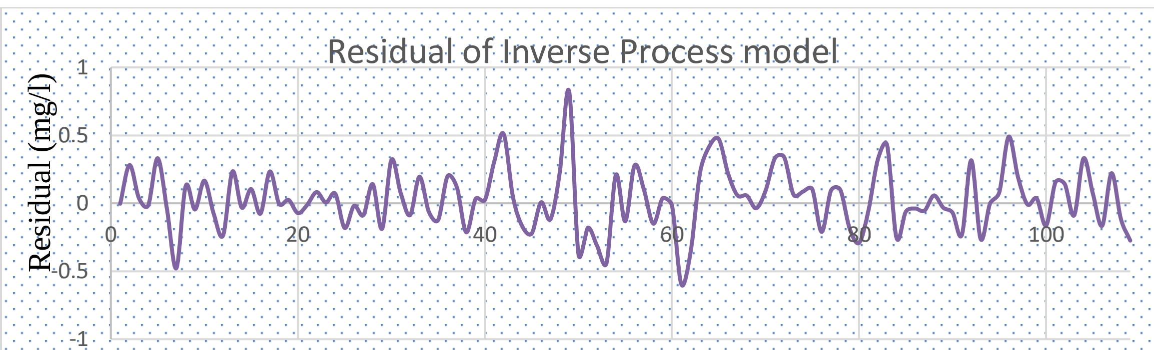


Figure 26: Residual Plots of the three models

The variation between the observed and model anticipated values can be determined using the residual plot and value. The results show that the process model produced a better result than the other models. Since the first and the third models were developed with the optimum point from the jar test sampling, the treated water turbidity values are between 3 and 4 NTU and they are similar and close to each other. For this kind of conditions, the pattern can easily be understood by the ANN. However, the result produced by the inverse process model shows that the model needs some sort of historical data to achieve a better result because the output values vary greatly. As the second process model was developed using only primary data, such residual difference is expected. It should be noted that this was developed to demonstrate the possibility of simulating the jar test using ANN if the secondary data have values beyond the optimum point.

Table 10:Summary of the models' performances

Model	R^2	MSE	RMSE
Model-1 (Process model)	0.6121	0.0055	0.0747
Model-1-1 (Process model -1)	0.9435	0.1307	0.3616
Model-2 (Inverse process model	0.9823	0.0506	0.225

In general, the results show that the models can simulate a process taken by Jar test within the range of the data that was used for training. Currently, the operators at the Legedadi Water Treatment Plant use these limited parameters to evaluate the chemical dosage needed for the available turbidity which were used in these model developments.

In the previous study (Maier,Morgan and Chow 2003) by using 202 available data at South Australian water developed three models to optimize the coagulant chemical dosage. The first model was developed to predict the water turbidity, color, and UV254 of the water. The second one was to predict the Residual chemical of treated water and the pH of the water. The third one was to determine the chemical dose needed for the desired water turbidity. The capabilities of these models were measured by R^2 and MAE. The results are summarized in Table 11.

Table 11: South Australian Water ANN model development result

Model	Model Output	R2	MAE
1	Turbidity of treated water	0.9	0.12NTU
1	Color of treated water	0.92	1.45HU
1	UVA-254 of treated water	0.98	0.01cm
2	Residual aluminum of treated water	0.96	0.02mg/l
2	pH of treated water	0.85	0.11
3	Alum dose	0.96	3.2mg/l

The third model MAE seems not as such good but the gap they took during the coagulant application in the jar was 5mg/l so the error below this is acceptable to predict.

Another study (Amin,2018) using 112 available data at Ardabil province drinking water treatment plant two models were developed to optimize the coagulation process. The first model was developed to predict treated water turbidity, Alkalinity, pH and water temperature. The second one was to predict the chemical dosage. The capability of these models was measured by R^2 and MSE.

Table 12: Ardabil province drinking Water Treatment Plant ANN model development result

Model	Output	R2	MSE
1	pH	o.85	0.01
1	Alk	0.99	1.86
1	Turbidity	0.9	0.024
1	Temperature	0.93	0.67
2	Dosage	0.95	0.12

These two research shows that the ANN has a good prediction capability within the given data interval. Comparing the result and the study of the previous finding with this research, this research has limitations such as lack of data and different parameter values. However, the results from the models for treated water turbidity and chemical dosage have almost similar R^2 and MSE values with the previous findings.

As described in the first section both jar test and model have been used to determine the optimum coagulant dosage for the unit process in the treatment plants. However, Jar test is used since the coagulation and flocculation process became common for water treatment. Even though, the test needs a minimum of an hour to conduct, cost for chemical and is not feasible if the water quality changes rapidly particularly rain seasons. Besides, the jar test is done by a human being and is therefore prone to error. Many utilities now days were tried to adopt Computational models particularly ANN to overcome the short coming from the jar test.

A well calibrated and validated ANN model, can give a result within a minute and the operator can check it within an hour interval since it is not time-consuming and easy for application. It saves time and energy, can be used in a proactive mode and minimizes cost and risk to human health. However, it does not mean that the jar test can be fully substituted by the model. The jar test results can be used for calibration of the ANN model when the water quality, quantity and coagulant type are changed.

4.4. Model implementation application result

Since ANN has been observed to be good in prediction of chemical dosage to treat the water, a model implementation application was prepared. In order to meet one of the research objectives, two model applications were developed.

The two applications have been packaged as one tool. For the process model, the measured parameters and coagulant dosages are used as inputs. Different coagulant doses are tested by trial and error method until the desired treated water turbidity is achieved (outputs of the model). This is the method used in this application to predict the optimal chemical dosage. For the second, the process is the same as the first one, however in this application there is no need of using a trial and error method. After the desired amount of treated water turbidity is set, the optimum coagulant is predicted. The GUI of the applications are attached in Appendix 1.

Figure 27: Model application software

These applications aimed at optimizing the unit process of coagulation and flocculation in the treatment plant. The Generated code from the ANN can serve as User Interface for those who are familiar with Matlab software. However, the application has interactive components to insert each parameter's measured value and as such it is very convenient for anyone who can open and close the computer. The application was designed with the function that was generated from the NN. Consequently, the output it generates depends on the NN performance. Besides, if the chemical type changes, or if additional parameters are required, this application, as well as the NN, should be modified.

4.5. Concluding remarks on the modeling study

The main challenge of this research to develop the model is ANN can be successful only where sufficient historical data for each process variable exist. It is known that many utilities have inaccurate and limited historical data to be used for calibration and validation. As this can also be the case for Legedadi treatment plant, it is very difficult to expect a best result.

This study was limited to modeling the coagulation and flocculation process in removing turbidity as a function of coagulant dose. The residual chemical and the pH changes (a small variation) are other factors that should be considered during model development. However, due to the absence of data these parameters were not considered. The secondary data have a limitation on the value of the treated water turbidity beyond the optimum point. As a result, even though an additional model was developed to demonstrate the potential of ANN to simulate the jar test, the process model may produce incorrect results if the user tries to adopt beyond the optimum point. The data used to develop these models were not taken from full-scale plant and the representation of this data may not be accurate. Thus, further studies are needed to improve the validity of the model by collecting primary data on the treatment plant consistently at least for a minimum of two years. The temperature was not measured at the site. Because, the measurements were taken at AAWSA lab and the raw water samples were brought from Legedadi reservoir.

Legedadi Water Treatment plant has been using polyelectrolyte as coagulant as well as coagulant aid since 1983 E.C. As a result, the pH of the water hasn't been altered drastically when the coagulant is added in the raw waters unlike other common coagulant such as Aluminum sulfate and ferric sulfate. ANN functions based on the data and parameters provided to train the network, if there is a need to include other parameters, the previous model is not suitable. For example, if the type of chemical is changed to Aluminum sulfate, the water pH also changes and requires lime to be added to balance it, besides the alkalinity of the water should be considered for the effectiveness of the process. Thus, in such situations, the model will not be suitable.

The model was developed with the current available data. If the water quality drastically changes beyond the normal it might not produce the expected result as it has not been trained under the new circumstances. Therefore, it is important to be assured that the data represent the whole circumstance that could happen in the treatment plant. Otherwise, if the change is occurred, the model should be updated or retrained to accommodate the change.

The possibility to apply the application in another treatment plant depends on the raw water characteristics and the chemical type used as coagulant. For instance, Gefersa is another large water treatment plant that supplies raw water to Addis Ababa town. However the coagulant type utilized there is still Aluminum sulfate due to the level of turbidity in the raw water and the raw water characteristics. As a result, this model is unsuitable. Because the quantity of polyelectrolyte and Aluminum sulfate coagulant required to remove the same level of turbidity varies owing to efficiency variations, the amount of the two coagulants utilized to remove the same type of turbidity also varies. However, the model may be appropriate if the chemical type can be changed to polyelectrolyte in the treatment plant, like the Legedadi water treatment facility.

5. Summary, Conclusion and Recommendation

5.1. Summary and Conclusion

Jar test experiments were conducted to study the coagulation process practices at Legedadi Water Treatment plant and develop ANN model for jar test simulation. Assessment of the Legedadi Water Treatment Plant coagulation practices included evaluation of the efficiency of the chemical used as coagulant in comparison with other commonly used coagulants and measurement of the treated water turbidity after coagulation treatment and before post chlorination at the treatment plant. It was not possible to take frequent turbidity measurements at the treatment plant. Interview and questionnaires were used to gather information from relevant experts on coagulation and flocculation processes. The response from the experts showed that the frequency of jar tests has been low due to its time-consuming procedure and high cost. In addition, the important parameters which have significant impact on the process have not been well considered during the addition of chemicals.

A jar test has some limitations that prohibit its application in different situations. First, the jar test must be taken frequently in such a way that it minimizes the cost and the risk to public health. In addition, during the coagulation process proper consideration of the key factors shall be made to get optimal results. For example, the temperature of the water has an impact on the reaction between the suspended particle and coagulant. The temperature should, therefore, be measured on site and the corresponding optimal dosage determined. Second, A Jar test takes time and the data is prone to human error; it is not also a feasible method in situations of high turbidity variations.

Thus, proposing new models for estimating the optimum amount of coagulant seems to be an appropriate way to minimize costs and generally improve the safety of drinking water. Modeling the jar test is one of the best solutions as most of the problems were related to jar test practices.

ANN is selected to develop the model as it is a machine learning method and is used to anticipate complex and nonlinear relationships. ANN is a parametric method as a result if the number of data increases the accuracy also increases. To increase the number of data, jar tests were conducted in this study and experienced operators were consulted. Totally 109 data points were used to develop the models. Data related to inputs, output, and process control parameters, i.e. concentration of polyelectrolyte were used. Two models were developed to predict the optimum chemical dosage. The first one was the process model which was used to predict the desired water turbidity by controlling the chemical dosage in trial and error procedure. The second one is the inverse process model which was used to predict the optimum coagulant dosage for the desired water turbidity. Both models were developed by ANN type MLP with the most popular back propagation algorithm (Levenberg-Marquardt backpropagation) using Matlab Software version2016a. Before Programming the code, the data was prepared to make it convenient for model minimum error convergence. The best Architecture was found by trial and error procedures. When the best R^2 and RMSE were found, model implementation software was developed.

In this research, the jar test was simulated for the first time at Legedadi Water Treatment plant using the available data. The parameters that have been considered during the process were raw water quality, temperature (but not on the site), and the desired water quality. During the simulation, those parameters including the pH of the water were considered. The ANN models developed can easily be applied and support the operators at Legedadi Water Treatment plant to control the coagulation process. The result from the model shows, ANNs can successfully predict the optimum coagulant dosage needed for different water turbidity ranges.

5.2. Recommendation

This research implies that there is a need for an improvement of the coagulation and flocculation process at Legedadi Water Treatment Plant and simulating the Jar test was considered to the best solution. As the study was carried out with lots of limitations**, the following further studies are recommended to improve the model**

1. Conduct further test at the treatment plant by considering the critical factors that have influence on the coagulation and develop a new ANN model.
2. There is a problem of converting the chemical amount from bench-scale test to full-scale plant. However, if the data is collected from the full-scale plant and used for the model development, a more accurate result Could be obtained.
3. As the coagulant chemical is expensive, it is necessary to minimize the dose by changing the processing time of flocculation and sedimentation for which a new ANN model should be developed.
4. Instead of preparing a single neural network for the whole process, dividing the network into a different season and water quality categories would have a best result.

The results of this study provide valuable insight into the feasibility of developing ANN based software to optimize the coagulation and flocculation process at the Legedadi Treatment Plant. The original data can be used in future studies, and AAWSA operators can use the knowledge from this study to create their own Tools.

6. Reference

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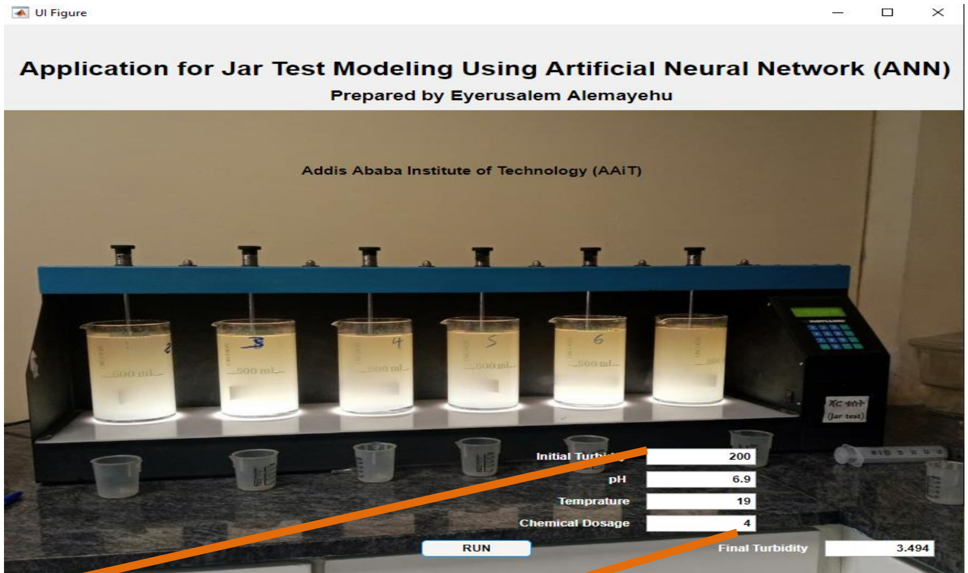
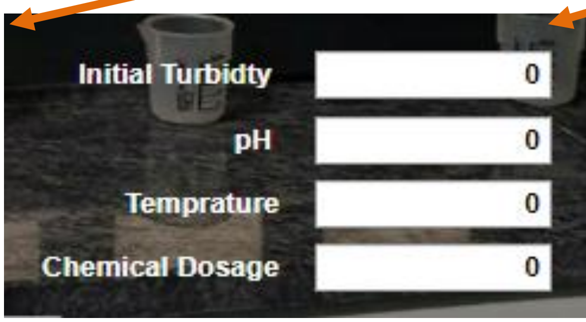
Appendix 1: The Application GUI

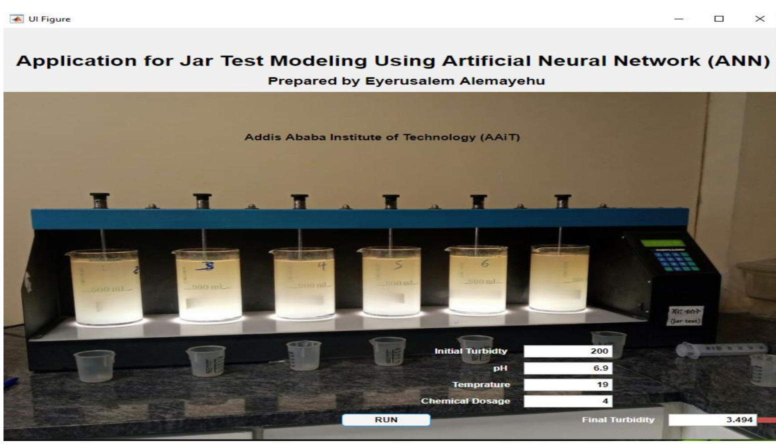
Model 1: Process model



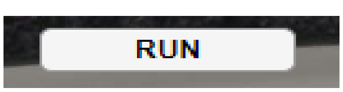


<u>The inputs parameters of the model and the units used in the app</u>

- Initial turbidity NTU
- Expected chemical dosage mg/l
- Measured pH value of the sample
- The temperature of the sample in °c



The value is displayed in this box

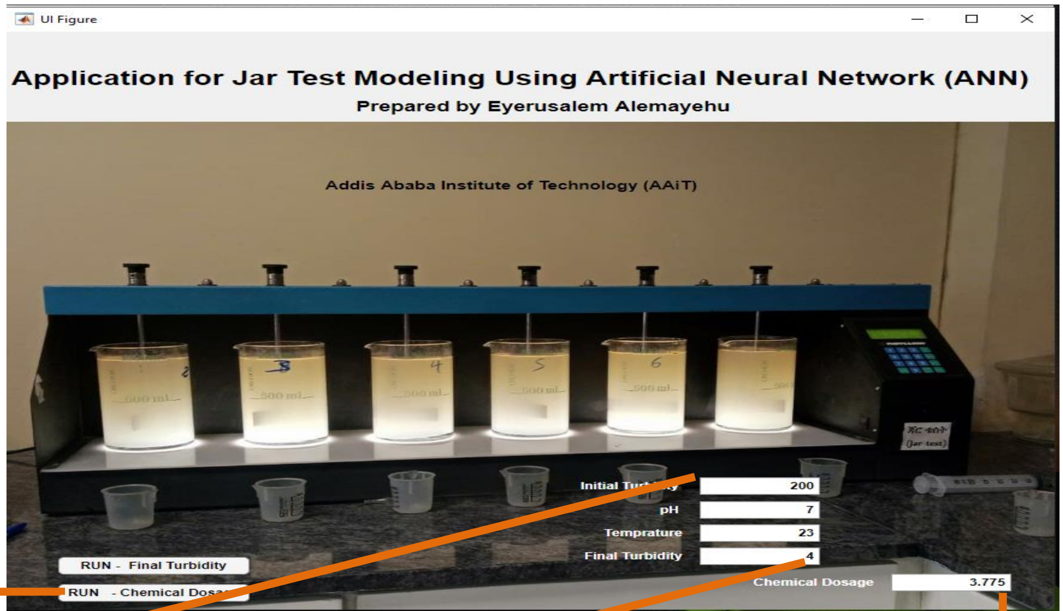


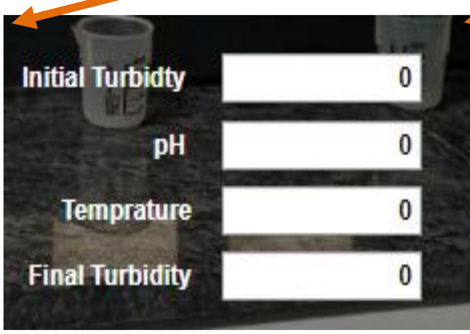
By clicking this bottom, the desired water quality can be predicted. Once the inputs are measured; insert each parameter measured value in the application then the user clicked this button. The value is executed by considering the function that was generated from ANN and called by the App designer.

%% This is the syntax used to create the relation between the inputs and the output parameter in the Matlab App design.

```
X=[app.Initial_Turbidity.Value;app.Chemical_Dosage.Value;app.pH.Value;app.Temperatu
re.Value];
Y=Final_TO_JAR(X)          % the function generated from ANN
app.Final_Turbidity.Value=Y
```

Model 2: Inverse process model

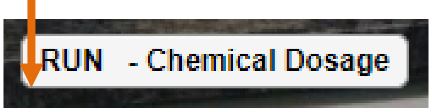




The inputs parameters of the model and the units used in the app

- Initial turbidity NTU
- Measured pH value of the sample
- The desired turbidity NTU
- The temperature of the sample water in °c

The value is displayed in this box

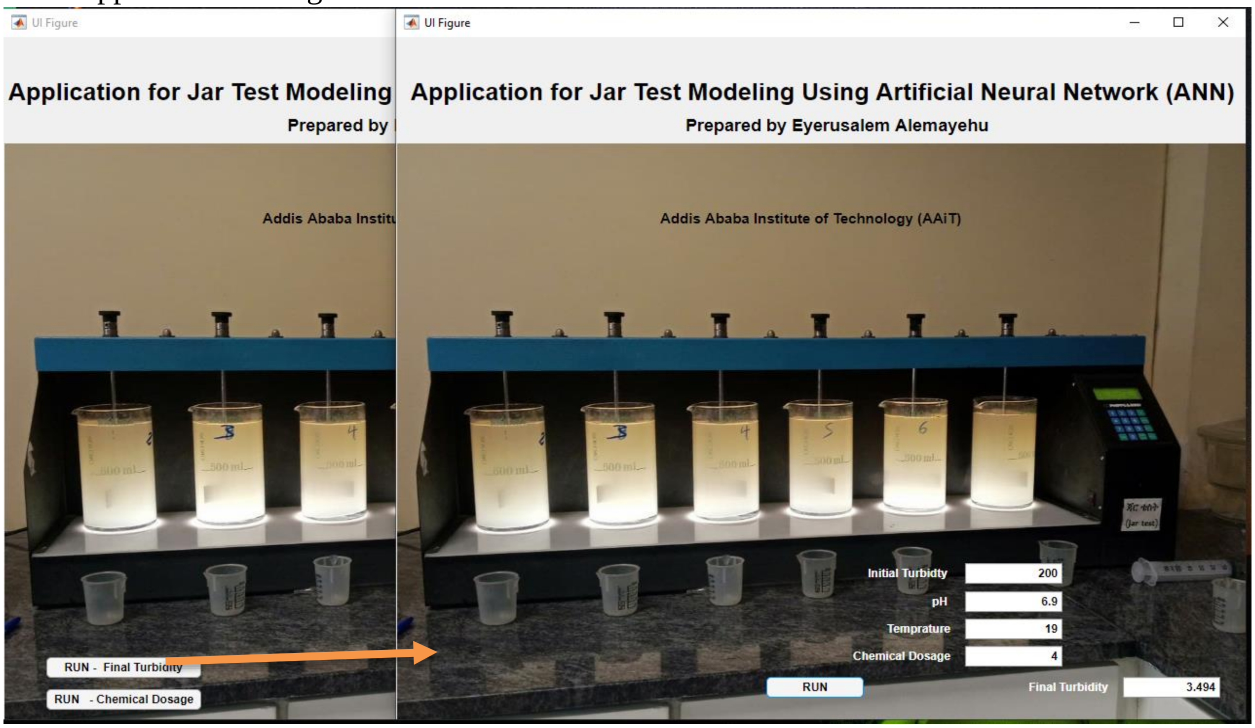


By clicking this bottom, the Optimum chemical dosage can be predicted. Once the inputs are measured; insert in the application, then the user clicked it. The value is executed by considering the function that was generated from ANN and called by the App designer.

This is the syntax used to create the relation between the inputs and the output parameter.

```
X=[app.Initial_Turbidity.Value;app.pH.Value;app.Temperature.Value;app.Final_Turbidi
ty.Value];
Y=Jar_modeling_PO(X);    % Generated from ANN and which is the function called back
for anticpate the relation ship between inputs and outputs parameter.
app.Chemical_Dosage.Value=Y;
```

Both Application are organized in one tool



When one of the pushbuttons is clicked the next application to get the desired water turbidity is displayed as shown in the above figure

Appendix 2: Jar test Apparatus

- Phipps & Bird jar test: -Jar tester material used to control the chemical for the process of coagulation and flocculation which have six paddles for agitation, power to turn on and off the system, and a displayer to count and control the time.
- HACH 2100AN TURBIDIMETER :- used to measure the turbidity
- Test tube:-used to hold the raw water during turbidity measurement
- Combo pH & EC :-pH and temperature meter
- Syringe: - used to suck the chemical from the bottle.
- OHAUS PIONEER Mass balance: - used to measure the mass of the chemical
- Large size baker: - used to hold the raw water
- Small size baker: - used to hold the chemical solution
- Pipette- used to control the volume of the chemical and add it to the jar beaker
- Pipette filler- to suck and eject the diluted chemical
- Volumetric flask:- used to mix the chemical with 1000ml of distilled water

A) The Jar test apparatus

Table 13: Log Sheet to record the result obtained from Jar test

	Jar No.					
	1	2	3	4	5	6
Row water turbidity (NTU)	650					
T° of the water (°C)	19					
PH of the water	7.07					
Rapid mix (rpm)	120					
duration (sec)	90					
Flocculation (rpm)	40					
duration (min)	20					
Settling time (min)	20					
coagulant concentration	6	7	8	9	10	11
final PH	7.09	7.01	6.9	6.87	6.8	6.75
Final turbidity	5.09	3.24	3.12	3.03	2.79	3
floc formation	Very fine	fine	Moderate	Course	Very coarse	Moderately fine

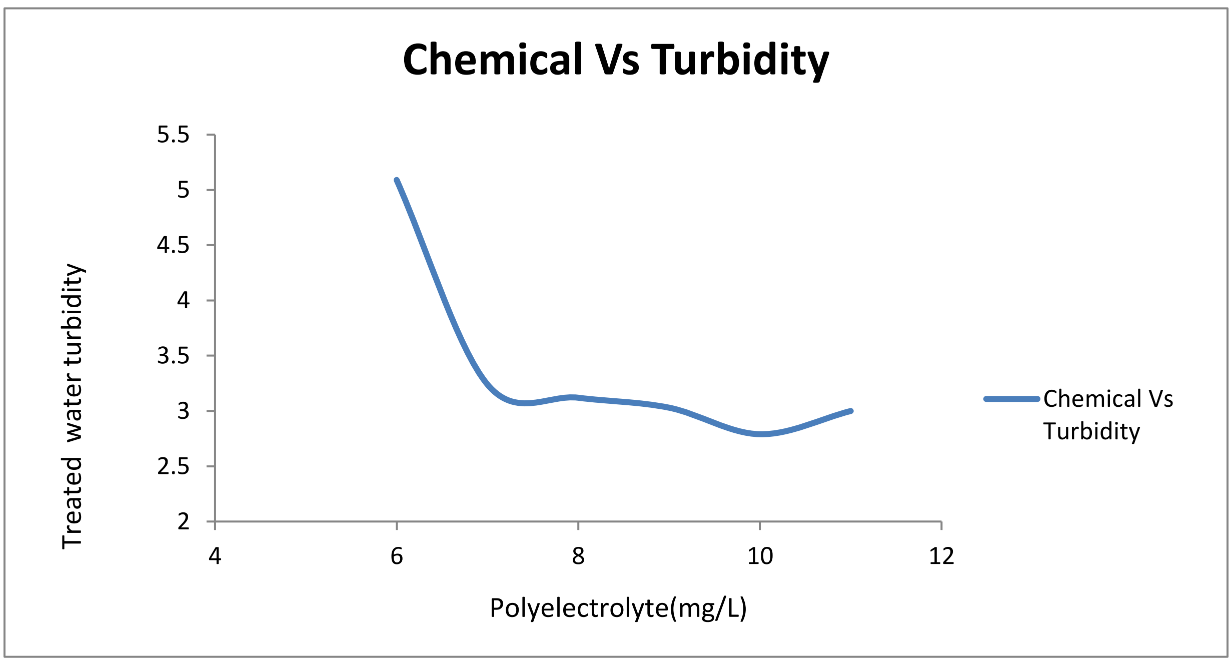
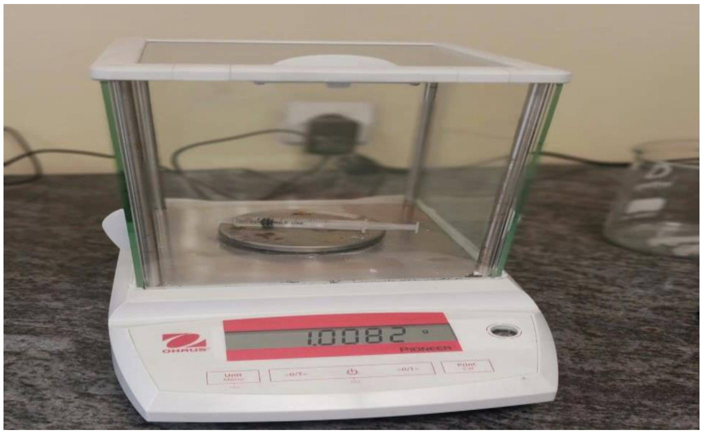


Figure 28: The relationship between polyelectrolyte coagulant vs final turbidity

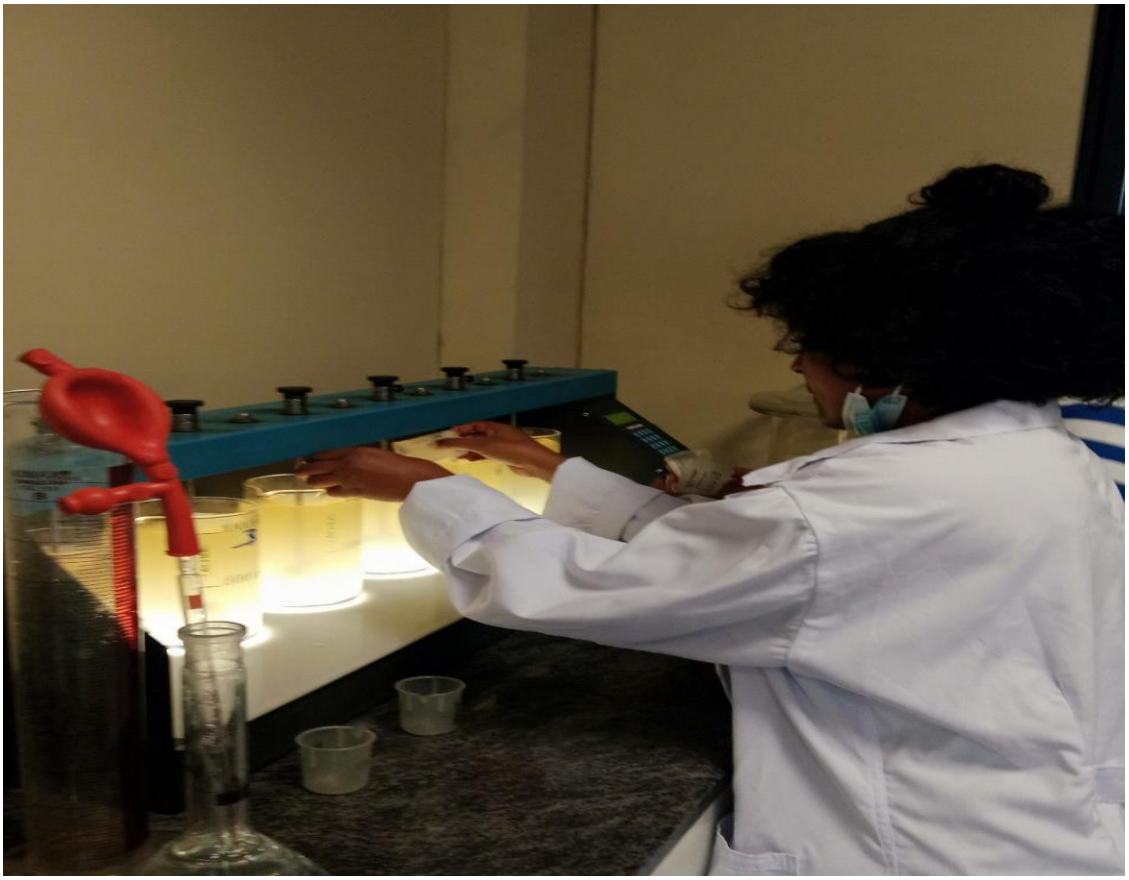
Appendix 3 : Laboratory pictures and samples

The sample water brought from Legedadi Reservoir

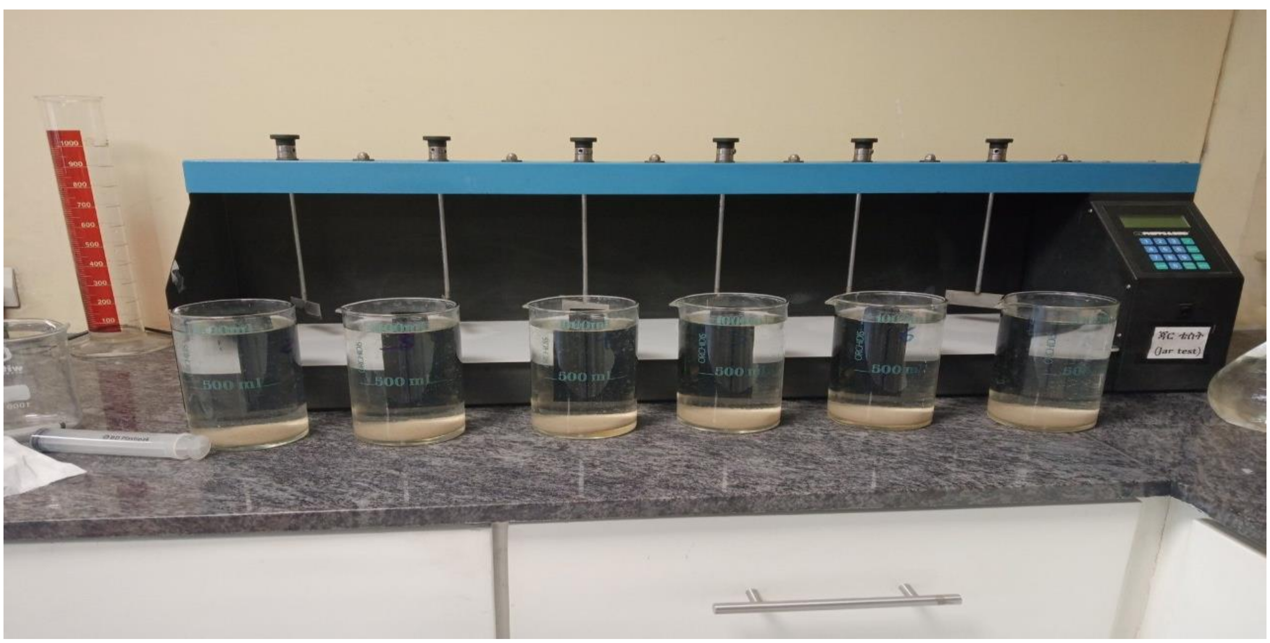


Mass balance and singer (1mg) measurement

One litter Solution which was prepared with distilled water



while the prepared solution added into raw water simultaneously with the stirrer start



The treated water after coagulation and flocculation process during Jar test

Appendix 4: Codes

```
%% This is a code that was programmed to train Artificial Neural Network
to simulate the Jar test.
clc
clear
%% The collected data was prepared by Microsoft excel, so the data
should be loaded into MatLab
data=xlsread('DataRearranged.xls','TO','B2:F110'); % Process model
data=xlsread('DataRearranged.xls','PO','B2:F110'); % Inverse process
x=data(:,1:4);% the number of inputs is arranged in the Preceding
columns
y=data(:,5); % the number of output is arranged in the final column
z=length(y);
% the number of raw in one column
xt=x'; % the transpose of the input and output values are needed to run
in the MatLab as it works with raw matrix
yt=y';
%% construct the network
% set no of neurons
hiddenLayerSizes=7; % Process model
hiddenLayerSizes=5; % Inverse Process model
% the optimum hidden layer which is found by trial and error procedure
net=newff(xt,yt,hiddenLayerSizes);
% the neural network is specified by the user
% the feed-forward network is selected to train
% the configured network is representing Multi-layer perceptron
% the network is assigned by the name 'net'
% net=newff(xt,yt,hiddenLayerSizes); syntax to configure the network
net.divideparam.trainRatio=80/100;
net.divideparam.valRatio=10/100;        % process model
net.divideparam.testRatio=10/100;

net.divideparam.trainRatio=75/100;
net.divideparam.valRatio=15/100;        % Inverse process model
net.divideparam.testRatio=10/100;

% parallel cross-validation technique is used to evaluate this neural
network
% eighty and seventy percent of the data used to train the network
% ten and fifty percent of the data used to validate the network
% ten percent of the data used to check the networks performance
transferFunction={'tansig','purelin'}; & Both model
% the 'tansig' hyperbolic tangent transfer function used to transfer the
% signal from the input layer to the hidden layer
% the 'purelin' linear transfer function used to transfer the signal
from the hidden layer to the output layer
view(net);
% the configured network can be seen by view net syntax
net.trainFcn='trainlm';
% Trainlm is a network training function that updates weight
```

```
% and bias values according to Levenberg-Marquardt optimization
net.trainparam.min_grad = 0.00000001;
net.trainParam.epochs = 1000;
% Epoch refers the number of cycles to train the NN and when the
% maximum number of epochs is reached even though the NN has no good
performance the training is stop
net.trainParam.lr = 0.6;
% learning rate is used to control that how the model adapted quickly
the problem and its value was found by trial and error
net.trainParam.max_fail =25;
% this syntax is used to control the maximum possible validation
failures
% when the error increased with the successive iteration: the training
set to stop the training
net.trainParam.mc=0.4;
% momentum is used to improve the speed and accuracy of the network
net.performFcn = 'mse';
% mse is a network performance function. It measures the network
performance according to the mean of squared errors.
%%  Train the network
[net,tr]=train(net,xt,yt);
% This is the final stage of model development
ynet=net(xt);
% ynet represent the network output from the network input
Y=ynet';
% as the original data was transposed to raw matrix, we need to change
the model output value to the column matrix
%% visualization of the real value and the predicted
plot(y) % plot the raw data output
hold on % used to hold the above plot to plot the next in it.
plot(Y) % plot the model output
hold off % stop to hold
title('Actual Vs Predicted')
ylabel('Final_turbidity')
xlabel('Number of data')             % process model
legend('Actual', 'predicted')

title('Actual Vs Predicted')
ylabel('Chemical Dosage')            % Inverse process model
xlabel('Number of data')
legend('Actual', 'predicted')

%% Evaluate the error by RMSE and R2
% RMS
N=z;
x_rms=sqrt(1/N.*(sum((y-Y).^2))); % it is a formula that coded in to
matlab
% to evaluate the model performance
%% weight value visualization
W1=net.IW{1,1};
```

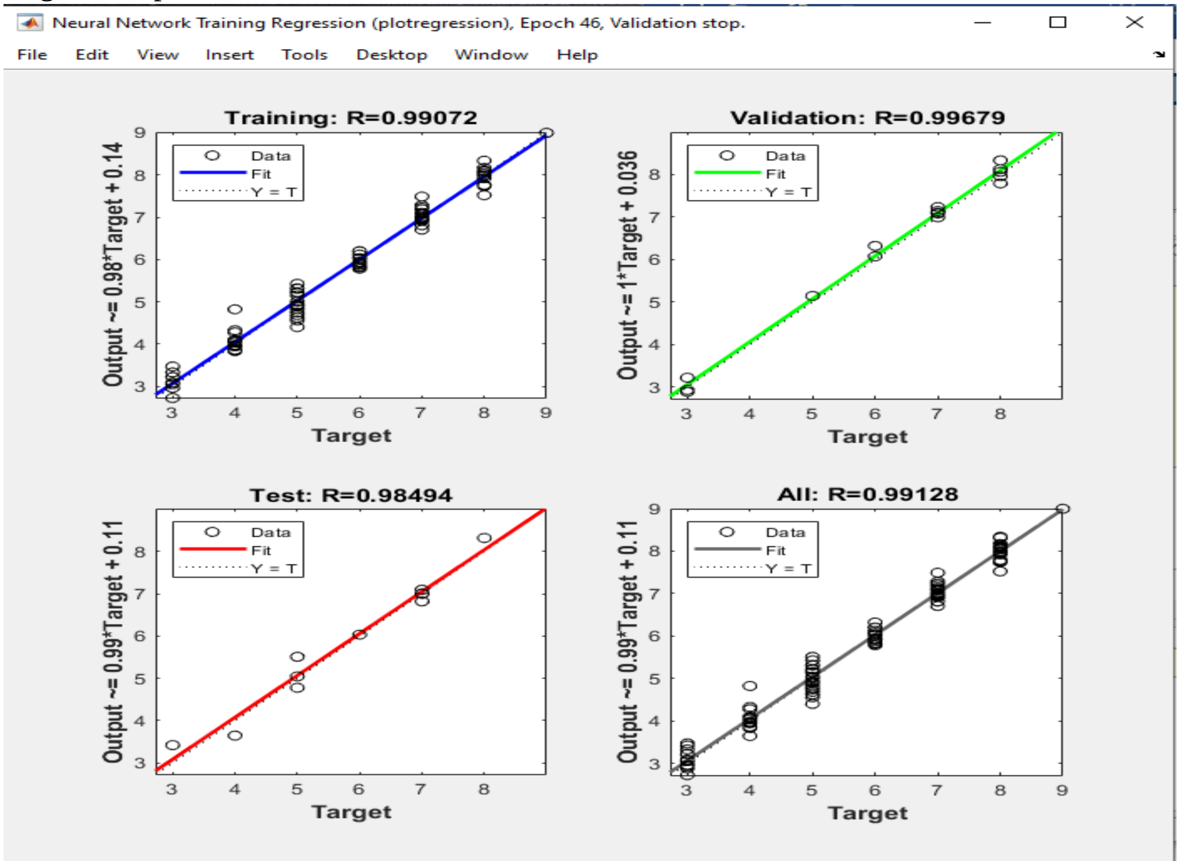
```
% this weights connecting the input layer to the hidden layer 7x4 cell
value as the number neuron in the hidden layer is 7 and the inputs are 4
W2=net.LW{2,1};
% this weights connecting the hidden layer to the output layer 1x7 cell
value
b1=net.b{1,1};  % this bias value is found in the input layer  7x1 cell
value
b2=net.b(2);    % 1x1 cell value is found the hidden layer
%% save the net and loading the network
Final_TO_JAR=net;
save Final_TO_JAR;          % process model

Final_TO_JAR=net;
save Final_PO_JAR;          % Inverse process model
% this is the syntax used to save the network to
%% To call the net
load Final_TO_JAR;          % Process model
load Final_PO_JAR;          % Inverse process model
% this syntax is tell us how loaded the network in the matlab after it
closed
%% generate Function
genFunction(net,'Final_TO_JAR')    % Process model
genFunction(net,'Final_TO_JAR')    % Inverse process model
% function is generated to use the ANN model to predict and serve as
Graphical user interface
%% Check the model ability of predicting (model stability
check)
% the following syntax helps the neural network to predict new unseen
data
data1=xlsread(' DataRearranged.xls,'stablity','B4:E8');
x2=data1(:,1:4); % x2 the new input which is never seen during model
development
x3=x2'
[predict]=net(x3);
%% The yield values of weight value randomization
rng('default');
% this syntax help to set the best weight value as a default
clear;
clc;
```

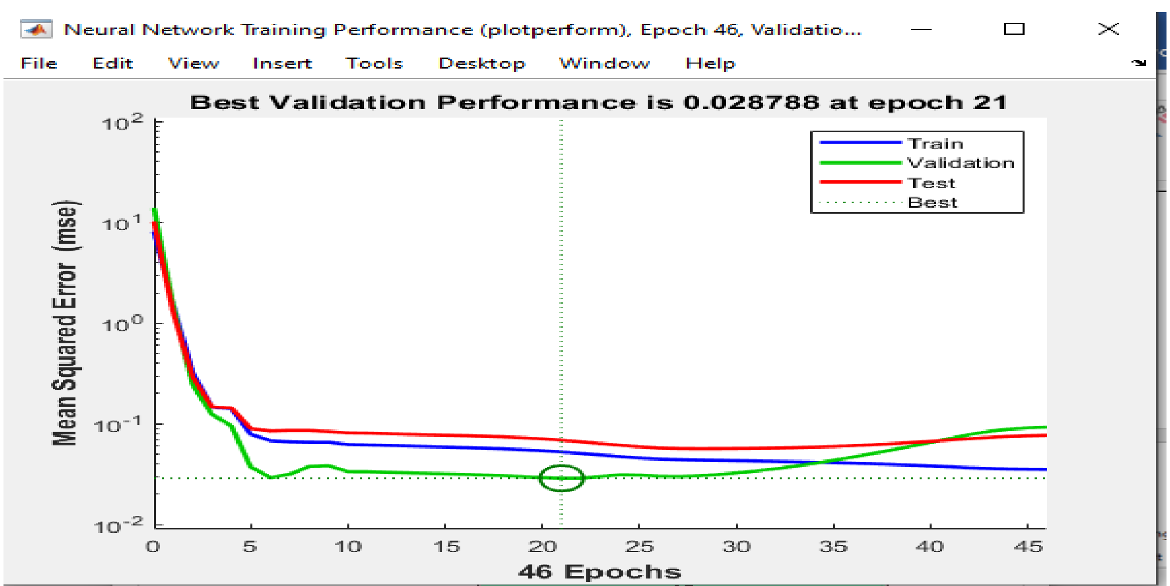
Appendix 5 : MatLab Result

Inverse process model

Regression plot



Performance plot



Appendix 6: Questionnaires

This questionnaire used to assess the coagulation practices of legedadi treatment plant. Four the municipality experts are filled the form.

The questions types are close and open ended.

1. It is known that, the turbidity in the Legedadi Dam has been decreased by the process of coagulation and flocculation. How do you determine the amount of chemical needed for the process?
   A) Jar test
   B) Experienced operators
   C) Both

   If you have any additional means of determining the dosage? Or any recommendation?

____

____

____

2. Does the jar test help you to perform the coagulation and flocculation process
   A) Yes
   B) No

If say yes

Do you really think that jar test represent the full plant scale?

A) Yes
B) No

If say yes how?

____

____

If say no, what is the solution you have been taken

____

____

____

3. If the process has been controlled by Jar test, how periodically it is done?
   Summer
   A) one a week
   B) once in two weeks
   C) Once a month

D) More than one month

Winter

A) one a week
B) once in two weeks
C) One month
D) More than one month

If the summer and winter time have a different period to conduct jar test, what could be the cause for its variation?

____

____

4. What are the important parameters you are considering during coagulation and flocculation Process? Thick them

Raw water turbidity	☐
Treated water turbidity	☐
Water Temperature	☐
Water pH	☐
Color of the water	☐
Alkalinity	☐
UV 254	☐
Chemical dosage	☐

5. Which of the following condition that has factors on coagulation and flocculation process?

Whether condition	☐	Mixing time	☐	Sedimentation type	☐
Clarification type	☐	Chemical type	☐		

6. Which one of the following chemical types would have the best outcome for the Legedadi treatment plant and currently used as coagulant?
   A) Polyelectrolyte
   B) Aluminum sulfate
   C) PACL
   D) Ferric sulfate

What are the advantages of the chemical you selected over the other?

____

____

Since when this chemical has been applied?

____

7. What is the challenges coagulation and flocculation process in Legedadi treatment plant currently faces?

____

____

____

8. Do you forecast any risk in the future in relation with this process?
   A) Yes
   B) No

   If say yes, please put some comment that you think would be a risk in the future

9. What are the maximum and minimum ranges of raw water turbidity that the treatment plant experienced in the last five years?

Max	above 800	☐	Min Below 100	☐
	500-650	☐	100-200	☐
	600-700	☐	200-300	☐