

**MODELING CONTROL AND SIMULATION OF A DRINKING WATER  
TREATMENT PLANT**

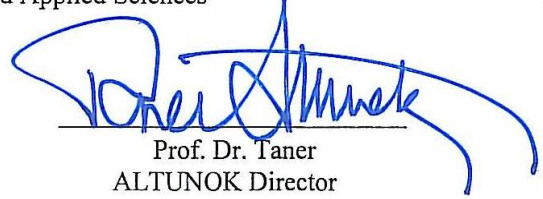
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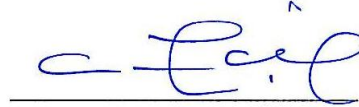
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## STATEMENT OF NON-PLAGIARISM

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To human master Muhammad bin Abdullah (peace be upon him), who commanded us to learn from the cradle to the grave. To my father and mother who have completed their lives for my upbringing and my education. To my brother and sisters who encouraged me to complete my studies. To my dear wife who stood to my and endured a lot of difficulties to complete my studies. To my daughter Sedef and my sons Mustafa and Ahmed who are bearing the rigors of foreignness in order to complete my studies. All employees in the Kirkuk Governorate Directorate of Water who helped to ensure the success of this thesis. Per teacher taught me characters helped me to get to this great place. And a special thanks to Associate Prof. Dr. Klaus SCHMIDT, who made a lot of effort and time to educate me and help me for the success of this thesis.

Thank you all

## **ABSTRACT**

### **MODELING CONTROL AND SIMULATION OF A DRINKING WATER TREATMENT PLANT**

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Clean water is an important prerequisite for human health. In this thesis, the water treatment for drinking water production is investigated with a focus on the compact unit as a specific water treatment plant. First, control problems related to the sub-processes of clarification and sterilization are identified and discussed. Then, a model of the sedimentation process is obtained based on real measurement data. In this thesis, a neural network model is chosen, since the validation of analytical models did not lead to satisfactory results. Together with the model, a control method for the sedimentation process is proposed. The control architecture is feedforward control in combination with feedback control. The feedforward controller is realized as a neural network, that is obtained from existing measurement data. The feedback controller is realized as a fuzzy logic controller based on expert knowledge of the sedimentation

process. Simulations of the control system with real input data show that the control architecture is suitable for the control of the sedimentation process. In addition, our discussion points out that the only modifications in order to implement the proposed control method are a water quality sensor and a variable speed pump. With these modifications, an un-experienced water treatment plant operator can be replaced by an automatic control system.

**Keywords:** water treatment plant, clarification and sterilization process, sedimentation process, neural network, data classification, alum prediction, fuzzy control.

## ÖZ

### MODELLEME KONTROL VE İÇME SUYU ARITMA TESİSİ SİMÜLASYONU

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Temiz su insan sağlığı için önemli bir ihtiyaçtır. Bu tezde, belirli bir su işleme tesisi gibi yoğunlaştırma ünitesi ile içme suyu üretimi için su işleme ele alınmıştır. İlk olarak temizleme ve steril etme işlemlerinin alt basamaklarındaki kontrol problemleri tanımlanmış ve ele alınmıştır. Daha sonra gerçek ölçüm verilerine dayanılarak çökelti işleminin modeli elde edilmiştir. Bu çalışmada analitik modellerin geçerliliği istenen sonuçlara uygun olmadığı için yapay sinir ağı modeli seçilmiştir. Bu modelle birlikte çökelti işleminin kontrol modeli öne sürülmüştür. Kontrolün yapısı ileri beslemeli kontrol ile geri beslemeli kontrolün birleşiminden oluşmuştur. İleri beslemeli kontrolcü var olan ölçüm verilerinden sağlanan yapay sinir ağı ile elde edilir. Geri beslemeli kontrolcü ise çözümlenmiş işleminin temel bilgilerine dayanan bulanık mantık kontrolcüsü ile oluşturulur. Gerçek giriş verileriyle oluşturulan kontrol sisteminin simülasyonları bu kontrol yapısının çözümlenmiş işleminin kontrolü için uygun olduğunu göstermektedir. Ek olarak, öne sürülen kontrol yöntemini

uygulamak için sadece su kalitesini ölçen algılayıcı ve hızı ayarlanabilir pompalar modifiye edilmelidir. Bu modifikasyonlarla birlikte kullanılmamış su işleme tesisinin operatörü otomatik kontrol sistemine dönüştürülebilir.

**Anahtar Kelimeler:** su işleme tesisi, temizleme ve sterile etme işlemleri, çökelti işlemi, yapay sinir ağları, veri sınıflandırmaları, alum tahmini, bulanık kontrol

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## INTRODUCTION

The production of qualitatively good drinking water is a task of utmost importance. It is usually performed in water treatment plants, whose operation is divided into two main parts: clarification and sterilization [3].

The clarification process can be defined as the removal of various kinds of suspended particles from raw water [2]. To complete the clarification process, we need to make sedimentation process for particles suspended in the raw water in a special basin. Very small particles that remain after sedimentation are then removed by a filtration process [2]. The speed of the sedimentation process can be controlled by the addition of a coagulant material to the raw water. After mixing with the water, this coagulant material reacts with the suspended particles to form larger particles, which are sedimented more easily. In current practice, the concentration of the coagulant material is determined experimentally by so-called jar tests. Such tests have to be performed on site by a human operator and the application of the result of the jar test is usually applied to the water treatment plant with considerable delay [5].

The aim of this thesis is the automatic control of the coagulant concentration without any manual intervention. This task is particularly useful for water treatment plants such as compact units. These units are used in remote areas without qualified operators. In this case, automation needs to replace lack of expertise. In the presented research, first a neural network model of the sedimentation process is obtained based on real measurement data [12]. It is shown that the model is suitable for a basic controller design. Then, a new control method for water treatment plants is proposed. The method combines feedforward control and feedback control. In the feedforward path, a neural network is used, that predicts the coagulant concentration from the previous measurement data. If the predicted concentration is inadequate, a fuzzy logic controller corrects the coagulant concentration. The fuzzy logic controller is

designed based on expert knowledge. Simulation results show that the control method is suitable for the control of the sedimentation process. The only basic requirement for its application is the presence of reliable measurement data for the neural network training .

The control of the water treatment process is discussed in the previous literature. [7] provides an analytical model of the clarification process. However, from the validation of this model in this thesis, it seems that the model is not reliable. A similar control scheme as in this thesis is used in [13]. This work also employs fuzzy control. However, no neural network training step is used for the prediction of the coagulant concentration. The work in [14] also uses neural networks for a control problem related to water treatment. However, they focus on tuning the parameters of a PID feedback controller and do not use feedforward control at all. [10] gives some guidelines for building neural network models of drinking water plants. The method in [11] also uses the combination of feedforward and feedback control based on a simple linear time-invariant model of the sedimentation process.

The thesis is organized as follows. Chapter I gives a description of the water treatment process with a focus on the compact unit. In addition, control problems in the water treatment process are identified and discussed. A neural network model for the sedimentation process is developed in Chapter II. The control method proposed in this thesis is presented in Chapter III including simulation experiments. Finally gives conclusions.

## **CHAPTER I**

### **WATER TREATMENT PROCESS**

This chapter gives an overview of important notions and concepts in the drinking water production process. First, a general description is given in Section 1.1. Then, the application of these general ideas for the water treatment in a particular compact unit is described in Section 1.2.

#### **1.1. WATER TREATMENT TECHNIQUES**

##### **1.1.1. Suspended particles in water**

The surface water such as rivers and streams, which are used as a source feeder for drinking water treatment plants usually contains solid objects, which can be divided into three groups. Suspended particles, colloids and dissolved solids [1].

Suspending particles consist of sand, clay and plants. They are characterized by particle sizes starting from 10 micro meters. That is, suspended particles are large in size compared to other types of objects in the water. As a consequence, such particles can be removed by traditional methods of sedimentation and filtration [1].

Colloids are characterized by very small sizes ranging from 10 nm to 10 micro meter. There are basically two types of colloids. Hydrophilic colloids form a solution with water and cannot be easily separated. An example for a hydrophilic colloid is soap. Hydrophobic colloids do not form a solution with water and can be separated from water more easily. Examples for such particles are small units of clay or oxides [1].

Dissolved solids come in the form of single atoms or ions and are characterized by their very small size, ranging between 0.1 nm and 10 nm. Special water treatment methods are needed to remove such particles [1].

The table below (table 1.1) shows details for different types of particles. The information includes the time needed for settling particle or solid one meter.

**Table 1.1** Details of all particles. [2]

Particle Diameter	Type of particles	Total surface area	Time required to settle one meter	Total number of particles	Mass (mg) per particle
10 mm	Gravel	3.1419 cm <sup>2</sup>	1 s	1	1386.8
1 mm	Sand	31.4193 cm <sup>2</sup>	10 s	1000	1.3868
100 µm	Fine Sand	314.1929 cm <sup>2</sup>	2 min	1E +6	1.3868E -3
10 µm	Silt ,Clay	0.3140 m <sup>2</sup>	2 hours	1E +9	1.3868E -6
1 µm	Bacteria , Alga	3.1340 m <sup>2</sup>	8 days	1E +12	1.3868E -9
100 nm	Viruses , colloids	31.7728 m <sup>2</sup>	2 years	1E +15	1.3868E -12
10 nm	Viruses , colloids	2832.7995 m <sup>2</sup>	20 years	1E +18	1.3868E -15
1 nm	Viruses , colloids	288327.995 m <sup>2</sup>	200 years	1E +21	1.3868E -18

### 1.1.2. Methods for water treatment

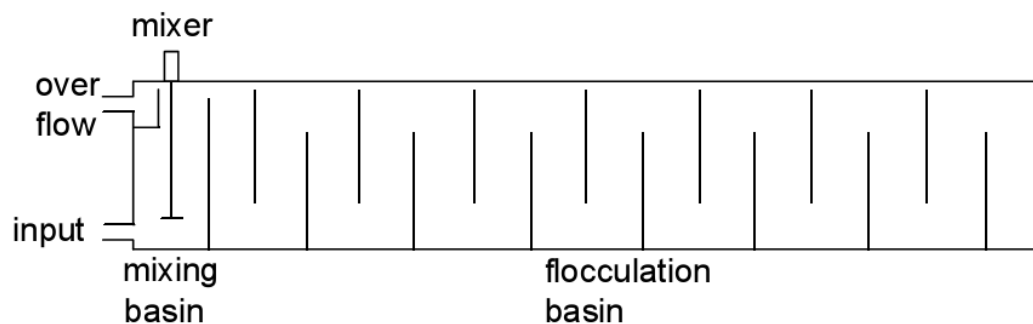
The treatment process of drinking water is characterized by several treatment steps, that are applied to raw water from a water source. These steps include the addition of a coagulants dosage in order to remove suspended particles, the addition of chlorine

in order to disinfect the water and the filtration in order to remove very small particles. The main characteristics of these processes are now described.

### 1.1.2.1. Coagulation

The process of coagulation is to add a chemical to the raw water to reduce the force that holds the particles in a stable state. The coagulant material has positive charge, which is opposite to the charge of the particles that are dissolved in water. The effect of the coagulant addition to the raw water is to cause neutralization of the particle charge. That is, the added particles and the dissolved particles form larger particles that can be sedimented and filtrated more easily [3].

The addition of coagulant dosage to the raw water is usually performed in a mixing basin in order to distribute the coagulant dosage equally. This ensures uniform reaction of the coagulant dosage with the particles inside the raw water. The mixing process in the mixing basin takes between 1 and 3 minutes [4]. It is performed by a mechanical mixer, that spins at high speeds such that homogeneity between the coagulant and the raw water is achieved. figure 1.1 shows the basic outline.



**Figure 1.1** Mixing and flocculation basin that used in compact unit

It is important to note that the amount of coagulant to be added to the raw water depends on the properties of the raw water. Here, parameters such as turbidity and PH are important. The usual procedure to determine the appropriate coagulant dosage is to take a probe of the raw water and perform a so-called jar test as described below.

### 1.1.2.2. Flocculation

Flocculation describes the process of forming larger compounds from particles in the raw water and the coagulants added to the raw water. The process is usually accompanied by either slow mixing or a zigzag motion of the water as shown in the flocculation basin in figure 1.1. The aim is to move the particles gently such that particles collide with each other to form a big floc that can even be viewed with the naked eye (0.1 to 0.3 mm) [4,5].

### 1.1.2.3. Sedimentation

Sedimentation is the process of separation of solids from the raw water by gravity. This process is one of the most important steps in the treatment of raw water [4].

There are different factors affecting the process of sedimentation [5]:

- the size, shape, density and electrostatic charges of the particles
- temperature and wind if sedimentation occurs outdoors
- the nature of the basin where sedimentation is performed and the flow rate in the basin



**Figure 1.2** Inside sedimentation basin for compact unit

In this context, the properties of the suspended can be controlled by adjusting the amount of coagulants added to the raw water. Regarding the flow rate, it is generally desired to have a slow flow rate in order to facilitate the sedimentation. However, the flow rate is usually determined by the user demand with small subject to adjustment. In principle, the main aim of sedimentation is to reduce the amount of particles as much as possible in order to reduce the pressure on the filters, that are passed by the water after the sedimentation process.

#### **1.1.2.4. Jar test**

The idea of the jar test is to experimentally determine the most suitable coagulant dosage by trying different dosages for a sample of the actual raw water. Components of the testing device and extra equipment and processed needed are as follows

- 4 or 6 numbered glass beakers with 1 liter capacity.
- all beakers have a mixer.
- each mixer can rotate at different speeds by electric motor.

This operation is used as a simulation of the sedimentation process in the actual water treatment plant. The different mixing speeds represent water in the mixing basin (high speed) and in the flocculation basin (slow speed). Then, the jar test is performed in the following steps

- A standard solution is prepared first by using distilled water with a volume of 1 liter and added to 1 g of material coagulants.
- Take the right amount of raw water and fill the beakers to their final limit.
- Add different amounts of standard solution to each beaker. Record the number of each beaker and the respective amount of standard solution are documented.
- Operation and monitoring of the device. The process starts with high-speed mixing, continues with slow mixing to form a floc. Finally, the device stops in order to simulate the sedimentation. Generally, the device is programmed to do all these steps automatically.

- After the test, each beaker is evaluated and the “best dosage” is determined from the beaker that provides the best water quality. This dosage is then applied in the real water treatment plant.
- In addition, the test results are documented for future use, since tests for similar raw water properties are expected to produce similar results.

Figure 1.3 shows a typical device that is used for the jar test.



**Figure 1.3** Jar test device. [2]

#### **1.1.2.5. Filtration**

The purpose of filtering is to remove suspended solids in water which have not been sedimented by previous operations such as the clarification process. These are usually small or microscopic particles. In the filtration process, the water is passed through permeable filter layers. An example of the materials used in the layers of the filter is sand or anthracite [5]. Upon passage of water through layers of filters, the large enough particles remain on the outer surface of the filter bed, because their size is greater than the spaces between the filters bed grains.

The filters are divided into several classes. In this thesis, we consider the type of rapid sand filters which are realized as gravity filters and pressure filters. As an effect of the filtration process, the filters regularly fill with particles that are accumulated on the top surface of the filter. In that case, the filter is cleaned by reversing the direction of flow of water. This process is called backwash [5].

## 1.2. COMPACT UNIT FOR DRINKING WATER TREATMENT

The main subject of this thesis is the study of control problems related to the treatment of drinking water. We focus on the compact unit as a specific type of water treatment plant, since it is a very important source of drinking water supply in Iraq. In this chapter, we describe the main components of the compact unit.

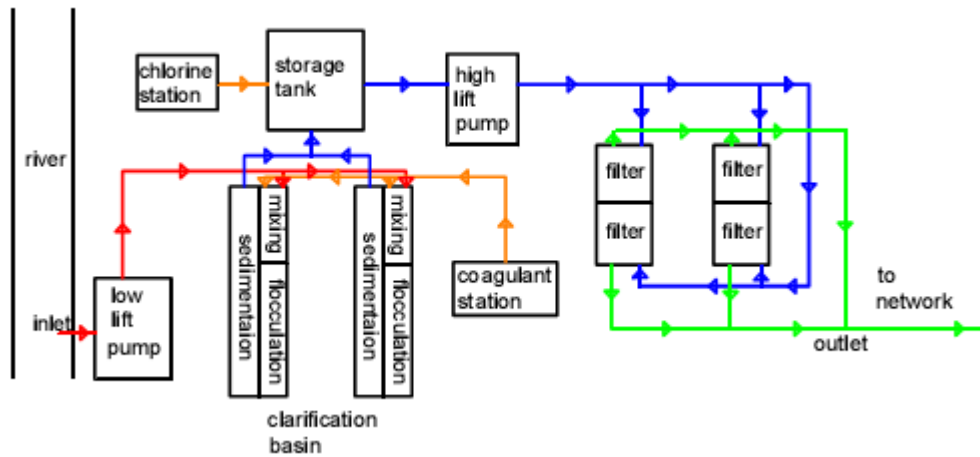
### 1.2.1. Basic overview

The compact unit for drinking water treatment is designed for drinking water production with small capacity. Its most important role is to supply drinking water especially in rural areas for small populations. Although the compact unit is small in size, it performs the classical tasks of water treatment. In particular, it must transform raw water, that is taken from some water source (for example a river) into drinking water according to the legal regulations. The figure below shows an overview of a compact unit.



**Figure 1.4** Compacts unit with capacity  $200 \text{ m}^3/\text{h}$  used in Iraq-Kirkuk

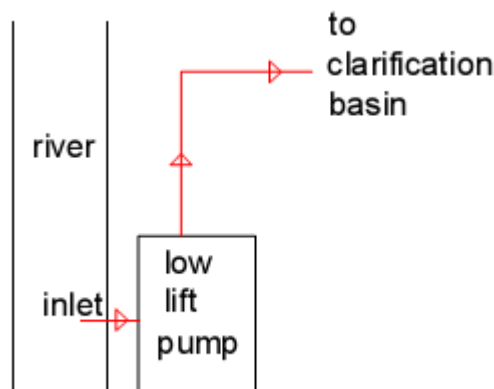
In addition, figure 1.5 shows a schematic of the compact unit with all the relevant components. The lines between the boxes indicate pipes for the transport of water. We next explain the compact unit components in detail.



**Figure 1.5** Schematic of the compact unit

### 1.2.2. Low lift pump

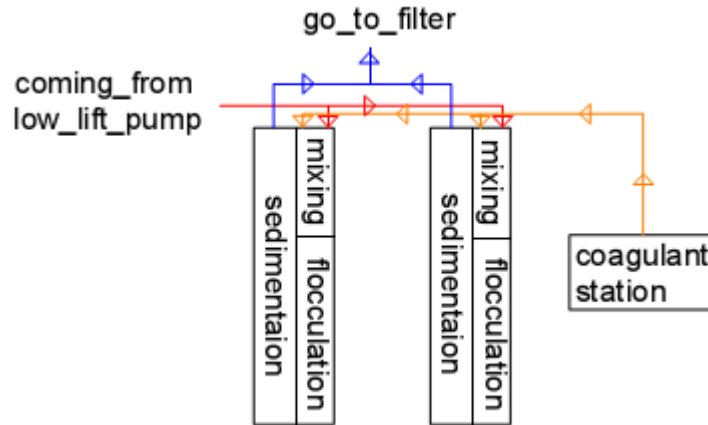
The low lift pump is the initial entry of water to the compact unit. The duty of this unit is to withdraw raw water from a source (river or canal or well) and move water to the first component of the compact unit, the mixing basin. In principle, the low lift pump is located outside the compact unit shown in figure 1.6.



**Figure 1.6** Low lift pump position for compact unit

### 1.2.3. Components related to clarification

Next, the components of the first part of the water treatment process, denoted as clarification, are described. There are three main components: the mixing basin, flocculation basin and sedimentation basin. figure 1.7 shows the basic structure.



**Figure 1.7** Clarification basin

In the mixing basin, a chemical substance called alum sulphate is added to the water. The main goal is to speed up the sedimentation of particles in the water as will be explained in more detail later. In order to dissolve the alum sulphate homogeneously in the water, there is a high-speed mixer in the mixing basin. From the mixing basin, water is moved to the flocculation basin.

The flocculation process occurs in a separate basin. A slow mixer is used to support the collision process between turbidity molecules (particles suspended in the raw water) and the alum sulphate. As a result, flocs (larger particles) are generated that can be sedimented easier in the sedimentation process. In some units, no mixer is used but the water follows a zigzag path in order to achieve flocculation. The flocculation process usually takes up to 30 minutes. From the flocculation basin, water is pushed to the sedimentation basin.

The water stays in the sedimentation basin for a longer period compared to the previous phases. The main objective is to remove (sediment) the bulk of colloidal particles from the previous treatment stages as a first part of the cleaning process. At the bottom of the sedimentation basin, clay scrapers or vacuum pumps are used to move away the sedimented material.

In summary, the clarification process relies on the addition of a chemical substance that is mixed with the water. As a result, large particles are formed and sedimented.

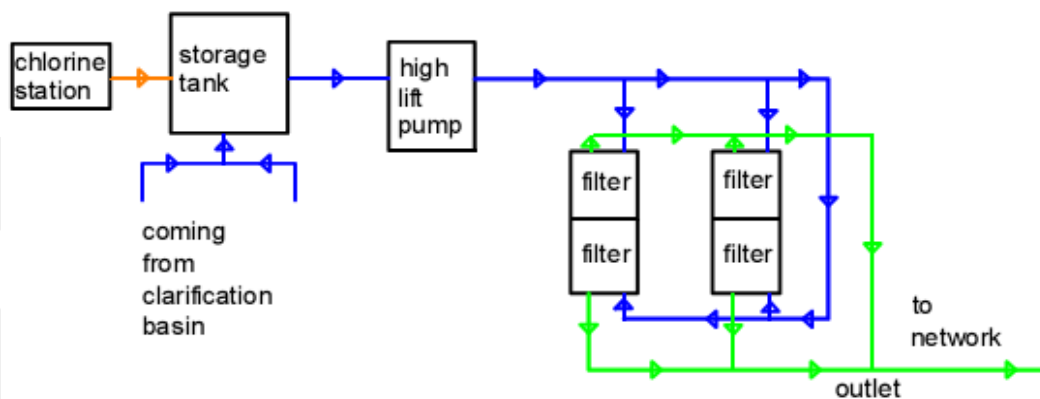
That is, the clarification process transforms turbid raw water into water with a significantly reduced turbidity.

#### 1.2.4. Storage tank and high lift pump

After clarification, the water enters a storage tank, where chlorine is added to the clarified water for disinfection. The main objective of this step is the sterilization of the water for the consumer and the protection of the following components in the treatment process. For example it is important to avoid growth of algae in the filters of the compact unit. The water is then pumped from the storage tank to the connected filters using a so-called high-lift pump.

#### 1.2.5. Filter

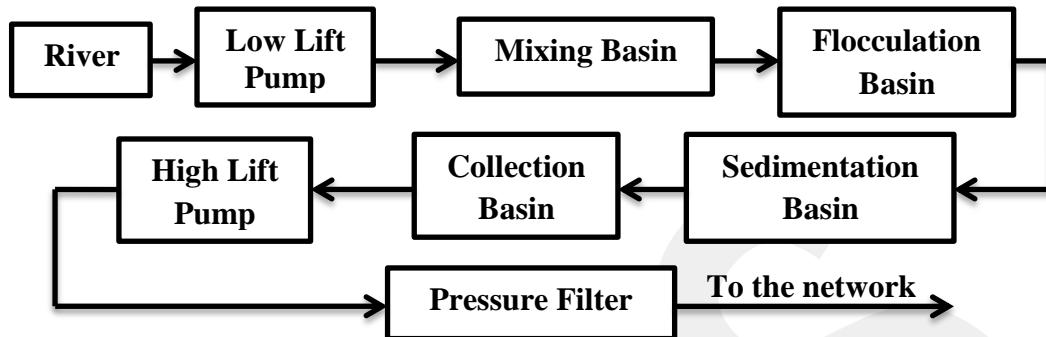
The clarification as described before removes large colloidal particles from the raw water. However, small particles are still suspended in the water coming from the storage tank. It is the task of the filter to deposit small colloidal that remain in the water after sedimentation. After filtration, the water is supposed to be suitable for consumption and is fed to the water network.



**Figure 1.8** Chlorine station and storage tank with high lift pump then filter

The overall water treatment process is summarized in figure 1.9. Raw water from a source enters the water treatment plant from a low lift pump, and is moved to a mixing basin, where the coagulant dosage is added to the water. Flocculation and sedimentation is performed in the following basins in order to reduce the turbidity of the water. After this clarification process, water is collected in a storage tank, where

chlorine is added for the purpose of disinfection. Afterwards, the water enters a pressure filter from the high-lift pump such that also small particles are removed. Finally, water is distributed to the consumer network.



**Figure 1.9** Sequential steps of the water treatment process.

#### 1.2.6. Compact unit feature and usage in Iraq

The main features of a compact unit are its small size and composition of modular components. The components such as the clarification basin, the storage tank, the filters and pipes are usually manufactured from iron and can be easily assembled and disassembled. This allows the transfer of the compact unit between different places, for example in case of crises, accidents and natural disasters.

It has to be noted that the lifetime of a compact unit is usually shorter than that of a conventional water treatment plant. This is mainly due to the use of iron material, which is subject to corrosion especially due to the contact with water in open air. As a consequence, the compact unit requires maintenance cycles, which are however not subject of this thesis. This thesis rather focuses on the efficient usage of the compact unit for the production of high-quality water during its lifetime.

This subject is of particular importance in Iraq, where compact units are used after 2003 extensively, especially in districts, counties and rural areas to meet the acute shortage in the amount of drinking water. There are various reasons for this development. On the one hand, Iraq lacks basic infrastructure in many parts of the country. In addition, new projects for drinking water production are delayed due to governmental and security situation in the country.

The compact unit provides a short term solution to the described problems, since it can be easily set up in locations with lack of clean drinking water. However, it has to be noted that the use of compact units also comes with a main disadvantage. The compact unit as it currently exists requires an operator that performs various manual control tasks during the daily operation. Unfortunately, such operators usually have a low educational qualification up to the lack of reading and writing skills. Hence, it is highly desirable to automate the operation of compact units as much as possible and to assist the operator with information that is obtained during the automated operation of the compact unit.

The first aim of this thesis is the identification of processes to be automated during the operation of the compact unit. Second, the thesis intends to provide solution approaches to a subset of the automation tasks. Third, suggestions for the implementation of the solution ideas in the compact unit are given.

### **1.3. CONTROL PROBLEMS**

As discussed before, drinking water treatment plants have two main functions: clarification and sterilization. The clarification process is performed in two stages, that is sedimentation and filtration. In this process, coagulant chemicals are used to help and speedup the process of sedimentation. The sterilization process is performed by using sterilize chemicals (usually used chlorine) addition to water before or after sedimentation and the amount of this sterilize chemicals depend on the flow rate, duration that the water remain in the distribution tank and the length of distribution network.

There are specific standards for drinking water. Several standards are issued by the World Health Organization. In addition, each country has its own standards in accordance with the specifications of water they own and use it.

Table 1.2 shows a working paper for testing the water properties (chemical, physical and bacteriological) in Iraq. It shows the highest tolerable values of each parameter especially for Iraq.

**Table 1.2** Worksheet for testing water properties (chemical, physical and bacteriological)

Ministry of Municipalities and Public Work

GDW/Water National Laboratory

<b>Governorate : Kirkuk</b>						
<b>Date of Sampling : / /</b>						
<b>Sampled By :</b>						
<b>Physical and Chemical parameters</b>						
<b>Sample Location</b>						
<b>Parameters in mg/L unless otherwise stated</b>						
<b>Sample Location</b>						<b>MPL</b>
<b>Turbidity , NTU</b>						<b>5</b>
<b>Temperature C</b>						<b>ACC</b>
<b>PH</b>						<b>6.5 - 8.5</b>
<b>E.C <math>\mu</math>S/cm 25C</b>						
<b>Alkalinity as CaCO<sub>3</sub></b>						<b>125 – 200</b>
<b>Hardness as CaCO<sub>3</sub></b>						<b>500</b>
<b>Calcium as Ca</b>						<b>150</b>
<b>Magnesium as Mg</b>						<b>100</b>
<b>Chloride as Cl</b>						<b>350</b>
<b>Iron as Fe</b>						<b>0.3</b>
<b>Aluminum as Al</b>						<b>0.2</b>
<b>Sulphate as SO<sub>4</sub></b>						<b>400</b>
<b>Sodium as Na</b>						<b>200</b>
<b>Potassium as K</b>						
<b>T.D.S</b>						<b>1000</b>
<b>T.S.S</b>						
<b>Nitrate as NO<sub>3</sub></b>						<b>50</b>
<b>Chromium as Cr<sup>16</sup></b>						<b>0.5</b>
<b>BOD 5 days</b>						<b>Nil</b>
<b>Fluoride as F</b>						<b>1</b>
<b>Silica as SiO<sub>2</sub></b>						<b>5</b>
<b>Remarks :</b>						
<b>Name and Signature of Chemists :</b>						

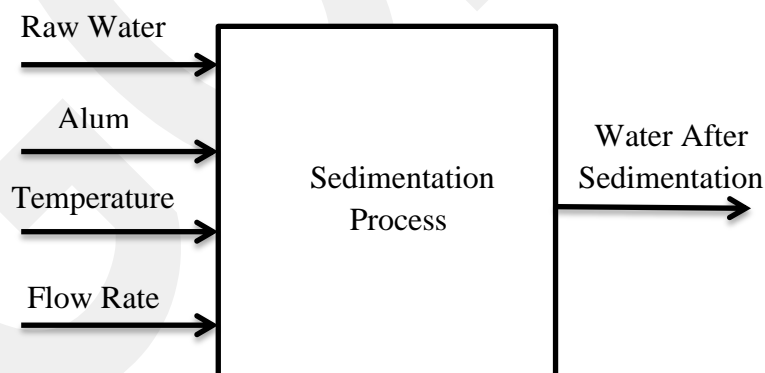
Bacteriological Parameters						
Date and Time of Sampling : / /						
Sample Location						MPL
Residual Chlorine						0.5 – 2.5
MPN Total Coli /100 ml						Zero
MPN Fecal Coliform /100 ml						Zero
Plate Count / 1 ml						100
Remarks :						
Name and Signature of Chemists :						

All drinking water treatment plants are supposed to apply the defined standards and stay within the limits of each parameter in order to supply high-quality water to the consumer.

In the following sections, the main control problems regarding the improvement of water quality are discussed.

### 1.3.1. Control problems related to clarification

clarification comprises sedimentation and filtration. As discussed before, sedimentation is supported by the addition of a coagulant to the raw water. In terms of control, the plant for the sedimentation process is given by the following block diagram in figure 1.10.



**Figure 1.10** The Sedimentation Process

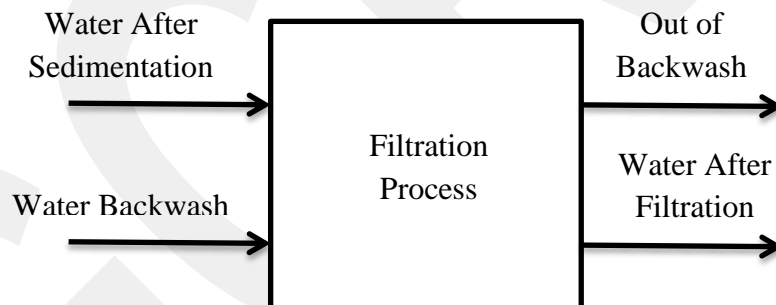
It can be seen that the plant input consists of the physical and chemical raw water properties, the flow and temperature of the raw water and the ALUM (coagulant) concentration. The plant output is given by the physical and chemical properties of the water after sedimentation. Considering the plant inputs, the raw water properties as well as the flow and temperature must be considered as disturbances, since these

parameters cannot be directly influenced. They are rather determined by the weather conditions. However, it is possible to measure these parameters either in the laboratory or with appropriate sensors. The only control input of the sedimentation plant is the ALUM concentration, which is added to the raw water at the beginning of the sedimentation process. Hence, the control task in the sedimentation process is finding the “best” ALUM concentration depending on the properties of the currently available water.

In the current practice, this control task is solved manually by using jar test as described in Section 1.1.2.4. Such tests need laboratories which are only available in large water treatment plants but not in compact units. That is, in compact units the added ALUM concentration depends exclusively on the experience of the operator with a high level of uncertainty. In addition, such jar tests require extra time, and hence, lead to a delayed application of the control input to the sedimentation plant.

In order to improve the control of the sedimentation process, it is required to automate finding the best ALUM concentration. A solution for this problem is proposed in the next chapter.

The plant for the filtration process is shown in the following figure.



**Figure 1.11** The filtration process

It can be seen that the input of the filtration plant consists of the water provided after the sedimentation process, whereas the output is the water provided to the consumer. The only control input is given by the decision of performing a backwash operation in order to clean the filter. This operation generally has to be performed manually and is hence not subject of this thesis.

### **1.3.2. Control Problems Regarding Sterilization**

After the completion of the clarification process comes the stage of sterilization. There are several ways to perform this operation using ozone, UV or chlorine. In drinking water treatment plants chlorine is commonly used because it has certain

advantages compared to other disinfectants. For example, it ensures that water remains sterile for long periods, since free chlorine in the water is effective against bacteria and viruses.

The control problem for the sterilization process is finding the “best” chlorine concentration to be added to the water depending on the current water properties. Here, it is required to sterilize the water, while guaranteeing that the percentage of free chlorine residual in the water is 0.5 ppm at the end of the network (as applicable in Iraq). In large water treatment plants, this control problem is again solved by laboratory tests. In compact units, the addition of chlorine depends on the experience of operators and is hence subject to fault. For this reason it is highly desirable to automate the process of chlorine addition.

## CHAPTER II

### MODEL FOR SEDIMENTATION

The main objective of this thesis is the development of automatic control methods for different processes in water treatment plants including compact units. In order to develop and evaluate such methods, plant models are required. In this chapter we find a model that represents the process of sedimentation in drinking water treatment plants. This model is verified using data from a real drinking water treatment plant located in Kirkuk, Iraq. In addition, we evaluate an existing analytical modeling method for simulating the sedimentation process in the compact unit.

#### 2.1. PREVIOUS WORK

The literature research on models for the sedimentation process has shown that there is limited work on this subject. There is only one analytical modeling approach proposed in [7] that is in principle suitable to represent the process of sedimentation in compact units. Since the evaluation of this model is part of this thesis, a brief description is given in the following.

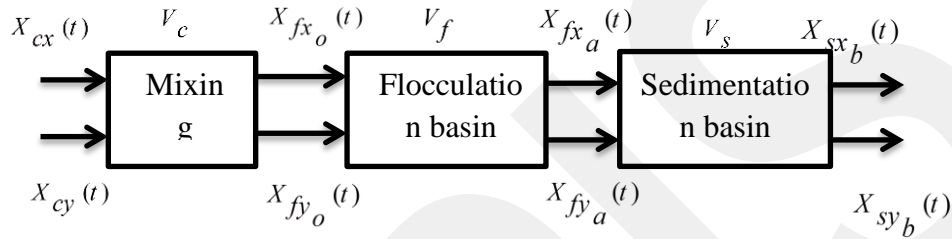
##### 2.1.1. Variables of the model

The model in [7] follows the sedimentation process with three stages as shown in figure 2.1. It tries to compute the micelle concentration (concentration of suspended particles) and the dosage concentration (coagulant dosage) after each stage. The following variables are introduced in the model (see also figure 2.1).

- Raw water: micelle and dosage concentration  $X_{cx}(t)$  and  $X_{cy}(t)$
- Same variable after mixing:  $X_{fx_o}(t)$  and  $X_{fy_o}(t)$

- Same variable after flocculation:  $X_{fx_a}(t)$  and  $X_{fy_a}(t)$
- Same variable after sedimentation:  $X_{sx_b}(t)$  and  $X_{sy_b}(t)$

In addition, [7] uses the spin rate of dosage metering  $n$  and the water flow  $q$ . The relevant output of the system is the micelle concentration after sedimentation  $X_{sx_b}(t)$ . In addition, several parameters are used such as the volume of the mixing basin  $V_c$ , the volume of the flocculation basin  $V_f$ , the volume of the sedimentation basin  $V_s$  and the maximum flocculation reaction rate  $r_m$ .



**Figure 2.1** Sequence of sedimentation process

The clarification process is performed in three basins, whereby each basins fulfills a dedicated task. The mixing basin only adds coagulant material to the raw water. The mixing basin is considered as a continuously stirred tank reactor in [7] The time evolution of the micelle and coagulant concentrations is modeled as follows.

$$X_{fx_o}(t) = \frac{1}{V_c} \int q (X_{cx}(t) - X_{fx_o}(t)) dt$$

for micelle concentration

$$X_{fy_o}(t) = \frac{1}{V_c} \int q (X_{cy}(t) - X_{fy_o}(t)) dt$$

for dosage concentration

After the water transfer from mixing basins to the flocculation basins, slow mixing between micelle and coagulant and creating flocs is performed in the flocculation basin. That is, both micelle and coagulant concentration are reduced due to the reaction between both materials. The dynamic equations are written as

$$X_{fx_i}(t) = \int \left[ \frac{q}{V_{f_i}} (X_{fx_{i-1}}(t) - X_{fx_i}(t)) - \frac{2}{3} m_x n_{f_i}^2 d_{f_i}^3 G_{f_i} \right] dt$$

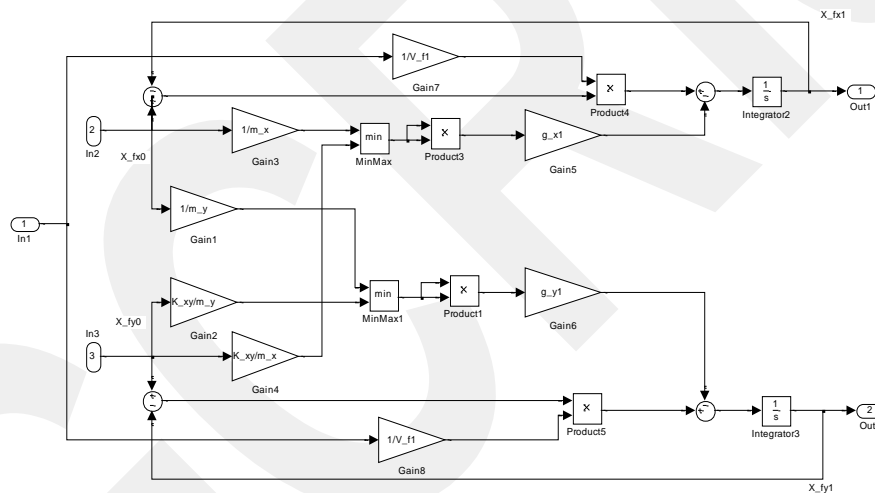
$$n_{f_i} = \min\left(\frac{X_{fx_{i-1}}, K_{xy} X_{fy_{i-1}}}{m_x}\right)$$

for micelle concentration

$$X_{fy_i}(t) = \int \left[ \frac{q}{V_{f_i}} (X_{fy_{i-1}}(t) - X_{fy_i}(t)) - \frac{2}{3} m_y n_{f_i}^2 d_{f_i}^3 G_{f_i} \right] dt$$

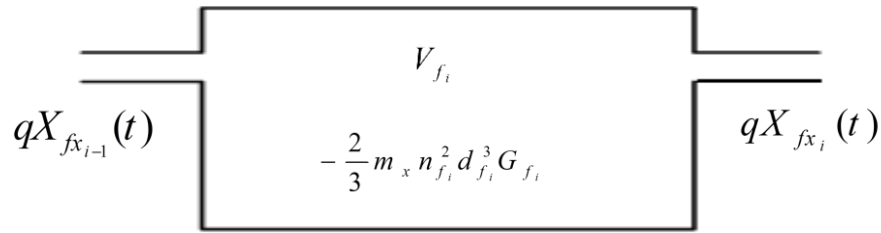
$$n_{f_i} = \min\left(\frac{X_{fx_{i-1}}, K_{xy} X_{fy_{i-1}}}{m_y}\right)$$

for dosage concentration. A Simulink block diagram of the flocculation model is shown in figure 2.2.



**Figure 2.2** Flocculation Process Model

We note that the flocculation model is an extension of the mixing basin model. The difference between them is that the value of the reaction rate in the basin mixing equal to zero, since no reaction takes place in the mixing basin. A schematic of the continuously stirred tank reactor, that represents both processes is shown in figure 2.3.

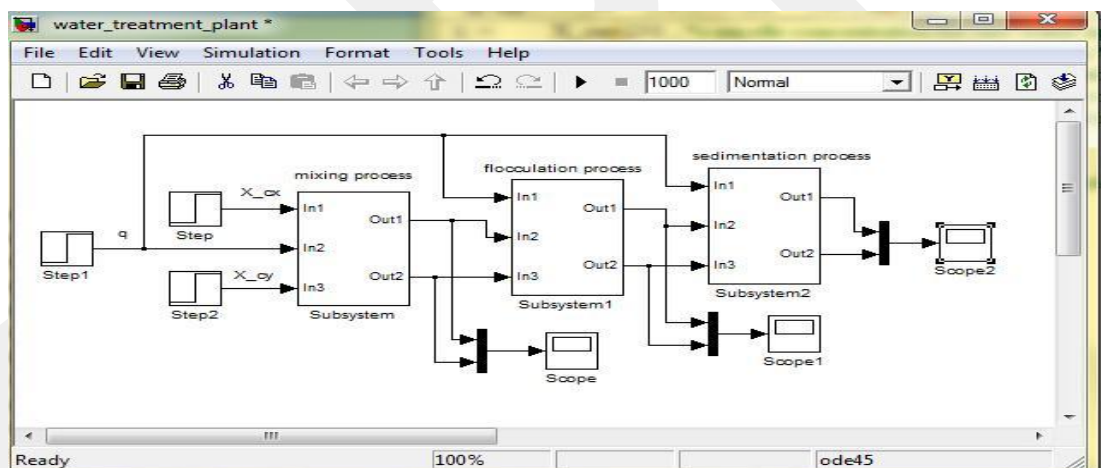


**Figure 2.3** Flocculation basin model

With regard to the sedimentation basin model, we only note that it is similar to the basin flocculation model, with possible changes in parameter values.

### 2.1.2. Problems of Previous Work

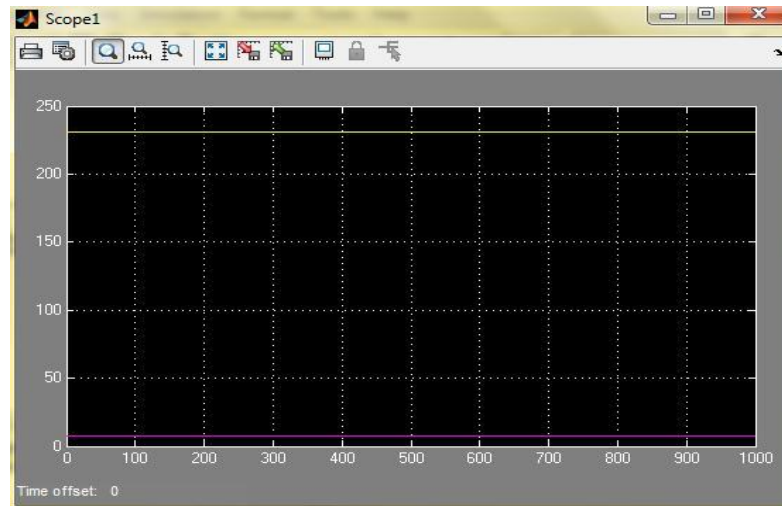
Figure 2.4 shows a Simulink model with the three processes mixing, flocculation and sedimentation. The content of the flocculation subsystem is already shown in figure 2.2.



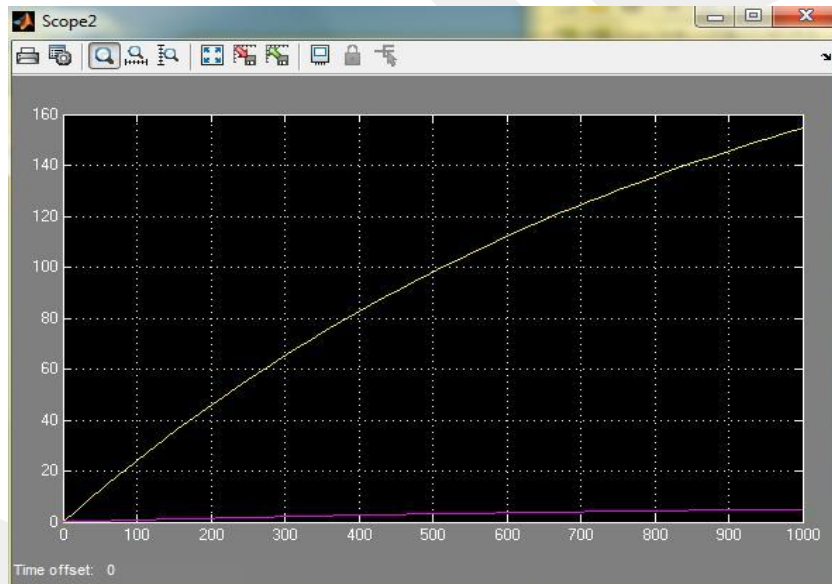
**Figure 2.4** Simulink of analytical model

We use the following parameters values for the compact unit as well as other parameters values for raw water and dosage. values of basin (mixing, flocculation and sedimentation) respectively, as well as the value of the flow rate . These values are taken from Table 1.1 and the average mass of dosage is taken from [7] The parameter assignment in Matlab is shown in figure 2.5.





**Figure 2.7** Output of flocculation basin



**Figure 2.8** Output of sedimentation basin

For this reason, we decide that the analytical model is not suitable for this thesis and pursue a different path as described in the next section.

## **2.2. Neural network of the sedimentation process**

As outlined in the previous section, there is no analytical model for the sedimentation process of drinking water treatment. For this reason, we choose Neural Networks as a modeling technique that works without an analytical model.

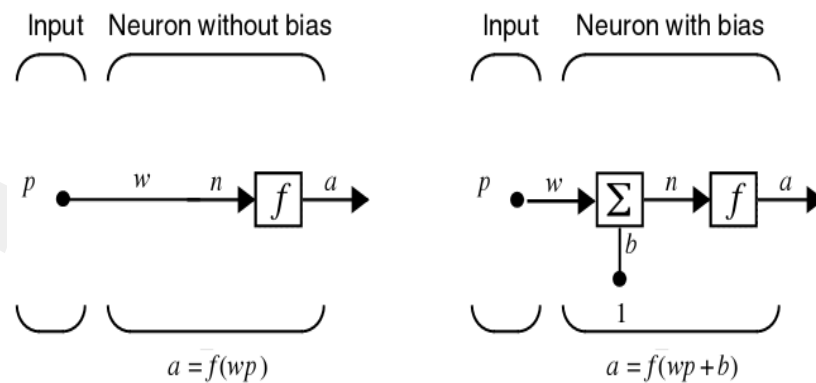
A neural networks realizes a (generally nonlinear) function between a set of input variables and a set of output variables. This function is obtained by training of the

neural network with known instances of input and output data. Neural networks are used in many industrial fields, control applications and signal processing [8].

### 2.2.1. Explanation of neural network

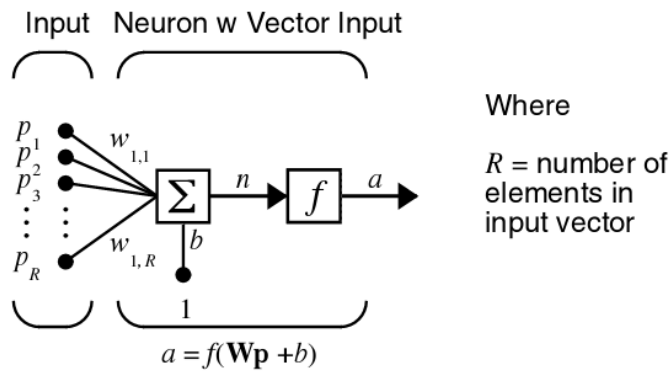
Artificial neural networks try to model the information processing capabilities of the neural system of a human or animal. Hence, the model tries to follow the structure of biological neural networks [9]. In principle a neural network consists of neurons, that are connected. The neurons process information from connected neurons using an activation function and output information to be processed by other neurons. In the following, the basics of neural networks are described.

The most simple neuron model is the single scalar input and can be with bias or without bias as shown in figure 2.9. For this neuron model, the single scalar input  $p$  is transmitted through a connection and its value is multiplied by a scalar weight  $w$  to form the product  $wp$ . Then, the so-called transfer function  $f$  is applied to  $wp$ , which produces the scalar output  $a$ . If required, a fixed bias  $b$  is added to the product  $wp$ . In that case, the value of the scalar output is  $a = f(wp + b)$  [8].



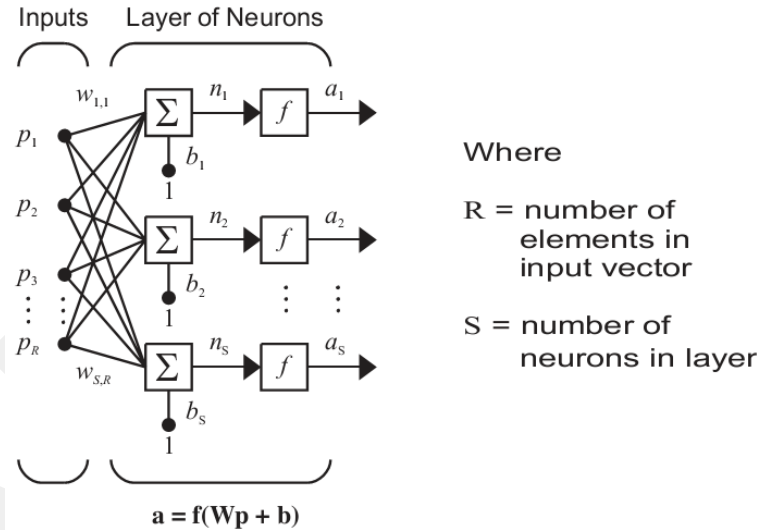
**Figure 2.9** Single scalar input and scalar output [8]

The second type of input into a neuron model is the input vector  $\mathbf{p}$ . In that case, each entry of the vector represents an input. The input vector is multiplied with a weight vector  $\mathbf{W}$  to produce the weighted input  $\mathbf{Wp}$ . Again, a bias can be added to the input as in figure 2.10.



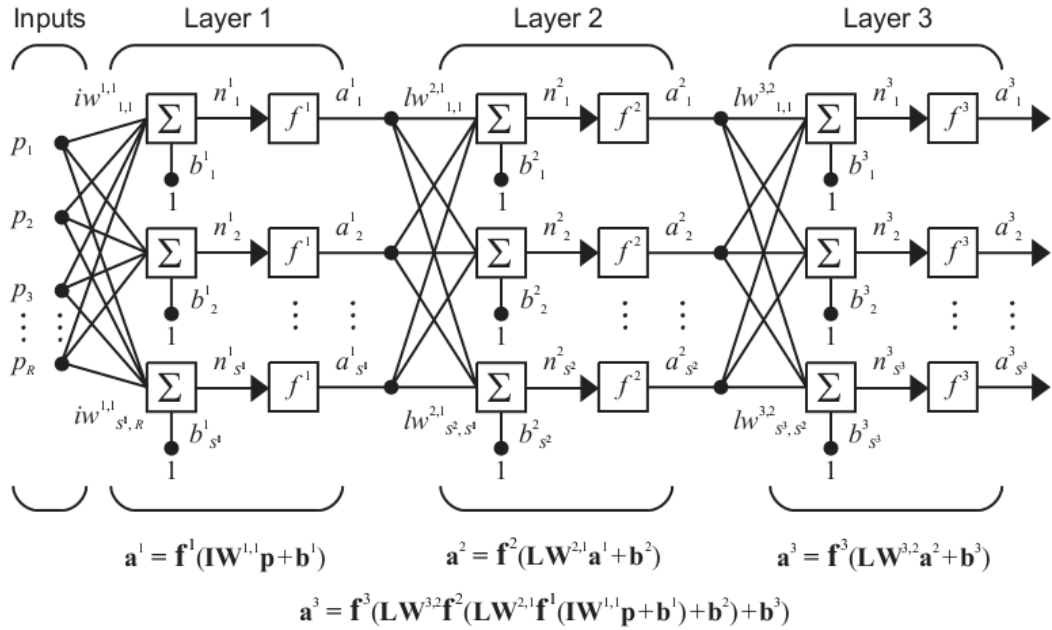
**Figure 2.10** Neuron model with multiple inputs

The neurons can now be combined to form a neural network. We explain the concept by a single layer of a neural network. It consists of a set of inputs that are directly connected to a set of neurons as is shown in figure 2.11. Now the input vector  $\mathbf{p}$  is connected to each neuron via one row of the weight matrix  $\mathbf{W}$  to produce weighted inputs  $\mathbf{Wp}$ . In addition, a bias vector  $\mathbf{b}$  is used, where each entry describes the input bias for one neuron. As before, each neuron computes its scalar output using the transfer function  $f$ .



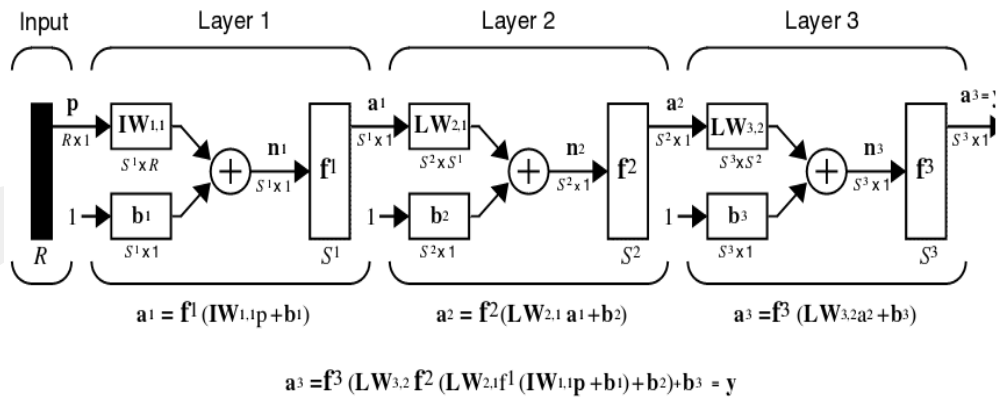
**Figure 2.11** Single layer of a neural network

Finally, we note that multiple layers of neurons can be added back to back, whereby the output of one layer is considered as the input of the next layer. The basic structure of a multi-layer neural network is shown in figure 2.12 [8].



**Figure 2.12** Input vector with multi-layer neurons [8]

Manual can be used abbreviated notation to keep all the information and avoid forgetting it and become as shown below [8].



**Figure 2.13** Input vector with multi-layer neurons abbreviated notation [8]

### 2.2.2. Training of Neural Networks

The use of the neural network is that it *learns* the behavior of the system to be modeled from given pairs of input data and output (target) data. This learning process is performed in the training phase, whereby the weight and bias parameters are adjusted to fit the given data. That is, when we want to train our network we have to define the input data as well as the corresponding output data.

Based on input and output data, it is then possible to apply any training method in order to train a neural network, whereby the structure of the network such as number of layers and number of neurons must be chosen. In this thesis, we use the neural networks toolbox in MATLAB for training and evaluating neural networks. It allows choosing neural networks with multiple layers, arbitrary number of neurons, different transfer functions and offers a variety of training algorithms.

### **2.2.3. Data for Our Neural Network**

As described in Section 1 of this chapter, it is desired to obtain a model of the sedimentation process of a water treatment plant. The input of the sedimentation process is raw water with a certain flow and temperature as well as a coagulant concentration (ALUM), that is added to the raw water in order to speed up the sedimentation. The output of the sedimentation process is clarified water. Since it was not possible to use an analytical model of the sedimentation process, we now use a neural network model .

In principle, we intend to develop a method for the control design of compact units. That is, we need a model of a compact unit. However, it has to be noted that. there are currently no laboratories for testing samples of water. Hence, the evaluation of samples taken from the compact units is done in a Central Laboratory (for example the Kirkuk Governorate Directorate of Water in Iraq), In addition, it has to be seen that there are many compact units deployed in rural areas. Because of this reason, the staff in the central laboratory cannot perform field visits to compact units every day for sampling and testing. A further problem of samples taken from compact units is that measurements are taken in an irregular fashion. For example, the sampling of measurements can be performed within several hours, which leads to incorrect readings.

In order to avoid the stated problems, we adopt readings from daily tests at the Kirkuk unified-water treatment plant. This water treatment plant is one of the major projects in the governorate Kirkuk, and has a laboratory of its own. Moreover, the experienced staff can collect samples of raw water input to the treatment plant as well as the samples of the water output after sedimentation and after filtration. This

process is repeated three times every day, the period between samples for each days is two hours.

Considering the working hours for the laboratory staff, time for samples is limited between 8 am and 3 pm.

The information from the laboratory of the Kirkuk unified water treatment plant used in this thesis starts from the first day of the year 2010 and is collected , for a period of two years and a half.

This information is in the form of tests for raw water and water output from the sedimentation basins and water output from filtration. In addition, the amount of ALUM added to the water per day, and the amount of chlorine used per hour, the water temperature and flows for each sample are also recorded. figure 2.14 shows a part of the recorded data in the form of a table.

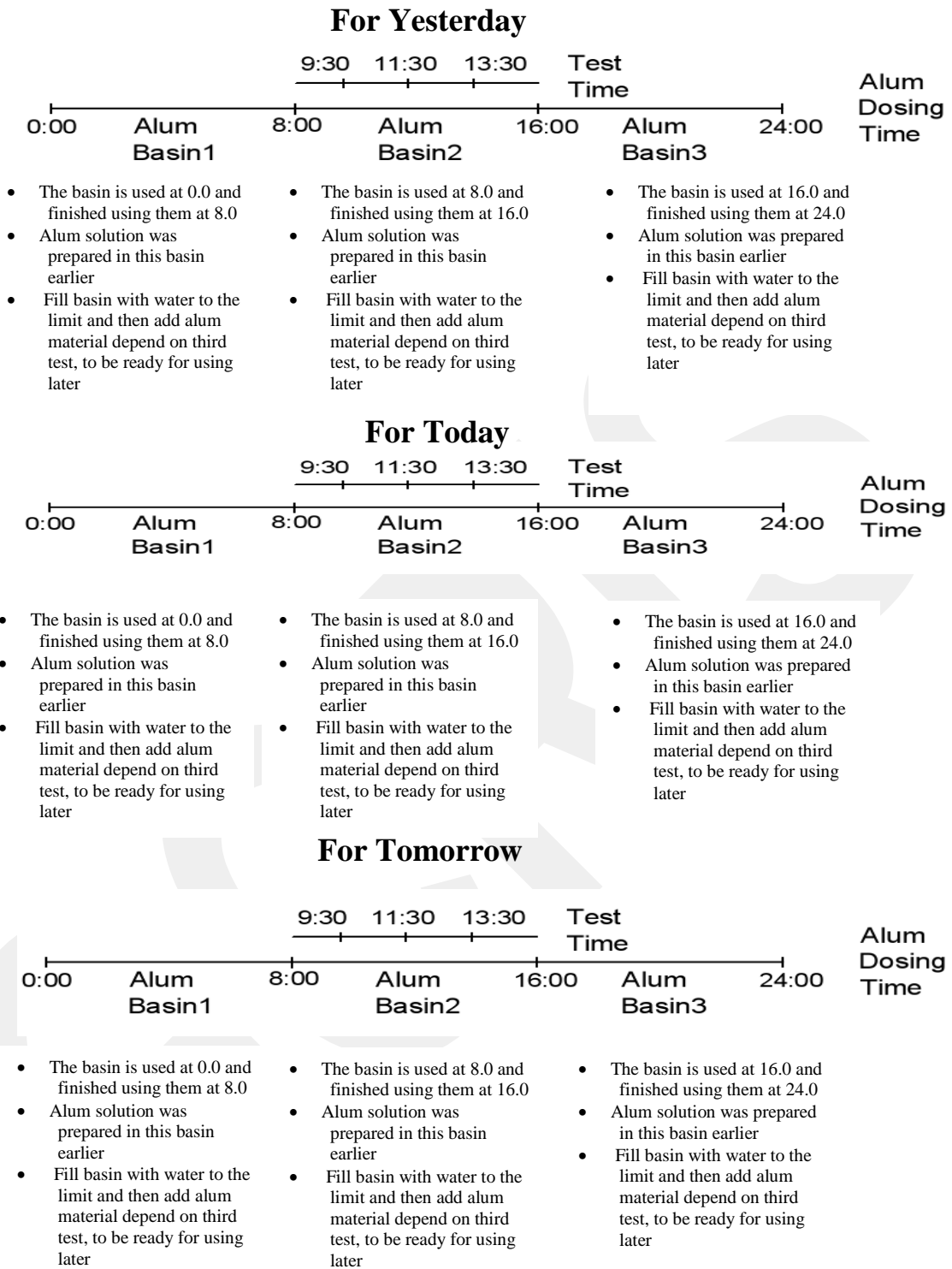
The amount of alum used per day, was determined by jar test, and the amount of chlorine used per hour, depends on the amount of water processed for consumers per hour.

We are interested in 5 parameters of raw water for our study. Turbidity (TU), PH, Total Suspended Solid (TSS), Total Dissolve Solid (TDS) and Electrical Conductivity(EC).

Subject		CHEMICAL TEST RESULTS																				
Location		KIRRIK UNIFIED WATER PLANT (KUWP)																				
Date		01 January 2010																				
ID AXIS	ID AXI B	ID AXIS C	ID AXIS D	SUPPLY (OUTLET WATER)					AFTER SEDIMENTATION					RAW (INLET WATER)					ALUM (mg/L)	CL2 (mg/L)	PH (pH)	
				CL2	EC	PH	TU	TDS	TSS	EC	PH	TU	TDS	TSS	EC	PH	TU	TDS				TSS
Friday	1-4pm	9:00am	12	4.4	333	7.3	3.5	345.0	9.0	339	7.4	37.0	335.0	21.0	342	7.5	123.0	348.0	66.0	24000	49	130000
		10:00am	13	4.2	337	7.4	3.7	351.0	7.0	342	7.6	33.0	344.0	17.0	347	7.6	128.0	352.0	57.0			
		11:00am	14	4.0	339	7.4	3.4	355.0	5.0	345	7.5	31.0	349.0	15.0	351	7.6	133.0	363.0	53.0			
Saturday	2-4pm	9:00am	13	4.9	335	7.4	3.0	352.0	11.0	339	7.5	35.0	355.0	22.0	342	7.6	231.0	362.0	59.0	48000	48	130000
		10:00am	14	4.5	337	7.5	3.7	358.0	13.0	345	7.6	31.0	361.0	18.0	345	7.7	211.0	373.0	51.0			
		11:00am	15	4.1	342	7.5	3.5	361.0	10.0	349	7.6	18.0	365.0	13.0	348	7.7	197.0	379.0	45.0			
Sunday	3-4pm	9:00am	13	5.0	332	7.3	1.7	433.0	8.0	336	7.4	33.2	380.0	46.0	345	7.6	115.0	355.0	44.0	22500	45	130000
		10:00am	14	4.7	338	7.4	1.5	421.0	6.0	339	7.5	38.5	324.0	38.0	349	7.7	123.0	371.0	42.0			
		11:00am	15	4.3	345	7.5	1.9	417.0	5.0	347	7.6	34.7	331.0	33.0	356	7.8	127.0	377.0	36.0			
Monday	4-4pm	9:00am	12	5.0	339	7.4	4.8	300.0	4.4	345	7.5	34.7	333.0	30.0	349	7.6	195.0	466.0	150.0	37750	49	110000
		10:00am	13	4.7	342	7.5	4.0	315.0	6.8	349	7.6	31.7	354.0	26.0	356	7.7	204.0	435.0	123.0			
		11:00am	14	4.2	349	7.5	3.3	323.0	8.3	353	7.6	27.5	366.0	22.0	361	7.8	213.0	423.0	115.0			
Tuesday	5-4pm	9:00am	12	4.8	339	7.3	5.0	700.0	13.0	343	7.4	29.6	766.0	34.0	349	7.6	166.0	388.0	88.0	20000	52	110000
		10:00am	13	4.4	345	7.4	4.6	659.0	15.0	348	7.5	25.3	745.0	31.0	355	7.7	169.0	383.0	76.0			
		11:00am	14	4.0	349	7.5	4.3	635.0	12.0	352	7.6	23.7	740.0	27.0	363	7.7	161.0	397.0	72.0			
Wednesday	6-4pm	9:00am	13	4.5	345	7.5	4.0	500.0	14.0	349	7.6	33.0	512.0	27.0	354	7.8	155.0	394.0	93.0	22500	50	110000
		10:00am	14	4.1	351	7.6	3.7	512.0	11.0	353	7.6	31.0	523.0	23.0	359	7.8	148.0	399.0	85.0			
		11:00am	15	4.0	355	7.6	3.3	523.0	10.0	356	7.7	30.0	529.0	20.0	363	7.8	142.0	393.0	79.0			
Thursday	7-4pm	9:00am	13	5.0	343	7.5	5.0	346.0	13.0	348	7.6	44.3	349.0	28.0	353	7.8	118.0	378.0	45.0	22000	48	110000
		10:00am	14	4.6	349	7.6	4.3	355.0	11.0	353	7.7	41.8	355.0	25.0	359	7.8	126.0	384.0	49.0			
		11:00am	15	4.2	352	7.6	4.0	362.0	10.0	358	7.7	36.4	363.0	21.0	366	7.8	125.0	399.0	55.0			
Friday	8-4pm	9:00am	15	4.5	357	7.3	3.0	333.0	13.0	361	7.4	31.0	376.0	23.0	365	7.5	65.0	387.0	57.0	11000	45	110000
		10:00am	16	4.2	359	7.4	3.5	345.0	11.0	365	7.5	34.7	365.0	25.0	368	7.6	69.0	389.0	52.0			
		11:00am	17	4.0	363	7.4	3.7	355.0	9.0	366	7.6	27.6	362.0	27.0	373	7.7	62.0	394.0	47.0			
Saturday	9-4pm	9:00am	15	4.3	353	7.4	2.5	234.0	15.0	355	7.5	27.8	365.0	21.0	359	7.6	78.0	392.0	49.0	9000	48	110000
		10:00am	16	4.0	356	7.5	3.4	255.0	12.0	359	7.6	23.8	361.0	18.0	366	7.7	72.0	395.0	41.0			
		11:00am	17	4.0	358	7.6	3.0	261.0	11.0	366	7.7	11.5	358.0	16.0	371	7.8	63.0	399.0	39.0			
Sunday	10-4pm	9:00am	14	4.0	351	7.5	3.3	333.0	10.0	355	7.6	21.8	386.0	33.6	362	7.7	53.0	400.0	53.0	11000	44	110000
		10:00am	15	4.0	353	7.5	3.0	341.0	7.0	358	7.7	18.7	376.0	27.5	367	7.8	48.0	411.0	47.8			
		11:00am	16	4.0	355	7.6	2.7	348.0	8.0	362	7.7	12.0	364.0	24.7	374	7.8	42.0	421.0	41.7			

Figure 2.14 Explanation daily tests

In order to build a valid model of the sedimentation process, we need to understand the relation of the different measurements and the ALUM concentration provided at the input of the process. ALUM is added to the raw water from one of three basins. The ALUM concentration in these basins is prepared every day based on measurements made the day before. In addition, the sedimentation process does not happen instantaneously. If ALUM is added to the raw water, it takes about 2 hours until this water exits the sedimentation process. Figure 2.15 shows a timeline of the events taking place in the water treatment plant.

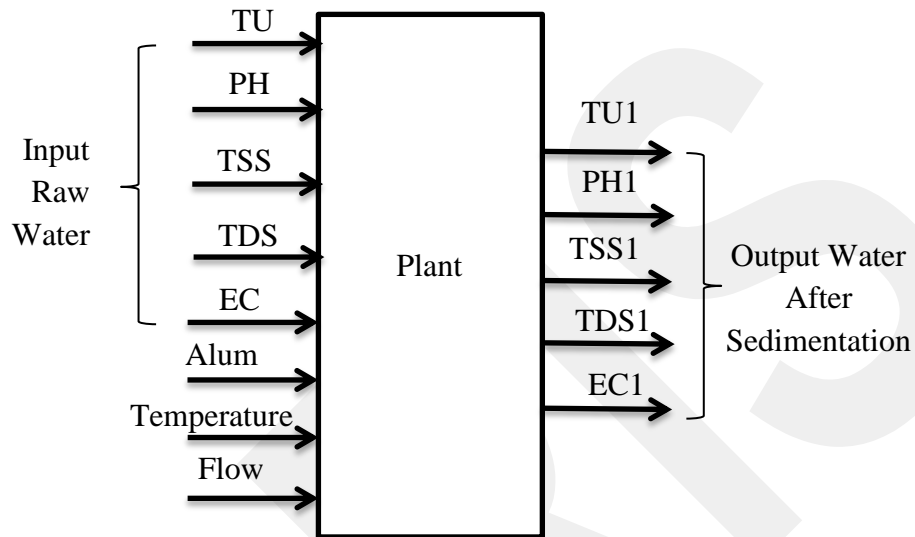


**Figure 2.15** Basin using time and testing time

According to this timeline, the measurement data are divided into inputs and targets.

### 2.2.4. Training and results for our plant neural network

The input parameters of the plant are the raw water parameters (TU, PH, TSS, TDS, EC), alum amount determined by jar test, temperature and water flow rate is considered as input data. The output parameters for the plant are the water parameters ( TU1, PH1, TSS1, TDS1, EC1 ) after sedimentation. figure 2.16 illustrates this explanation



**Figure 2.16** Plant block diagram

Table 2.1 and 2.2 shows examples of the structure of the real data we used for training. In total, we have 2022 instances of these data, that were, obtained from Kirkuk unified water treatment plant. All this instances represent real measurements for a period of two and half years.

**Table 2.1** Real measurements for input data

Input							
TU	PH	TSS	TDS	EC	Alum (mg/L)	Temp C <sup>0</sup>	Flow (L/h)
231	7.6	59	362	342	7.69	13	13000000
211	7.7	51	373	345	7.69	14	13000000
123	7.61	44	267	345	12.8	13	13000000

**Table 2.2** Real measurements for target data

Target				
TU1	PH1	TSS1	TDS1	EC1
21	7.6	18	361	345
18	7.6	13	365	349
33.2	7.4	46	200	336

In order to use the data for training, we first normalize the data such that all values are in the range from -1 to 1. The formula for normalization is as follows :

$$X_{nom} = \left( \frac{X - X_{min}}{X_{max} - X_{min}} \right) 2 - 1$$

This formula is applied to all input and target parameters. The maximum and minimum values for the different parameters are shown in the following tables (Table 2.3, Table 2.4).

**Table 2.3** Min and max real data for input data

Input							
TU max	PH max	TSS max	TDS max	EC max	Alum (mg/L)max	Temp C° max	Flow (L/h) max
650	8.8	372.1	466	462	19.9	40	13500000
TU min	PH min	TSS min	TDS min	EC min	Alum (mg/L)min	Temp C° min	Flow (L/h) min
22	7.5	9	145	110.1	1	6	10000000

**Table 2.4** Min and max real data for target data

Target				
TU1 max	PH1 max	TSS1 max	TDS1 max	EC1 max
129	7.9	167	766	458
TU min	PH min	TSS min	TDS min	EC min
7	7.3	4	133	169

For illustration, we now apply the normalization to the input data in table 2.1 and the target data in table 2.2. The result is shown in the following tables.

**Table 2.5** Input normalized data

Input							
TU	PH	TSS	TDS	EC	Alum (mg/L)	Temp C <sup>0</sup>	Flow (L/h)
-0.33	-0.84	-0.72	0.35	0.31	-0.29	-0.58	0.71
-0.39	-0.69	-0.76	0.42	0.33	-0.29	-0.52	0.71
-0.67	-0.83	-0.8	-0.23	0.33	-0.24	-0.58	0.71

**Table 2.6** Target normalized data

Target				
TU1	PH1	TSS1	TDS1	EC1
-0.77	0	-0.82	-0.27	0.21
-0.81	0	-0.88	-0.26	0.24
-0.57	-0.66	-0.48	-0.78	0.15

It has to be noted that our neural network model is constructed for the normalized data. That is if we want to recover the original data values, we can use the following formula .

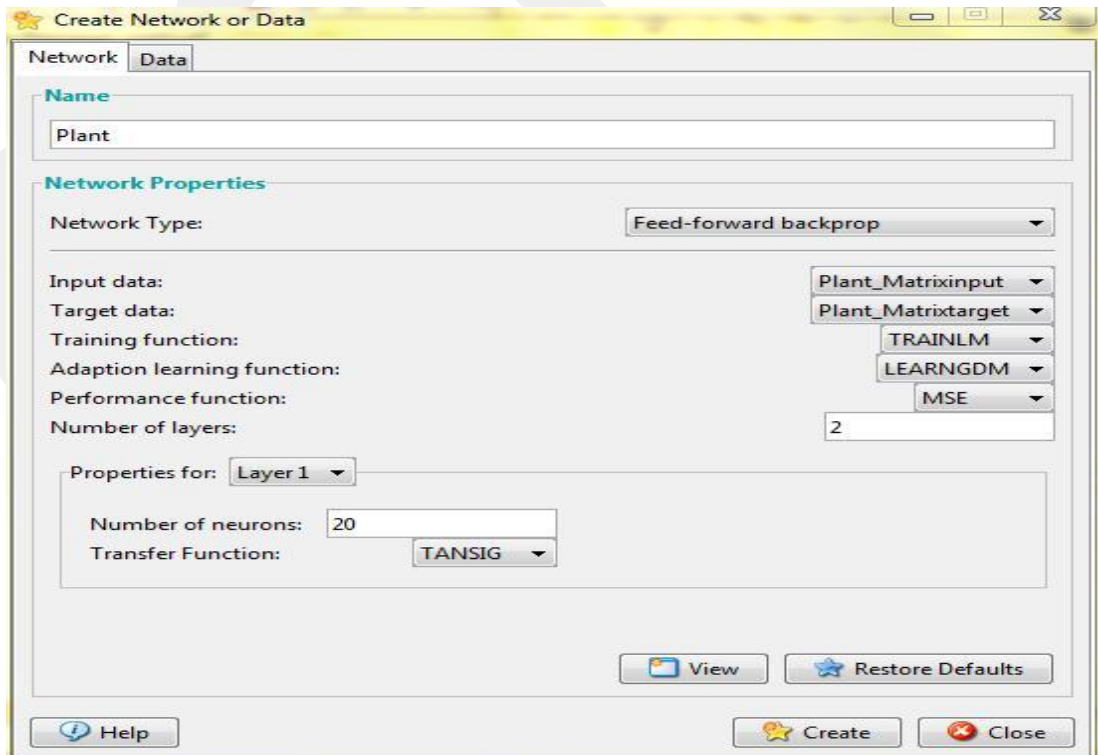
$$X = \left( \frac{X_{nom} + 1}{2} \right) (X_{max} - X_{min}) + X_{min}$$

With the processed input and training data, we use the Matlab Neural Networks Toolbox to find a neural network model of the sedimentation process. When applying the toolbox, we choose the following settings shown in Table 2.7.

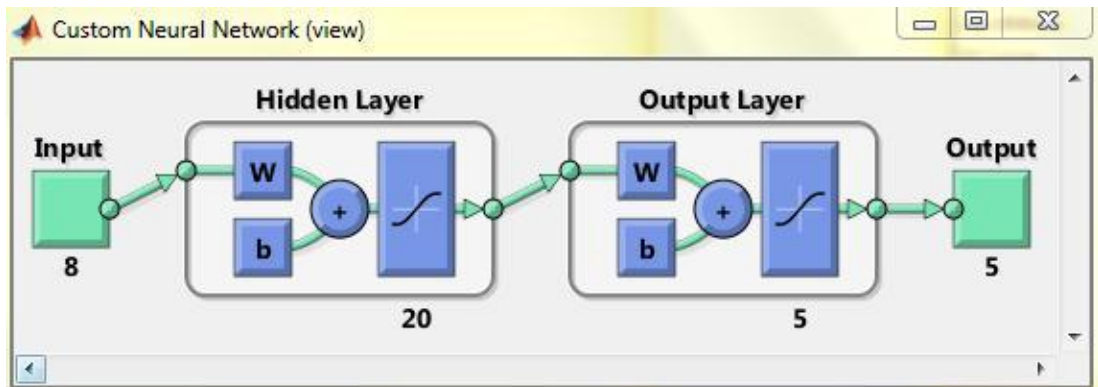
**Table 2.7** Neural network function

Type of network	feed-forward back-propagation
Training function	TRAINLM
Adaption learning function	LEARNGDM
Performance function	MSE
Number of layers	2
Properties for layer 1	Number of neurons 20 and Transfer Function TANSIG
Properties for layer 2	Transfer Function TANSIG

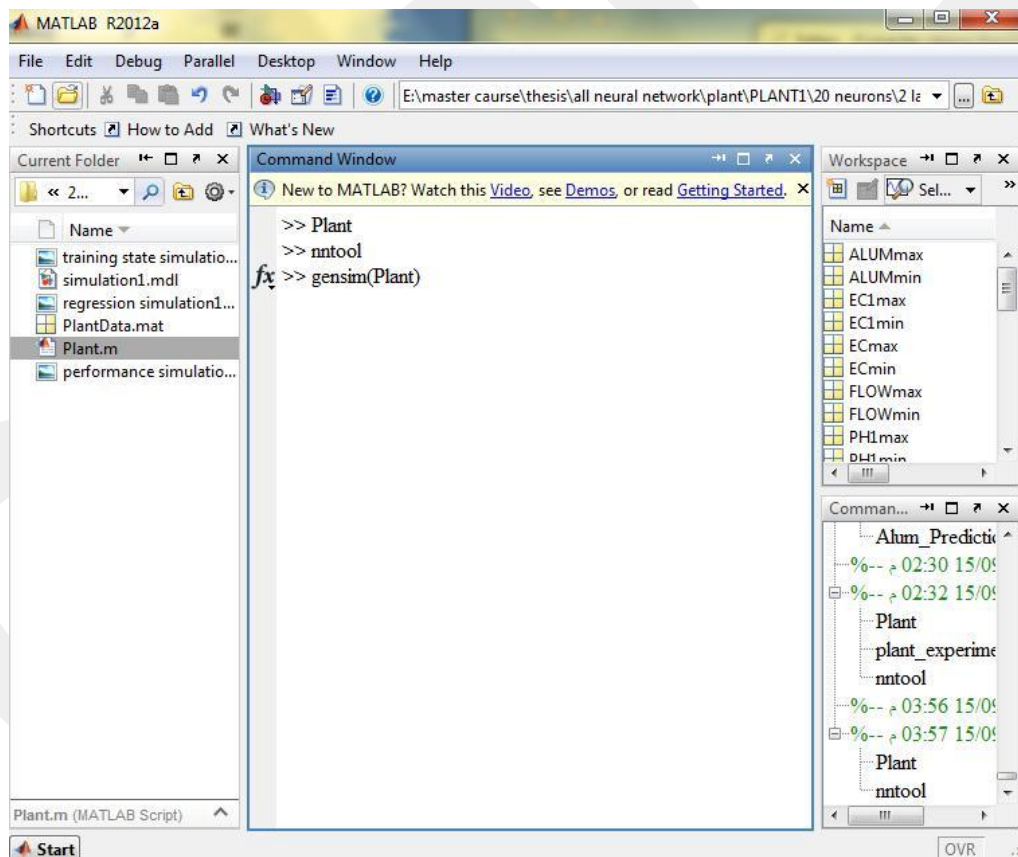
Figure 2.17 and 2.18 show the related Matlab input.



**Figure 2.17** Neural network toolbox to create Simulink for plant

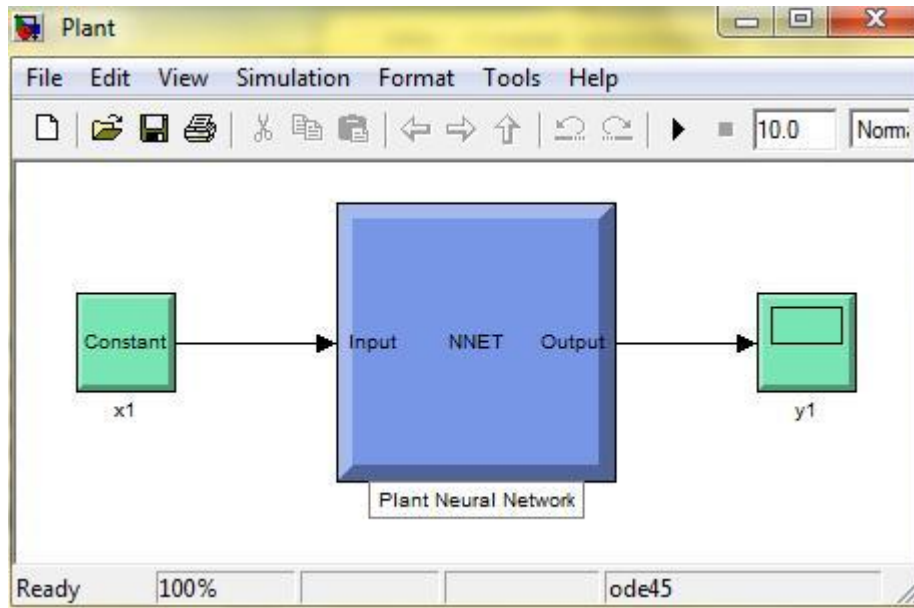


**Figure 2.18** Check our data we choose to create plant Simulink



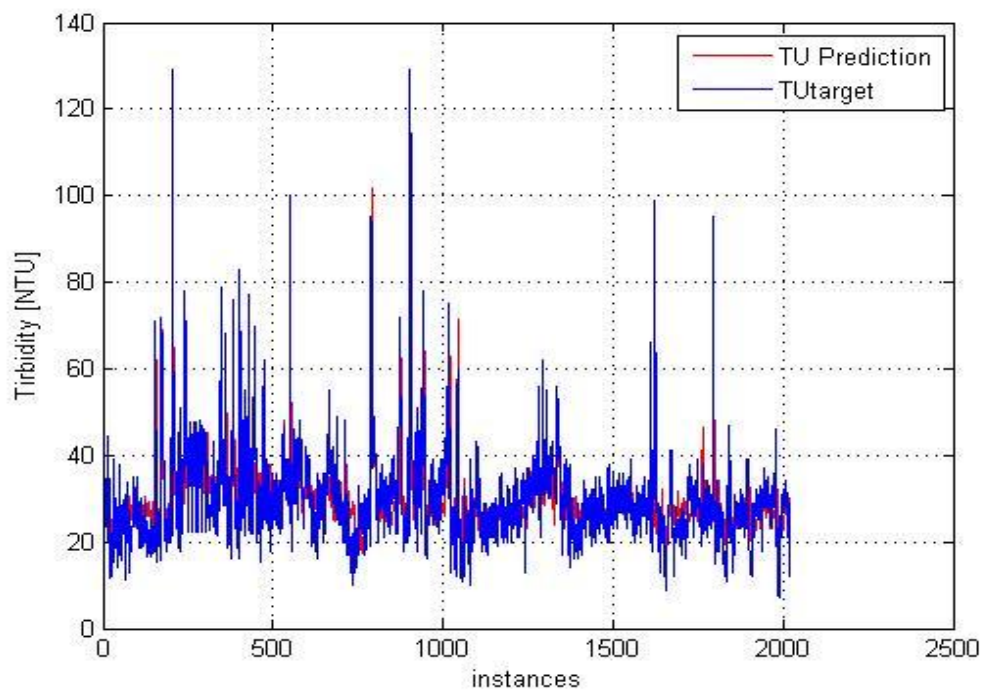
**Figure 2.19** In command window type (gensim) to generate plant Simulink

After training, we obtain a Simulink model as in figure 2.20 of the sedimentation process.

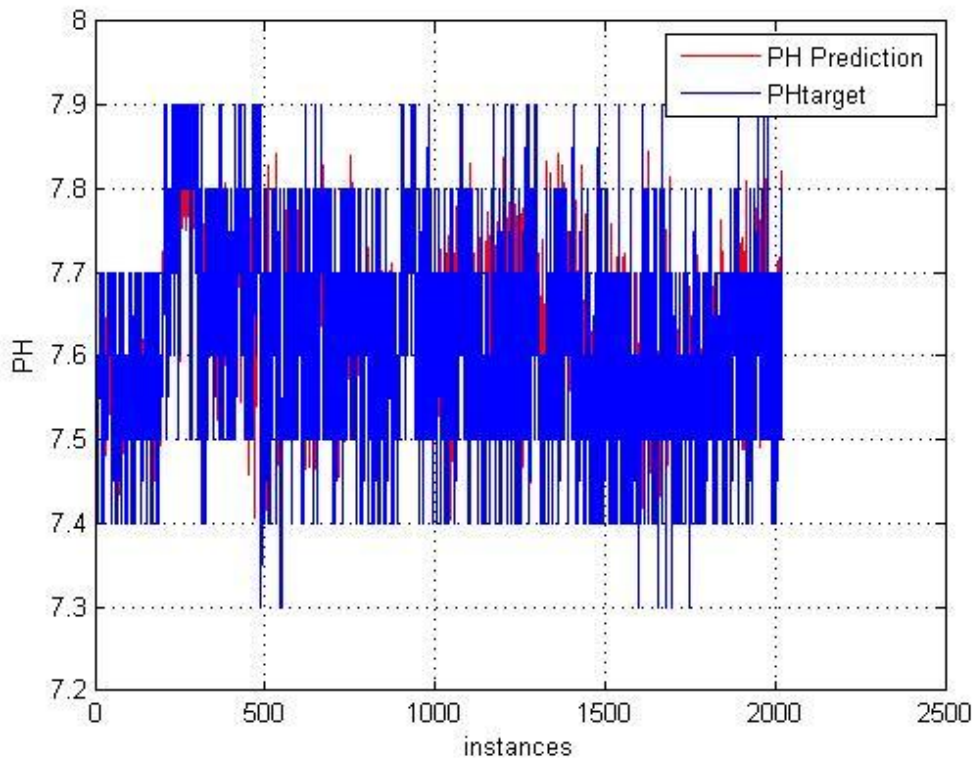


**Figure 2.20** Plant Simulink

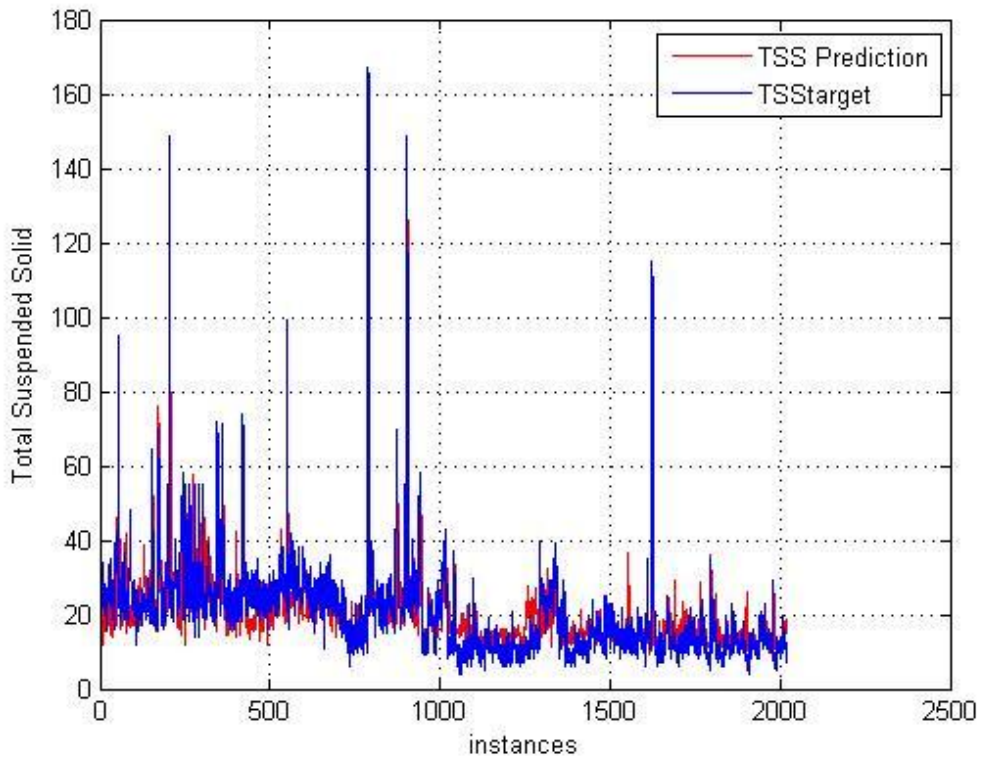
In order to validate the model for our research, we now simulate the sedimentation process with the input data instances used in the training process and compare the simulation output to the measurement target data. The result is shown for the different parameters TU, PH, TSS, TDS, EC in the figures 2.21 to 2.25.



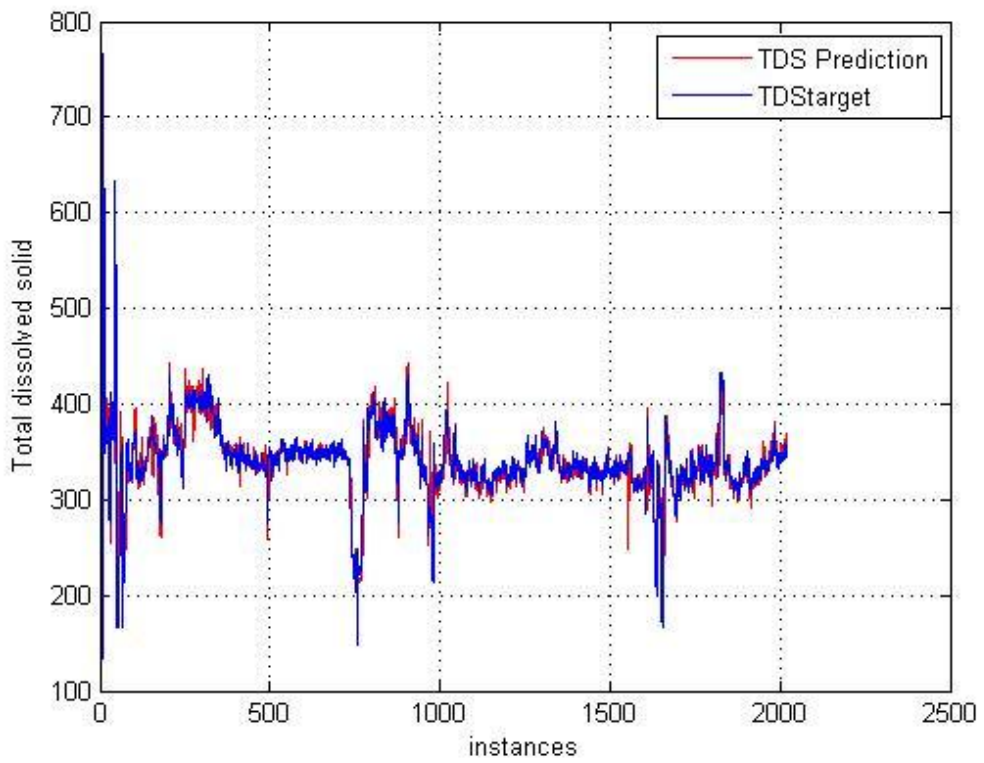
**Figure 2.21** TU prediction compared with TU target



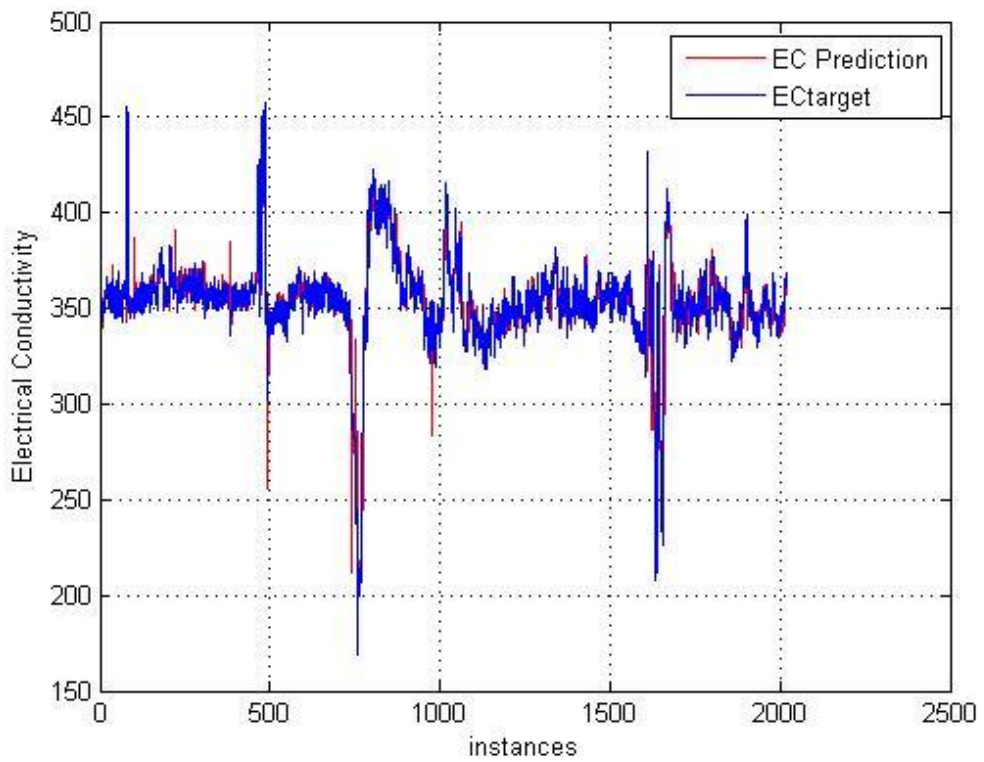
**Figure 2.22** PH prediction compared with PH target



**Figure 2.23** TSS prediction compared with TSS target



**Figure 2.24** TDS prediction compared with TDS target



**Figure 2.25** EC prediction compared with EC target

It is readily observed from the validation experiment that the model does not perfectly match the target data. However, since our research is not focused on the exact control of the Kirkuk water treatment plant but on the proof of concept of a control method for compact units, we employ this model in the remainder of this thesis.

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## CHAPTER III

### CONTROL METHOD FOR SEDIMENTATION

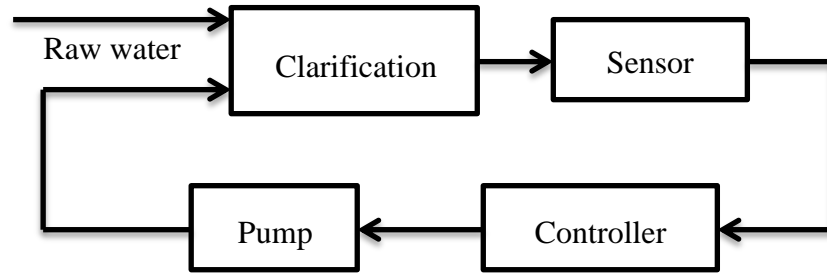
In this chapter, we study the automatic control of water treatment plants with the objective of controlling compact units and with data supplied from the Kirkuk water treatment plant. We propose to use the combination of a feedforward controller, that is represented by a neural network and a feedback fuzzy controller. First, Section 3.1 states basic requirements for the control system. Then, Section 3.2 elaborates our control method .

#### 3.1. CONTROL REQUIREMENTS

##### 3.1.1. Hardware modifications

Many operations in a compact unit are performed manually, as described in Chapter 3. In order to realize the automatic control as proposed in this thesis, several modifications in the sedimentation process are required as follows.

- **Sensors** : in order to realize feedback control, the input data (raw water parameters, temperature and flow) as well as the output data (water parameters after sedimentation) have to be measured. Such sensors are available for example in [15].
- **Variable speed pump** : A pump with adjustable speed is needed to change the concentration of ALUM that is added to the raw water in real time. Such pump can either be realized as DC or AC pump.
- **Digital Controller** : The processing of sensor data, evaluation of the control algorithm and modification of the pump speed requires a digital controller device. In industrial practice this device is realized by a programmable logic controller (PLC) such as [16]



**Figure 3.1** Control process schematic

In the remainder of the thesis, we assume that the above items are realized in a satisfactory form in the water treatment plant. Hence, we focus on the development of the control method.

### 3.1.2. Desired operation

To monitor the performance of the designed automation system and knowledge of its efficiency, we use the following table (Table 3.1) for the classification of water quality after sedimentation. It can be seen that the most important parameters are the turbidity (TU) and the PH value of the water, since they have a direct impact on the consumers' health.

**Table 3.1** Efficient sedimentation process

<b>Turbidity</b>	<b>PH</b>	<b>Classify</b>
<b>TU ≤ 20</b>	<b>7.2 ≤ PH ≤ 7.8</b>	<b>Very good</b>
<b>TU ≤ 30</b>	<b>7 ≤ PH ≤ 8</b>	<b>Good</b>
<b>TU ≤ 35</b>	<b>6.8 ≤ PH ≤ 8.2</b>	<b>Pass</b>
<b>TU ≤ 40</b>	<b>6.5 ≤ PH ≤ 8.5</b>	<b>Acceptable</b>
<b>TU &gt; 40</b>	<b>6.5 &gt; PH &gt; 8.5</b>	<b>Bad</b>

The parameter values were adopted on the basis of

- When the turbidity in the raw water become 25 NTU or less, then it is not required to add ALUM to the raw water. Hence, this value can be seen as a good reference point for the performance of the sedimentation process.
- To the allowable limits for pH as shown in Table 1.2, the allowable limits are 6.5 to 8.5. Knowing that the best pH value is 7.5 any deviation of this value negative effect for the PH.

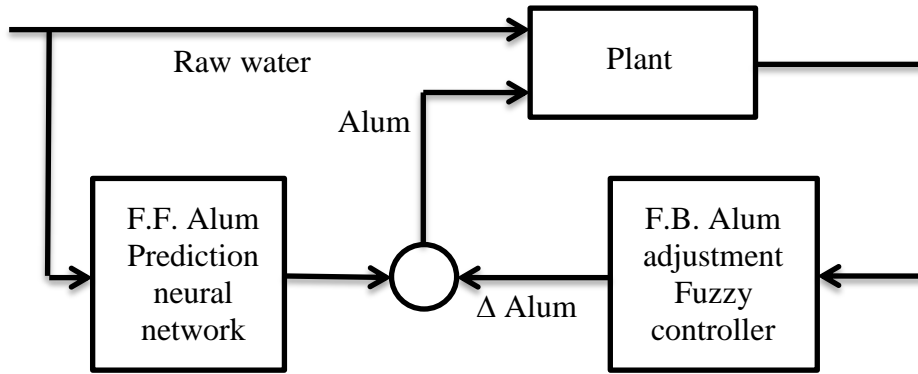
## **3.2.CONTROL METHOD**

### **3.2.1. Properties**

Since there is no analytic model for plant to be used for the controller design, we build a controller based on the measurement data from the sedimentation process. It is known from the water treatment plant operation that the ALUM concentration has to be chosen based on the parameters of the raw water. That is, we need a functional relationship between the raw water parameters and the ALUM concentration to be added to the raw water. In addition, if the water quality after sedimentation can be measured, this information can be used to correct the ALUM concentration in case the water quality is not good enough. Finally, it needs to be taken into account that there is a time delay in the water treatment plant. It takes about two hours to complete the sedimentation process.

### **3.2.2. Proposed control architecting**

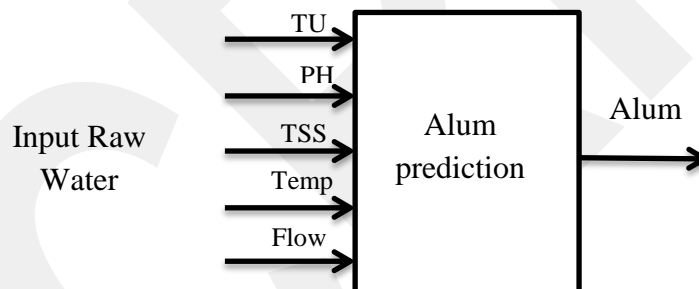
The control input for the sedimentation process is the ALUM concentration. We propose to determine the appropriate ALUM concentration using the control architecture in figure 3.2. The functional relationship between the input parameters of raw water and the ALUM concentration is used to predict the required ALUM concentration in a feedforward path. In order to determine this functional relationship, we suggest training a neural network with the real measurement data from the Kirkuk water treatment plant. Note that the ALUM concentration in these data is determined using the jar test. In addition to the ALUM prediction, we use feedback to correct the ALUM concentration in case the measured water quality is not suitable. Since no analytical model of the sedimentation process is available, we use fuzzy logic control to realize this feedback.



**Figure 3.2** Alum control schematic

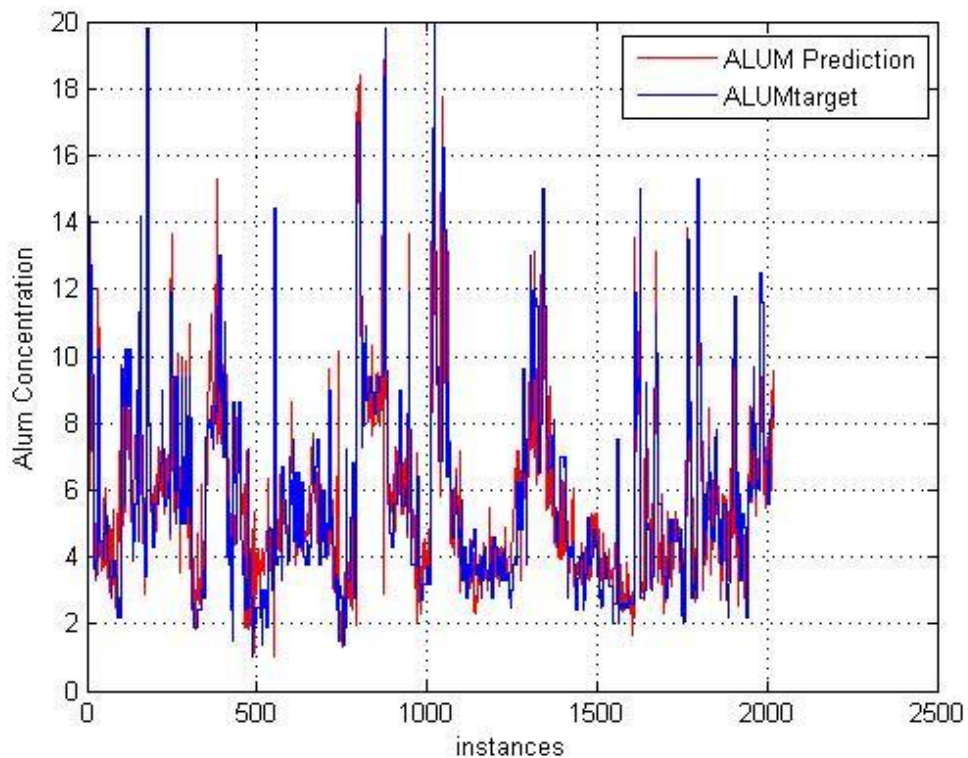
### 3.2.3. Alum prediction

For the input parameters of the alum prediction, the raw water parameters TU, PH, TSS, temperature, water flow rate are considered as input data. The output parameter for the alum prediction is the alum concentration determined by jar test. figure 3.3 illustrates this explanation.



**Figure 3.3** Alum prediction plant block diagram

For training the alum prediction neural network we follow the same procedure as in Section 2.2.4 including normalization of data. The result is shown in figure 3.4 by comparing the predicted ALUM concentration with the target concentration. The figure shows that the predicted value of the ALUM concentration is always very close to the target value. In practice, this means that we can use the neural network model to determine a suitable ALUM concentration. We recall that the neural network is based on data from jar tests and experience of human operators in the real water treatment plant. Because of this reason, the neural network model can replace the human operator in the water treatment plant because it provides the same decisions. Looking at Figure 3.2, it remains to design the fuzzy control.

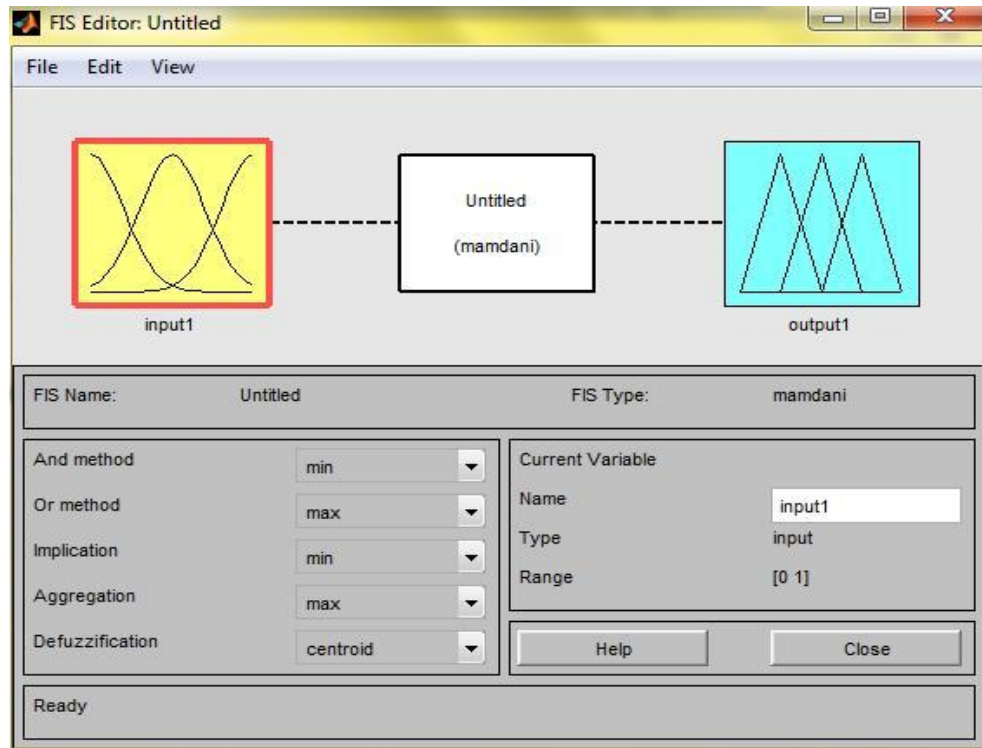


**Figure 3.4** Alum prediction comparison with alum found by control

### 3.2.4. Fuzzy control with TU measurement

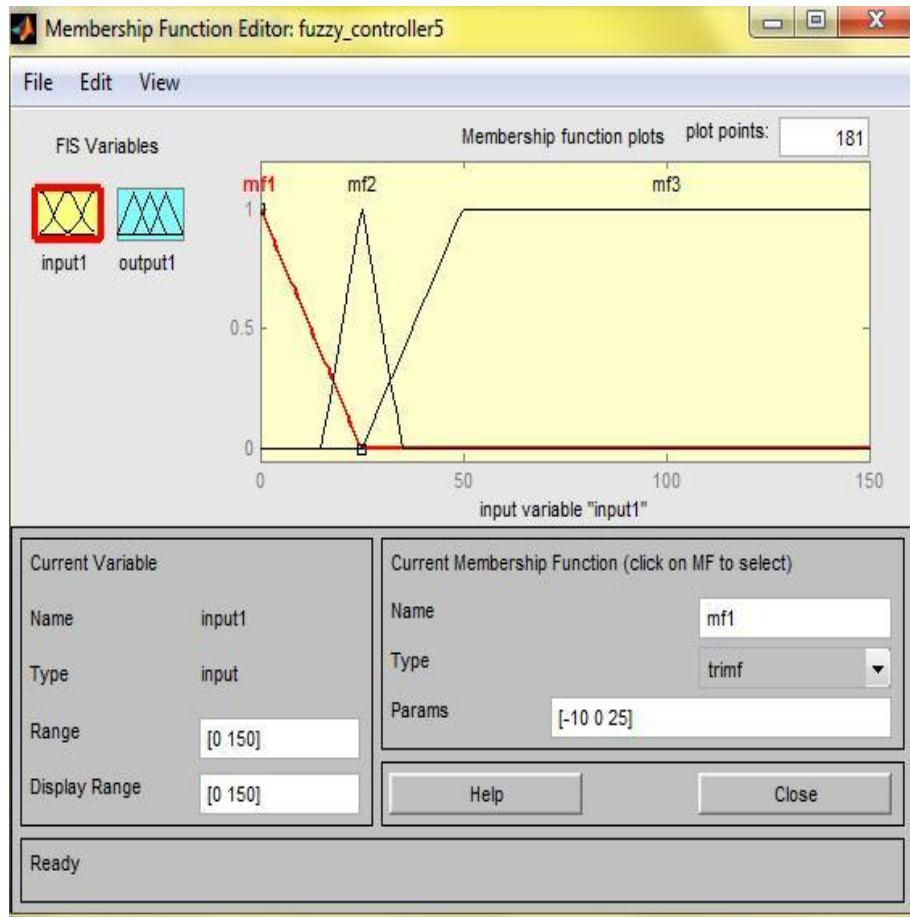
Fuzzy logic control is based on the concept of fuzzy logic, where a continuous valued variable is mapped to the range between 0 and 1 instead of the Boolean values 0 and 1. The inputs of a fuzzy control system are usually processed by a set of such fuzzy logic rules, denoted as a fuzzy set. The evaluation of the rules is done using so-called membership functions, and leads to the fuzzified input. It describes the degree of membership of the input in the members of the fuzzy set. Next, the fuzzified input is modified using a set of IF THEN rules. These rules describe the dependency of the fuzzy controller output on the degree of membership in the fuzzified input. Based on these membership functions, a de-fuzzyfication step is applied to determine a real value for the output. That is, in principle, fuzzy control requires the design of three components: Membership functions for the fuzzyfication, IF THEN rules and membership functions for the de-fuzzyfication. Fuzzy Control consists of three sections, input section that mean membership function defined as curve show location input data into input space and between 0 and 1.

We now describe the fuzzy controller used for the ALUM correction. We use the Fuzzy Control Toolbox in Matlab in order to realize the fuzzy controller. The main graphical user interface to this toolbox is shown in figure 3.5.



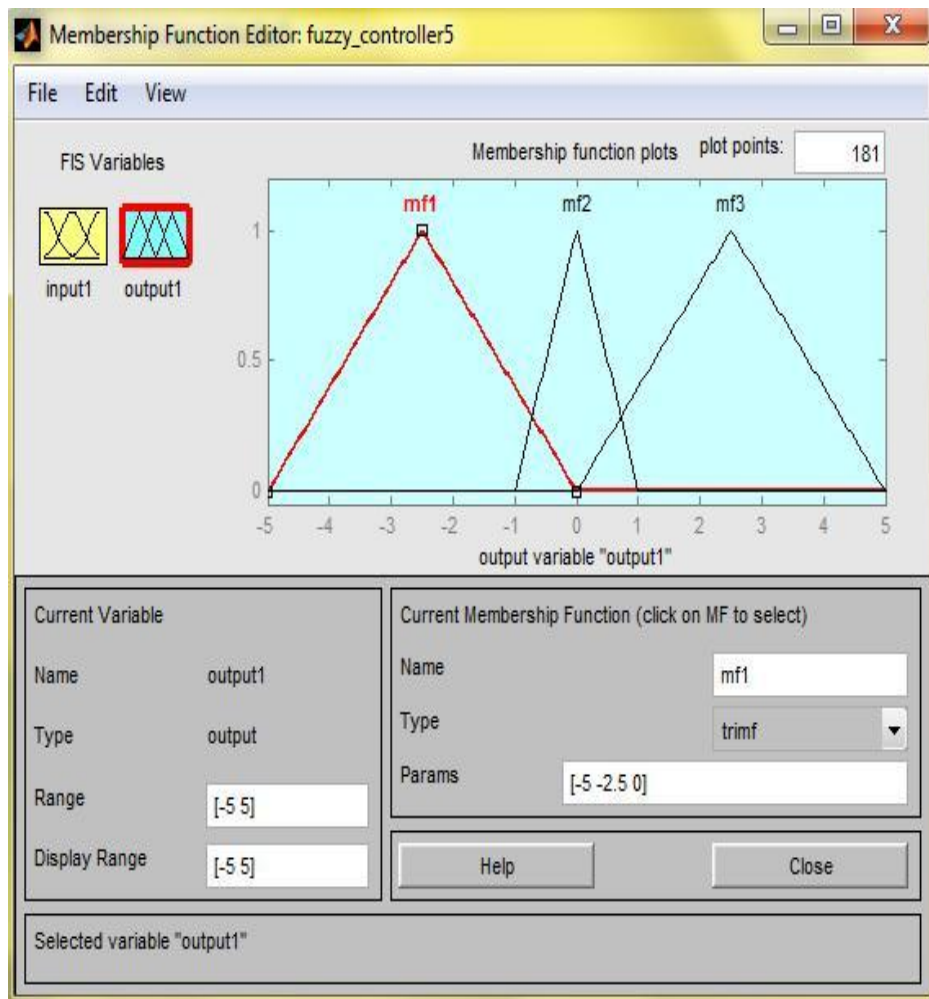
**Figure 3.5** Fuzzy logic control panel

Regarding the fuzzyfication, we consider the desired system operation as described in Table 3.1 for the value of TU. We consider a possible range of TU (after sedimentation) between 0 and 150. This range is chosen because the maximum value of TU observed after sedimentation is 129 as shown in Table 2.4. It is desired to obtain a TU value of about 25 or less. We divide the possible TU values into three fuzzy sets, that are described by the membership functions mf1, mf2 and mf3. Mf1 represents a low turbidity below 30 which means that the sedimentation process is very successful. mf2 represents an acceptable turbidity which means that the sedimentation process is good. mf3 represents a high turbidity which means that the sedimentation process is not successful. The membership functions are shown in Figure 3.6. We use a trapezoidal membership function for mf3, since we anticipate that very large values of the TU value should lead to the same value of the controller output.



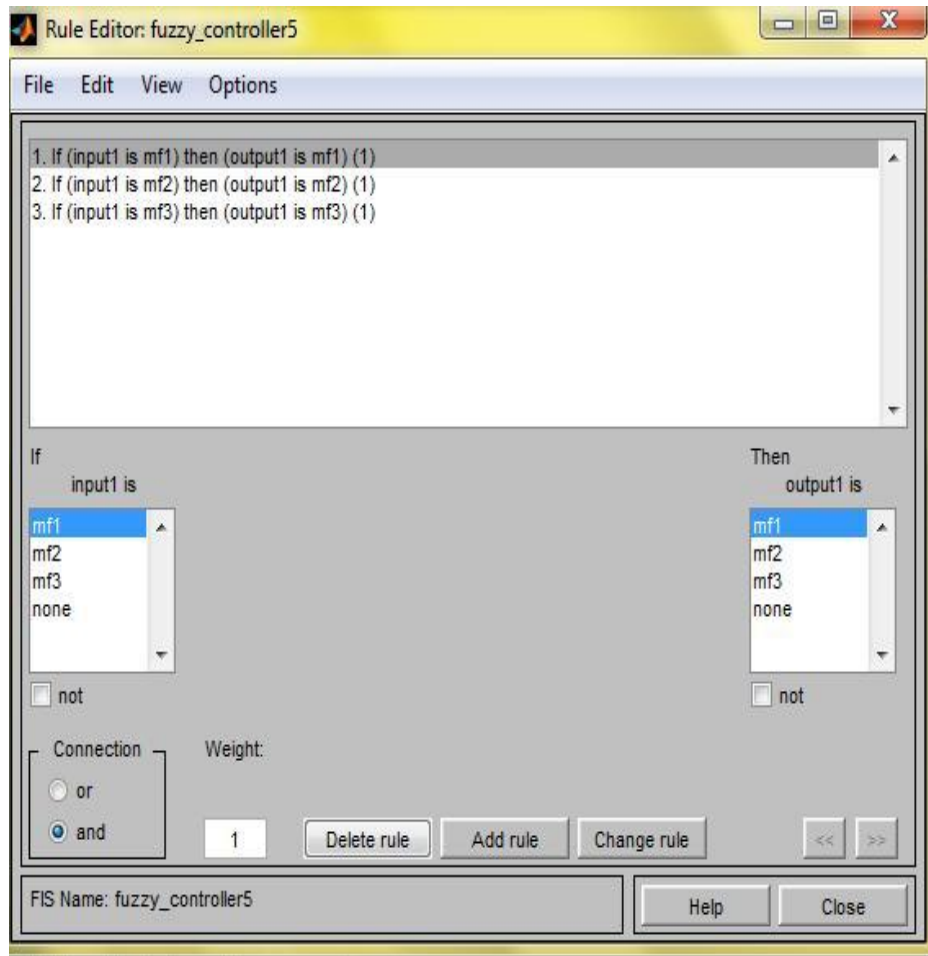
**Figure 3.6** Membership function for fuzzy control one input TU panel

For the de-fuzzyfication, we allow to increase/decrease the ALUM concentration by a value of 5 as shown in figure 3.7. It is intended to relate mf1 from the input to mf1 of the output, mf2 from the input to the mf2 of the output and mf3 from the input to mf3 of the output. Hence, mf1 can be associated with “decrease”, mf2 can be associated with “no change” and mf3 can be associated with “increase” of the ALUM concentration. We use mean of maxima (mom) as de-fuzzyfication rule.



**Figure 3.7** Membership function output panel

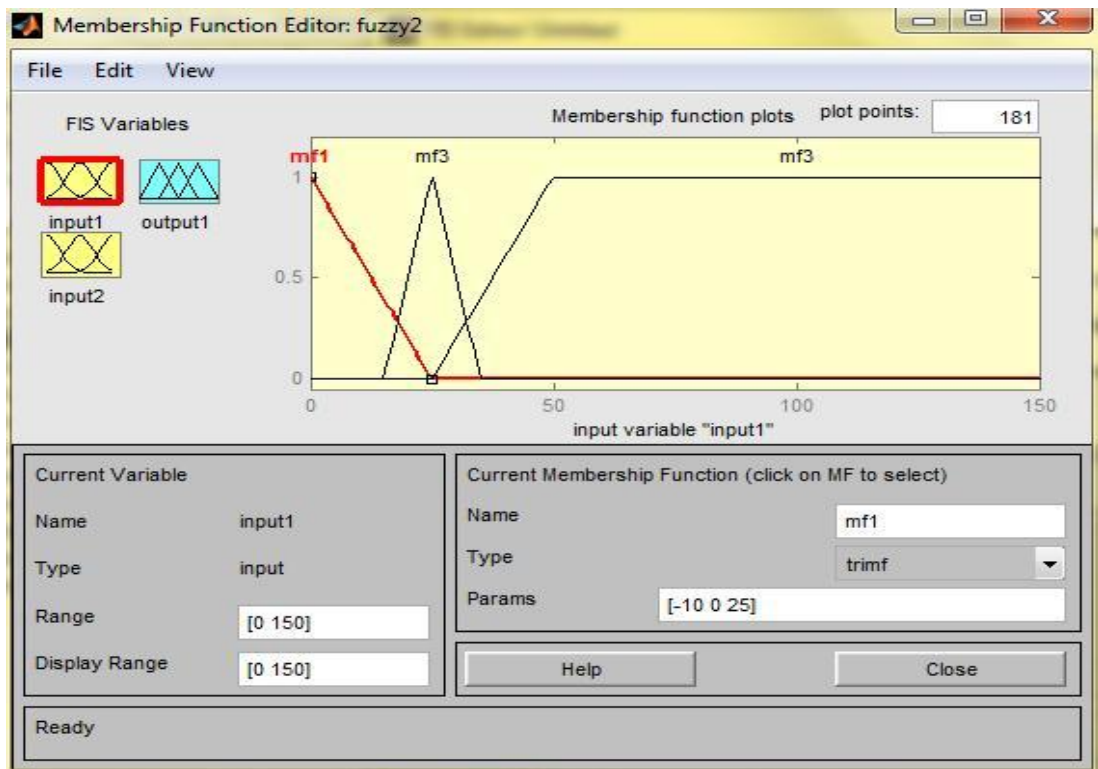
Finally, we consider the choice of the IF THEN rules. Following the previous description, three IF THEN rules are used as shown in Figure 3.8. In summary, the fuzzy controller uses the TU measurement after the sedimentation process as input and adjusts the ALUM concentration if TU is not satisfactory.



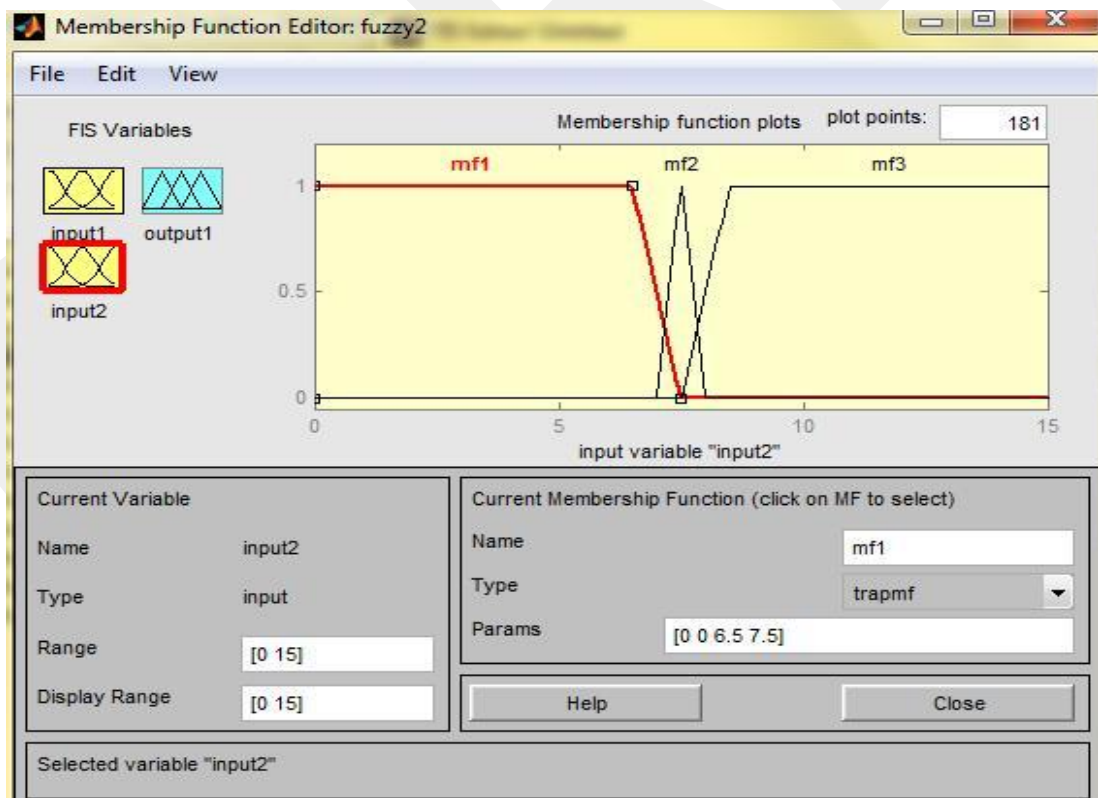
**Figure 3.8** If-then rule panel

### 3.2.5. Fuzzy control with TU and PH measurement

The previous section explains fuzzy control with a single input TU. We now add the measurement of PH as an additional value, because PH is the second important parameter for water quality. Also the PH concentration depends on the ALUM concentration added to the raw water. As is shown in Table 1.2 and Table 3.1, the minimum and maximum value for PH is (6.5- 8.5) respectively. Any change in water component concentration effect directly to the PH value. Figure 3.9 to 3.11 describe the membership functions for two inputs and one output in the fuzzy logic controller. Figure 3.12 shows the IF THEN rules.



**Figure 3.9** Membership function for fuzzy control with two inputs TU panel



**Figure 3.10** Membership function for fuzzy control with two inputs PH panel

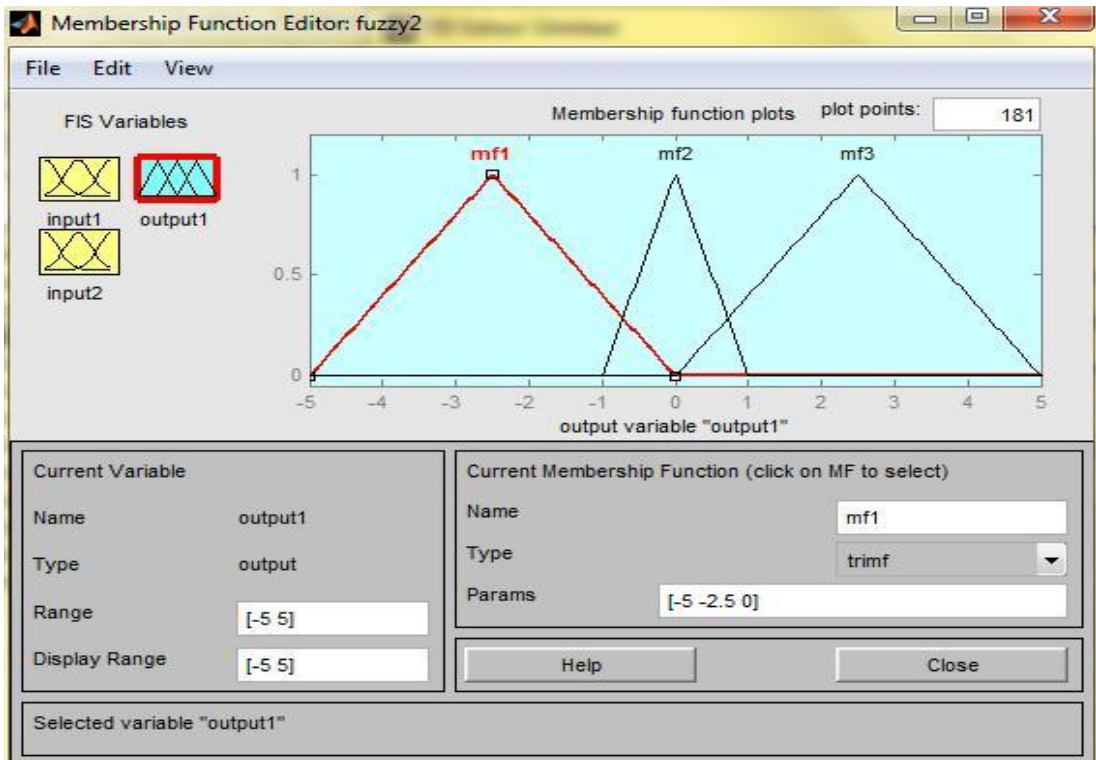


Figure 3.11 Output membership function for fuzzy control with two inputs

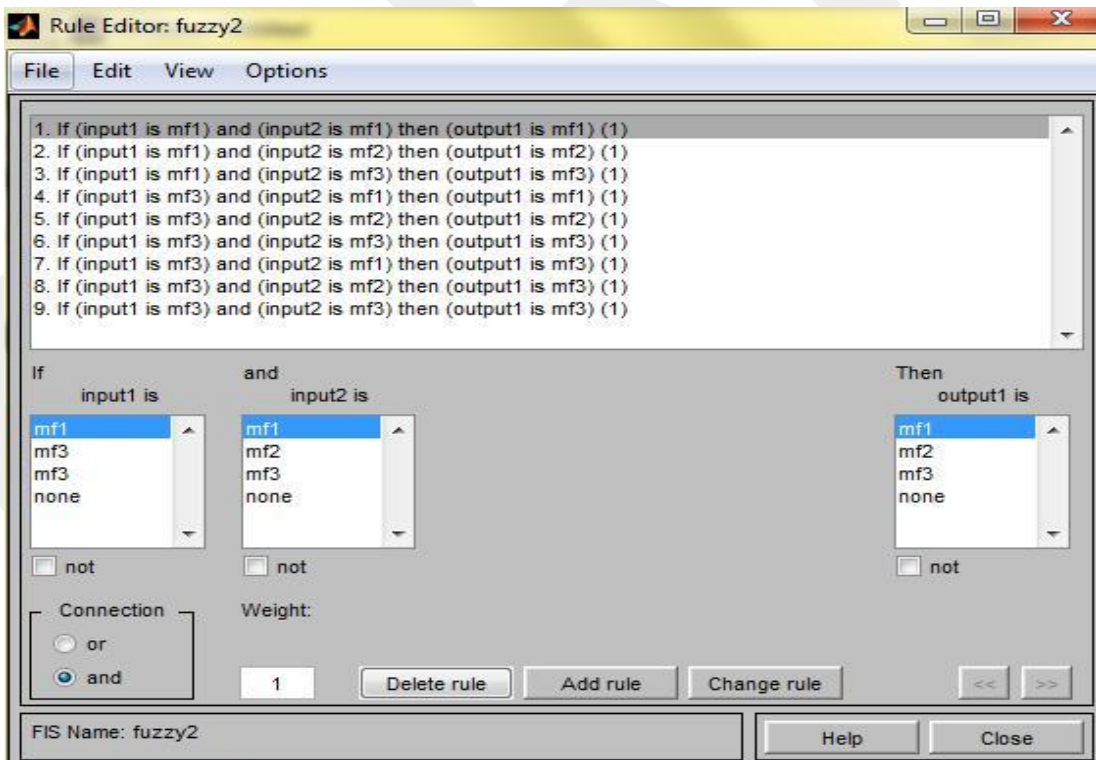


Figure 3.12 If-then rule for fuzzy control with two inputs

### 3.2.6. Results

We perform simulations of the overall water treatment plant using the control architecture described in Section 3.2.2. In all our experiments, we apply raw water instances at the input of the system and measure the quality of the water after sedimentation . Figure 3.13 and 3.14 show Simulink for 1 input and 2 input respectively.

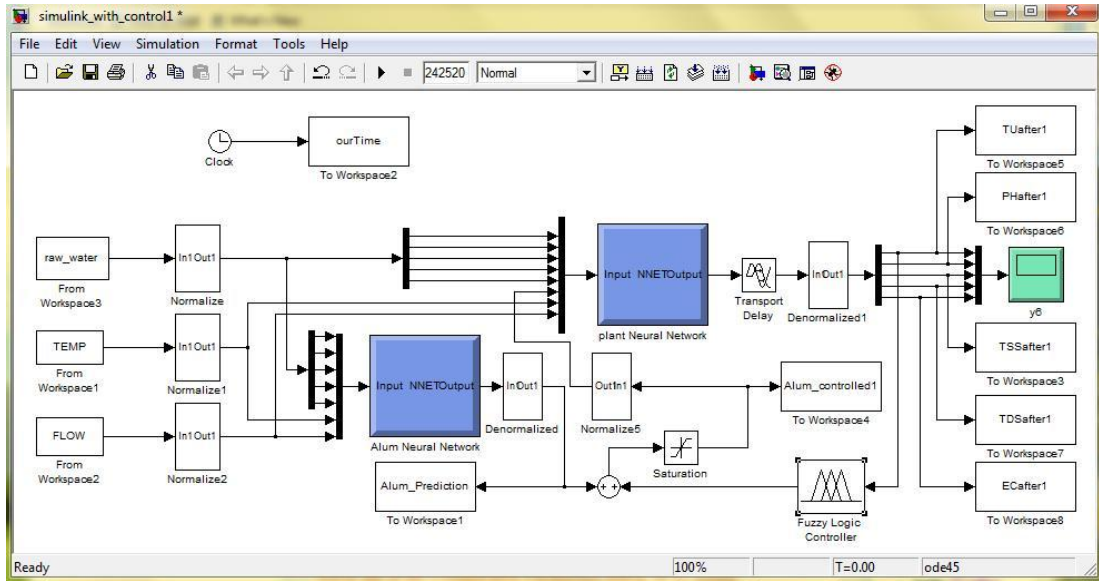


Figure 3.13 Simulation for fuzzy control with one input

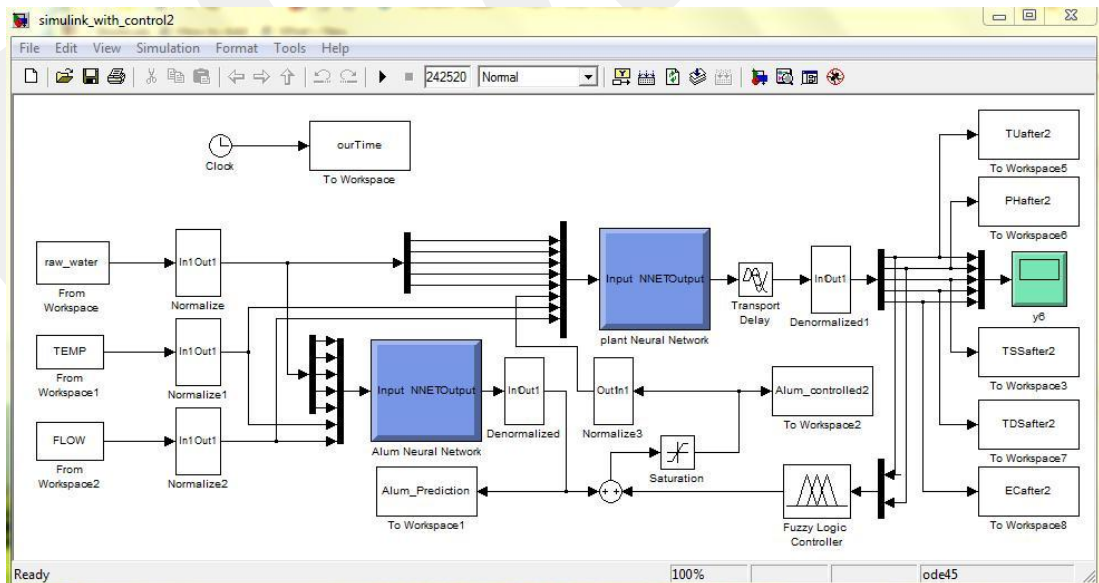
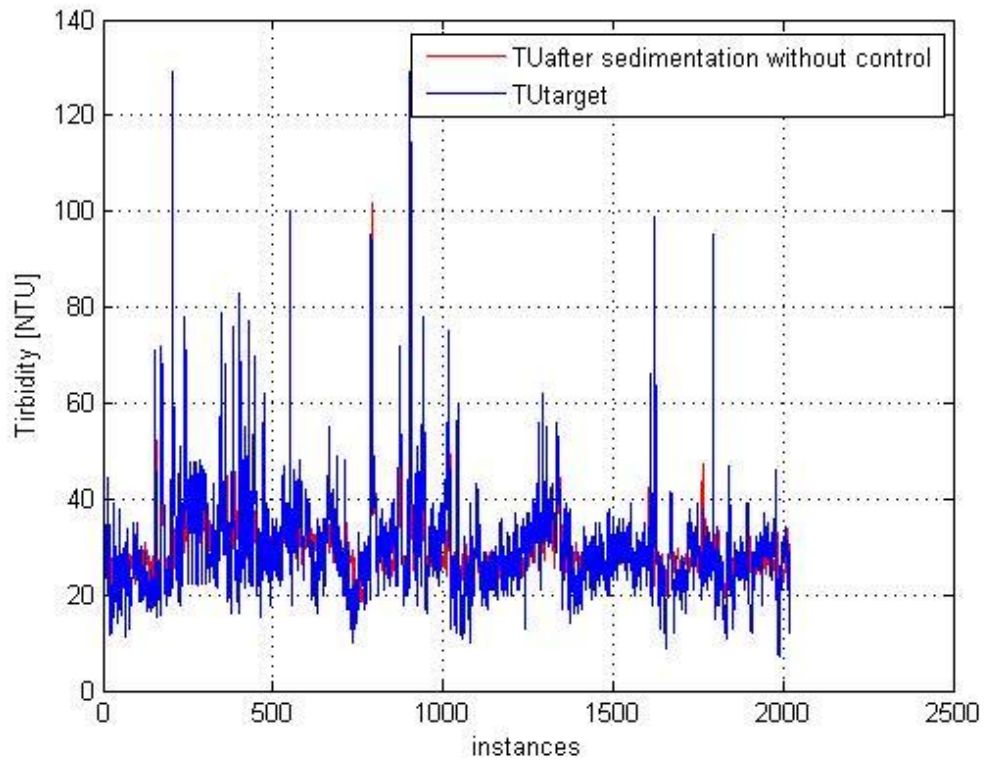
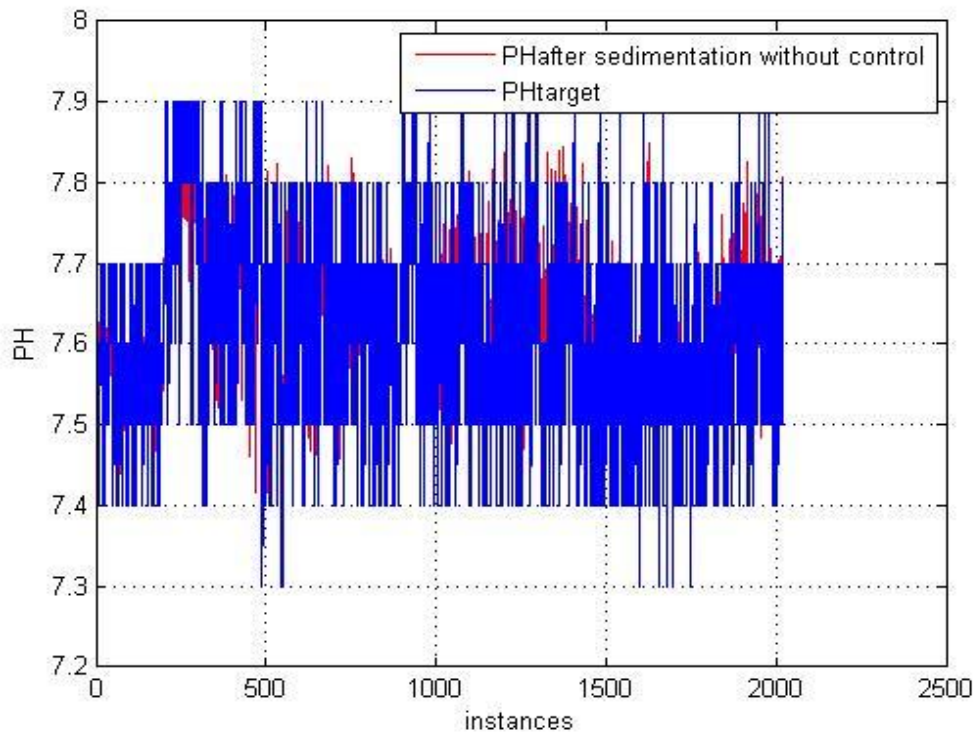


Figure 3.14 Simulation for fuzzy control with two inputs

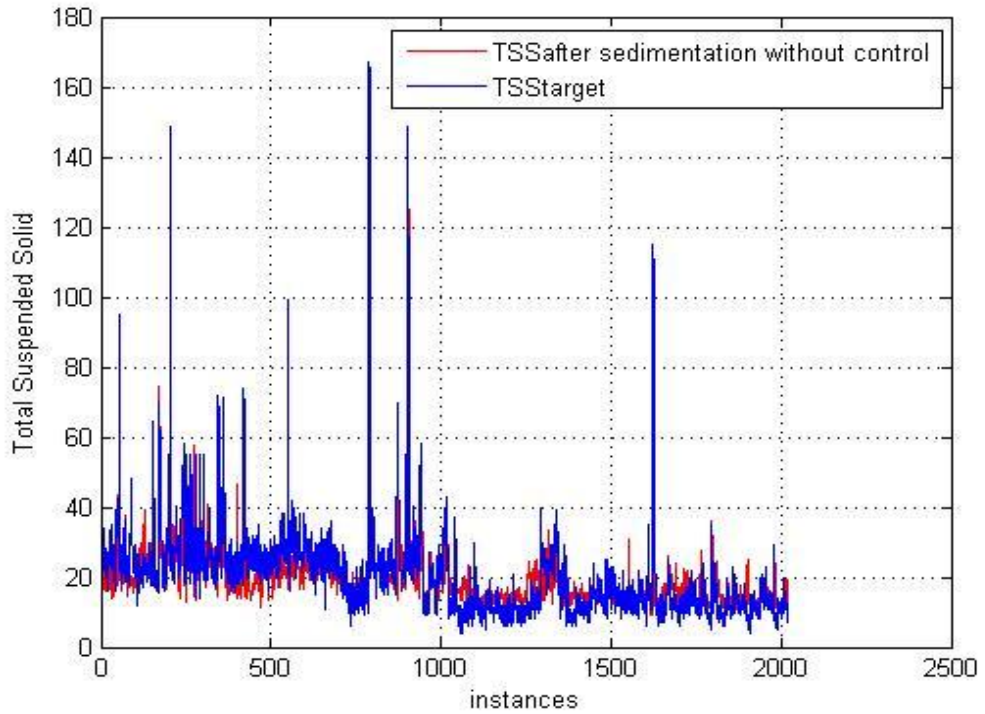
In the first set of experiments, we only use the ALUM prediction without fuzzy control feedback in order to evaluate the result from the prediction. We compare the result using the prediction and the target data from the real measurement. The following figures show this evaluation for the parameters TU, pH and TSS .



**Figure 3.15** TU prediction comparison with TU target



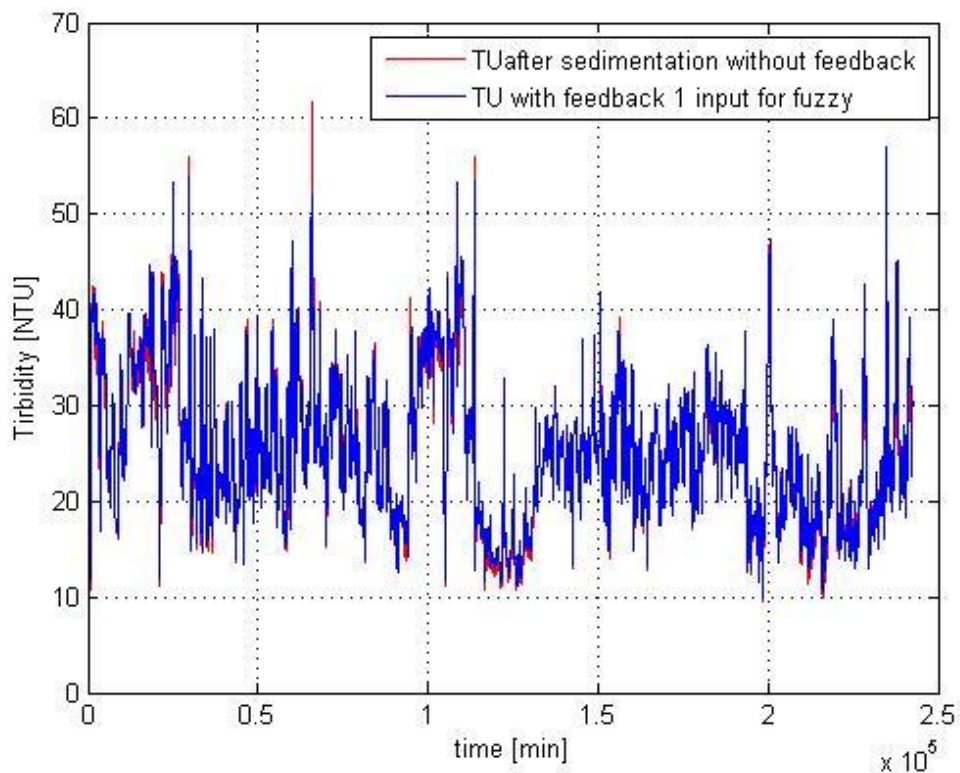
**Figure 3.16** PH prediction comparison with PH target



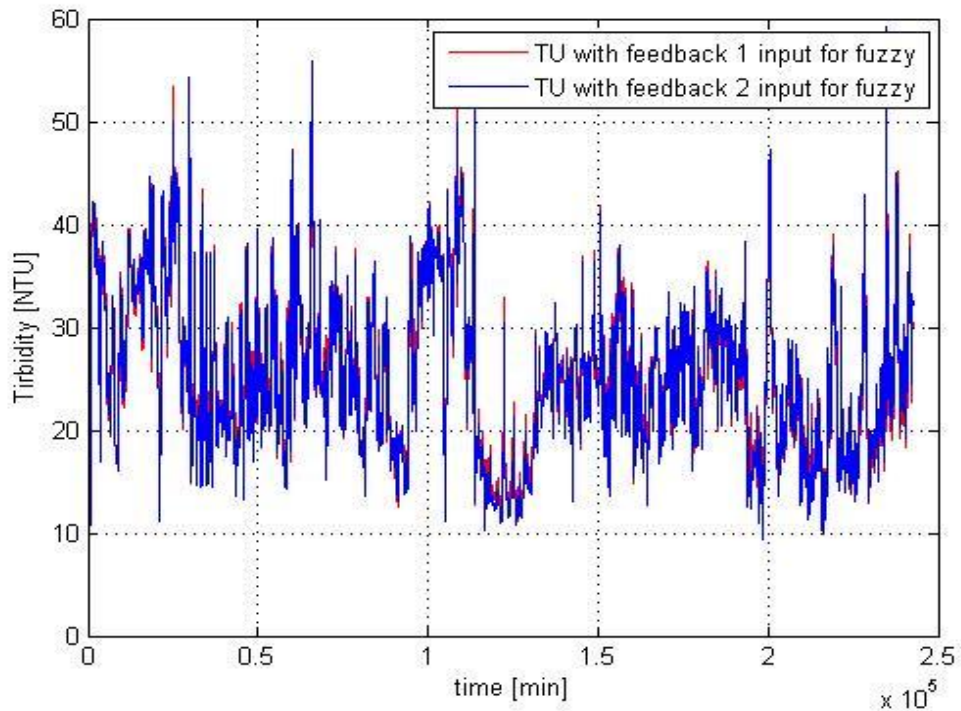
**Figure 3.17** TSS prediction comparison with TSS target

It can be seen from figure 3.15 to 3.17 that there are no large discrepancies between the predicted value and the target value. Hence, the neural network model is suitable for the prediction of ALUM in our control architecture.

Next, we close the feedback loop with the fuzzy controller and perform the same experiment as before. Since we focus on the improvement of the TU value, Figure 3.18 and 3.19 show the comparison of the TU value in the case of prediction without feedback control and the case of prediction in combination with feedback control. It can be seen that the fuzzy control further improves the TU value. In fact, it is now the case that almost all values are below 50, which is the border for acceptable water quality. It can further be seen that the feedback control experiment for fuzzy control with two inputs in Figure 3.19 leads to a very similar result.

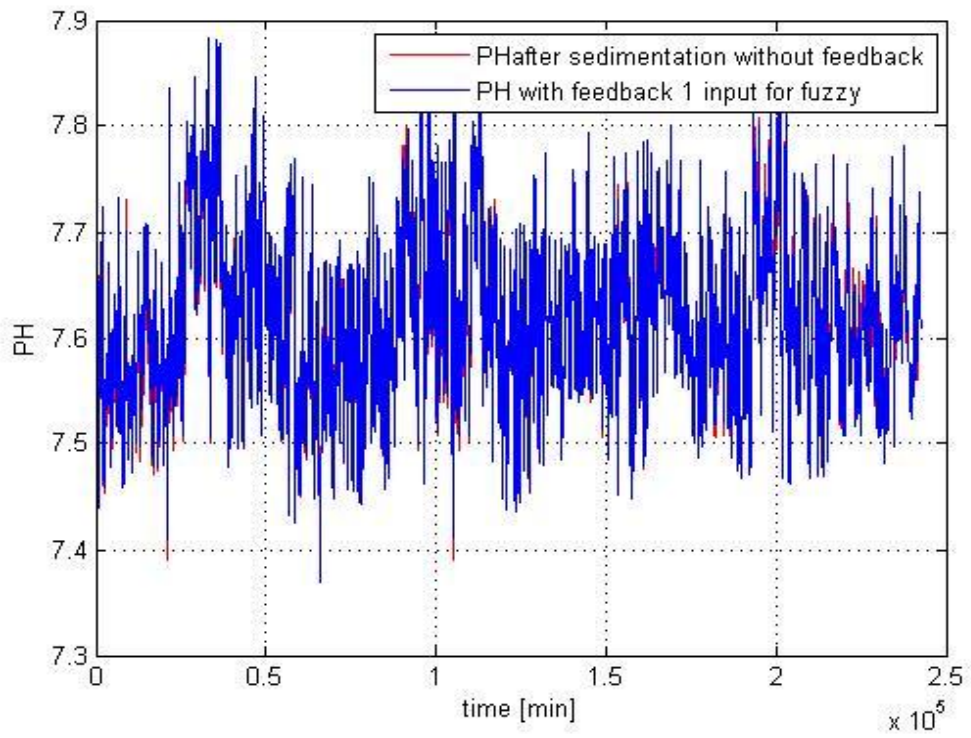


**Figure 3.18** TU comparison for fuzzy control with one input

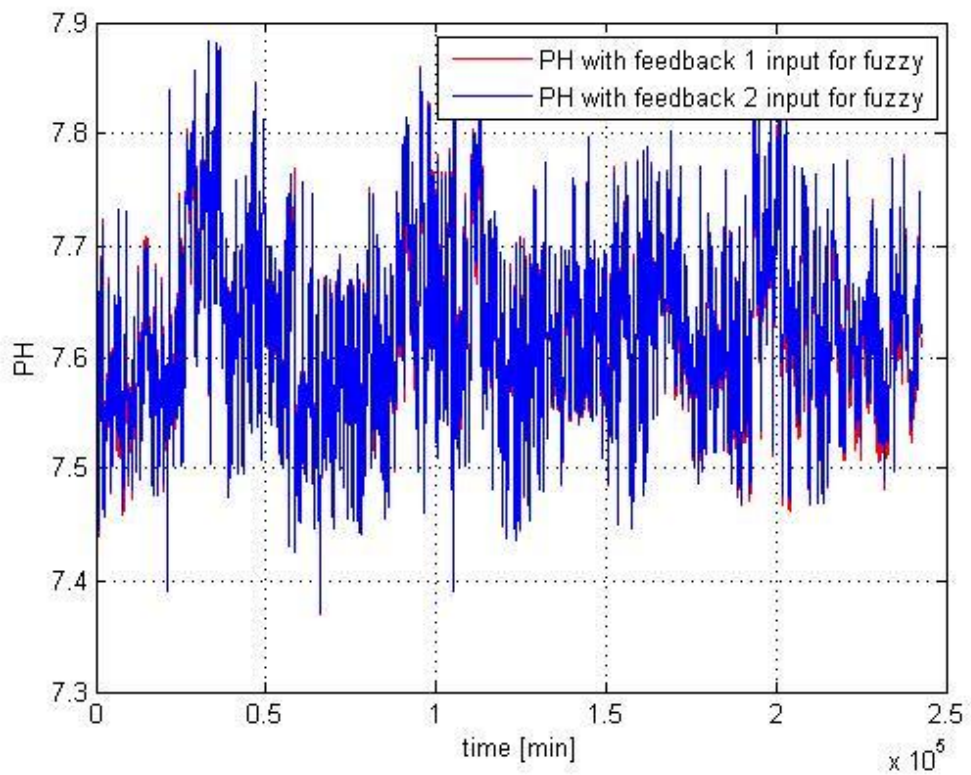


**Figure 3.19** TU comparison for fuzzy control with one input and two inputs

Looking at the PH concentration, there is a slight improvement of the PH value if fuzzy control is used (Figure 3.20). The values are closer to the most desirable value 7.5. It can also be seen that there is again not much difference between the fuzzy control with one input and with two inputs (Figure 3.21).

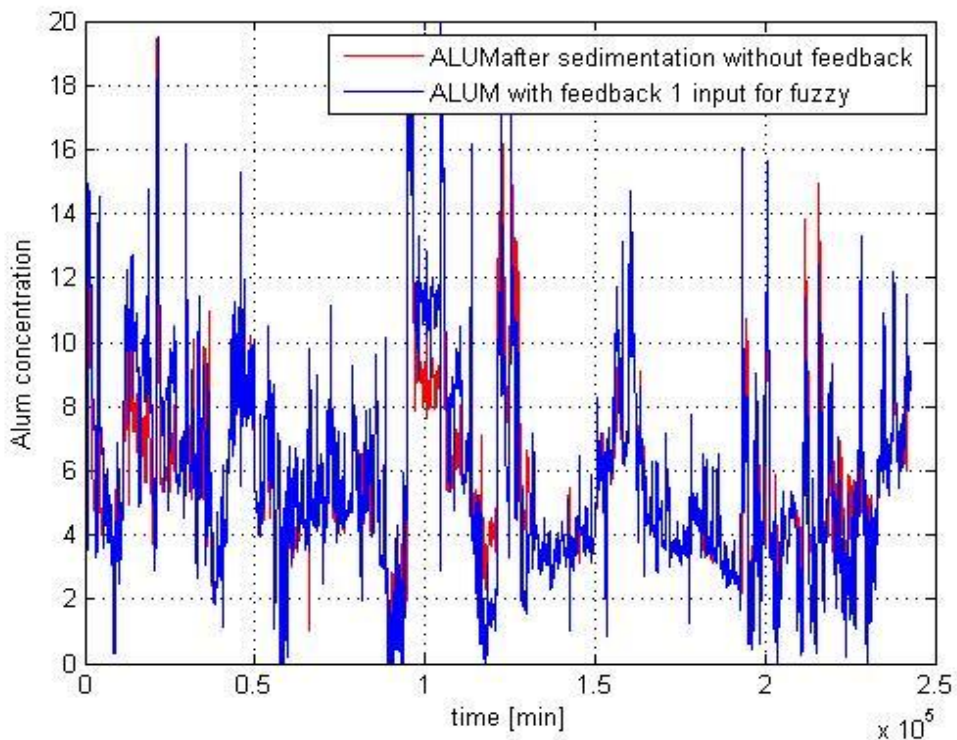


**Figure 3.20** PH comparison for fuzzy control with one input

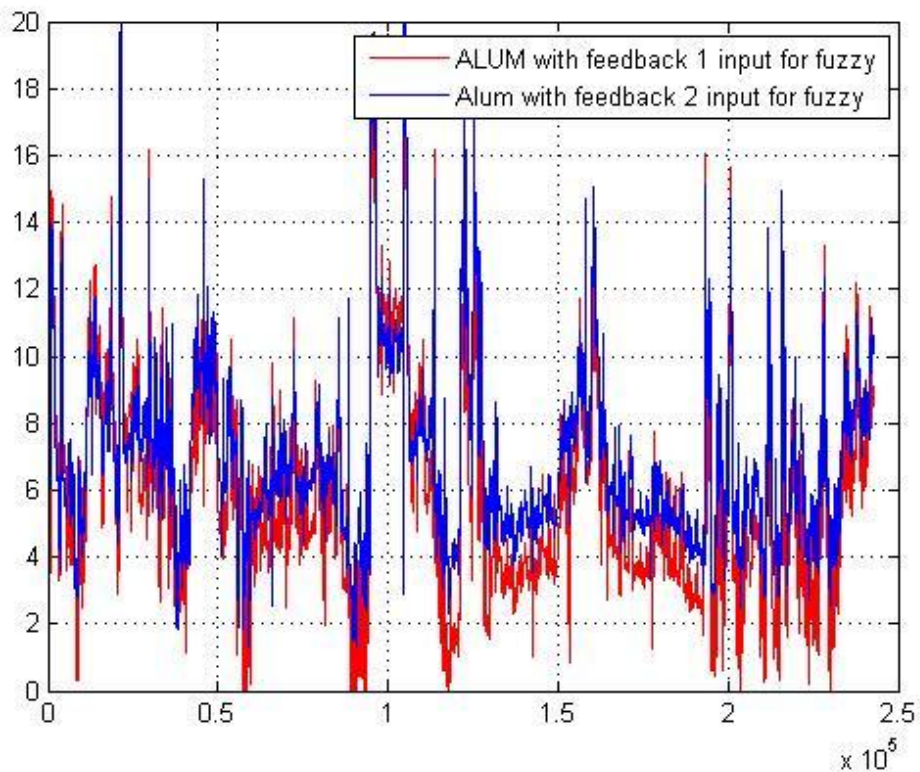


**Figure 3.21** PH comparison for fuzzy control with one and two inputs

It is also interesting to compare the ALUM concentration with and without feedback control. The result is shown in Figure 3.22. It can be seen that feedback control generally increases the ALUM concentration in order to improve the value of TU. Only in some cases where the TU concentration is already very good, a decrease of the ALUM concentration is possible. When comparing fuzzy control with one input and fuzzy control with two inputs (Figure 3.23), we see that more ALUM is used in the case with two inputs. A further study of this result is subject of future research.



**Figure 3.22** Alum comparison for fuzzy control with one input



**Figure 3.23** Alum comparison for fuzzy control with one and two inputs

In summary, we can say that the control architecture as proposed in this thesis is suitable for the automatic control of the sedimentation process. The neural network for ALUM prediction very well replaces the task of a human operator. In addition, the fuzzy feedback controller provides an additional improvement of the water quality. It is important to note that the designed controller incorporates data from real measurements for the prediction of the ALUM concentration as well as expert knowledge about the desired system operation for the fuzzy control. Hence, our controller tries to replace and improve the control action taken by a human operator.

## CONCLUSION

The subject of this thesis is the automatic control of water treatment plants with a focus on the clarification process. This process is performed in a clarification basin, and is divided into mixing (with addition of a coagulant material), flocculation (reaction of coagulant and water particles to form larger particles) and sedimentation (accumulation of particles on the bottom of the basin). The input to the process is the coagulant concentration and the output of the process is the water quality, which is specified by desirable values of various water parameters .

In this thesis, a new control method for the clarification process in water treatment plants is proposed. It is first shown that such method cannot be easily based on an analytical model of the water treatment process. Precisely, it is shown that an analytical model provided in the literature seems to provide incorrect results. Because of this reason, the control method is based on a neural network model of the water treatment process, that is obtained from real measurement data. The control method consists of feedforward control and feedback control. The feedforward path is again obtained as a neural network, that produces the coagulant dosage as obtained from the measurement data. The feedback path is realized as a fuzzy controller, that modifies the coagulant dosage based on expert knowledge of the process. The propose method is validated using simulations in Matlab/Simulink. From the simulation results, it is concluded that the proposed method is suitable for the control of water treatment plants. In particular, using feedback control leads to an additional improvement of the water quality .

It has to be noted that the results presented in this thesis only focus on the clarification process. It is an important task for future work to also automatize the disinfection process and the filtration process of the water treatment plant. In addition, the management of the different processes is subject of future work.

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GCPRIS

## APPENDIX A

### CURRICULUM VITAE

#### PERSONAL INFORMATION

Surname, Name: GHAZY SABER, Faisal

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#### EDUCATION

Degree	Institution	Year of Graduation
MS	Çankaya Univ. Department of Electronics and Communication Engineering	2012
BS	Mustansiriya University - Faculty of Engineering - Department of General Electric	2001
Technical Diploma	Oil Training Institute - Kirkuk	1992
High school	AL-Risalah - Baghdad	1989

#### WORK EXPERIENCE

Year	Place	Enrollment
2003-2010	The Kirkuk water directorate	Senior Engineer
2001-2003	Al-Faw General Engineering Contracting	Engineering
1992 - 1997	General Company for oil refineries - Baiji	foremen Electricity