Modeling and Optimization
of
Desalting Process in Oil Industry

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Abstract

Throughout a very long piping network crude oil in Saudi Arabia is sent to Gas Oil Separation Plant called GOSP. The main objectives of the GOSP are:

- Separation of the associated gas through pressure drop in two series stages one to 120 psig and the other to 50 psig.
- Separation of water by gravity separators called High Pressure Production Trap (HPPT), Dehydrator, Desalter and Water Oil Separator (WOSEP).
- Reducing salt concentration to less than 10 PTB utilizing wash water and demulsifier.

During the desalting process, the challenge is to overcome the existence of an emulsion layer at the interface between oil and water. In petroleum industry normally emulsions encountered are some kind of water droplets dispersed in a continuous phase of oil. In crude oil emulsions, emulsifying agents are present at the oil-water interface, hindering this coalescence process. Such agents include scale and clay particles, added chemicals or indigenous crude oil components like asphaltenes, resins, waxes and naphthenic acids.

Many techniques made available to gas oil separation plant operators to minimize the effect of tight emulsions. These techniques include injection of demulsifier, increasing oil temperature, gravity separation in large vessels with high retention time as well as electrostatic voltage. From experience and studies these variables have been already optimized to a good extent; however, from the believe that knowledge never stop, this study is conducted targeting enhancing the demulsifier control and optimizing the wash water rate.

The objective of this study is to design an Artificial Neural Network (ANN) trained on data set to cover wide operating range of all parameters effecting demulsifier dosage. This network will be used to work as a control black box inside the controller in which all effecting parameters are inputs and the demulsifier dosage is the controller output. Testing this control scheme showed an effective reduction in demulsifier consumption rate compared to the existing linear method. Results also, showed that the existing control strategy is highly conservative to prevent the salt from exceeding the limit. The generated function from the ANN was used also to optimize the amount of fresh water added to wash the salty crude oil. Finally, another ANN was developed to generate an online estimate of the salt content in the produced oil.

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Chapter 1

Introduction

Processing crude oil with high concentration of salt, i.e. higher than 20 Pounds per Thousand Barrel (PTB), causes damages to piping system and equipments. This forces refineries to install desalting trains in upstream Gas Oil Separation Plants or specifying a maximum salt concentration if crude is provided by other companies. During the past few years, the desalting process developed rapidly as a result of the growing global demand of oil. Along with this development, refineries also increased its expectation of the quality of feed oil especially in terms of low salt concentration. Effects of high salt concentration oil on a refinery can be described as follows:

1. Refining equipments and pipelines experience high corrosion rate when treating salty oil. [(1)]
2. Fouling of salt inside refining equipments has severe impacts on the process efficiency. For example, it reduces heat transfer rate in heat exchangers and furnaces. Also, fouling of salt in fractionators plugs some trays which then reduces the separation efficiency due to the reduction in heat transfer rate. Due to fouling of heating equipments, pressure drop increases and more pumping energy is needed to recover for the potential loss. In fractionators, the duties of re-boiler and condenser should be increased when fouling occurs. [(1)]
3. Metallic compounds contained in salts can poison (deactivate) catalysts. One of these metals is sodium which has been found to be the most harmful to the catalyst. [(2)]

Salt does not exist in dry oil but when crude oil has water cut then salt is dissolved in the water [(4)]. The water mixed with oil is either free water or as a part of emulsion. Free water settles in gravity separator and can be easily separated from oil if enough time is given [(3)]. Water in oil emulsion is formed during the different stages of crude oil production and treatment. The formation of emulsion lowers the performance of gravity separators since emulsions gather at the interface between water and oil to form a layer which does not allow the settling water to drop to the bottom of the vessel. Emulsion stability is caused by the existence of interfacial barrier surrounding droplets and stopping coalescence. As the emulsion stability increases, the cost to lower the salt and water content in the shipped oil from the gas oil separation plant also increases. The tendency to form stable emulsion becomes more serious when the mixture contains surface active components like asphaltenes, resins, waxes and naphthenic acids. [4]

Therefore, it is necessary to separate the accompanying water before transporting or refining the oil for economic and operational reasons. The most efficient method to overcome the emulsion stability problem is to add a chemical “demulsifier” which aid the separation of emulsion by destabilizing the interfacial film between droplets [4]. The control of the demulsifier dosage has been automated in the past few years. The controller has different linear equations for the different ranges of the operating parameters (feed oil temperature, desalter electrostatic voltage, water cut and the total feed flow rate). In Saudi Aramco Gas Oil Separation Plants, the demulsifier injection controller has four equations and the controller would select the best equation upon the current readings of the early mentioned parameters. The controller performance is best checked through the salt content in the produced oil. The company specification for the salt concentration in the final product is 10 PTB (Pound in Thousand Barrels) and water content should be less than 0.20 %. High reduction in salt content on a long time scale means:

- The control strategy is designed to be conservative in a way it would over-estimate the situation to keep the product within specification limits in case of an upset event.
- The crude specification has changed; such as the water cut, specific gravity or the salt concentration.
- Other parameters which are not included in controlling the demulsifier rate has changed as well, like wash water rate.

To find the most practical control strategy of demulsifier consumption, the parameters affecting the salt content in the crude oil should operate at their optimum. These parameters are:

1. Crude Oil Temperature
2. Desalter Electrostatic Voltage
3. Dehydrator Electrostatic Voltage
4. Wash Water Rate
5. Water Concentration in Feed Crude Oil

6. Total Crude oil Flow Rate
7. Demulsifier Flow Rate and Type

Al-Otaibi *et al* [5], made an optimization study on the performance of desalting/dehydration process. The study included the influence of demulsifying agent concentration, heating, wash water rate, salt concentration, and mixing time with wash water. In the study, the performance of the desalting/dehydration process was evaluated by calculating the salinity and water cut efficiencies that are expected to depend on the values of these five process parameters. The work concentrated on modeling and optimizing the performance of the desalting/dehydration process system but it did not include the electrostatic voltage effect and water cut in the introduced oil. Also, the oil temperature was one of the controllable parameters.

Some of the fundamental parameters of the system are not constant and have a nonlinear effect on salt concentration in the treated oil, i.e., inlet crude flow rate, inlet temperature and water cut. This situation requires the use of a controller that has the ability to adjust with changes by adapting its behaviour. Adaptive controller reads the process variables and upon any change adjusts its response. This means a nonlinear controller with the ability to adjust the tuning parameters according to the instantaneous input readings should be used. According to the above description, this thesis proposes a new technique for demulsifier injection rate control that uses an intelligent control scheme. The proposed technique is the Artificial Neural Network (ANN).

In order to show the necessity of changing the control scheme of demulsifier rate, the performance of the existing controller in Saudi Aramco Gas Oil Separation Plants (GOSP's) will be evaluated. To achieve this objective, an Artificial Neural Network will be designed and trained on a large data set that was collected from one of Saudi Aramco GOSP's. Network performance will be validated on another set of collected data. This process of network designing, training and testing will continue until an acceptable model performance is reached. The generated trained network will be used to predict the demulsifier consumption rate at the same operating conditions but now with a salt concentration of 9.0 PTB in the treated oil. The generated network will be proposed to be used in place of the existing linear controller in Saudi Aramco Plants.

The fresh water used for washing crude oil is produced from underground formation by gas lifting method and any reduction in the used quantity is appreciated from the view point of saving energy used to recover the pressure drop in the lifting gas and conserving water as a natural resource. The relation function generated from the trained network will be utilized to optimize the wash water rate as a function of oil temperature. This objective will be done using MATLAB.

At this moment, an online salt analyzer is not available at Saudi GOSP's. The existing models require frequent maintenance and they were below standard in accuracy and reliability when tested. Thus, the third objective of this study is to develop a well trained neural network to simulate the salt reading in the treated oil at the current situation. This tool will help operations to have salt readings online which will assist quick process trouble shooting as an alternative of the manual sample collection and lab testing which take at least 15 minutes to have a single salt content reading.

As discussed, results of this study will benefit in reducing the cost per barrel of the treated oil. The saving is mainly from lowering the consumption rate of demulsifier and also by minimizing the wash water rate. At the specific Gas Oil Separation Plant from which data were collected, the consumption of demulsifier used for desalting costs the company approximately about $100,000/month. Also, the salt prediction neural network generated in this study could be trained on more historical data and used instead of purchasing online salt analyzers.

Chapter 2

GOSP Operation and Emulsion Overview

2.1 Gas Oil Separation Plant’s Process Overview

2.1.1 Introduction:

Crude oil coming out of production wells is transported through a network of pipeline to the nearest Gas Oil Separation Plant (GOSP) to process it and make it safe, less harmful to the transporting pipeline, free of unwanted associates, higher in driving force and economically feasible for storage, processing and export. As the crude oil produced from wells also contains water, gas and salt, transporting oil to a refinery is not safe due to the existence of the accompanying gas which is rich in toxic components such as hydrogen sulphide H_2S . The salt exists in water tend to cause corrosion along the pipeline and as the distance increases the pressure drops and minimizes the flow rate which increases the corrosion potential. Water separated at the GOSP is re-injected back through injection wells to maintain the reservoir potential while the separated gas is sent to a gas plant. This will prevent the cost of pumping water and gas to the refinery to be separated and then pumping them back. Figure 2.1 shows the desalting process in Saudi GOSP’s. The main processes that take place in a GOSP are:

- Separating the associated gaseous components for further processing in a gas plant.
- Separating the accompanying water.
- Lowering the salt content up to an acceptable limit.

2.1.2 Gas Separation:

The produced oil reaches the GOSP with high pressure which makes the gaseous components dissolve in oil. The way to perform separation at low operating cost is by reducing the pressure and increasing the volume. An increase in the volume is achieved by introducing oil to large vessels while the pressure reduction in these vessels is controlled through pressure control valves. At first, oil is fed to two High Pressure Production Traps (HPPTs) where the pressure is controlled at 150 psig. HPPT is a three phase separator where oil, water and gas are partially separated. Oil out from the HPPT, that still contains gas which cannot be flashed at this relatively high pressure, is introduced to the Low Pressure Production Trap (LPPT) which is a two phase separator that operates at 50 psig. Under this low pressure the produced oil is considered to be free of gas content.

2.1.3 Water Separation:

As mentioned above, the water separation starts at the high pressure production traps by allowing the produced oil to settle in a large volume where gravity separation could take place. The remaining water exists in the form of water-in-oil emulsion or free water but the settling time in HPPT was not enough to get it separated. The free water is easily removed in settling vessels but the emulsified water requires more to break stable emulsions. Crude oil is then processed in the dehydrator vessel. Unlike HPPT, the dehydrator is full of liquids. The technique used to remove the emulsion inside the dehydrator is known by electrostatic coalescence. There are three equally spaced transformers mounted at the top of the vessel. The transformers operate at almost 16,000 Volts. They send electrical current through the crude and excite the water droplet. The demulsifier works to break the oil film around the water droplet while the current helps droplets to move and combined with each other forming larger droplet where it can separate itself from oil by gravity.

Crude oil is then introduced to the desalter where washing takes place. After separating water from the crude, there is one more treatment needed before shipping it outside the GOSP i.e. the salt removal. The desalter is responsible for this mission. When the crude leaves the dehydrator and before it enters the desalter fresh water is injected into the stream using wash water pumps. The mixture then passes through three partially open globe valves (mixing valves) to ensure high mixing efficiency. The reason behind fresh water injection is that salt have high tendency to dissolve in water than in oil.

Once the oil has been washed, the demulsifier is injected to the oil stream and then crude enters the vessel. The same transformers on top of the dehydrator are presented in the desalter. The transformer sends the water to the bottom of the vessel keeping the crude at the top. The crude is then sent to the shipping pumps where it can be shipped to the refinery.

Shipped crude oil should meet the following specifications:

1. The water concentration is less than 0.2% of the shipped crud.
2. The maximum salt content is 10 PTB (Pound per Thousand Barrels).

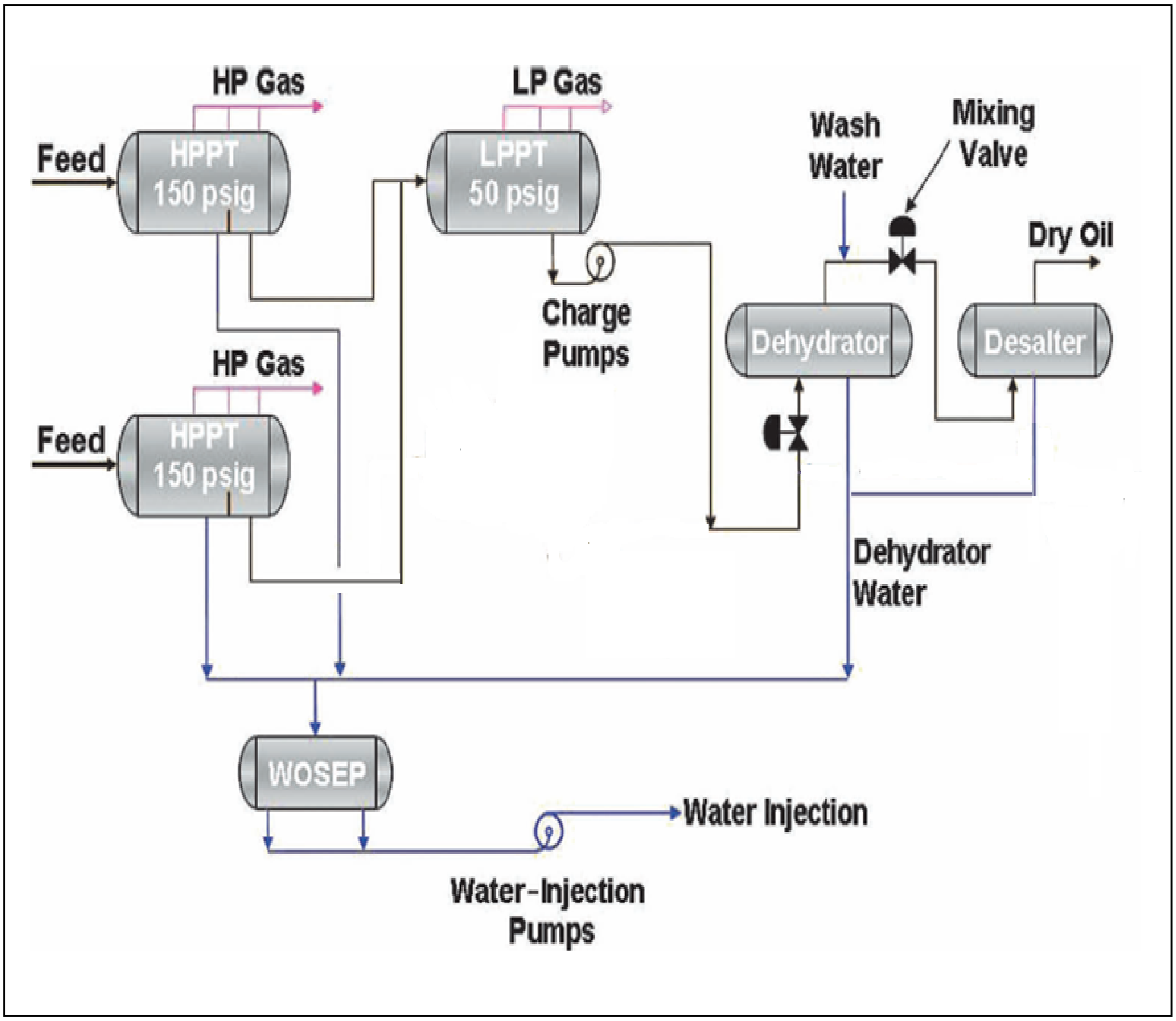


Figure 2.1: Gas Oil Separation Plant's process

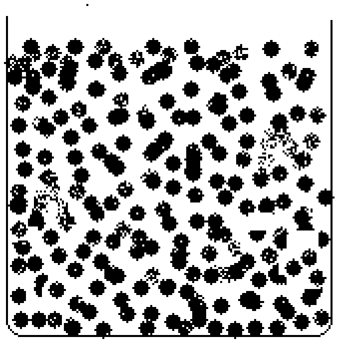
2.2 Formation of Crude Oil Emulsion

2.2.1 Introduction:

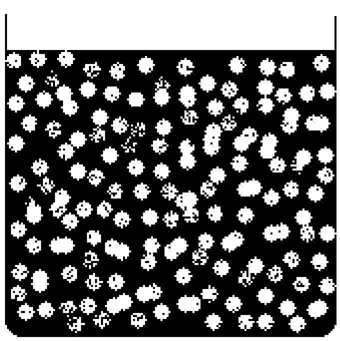
IUPAC (1972) created a comprehensive definition of emulsions as [6] :

"An emulsion is a dispersion of droplets of one liquid in another one with which it is incompletely miscible. In emulsions the droplets often exceed the usual limits for colloids in size."

In oil industry the two well known kinds of emulsions are oil in water (O/W) and water in oil (W/O). As illustrated in Figure 2.2A, in oil-in-water emulsion the continuous phase is water and oil is dispersed through it [8] . It normally occurs in the disposal water from GOSP and during oil spill in oceans. On the other hand, in water-in-oil emulsion the continuous phase is oil in which water is dispersed as illustrated in Figure 2.2B and it is encountered during the separation process of crude oil.



A. oil in water emulsion



B. water in oil emulsion

Figure 2.2: Types of emulsion encounter in oil industry

During the process of transporting crude from underground reservoir until it reaches the inlet of the desalter, oil passes through valves, orifice plates and pipe size reduction. Also, it passes through many flow restrictions such as elbows and flow to a higher pressure pipes. Under these shear forces and along with high pressure and temperature, the formation of emulsion occurs. Moreover, the existence of some surface active particles e.g. sand, salt or clay stabilizes the emulsion. Stability of emulsion is expressed as degree of emulsification and it depends on several factors. (16)

2.2.2 Factors Affecting the Degree of Emulsification:

In the past days, the degree of emulsification was directly judged through physical properties of oil which are the specific gravity and viscosity. Later, studies showed that such properties only influence the emulsion separation rate. After performing more investigations through experiments, it was discovered that interfacial tension between water and oil and conductivity play an important role in identifying emulsion stability.

Even though crude oil is mainly a homogenous mixture of hydrocarbon fractions it also contains non-homogeneous compounds, such as surfactants, anions, cations, clay and sand. These compounds concentrations vary from small traces to appreciable levels, leading to differences in degrees of emulsification. The formation of a stable emulsion is controlled by different characteristics. Water in oil emulsion stability relays on most of the following factors:

a) The size of dispersed water droplets

b) The age of emulsion

c) The viscosity of oil

d) The difference in the density between water and oil

e) The volume percentage of the water cut

f) The interfacial tension of water droplets

g) Asphaltenes, paraffin and suspended solids content

In addition, several water properties such as water density, pH, salinity and suspended solids are also important and contribute to the emulsion stability.

2.2.3 Controllable Factors:

Some of the factors behind emulsion stability in oil industry are either uncontrollable, i.e., the size of water droplet and the presence of surface active agents, or hard to be controlled such as the water cut at the entrance of the desalter. Several techniques were designed to control some of the factors responsible for emulsion stability like the interfacial tension, density deference between water and oil, oil viscosity and water cut. In the next sections, after providing an overview of the emulsion separation process, the most economically feasible and practical techniques in breaking the emulsion layer formed inside the desalter will be discussed.

2.2.4 Emulsion Separation Process:

Thermodynamically as the size of the dispersed phase increase in the emulsion, it tends to be unstable and can be separated under the effect of gravity. On contrast small emulsions "micro-emulsions" are thermodynamically stable and gravity separation is impractical unless another treatment is involved such as chemical or mechanical.

The destabilization process of water-in-oil emulsion is basically a combination of three steps which are illustrated in Figure 2.3 and described below: [15]

1- Flocculation occurs when two or more droplets come into contact but each droplet maintains its integrity.
2- Sedimentation of water droplets due to density differences. Sedimentation is enhanced by large size of the droplet, high difference between oil and water densities and low viscosity of oil.
3- Coalescence where two or more droplets of the disperse phase merge together to form a droplet of larger size.

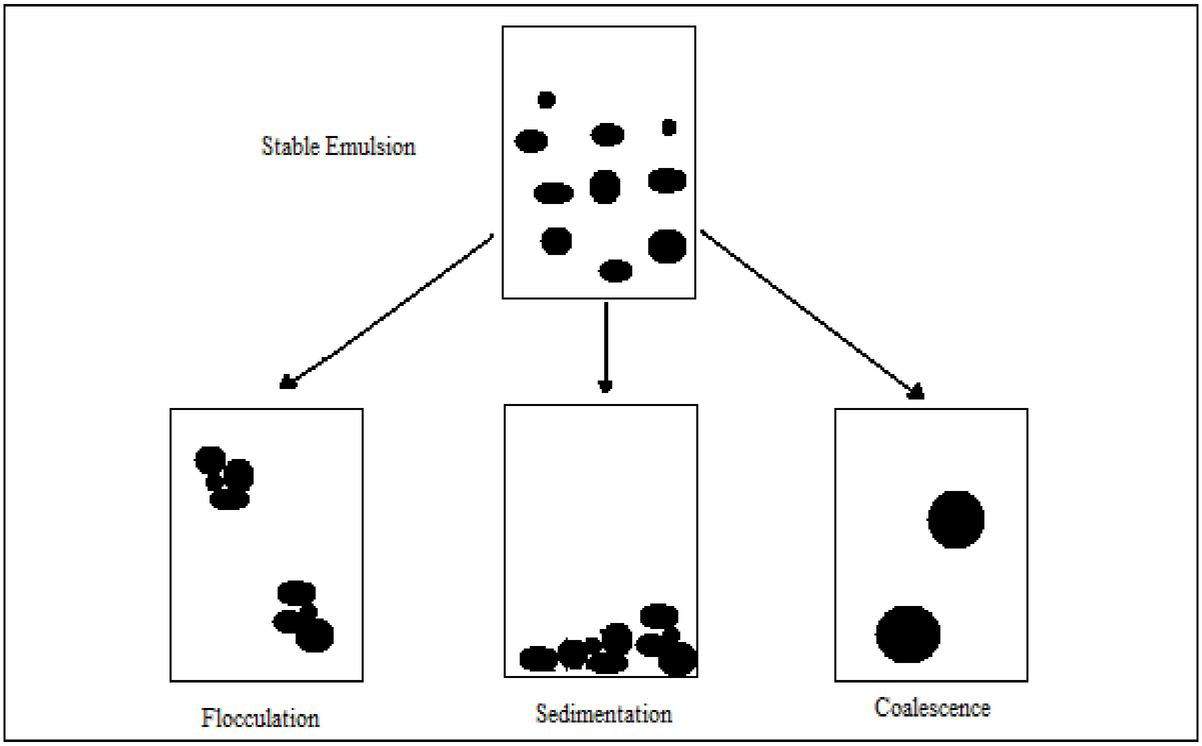


Figure 2.3 Processes lead to instability of an emulsion

Breaking an emulsion is an important process in many applications like waste water treatment, painting, environmental technology and petroleum industry [8] . Methods used in demulsification are classified as gravity separation, chemical (demulsifier) injection, electrostatic field and heating.

2.2.5 Desalter Settling Time

In Gas Oil Separation Plants, GOSPs, desalters are designed to have an optimum settling time to allow gravity separation process of water to take place. The required settling time is dependent of the processed crude characteristics and process variables. The major crude properties that participate in determining settling time are viscosity, density, water cut, amount of suspended particles and fraction of asphaltenes. Process variables considered during the design of a desalter are feed temperature, feed pressure and outlet flow rates.

The water contained in the crude oil fed to the desalter exists in two forms either being emulsified or totally separated from oil which is usually called free water. In order for the free water molecules to have a lower interfacial tension, it tends to have a spherical droplet shape and also exists in large droplets to minimize the contact area. At the time crude oil inters to the desalter vessel, the free water settles down to the bottom of the vessel under gravity effect. For the emulsified water, since it has low interfacial tension because of the existence of surface active agent (surfactant), it exists in the form of tiny droplets contained in a continuous phase of oil which is called water in oil emulsion. In this case, gravity separation is not any more effective to remove water even if the flow rate is decreased to maximize the settling time. Thus, to have the separation process achieved in a finite settling time, further techniques should be used like chemical injection, wash water dilution, mixing, heating, and electricity.

Gravity separation is the most effective method for separating free water. After water droplet is separated, gravity start to force the water to settle to the bottom of the separator which generates a drag force. This drag force always resists gravity. The velocity of a droplet under the gravity effect can be calculated from Stokes' equation as follows:

$$\nu = \frac{2\pi\, \mathrm{r}^2 (\Delta\rho)}{9\eta} g \tag{2.1}$$

Where ν is the downward velocity of a water droplet, r is the water droplet radius; Δρ is the density difference between the two phases, g is the gravity constant and η is oil phase viscosity.

Equation 2.1 means that gravitational separation can be maximized by maximizing the size of water droplets and the density difference between water droplets and the oil phase. Also it can be maximized by minimizing the viscosity of oil phase.

Heating feed oil to the GOSP helps to maximize the density difference between water and oil also; as the oil temperature increases its viscosity decreases. Both the addition of fresh water and applying electrostatic field helps to maximize the water droplet size.

2.2.6 Injection of Demulsifier:

To separate the fine dispersed water droplets in oil, the interfacial tension should be maximized such that the oil surrounding water droplet becomes hydrophobic and gravity separation can occur. This goal is achievable through injecting demulsifier at the desalter inlet. The demulsifier molecules are adsorbed at the water-oil interface and allow breaking the film surrounding water droplets. After that, water droplets combine together to form bigger droplets upon which the gravity force could work.

The criterion considered by demulsifier supply companies, to produce new chemical that could be effective in breaking water-in-oil emulsion, are:

1- It should have a polar identity to be attracted by the organic skin surrounding water drops.
2- It should be able to dissolve in the surface film surrounding the water drops.

Feed stock to the plant desalter usually contains many different materials that contribute in stabilizing a water-in-oil emulsion. These materials either naturally exist in crude oil like precipitating organic materials such as asphaltenes and waxes, suspended solids like mineral scales and corrosion products or these materials are added to the crude to perform a special job like residual fluids after work over jobs, injected corrosion and scale inhibitors. Efficient demulsifier must be designed to work against stabilizing influences existing in the inlet stream to the desalter. However, the process procedure used to identify the best possible chemical blends for a given condition is a trial and error step.

2.2.7 Electrostatic Field:

Breaking emulsions using electrical current is normally known as electrostatic separation. This technique was used first in oil refineries in 1930 to separate the water-in-oil emulsions. Large desalter vessels are normally equipped with at least three transformers producing high potential field between 10,000 and 25,000 volts. The electrostatic method is not as efficient as the chemical injection or heating oil in breaking the emulsion, but it increases the desalter efficiency at high flow rates by lowering the required settling time through speeding up the coalescence step.

The condition that should be satisfied to have efficient separation using the electrostatics voltage is the dispersion of a conducting liquid in a non-conducting one. In oil dehydration this condition is met since water (conductor) is dispersed in oil (non-conductor). (19)

A water droplet is formed of polar molecules since oxygen is negatively charged whereas the hydrogen atoms are positively charged. The polar forces are magnetized and respond to the electrical field that would generate a dipole attraction between water droplets. This attraction leads to coalescence and finally separation. As a response to the high voltage through the system water droplets vibrate rapidly forcing the surrounding film to break. Then the surface area of water droplet increase, as a result of shape transformation to ellipsoid. Finally these droplets start to gather and grow in size and under gravity effect they settle to the bottom of the desalter. The attraction between droplets under the influence of electrostatic field can be described by the following equation:

$$F = \frac{Kd^6 E^2}{S^4} \tag{2.2}$$

Where F is the electrostatic force between two adjacent droplets (N), K is the dielectric constant for crude oil-water system, d is diameter of water droplets, E is the voltage gradient (V/m) and S is the distance between the two centers of two adjacent droplets

The alignment of the polar water molecules in the droplet produces dipole forces. These forces are proportional to the water droplet size, the electric field gradient and the distance between droplets. This relation is applicable until the electrostatic voltage exceeds the critical value. After this voltage water droplets start to break forming smaller droplets with higher interfacial tension which thermodynamically prefer to form stable emulsions. The critical voltage can be calculated using Equation 2.3:

$$E_c = k\sqrt{\frac{T}{d}} \tag{2.3}$$

Where E_C is the critical voltage gradient (V/m), k is the dielectric constant for crude oil-water system, T is the surface tension between water droplets and oil phase and d is the droplet diameter.

2.2.8 Heating

In countries where the weather is cold, installation of heaters at the oil inlet is a necessity if high production rate is required and it is mandatory to lower the consumption rate of demulsifier and wash water. The case is different in countries like Saudi Arabia where the normal practice is not to install heaters in desalting facilities since the lowest temperature the crude could have just at the inlet of the desalter is about 70 ^{o} F.

Studies showed that, an increase in process temperature has two opposite effects on emulsion. The first effect of increasing oil temperature is decreasing both oil density and viscosity, which yields a significant improvement in the settling rate of water droplets. This effect of raising oil temperature increases the profit of desalting process. On the opposite side, as crude oil temperature increases its conductivity also increases exponentially resulting in a higher rate of power consumption. [(18)]

Under these opposite effects of raising the treated oil temperature, there should be an optimum temperature at which the gain of oil heating can be maximized. In order to achieve this goal, the dependence of density, viscosity and conductivity on temperature should be determined for the specific type of oil being processed.

2.2.9 Dilution with Wash Water

Salt in crude oil exists in many forms like crystals, water soluble, water insoluble (scale and chemical inhibitor) and metallic compounds (naphthenate) [(22)]. Most of salt types in processed oil can be extracted through dilution with water of low salt concentration. The normal practice in most of gas oil separation plants is to inject the fresh water to oil stream through a tee connection located ahead of partially open globe valves “mixing valves” with pressure drop of 15-25 psi. Mixing valves maximize the dispersion of water droplets in the bulk phase of oil. The mixing process improves the desalting efficiency and lowers the amount of consumed wash water especially when pressure drop is manipulated to minimize tight emulsion formation during mixing.

Fresh water is injected so that water drops in emulsions can be washed out and then be drained off, hence the term “wash water” is used. The quantity or ratio of fresh water injected depends on the API gravity of the crude. Generally the injection rate is 3-10% of the total crude flow [(3)].

Chapter 3

Artificial Neural Network Design

3.1 Existing Control Strategy:

In gas oil separation plants operating the desalting train at the optimum operating conditions while product target specifications still met, is cost effective and helps to conserve both energy and water. Several processes were automated, one of them is demulsifier consumption rate. In practice the control system collects instantaneous readings of predefined variables through the field instruments and then determine the band in which the collected readings fit. Up on the selected band, the dosage rate is calculated through a linear relationship as a function of assigned variables like temperature, oil flow rate and transformer voltage. Automation eliminates human intervention in adjusting demulsifier rate which may lead to error and some sort of delay in response. Automation of a process in which all the interfering variables are measureable, like pressure, temperature, flow rate, etc, can help to operate at or close to the optimum. In a gas oil separation plant, challenges to automation can be summarized in the following points:

1- Dynamic behaviour of the oil reservoir: Oil specifications like water cut, viscosity and density keeps changing and there is no means of online monitoring.
2- Emulsion formation: Through the piping system and equipments, pressure drop and agitation forces act to from water in oil emulsions. At this moment, there is no practical instrument to give online readings about the tightness of emulsion, the emulsion layer thickness or any other physical properties like surface tension.
3- Online feedback: Salt concentration in the produced oil is the controlling specification but since there is no online analyzer installed the salt concentration reading is not available to the control system to read the controllable variables.

The performance of demulsifier automated controller is normally checked by turning the controller to the manual mode and start lowering the dosage rate, collect sample from the treated oil, find the salt concentration and the process continues until the salt concentration reaches 10PTB. Based on offset results show, the controller performance would be judged and adjustment is expected. In practice as long as the product meets the required specification, the control scheme might not undergo a performance test. In this case a chance of cost effective optimization might not be recognized at the right time. The reason that operation people do not frequently modify the controller logic is that they do not have a handy tool and a clear procedure. Searching for new techniques to control the demulsifier rate, the ability of artificial neural network (ANN) technique to adapt with changes was the reason of selection. The next sections in this chapter will give a brief description about ANN that will help later during designing the controller.

3.2 Introduction to Artificial Neural Network:

Artificial Neural network (ANN) is a kind of statistical modelling designed basically to act as human brain in its ability to arbitrate inputs and finally reach to conclusion(s). These networks are designed to learn from the provided data "exemplars" and then estimate the parameters of some populations. Applications of neural networks can be found in data modeling, system optimization and statistical analysis. Fields like econometrics, engineering, psychology and physics use neural networks as the statistical tools. [(13)]

Neural networks strength is extended from its ability to approximate arbitrary continuous functions based on a set of given examples. This ability is gained during the stage of training or sometimes called learning. As this ability is obtained, they are known as truly adaptive systems, which do not require any previous knowledge about the nature of relationships between parameters [(14)]. Also, ANN models can function to provide relationship between multiple-input and multiple-output systems [(15)].

Neural networks are structured from simple units called neurons and represent cells by analogy to human brain. In a network, neurons are connected through weighted connections. Throughout adjusting these weights, learning process inside the network is achieved [(16)]. Networks are usually arranged in the form of layers where the first layer corresponds to the input and the last one to the output. Hidden layers exist as intermediates between input and output layers. So, a neural network could be in the form of basic where the input is processed to predict the output, single-layer or multi-layer network.

The process of analyzing data starts with feeding inputs to the first layer neurons and then data propagates to the neurons of the second layer for further adjustment. Then results are transferred to the next layer and so on until they reach the output layer. During data transfer, input to each unit is either from other units or could be from external sources. These inputs processed and the unit results are generated.

Neural networks goal is to learn by discovering a logical connection between input and output patterns, or to analyze, or to find the structure of the input patterns. By providing the network with data, network training achieved through the modification of the connection weights between units. This process is similar to interpreting the value of the connections between units as parameters from statistical point of view. The training process identifies the “algorithm” used to find these parameters. [(13)]

3.3 Neural Network Architecture

The best way to think of a neural network is as if it were a black box in which inputs are processed to produce outputs. The typical structure of a neural network is shown in Figure 3.1. The main components of this structure are:

- Input Layer: A layer consists of neurons that have the same number as the system inputs. Inputs are received from external source and passed through the network during data processing. Inputs could be sensory inputs or signals from other systems not involved in the modelling process.

- Hidden Layer: A layer consists of neurons that receives data from the input layer and processes them in a hidden manor. Number of neurons in this layer is variable and is set during the stage of writing the algorithm. A hidden layer does not receive data from the outside world through inputs or outputs and it is only connected to layers within the system.

- Output Layer: A layer consists of neurons that have the same number as the system outputs. It is an interface layer where the processed information is received and outputs are sent out of the system.

- Bias: A number determined by the network algorithm to adjust the offset of a neuron. The purpose of the bias is to provide a threshold for neurons activation. Also, biases are connected to each of the hidden and output neurons in the network.

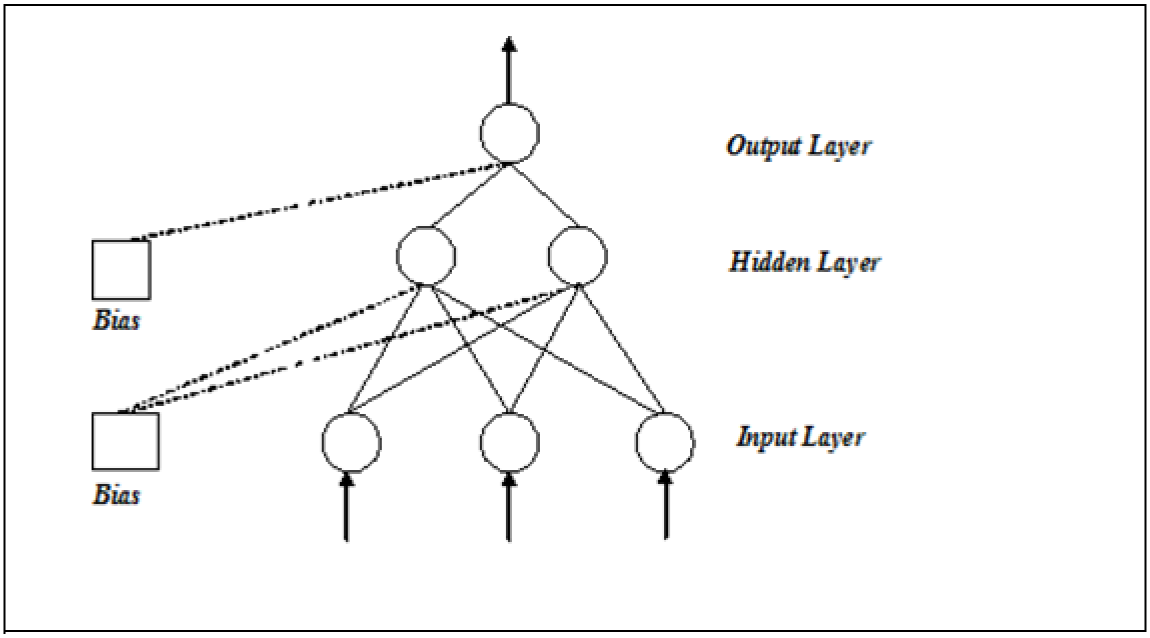


Figure 3.1 Typical neural network’s structure

3.4 Elements of Neural Network

Generally the three different types of layers are formed of basic components called neurons or nodes. The operation of a neural network is controlled by mathematical processing elements contained in neurons. Figure 3.2 illustrates a single node of a neural network.

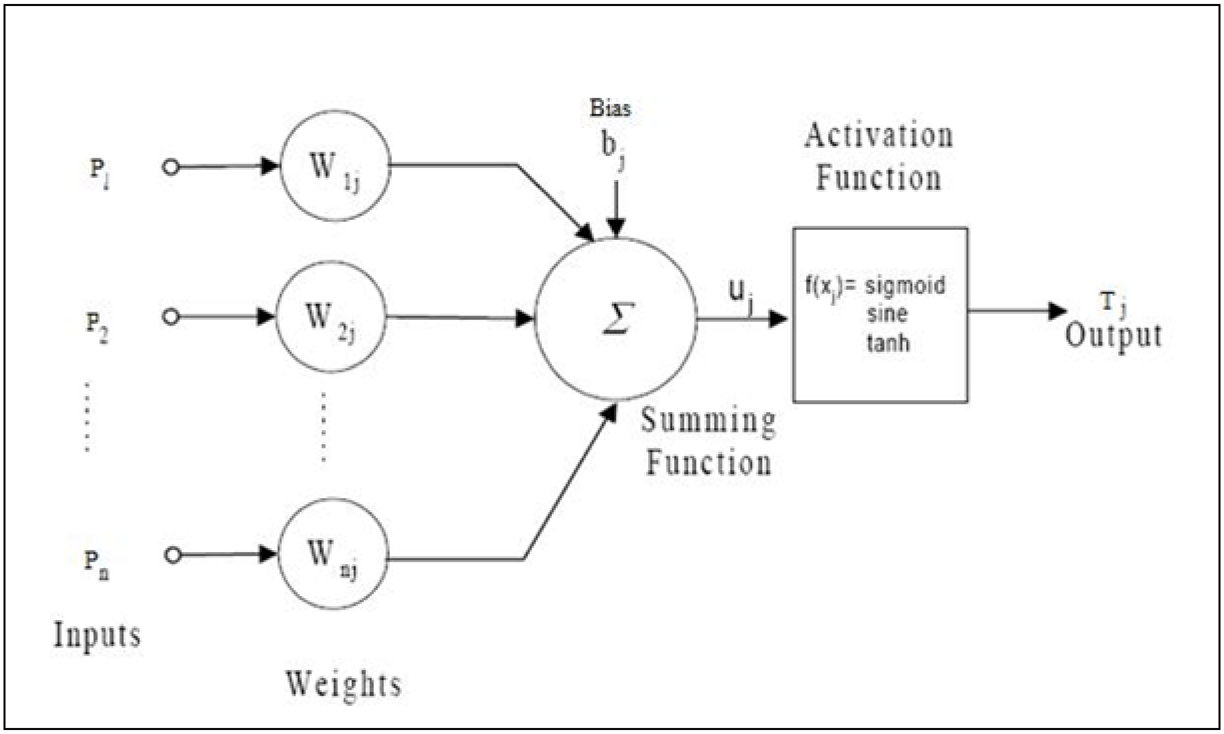


Figure 3.2 Structure of single node network

3.4.1 Inputs and Outputs

In order for the network to learn, both inputs and outputs are fed to the neural network. Inputs in the single node network illustrated in Figure 3.2 are P_1, P_2 and P_n and the output is T_j. In the case of single node network, many inputs are processed to reach a single output value.

3.4.2 Weighting Factors

In the structure of the network for each input there is an associated weight factor. In the early illustrated single node network weight factors are w_{1j}, w_{2j}, and w_{nj}. Weights play the same role of the varying synaptic strengths of biological neurons. Also, they are adaptive coefficients within the network that decide the strength of the input signal. Results from multiplying each input with the corresponding weight factor are used by neurons to perform further calculations. Positive weight factor tends to excite the neuron while negative weight inhibits the neuron.

3.4.3 Bias Correction Factor

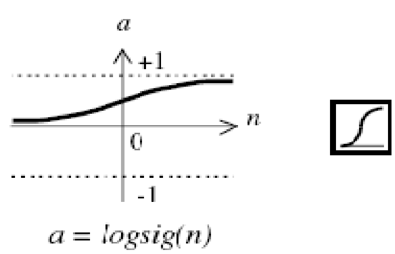
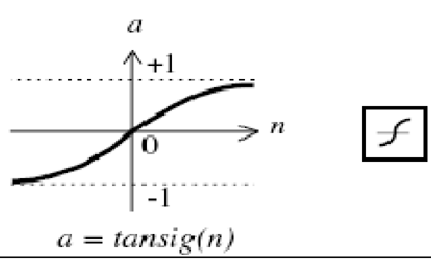
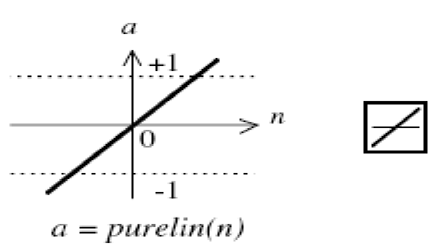
The third input to the neuron, b_j, is the bias correction factor. A random value is normally assigned to this factor at the beginning of the training process. The main objective of the bias factor is to govern the "activation" or total input of the neuron through the following equation.

$$\text{Total Activation} = \eta_i(t) = \sum_j W_{ij} P_j + b_j \tag{3.1}$$

Transfer Functions

Transfer function is the mathematical operation which is used to determine neuron's output through controlling the total activation of the neuron. The transfer function can alter the neuron's activation in a linear or nonlinear manner. The typically used transfer functions are listed in Table 3.1.

Table 3.1: Most popular transfer functions used in ANN

Function	Function Behaviour	Range
Log-Sigmoid Transfer Function		$0 \le a \le 1$
Tan-Sigmoid Transfer Function		$-1 \le a \le 1$
Linear Transfer Function		$-\infty \le a \le \infty$

3.5 Topology of a Neural Network

Upon the connections between the various components of the network, there are two different classification levels. Those two types are the external and the internal structure. The external structure describes the overall connections between inputs, outputs, and hidden layers in a network. The internal structure describes the connections between individual neurons both within and between layers. The different arrangements of neural networks integrate both internal and external connections through various techniques which depend on the application of the network, data and the ease of use. (26)

3.5.1 External Structure

The external structure of a network can have different arrangements and generally there are four major classifications and the selection of which arrangement to be used is purely dependent on the application the network designed for. The first type is single-input and single-output (SISO). It is used to predict the behaviour of one output variable based on data for one input variable. The second type is the multiple-input and single-output (MISO), the target for this structure is to predict the value of one output based on the feed data of many inputs. MISO structure is preferable when data from many sources in a process are used to predict a single downstream variable such as the demulsifier rate in this study. The third type is the multiple-input and multiple-output (MIMO). This is the most complicated structure and it works to predict values of several outputs based on several inputs data fed to the network. The last structure is the single-input and multiple-output (SIMO). SIMO structure is not generally used, because data for a single input are not adequate to help the network in precise prediction of the behaviour of the multiple output variables. (26)

3.5.2 Internal Structure

The internal network structure describes the connections between neurons in the network. These connections fall in one of three categories which are inter-layer, intra-layer and recurrent. In the inter-layer mode, connections are established between neurons in adjacent layers in the network. Intra-layer connection means that neurons can only communicate if they are at the same layer. In recurrent mode, a connection is initiated and terminated at the same neuron. Figure 3.3 shows the three options for communication between neurons, and layers C, D, and F could be in any place in the network.

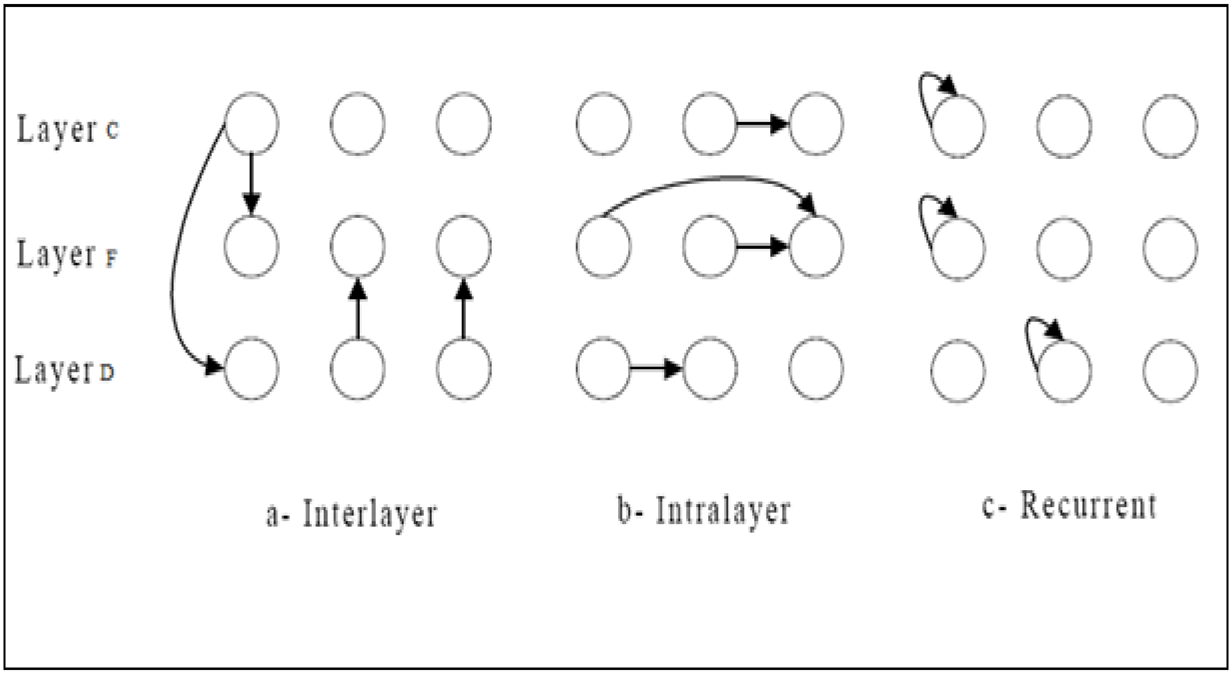


Figure 3.3 Types of connections (internal structure) in a neural network

Under the interlayer connection, there are two major forms of communication between the network neurons. Those two forms called “feedforward” and “feedback”. In the feedforward network, the signal flows only in one direction from the input layer through the hidden layers till the output layer. In a feedback network, the signal could flow to neurons in the same or preceding layer. Both types of neurons communication are illustrated in Figure 3.4.

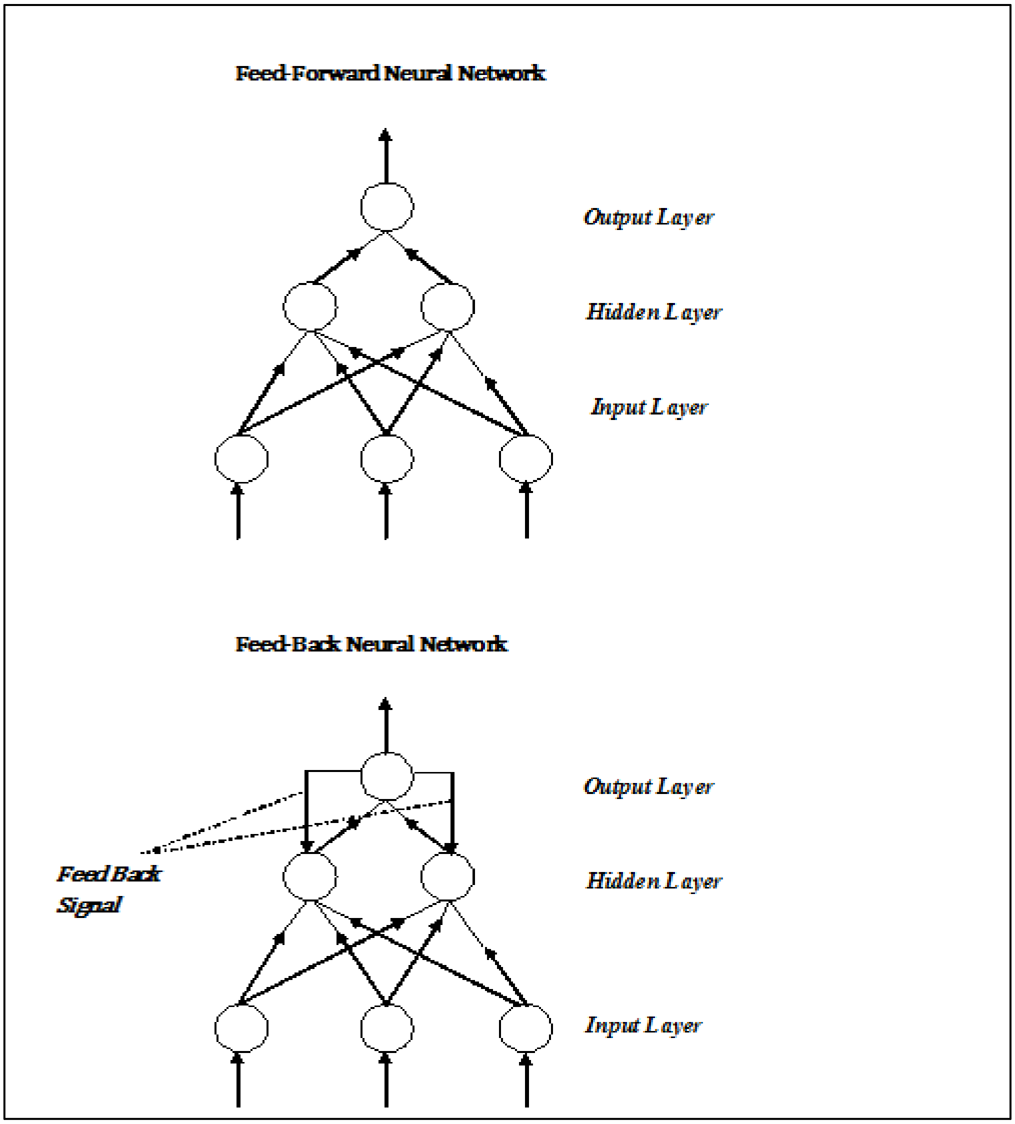


Figure 3.4 Feed-Forward and Feed- Back neural networks

3.6 Training and Testing the Network

After selecting the architecture of the network and specifying the initial weights and characteristics of neurons, the network becomes ready to be trained. Training a network means adjusting the interconnecting weights between neurons in a way to predict closer values to the actual outputs. To have the best possible trained network, a large set of historical input and output data is needed.

3.6.1 Training Modes

The different methods to train a neural network fall under one of the below described methods:

1- Supervised Learning Method: Supervised learning requires an external teacher called knowledge expert who develop a response function upon a given set of data fed to the system from the outside world. The same set of data used by the knowledge expert is also used by the learning system which develops another function. The error between the two outputs is measured and the generated error signal is used to adjust the learning system response through adapting weights of the neural network and that would make the response closer to that found by the knowledge expert. Knowledge expert can be a function, set of output data or set of constraints. Varity of methods were developed to train supervised neural networks like back propagation, fuzzy logic, expert system rules or statistical methods. (17)

2- Unsupervised Learning: The major difference between supervised and unsupervised network is that unsupervised network is not monitored by a knowledge expert and the network teaches itself through well defined internal criteria and local information set up for the network. The most popular unsupervised learning techniques are the self organizing and the adaptive resonance theory network. (17)

3.6.2 Testing the Network

After training the network, the network performance can be tested and this is usually done by performing the following two steps:

1- Recall step: test the ability of the trained network to predict the output for inputs used during the training process.

2- Generalization step: test the ability of the network to predict the output for inputs never used during the training process.

Well trained network will predict outputs that are too close to the actual values. During the testing process, the weight factors are not modified and they keep their values they had at the end of the training process. After testing with both types, the plot of the generated error versus the number of data samples in the testing set is called the learning curve.

3.7 Designing the Neural Network

To design a neural network with high accuracy in prediction, there are many neural parameters that must be adjusted. These parameters are the number of hidden layers, number of neurons in each hidden layer, normalization of all inputs to the network, initialization of weight factors,

3.7.1 The Number of Hidden Layers and Neurons

The application the neural network is designed for play a major role in selecting the number of hidden layers and the number of neurons in each hidden layer. In applications where high accuracy is required regardless of the processing time, the network in most cases would consist of many hidden layer and large number of neurons in each of these layers. In contrast, when networks designed for application the fast response is the bottle neck, the network normally is formed of small number of hidden layers and small number of neurons in hidden layers. So, determining the number of hidden layers is a critical part of designing a network. To find the optimal number of hidden layers and the optimal number of neurons in each layer, there is no procedure except the trial and error; in this case the network is trained with different configurations. The configuration that have the lowest number of layers and neurons and still gives satisfying results with minimum error and acceptable response time should be selected.

Cybenk (1989) reported that a network with only one hidden layer and sufficient number of neurons could lead to satisfying results. Baugham and Liu (1995) found that the addition of a second hidden layer significantly enhance the network capability in prediction of outputs without having any major influence on the generalization of the testing data set. However, adding more hidden layers even maximize the prediction capability but since the network structure becomes more complicated, longer processing time is expected. Baugham and Liu (1995) reached to a conclusion that the best initial network structure for two hidden layers is 30:15.

3.7.2 Input and Output Data Normalization

When inputs and outputs of the network are decided and row data is collected, data normalization before training the neural network is mandatory to make all parameters of the same order of magnitude. To illustrate this case more consider that input variable 1 has a value of 1,000 and input variable 2 has a value of 1, the assigned weight for the second variable entering a node of hidden layer 1 must be much greater than that for the first in order for variable 2 to have any significance. Depending on the function used for normalization, all feed data to the network will have values between 0 and 1 or between -1 and 1.

Introduction the data set to the network without normalization forces the training algorithm to manipulate the network weights to compensate for order of magnitude differences. This process is not efficient in many of the training algorithms. Moreover, when two values of a variable are very large, transfer functions, like the sigmoid function cannot distinguish between them since they generate the same threshold output values of 1.0.

To prevent confusing the network with data of different order of magnitude it is recommended to normalize all input and output data set before introducing them to the network. In literature, many methods are used for data normalization; Table 3.2 shows a brief description of the most used three methods.

3.7.3 Initializing the Weight-Factor Distribution

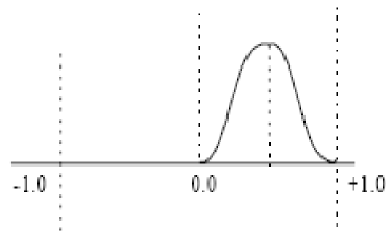
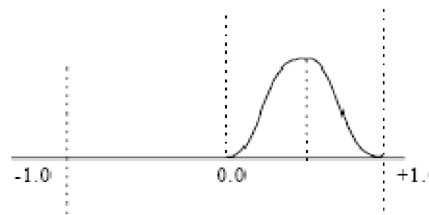
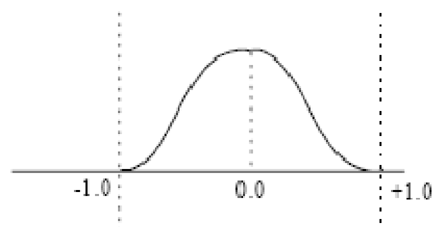
The closer the final weights of the neural network to the optimal values the more accurate the network output. Normally weights are randomly assigned at the beginning of the learning process but during the development of the network weights are adjusted. In order to lower the training "learning" process many methods were established to initialize weights; seven of these methods are described and compared in reference 23. In addition, the speed of convergence, the probability of convergence and the generalization are affected by the weight initialization. [23]

3.7.4 Setting the Learning Rate and Momentum Coefficient

The major function of the learning rate is to speed up the rate at which the network converges. The other technique could be used to achieve the same purpose is done by multiplying the learning rate by the change in weight factor from the previous run "iteration" to find the new weight factors.

The objective of the momentum coefficient is to prevent the training algorithm from settling in local minima and increases the speed of convergence. When, the algorithm successes in avoiding local minima in the RMS error it will finally reach the global minimum which corresponds to the best set of weight factors.

Table 3.2: Three methods used mostly to normalize data

Method Name	Equation	Behaviour and Range
Normalization to The Maximum	$x_{i,norm} = \frac{x_i}{x_{i,max}}$	
Simple Range Scaling	$x_{i,norm} = \frac{x_i - x_{i,min}}{x_{i,max} - x_{i,min}}$	
Zero-Mean Normalization	$x_{i,norm} = \frac{x_i - x_{i,avg}}{R_{i,max}}$ $R_{I,max}$ is the maximum range between the average value and either the maximum or the minimum.	

3.7.5 Selection of Transfer Function

In most cases the selection of the transfer function is done based on the application and the function of the neural network. The most popular transfer functions used in neural networks are shown in Table 3.1. The hyperbolic tangent and sigmoid functions always show a great ability in predicting results while the Gaussian function shows comparable ability when used in classification networks.

3.8 Back Propagation:

Back propagation is one of the most commonly used algorithms due to its high performance in lowering the generated error. In a feed forward interlayer network when the set of input data introduced to the network, back propagation algorithm generates the output and calculates the difference between the actual and the simulated values "error". Then the network start going backward to adjust layers' weights. By the time all the weights have been updated, the network returns the forward propagation to predict the output for the same set of input data. Also, this time the error in predicting the output is calculated and the same process of output prediction, error calculation and weight adjustment continues until the generated error reaches a minimum. (18)

3.9 Neural Network Application Disadvantages:

The main three disadvantages of using artificial neural networks are described below:

1. Weakness in extrapolation: When a neural network is trained on a set of data, the neural build its experience within the range of input variables. When any of the variables exceeds the training range, the network will face a difficulty to have accurate prediction. (19) This means that the output of the network will have error if the neural network was not trained on a given set of conditions. This error happens without any previous warning. To resolve such problem, the training set should be updated to include a broader range of conditions.

2. Accuracy versus delay: to have a neural network that produces highly accurate output additional layers and connecting weights are required which lead to slow execution time. (19)

3. Large data set: to train a neural network to predict accurate output a large training data set is required and also, large data set is required too during the testing process. (20)

3.10 Model Performance:

To determine the performance of data fitting, the coefficient of determinations R^2 is usually the most popular indicator. In neural network applications, R^2 is a measure of the model accuracy in predicting outputs.

$$R^2 = 1 - \frac{\sum (Y_R - Y_S)^2}{\sum (Y_R - \frac{\sum Y_R}{N})^2} \tag{3.2}$$

Where

Y_R is the output data sample reading

Y_S is the output simulated (predicted) value

N is the total number of readings in the data set.

In most of modelling cases the coefficient of determination doesn't fully express the model performance and another indicator is needed such as the mean square error (MSE) or the classification error. In this study the performance of the neural network in output prediction is judged using both R^2 and MSE. MSE for this application is expressed by equation 3.3.

$$MSE = \frac{1}{N} \sum (Y_R - Y_S)^2 \tag{3.3}$$

The model is accurate as the R^2 value approaches 1 and MSE approaches 0. The performance of algorithms generated in this study is monitored by both described techniques to find an optimum structure of the network.

Chapter 4

Data Processing and Neural Network Design

4.1 Introduction

The data utilized in this work were collected from HwGOSP-3 (Hawiyah Gas Oil Separation Plant 3) in Saudi Arabia. The knowledge established in chapter 3 will be utilized here to develop a well trained neural network to be able to predict the demulsifier addition rate. The external structure will be multiple inputs single output (MISO) and the internal structure will be feedforward. The network will be supervised and back propagation method for error calculation will be used. Number of layers, number of neurons and the appropriate combination of transfer functions will be determined through trial and error procedure.

4.2 Data Collection:

This work results can be more significant if the data collected covers wide ranges of the most effective factors on the emulsion instability in the desalter vessel. To ensure that the data collected would have broad ranges, a survey was done on seventeen gas oil separation plants in Saudi Arabia. The survey showed that HwGOSP-3 (Hawiyah Gas Oil Separation Plant-3) has the best combination of wide ranges in wash water rate, oil production rate and demulsifier rate.

To maximize oil temperature range data were collected on a time frame of one year to count for the seasonal weather effect. Therefore, all the used data are real and the source is HwGOSP-3. Factors which play major role in determining demulsifier rate are listed in Table 4.1 with their maximum and minimum readings in the collected data. The collected data showed that demulsifier consumption rate resulted from a linear controller was between 70 and 450 GPD (Gallon Per Day). The data distribution of demulsifier rate and the proposed controlling parameters are shown in Figures 4.1a through 4.1h.

Table 4.1 Factors Effecting Demulsifier Consumption

Factor	Minimum	Maximum	Unit
Water Cut	14	20	%
Wash Water Rate	30	190	GPM
Oil Temperature	70	130	^{o}F
Dehydrator voltage	2099	16508	Volt
Desalter Voltage	15056	16374	Volt
Total Inlet Rate	232	442	MBD
Salt Content in Treated Oil	6	16	PTB

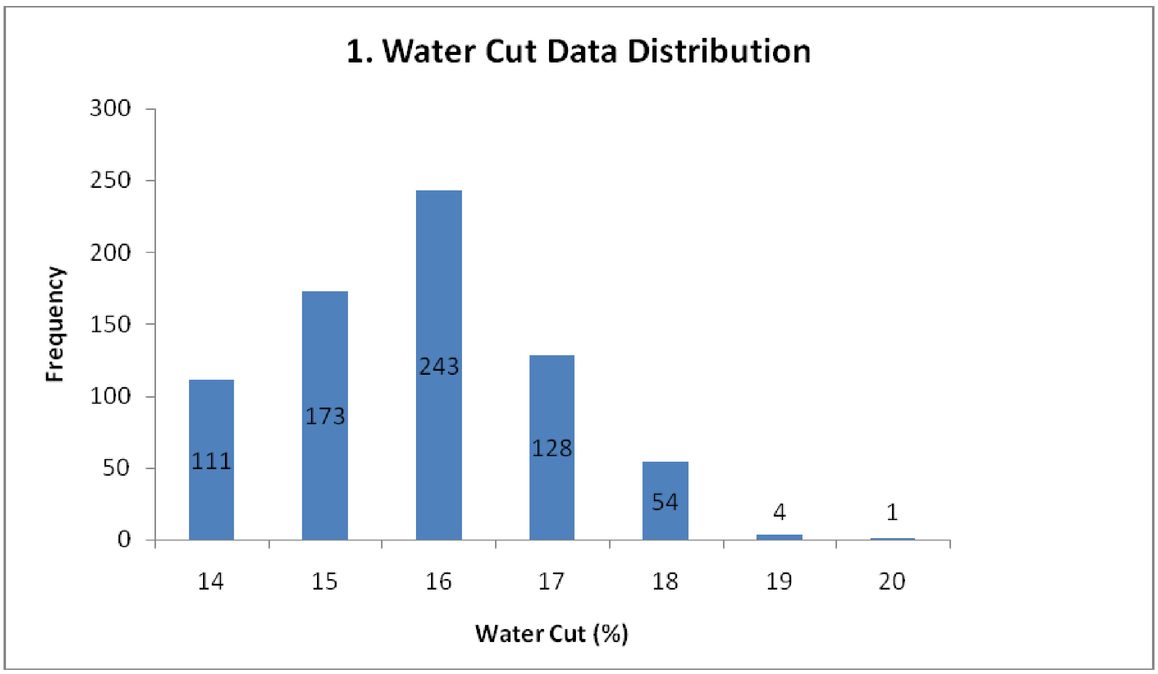


Figure 4.1a: Distribution of water concentration data

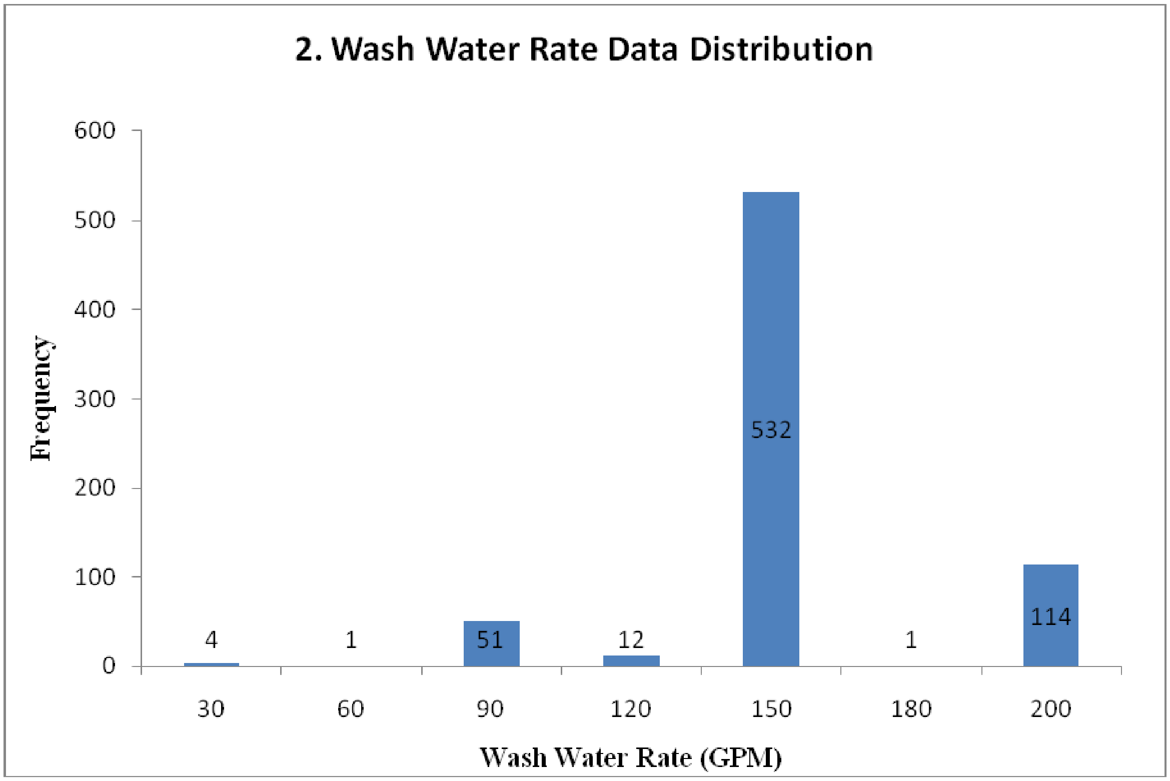


Figure 4.1b: Distribution of wash water data

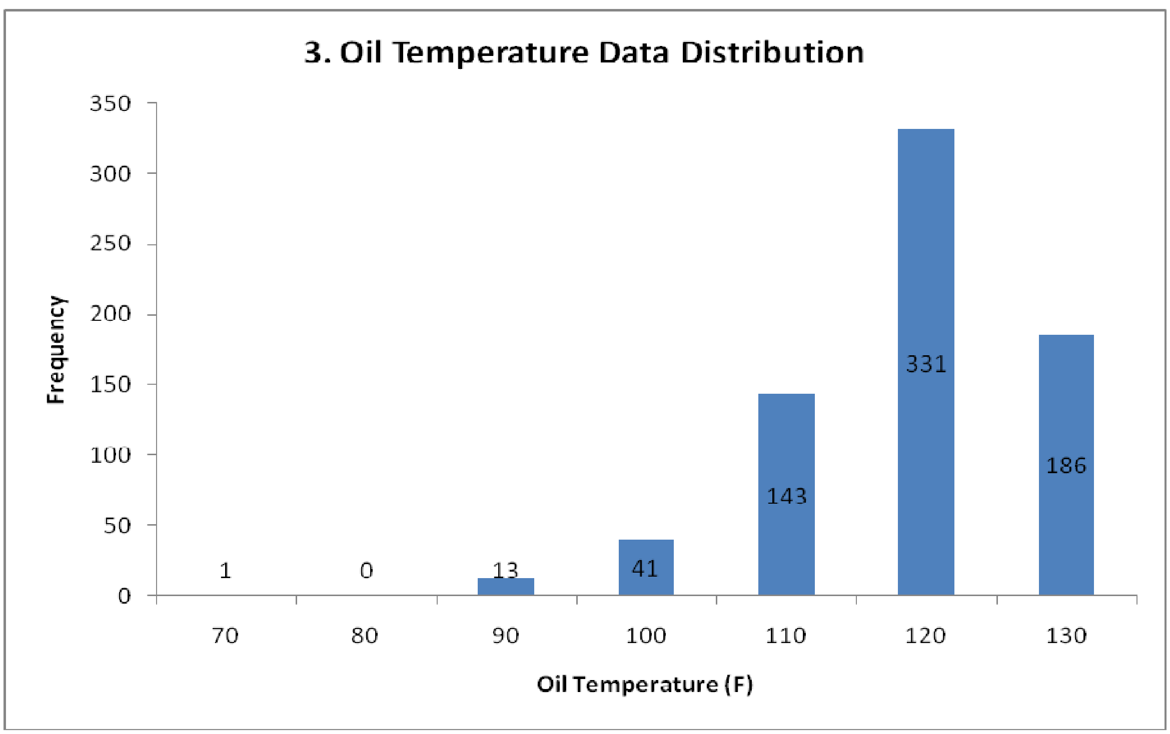


Figure 4.1c: Distribution of oil temperature data

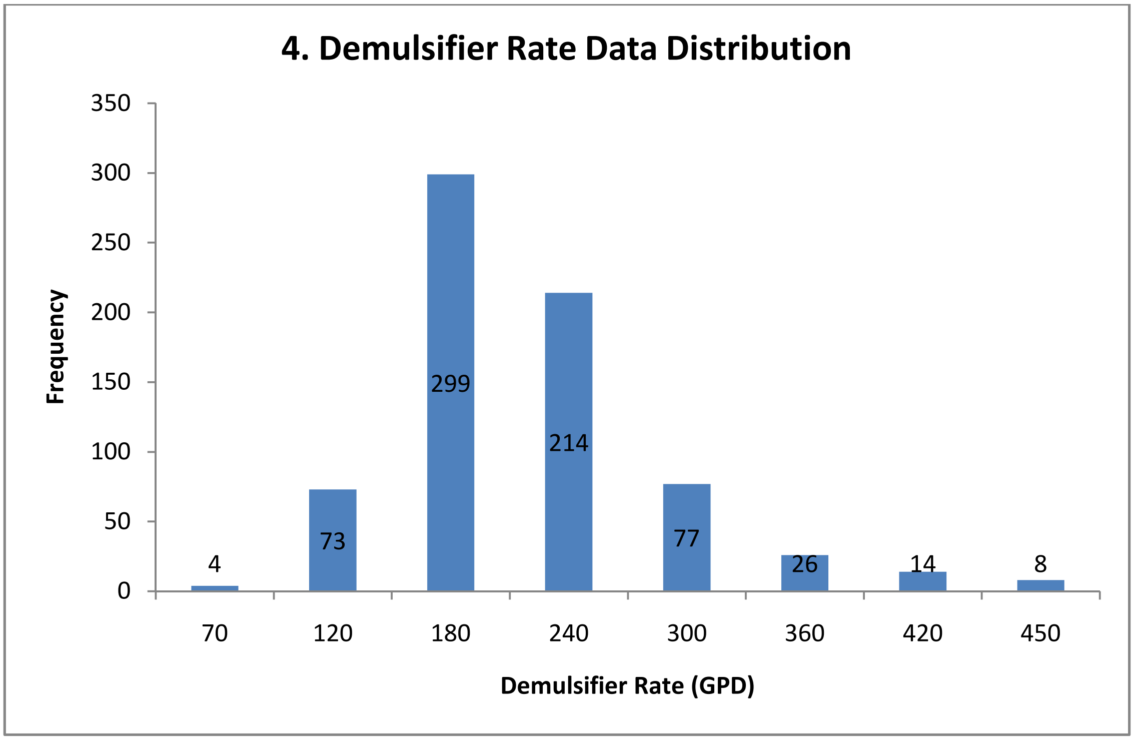


Figure 4.1d: Distribution of demulsifier rate data

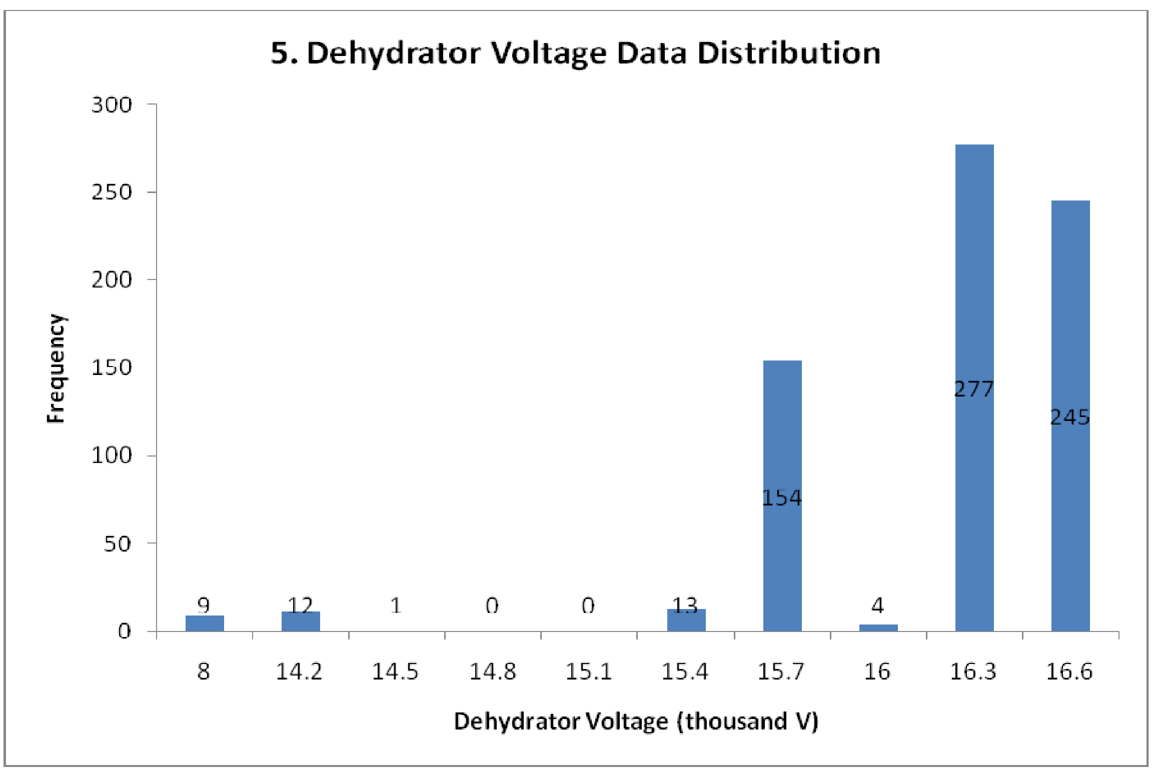


Figure 4.1e: Distribution of dehydrator transformers voltage data

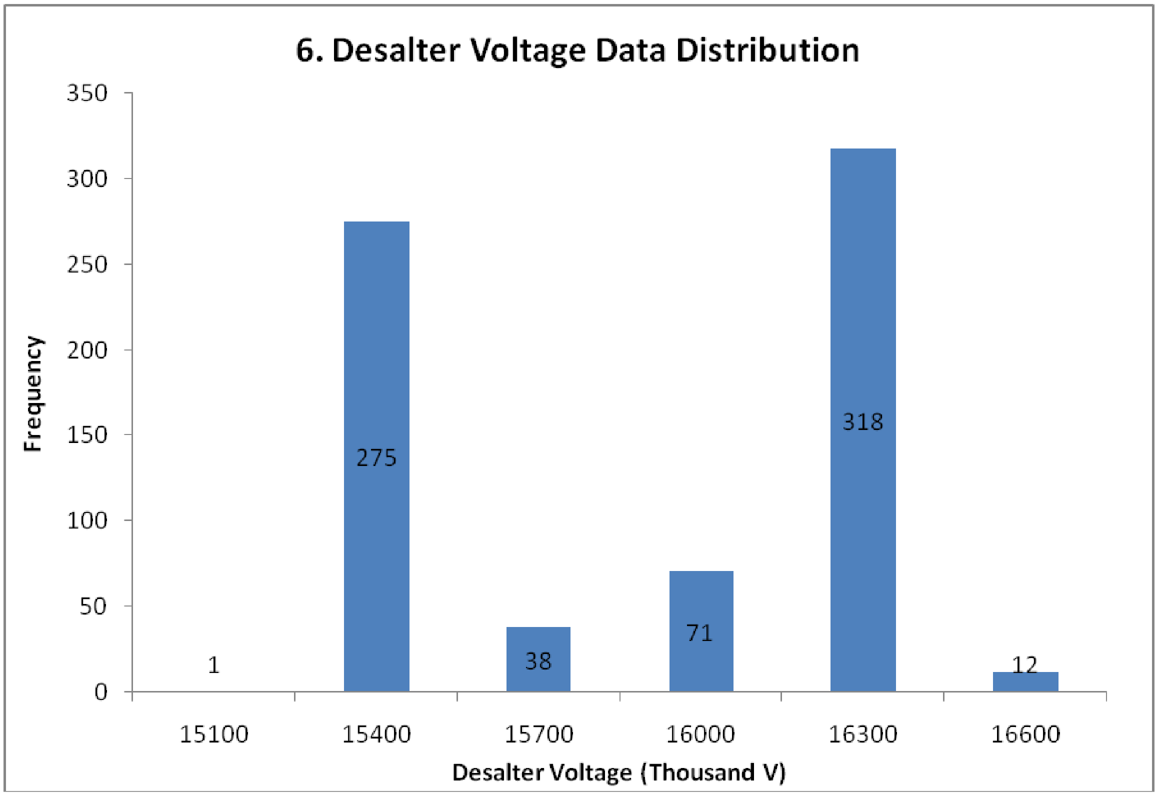


Figure 4.1f: Distribution of desalter transformers voltage data

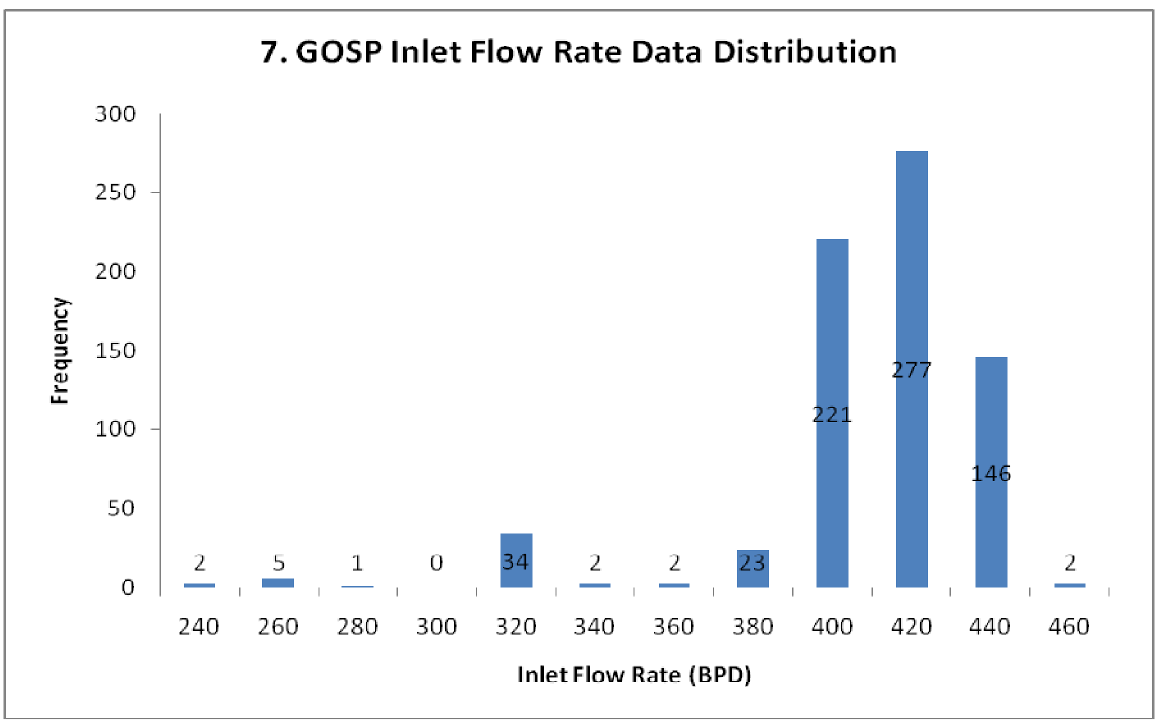


Figure 4.1g: Distribution of the inlet crude flow rate data

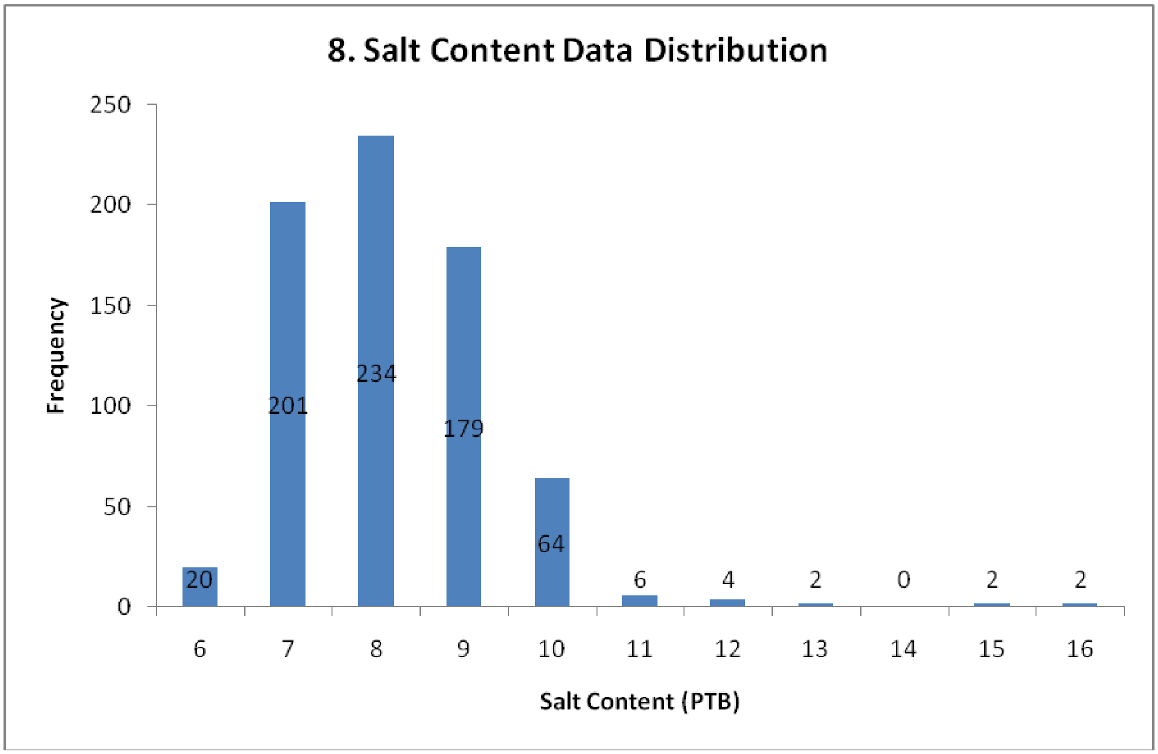


Figure 4.1h: Distribution of salt concentration in the treated oil data

4.2.1 Data Collection Method:

In HwGOSP-3, all readings of these factors except salt content are online measured through field mounted transmitters and then data transferred to the control system from which data are copied and stored in special server called Plant Information. Salt concentration is measured three times daily (once every shift) and data recorded on an electronic data log.

Since the operation log file has the exact time at which each oil sample was collected to perform salt content test, the mission to find the other variables reading at the same time was quite easy. For example the operation log shows that the salt concentration is 9 PTB at 8:15 a.m. From the Plant Information (PI) server the readings (oil temperature, oil production flow rate, wash water flow rate, the desalter electrostatic voltage, the dehydrator voltage, water cut and the demulsifier total consumption rate) are found.

4.2.2 Data Filtration:

Outliers or wrong data misleads any data fitting algorithm especially in the case of process data modeling. The success of adaptive control algorithms depends on the quality of the used process data. The reason for finding outliers in a data set is that they have a significant effect on estimating the model parameters which at last influence the output [21]. In the case where outliers heavily exist, the generated model is no longer presenting the process dynamics [22].

Throughout scanning real data outliers can be discovered easily by careful observation because they do not reasonably fit within the pattern of the bulk data points and do not have logical behaviour compared to the rest of data. Outliers occur in a data set because of incorrect measurement resulted from malfunctioning or out of calibration instrument. The other reason for the appearance of outliers is the occurrence of unusual process phenomena that could be of great interest to the data analyzer. It is clear now that discovering an outlier is a relatively easier task compared to finding which type of outliers this point belongs to. In order to observe this distinction, the data require careful inspection and examination. [20]

The outliers' detection is a crucial process to have reliable data from which conclusions are made and decisions are taken or models are developed for the operation of a process. In neural network and statistical analysis outliers are given special importance to discover the reasons cause these points behave differently from the remainder of the data set. Outliers being included in the training data force the network to consider a wider solution space which finally could result in a massive reduction in the resulting network precision. [27]

To identify the outliers in the collected data set in this work, visual scanning was performed and all suspected data points were listed. The seven process variables measured through field instruments were grouped to three classes upon the expected change on time interval for example the oil temperature is not expected to vary much on time interval of 10 minutes while the wash water rate may do. The first class categorized with slow variation over time period and includes the oil temperature and inlet oil water cut. Any sudden change in the variable reading means spike in the instrument reading caused by malfunctioning and such reading represents the misleading outlier and should be excluded but if the change is not sudden but suspected then for the oil temperature can be verified against readings provided by other transmitters on streams that are believed to have close readings like the HPPT gas out temperature. In the case where the water cut has the suspected reading, the check could be done by referring to operations well status log, if there is no major change then the data point should be excluded. The second class includes dehydrator/desalter voltages which have moderate behaviour over short time period but their effect at abnormal situations significantly serves the study purpose. Outliers in this class can be checked by generating a trend which includes both the voltage drip and its recovery; if the voltage recovery occurs on a reasonable time period then the corresponding data point is real and should be considered in training the network otherwise it should be excluded. Flow readings are included in group three which is categorized with high variation on short period of time. Parameters under this class when behave unreasonably, for extra caution not to mislead the network, data points should be excluded from the data set because it is impossible to verify the measurements and including them would not be of great help to the study target.

After scanning the collected data, there were 9 outliers from whom 6 were due to spikes or malfunctioning instruments. These six data points were excluded from the data set. The other three appear to be correct and represent the actual process conditions so they were kept in the data set.

4.2.3 Data Normalization:

Even if data reflect the real system behaviour, the trained network may produce results with high error and one of the main reasons is either not normalizing the data set or normalization with unsuitable method. To identify the most suitable normalization method for this study, the network was fed with data normalized with different methods and the corresponding error was calculated as shown in Table 4.2. The simple range scaling method showed the lowest error, so it has been selected for data normalization.

Table 4.2 Performance of the designed neural network with different methods of normalization

Normalization Method	**Network Error**
Normalization to The Maximum	0.000998
Simple Range Scaling	0.000859
Zero-Mean Normalization	0.001665

4.3 Designing the Neural Network

In developing a neural-network model, the goal is to develop a network that produces the lowest error between the actual and predicted values for the output variable. The question then arises what is the optimum design criteria for a network in selecting the transfer function(s), the number of hidden layers and the number of neurons in each layer.

4.3.1 Transfer Function Selection:

The network output accuracy is highly affected by the selected transfer function. As shown in chapter 3, there are three main transfer functions normally used in neural network modeling. To determine the best combination of transfer functions in network with one and two hidden layers, different transfer function used in the developed network. Testing the performance of the network with one hidden layer consisting of 30 neurons shows that using “Tansig” transfer function (refer to table 3.1) between the input and the hidden layer and with a “purelin” transfer function between the hidden layer and the output layer generates the highest coefficient of determination and the lowest mean square error (MSE). The experiment results are shown in table 4.3. The same procedure was conducted on two hidden layer network and results show that the best combination of transfer functions is “Tansig” between the input and the first hidden layer, “logsig” between the first and second hidden layers and “purelin” between the second and the output layer.

Table 4.3: Transfer function selection trails for one hidden layer network

Transfer Function		Network performance	
Input-Hidden	Hidden-Output	R^2	MSE
Tansig	Purelin	0.908	419
Logsig	Purelin	0.876	561
Tansig	Logsig	0.866	606
Logsig	Tansig	0.881	537
Purelin	Logsig	0.869	593
Purelin	Tansig	0.872	580
Tansig	Tansig	0.904	475
Logsig	Logsig	0.895	433
Purelin	Purelin	0.807	872

4.3.2 Number of layers:

The selection of the numbers of hidden layer is critical for the network to predict the network output with less error. Usually the optimum number of hidden layers is decided through trial and error procedure and the lowest number of hidden layers with satisfactory generated error is selected. The reason for such selection is that as the number of hidden layers kept at an optimum low, the less time required for training the network. The majority of optimization problems can be solved with acceptable calculated error with one or two hidden layers. Studies shows that only 1-2% of neural networks require three or more hidden layers to find accurate solution. Table 4.4 shows different trails to define the optimum hidden layers for this study. Upon the results, the decision was made to use a network of one hidden layer.

Table 4.4: Performance of one and two hidden layers network

Number of layers	Number of neurons	R2	MSE
3 (one hidden layer)	10	0.8807	538
3 (one hidden layer)	20	0.9066	424
4 (two hidden layer)	10 5	0.9047	418
4 (two hidden layer)	20 10	0.9004	450

The ability of neural network to learn complex mapping function is enhanced by the proper selection of the number of neurons in the hidden layers (23). Neural networks are highly responsive to the number of neurons in the hidden layers. Using too few neurons will make the network not able to learn al1 often patterns accurately. In contrast, too many neurons will make the network tending to remember the patterns rather than learning to distinguish the global characteristics of the pattern (22). Table 4.5 shows the different trail done to find the minimum number of neurons in the hidden layer. For this application it was found that the optimum configuration of the neural network is to have one hidden layer consists of 21 neurons.

Table 4.5: Performance of one layer network with different number of neurons

Number of neurons	R^2	Error (MSE)
10	0.8807	538
15	0,8947	475
18	0.9052	407
20	0.9066	424
21	0.9125	395
22	0.9014	445
24	0.8975	463

4.3.3 Weight Initialization

After the number of layers and neurons in each layer are decided and before training the network, network weights should be set otherwise the Matlab (which is the software used in this study) initializes weight to random values. The process of training neural network with Backpropagation algorithm can be described as an optimization process in which the error is minimized through manipulating the network weights Backpropagation follow the local optimization technique which works to reach the minimum error (24).

Defining the local minimum by the algorithm is critical for the training process and consequently on the network output. The network solution will be close to the real value if the selected minimum is close to the global one otherwise the trained network will have a poor performance leading to generate solution not reflecting the actual process. Determining the local minimum in backpropagation procedure is controlled by the process of initializing the network weights. Moreover, the weight initialization plays a major role in determining the speed of convergence [24] .

The method used for weight initialization in this work is very simple but shows high performance. The method can best described in the following steps:

1. All weight connections of the first and second layers are initialized with zero values and biases of the two layers are ones.
2. Train the network and save the layers weight and bias.
3. Make a for loop in which the network will use the calculated weight and bias to train the network with a condition that the new generated weights and biases will replace the old values only if the network performance has enhanced.

Implementing this procedure on the network lead to a major development in enhancing the network performance so the mean square error was lowered and the coefficient of determination was increased. Table 4.6 compares the network performance using this method with the random initialization method for 10 different trails.

Table 4.6: Network performance with two weight initialization methods

Initialization Method	R^2	MSE
Weight and Bias Update	0.9125	395
Random Initialization method (Trail 1)	0.8697	588
Random Initialization method (Trail 2)	0.8995	453
Random Initialization method (Trail 3)	0.8910	492
Random Initialization method (Trail 4)	0.8937	480
Random Initialization method (Trail 5)	0.8705	584
Random Initialization method (Trail 6)	0.8908	493
Random Initialization method (Trail 7)	0.8662	604
Random Initialization method (Trail 8)	0.8396	723
Random Initialization method (Trail 9)	0.8854	517
Random Initialization method (Trail 10)	0.8966	467

Chapter 5

Results and Discussion

The artificial neural network designed in the previous section showed an acceptable performance in both the coefficient of determination (R^2) and the mean square error (MSE). In this section the ability of the network to predict the output (demulsifier rate) will be further tested.

After validating performance, the network compared to the existing demulsifier control scheme.. Also, the function used to train the network is used in a MATLAB program to find the optimum wash water rate which is injected at the desalter inlet to wash salty oil. Based on the results from the optimization, the feasibility of automating wash water pumps will be evaluated In some cases optimization of wash water rate becomes as important as demulsifier rate. Thus, a second optimization program was designed to optimize both factors. Moreover, the trained neural network was used to predict the salt concentration in the treated oil as if a salt analyzer were installed. The results were compared to the those tested at the plant lab and at the same operating conditions.

5.1 Neural Network Testing

In the process of designing and training the Artificial Neural Network, the network accuracy was developing inside the loop which was made to reinitialize the weights and biases until it reached optimum values in terms of R^2 and MSE. Normally neural networks are tested in two different steps to validate their performance in predicting outputs:

1. Recall Step: in this step the same data set employed to train the neural network is used to validate network performance.
2. Generalization Step: in this step the network performance is validated using a new set of data.

5.1.1 Recall Step:

In this step, the network performance was checked against the actual data used during the training stage. The average accuracy of the predicted values was 0.9144 and 384 in terms of R^2

and MSE respectively. The high value of R^2 is a good indication about the model ability to predict the demulsifier rate. The average deviation between the model prediction and the actual demulsifier rate is 19.6. This deviation is the square root of the calculated mean square error (MSE). Later, the MSE value will help to select a set point for the neural network controller. Figure 5.1 compares the actual readings versus the predicted values. As shown in the figure, the model prediction is more accurate on the range of demulsifier consumption between 110 and 350 GPD. This is because the network was not trained on enough data outside the mentioned range. This range represents the demulsifier rate at normal operating conditions. The dosage only exceeds it during the plant start up, plant shutdown or when a transformer is tripped.

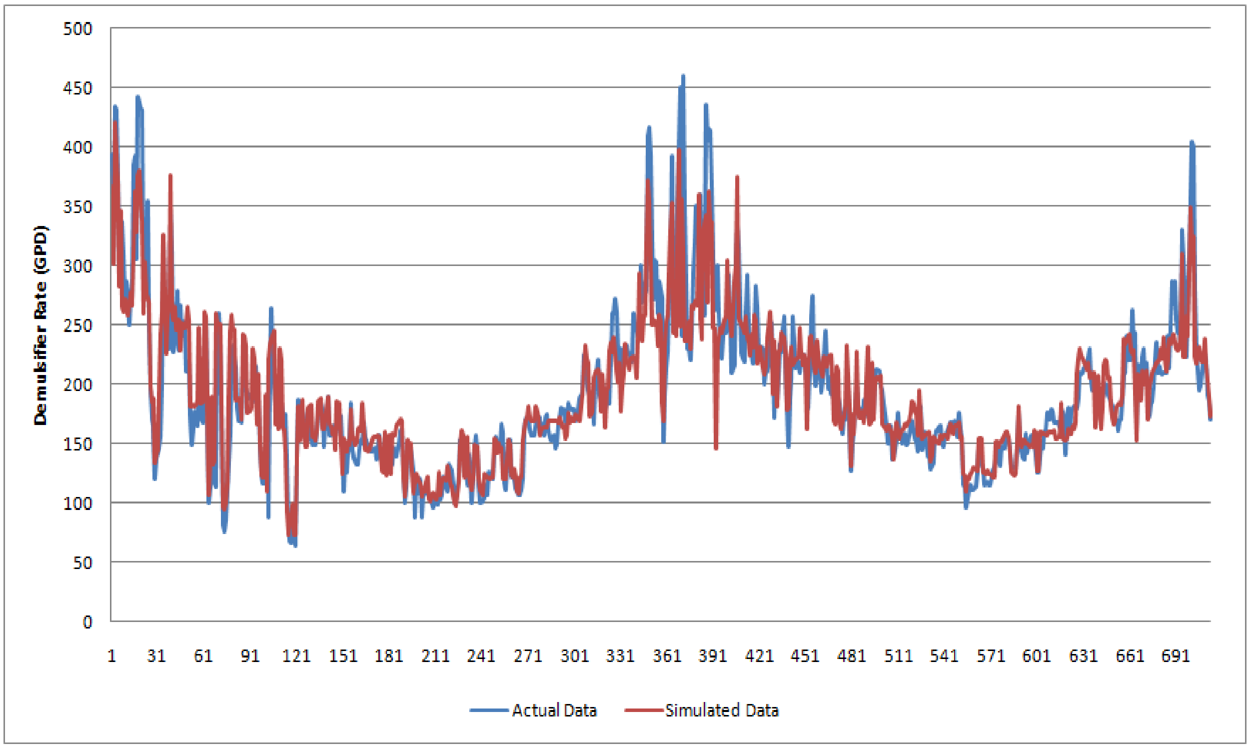


Figure 5.1: Plot of the simulated values versus the actual process readings for data set used in training the network

5.1.2 Generalization Step:

Based on the analysis made on the training data set, in this section the network performance was tested through predicting the function output for new process data. The new data set contains 104 data points randomly selected. Since Artificial Neural Network is weak in extrapolating data, data was checked to be within the training data range. The performance of this step is 0.9047 and 264 in terms of(R^2) and MSE respectively. In Figure 5.2 the predicted values were plotted against the plant readings. The model showed high accuracy at low demulsifier rates for the same reasons described in section 5.1.1. To enhance the network prediction accuracy at conditions corresponding to demulsifier rate of more than 350 GPD, one of the following recommendations should be considered.

1. Network training on more data at high demulsifier rate.
2. When the predicted demulsifier rate is higher than 350 GPD, the controller considers a safety factor which ensures that its action is more conservative to prevent the salt concentration in the treated oil from exceeding the quality limit.

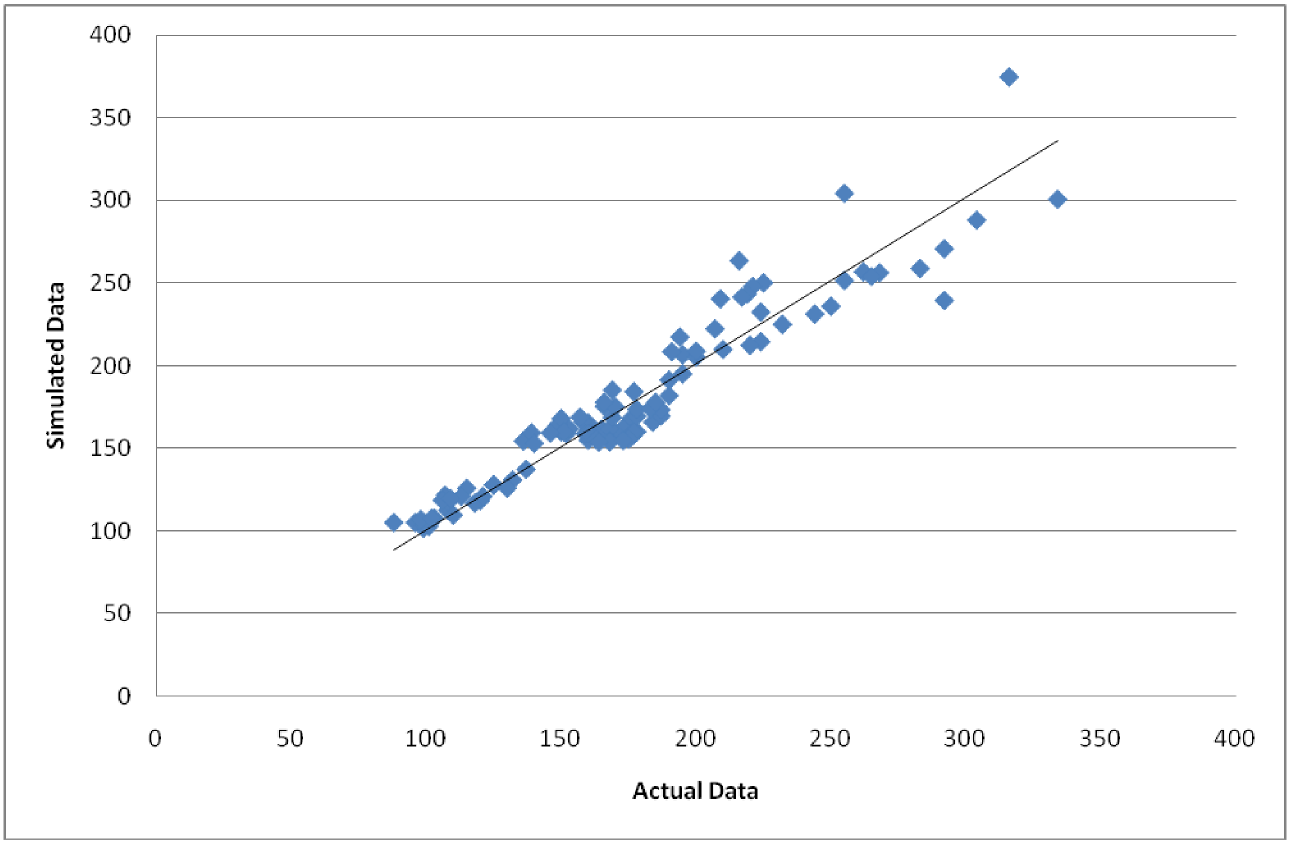


Figure 5.2: Plot of the simulated values versus the actual process readings for data set not used in training the network

5.2 Existing Control Scheme Evaluation:

The demulsifier controller's main objective is to inject demulsifier at or close to the optimum rate. The optimum demulsifier rate is the lowest rate which can maintain the salt concentration in the produced oil equal to 10 BTP at the instantaneous online measurements of all parameters that affect the salt concentration. Additional desalting increases the operating cost but does not affect the selling price. Thus, it is clear that the controller designer should consider a feedback controller which read all the parameters affecting the desalter performance to estimate the demulsifier rate. The existing controller follows the same concept except that the salt content reading is not available to the controller since there is no installed online analyzer that could provide such reading. The lack of such on-line analyzer is expected to heavily affect the controller output accuracy. Figure 5.3 shows the performance of the existing control scheme by considering the deviation of salt concentration from the quality target, 10 PTB. In the figure, the shaded area represents the demulsifier amount that should not be injected if an accurate control scheme was used. Also, the histogram chart in chapter 4 showed that 455 samples have salt concentration equal or less than 8 PTB, 179 samples have 9 PTB, 64 samples have 10 PTB while 16 samples have more than or equal to 11 PTB. This indicates that the controller at most of the time over inject demulsifier.

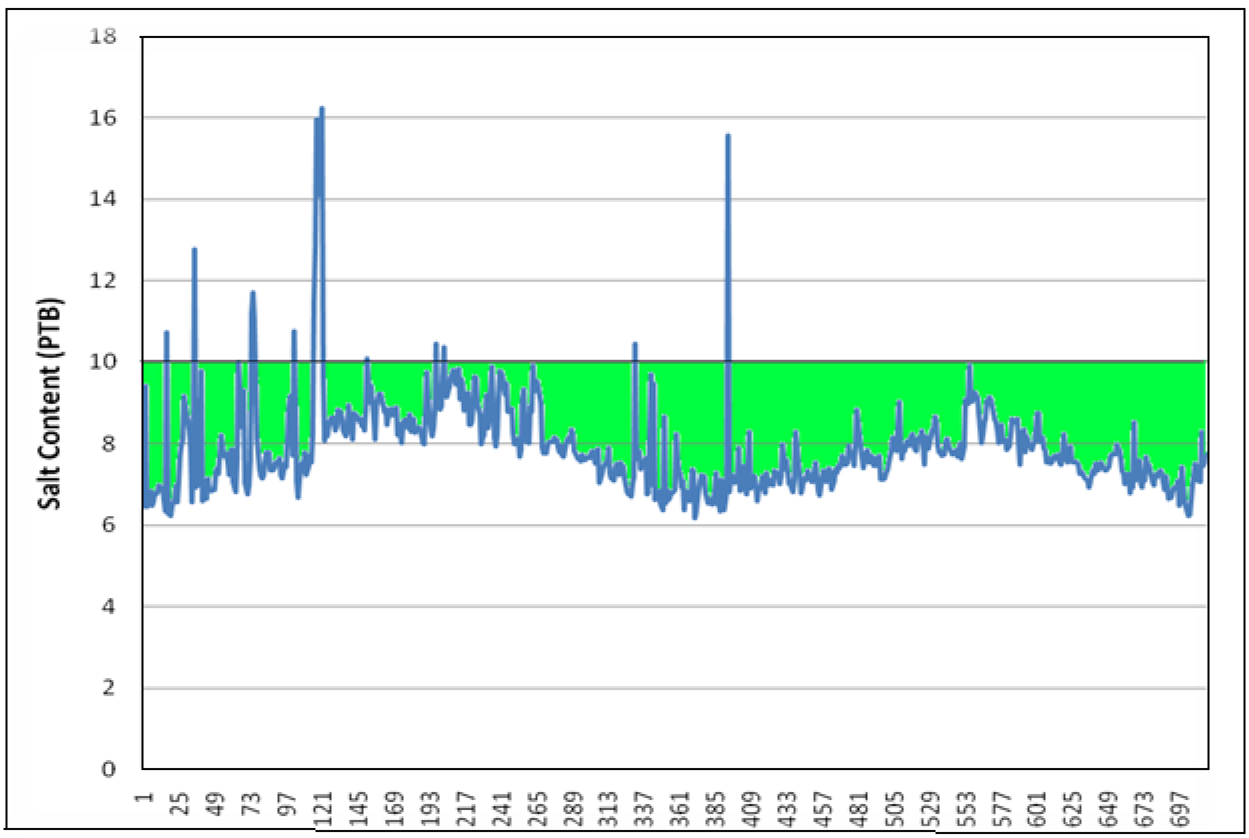


Figure 5.3: Plot of the salt content in the treated oil while using the existing demulsifier control

5.3 New Control Scheme Using ANN:

Training the designed Artificial Neural Network (ANN) on data set which contains all parameters affecting the demulsifier rate including the salt concentration in the produced oil will be able to sense the effect of demulsifier injected amount on salt content. Therefore, this method is best described by blind but experienced. Blind of the real salt readings but experienced due to the knowledge gained during the training stage. In this control scheme inputs are the online readings of desalter/dehydrator voltages, oil temperature, wash water rate, flow rate and water cut of crude oil entering the GOSP. The salt concentration is also an input but since there is no mean of online monitoring it will be adjusted to an optimum value which meet the following two conditions:

1. The actual salt reading in the treated oil does not exceed the company specification which is 10 PTB.
2. The demulsifier rate is maintained at an optimum value.

The average deviation between the predicted and actual readings in the recall step was found to be 19.6. Therefore, the salt concentration set point was selected to be 9 PTB to ensure that even at the worst case scenario the concentration will not exceed 10 PTB. Implementing this controlling methodology on the collected data, results showed a great improvement in demulsifier injection rate as shown in figure 5.4. The average reduction is about 49 GPB which is 25% of the current average consumption rate.

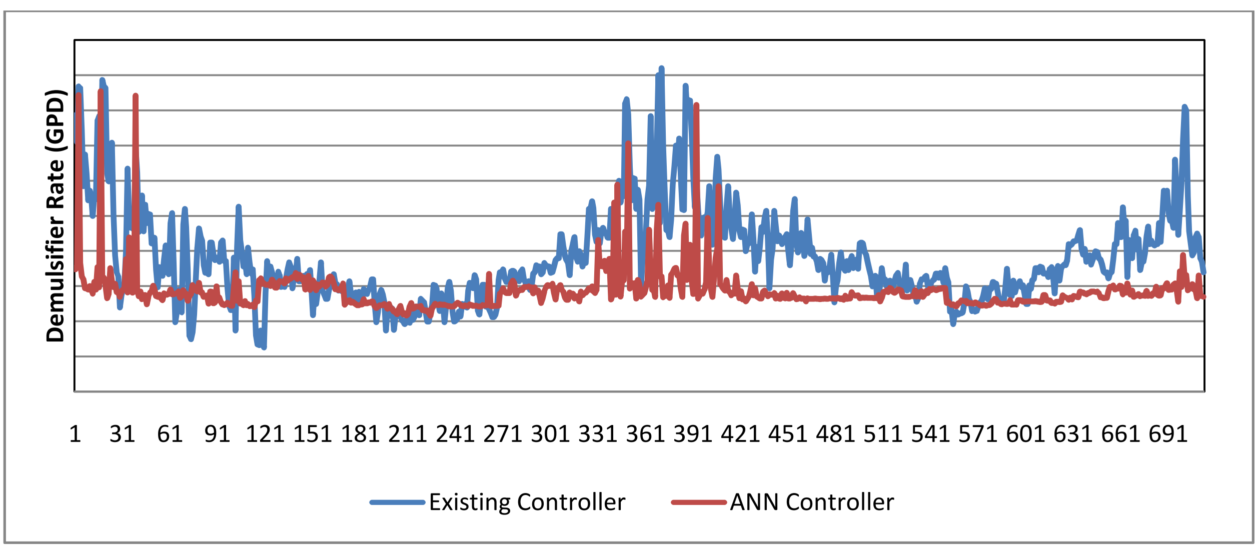


Figure 5.4: Plot of the existing controller output versus the output of the designed ANN controller

To test the ANN controller at the selected GOSP, it would take a long time to switch the control strategy but instead the below described procedure was followed:

1. Record the present values of the network input parameters from the control system.
2. Introduce these reading to the trained network.
3. Set the salt concentration to 9 PTB.
4. Switch the demulsifier controller from AUTO to MANUAL mode.
5. Adjust the controller output to the value recommended by the ANN.
6. Update the output every 5 minutes unless there is a major change in the desalter or dehydrator voltages.
7. Collect a sample from the produced oil every 1 hour and record the salt content.

This procedure was implemented at the plant for 24 hours. Results showed that the salt content did not exceed 9 PTB and a total reduction of 23% in the demulsfier rate was achieved compared to the AUTO controller output.

5.4 Optimization:

Designing a controller that determine the amount of injected demulsifier to produce oil containing salt at 9 pounds per 1000 barrel upon the knowledge gained from training on historical data covers a wide range of the operating conditions, leads to minimize the chemical consumption rate by 23% without any trail to adjust parameters that may effect. In this section, the target is to optimize the controllable parameters which affect the demulsifier controller output like wash water rate, desalter voltage and dehydrator voltage. In some cases, optimizing wash water rate is a priority to Operations and has the same importance as demulsifier rate does. Therefore, another optimization trail will be carried out to satisfy this need.

5.4.1 Demulsifier Optimization:

The objective function is to minimize demulsifier rate by setting the other parameters at their optimum values. The optimization problem in this case is slightly complicated since some parameters are not controllable and some are not feasible to be controlled.

Adjustable Parameters:

- Wash water rate
- Dehydrator voltage
- Desalter voltage

Controlled Variable:

- Salt Content

Disturbances:

- Oil temperature
- Water concentration in crude oil

Parameters economically infeasible to be controlled:

- Oil flow rate

The optimization problem can be simplified by making some assumptions and optimization results accuracy increases as these assumptions are close to the real situation. The first assumption is that the GOSP operates at the design capacity which is 400 MBD (oil and water). This assumption is too close to the reality because the average oil rate of data on which the ANN was trained is 394 MBD and from data histogram almost 94% of these data were between 380 and 440 MBD.

The second assumption is that the water concentration in crude oil is at 16 % and this assumption is also close to the real situation for such reasons described to justify the first assumption. Oil temperature from experience has a heavy weight on desalting process efficiency. Thus, optimization will be carried out at different temperature values.

Fixing dehydrator and desalter voltages at their average values which are 15612 and 15512 respectively, keeping the wash water rate floating between 50 and 400 GPM and setting the salt concentration at 9 PTB will help more in simplifying the optimization process. Minimum demulsifier rate was determined as a function of wash water rate at different oil temperatures. Results were listed in Table 5.1. Plot of temperature versus the optimum wash water rate shows three regimes behaviour. The first regime is at the oil temperature between 70 and 81^{o}F with average wash water rate of 276 GPM. The second regime occurs at temperature between 82 and 94^{o}F with an average optimum wash water rate of 82 GPM. The third regime corresponds to the temperatures higher than 94^{o}F and the average optimum wash water rate is at 246 GPM.

To simulate the effect of the optimization results on demulsifier rate the three conditional if loop shown in figure 5.5 were added to the artificial neural network to adjust the wash water rate. Running the network on the same data but with the adjusted wash water rate shows a reduction in demulsifier rate by almost 28.5%.

```
if (Temperature<=81)
        Wash_Water= 276;
    elseif (Temperature>=95)
        Wash_Water= 246;
    else
        Wash_water= 82;
 end
```

Figure 5.5 If loop control for optimum wash water rate covering normal oil temperature range

Table 5.1: Optimum wash water rate at which minimum demulsifier rate can be achieved at different oil temperatures

Oil Temperature (^{o}F)	Minimum Demulsifier Rate (GPD)	Optimum Wash Water Rate (GPM)
70	231	285
75	218	276
81	205	267
82	218	79
85	212	75
87	206	73
90	188	92
94	166	89
95	137	268
100	125	263
110	118	224
115	119	236
120	121	257
125	125	230

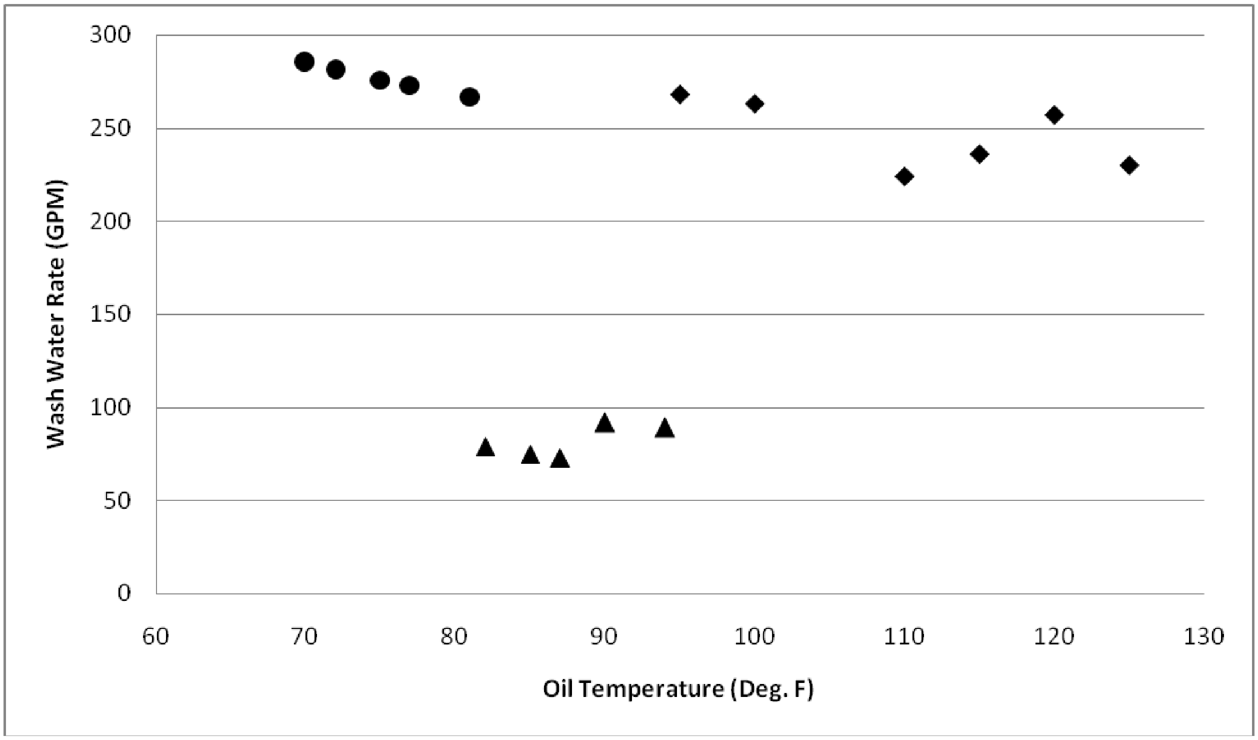


Figure 5.6: Plot of the optimum wash water rate at different temperature of inlet oil.

5.4.2 Demulsifier and Wash Water Optimization:

In situations where water is cheap or even has no price (free) except the lifting cost, it would be the sacrifice of operating cost minimization since increasing wash water rate lowers the demulsifier rate. In Saudi Arabia the case is different and fresh water is considered to be a valuable resource and so in the oil industry optimizing wash water is a priority.

The optimization problem now becomes more complicated since two parameters need to be optimized which are the wash water injection rate and the demulsifier consumption rate. The complication comes from linking the two parameters in the optimization objective function. Consider the cost of the two parameters is very hard since wash water cost per gallon cannot be measured. Finally the decision was made to consider the importance of parameters optimization to the plant Operations personal. The convenient objective function is the sum of the two rates with different weights as shown in Equation 5.1.

$$\text{Minimize } [Y_1(x_i) + 0.5Y_2(x_i)] \quad (5.1)$$

Where Y_1 is demulsifier rate, Y_2 is wash water injection rate and x's are the six effecting parameters. Constraints are the upper and lower values of each parameter as shown in Table 4.1.

The selection of 0.5 for wash water rate weight factor was made to reflect its importance in the optimization function. This value represents a midpoint between ignorance and full consideration. Ignoring wash water rate was tried before when the objective function was to minimize demulsifier rate. Also, in real situation the importance of wash water is not comparable to demulsifier.

Two neural networks were developed to produce independent functions describing the relation between each of wash water rate and demulsifier rate with the effecting parameters. The two networks showed small error between the simulated values generated from the trained networks and the plant readings.

5.4.2.1 Optimum Conditions over the Operating Temperature Range:

Feed oil temperature was kept changing between its upper and lower limits in the training data. Oil temperature in the studied GOSP is not controlled and there is no heaters installed on oil pipes but this optimization run results would assist to generalize the present study results to any desalting facility and also help to predict the savings generated from the installation of a heater installation. Some parameters were restricted to values such that they reflect the normal operating conditions like water concentration, daily oil flow rate and salt content. Optimization showed an optimum of the objective function at desalter voltage of 15.3 KV, dehydrator voltage at 15.0 KV and at an oil temperature of 120 ^oF.

Results showed that the plant is running close to the calculated optimum voltages for both dehydrator and desalter vessel transformers. Controlling oil temperature at 120 ^oF showed a minimum of the objective function at 191 which means the demulsifier injection rate is 152 GPD and the wash water injection rate is 78 GPM. Comparing the obtained minimums with one year period averages which are 191 GPD for demulsifier and 148 GPM, installation of heat exchanger is not feasible since the major cost saving comes only from demulsifier rate reduction which is around 20%. This saving does not cover the maintenance and operating costs of the heater. The reduction in wash water rate is around 47% and even it is a major evidence to convince plant

Operations to install heater but a solution could come up by automating the wash water pumps and the next run will target this aim.

5.4.2.2 Optimum Conditions at Different Temperatures:

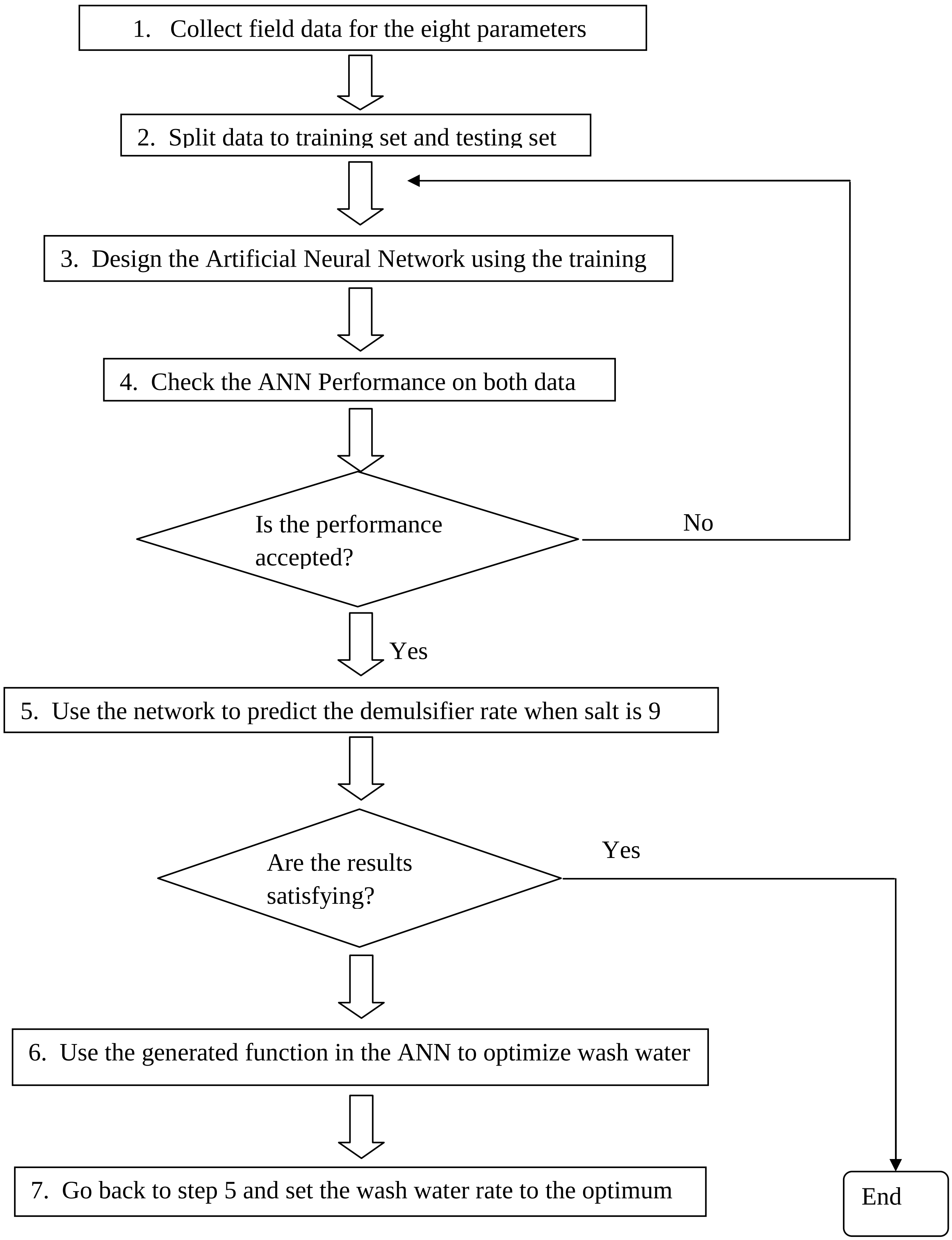
In this run the same procedure done previously will be followed here exactly with the same objective function and constraints except that the temperature will be set to various values to cover the operating range which is between 70 and 130^{o}F. Implementing this change to the MATLAB optimization program, results are shown in Table 5.2.

Table 5.2: Optimum demulsifier and wash water rate at different oil temperatures

Oil Temperature (^{o}F)	Optimum Demulsifier Rate (GPD)	Optimum Wash Water Rate (GPM)
70	242	80
75	242	80
78	204	180
80	185	180
85	175	130
88	150	145
90	147	139
95	205	189
100	180	180
110	109	133
120	152	77
130	172	61

Feeding these results to the trained network and simulate the output for the testing data, demulsifier showed a reduction of 8.4% while the reduction in wash water rate is about 21%.

5.4.3 Demulsifier Optimization Flow Chart:



5.5 Feasibility of Wash Water Automation:

The existing control of wash water flow rate is manual which means to change the existing rate an operator should change the control valve opening until the required rate is achieved. The cost of automating the control of wash water injection rate is mainly the price of a 6” control valve, controller programming in the control system and adjusting the controller tuning parameters. Adding all of these costs together makes it roughly 10,000$. A reduction of more than one fifth of the injected wash water rate worth’s automating the controller.

5.6 Salt Content Analyzer Using ANN:

During operation upset, salt measurement in the produced oil must be provided in short time and frequently to assist in trouble shooting the process. The method used these days is manual sample collection and testing. The manual procedure takes long time to generate a single snap shoot data point and reduces the plant man power during times where operators are needed for other actions. These reasons make the search for an online salt analyzer mandatory.

Many online salt analyzers are available in the market today and many of them were test by Saudi Aramco but unfortunately all of them were rejected due to concerns regarding the system maintenance, results accuracy or inability to run without operator’s help by refilling chemicals, resetting or adjusting. During the plant normal operation, the product quality testing is done three times per day once in each shift and salt concentration readings are recorded in the process log.

The aim of this section is to design an Artificial Neural Network trained on the collected historical data to predict the salt concentration as if there is an online salt analyzer installed on the treated oil header. The inputs to the neural network are:

1- Water concentration in the feed crude oil.
2- Wash Water rate.
3- Crude oil temperature.
4- Demulsifier rate.
5- Dehydrator voltage.
6- Desalter voltage.
7- Feed crude oil flow rate.

In this case, the designed neural network for demulsifier rate prediction will be tested on predicting the salt concentration. To test the network performance the same procedure followed before in simulating the demulsifier rate was done again. The recall step showed a performance of 0.964 and 0.056 in terms of R^2 and MSE respectively. The accuracy of the model is shown in Figure 5.7. Then, the model was tested again on new set of data and it showed a performance of 0.96 and 0.057 in terms of R^2 and MSE respectively.

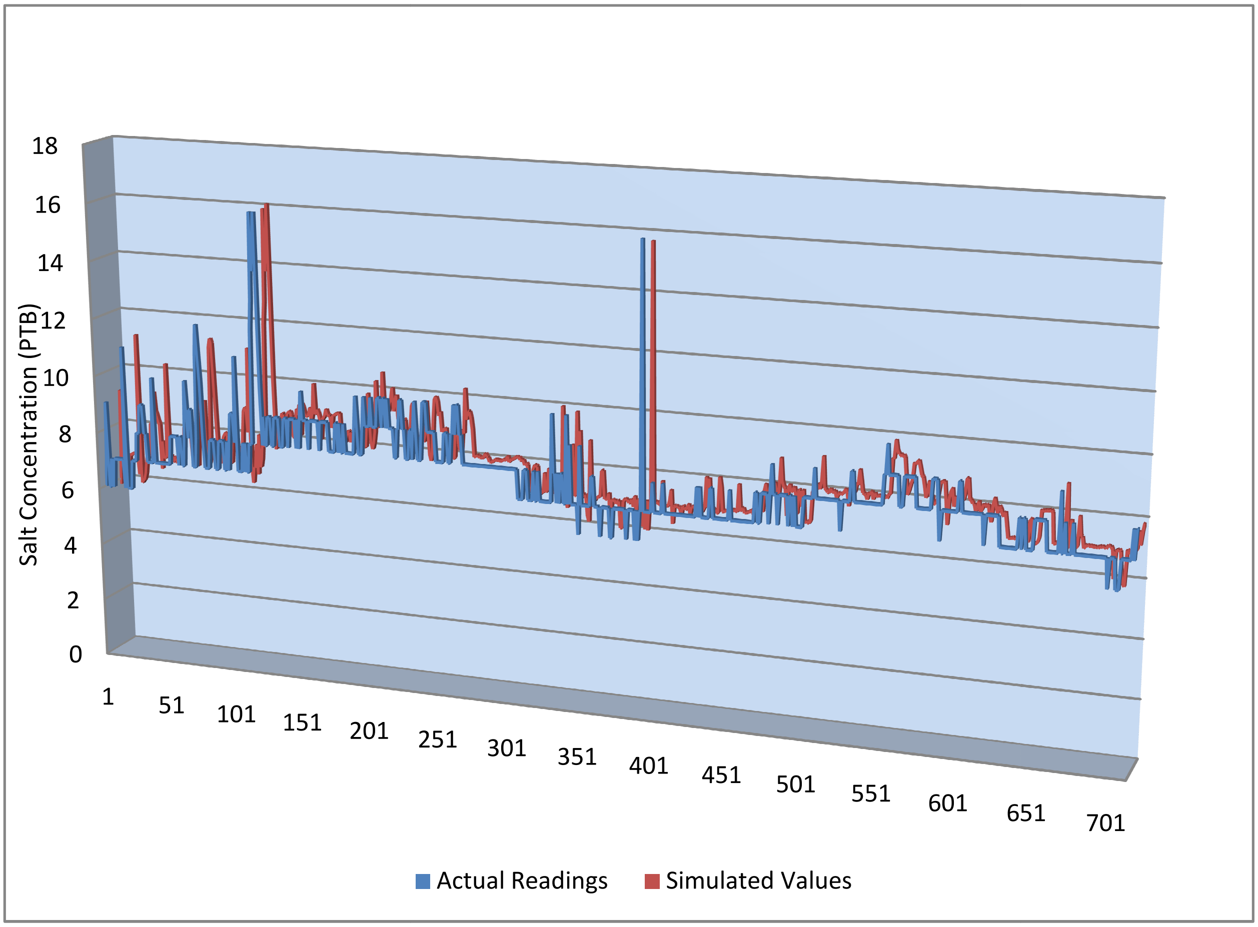


Figure 5.7: Results of the recall step for the salt analyzer designed by ANN compared to the actual readings

In the recall step and after rounding results to the closest integer number, out of 713 salt readings in the training data set, the model was accurate in predicting all readings except 30 in which the offset is 1 PTB.

In the generalization step and after rounding results to the closest integer number, out of 104 salt readings in test data set the model succeeded in predicting 98 while the offset in calculating the other 6 readings was 1 PTB at 4 of them and 2 at the other two. Results of the generalization step are shown in Figure 5.8.

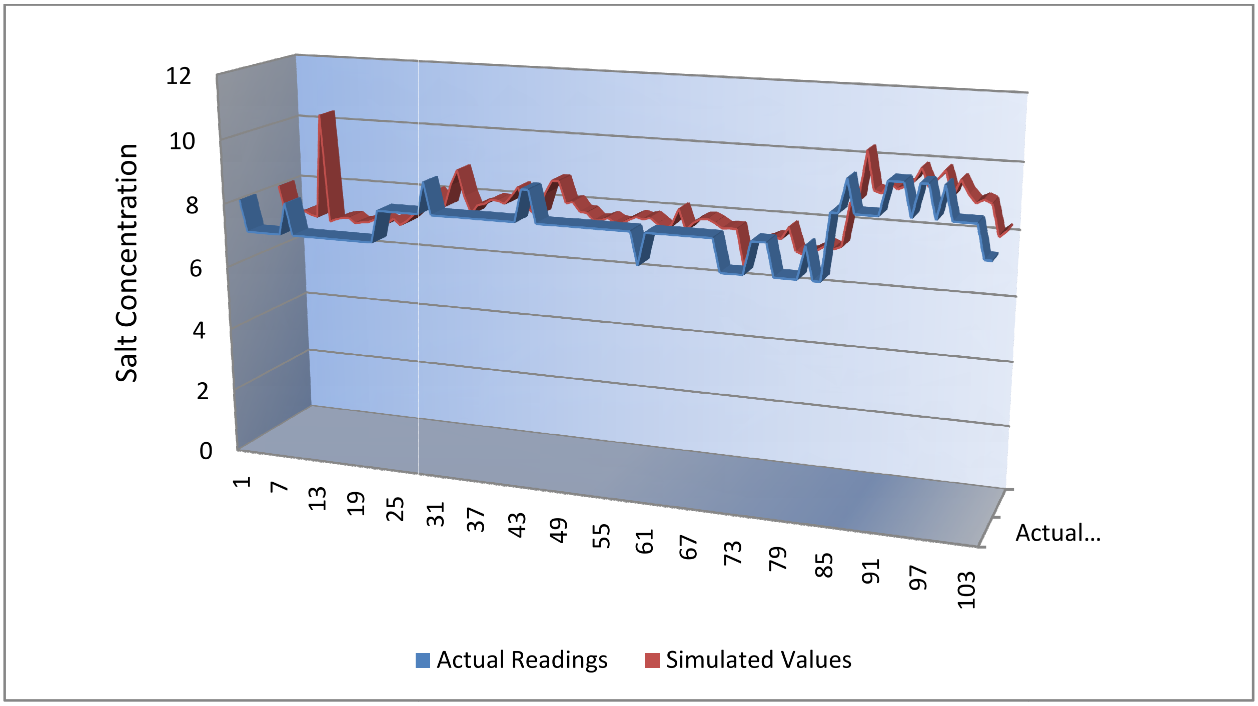


Figure 5.8: Results of the generalization step for the salt analyzer designed by ANN compared to the actual readings

Chapter 6

Conclusions and Recommendations:

Working in oil industry and experiencing how the plant Operations in Gas Oil Separation Plants are trying with all effort to improve the separation process efficiency to lower the operating cost per produced barrel of crude oil is the main driving force for this research. Reviewing the salt results of the treated oil, it was obvious that crude is going through extra-desalting process. Oil companies' specification of the produced oil in term of salt concentration is 10 PTB. In the GOSP, from where data were collected, the average salt content is 7.7 PTB which clearly describes the extra-desalting situation.

The parameters involved in determining the salt concentration are many but in this study the focus was made on seven parameters which seem to be the most effective. The selected parameters are oil temperature, wash water flow rate, crude oil flow rate, demulsifier injection rate, desalter voltage, dehydrator voltage and water concentration in crude oil. Controlling all or some of these parameters is the basis of any desalting plant.

Crude oil temperature in countries like Saudi Arabia is not controlled since the feed oil even during winter season has relatively high temperature. Oil temperature and demulsifier rate share the following property:

- The largest effect on salt concentration in the treated oil.
- Huge saving results from reduction (optimization).

In plants where oil temperature is not controlled, lowering the demulsifier rate to its optimum value at the present process operating conditions is the way to have the plant running at high efficiency. To achieve this objective, the plan was made to evaluate the existing demulsifier control method performance and then if it is not efficient a new control scheme will be developed and tested against the collected data.

The existing demulsifier control scheme was designed based on the assumption that the relation between demulsifier rate, desalter voltage, water concentration and temperature is linear. The collected data showed that the controller is significantly over estimating the situation in most cases which leads to higher injection rate of demulsifier than that at which the product will meet the required specification.

Some of the fundamental parameters of the system are not constant and have a nonlinear effect on salt concentration in the treated oil, i.e. inlet flow rate, inlet temperature and water cut. This situation requires the use of a controller that has the ability to adjust with changes by adapting its behaviour. Adaptive controller reads the process variables and upon any change adjusts its response. This means a nonlinear controller with the ability to adjust the tuning parameters according to the instantaneous input readings should be used. According to the above description, this thesis proposes a new technique for demulsifier injection rate control that uses an intelligent control scheme. The proposed technique is the Artificial Neural Network (ANN).

Designing a neural network, which is best trained on the provided process data to establish a relation between inputs and the output through adjusting weights and biases, was done through trial and error procedure to:

- Find the optimum number of neurons in the hidden layer.
- Determine the most suitable combination of transfer functions (one between the input layer and the hidden layer while the other is between the hidden layer and the output layer)

The network efficiency was judged based on the coefficient of determination and the mean square error. To improve the ability of the network to fit data, a loop of iterations was added to the network program to find the proper first guess of weights and biases. This addition to the normal neural network design showed a significant improvement in accuracy.

The designed neural network was trained on a data set consisting of 713 data points for each of the eight defined variables. The trained network tested on the same data set was used for training and results reflected a high ability to simulate real readings with R^2 of 0.9144. To further validate the network efficiency, it was used to predict the output of new set of data consisting of 104 data points. The calculated R^2 and MSE of this step were very promising at 0.9047 and 264.

The trained network was used in a MATLAB program which can function as a nonlinear controller in which online readings of oil temperature, water concentration, wash water rate, crude oil flow rate dehydrator and desalter voltages are fed while the salt concentration is set to a fixed value of 9 PTB and the expected output is the demulsifier rate. Upsets at the desalter or dehydrator control like dramatic changes in the interface level or foam formation could cause a huge drop in voltage. To make the controller able to absorb such changes the salt concentration was set to 9 PTB.

Implementing this controlling methodology on the collected data, results showed a great improvement in demulsifier injection rate. The average reduction was about 49 GPB which is 25% of the total average consumption rate.

The generated function from training the neural network was then used in an optimization program. The objective function is to minimize demulsifier rate while the constraints are in the form of fixed values at the plant normal operating conditions for water concentration, total inlet flow rate, desalter and dehydrator voltages. Salt concentration was adjusted to 9 PTB. The program was run several times at different temperatures to cover the normal operating temperature range between 70 and 130 ^{o}F. This procedure was intended to find optimum wash water along the temperature range and results showed that there are three temperature regimes at which wash water rate can be expressed by a single average value.

To test the effect of controlling wash water as a function of the feed oil temperature, results from the optimization problem were implemented in the designed neural network controller. As it was expected, the simulated results showed a reduction in demulsifier rate by 28% compared with the plant actual consumption.

Targeting to make this study comprehensive, two neural networks were developed to predict wash water rate and demulsifier rate. The generated functions were used to optimize both parameters. The objective function was to minimize the sum of both rates but with different weights. The weight value was chosen to reflect the importance of the parameter in the optimization process. The selected weights were 0.5 and 1 for wash water injection rate and demulsifier dosage, respectively. The optimization program was performed in two runs.

In the first run, the constraints were the upper and lower values of oil temperature, desalter voltage and dehydrator voltage. Feed flow rate, salt concentration in the treated oil and water concentration in feed oil were set to 400, 9 and 16, respectively. The optimization showed an optimum of the objective function at desalter voltage of 15.3 KV, dehydrator voltage of 15.0 KV and at an oil temperature of 120 ^{o}F. The results showed that the plant is running close to the calculated optimum voltage for both dehydrator and desalter vessel transformers.

In the second run, desalter voltage, dehydrator voltage, feed oil flow rate, salt concentration, water concentration were set to the normal operating conditions. The optimum wash water rate and demulsifier rate were found at different values of oil temperature. Feeding these results to the trained network and simulate the output for the testing data, demulsifier showed a reduction of 8.4% while the reduction in wash water rate is about 21%.

Most of oil companies are still measuring the salt concentration in the produced oil manually due to the lack of accurate online salt analyzers. In this study a neural network was designed to read online data of the defined parameters and provide a prediction of the salt concentration. Testing this tool on the collected data, results showed a high prediction accuracy.

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