Modelling of Libyan Crude Oil Using Artificial Neural Networks

by

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CERTIFICATE OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this thesis, that the original work is my own except as specified in acknowledgements or in footnotes, and that neither the thesis nor the original work contained therein has been submitted to this or any other institution for a degree.

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Abstract

The preparation and analysis of input and model data was carried out. The importance of the correct technique of data filtering was highlighted with particular focus being emphasised on the removal of outliers in raw data.

An important process in the use of Artificial Neural Network (ANN) models was identified as being the selection of the right input variables.A comparison between using factor analysis and statistical analysis in the selection of inputs and it was observed that the former gave significantly better results.

The training and testing phase of Artificial Neural Network (ANN) model development was shown to be an important step in Artificial Neural Network (ANN) model development. If this phase was wrongly done then the ANN model would not be accurate in its predictions.

Optimisation of the ANN model architecture was carried out with the amount of hidden layers, amount of neurons in the hidden layers, the transfer function used and the learning rate identified as key elements in obtaining an Artificial Neural Network (ANN) architecture that gave fast and accurate predictions.

Fresh water addition and demulsifier addition were identified as key parameters in the economic performance of the desalting process.

Due to a scarcity of water and the high cost of the demulsifier chemical it was important to try and optimise these two input variables thus reducing the cost of operations.

Contents

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List of Acronyms

ANN	Artificial Neural Network
ART	Adaptive Resonance Theory
MIMO	Multiple Input Multiple Output
MISO	Multiple Input Single Output
RMSE	Root Mean Square Error
SIMO	Single Input Multiple Output
SISO	Single Input Single Output
SOM	Self-Organising Map
BS&W	Basic sediment and water
PTB	Pounds per Thousand Barrels
O/W	Oil-in-Water emulsion
W/O	Water-in-Oil emulsion
PPM	Part Per Million
BP	Back Propagation

List of Symbols

A^k	Class Label
e	Error
N	Total Number of Observations
R^2	Correlation Factor
t^q	Target Vector
w	Weight Factor
W_k	Weights
x	Net Input
$x\|$	Normalized Data Point
x_i	Raw Data Point
x_k	raw data point
x_{max}	Maximum Value of Raw Data
x_{min}	Minimum Value of Raw Data
x^q	Vector Input
y_i	True Output Values
$\hat{y}_i$	Networks Output

$\bar{y}_i$	Mean Value Over All Samples
y_k	Output Vector
Θ	Threshold Value

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Chapter 1

INTRODUCTION

1.1 Research motivation

Crude oil feed to refineries contains water soluble salts such as sodium chloride, calcium chloride, magnesium chloride, sulphates etc., along with insoluble salts, solids and water.

There may be up to 5% of water [10] present in the crude oil feed having soluble salts dissolved in it. Water present in feed is in the form of emulsions and this emulsified crude oil is treated in a special kind of operation to remove the water, salts and suspended solids before further processing. This kind of operation is known as desalting.

Desalting of crude oil is done in several steps in series depending on the crude oil feed quality requirement for further processing. Removal of salts from the crude is important as the salts at higher temperature cause hydrolysis and form HCl that causes corrosion in the downstream equipment and at lower level of pH chlorides results in more rapid corrosion.

Demulsifying chemicals are added to emulsify the crude oil in the desalting process.

The feed stream is well mixed and some residence time is given in a vessel called the desalter. An immense voltage electric field is applied to the emulsion formed by crude/water between two plates using alternating current in the desalter. The voltage may range from 300 to 30,000 volts.

The high voltage affects the interface of emulsion droplets of water present in the crude and causes them to coalesce. This coalescence of water droplets further helps in phase separation of the water and salts from the crude oil hydrocarbons. Water due to higher value of density is collected at the bottom of the desalter leaving crude oil, with smaller amount of water and salts, at the top.

The temperature normally used in desalters range from 95 to $150^{o}C$.

There are lots of parameters that are considered important for kinetics of demulsification which favours desalting operation.

Demulsification operations depend upon voltage, temperature, degree of mixing, distance between two plates and emulsion properties; that is density, viscosity, and water drop size.

1.2 Objectives of the Study

This research aims at developing a neural network (NN) model that would help in the forecast of salt removal performance of a desalter from the Arabian gulf oil company situated in Libya. The specific objectives are as follows:

1. Data collection from the **Arabian Gulf Oil Company**
2. Data arrangement for instance statistical analysis
3. Discovery and Identification of outliers
4. Building the Artificial Neural Network (ANN) model
5. Analysis of the data using the Artificial Neural Network (ANN) model

1.3 Structuring the Thesis

The thesis is organised as follows;

Chapter (1) puts the research into general situation.

Chapter (2) reviews relevant literature related to the current topic.

Chapter (3) outlines the artificial neural networks.

Chapter (4) discusses methodology and data collection.

Chapter (5) then discusses findings from this research.

Chapter (6) consummates the thesis by providing in general conclusion and suggestive of possible future research work.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

This chapter contains a review of literature related to crude oil desalting and artificial neural networks. It should be noted that the theory behind this research is based on the formation, destabilization and stabilization of crude oil emulsions in addition to the chemistry behind the natural surfactants which are responsible for stabilizing the emulsions.

2.2 Crude oil components

Crude oil is a mixture of hydrocarbons containing small amounts of sulphur, oxygen, and nitrogen. Other components include microelements which are metallic in nature such as vanadium, nickel, iron and copper [11]. A sample of Libyan crude oil from the Arabian Gulf oil company consists of 84.5% carbon, and the hydrogen content varies between 11 and 13%. In addition, varying small amounts of nitrogen 0.5%, Asphaltenes 0.25%, sulphur 1.5% and oxygen 0.5%. The characteristics of Libyan crude oil are summarised in Table (2.1).

Table 2.1. Libyan crude oil properties

Property	Value
Density by 15C g/ml	0.8296
Specific Gravity by 60F	0.8300
API Gravity by 60F	38.98
Reid Vapour Pressure KPa (psi)	20 (2.9)
Pour Point C (F)	-9 (+16)
Viscosity by 70F, cST	7.581
Viscosity by 100F, cST	4.331
Asphaltenes $\%wt$	0.25
Mercaptan sulphur ppm wt	4
Total water cut $\%wt$	0.08

The asphaltene content in crude oil determines its ease of refining. The separation of crude oil leads to four major fractions, saturates that include water, aromatic, resins and asphaltenes, non-volatile, polar and insoluble fractions. The aggregation and precipitation of asphaltenes [12], [13], [14], [15], [16] and [17] leads to significant refining problems. Aggregation and self-association of asphaltenes increase in the presence of aromats [18]. The higher the aromatic ratio in the solvent the greater the association and vice versa and as a result the measurement of the molecular weight and size of the aggregates becomes difficult. The aggregate building size has been suggested to be stuck between 3 and 24nm in diameter [19], [20] and [21] with molecular weight tending to be among 600-1500 $gmol^{-1}$ [22], [23], [24], [25], [26], [27] and [28].

The description of asphaltene self-association is inconsistent [29], [30], [31], [32] but is thought to arise through hydrogen bonding. Both micelles and colloids are referred to in asphaltene formation. The colloid is a very small particle (smaller than a micron) which consists of asphaltene molecules that are bound by pi-bond interactions within polyaromatic clusters. The micelles are similar to a surfactant micelle, where the association of molecules is driven by hydrophobic-hydrophilic interactions. Resins dissolve the asphaltenes in the crude oil by attaching to the asphaltene micelles/aggregates with their polar groups, and stretching their aliphatic groups outward to form a steric-stabilisation layer around asphaltenes [33] and [34]. On the other hand, debate still remains whether the asphaltene and resin molecules can be seen as a mixed micelle or if the micelle, as long as it is made only of asphaltenes, can be described as homogenous [28], [29], [30], [31], [32] and [33].

In general, resins can be said to be placid and the polar fraction of crude oil soluble in n-alkanes and aromatic solvents and insoluble in liquid propane. They are similar in structure to asphaltenes and their molar mass and heteroatom content are lower while maintaining a higher hydrogen/carbon ratio. Stabilizing asphaltenes is not only dependent on elimination of resins from the crude oil through the method of adsorption chromatography does not stabilise asphaltenes [35]. Such as a result of high pressure in the reservoir the asphaltenes self-associate due to pressure depletion [36], [37], [38] and [39]. The reduction of the pressure leads to the molar volume and the solubility parameter difference increasing to a maximum between asphaltenes and crude oil close to the bubble point of the crude oil.

2.3 Stability of emulsions

Emulsions occur in everyday life and are of great practical interest. They originate in areas for instance food, cosmetics, pharmaceutical, agricultural as well as the oil and gas industry. They are undesirable and result in high costs in pumping, flow reduction and necessitate special handling equipment. Emulsions are defined as systems comprising of a liquid dispersed in another immiscible liquid with droplets of colloidal sizes ($\sim 0.1-10\ \mu m$) or larger [40]. When the crude oil is the dispersed phase, the mixture is termed as oil-in-water (o/w) mixture and when the aqueous medium is the dispersed phase; the mixture is named water-in-oil (w/o) mixture. A growth in the systems free energy is shown by the interfacial area among between the dispersed droplets and the bulk phase. This implies that mixtures are not thermodynamically stable and as such they reduce the surface area by separating into the dissimilar phases. The drops of emulsion must merge for separation to occur.

The separation processes are sedimentation, a concentration gradient of emulsion droplets arises resulting in adjacent packing of the droplets [41], [42] [43], [44] [45], [46]. In sedimentation a droplet concentration gradient arises resulting in a close packing of the droplets. Aggregation occurs when droplets are adjacent to each other for a long period of time with no attractive forces acting among them. Thus size and shape of the individual droplets remain similar. Coalescence occurs in two stages; the first stage is called the film drainage while the second stage is the film rupture stage. In the film drainage stage, fluid flows into the film and a pressure gradient develops. When the interfacial film between the droplets has thinned to below a serious critical thickness with the difference between capillary pressures leads to droplet fusion. When droplets deform the interfacial area and path drainage increase and lower drainage rates arise. The electrical double layer repulsion prevents the droplets having point contact. Surfactants conceive a physically strong and elastic interfacial film that impedes aggregation and coalescence. Oil wet particles stabilise water/oil mixtures emulsions while water-wet stabilise Oil/Water mixtures. To enable stability of emulsions the particles should have a high concentration and also be at least smaller in magnitude by at least one order compared with the emulsion droplets.

Emulsion stability is favoured by low interfacial tension, high bulk phase viscosity and comparatively insignificant volumes of dispersed phase; narrow droplet size distribution is advantageous as polydisperse dispersions lead to growth of large. This effect is known as the Ostwald ripening [47]. In addition, it is possible that special features of surfactant connote into liquid crystalline phases with lamellar geometries which enable the stabilisation may also take place [40].

2.4 Water in crude oil emulsion stabilisation

The interests in oil emulsions especially from the oil and gas industry are as a result of:

1. Formation of water-in-crude oil emulsions during processing of fluids from the reservoir in the refinery especially during clean up and extraction. This is due to the copious corrosion that may arise in the pipelines as a result of emulsion formation. This leads to unnecessary costs which hinder profitability in the long run.

2. Great environmental damage may arise when oil spills occur in the ocean as the oil phase is difficult to remove. This is as a result of the stability of water in crude oil emulsions.

To be able to design treatment techniques for water in oil mixtures the mechanisms of their stability have to be studied. The main mechanism resulting in oil and gas emulsions is by the formation of films which offer both elasticity and viscosity. The film is made up of a network of cross-linked asphaltenic molecules. The lateral intermolecular forces aggregate forming micelles at the water oil interphase [48], [49], [50], [51], [52] and [53] and [54]. The strength of the film may be realised by the adhesion of solid particles arising from wax, inorganic material, clays and naphthenates. Hence, the the crude oil emulsion stability occurs because of a barrier that blocks the film from breaching as a result of scarce energies that are involved in impacts between droplets. When water is added to the crude oil, aggregates of asphaltenes in the oil phase adhere onto the new oil water boundary and as a result resins shed thus they do not take part in film stabilisation [55]. The structural arrangement at the oil water interfaces and the intermolecular interactions brought about by asphaltenes are not well understood.

2.5 Destabilisation of crude oil emulsions

A major operation of crude oil desalting is to make the emulsions unstable. The emulsions in the crude oil are usually broken down by physical or mechanical efforts that incorporate settling which applies gravity or centrifugal force. Another more common method is the use of chemicals called demulsifiers with the aid of electric current. Other methods that are used but not frequently include pH adjustment, membrane separation and filtering and use of heat treatment. The destabilisation of emulsions is one of the most capital intensive processes in crude oil desalting. For example the use of gravity settling tank and separators would incur high costs due to the size of the equipment and their high costs of purchase and running. With this in mind many refiners prefer the use of chemical destabilisation method as it is less expensive and it does not lead to plant shut downs.

The rate of separation of a water/oil mixture is dependent on the concentration and stability of the emulsion, residence time, temperature, vessel type, rate of mixing and type of mechanism of stabilisation. By understanding the process of stabilisation and break up of emulsions, more environmentally friendly chemicals for emulsion destabilisation may be developed. By optimising this process one may reduce the oil content in produced water after destabilisation.

Demulsifiers are chemical combinations of several components with various chemical structures and molecular weight distribution [56], [57]. The components of a demulsifier must possess different dividing abilities and different interfacial activities. The destabilising properties of a good demulsifier are:

1. Being able to destabilise the protective film surrounding the water droplet by having a strong attraction to the oil/water interface.

2. Behaving similarly to a wetting agent by altering the contact angle of solids

3. Being able to promote flocculation

4. iv) Being able to promote film drainage and inter droplet lamella thinning by changing boundary rheological properties like decreasing the interfacial viscosity and increasing the compressibility [58], [59], [60].

As two water drops come closer liquid is squeezed out through the capillary pressure that acts normal to the boundary. Due to fluid flow viscous drag acts on the surfactants in the sub layer. Non uniform distribution of adsorbed emulsifier drops arises as they are transported towards the film. The empty spaces available for adsorption are then occupied by demulsifier molecules as a result of high interfacial activity of the demulsifying agent. This results in reduction of interfacial surface tension. The rate at which the film thins increases and if it decreases below a critical point film rapturing occurs and with it coalescence is promoted.
Strong attractions at the oil and water interface depend on the interfacial activity and the ability to diffuse of the demulsifier. When rapid diffusion occurs then the molecular load of the demulsifier is significant. As the demulsifier is highly soluble it promotes mass transfer to the interface however if it lacks solubility strength then carrier solvents may be used. The Gibbs-Marangoni effect that counteracts film drainage is then inhibited by solubility changes in the continuous phase and viscosity changes in the interfacial film at the interface.

Residual emulsions have droplets that are well and widely dispersed and distributed. Highly networked demulsifiers which have an attraction for water droplets are required. Demulsifiers which act as wetting agents are suitable for emulsions which have particle stabilised films. Temperature may lead to solubility changes of crude oil surfactants, the density if the oil decreases at a faster rate compared with water density as temperature increases thus settling rate is increased. The bulk viscosity decreases thus collisions between water droplets increase and this leads to an increase in settling rate. The interfacial viscosity may increase, decrease or remain unchanged depending on the type of interface [56].

The application of electrostatic force in crude oil emulsions is conjoint in the oil and gas industry. A massive electric field is used to separate water from an by applying a high charge onto the flowing oil emulsion which promotes fusion of water droplets. The main principles of coalescence of water droplets in high voltage electric fields are [61], [62] and [63] :

1. Dipole-dipole coalescence where separation results from dipole charges between particles
2. Electrofining where separation is as a result of forces between particles with a net charge and one-directional fields.

The coalescence induced electrically can be divided into:

1. The particles that don't attract approaching each other
2. Plane parallel film formation and deformation of droplets
3. Critical thickness of films causing instability which results in ruptures and thus leading to the formation of a large droplet

Electrocoalescers are used in the oil and gas industry and use both alternating and direct current to assist the separation of water in oil emulsions [64].

2.6 Crude oil desalting

Crude oil feed to refineries contains water soluble salts such as calcium, sodium and magnesium chlorides, sulphates, and so on along with insoluble salts, solids and water. There may be up to 5% of water present in the crude oil feed having soluble salts dissolved in it. Water present in feed is in the form of emulsions and this emulsified crude oil is treated in a special kind of operation to remove the water, salts and suspended solids before further processing. This kind of operation is known as desalting. Desalting of crude oil is done in several steps in series depending on the crude oil feed quality requirement for further processing. Removal of salts from the crude is important as the salts at higher temperature cause hydrolysis and form HCl that causes corrosion in the downstream equipment and at lower level of pH chlorides results in more rapid corrosion.
Demulsifying chemicals are added to emulsify the crude oil in the desalting process. The feed stream is well mixed and some residence time is given in a vessel called the desalter. An immense net charge is applied to crude oil/water mixture flanked by two plates using alternating current in the desalter. The voltage may range from 300 to 30,000 volts. The high voltage affects the interface of emulsion droplets of water present in the crude and causes them to coalesce. This coalescence of water droplets further helps in phase separation of the water and salts from the crude oil hydrocarbons. Water due to higher value of density is collected at the bottom of the desalter leaving crude oil, with smaller amount of water and salts, at the top. The temperature normally used in desalters range from 95 to 150^oC. There

are lots of parameters that are considered important for kinetics of demulsification which favours desalting operation. Demulsification depends upon operating condition (voltage, temperature, degree of mixing, distance between two plates etc.) and emulsion characteristics (density of crude oil, viscosity of crude oil, water drop size etc.). A desalter flow diagram from Libya Oil Company is shown in Figure (2.1). The final product from the

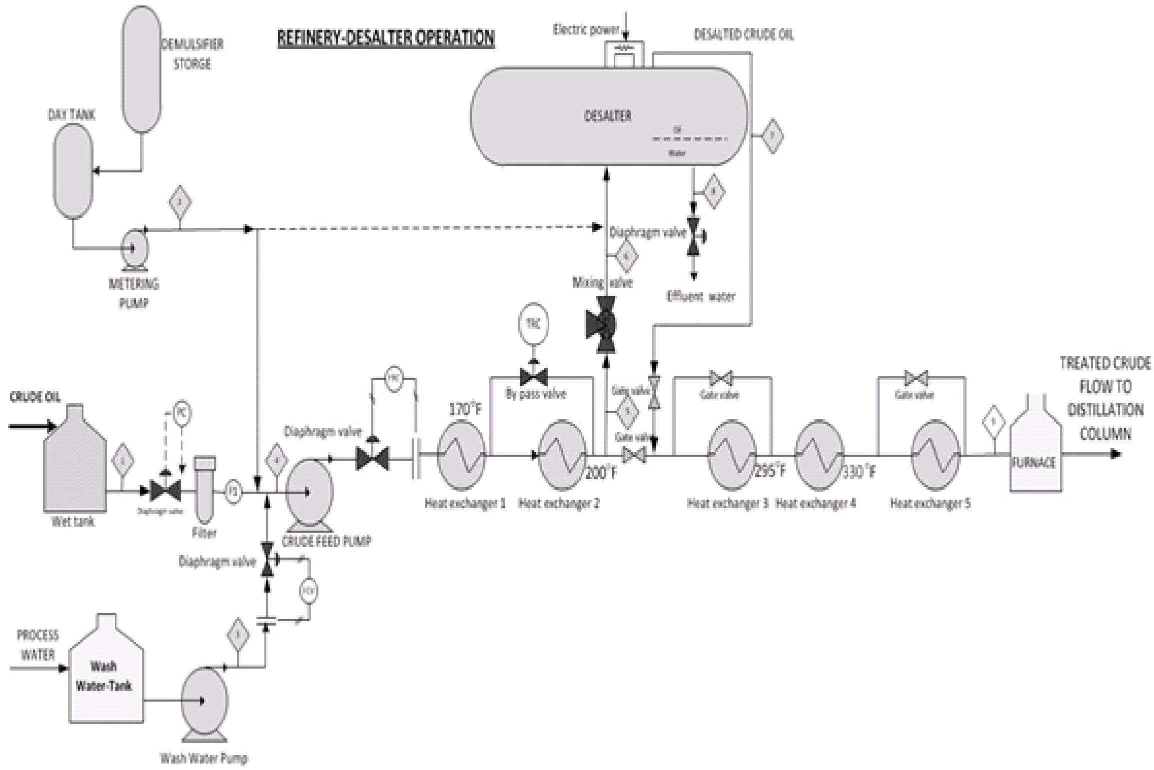

Figure 2.1. Schematic flow diagram of a typical desalting and dehydration plant layout (Arabian GulfOil company).

desalting process is then checked to see if it meets the required specifications for further processing that is 5 PTB (pounds per thousand barrels) of salt and 0.1% bulk solids and water ($BS\&W$).

Salt water in crude oil is typically present as an emulsion. The primary aim of this desalting process is to shatter the emulsion and remove the salt water.

The main process principles involve.

1. The injection of demulsifier chemicals
2. Heating the oil
3. Injecting fresh water
4. Using an electrostatic desalter

The major variables that affect the performance of a crude oil desalter are

1. Crude oil feed rate
2. Dosage of demulsifier
3. Crude oil temperature
4. Fresh water addition

The equipment used in crude oil dehydration and desalting use gravitational force in separate droplets of water from the moving phase of the crude oil. Usually it is achieved by using large holding vessels such as tanks. These vessels provide the required residence time for settling. They are used to remove large percentages of free water that is carried in the produced stream that has not emulsified in the oil. They usually operate with the produced water occupying the bottom third and crude oil the top two thirds. Usually the emulsion feed is introduced just below the oil-water interface which allows for agitation which promotes coalescence and thus water droplets are removed from the oil stream.Solids coated in thin films of oil or just flowing freely in the emulsion and salts are often found in produced water [65].

Emulsions are treated by the use of chemical destabilisers called demulsifier. These chemicals usually adsorb onto the water/crude oil boundary which causes the film encompassing the drops of water to rupture. Usually in the oil field the rule of thumb is that the smaller the percentage of water in the emulsion the greater the difficulty in destabilising it.

Heat treatment of desalting reduces the viscosity of the crude oil thus promoting the free movement of the water drops and coalescence. It also reduces the thickness and cohesive forces of the film that surrounds the water drops. It is important to control the heat as too much heat could lead not only to evaporation of the crude oil but a decrease in the ^0API gravity of the crude oil. This decrease is bad as it signifies low quality crude thus it sells at a low price.

Usually in crude oil salts in the emulsion from solid crystal structures and as a result addition of fresh water is required in order to dissolve them. Fresh water is also injected in order to wash out the drops of water in the mixtures which are flashed out and drained. The ratio of freshwater quantity injected is dependent on the API gravity of the crude oil, however generally the injection rate is $4 - 10\%$ of the total crude oil flow [66].

Too high a shear rate promotes emulsion formation during crude oil desalting. During fresh water addition mixing is required in order to ensure the perfect dissolution of salt crystals as well as to promote coalescence.

2.7 Artificial Neural Networks

Towards the end of the 80s' digital computing started taking shape and as a result most data processing programmes started applying programming computation which required the development of a mathematical or logical algorithm that would solve the problem and this was done by being translated into a modern programming language. Neural networks started making an impact because they did not require development of algorithms for data analysis.

As a result the time needed to code was significantly reduced. An advantage of this system is that it is able to identify relationships in real data thus the development of a model is curtailed. Artificial neural networks are data driven and as a result can approximate solutions to various problems, there has been a considerable rise in the use of neural networks particularly in modelling of chemical and biochemical processes where there is a huge set of input and output data whose relationships cannot be derived by using the known route of linear or nonlinear models. In the modelling, there exist two types of models that is knowledge and black box based. In the former, the model constructed from prior knowledge and parameter estimation. In the case of neural networks it is a black box based system where physical knowledge of parameters is not needed.

Due to high costs and time allocated in developing complex industrial process mathematical models it is more often the case that process data analysts use system identification methods in developing dynamic models. In chemical engineering processes many monitoring and process control methods are dependent on the relationship among the input and output variables. They are usually approximated by using linear models and this is then coupled with the monitoring and process control system to offer a robust solution to a problem. Artificial neural networks are able to approximate the input and output relationship. As opposed to linear models which cannot capture nonlinear relationships, artificial neural networks have the added advantage of being able to capture nonlinear relationships thus being robust in provision of modelling solutions. Material on the use of artificial neural networks chemical engineering processes like fault detection, process control and design can be found in numerous journal publications [1].

An artificial neural network is a parallel distributed processor which has a natural affinity for data storage and analysis. Resemblance to the human brain comes mainly in two forms that is:

1. A learning process that enables the network to acquire knowledge

2. The weights that interconnect nodes storing the gained knowledge

Typically an artificial neural network gains knowledge through a learning algorithm giving rise to the learning process.
A human neuron is shown in Figure (2.2) and a model neuron used in artificial neural network modelling is shown in Figure (2.3) The basic elements

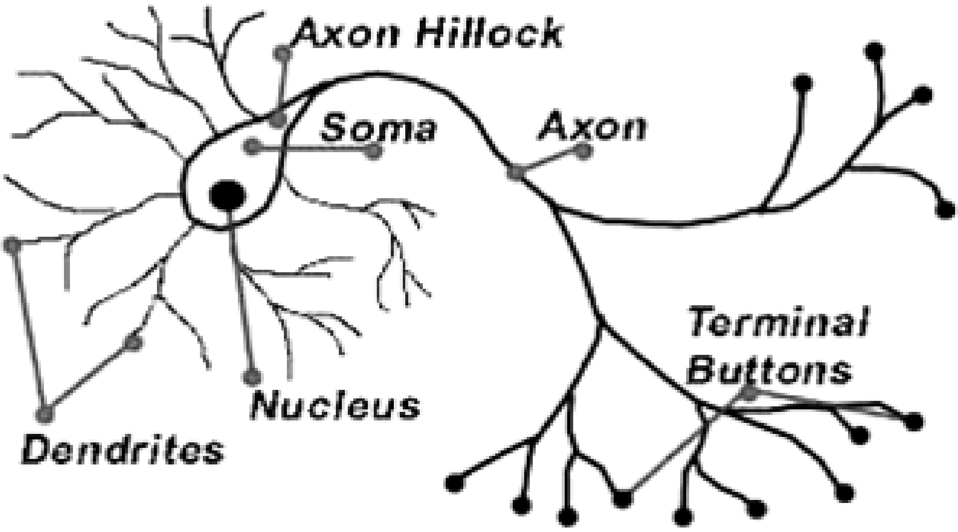

Figure 2.2. A single biological neuron [1].

of a neuron are:

1. The connecting links or synapses which have a weight
2. The adder whereby the input signals are summed
3. Limitation of the amplitude of the output of the neuron through the activation function

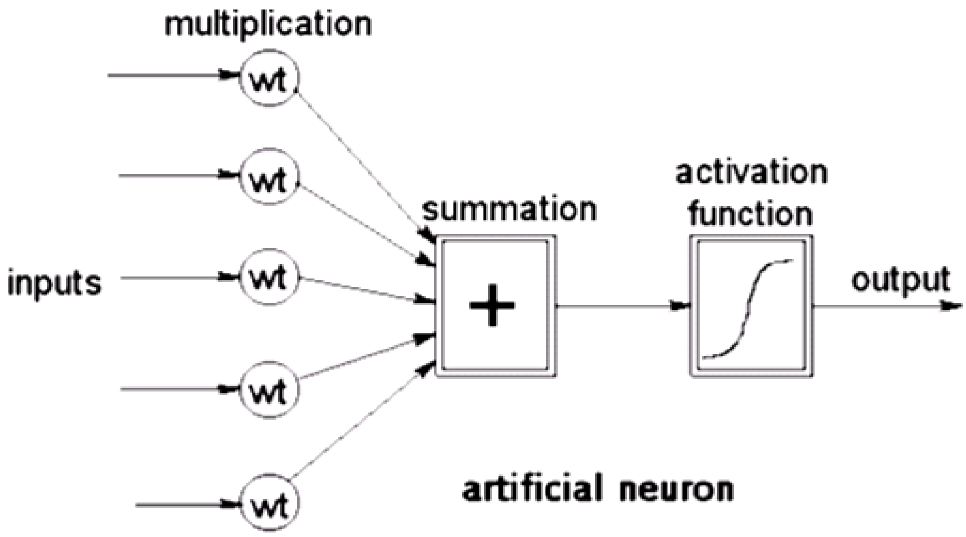

Figure 2.3. Model of a perceptron with a sigmoid activation function [2].

2.8 Closure

Crude oil desalting is an operation that normally is characterized by the minimisation of the manifestation of water in oil emulsions.

It is important in the decrease of salinity of crude oil feed to the refinery by reducing corrosion.

In the proceeding chapters the modelling of desalting processes will be intricately discussed and a model presented to help in the modelling of the desalting process.

It is very clear that the desalting process is a rather complex process with many variables often to be considered.

Chapter 3

ARTIFICIAL NEURAL NETWORKS

In this chapter the following will be discussion; the artificial neural networks (ANN) and there several methods particularly those that will be employed in the modelling approach of the crude oil desalting process.

3.1 Introduction

The concept of Neural Networks takes its basis from nature and the way the human brain works. Using its senses to gather information and act as inputs to the human body, human beings process all information using the brain. The average human brain consists of billions of neurons with corresponding synapses between them [2]. Like the human brain, a Neural Network consists of a network of interconnecting nodes (called neurons) and which transmit signals between these nodes based on pre-set firing rules. In general, a Neural Network can be represented by three different layers [67], [68]:

- Input Layer -this layer receives data/information from an external source which could be a sensor or a computer database software
- Hidden Layer -this layer(s) receives the information passed on by the previous layer (i.e.input) and processes it. If there is more than one hidden layer, the layers pass information sequentially from left to right

depending on the network model used (see Section 3.3).

- Output Layer -the processed information from the hidden layer is passed on to this layer which sends it to an external receiver.

3.2 The neuron

To fully understand the Neural Network, one needs to get a full understanding of how its human work. The human brain consists of millions of neurons. Figure (3.1) depicts a simple representation of a single neuron. In general,

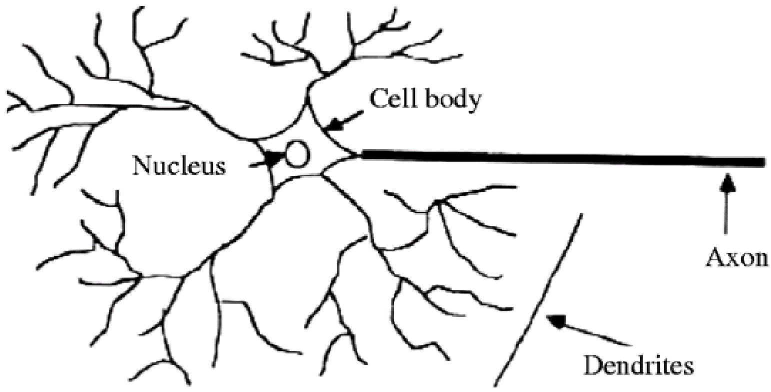

Figure 3.1. A single biological neuron [3].

a single neuron is made up of a nucleus surrounded by a cell body which also has protrusions called dendrites. Extending from these dendrites are the axons which end up at the synaptic terminals and attached to another neuron. In terms of their working principle, when a stimulus (information) is received by the human body from the environment via its sensors (sense of touch, taste, sight, smell and hearing), and transmitted to the neurons which receive them through the dendrites. Once the neurons receive the signals, they are sent out via the axons as spikes of electrical activity. The axons branch out into thousands of branches of which at the end of each are the synapses. The work of each synapse is to convert the signals from the axons into electrical impulses which either block or excite the signals com-ing from the axons of one neuron to that of another. If the input is excited enough compared to the inhibitory input, a spike of electricity sent down its axon and the process is repeated for millions of other neurons. The brain 'learns' by changing the effectiveness of the synapses which goes on to cause a change of influence from one neuron to another [3], [69].

The artificial neuron works using similar principle described above. As shown in Figure (3.2), a simple artificial neuron architecture is simple a model of the biological neuron [4] (figure (3.2)) The inputs to the neuron are the u_i

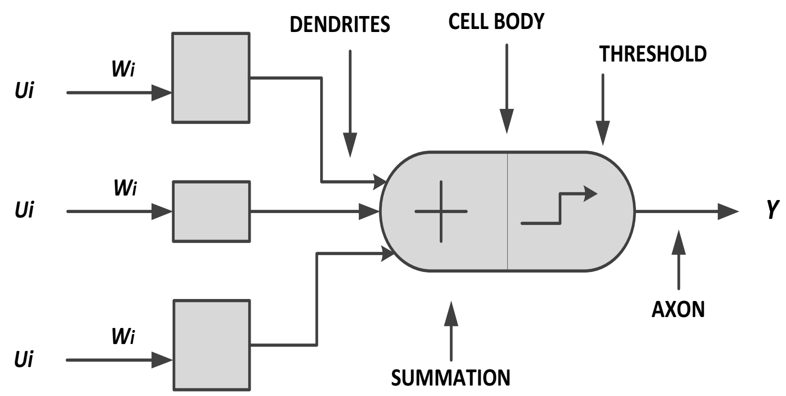

Figure 3.2. A simple artificial neuron model [4].

(in these case three inputs) and the neuron receives them through the 'dendrites'. The synapses contain weights wi which can be said to represent the 'importance' of the corresponding input representing the synapse. The cell body (nodes) sums up all the incoming weighted inputs and when they are above a certain externally applied threshold, the neuron fires via the 'axon' yielding an output 'y'. In many cases, depending on the activation function, the output y can either be continuous or binary. Many ANNs use activation functions which limit the range of the neurons to a binary interval of [-1 1] or [0 1]. Mathematically if θ is the threshold value,

$$x = \sum_{i=1}^{n} w_i u_i - \theta \tag{3.2.1}$$

And

$$y = \varphi x \tag{3.2.2}$$

where x is the net input and $\varphi(.)$ is the activation function. The above represents a feed forward network where the output results from the sum of the products of the connected inputs. As explained the neuron is fired when the activation is above a pre-set threshold. This threshold can be a step function, a Heaviside, Sigmoid or Gaussian function. The step function is commonly used in back propagation algorithm (BPA) Neural Network, developed by Rosenblatt in 1961 and modified by Werbos in 1974, as this type of Neural Network requires that the threshold be non-differentiable [70]. The sigmoid and Gaussian functions are differentiable everywhere. In addition to the functions listed, other common functions include the ramp functions and the piecewise linear functions. Overall, the function used in a Neural Network algorithm is dependent on the application and desired results. The combination of the data (input), function and nodes give the Neural Network model. The next section of this chapter will discuss some Neural Network models, their drawbacks and applications.

3.3 Neural Network models

3.3.1 The perceptron

The perceptron is the simplest Neural Network model known. It was proposed in 1958 by Rosenblatt as an algorithm for classifying linearly separable data via a learning process [71]. It is simply a network with a single node, a single output and input interconnections. It also has a dummy node which is always set to unity. When the input pattern is applied to each of the input connections to the node, the perceptron learning algorithm updates the weight such that the output from the node is within the threshold value for each class. Therefore, mathematically for a class label A_k, and weights w_k,

$$A_k = w_0 + \sum_{k=1}^{n} w_k \tag{3.3.1}$$

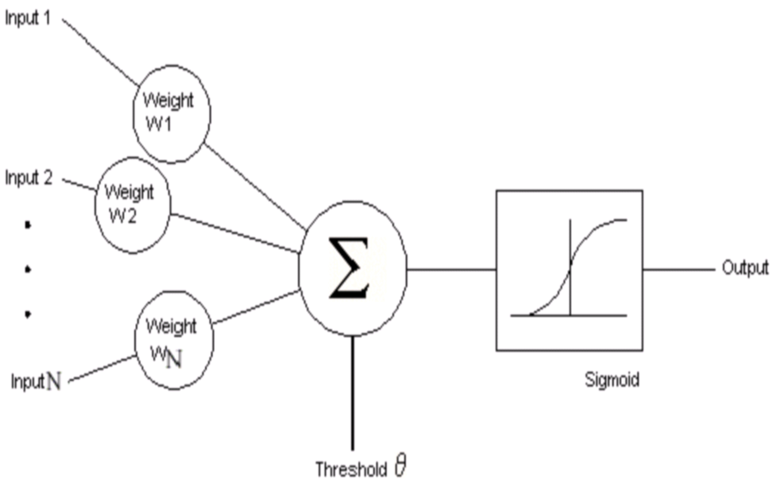

Figure 3.3. Model of a perceptron with a sigmoid activation function [5].

It should be noted however, that the perceptron can only be used for linearly separable classifications i.e. in classifications where data are used in deciding if an object belongs to a group or not. It thus can be used for basic Boolean like OR, AND, NAND but cannot be used for the XOR.

3.3.2 Layered networks

If one considers a Neural Network in terms of layers such that each section is described as a layer that is, the input section with the input node(s) is called the input layer while the output section with the output node(s) is called the output layer, the perception may then be referred to as a two layered network. However, if there are other layers present in among the input and output layers, these layers are named the hidden layer(s). For a given Neural Network, there may be more than one hidden layer and like the input layers and output layers, each hidden layer may contain more than one node. Interconnections between layers are done in such a way that connections are allowed only between nodes in the same layer and to nodes in the successive layer and there are no reverse connections from nodes closest to the output nodes to nodes closest to the input nodes. The network described is known as layered network.

However, if nodes in a layer are not allowed to have interconnections and nodes are strictly interconnected with the nodes in the following layer, the network is known as the popular feed forward network [70] as shown in Figure (3.4).

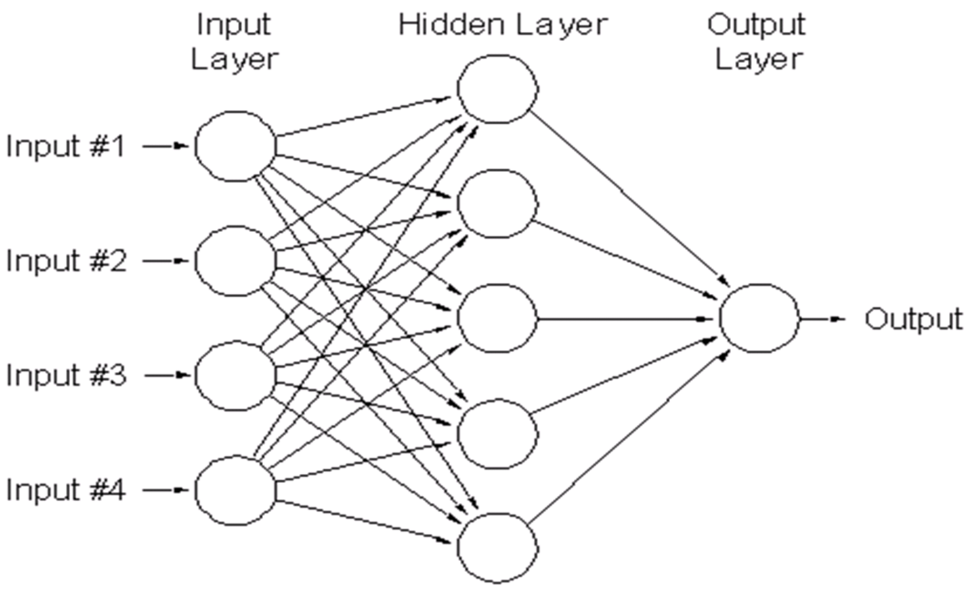

Figure 3.4. A typical 3-layered (4-5-1) feed forward network [6].

3.3.3 Fully connected network

As the name suggests, a fully connected network is one which has an interconnection between all the nodes in the network. Where the weights between the forward and reverse connections defer, the network is known as asymmetrically fully connected network. For an asymmetric fully connected network with n nodes, there are n^2 possible connections and corresponding connection weights which also interpret to an increased need for memory allocations to store the parameters. This thus makes the asymmetric fully connected network impracticable. However, if the weights in the forward and reverse connections are maintained constant, the memory needed is reduced and thus may be more practicable. An application of this network which maintains constant weights in forward and reverse connections is in associative memory models [72]. Also, this type of network is known as the symmetric fully connected network.
In general, when a Neural Network has multiple layers (including hidden layer(s)), it is known as a multi-layer Neural Network

3.3.4 Neural Network activation function

The Artificial Neural Network (ANN) activation function, also known as the transfer function has been mentioned in an earlier section. Although there are many forms, the activation functions can be grouped in three major categories

- Linear (Figure (3.5))
- Sigmoid (Figure (3.6)) and
- Threshold (Figure (3.7))

3.3.5 Linear function

The linear activation function is simply a straight line activation function and can be mathematically represented with the equation

$$y = x \tag{3.3.2}$$

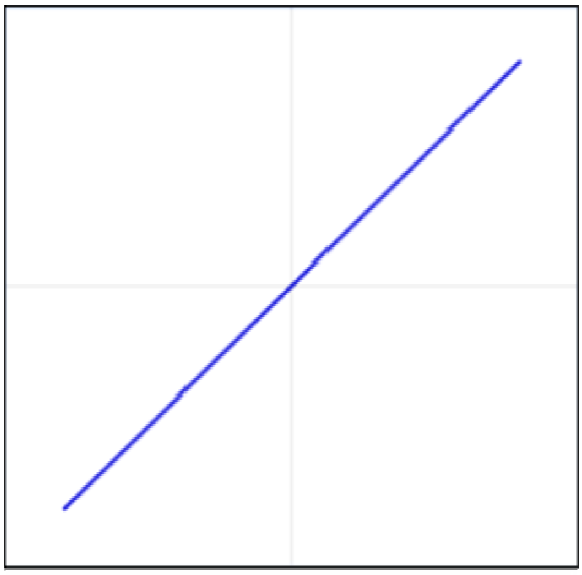

Figure 3.5. A linear function.

The simplicity of this function makes it unpopular as it represents only a linear function.

3.3.6 Sigmoidal function

This is the most common activation function and is used in non-linear multi-layered neural networks.

Mathematically, the sigmoidal function can be represented as:

$$y = \frac{1}{1 + \exp^{-x}} \tag{3.3.3}$$

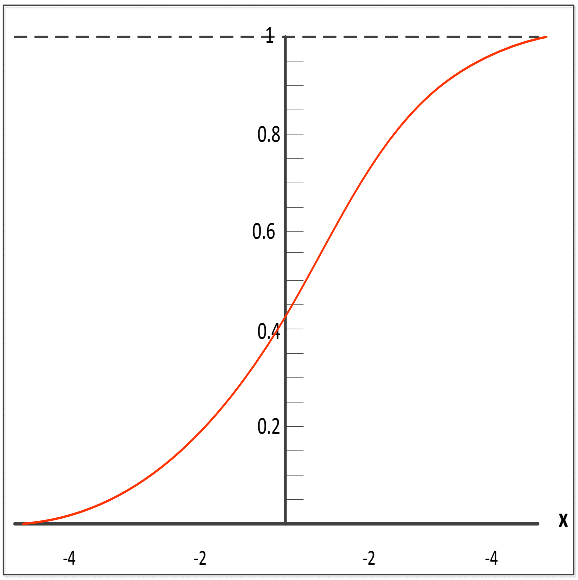

Figure 3.6. A sigmoid function.

Its advantage lies in its ability to be applied for non-linear, continuous and differentiable problems [1]. The latter being a condition that enables its application in back propagation algorithm as mentioned earlier.

3.3.7 Threshold function

The threshold function is another activation function suited for non-linear problems.

It is a simpler activation function compared to the sigmoidal function and can mathematically be represented as:

$$f(x) = \begin{cases} 0 & if x \leq 0 \\ 1 & if x > 0 \end{cases}$$

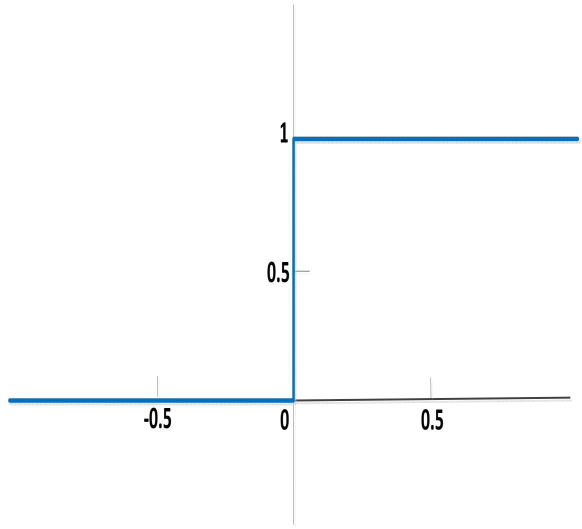

Figure 3.7. A threshold function.

This function is not continuous which serves as a drawback despite the fact that it is much more powerful than a linear function and thus, may imply the need to implement an exponential search to obtain the weights needed to train the network. Also the fact that its output is binary also means that its functionality is limited.

3.3.8 Network structure

The previous sections have dealt with major parts of the artificial Neural Network including the neurons, the network models and the activation functions. This section will consider the methods by which inputs and outputs of a Neural Network can be combined.

As explained earlier, a Neural Network model receives input from the environment. This could be in form of sensor data, feature data, etc. The output of the model is the outcome which may be a probability of an event happening or classification of a set of data into a class Ak. In among the input layers and output layers are the hidden layers which could be one or more depending on the complexity of the system. Neural Networks can thus be classified depending on the number of input and output nodes. Based on this, there are four possible classes.

1. Single Input Single Output (SISO)

2. Single Input Multiple Output (SIMO)

3. Multiple Input Single Output (MISO)

4. Multiple Input Multiple Output (MIMO)

3.3.9 Single input single output

The SISO configuration is the simplest ANN structure. It basically consists of a single node in the input layer and a single node in the output layer as seen in Figure (3.8).

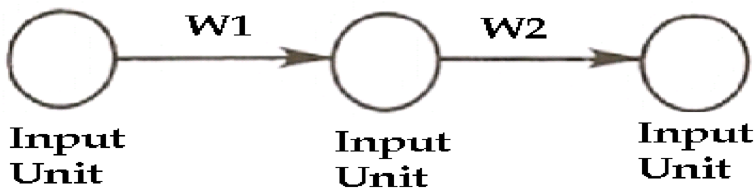

Figure 3.8. Representation of a SISO network.

3.3.10 Single input multiple output

The single input multiple output is an architecture which has a single input and multiple output values. A SIMO as seen in Figure (3.9) was used for Blood Input Function (BIF) estimation problem and obtaining an error of 0.82 4.32 % which compared to the result from the benchmark of 4.63 10.67%, was an improved result [73]. Though this type of network may not be common in ANN applications, the above research shows that it is useful in some cases. Basically, it involves passing singular data values as inputs to a network with corresponding multiple node outputs. This architecture can be used as a feature extraction network. For example, a value may be inputted to represent an object with a set of values representing the output. The output node values will represent the features of the input node and if trained over time, the network will be able to extract similar features when presented with another set of objects.

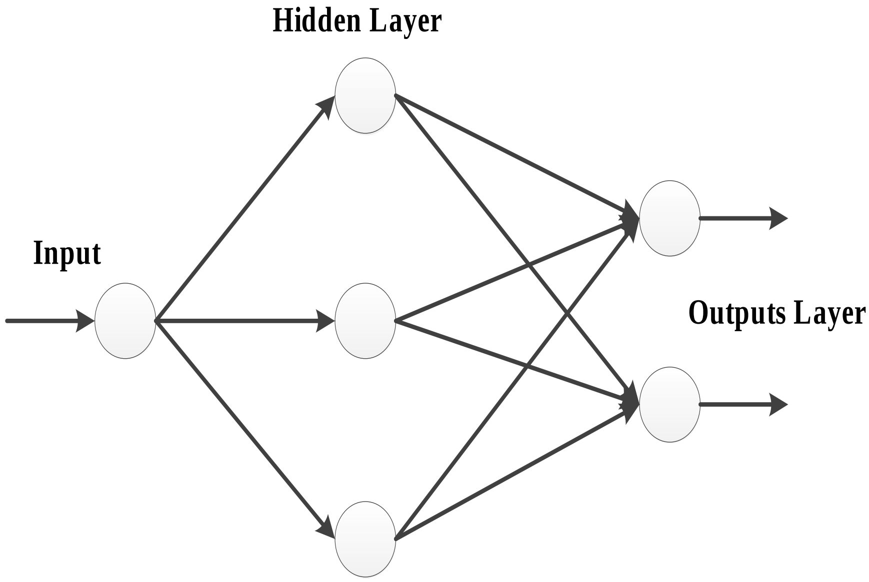

Figure 3.9. Representation of a SIMO network.

3.3.11 Multiple input single output

The multiple input single output as seen in Figure (3.10) is a common type of Neural Network architecture. It contains an input layer of at least two input nodes and an output layer of a single node. Usually, the network is trained in such a way that the output layer returns either of two possible values i.e. ‘1’ or ‘0’. An example is in the development of a network for classification with more than two input features.

When the features are presented to the network, it is trained in such a way that if it belongs to class A, it returns ‘1’ in the output and ‘0’ otherwise.

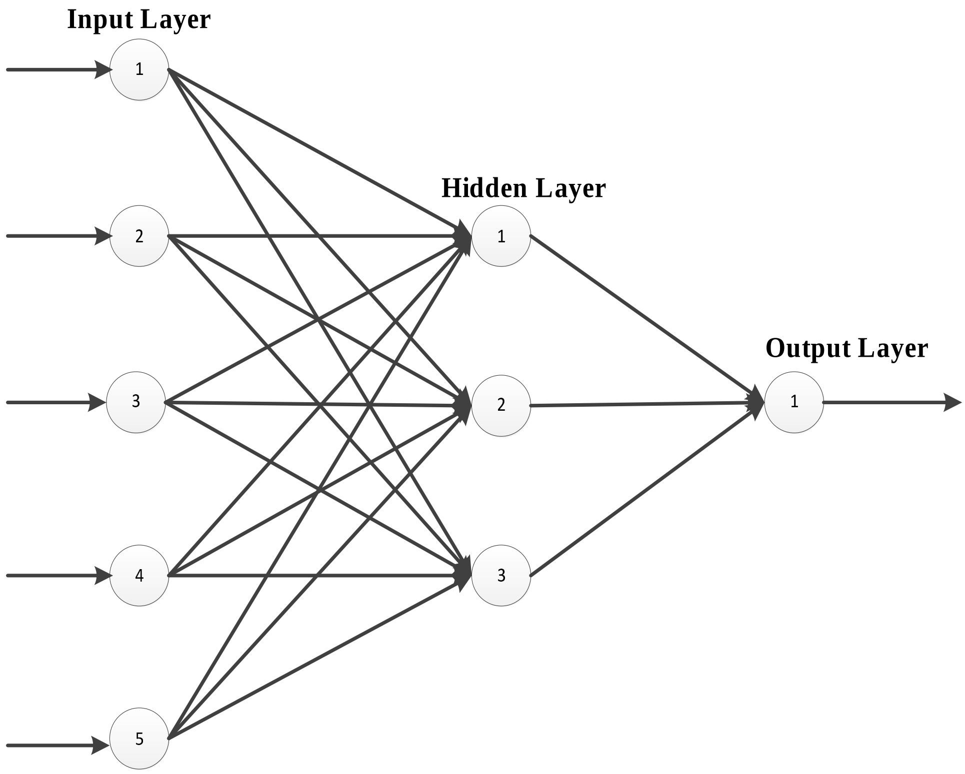

Figure 3.10. A MISO ANN architecture.

3.3.12 Multiple input multiple output

A multiple input multiple outputs (MIMO) network (shown in Figure (3.11) below) is a Neural Network architecture which contains more than one input and at least two outputs. As with other network architectures, this network may contain more than one hidden layer depending on the complexity of the system. For example, Figure (3.11) shows ANN architecture with two hidden layers, three input neurons and two output neurons. Typical applications of the MIMO network would be in the character recognition where each box in a grid represents an input node and the output would have 26 nodes, each combination representing a letter of the English alphabet. If a box is marked, it is recorded as '1' and an unmarked box represented as '0'. The letters of the alphabet are used to train the network based on the marked grid and output pairs. After training, the network is able to predict inputted characters.

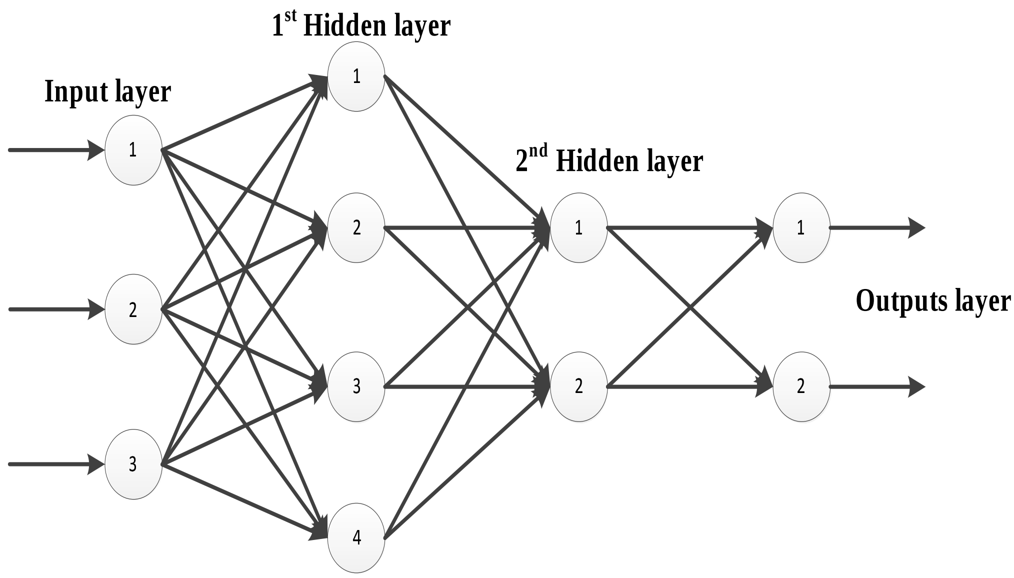

Figure 3.11. A MIMO Neural Network.

3.3.13 Network training

Training a network is the goal of a ANN application. Training involves trying to fit the network function to a set of data. It is performed by searching for the appropriate set of weights which minimizes some error function as shown in Equation (3.3.4) [74].

$$e = \frac{1}{2}\sum_{q=1}^{n}\sum_{k=1}^{c}\{y_k(x^q;w) - t_k^q\}^2 \tag{3.3.4}$$

where e is the error, x^q is the vector input t^q is the target vector y_k is the output vector and w is the weight Therefore, the challenge for network training will then be searching for the minimum of an error surface if the error function is seen geometrically as the error surface sitting over weight space [74]. It is possible for the error function to have more than one minimum. However, the absolute minimum of the error function is called the global minimum while the other minima are known as local minima. The solution of the error function is simplified for single layer activation functions as the sum of squares is simply a generalized quadratic function with only a single minimum hence no local minima. The global minimum is found by solving a set of linear equations. However, for multilayer Neural Networks, the error function is non-linear function of the weights [75] [74] and thus requires an iterative search for the global minimum. Due to the fact that the first step in this iterative process is selected randomly, it is possible that the chosen algorithm may first find the nearest local minimum. In many cases, this is may be sufficient enough to give good results although some algorithms can provide a means of bypassing the local minima and finding the global minimum [74].

3.3.14 Learning

3.3.14.1 Supervised learning

Supervised learning in ANN refers to training a network based on pairs of input data and desired or target output. Usually, the entire dataset is divided into three - training and validation data sets. The training set is used in training the network by pairing the input and output data over a certain number of iterations (depending on the set criteria). Once the weights have been appropriately set, the validation data is used to confirm if truly learning has taken place. This is done by feeding the network with input data that was not involved in training and the predicted output is crosschecked with the real output.

In supervised learning, some factors have to be considered when applying this type of learning:

Data Redundancy: The input data should ideally not contain highly correlated values (redundant data) else the network will perform poorly.

Dimensionality: high dimensionality refers to having a high amount of input data. A high dimensionality may lead to the learning algorithm having a high variance. A high variance implies that the algorithm will predict different outputs when presented with a different input dataset.

Noise: When training the dataset, if the desired output data contains a lot of noise, the algorithm will try to match the desired output with the training input data therefore leading to overfitting. This can however be avoided though a variety of means including stopping the training early [76].

3.3.14.2 Unsupervised learning

Unsupervised learning describes the challenge of searching for a structure or pattern in seemingly random data. In other words, for unsupervised learning, input data has no target data to compare with and as such, there is no error calculation to be made. There are several Neural Network algorithms developed to execute unsupervised learning including Self-Organising Map (SOM) and the Adaptive Resonance Theory (ART) techniques. The self-organising map, also known as the Kohonen map [72] takes the following 3 steps:

1. Select vector from data
2. Find node with the nearest weight vector closest to that from step 1
3. Replace the vector from step 2 with that from step 1

The result of following the three steps is that the mapping of low dimensionality is produced from the initially high dimension data.
The Adaptive Resonance Theory comes in 2 classes. The first architecture known as ART1 can recognize binary patterns whilst the second class known as ART 2 can categorize random sequences of input data [77]. In general, the ART system has four basic characteristics - self-scaling computational units, self-adjusting memory search, previously learned patterns can then directly find their groups and then the system will be able to modulate attention vigilance using the environment as the teacher.

3.3.15 Artificial Neural Network applications

Due to their versatility, Neural Networks have been applied in many fields. In healthcare for example, they has been used for clinical diagnosis and image analysis.
It is also used in telecommunications for the detection of cloned software, for finding optimal call routes, for predicting traffic trends and for detecting the fraudulent use of mobile phones [78].
In stock broking, Neural Networks are also used for predicting of share prices. By using the right indices as input, Neural Networks can be used to give close to accurate future stock prices. A claim is made on how Neural Networks

was used in getting 'good results' by using six financial indicators as inputs including the ADX value over previous 18 days, $S\&P500$ value from previous five days and other indicators [79] [76].

Perhaps a popular application of Neural Network is in character recognition. Using the supervised training (described above), patterns of handwritten characters are used as input to a Neural Network system with the correct letter used as desired output and this pair is used to train the Artificial Neural Network. Once training is complete, a well-trained system will be able to identify hand written characters.

In addition to the above applications, Neural Networks can also be used in desalination systems. Potential applications of ANNs to desalination systems with focus on detection of faults, security assessment amongst other factors are discussed in [1].

All the above are a summary of current applications of Neural Network. In fact, there are many more applications to the list above including analysis of market research data, forecasting applications and industrial process control. This shows the promise of using ANN for classification, prediction and optimization problems. However, ANN do have their drawbacks. The next section will discuss some of these drawbacks and some advantages that make this tool attractive.

3.3.16 Merits and demerits of Artificial Neural Networks

The advantages and disadvantages of using ANN for predictions and classification problems are highlighted in Table 3.1 [9].

Table 3.1. Neural Network merits and demerits [9]

Merits	Demerits
Neural Network can detect all possible interactions between predictor variables	Application of Neural Networks may not be easy to implement on field
Developing a Neural Network does not require too many formal statistical training	Modelling of a Neural Network requires large computational resources
Neural Network can be developed using more than one different training model	Over-fitting is a common and major problem with Neural Network models
ANNs have the ability to generalize in the sense that they can get knowledge from the environment by adapting their internal parameters which are responses to external stimulus (training data)	Because Neural Network is basically a 'black box', its ability to define to details relationship between inputs and outputs is limited.
ANN can determine relationship between pairs of training data and also classify input data without requiring additional model	

3.3.17 Building steps of an Artificial Neural Network

In developing an artificial Neural Network for any application, the following steps should be taken:

1. Collect data
2. Pre-process the data
3. Determine the structure of the network (number of hidden layers and nodes)
4. Create the network
5. Initialize weights and biases
6. Train network
7. Validate network
8. Use network

Data collection can be done by using sensors or manual collection of data from other sources. Data pre-processing involves identifying noisy data and removing them and then normalising data. Normalisation of data for Neural Network involves converting all data values to the [0,1] or [-1,1] range. This normalization is very critical to the Neural Network process as it could help improve the performance of the system. There are different types of normalization techniques and some will be discussed later in this section.
Another important step is the determination of the number of hidden layers and nodes in the hidden layer(s) Usually, the ideal number of hidden layers is determined based on some performance criteria (mean squared error and/or regression). This is also further highlighted in this section. There is software available which will implement the remaining steps listed above. MATLAB, software developed by Mathworks is one of the common ones and the one used in this thesis.

3.3.17.1 Normalisation

Normalising the input data for a Neural Network application has great impact on the performance of the system. Not pre-processing the data (input and target data) in this way and using the raw data instead could result in a slow system [80]. By starting the training process for each data on the same scale, normalization would help increase the speed of the training time. Thus in cases where the input data are on different scales, normalization would help to align the data on to the same scale. There are various means by which data can be normalized. In this thesis, we will outline four methods - the statistical, min-max, median and sigmoid methods [80].

Median: Using the median method requires that each sample data be normalized with the median of the raw data for all data samples. A merit of this method is that the median of a set of data sample is not affected by variations within the data space. Mathematically, if $x|$ is the normalized data point, x_k the raw data point and median (.) the median of the raw data, then.

$$x| = \frac{x_k}{median(b_k)} \tag{3.3.5}$$

Min-Max: This normalization technique translates the raw data points from their original raw form into a new scale usually in the range [0,1] or [-1,1] using a linear interpolation. Mathematically, for normalized data $x|$, if x_{max} and x_{min} are the maximum and minimum data values of the raw data and x_i the raw data point, then,

$$x^| = (x_{max} - x_{min}) \times \frac{(x_i - x_{min})}{(x_{max} - x_{min})} + x_{min} \tag{3.3.6}$$

3.3.17.2 Hidden layer selection

Selection of the number of hidden layers in Neural Network architecture is a very important aspect of developing a network. The hidden layers handle the 'complexity' of the neural network and so, the more complex the problem is, the more hidden layers/hidden layer nodes needed. Therefore, for a simple linearly separable problem, no hidden layer is needed at all. However, one should be careful when adding hidden layers and performance criteria must be put defined and put into consideration when designing Neural Network architecture. Typical performance criteria used are the root mean square error (RMSE) and the correlation factor (represented by R2). The root mean square error is a common criterion used by researchers to calculate the ability of a network to make precise predictions. It is calculated by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{N}} \tag{3.3.7}$$

Where y_i is the true output values, $\hat{y}_i$ the network's output and N the total number of observations. The lower the Root Mean Square Error (RMSE) value, the more precise the prediction of the network.

The correlation factor (R^2) is a standard statistical ranging from between 0 and 1 where 1 implies a perfect fit and 0 implies no fit.

$$R^2 = 1 - \frac{\sum_{i(y_i - \hat{y}_i)^2}}{\sum_{i(y_i - \bar{y}_i)_2}} \tag{3.3.8}$$

where y_i is the true output, $\hat{y}_i$ is the response of the network for the and $\bar{y}_i$ is the mean value over all samples.

Hidden layer parameters are usually found by a trial by error method [81]. Starting from a single layer with minimum number of nodes, this performance of the network is checked based on the criteria values discussed above. If satisfied, the network with the current number of hidden layers and hidden layer nodes is used. If not satisfied, the nodes are increased until the performance criteria meet some determined set values.

3.3.18 MATLAB simulations

In this thesis, MATLAB software is used in implementing the Neural Network architecture. This section gives a brief explanation on how MATLAB is used to implement artificial Neural Network (ANN) problems.
As described in Section 3.10, collection of data is the first step to implementing a Neural Network problem. MATLAB uses the command function $newff$ to create a multilayer feed forward artificial Neural Network. In MATLAB, this multilayer feed forward network is called net. The net usually requires four inputs. The first input is a C by 2 matrix which defines minimum and maximum values for C input values. The next is a 1 by N matrix which defines the number of nodes in each layer beginning from the second layer. Therefore, if a network has 2 hidden layers which 3 nodes in each and one node in the output layer, this is inputted as [3 3 1]. Next to this is the transfer functions used in each layer for example, for the network described above, with the first two layers represented with two tansigmoid functions and the last hidden layer by a purely linear function, it is described as $`tansig', `tansig', `purelin'$. The final input is the training function used for the network. For example, to create a three layered network with two input nodes (first element ranging from -7 to 3 and second node elements ranging from -9 to 5), one hidden layer with 3 nodes and one node in the output layer, trained with a Levenberg-Marquardt function, the command in MATLAB will be:

$$net = newff([-73; -95], [3, 1], `tansig', `tansig', `trainlm')$$

To train the network, training parameters must be set. Details of network training has been described in a previous section. To code this in MATLAB

$net.trainParam.show = 1000;$

The training results be displayed after every 1000 epochs

$net.trainParam.lr = 0.05;$

Defines the network's learning rate as 0.05

$net.trainParam.epochs = 1000;$

Sets the max number of iterations as 1000

$net.trainParam.goal = 1e - 3;$

Sets the training stopping criterion as 1e-3

Once this is defined, the network is trained using

$[net, tr] = train(net, p, t)$

where 'p' is the input data and 't' the target data.

After training, the network is tested by simulation to confirm is the network output say 'z' results from a set of input 'p1' which was not used as part of the training. In MATLAB, the command used for simulating the network is

$Z = sim(net, p1)$

The output values from this simulation can be compared with the target output values. The difference is the error between the network output and the target output. This error should be minimal depending on the performance of the training.

This section has shown a summary of how ANN is implemented in MATLAB. It started by showing how to build the network with required input, hidden and output layers. It then went on to show how to train the network with appropriate MATLAB codes for the training parameters and finally, the section outlined the steps and command line used for simulating the network and for calculating the error between the target output and true output values.

3.3.19 Closure

This chapter aimed at describing the artificial Neural Network (ANN) and its applications including steps to be used in implementing a networks using MATLAB software. The section began by explaining the origins of the artificial Neural Network (ANN) and its similarities to the biological neuron. It then went on to outline the various components of a network including its input, output and hidden layers. Different types of networks were also briefly discussed. Finally, the process of implementing a Neural Network using MATLAB software was discussed and outlined.

Chapter 4

METHODOLOGY

This chapter introduces the concept of dehydration and desalting. In this chapter, the following will be discussed; the desalting process and plant as pertains to the Arabian gulf oil company, how the experimental data was collected and finally how the collected experimental data was analysed in the context of Artificial neural network approach.

4.1 Dehydration and desalting

Crude oil production is accompanied by a lot of water usage, water in crude oil ratios greater than 10 are not uncommon meaning emulsion formation is crucial in oil production.

On the onset of petroleum production emulsions proved to be difficult due to poor facilities for breaking them down and disposal was prohibited. [82].

The major reasons for dehydrating and desalting crude oil are:

1. To meet the specifications for contents of sediments and water in crude oil for crude oil purchasers
2. Water affects the ^{0}API gravity by lowering its value thus reducing its selling price.
3. High amounts of water increase viscosity of crude oil
4. The minerals ions present are corrosive and cause major damage to expensive refining equipment

Several methods for removing impurities such as sand, mineral ions and sediments exist. The major goal is to allow gravity to separate the impurities from the crude oil. Common treatment methods are:

1. Increasing the residence time by using low velocity thus free water separates form the crude oil
2. Using chemical treatment by adding demulsifiers
3. Continuous water washing the crude oil
4. Reducing oil viscosity by heating thus accelerating phase separation
5. Applying electric current
6. Promotion of coalescence by increasing surface area

By utilising and optimising demulsification, residence time, heat and electricity one is able to dehydrate crude oil. The use of demulsifiers and electricity incur a lot of cost and it is worthy optimising the dehydration process and reduces the use of the said two by increasing the residence time and heating the oil to reduce its viscosity [83].

4.1.1 Chemical treatment using demulsifiers

The main way in which demulsifiers must act are as follows:

1. They should have a strong attraction to the oil-water interface thus displace and neutralise emulsifiers on the droplet interface.
2. They should promote flocculation by neutralising repulsion between dispersed drops.
3. They should promote coalescence by allowing the combination of small droplets into larger ones allowing for faster settling.

For effective use of demulsifiers it is often encouraged to carry out early injection for example injection before the pumping section thus ensuring perfect mixing and negating the formation of emulsions from pumping action. The advantages of using demulsifiers are:

1. Curbing emulsion formation almost completely
2. Reduced need for energy due to emulsions breaking down at low temperatures

The disadvantages of using demulsifiers are:

1. In the case of overdosing then new emulsions may arise which are more difficult to break down
2. Due to the cost of emulsion break down more often than not more energy has to be utilised in order to reduce the amount of demulsifier used as they are costly chemicals.

4.1.2 The use of gravity and residence time

Usually it is achieved by using large holding vessels such as tanks. These vessels provide the required residence time for settling. They are used to remove large percentages of free water that is carried in the produced steam that has not emulsified in the oil. They usually operate with the produced water occupying the bottom third and crude oil the top two thirds. Usually the emulsion feed is introduced just below the oil-water interface which allows for agitation which promotes coalescence and thus droplets of water droplets are eliminated from the oil stream.

4.1.3 Heating

Heating reduces the viscosity (thickness) of the continuous oil phase which increases water drop collisions and thus increases settling rates. The increase of Brownian motion and convection currents in the emulsion increases and intensifies water drop collisions. Heating also causes a rise in the density difference between the crude oil and brine.

4.1.4 Electric treatment

The use of gravity settling alone as a treatment procedure causes very slow settling velocities if one uses stokes law. As water drops are polar, addition of an electric field would enhance coalescence through two mechanisms:

1. A net charge is delivered to the water droplets through direct contact with a charged electrode

2. The water droplets are polarised by the external field and charged particles distributed inside the droplets

The results of this are that due to an increase in drop size the drop velocity increases thus increasing the settling rate. Drag force increases which limits the size of droplets that can exist. When the electric current increases the maximum allowable drop size decreases.

4.2 Desalting process

After removal of emulsions, the dehydration process, the crude oil more often than not contains sediments and water. The processing of this crude oil in the refinery may lead to significant problems such as plugging thus poor flow problems arise. Another problem owing to brine formation which is highly corrosive may be corrosion of pipeline as well as catalyst poisoning used in the fluid catalytic cracking unit. Due to this, refineries usually desalt the crude oil to less than 10 PTB (pounds per thousand barrels) before its entry into the refinery process.

4.2.1 Desalting process description

Desalting process usually is a process carried out after dehydration. It involves the following procedure.

1. Addition of fresh water to the crude
2. The mixing of fresh water and the crude to dilute sediments and water present in the crude oil
3. Addition of demulsifires to separate the crude oil and the mixture of dilute sediments and water

The overall result is to reduce the amount of sediments and water present in the crude through dilution thus obtaining crude oil with less than 10 PTB (pounds per thousand barrels).
Different configurations of desalting equipment exist that is single stage and double stage recycling as shown in Figures (4.1) and (4.2) respectively.

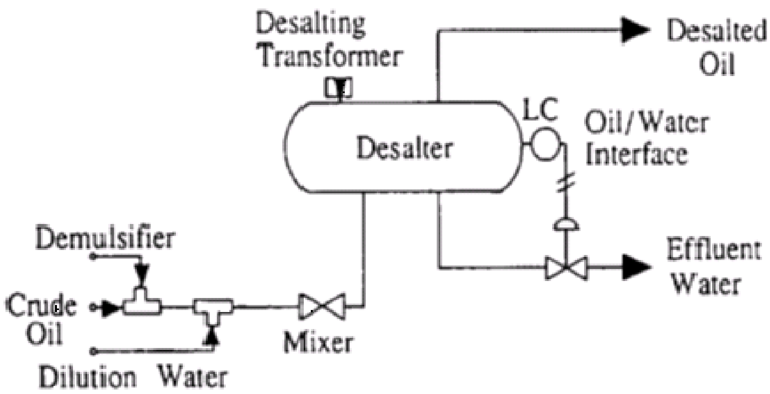

Figure 4.1. Single stage desalter [7].

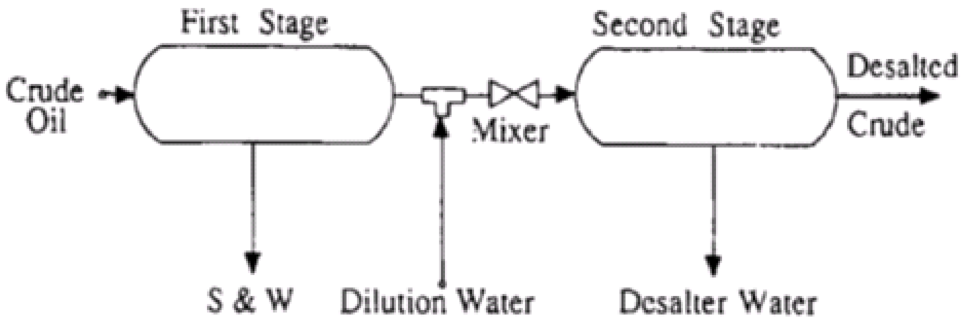

Figure 4.2. Two stage desalter [7].

Libyan process flow diagram of a single stage desalter is shown in Figure (4.3).

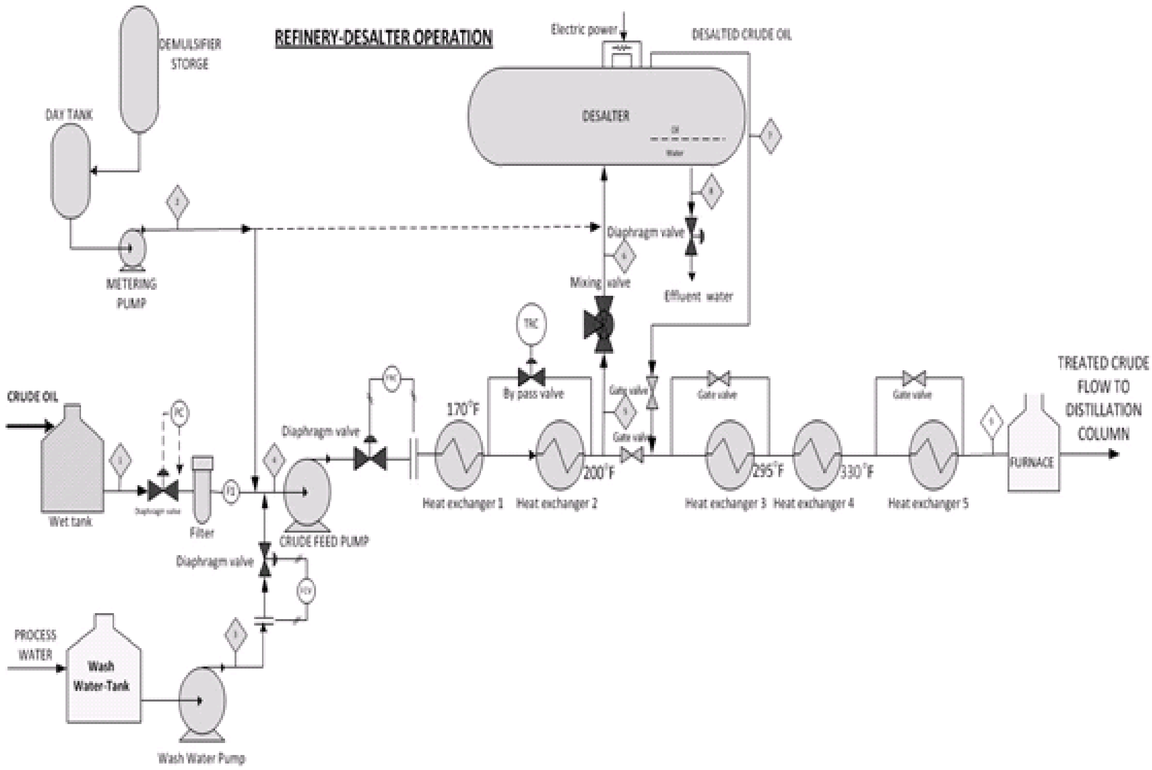

Figure 4.3. A typical desalter plant layout single stage desalter with recycle stream (Arabian Gulf Oil Company).

The "Petreco" Electric Desalter is operated with electrical power from the regular refinery, distribution system which is fed to a junction box or circuit breaker on the local unit switchboard. From here, individual supplies are fed to each of the transformer/reactor units mounted on the platform above the vessel. Localised switching is provided by means of an ON-OFF push-button station on the unit switchboard which is connected to the trip coil on the main switch house contactor remote from the unit. If a circuit breaker is used instead of a junction box and push-button station, the localised switching will be incorporated in the circuit breaker itself [84].
The high voltage connection from each transformer to the electrodes is made via a length of copper tube contained within a large bore vertical pipe which is bolted at its lower end to the entrance bushing nozzle on top of the vessel and at the upper end to a special bushing pocket forming part of the transformer.
A specially designed horizontally mounted bushing projects from the transformer tank into the bushing pocket. From this bushing pocket, the bushing then links to the upper end of the copper tube. The lower end of this tube connects to another special bushing which is screwed into a flange in the entrance bushing pocket forming a pressure tight joint. The complete high voltage assembly is finally filled with transformer oil and sealed at the top end with a blind flange. The power is fed to the electrodes by means of a flexible connection linking the entrance bushing with a contactor rod on the electrode frame. A number of protective devices are incorporated in the electrical circuit to ensure continuity of operation, such as the integral reactors in the main transformers which limit the current flow to a maximum value below that of the main breaker settings such that excessive loads due to abnormal operation do not interrupt the operation. These reactors also prevent the equipment from being overloaded. A low level device is fitted to trip the electrical supply in the event of low liquid level with the vessel and

also to prevent power being applied to the electrodes until the vessel is full of liquid [84].

Accessory equipment normally supplied as standard in all “Petreco” desalters includes a sampling feature located in the head of the Vessel. This device permits the taking of samples from within the vessel at any level starting from the base of the shell to a point approximately 8”(203mm) below the lower electrode.

Instrumentation in the form of one voltmeter and one ammeter is provided for each Transformer/Reactor unit, these meters being mounted on the local unit switchboard. A pilot light is also supplied for connection in parallel with the voltmeter, this light providing visual indication of a fault condition in the unit such as a short circuit, under which condition this light will be reduced in intensity or extinguished completely.

An interface level controller is utilised on all units to maintain the emulsion-water interface at a constant level, this instrument being mounted on a nozzle in the top of the vessel through which the float rod is suspended, the float itself being contained within a shield in the lower half of the vessel. This instrument works in conjunction with a draw-off valve in the effluent water line, this valve is automatically opened or closed depending on the signal from the level controller. One of the most important parts of the plant is the mixing valve, the device used to create the crude oil-water emulsion. This item is normally located in close proximity to the unit, and is installed at grade.

4.2.2 Instrumentation

The three main instruments that aid in the operation of the Desalter are the mixing valve, the interface level controller and process water valve.

4.2.2.1 Mixing valve

The mixing valve controls the degree of mixing of oil, water and demulsifiers as they flow through. This is controlled by the pressure difference across the valve. The pressure difference is maintained by a back pressure controller which is usually located downstream of the desalter. The objective is to ensure dispersal of the fresh water into the crude oil as efficiently as possible thus reducing the formation of a stabilised emulsion which would cause problems in trying to demulsify it.

4.2.2.2 Interface level controller

One of the major reasons for this control is to regulate the level of water in the bottom of the desalter. This is because if the levels of water are high in the desalter reduce the residence time of crude oil in the desalter thus negating the desalting operation. High water levels also may cause short circuiting of the electrodes thus no desalting occurs. On the other hand low levels of water will allow oil deposits to be discharged into the effluent draw-off valve.

4.2.2.3 Effluent draw-off valve

This valve is controlled by the interface level controller which feeds an air signal to the diaphragm which houses it. When the crude oil/water interface rises, the level controller will send a signal to the diaphragm and it pressure will increase thus causing the valve to open in order to get rid of effluent. When the crude oil/water interface falls then a decreased pressure on the diaphragm arises and the valve shuts close.

4.2.3 Instrument installation

In general the mixing valve may most conveniently be situated at grade level. It is normally recommended by Petrolite that this valve be provided with a by-pass line as indicated on the standard flow diagram, but again, the installation of any such line is entirely dependent upon customer requirements and site conditions. In most instances the mixing valve body will be flanged in a size smaller than the crude line, and connection into the line must be made via concentric reducer at either side of the valve. These reducers, together with general line pipe work, do not form part of the equipment supplied by Petrolite.

The interface level controller, as previously discussed is mounted to a spool piece which in turn connects to a nozzle on top of the vessel. This apparatus may be orientated throughout a full 360^O such that the most suitable position is found to facilitate access to the controls within the instrument case. Usually the float shield will be supplied as part of the vessel and will already be assembled to the brackets in the bottom of the vessel. When correctly positioned, the internal displacement float should be positioned centrally within the body of the float shield, the latter item being designed to restrain the float from excessive sideways movement. Installation of the draw-off valve is, like the mixing valve, dependent to a certain extent on the nature of site conditions. However, this is generally installed in the effluent line either immediately underneath or adjacent to the desalter vessel which allows the instrument air connection from the level controller to be kept reasonably short and also allows convenient access for adjustment or maintenance.

4.3 Factors affecting desalter perfomance

With any process certain parameters can be controlled and others cannot. The main factors affecting desalting plant operations are.

1. Crude oil feed rate

2. Dosage of demulsifier

3. Crude oil temperature

4. Fresh water addition

4.3.1 Crude oil feed rate

The feed rate of crude oil into the desalter affects the residence time in the desalter. A high feed rate will lead to an increase in sediments and water thus reducing the quality of crude as the PTB (pounds per thousand barrels).value will exceed 10.

4.3.2 Demulsifier dosage

As previously described, demulsifiers aid in the breaking of a water-in-crude oil mixture, If the dosage of the demulsifier is too high, more stable emulsions may form which would be difficult to break thus hindering the performance of the desalter.

4.3.3 Crude oil temperature

The temperature of the crude oil affects its density and viscosity. Too high a viscosity of the crude oil will lead to the settling velocity of the water droplets decreasing thus hindering desalter performance. On the other hand to high crude oil temperature will increase the conductivity of the crude oil which will lead to a reduction in grid voltage in the desalter thus reducing the performance of the desalter.

4.3.4 Fresh water addition

The rate of fresh water addition and its salinity affect desalter performance. A very low rate of fresh water addition would result in poor mixing of the demulsifier and crude oil in the mixing valve thus hindering the performance of the desalter. If the pH is too high soaps can be formed which form emulsions which would be hard to remove in the desalter.

4.4 Data acquisition

There are seven parameters that will be studied in the course of this work. That is crude oil production, salt in and salt out, crude oil temperature in and out, amount of chemical demulsifier and amount of fresh water added. The experimental setup required several forms of equipment, testing and analysis methods. The apparatus were designed to accommodate running the tests precisely and to allow accurate collection of data.

4.4.1 Equipment and materials

The experimental equipment used throughout the tests was collected from various location, i.e. Arabian gulf oil company' lab, local market and some were found available in Libyan University' petroleum Department's laboratory. The majority of the laboratory tests were carried out in the petroleum Department, Libyan University. The list of the equipment used includes the following items:
The tested materials in this experimental study are as follows; the crude oil; collected from Libyan Oil field wells. Dilution water; collected from field operation in Arabian gulf oil company. Demulsifier/ Chemical, Servo CC 3408.

4.4.2 Investigated variables

The investigated variables were crude oil production, salt in and salt out, crude oil temperature in and out, amount of chemical demulsifier and amount of fresh water added. In real Desalting/Dehydration Plant (DDP) processes the temperature is less commonly varied. This is due to crude oil temperature being determined early on in the design and manufacturing of desalting/dehydration plants. At the staging design, the manufacturer builds the DDP in accordance to the customer's preference. Nevertheless, this experiment will focus on the amount of salt in the crude before and after desalting.

4.4.3 Testing methods

Initially, the sample is first analysed and tested for salt result Pounds per thousand (PTB) and water cut (W/C). This initial test is recorded in a sheet. The equipment used for this are shown in Figures (4.4)-(4.6) respectively.

Figure 4.4. Weight balance (Arabian gulf oil company)

It is worth noting that no experiments were carried out in this research, however it is important to mention techniques used in obtaining the data for

Figure 4.5. Crude oil sample (Arabian gulf oil company).

Figure 4.6. Centrifuge (Arabian gulf oil company).

this research. The tests of the initial and final salt and W/C results were obtained by the following techniques:

4.4.3.1 Salt in crude oil testing method

A salt in crude analyser was used for the salt in crude test. The salt content in the crude oil is determined by placing a sample of crude oil in a polar and subjecting it to alternating current and thus measuring the conductivity. The salinity is obtained by comparing the conductance to a calibration curve usually of a known salt mixture. The steps in salt in crude oil tests are shown below:

APPARATUS:

The equipment used for the salt in crude oil test is as follows:

1. Test beaker
2. 10ml pipet
3. 100ml stoppered cylinders
4. Volumetric and graduated flasks and pipets

PROCEDURE:

1. In a 100ml graduated and glass stoppered cylinder add 15ml of xylene and pipet in a 10ml sample of crude oil
2. Rinse the pipet with xylene until free of oil
3. Make up 50ml with xylene
4. Stopper and then shake the cylinder vigorously in a centrifuge for 60s
5. Add mixed alcohol solvent and dilute to 100ml
6. Shake vigorously in the centrifuge for approximately 30s
7. Allow to stand for 5min and then our into a dry test beaker

8. Place electrodes into the solution in the beaker and adjust the voltage to a series of values.

9. Record the reading of the current and voltage displayed

10. Remove the electrodes from the sample solution and clean the apparatus

CALCULATION:

1. Deduct the value obtained from the blank measurement form the one obtained from the specimen measurement to obtain a net current reading

2. From the calibration graph read the salt concentration corresponding to the net current reading

3. Calculate the concentration in mg/Kg by using:

a) Salt,mg/Kg=X/d

b) Salt,mg/Kg=Y/d

Where:

X = measured salt concentration in mg/m^3,

Y = measured salt concentration in PTB, and

d = specimen density at 150 C in Kg/m^3

4.4.3.2 Water in crude oil testing method

Test samples of crude oil in the feed before entering the desalter and after desalting were measured. The resulting difference between the input and output was then determined as the water cut. The water cut is usually the ration of water produced compared to the volume total of the liquid being produced.

APPARATUS:

The equipment used for the water in crude oil by distillation is as follows:

1. a glass distillation flask
2. a condensor
3. a graduated glass trap
4. a heater

PROCEDURE:

1. Chemically clean the equipment to get rid of water droplets adhered to the surface
2. Add sufficient xylene to the flask to make the total volume xylene volume of 400 ml to determine water content on a volume basis
3. Add sufficient xylene to the flask to make the total volume xylene volume of 400 ml to determine water content on a mass basis
4. Stir using a magnetic stirrer to reduce bumping
5. Assemble the distillation equipment and circulate water between 20 and 25^0C
6. Apply heat to the flask care being taken especially in the initial stages in order to prevent bumping and loss of water.
7. After completion of carry-over of water, allow the trap and contents to cool down to 20^0C

CALCULATION:

1. Water in the sample is calculated as follows

$$Volume\% = \frac{(A - B)}{C} \times 100 \qquad (4.4.1)$$

$$Volume\% = \frac{(A - B)}{M/D} \times 100 \qquad (4.4.2)$$

$$Volume\% = \frac{(A - B)}{M} \times 100 \qquad (4.4.3)$$

where:

A= mL of water in trap

B= mL of solvent blank

C= mL of test sample

M= g of test sample, and

D= density of sample, g/mL

4.5 Normalising and filtering data

When modelling data with the use of computer codes, if one uses data with many errors the computer program will usually tend to give wrong results of what is expected and redundancy problems arise as a result. These errors are usually referred to as outliers. It is best to perform a data analysis and identify these outliers as they effect the estimation of model parameters thus influencing the output. In the case of ANN algorithms if outliers are present they heavily influence the outcome of the result [8] and majority of the time the results are usually wrong with the programmed code taking long to arrive to the wrong solution.

Of significance is that even when the input data portrays a real system more often than not the trained network will produce high error results. A contributing factor of these phenomena is lack of normalisation of the input data. Normalisation of data is also case specific, wrong normalisation will contribute to high error results as well.

Zero mean normalisation method was used to normalise the input data during the course of these research. The data set was normalised between the limits -1 and +1, with the average value being set to zero. It is represented by Equation 4.4.1 [8] and represents the normalisation variable $X_{i,norm}$ by:

$$X_{i,norm} = \frac{X_i - X_{i,avg}}{R_{i,max}} \quad (4.5.1)$$

And

$$R_{i,max} = Maxmum[(X_{i,max} - X_{i,avg}), (X_{i,avg} - X_{i,max}) \quad (4.5.2)$$

Here x_i is the an input nodes variable or output nodes variable, x_i, is the normalised value of the variable of the data, $x_{i,min}$ and, $x_{i,max}$ are variable minimum and maximum values respectively, and $R_{i,max}$ is the maximum range among the average value and either the minimum or the maximum value.

The frequency of the normalised input data is viewed in Figures (4.7) to (4.13)

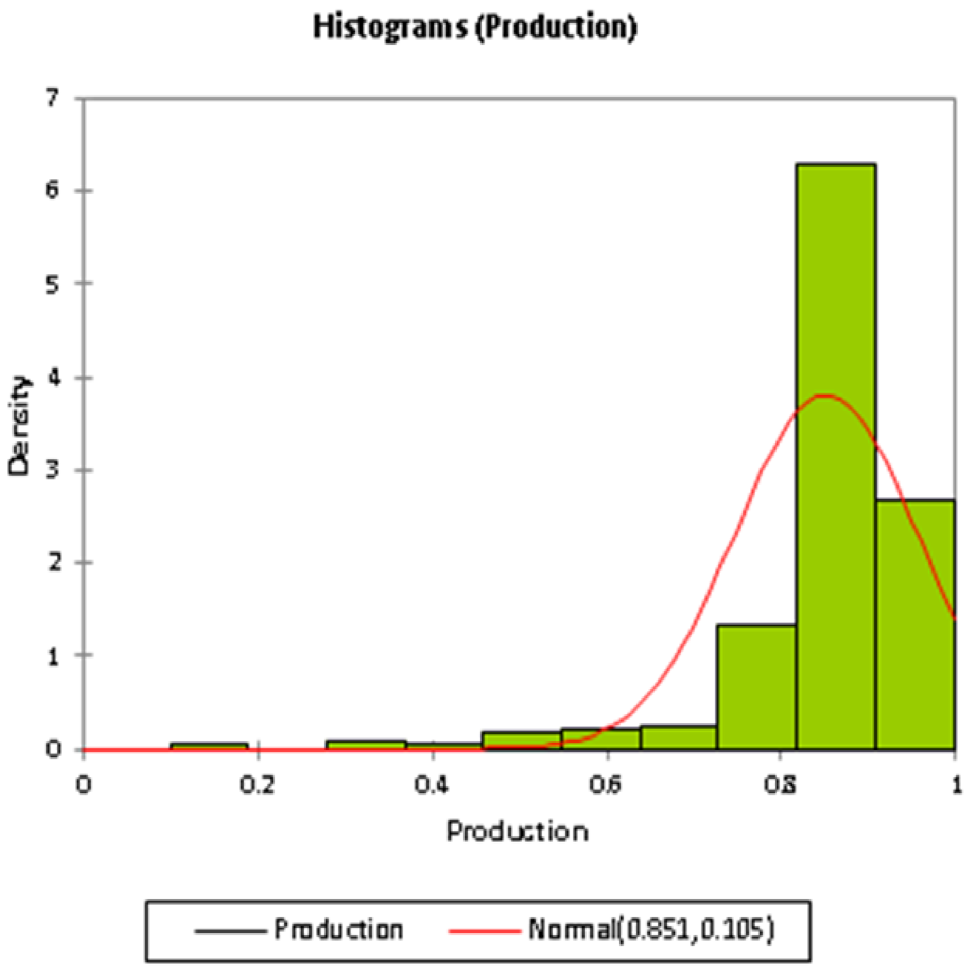

Figure 4.7. Salt in with outliers present.

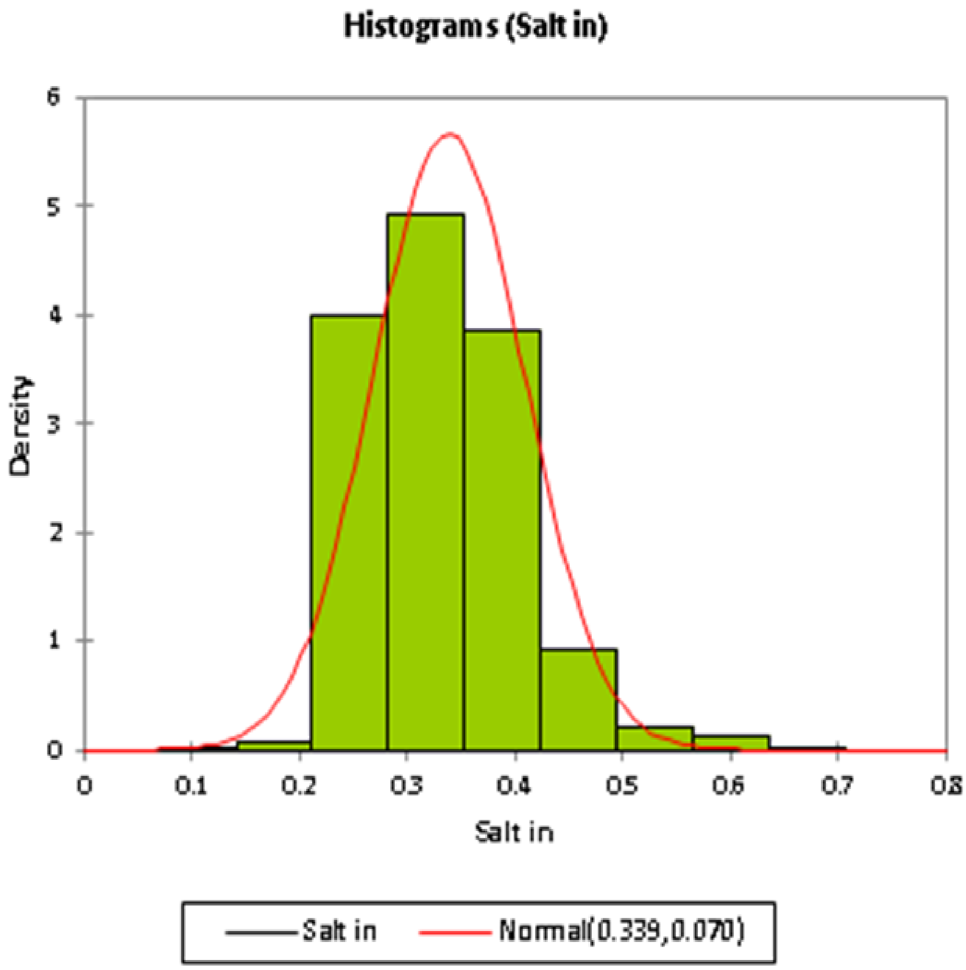

Figure 4.8. Salt in with outliers present.

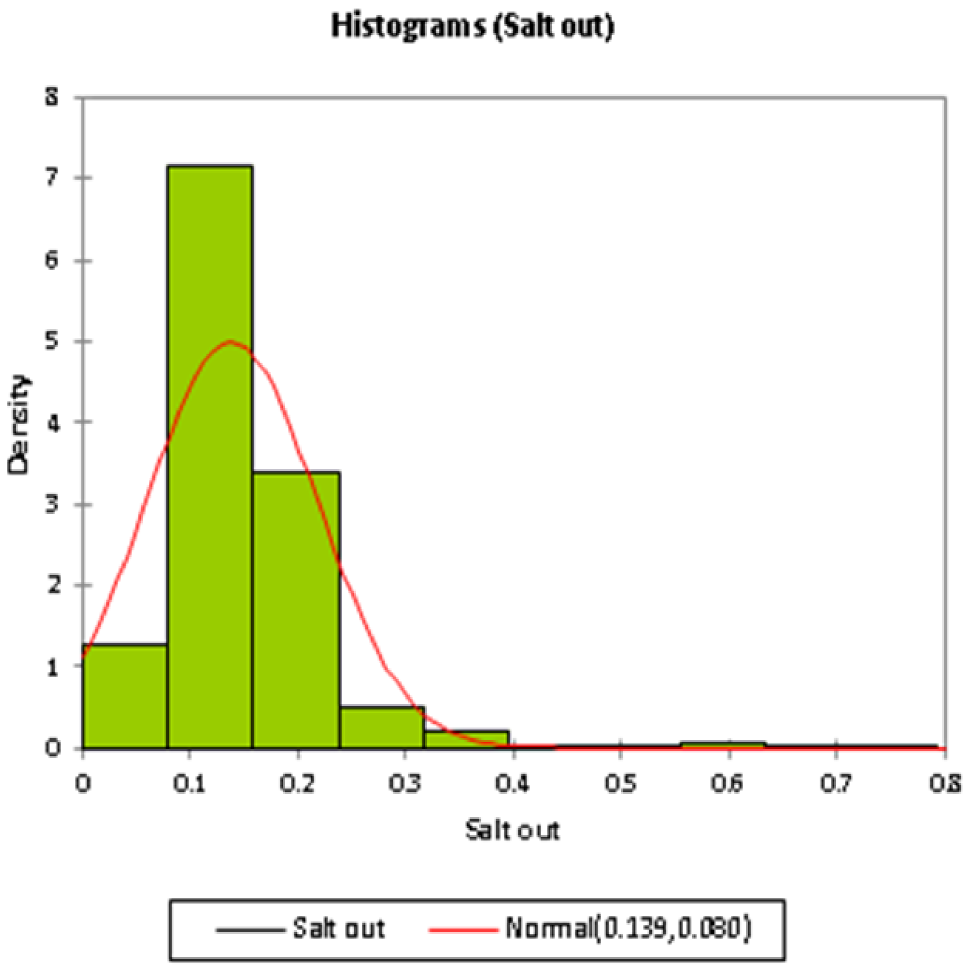

Figure 4.9. Salt out with outliers present.

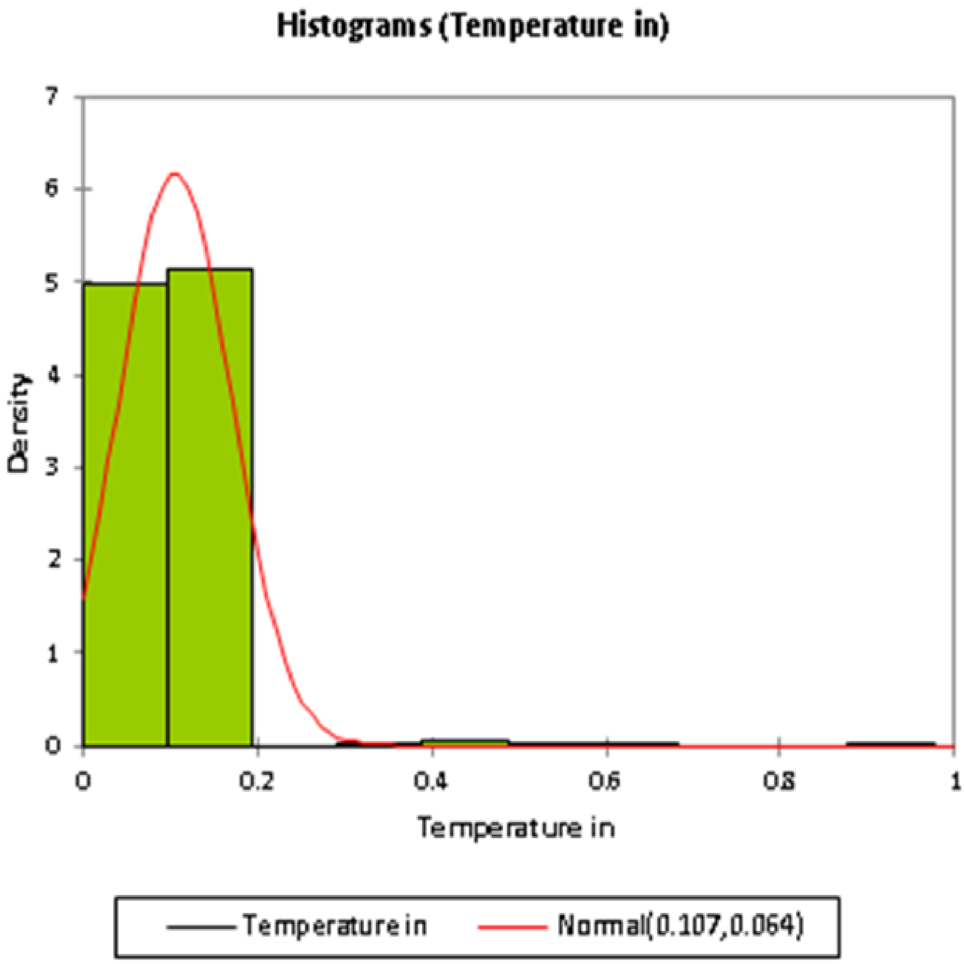

Figure 4.10. Temperature in with outliers present.

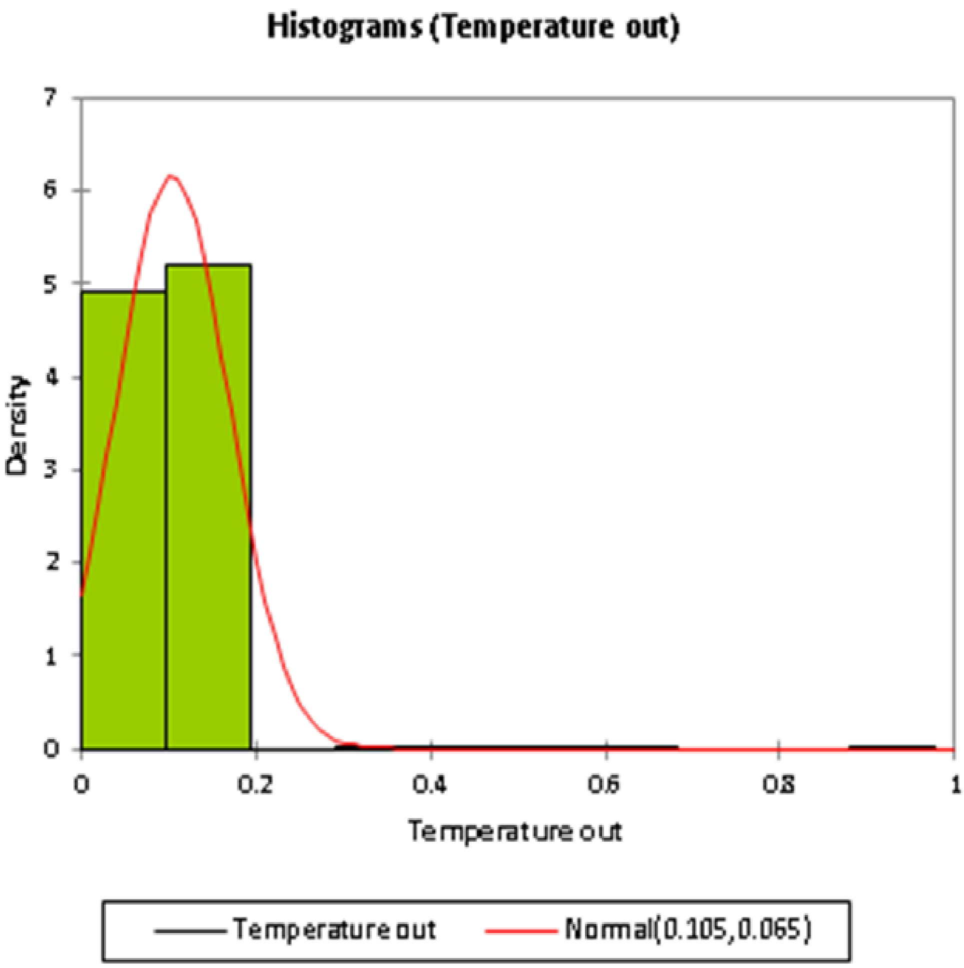

Figure 4.11. Temperature out with outliers present.

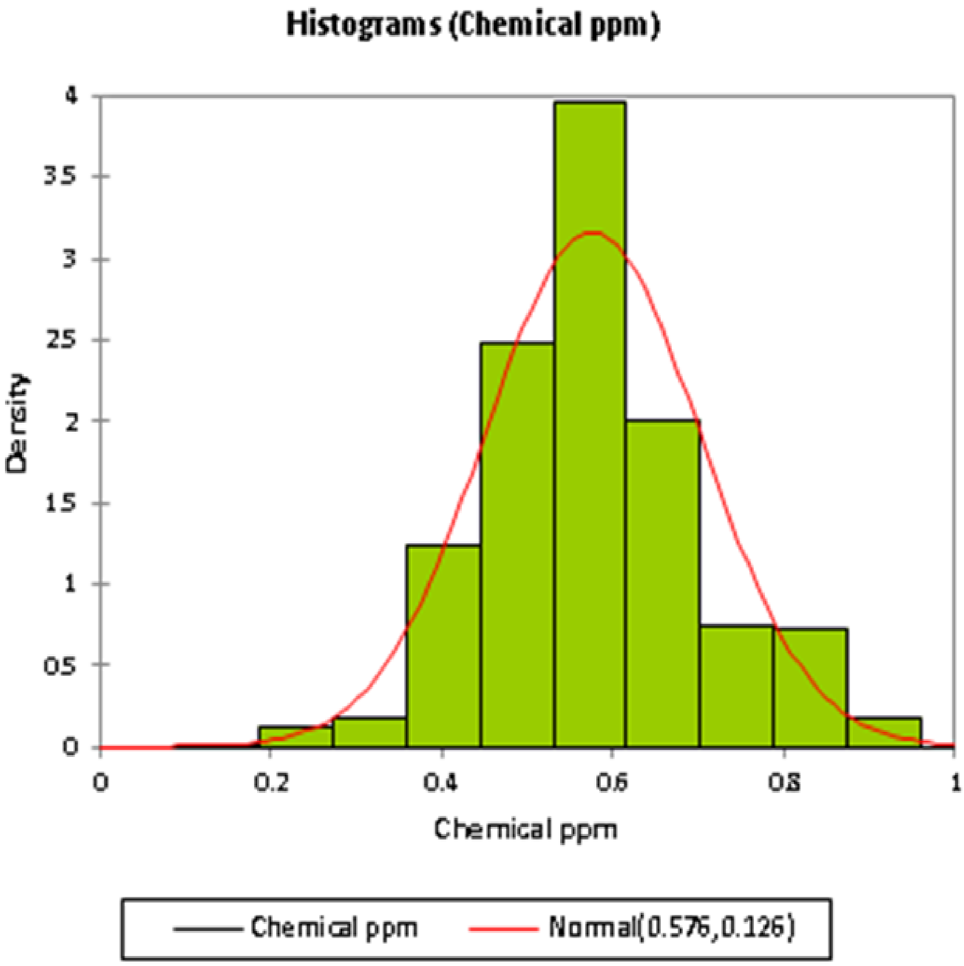

Figure 4.12. Chemical addition with outliers present.

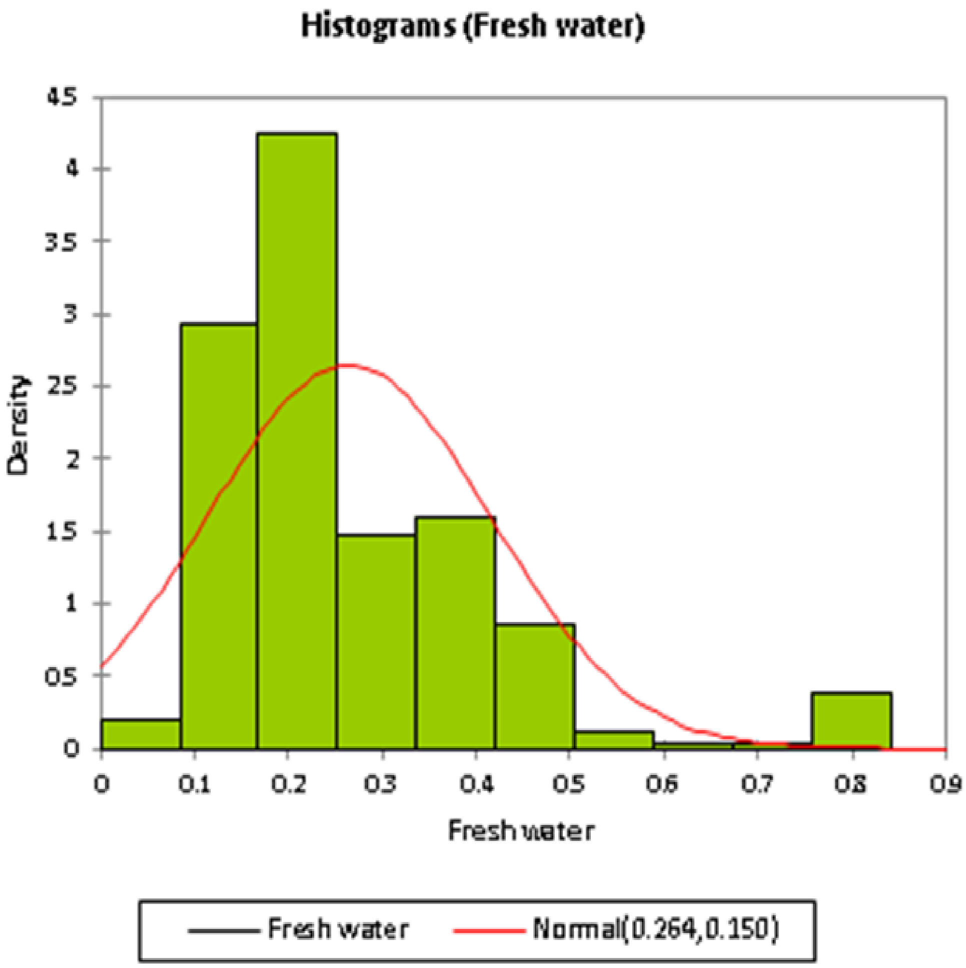

Figure 4.13. Fresh water with outliers present.

4.6 Closure

The dehydration and desalting process have been briefly explores and those pertaining to the Arabian gulf oil company have been explained along with how the experimental data was obtained and how it was analysed in order to get basic inputs for artificial neural network design.

The proceeding chapter will show the application of the neural network procedure the results obtained discussed in the context of the aims that pertain to this work of research.

Chapter 5

MODELLING OF LIBYAN CRUDE OIL DESALTER USING AN ARTIFICIAL NEURAL NETWORK

This chapter focuses on how Artificial Neural Networks (ANN) is applied for the prediction of salt removal efficiency from a crude oil desalter from the Arabian Gulf oil company. Basic desalting principles are described, then the networks ability to predict the output is describe along with statistical techniques used to identify the major input variables. A comparison is then made between the network model and statistical model.

5.1 Desalting

The application of artificial neural network architecture in the desalting process cannot be over-emphasised. They have proved useful especially in the design of the desalter itself, operation, control and optimisation of the system thus leading to improved design, higher efficiency, better safety and overall optimization of profit margin by the organization [1].

It is thus for these reasons that Neural Network is considered in this research.

A neural network model for the prediction of salt removal efficiency is developed. In addition, extensive data preparation and analysis was performed with the aim of maximising the salt prediction performance. Furthermore, statistical analysis was done in order to identify any underlying problems that arose.

A step by step flow chart in the development of the ANN is shown in Figure (5.1). The back propagation algorithm was used for prediction salt removal efficiency.

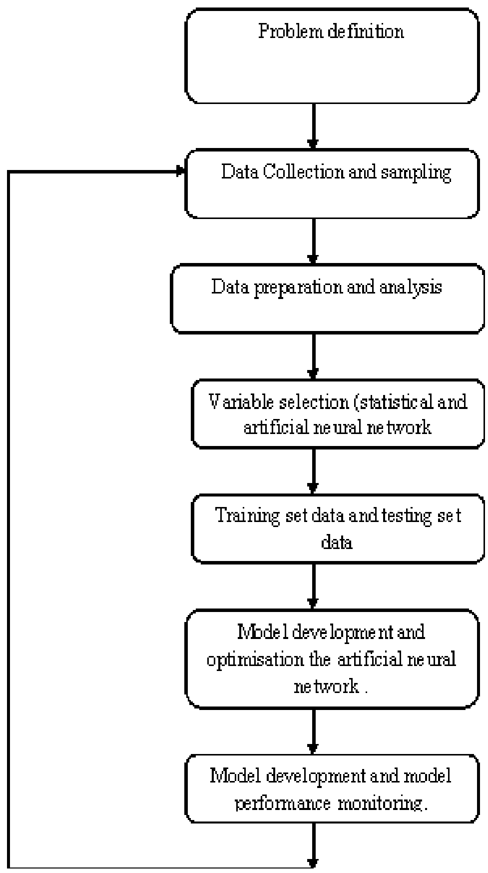

Figure 5.1. Methodology of neural network development [8].

One of the importance of this research is that it has used real data from a crude oil desalting plant as against many other researches which used simulated data. As will be shown later on in this chapter, real operating data have been shown to be complex in nature often resulting in nonlinear behaviour of the input and output variables with several degrees of freedom.
It is hoped that the robustness of Artificial Neural Networks (ANN) in the forecast of a Libyan crude oil can be obtained. Due to the significant amount of input data available, and presence of noise, statistical techniques such as outlier removal as well as feature selection using principal component analysis will be used. By performing these data filtering process, it is expected that an agreeable model prediction will be obtained. Once the network has been developed and implemented, the output of the neural network will be compared with the statistical output to show the strengths and limitations of using ANN in the prediction of desalter salt removal efficiency.
The statistical analysis carried out in the course of this research was done so by utilising Minitab and XLSTAT software. After data pre-processing, the next step was using ANN. Matlab software was utilised, the inbuilt ANN tool box was found to be inefficient hence a code was written manually in order to aid in flexibility.

5.2 Preparation and analysis of input and output model data

The main objective of pre-processing the data is in order to be able to remove noise and also to obtain a training data set that is characteristic of the input and output data. If raw data without pre-processing is used, there are bound to be errors and the results obtained from the model will not represent of what one expects. Therefore it follows that the next logical step in preparation of the input data was to clean the data. One reason for this is that huge data sets have imperfections as a result of values missing, un-

measured noise, outliers and false measurements. The incomplete data may be due to poor data recording, time sensitive data and human error. The noise in data arises in the process of data collection, entry and transmission. Outliers are observations that do not follow the same pattern as most data points and as a result are dissimilar to the rest of the data. They arise most of the time due to incorrect measurement and are difficult to spot unless a statistical analysis is done. If one ignores these imperfections whilst using ANN models then the result obtained from the model will be incorrect. A reason for this is that during the training step which is the most significant part of neural network modelling, accuracy of predictions are reduced due to their being a large difference between calculated and actual variables thus network performance is hindered. The removal of these imperfections not only improves the performance of the network but more reliable results arise. A Visual Basic programme was written to identify and deal with the outliers present in the plant data that was to be used in the ANN model. The outlier removal involved obtaining the upper (Q_1), middle (Q_2), lower (Q_3) and interquartile range. Once this was achieved then the upper and lower outlier boundaries were obtained. It was then determined that the data falling outside these boundaries were outliers and the rest was normal data to be used as input and output data. By plotting the occurrence of the data within a specific range per selected variable one was able to observe the data frequency histogram and therefore observe the outliers as well as their removal.
In Figures (5.2) to (5.18), the frequency distribution of the 7 input variables after outliers had been identified and removed. As can be seen, this expectedly follows a normal distribution implying removal of outliers.

Once the outliers have been removed, the next stage involved analysing the new data by plotting graphs and obtaining best fit equations. As expected, the complexity of the data ensures that the best fit data equations

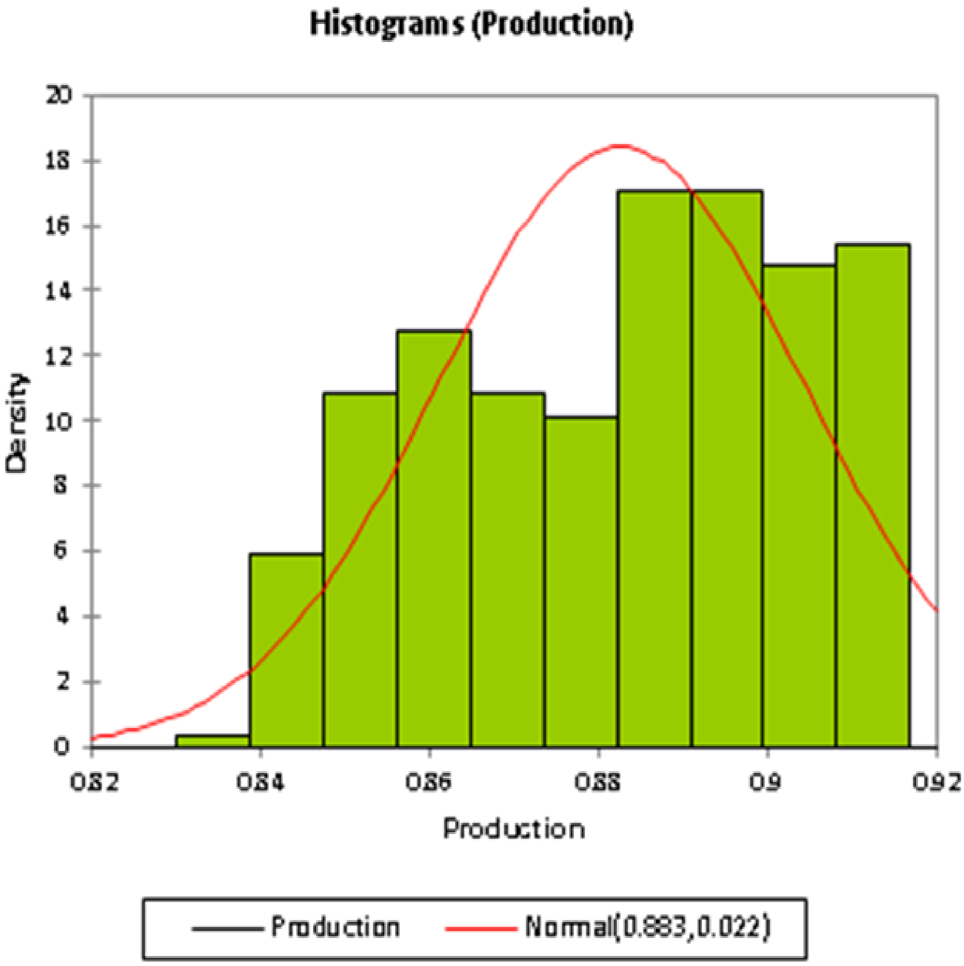

Figure 5.2. Production without outliers present.

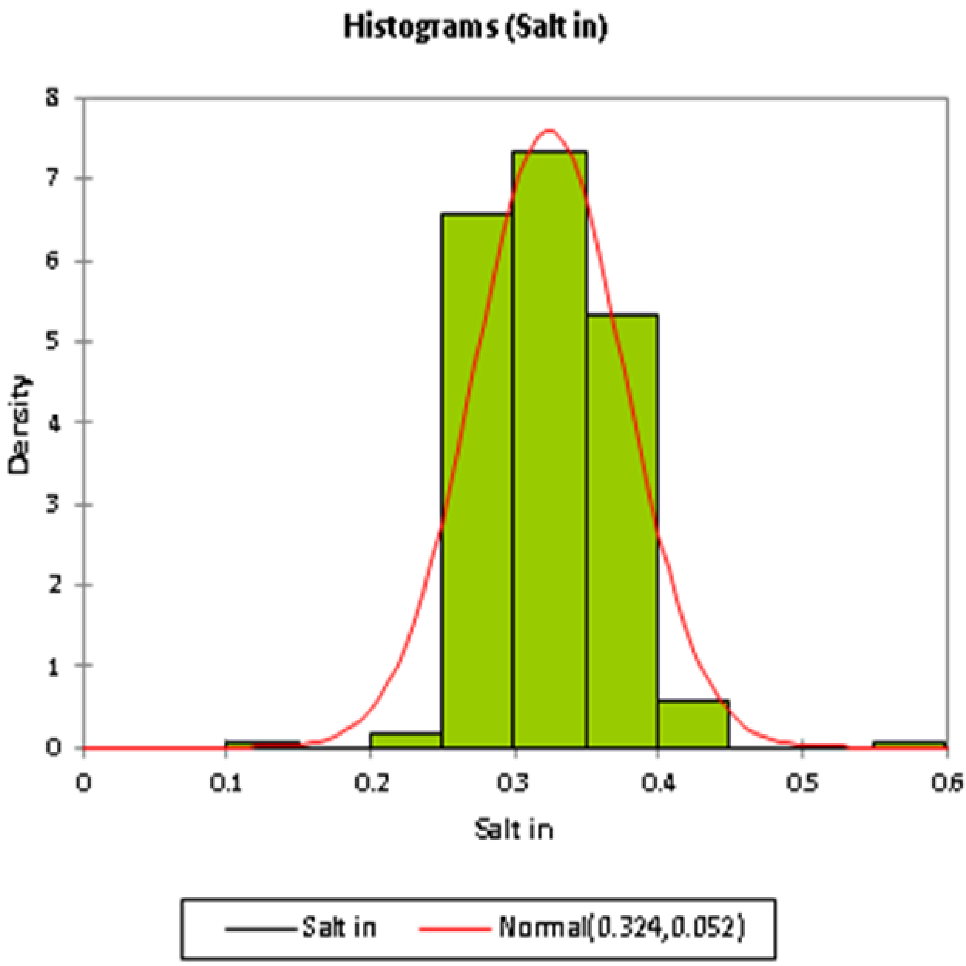

Figure 5.3. Salt in without outliers present.

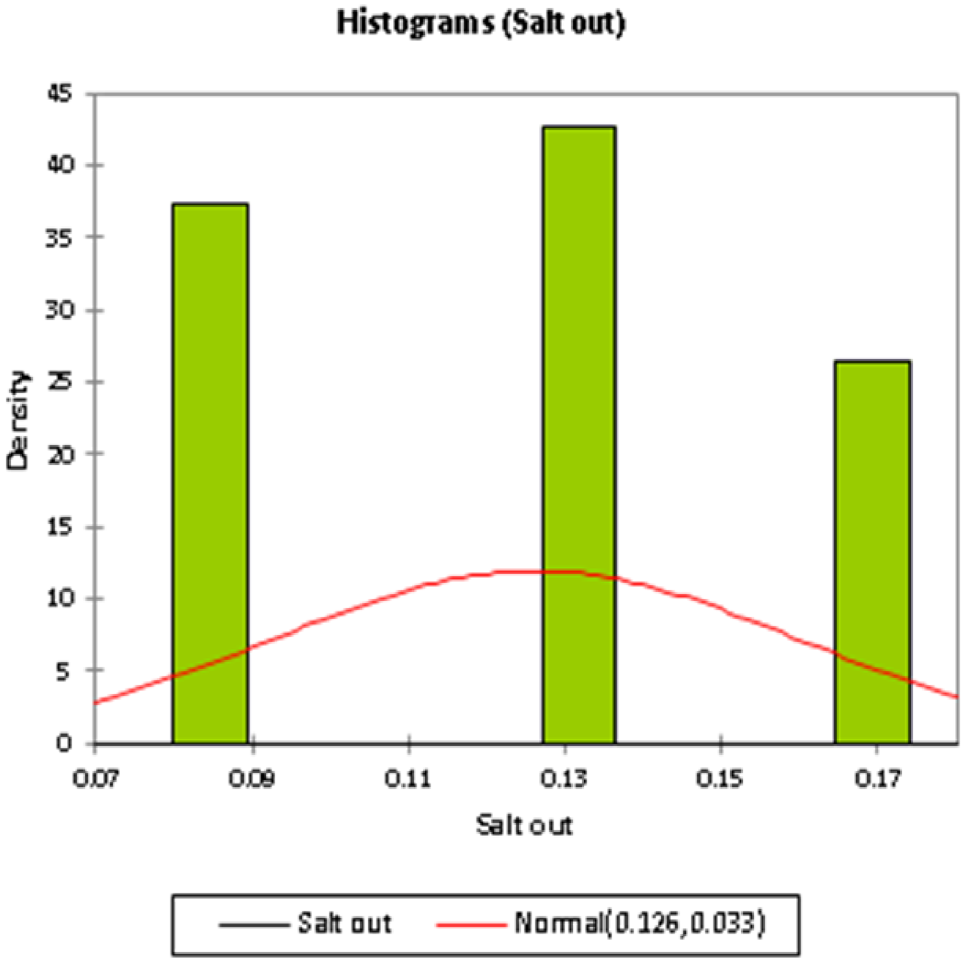

Figure 5.4. Salt out without outliers present.

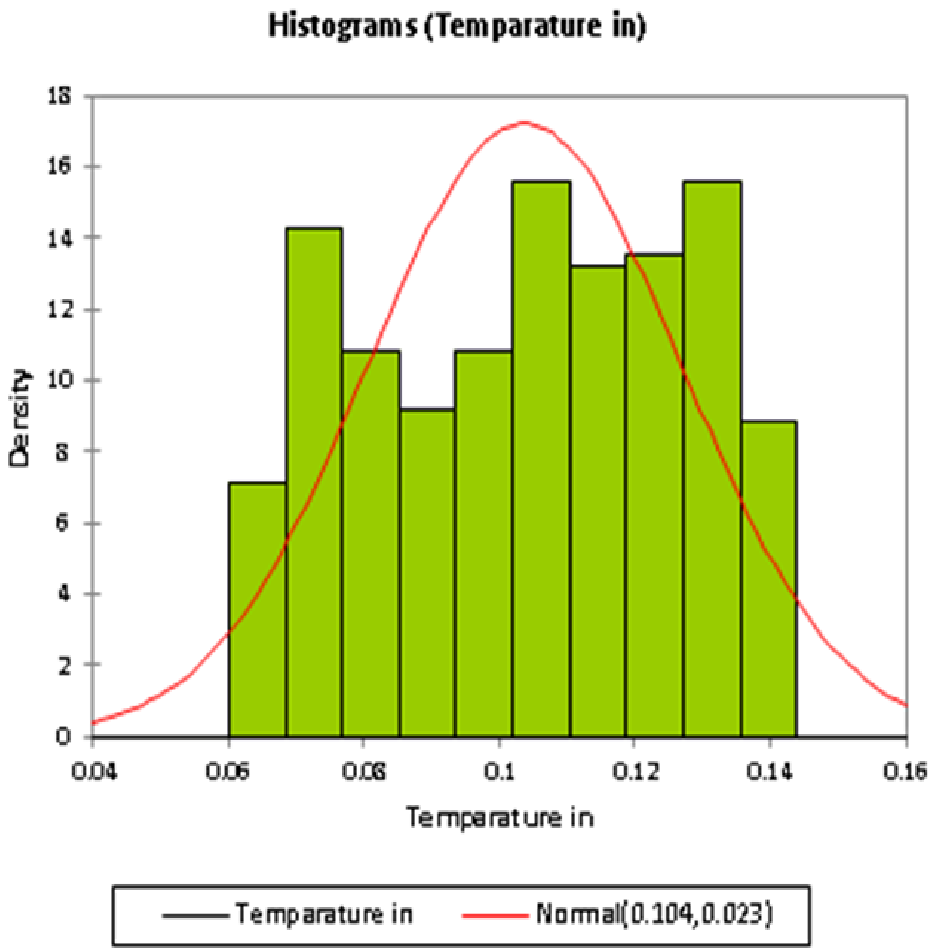

Figure 5.5. Temperature in without outliers present.

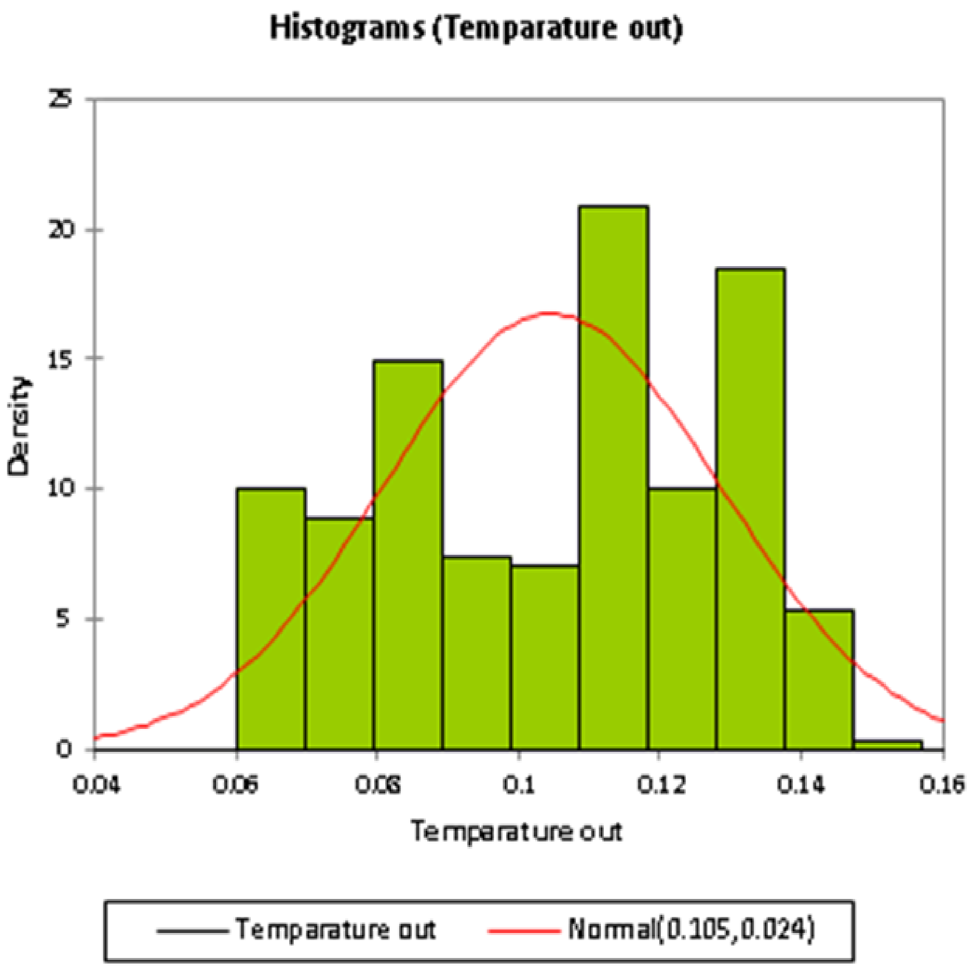

Figure 5.6. Temperature out without outliers present.

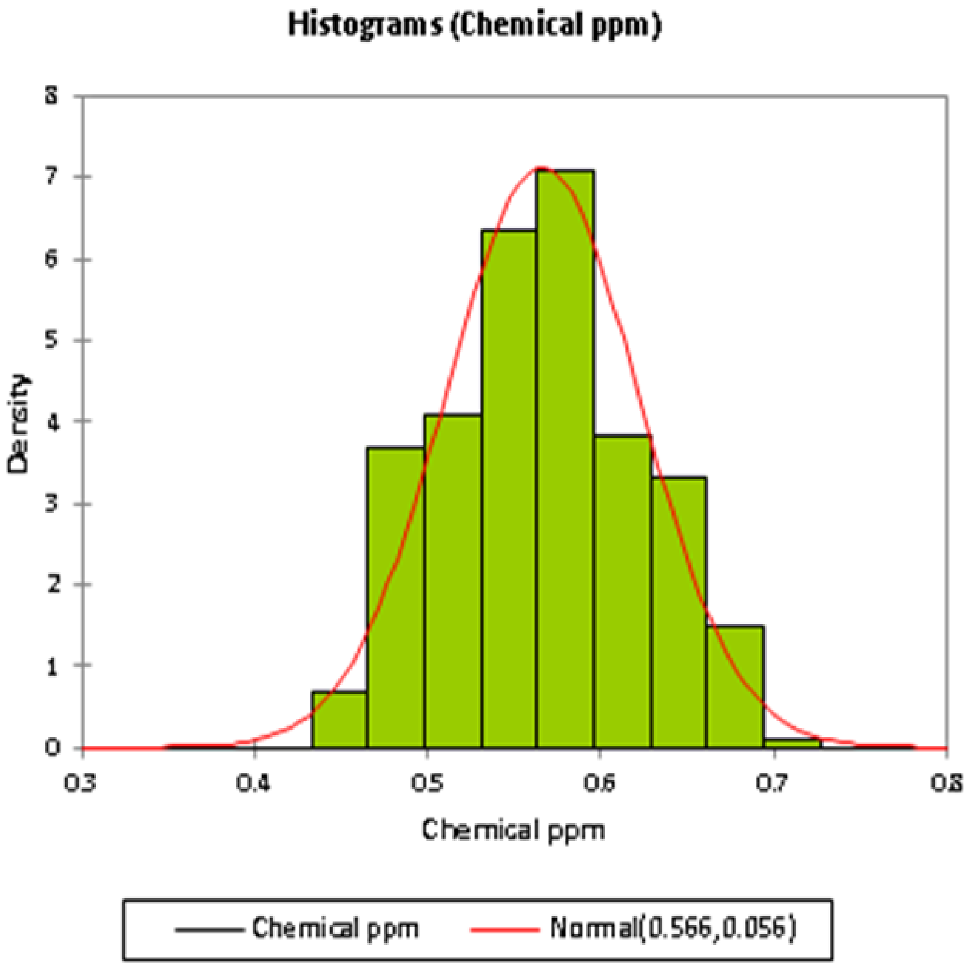

Figure 5.7. Chemical addition without outliers present.

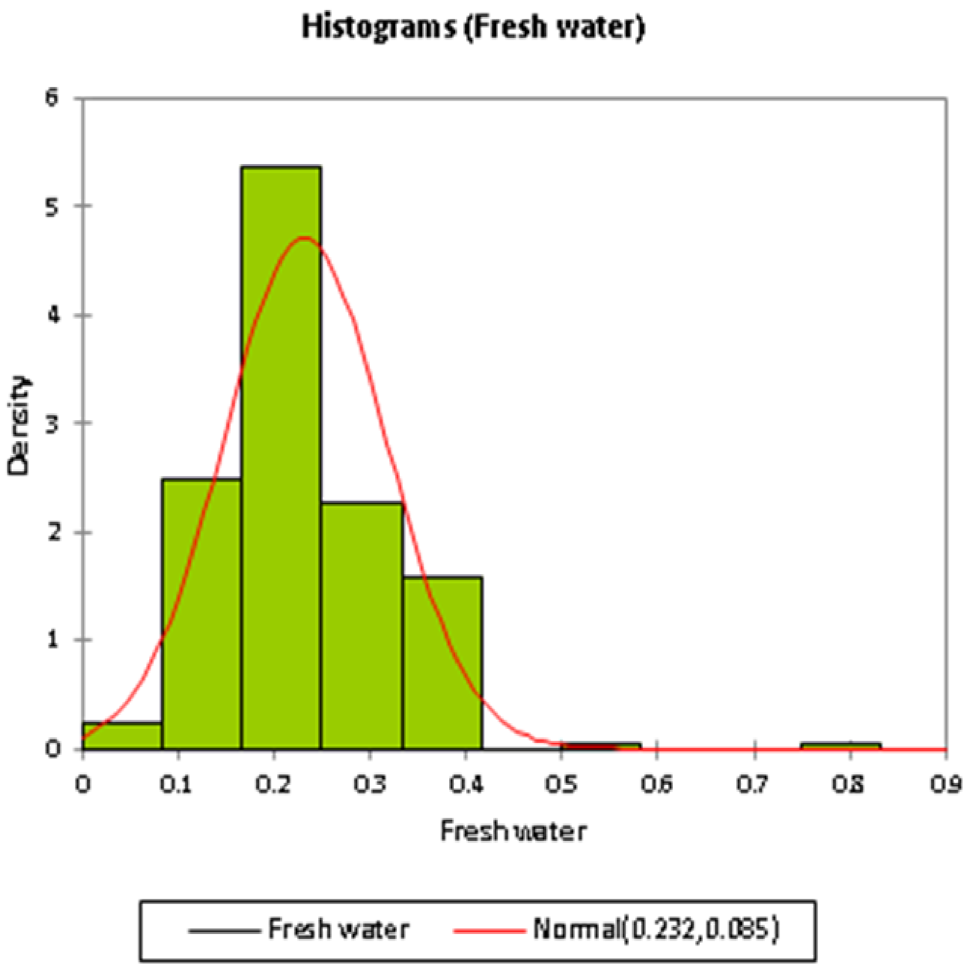

Figure 5.8. Fresh water without outliers present.

are non-linear functions. Although the coefficient of regression,correlation coefficient R^2, which measures how a line fits, good or undetermined to data, is usually a good means of identifying a good model, other factors such as insignificant variables in the model could also contribute to obtaining a good R^2. The various variables and the non-linearity of their fits are shown in Figures (5.9) to (5.15).

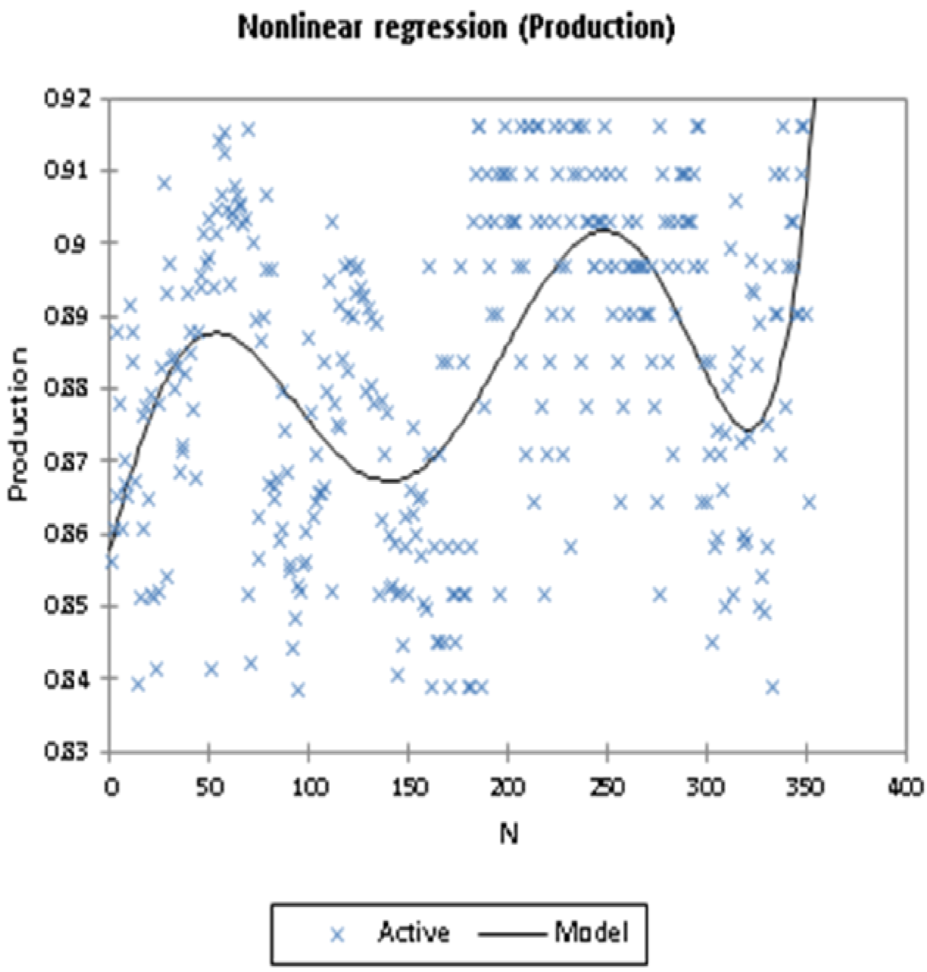

Figure 5.9. Nonlinear regression plot of production after outlier removal.

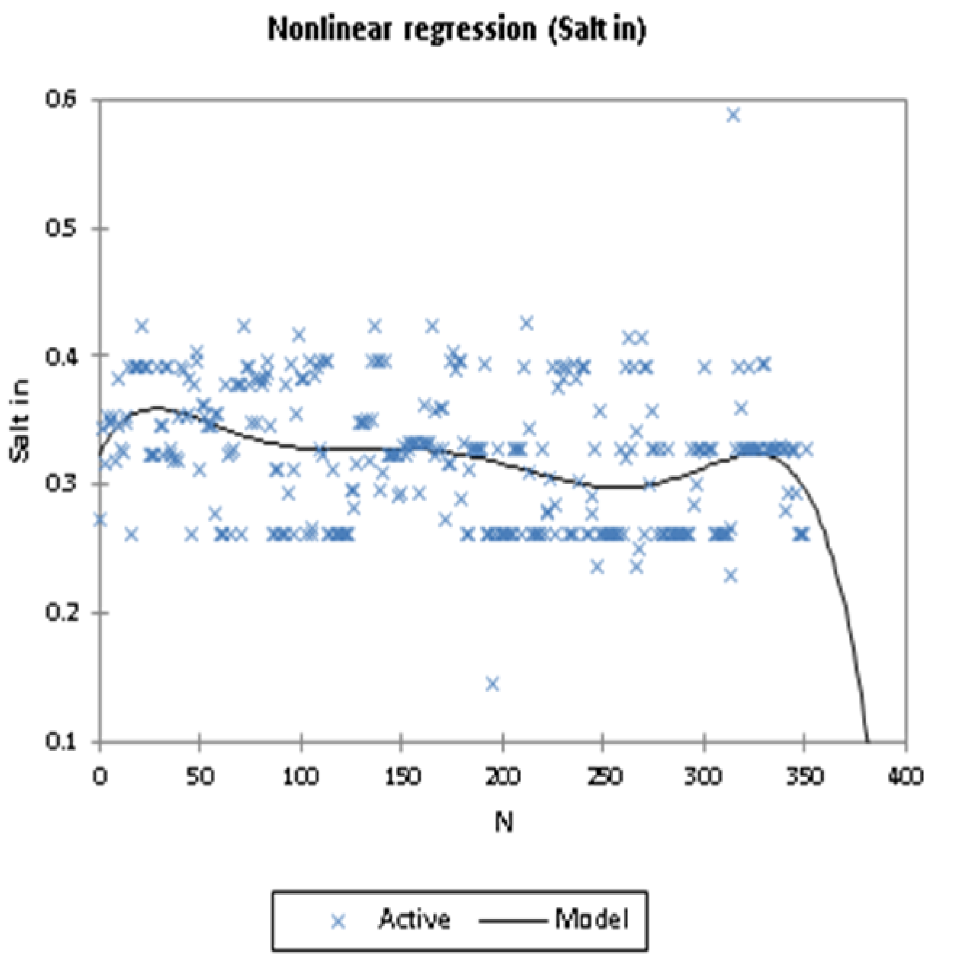

Figure 5.10. Nonlinear regression plot of salt in after outlier removal.

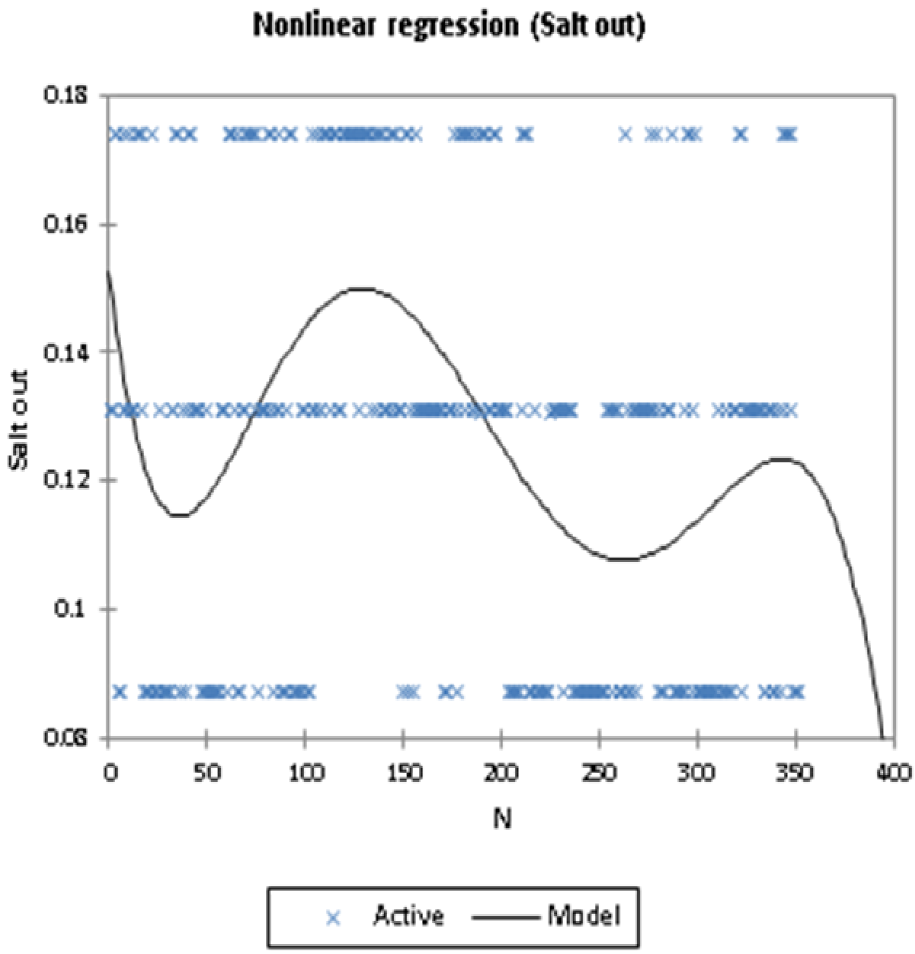

Figure 5.11. Nonlinear regression plot of salt out after outlier removal.

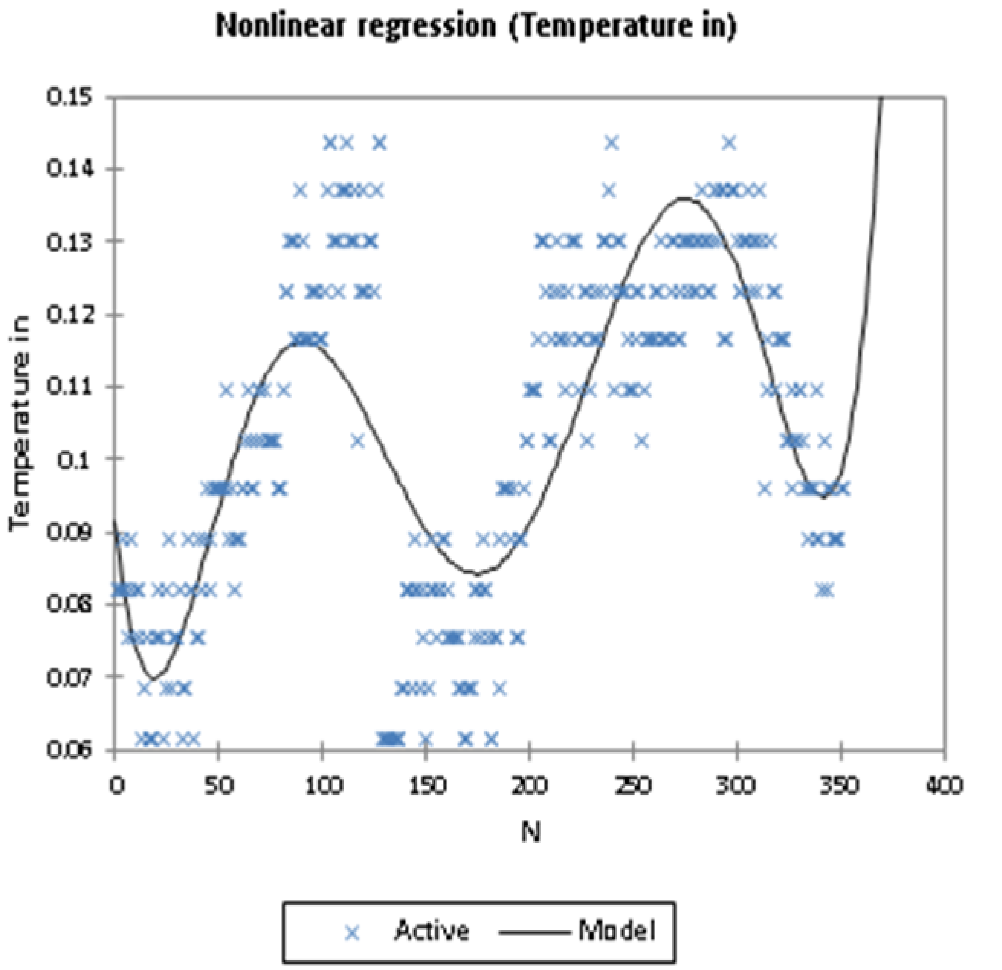

Figure 5.12. Nonlinear regression plot of Temperature in after outlier removal.

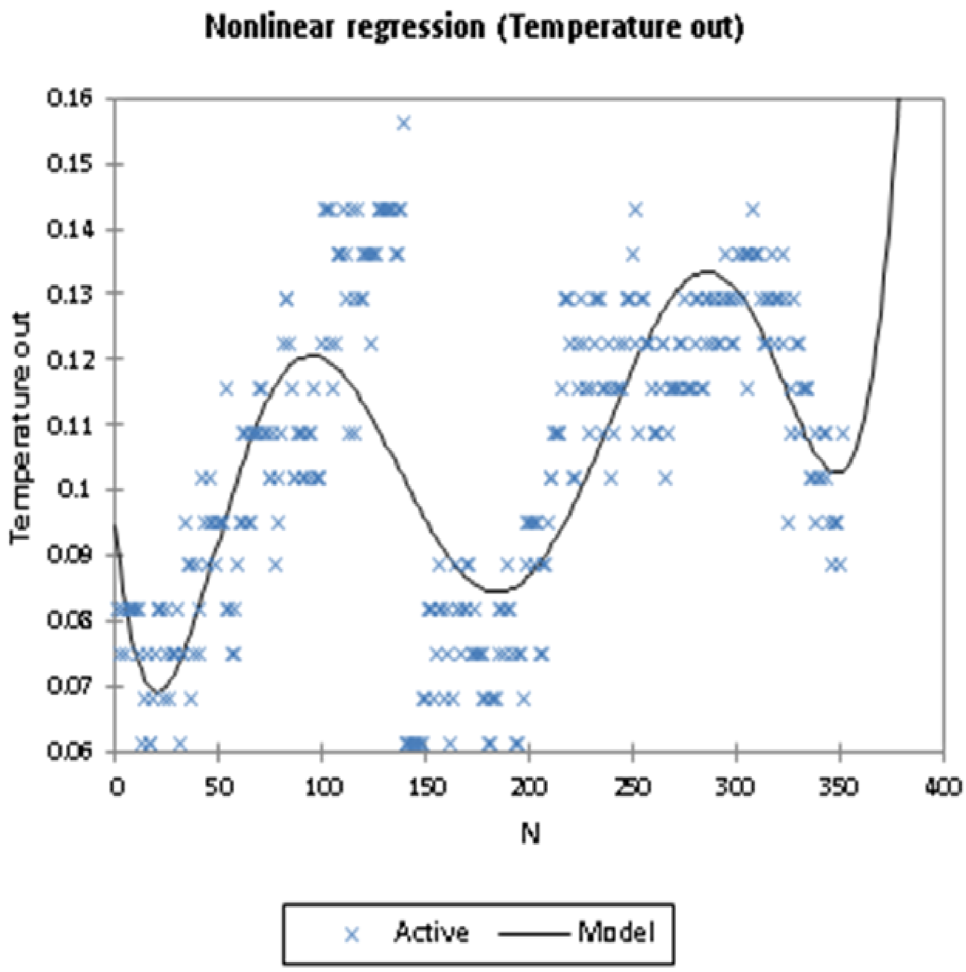

Figure 5.13. Nonlinear regression plot of Temperature out after outlier removal.

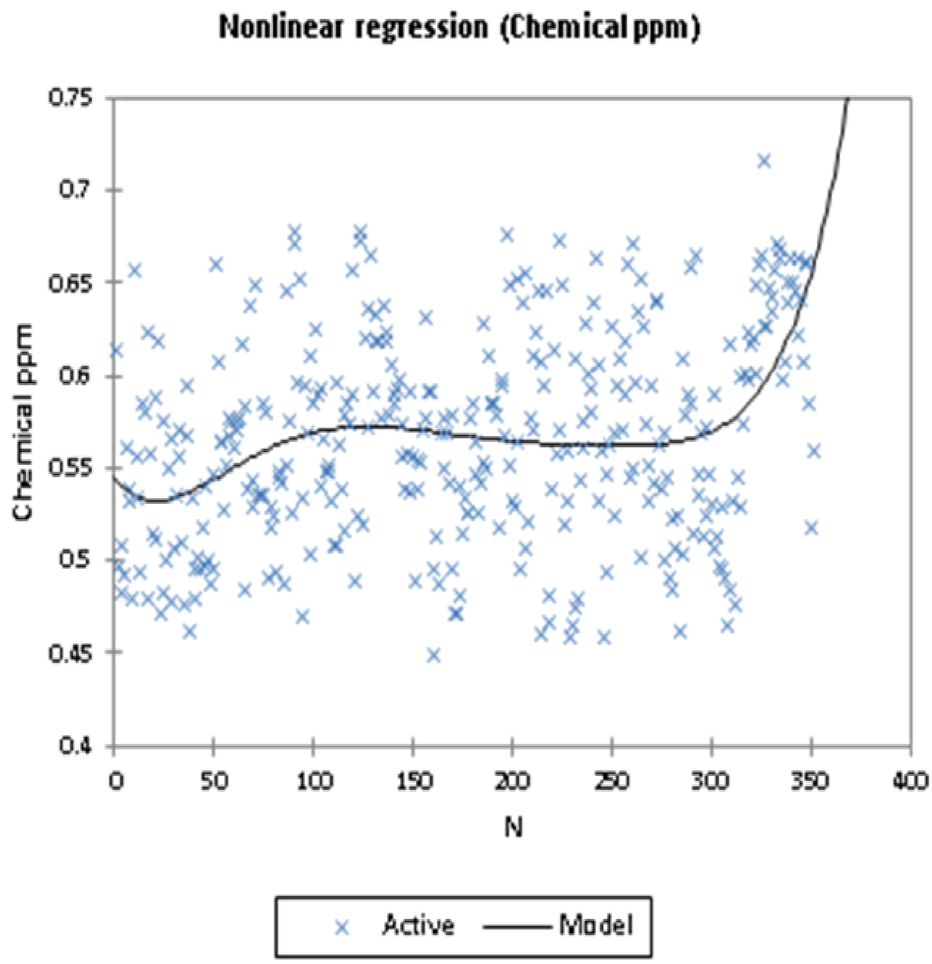

Figure 5.14. Nonlinear regression plot of demulsifier addition after outlier removal.

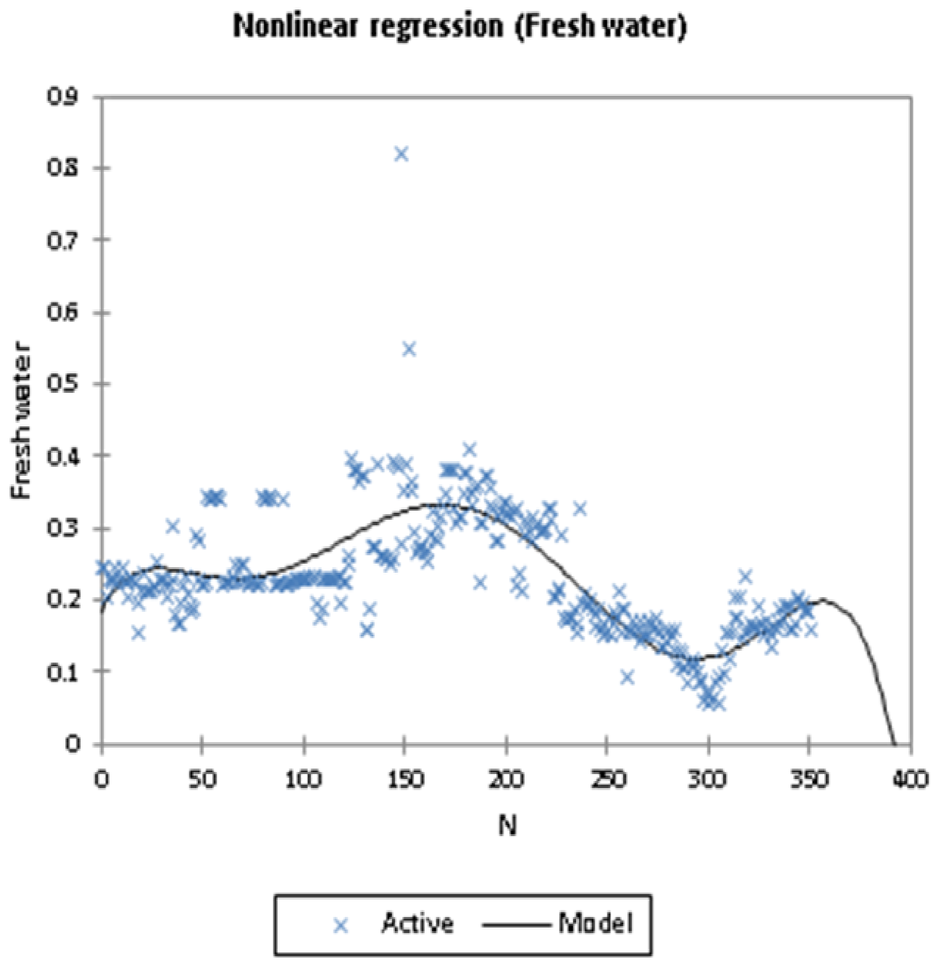

Figure 5.15. Nonlinear regression plot of Fresh water addition after outlier removal.

Determination of The best-fit equations and R^2 values of the variables are shown in Table (5.1).

Table 5.1. Best fit equations and correlation coefficient R^2 values after outlier removal

Variable	Equation of the Line of Best Fit	R^2
Production	y=6.36E-15X^6-5.45E-12X^5+1.53E-9X^4-1.27E-7X^3-7.03E-6X^2+1.11E-3X+0.85	0.8296
Salt in	y= -1.23E-14X^6+1.30E-11X^5-5.17E-9X^4+9.74E-7$X^3$8.74E-5X^2+3.05E-3X+0.32	0.107
Salt out	y= 1.25E-15X^6-2.40E-12X^5+1.55E-9X^4-4.44E-7X^3+5.60E-5X^2-2.57E-3X+0.15	0.171
Temperature in	y= 1.62E-14X^6-1.75E-11X^5+7.04E-09X^4-1.29E-6X^3+1.03E-4X^2-2.69E-3X+9.16	0.602
Temperature out	y= 1.42E-14X^6-1.59E-11X^5+6.64E-9X^4-1.27E-6X^3+1.07E-4X^2-2.95E-3X+9.46	0.561
Chemical addition	y= 5.94E-15X^6-6.27E-12X^5+2.60E-9X^4-5.20E-7X^3+4.83E-5X^2 - 1.42E - 3X + 0.55	0.137
Freshwater addition	y= -2.69E-14X^6+2.95E-11X^5-1.19E-8X^4+2.13E-6X^3-1.68E-4X^2+5.40E-3X+ 0.18	0.601

5.3 Selection of best input variables

The nature of input data fed into the ANN model is very important. Too many input variables will result in slow network performance as well as poor predictions made by the model. It is imperative to get the right input variables in order to get the best possible predictions. This is achieved by using factor analysis.

5.3.1 Factor analysis

Where there are a lot of variables (features) available, there are many techniques for feature selection or variable reduction. These techniques are as discussed in [4]. One of such techniques is Factor Analysis.

Factor analysis is used to analyse multivariate data. It minimises the number of minimal unobservable variables by trying to account for covariation among random observable variables in the data represented as X. The unobserved variables are anticipated to be linear combinations of the variables which make up the set X. The objective becomes the reduction of the complexity of the set X into as limited linear combinations of those variables within X as possible. In order to decrease the set X, the technique of Principal Component Analysis is used It limits the nature of complexity of X by doing a conical examination of the correlation matrix of X. The principal factors of X are taken to be the most domination eigenvectors of X. The elements encompassing the eigenvectors are then taken to be the weights which produce the linear blend of the set of variables within X. By denoting the first factor as F1, as seen in Equation 5.1, it is then said to be a linear combination of the variables in X. The weights in X are determined by the elements of the most domineering eigenvector in the correlation matrix of X [66]. Equation 5.1 shows the how one obtains the first factor, F1.

The elements comprising the eigenvectors are then taken to be the weights which produce the linear combination of the set of variables within X. By denoting the first factor as F_1, as seen in Equation 5.1, it is then said to be a linear combination of the variables in X. The weights in X are determined by the elements of the most domineering eigenvector in the correlation matrix of X [4]. Equation (5.3.1) shows the how one obtains the first factor, F_1.

$$F_1 = e_{11}x_1 + e_{21}x_2 + ... + e_{p1}x_p \tag{5.3.1}$$

Here $e_1 = e_{11}e_{21}.......e_{p1}$ are the dominant eigenvectors of the correlation matrix X. The elements of e_1 are known as the factor loadings for each of the p variables that comprise X. The factor loadings are always between -1.0

and 1.0. The variables whose factor loadings have an absolute value that is greater than 0.4 are then said to be related to the corresponding factor. Thus principal component analysis can be summarised in the following steps:

1. Variable selection
2. Computation of the correlations of the matrix
3. Extraction of unrotated factors
4. Factor rotation
5. Interpration of factor rotations

Factor analysis and principal component analysis was done on thirteen inputs from the raw data, XLSTAT software was used to carry out both factor and principal component analysis. From these analyses it was observed that six sets of input variable were determined not to be of importance and were discarded accordingly. The main input variables determined as well as their factor loadings are summarised in Table (5.2). Using the criterion deter-

Table 5.2. Factor loadings for the seven process operating variables

Variable	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Production	0.682	-0.289	-0.278	-0.001	0.323	0.008	-0.768
Salt in	0.379	0.281	0.297	0.297	-0.795	-0.795	0.681
Salt out	0.368	-0.330	0.798	0.326	-0.108	0.024	-0.028
Temperature in	0.381	-0.281	-0.323	-0.069	-0.602	-0.530	0.653
Temperature out	0.383	-0.206	-0.238	-0.136	-0.136	0.790	0.305
Chemical dosage	0.384	0.061	-0.187	0.752	0.620	-0.249	0.493
Freshwater addition	0.370	0.370	0.777	-0.037	0.338	-0.293	0.104

mined before whereby the variables with factor loadings greater than 0.4 are chosen as representative for that factor it can be seen that for example PC2 has a high loading value for the variable fresh water in and much lower values for all the rest. PC3 has a high loading factor for salt out and much lower values for the rest of the variables. Thus with this the input variables that were significant were chosen by matching an input variable to the highest loading value and as previously stated data with factor loadings less than 0.4 was deemed non useable.

5.3.2 Input data selection with the use of statistics

It is possible to feed all the selected input variables into the model in order to obtain model predictions. However this is quite a wrong approach especially in artificial neural networks because too many variable lead to poor predictions and computing time as the calculation sequence will take long.
The input data was analysed statistically and most of them were found to be non-linear. With this in mind polynomial curve fitting was done and the equations and R2 values are seen in Table (5.1). It can be seen that the R^2 values were similar in nature thus it proved difficult to determine the main input variables. It can be said that this would certainly be a guess work and trial and error type of approach if one used this technique. If one was to adapt this approach then a lot of time and effort would be needed to determine the right inputs. If one was to utilise this method then one needs to have plant know how. One needs to be made aware from an engineering point of view the design equations as well as the physical equations describing the process so that an estimate of the input variables can be made.
A summary of the known input variables from the plant as well as those from principal component analysis are shown in Table (5.3). One can see that there were twelve inputs if one was to use the statistical method whereas using principal component analysis reduced this to the seven which were deemed the most important variables pertaining to desalter performance.

Table 5.3. Input variables using statistical and principal component analysis methods

Statistical input data selection	Principal component analysis input data selection
Production	Production
Salt in	Salt in
Salt out	Salt out
Temperature in	Temperature in
Temperature out	Temperature out
Chemical dosage	Chemical addition
Freshwater addition	Fresh water addition
Fresh water flowrate	
Crude oil flowrate	
Condensate flowrate	
pH adjustment injection rate	
Steam flowrate	

An ANN prediction using statistical input data selection method with thirteen inputs was used to with the model to predict salt removal efficiency of the desalter. The resulting predictions can are seen in Figures (5.16) to (5.18). compared the neural network performance of salt removal forecast as an output based on principle component analysis and statistical analysis variable selection. It was evident that the network with variables selected based on more variables, statistical analysis, provided a lesser amount of reliable results than those based on factor study.

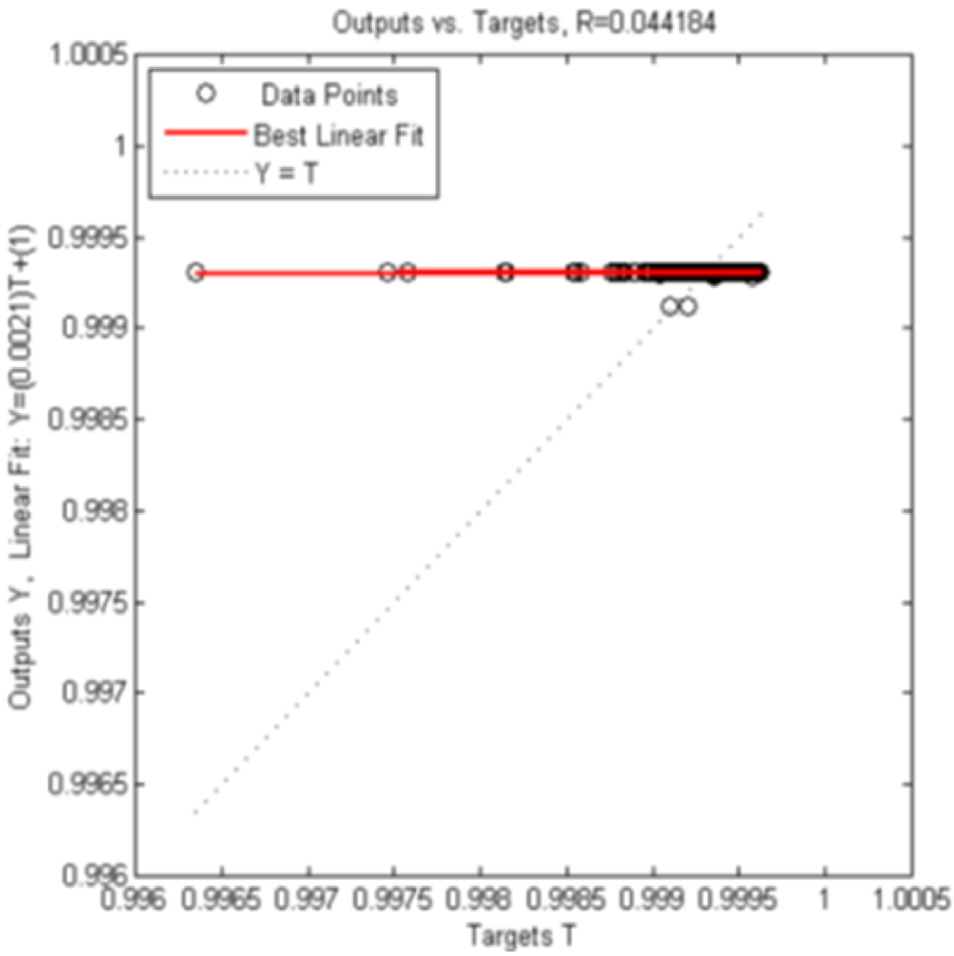

Figure 5.16. Actual and predicted output variables for salt removal by statistical based method.

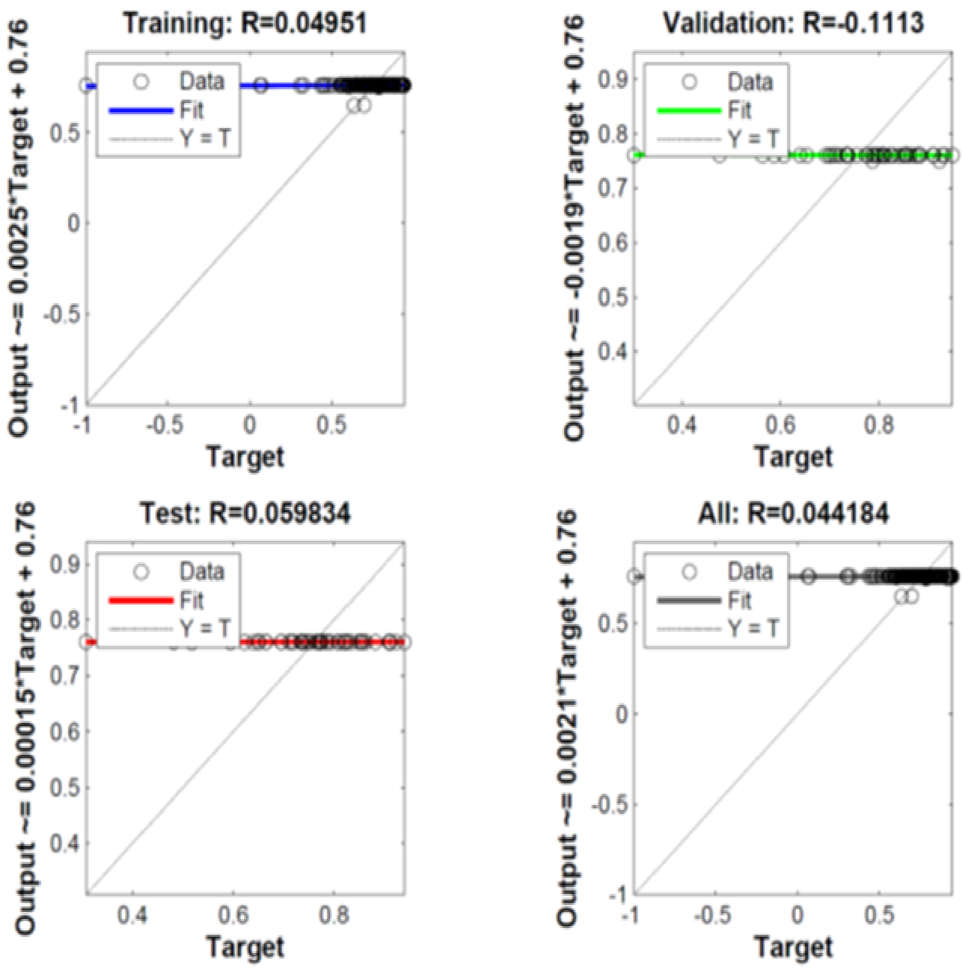

Figure 5.17. R^2 values for training, testing and validation using statistical input variables.

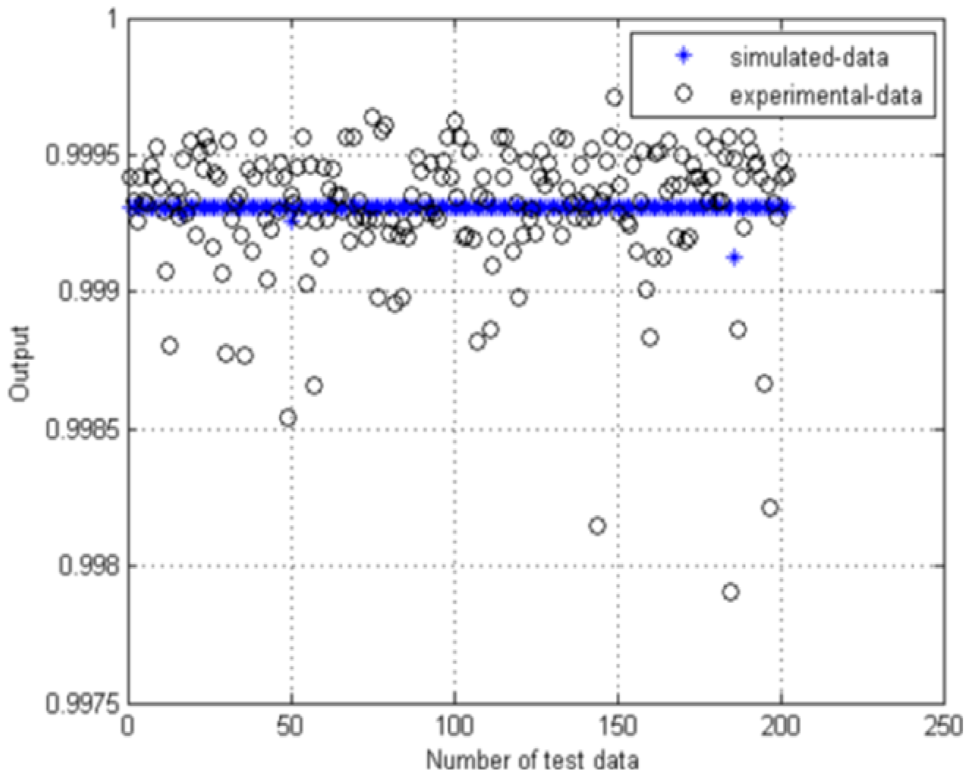

Figure 5.18. Network prediction compared to experimental data using statistical input variables.

The neural network architecture was adjusted by adding more neurons to the hidden layer, increasing the number of hidden layer to two and subsequently varying the nodes in each layer. With these changes one would expect the value of R^2 to be better but ultimately gave poor predictions. To highlight the significance of having the right input data, the same network architecture was used to test input variables obtained from principal component analysis. Figures (5.19) to (5.21) show the results obtained using principal component analysis. One can see that a far better R^2 value is obtained and the predictions obtained give good representation of the plant data. One would argue that this was random, however each simulation was ran ten times in order to validate the results obtained.

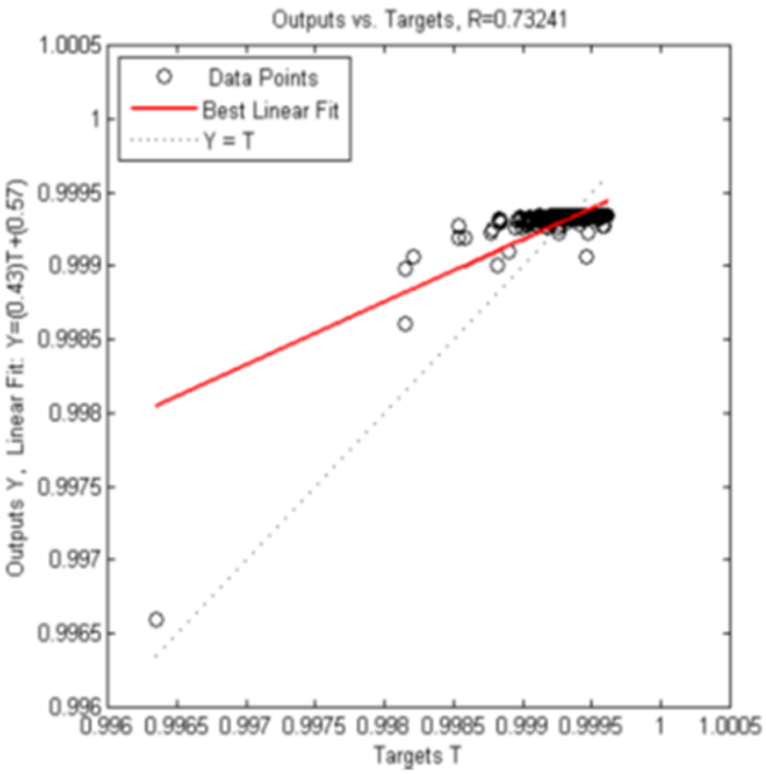

Figure 5.19. Actual and predicted output variables for salt removal using principal component analysis input variables.

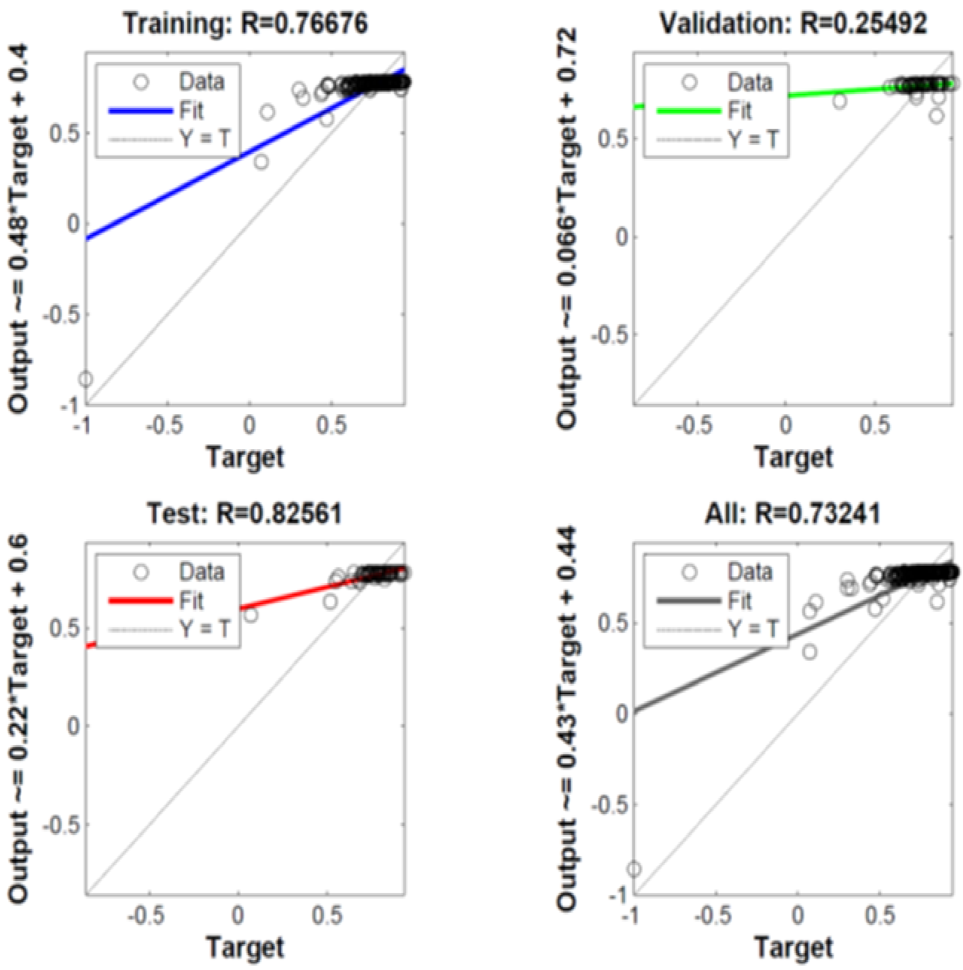

Figure 5.20. R^2 values for training, testing and validation using principal component analysis input variables.

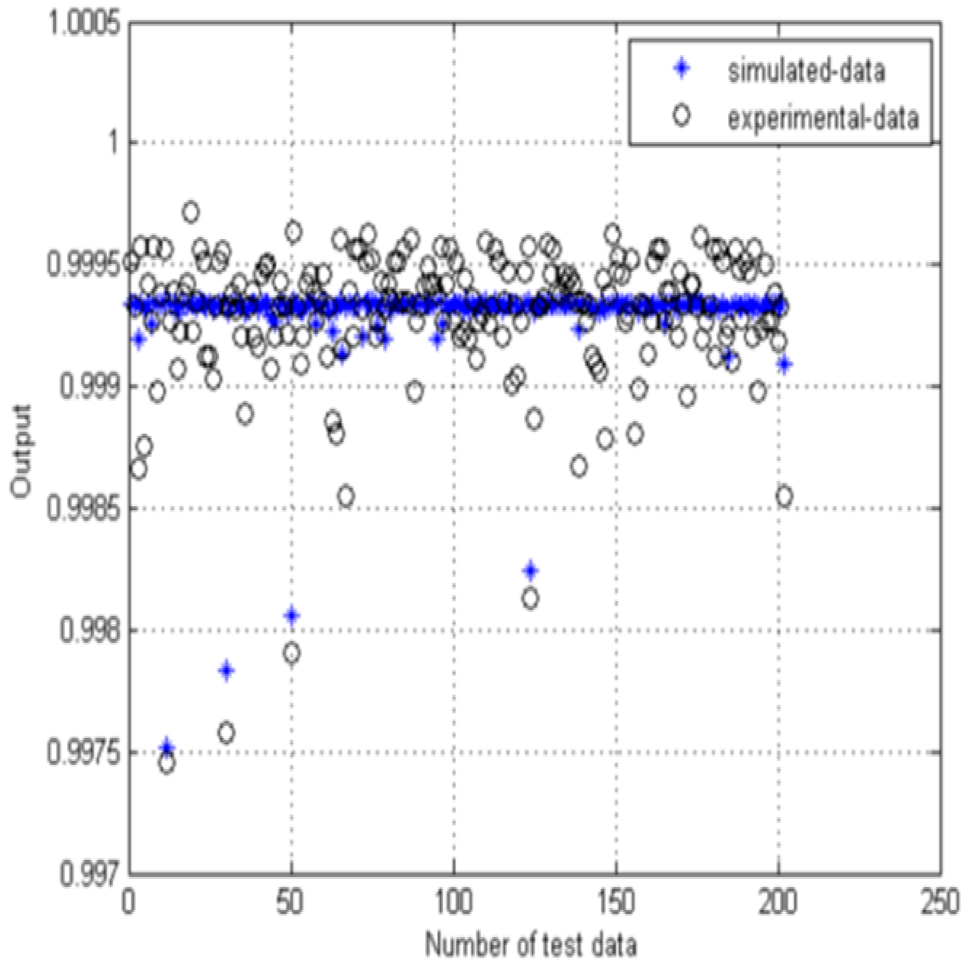

Figure 5.21. Network prediction compared to experimental data using principal component analysis input variables.

The mean square error method was also used to determine which method of obtaining input variables gave better predictions. It was observed that when one used the statistical method, the mean square error was greater and when one used the principal component analysis method one the error was far less.

5.4 Neural network based model for the predicton of salt removal efficiency

Salt removal data was collected from the Arabian gulf oil company. It had seven input parameters obtained using principal component analysis as described in Table (5.3). With the data ready the next step was to build the network. This was done by the following steps:

1. Data filtering
2. Dividing the data into training and testing data
3. Developing and optimising the model
4. Obtaining the optimal network architecture used in the prediction of salt removal efficiency

5.4.1 Division of data to obtain training data sets and testing data sets

The original data contained 608 sets of data. This was checked for outliers and after their removal 351 sets of data for each of the seven input variables was obtained. The new input data was then divided with 70%, 20% and 10% of the data used for training, testing and validation respectively. It is normal in artificial neural networks to have training and testing data. In order to have a neural network that achieves stability and its solution converges then one ought to have a training step and a large percentage of data should be used for this. More often than not, neural networks do not extrapolate data but instead interpolate it thus requiring a major percentage of training in order to have data that covers the entire output data range.

After outlier removal there were 351 sets of data for each input variable. 246 sets of data were used a the training set which represented 70% of the raw data whilst 70 sets of data were used as the testing set representing 20% of the raw data and 35 sets for validation which represented 10% of the data. This division of training and testing data is the one that is usually recommended. The training phase was needed in the creation of neural network that was stable and converged to a solution hence it was crucial to get the training phase correct in order to obtain a neural network that worked correctly. One ought to remember that neural networks interpolate and do not extrapolate data hence

data selection had to incorporate date from all regions of the desired output. Once training has been achieved the next step is to test the created artificial neural network. In the testing phase the network is tested to see how well it recollects the predicted data in the training phase. Also the ability of the network to predict the output data using non-trained data is carried out. This step is usually called the generalisation step. The next phase of the network is the recall step where its ability to acquire the initial input data is determined. The difference between the generalisation step and the recall step is that in generalisation the network is fed non-trained input data whereas in the former it is fed trained input data. If the steps are followed properly and the network is trained properly then it will be able to predict the output data with very little difference between the predicted and actual value. However this can only be realised through further development of the model and involves looking at the number of nodes and the number of layers used in the architecture of the model.

5.4.2 Development of the neural network model

The major objective of the neural network model is to maximise the speed at which the network converges to a solution and the accuracy of its prediction. The remaining objective is to obtain the number of hidden layers and the number of neurons per hidden layer used. However this is more often easier said than done. The reason for this is that no standard method exists [3].

A neural network code was written with the aid of MATLAB. The program created different sets of models which had different number of layers and different number of hidden neurons per layer used. The model performance was given by the mean square error method as well as the regression value, R^2. The epoch size, transfer function and the learning rate were the constraints that were set in the program before data training. Prior to the training step the weight factors between the nodes in the hidden layers were initialised. This was done by setting the free parameters of the modelled data to randomly and uniformly distributed data that had a zero mean range.

Once all this had been determined it was then determined that with the Levenberg-Marqurdt back propagation algorithm one was able to obtain the best performance as well as faster predictions. The activation functions in the hidden neurons that gave the best results would be the sigmoid type as the data had been normalised using the zero mean normalisation technique as shown in Equation 4.4.1. The epoch size is also important in ensuring good network performance. The epoch size that produces the lowest R^2 value was chosen after several tests. A default epoch size of 100 was chosen for all network predictions.

Initially one hidden layer was used and the number of neurons was increased in increments of 5 beginning with 5 neurons. To determine optimal number of neurons the average absolute error was calculated for increasing number of neurons as can be seen in Figure (5.22). It was observed that the absolute error continued falling as the number of neurons was increased which coincided with increase in regression value as seen in Figure (5.22).

Finally it was observed that with one hidden layer the optimal number of neurons to be used was 20. Any more addition of neurons was insignificant as the absolute error did not fall any further. The resulting predictions can be seen in Figures (5.23) to (5.25). Normally the use of one hidden layer is enough to obtain predictions for nonlinear type of data [80] however in this case what was found was that it was taking a long time to arrive to a prediction. A network with two hidden layers can approximate nonlinear functions and generate good predictions for prediction problems [80].

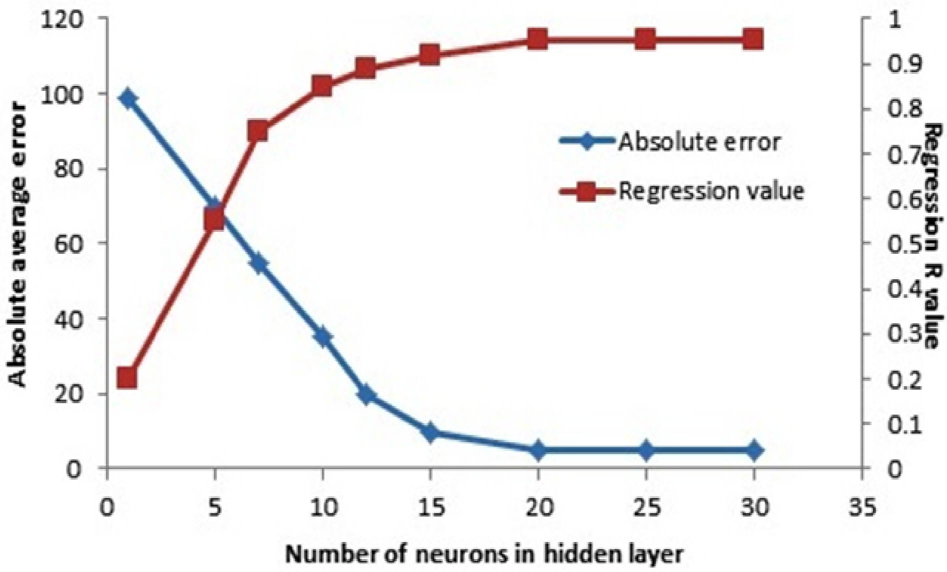

Figure 5.22. Average absolute error and Regression based performance measures using.

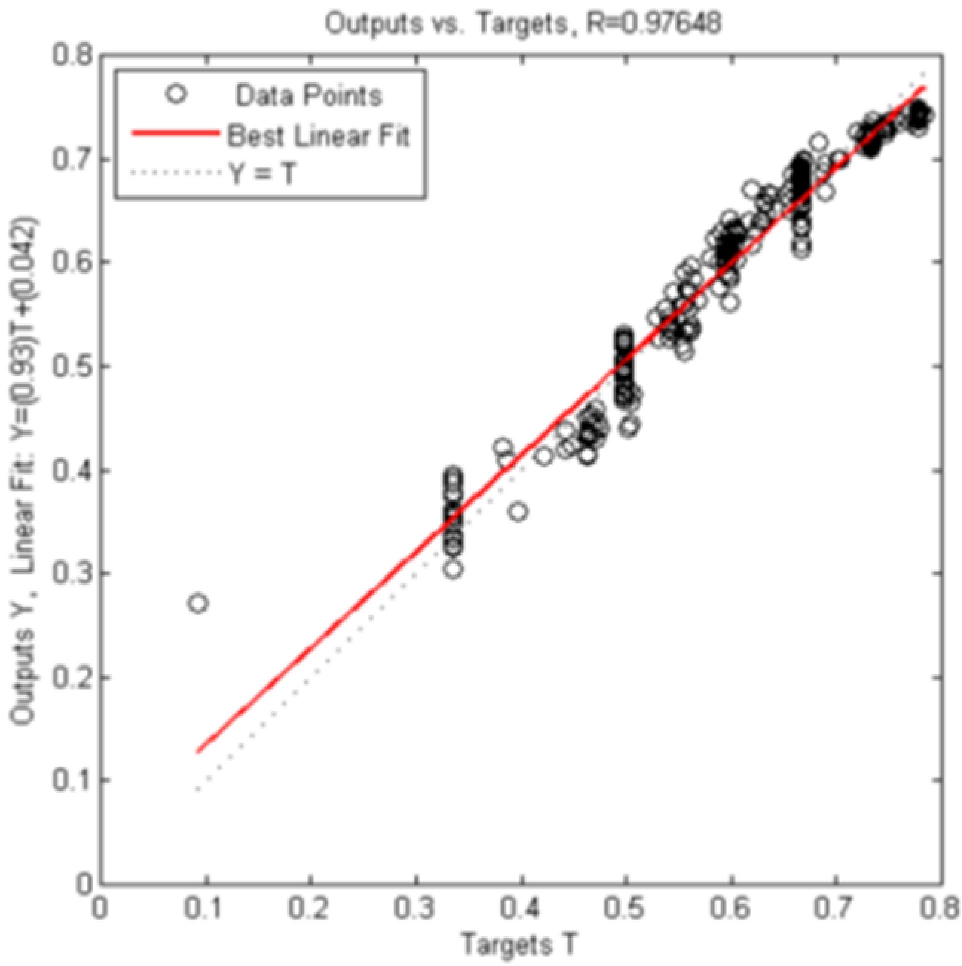

Figure 5.23. Actual and predicted output variables for salt removal using one hidden layer and with 20 neurons.

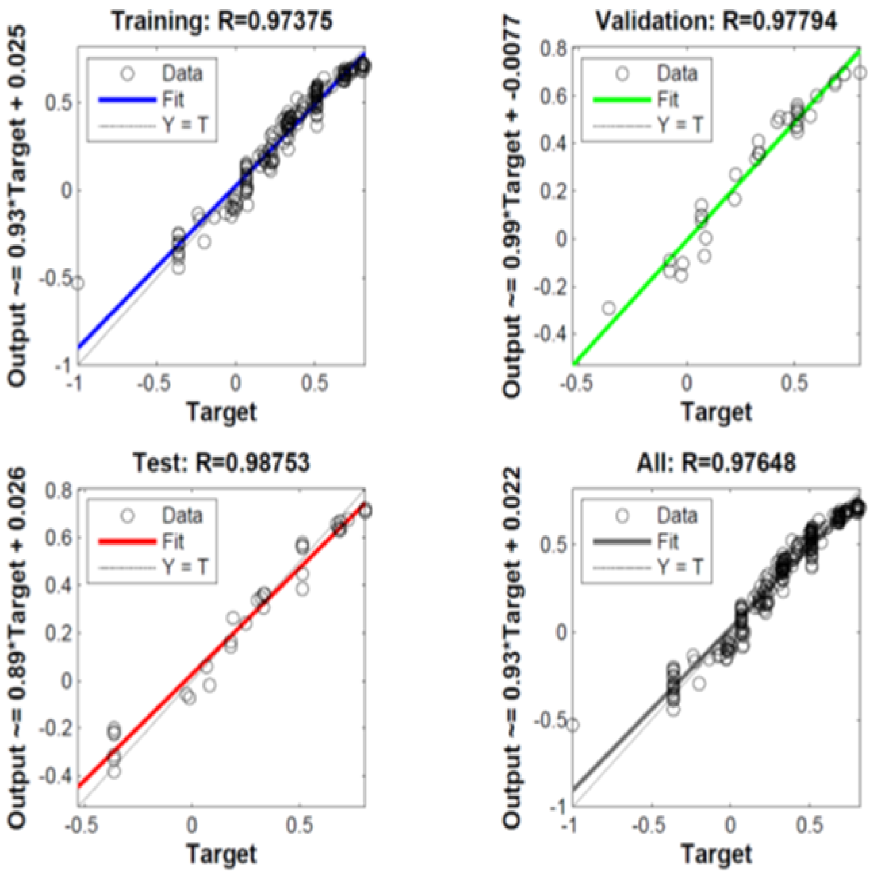

Figure 5.24. R^2 values for training, testing and validation for the prediction of salt removal efficiency using one hidden layer and with 20 neurons.

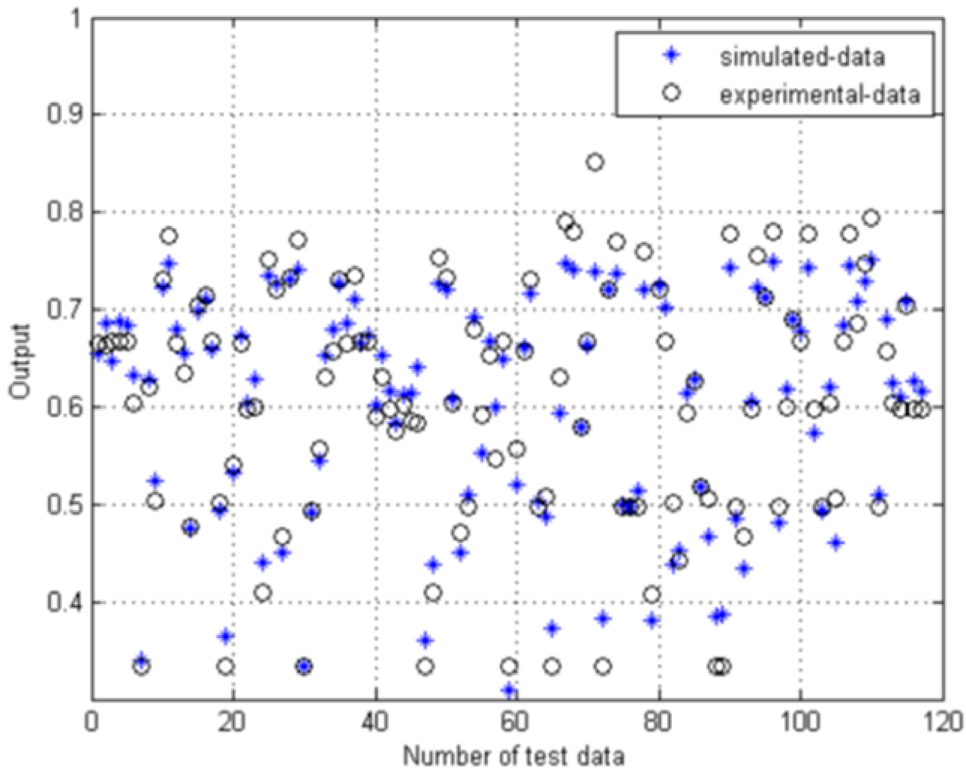

Figure 5.25. Network prediction compared to experimental data for the prediction of salt removal efficiency using one hidden layer and with 20 neurons.

A two hidden layer network was next investigated to see whether the computations would be much faster and better predictions would be obtained. To determine optimal number of neurons the average absolute error was calculated for increasing number of neurons as can be seen in Figure (5.26). It was observed that the absolute error continued falling as the number of neurons was increased which coincided with increase in regression value as seen in Figure (5.26). Finally it was observed that with two hidden layers the optimal number of neurons to be used for the first layer was 25 and for the last layer were 10. Any more addition of neurons was insignificant as the absolute error did not fall any further. The number of nodes in the input and output corresponded to the number of inputs and outputs of the network. The number of nodes in the hidden layers depends on what the network will be used for. Like has been discussed before, using one hidden layer is okay for solving simple problems but for more complex problems two hidden layers are preferred [8].

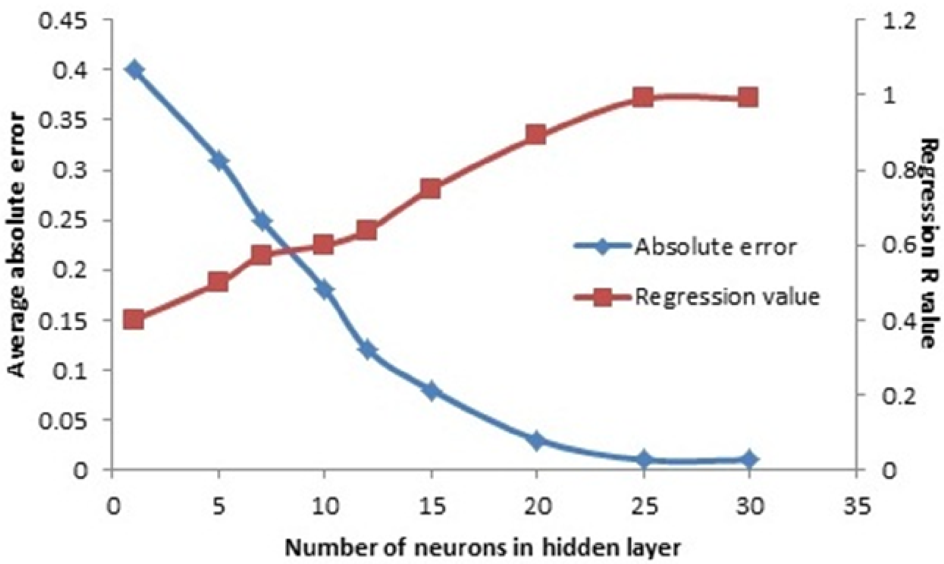

Figure 5.26. Average absolute error and Regression based performance measures using two hidden layers 25:10 neurons combination.

To further optimise the process, the learning rate was adjusted accordingly. The learning rate determines how effective the training of the network is by controlling the rate at which the weights are changing during the process. To see the effect of learning rate on network training of 246 sets of data a back propagation algorithm with two hidden layers with a ratio of 25:10 nodes in each layer, a sigmoid hyperbolic transfer function was used to predict salt removal. Figure (5.27) shows the effect of learning rate on the rate at which the mean error is obtained. It can be seen that at increasing the learning rate to a value of 0.9 increases the rate at which the answer converges however this has more often than not got to go hand in hand with

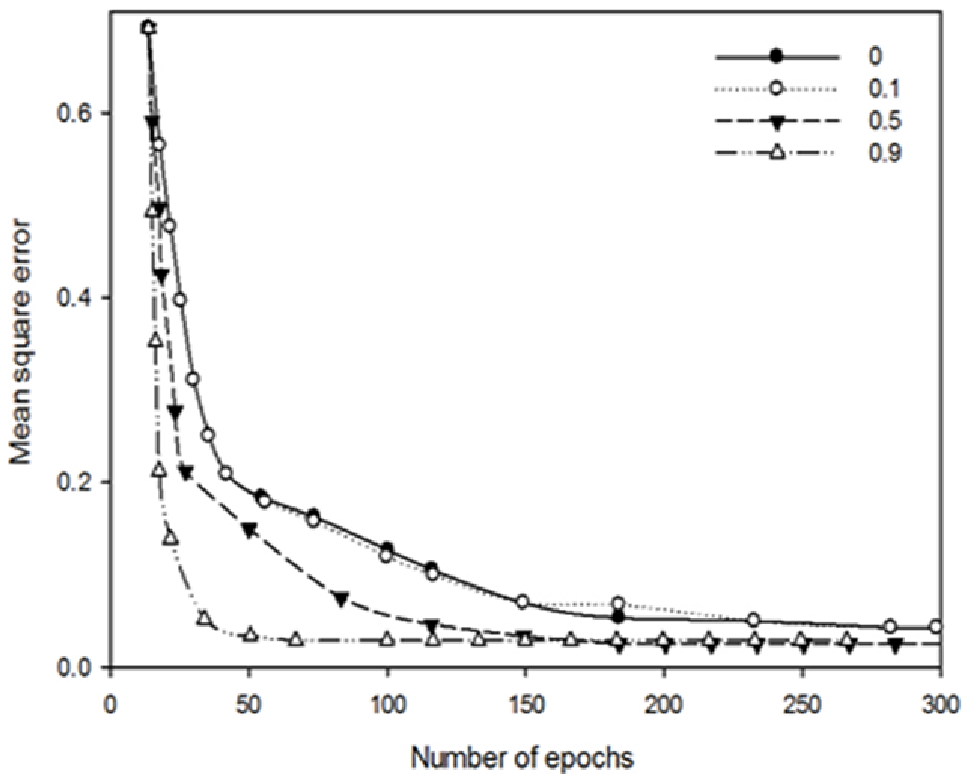

Figure 5.27. Mean square error against number of epochs at different learning rates.

The effects of learning rate in the absolute error are further observed in Figures (5.28) to (5.30).

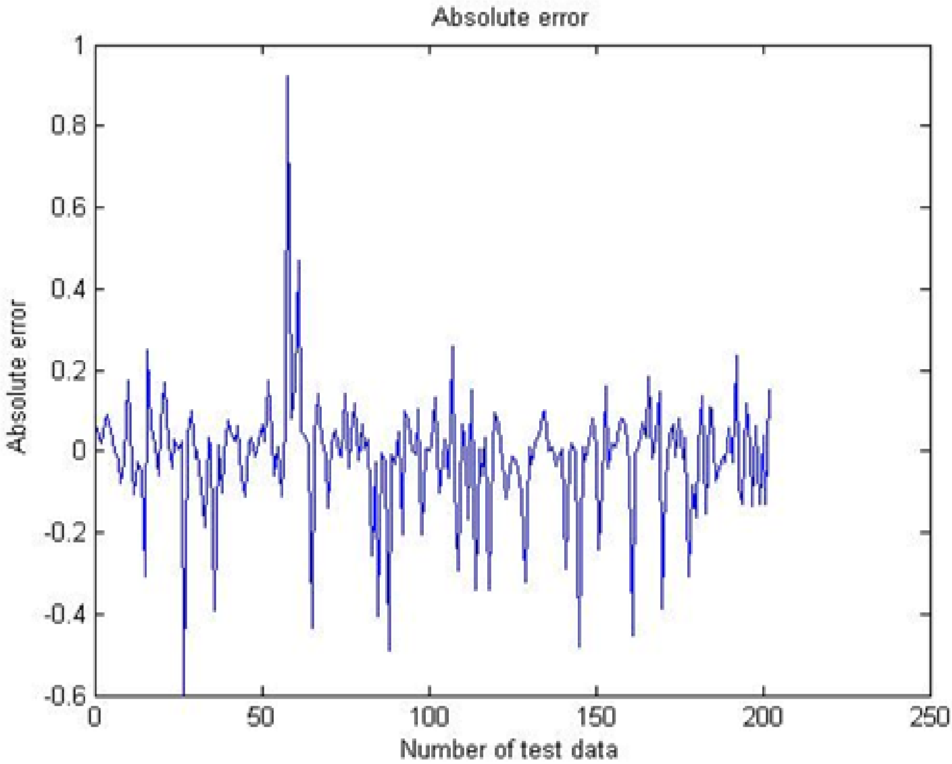

Figure 5.28. Absolute error for salt removal efficiency by principal component analysis learning rate set at 0.01.

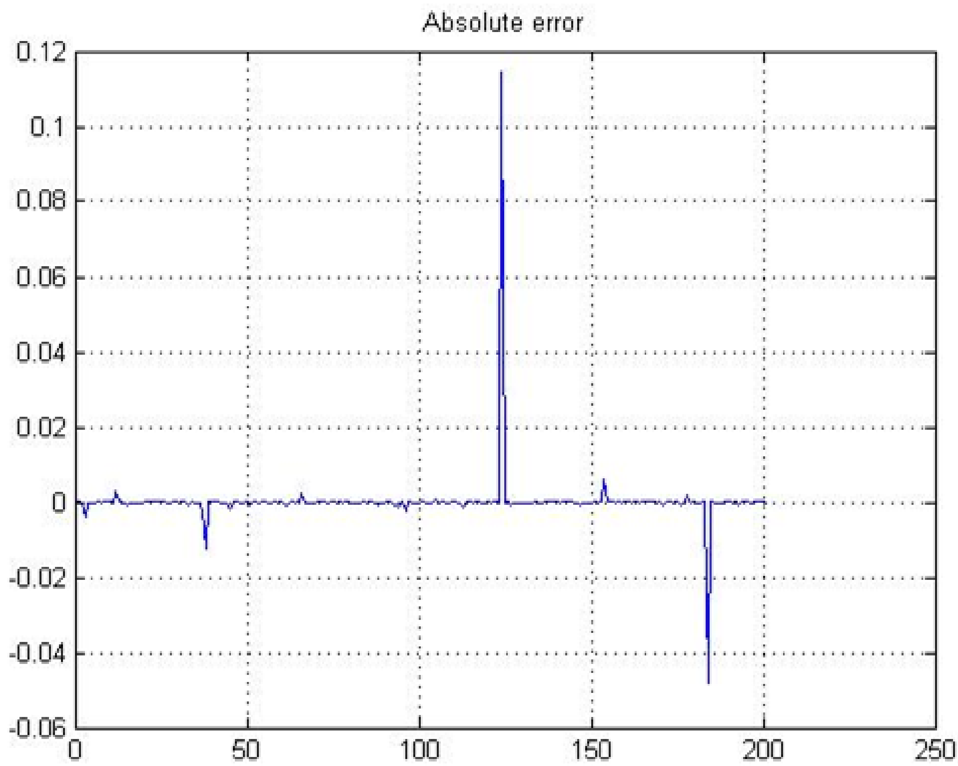

Figure 5.29. Absolute error for salt removal efficiency by principal component analysis learning rate set at 0.3.

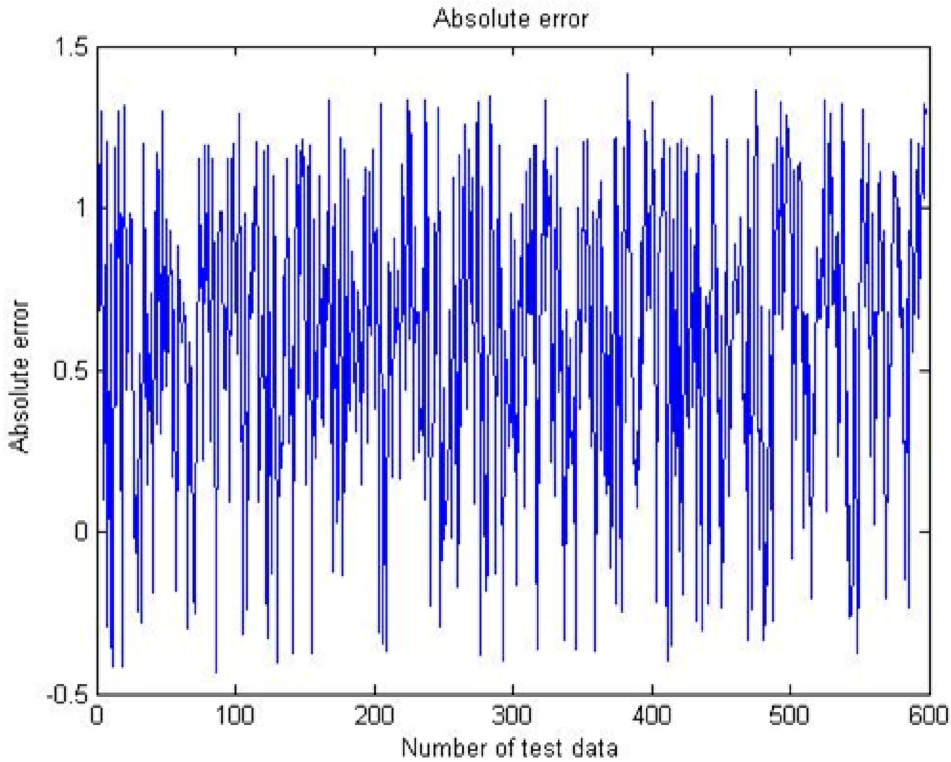

Figure 5.30. Absolute error for salt removal efficiency by principal component analysis learning rate set at 5.

Having carefully analysed the use of one hidden layer and two hidden layer neural network models the optimal network model recommended for the salt removal efficiency of the Libyan crude oil desalter would be a multi input single output model as shown in Figure (5.31). Based on the above results, the optimal network architecture recommended for the salt removal prediction network is one based on Levenberg-Marqurdt back propagation algorithm, using the delta learning rule, and the hyperbolic tangent transfer function. The learning rate was set to 0.3. The two hidden layers have 25 and 10 nodes, respectively, whereas the maximum number of training iterations is 100 and the epoch size is fixed at 10 examples. The data was divided into 264 sets of data for training and 70 for testing.

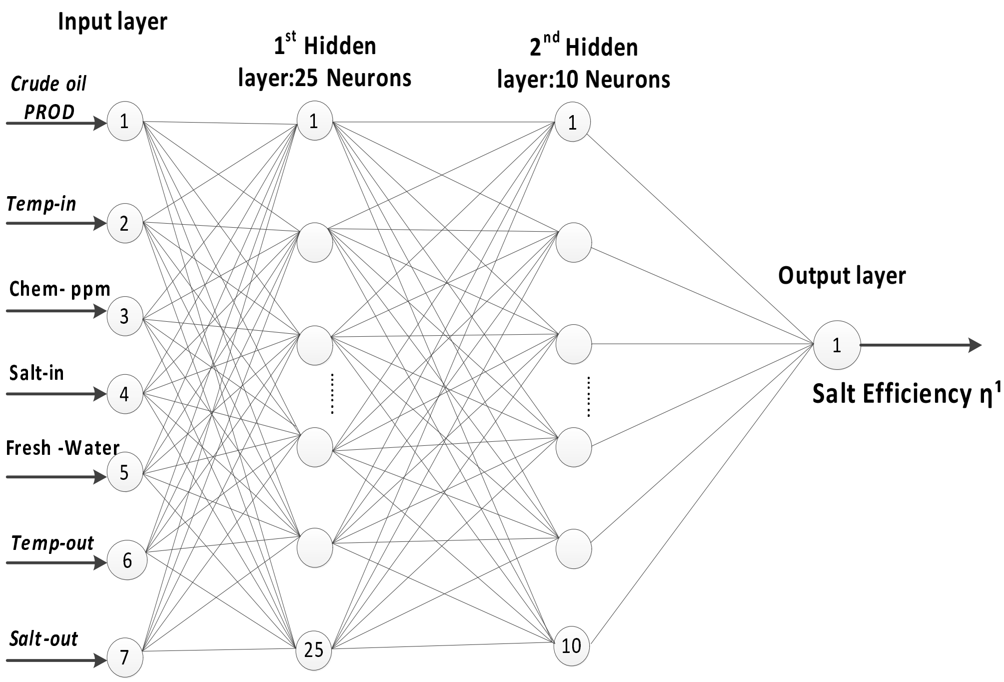

Figure 5.31. Optimal multiple input single output neural architecture for Libyan crude oil desalter with two hidden layers and 25:10 neurons.

The final predictions obtained from the optimal neural architecture are shown in Figures (5.32) to (5.34) respectively

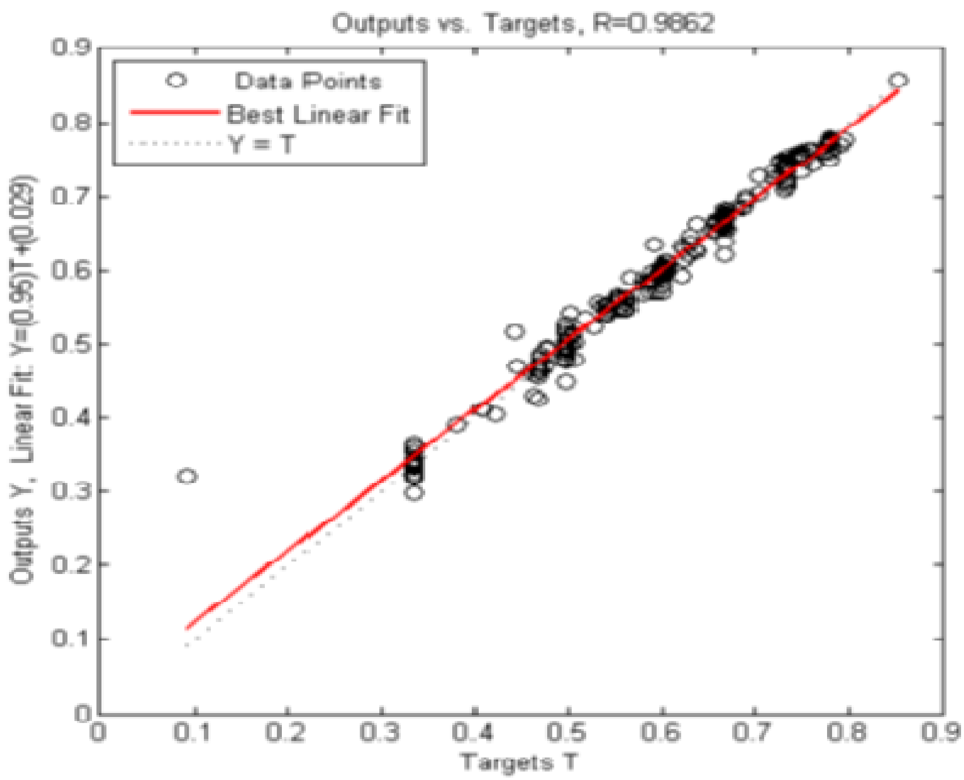

Figure 5.32. Actual and predicted output variables for salt removal using two hidden layers and with 25:10 neurons.

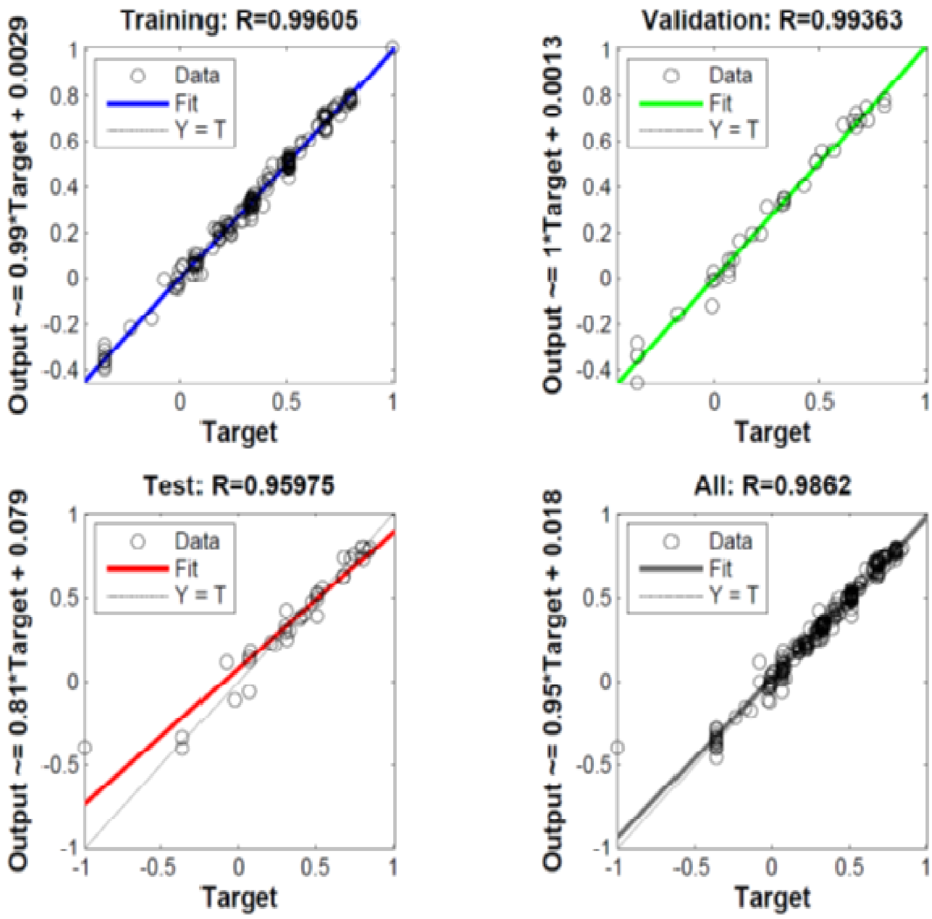

Figure 5.33. R^2 values for training, testing and validation for the prediction of salt removal efficiency using one two hidden layers and with 25:10 neurons.

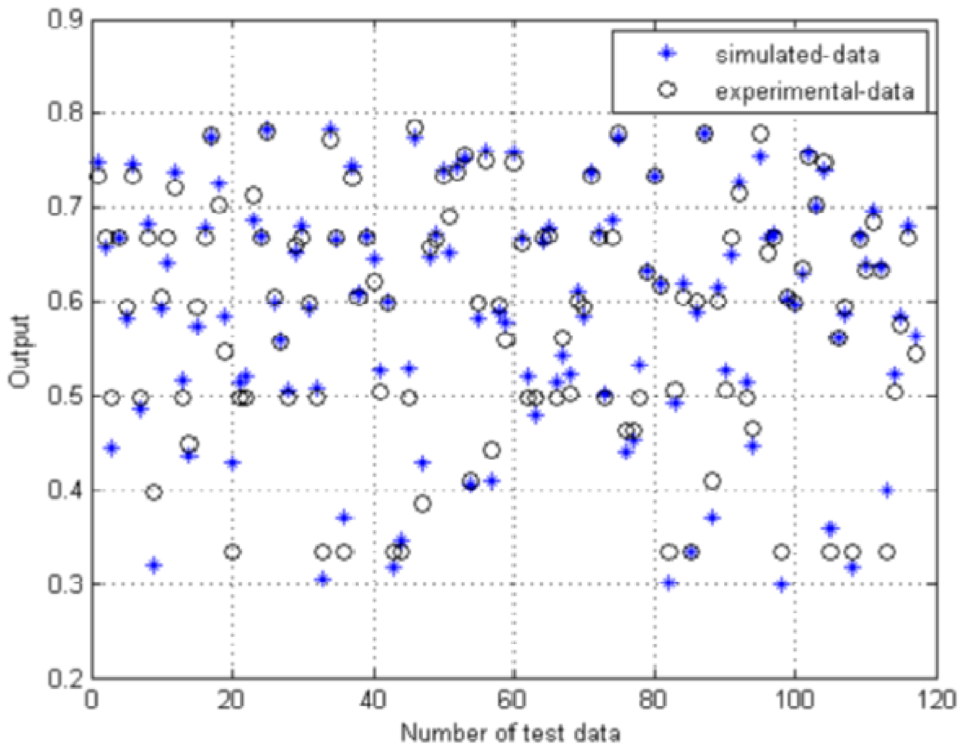

Figure 5.34. Network prediction compared to experimental data for the prediction of salt removal efficiency using two hidden layers and 25:10 neurons.

5.4.3 Comparisons of statistical model predictions with neural network model

A nonlinear regression analysis was done on the output data and the best R^2 value was obtained at 0.11 which was a sixth order polynomial fit whose equation is shown in Table (5.4).

The predicted output from this equation is shown in Figures (5.35), it can be seen that the statistical approach is not robust enough in its ability to predict the output. Using this approach also does not highlight any relationship between the inputs and outputs as compared to the neural network method thus one can safely say that the statistical method is null and void for this particular set of data and should not be used as a modelling approach.

Table 5.4. Best fit equations and R^2 values for predicting salt removal efficiency

Variable	Best fit equation	R^2
Salt removal efficiency	y= -1.88E-14X^6+2.31E-12X^5-1.10E-8X^4+2.54E-6X^3-2.77E-4X^2+0.52E+0.109	0.109

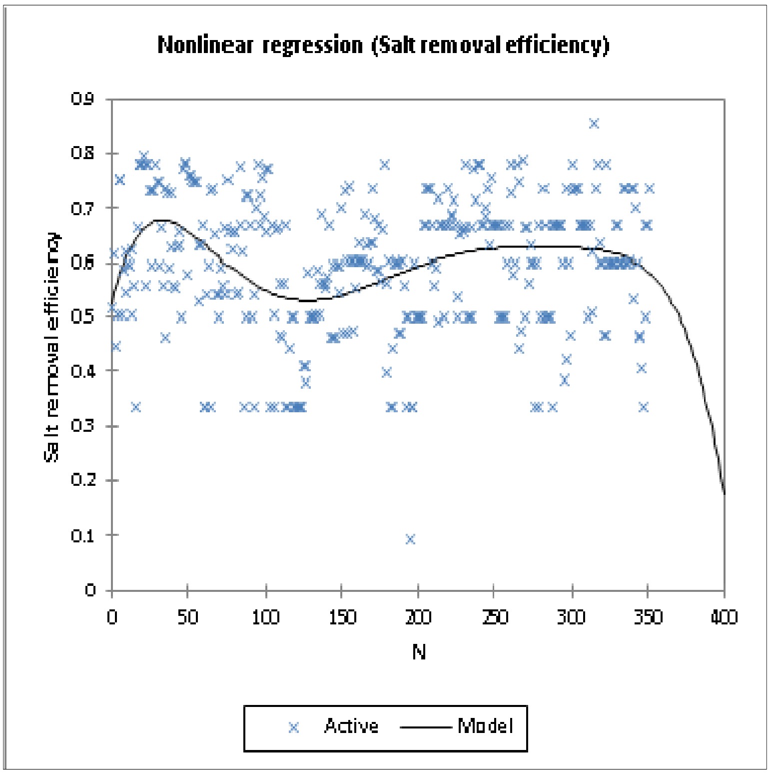

Figure 5.35. Nonlinear regression plot of salt removal efficiency.

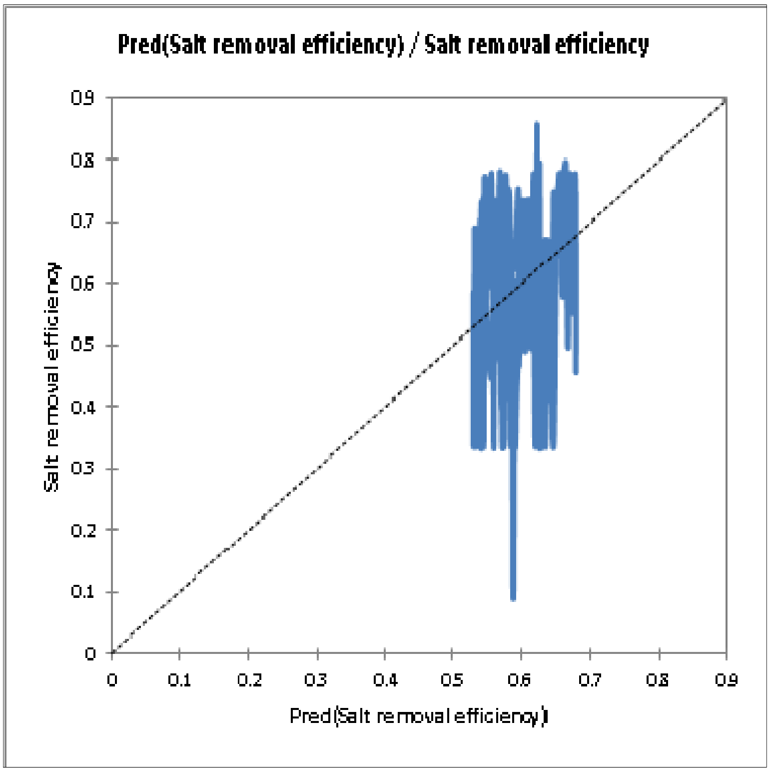

Figure 5.36. Predicted model output of salt removal efficiency.

5.5 Optimisation of demulsifier injection and fresh water addition

The optimisation problem at hand was one of a nonlinear constrained type in nature. Using the MATLAB optimisation toolbox, upper and lower band were set for demulsifier injection and fresh water addition. These two processes are quite important in desalting process. and aid in the breakup of emulsions. If the dosage of the demulsifier is too high, more stable emulsions may form which would be difficult to break thus hindering the performance of the desalter. The rate of fresh water addition and its salinity affect desalter performance. A very low rate of fresh water addition would result in poor mixing of the demulsifier and crude oil in the mixing valve thus hindering the performance of the desalter. If the pH is too high soaps can be formed which form emulsions which would be hard to remove in the desalter. The impact of these economically on desalting operations is quite high with the demulsifier being very expensive and there being a scarcity of fresh water availability hence optimum values of fresh water addition and demulsifier injection have to be hopefully obtained thus reducing the costs to the operation.

It can be seen in Figure (5.37) that the plant readings collected for the demulsifier flow rate and the demulsifier flow rate values predicted at the training stage by the ANN. As shown in the figure, there is a good agreement between the predictions made by the ANN and the plant readings when the demulsifier consumption rate is between 12.09 and 105.3 part per million (ppm). However, the proposed ANN model fails to provide an accurate prediction when the demulsifier rate is outside this range.

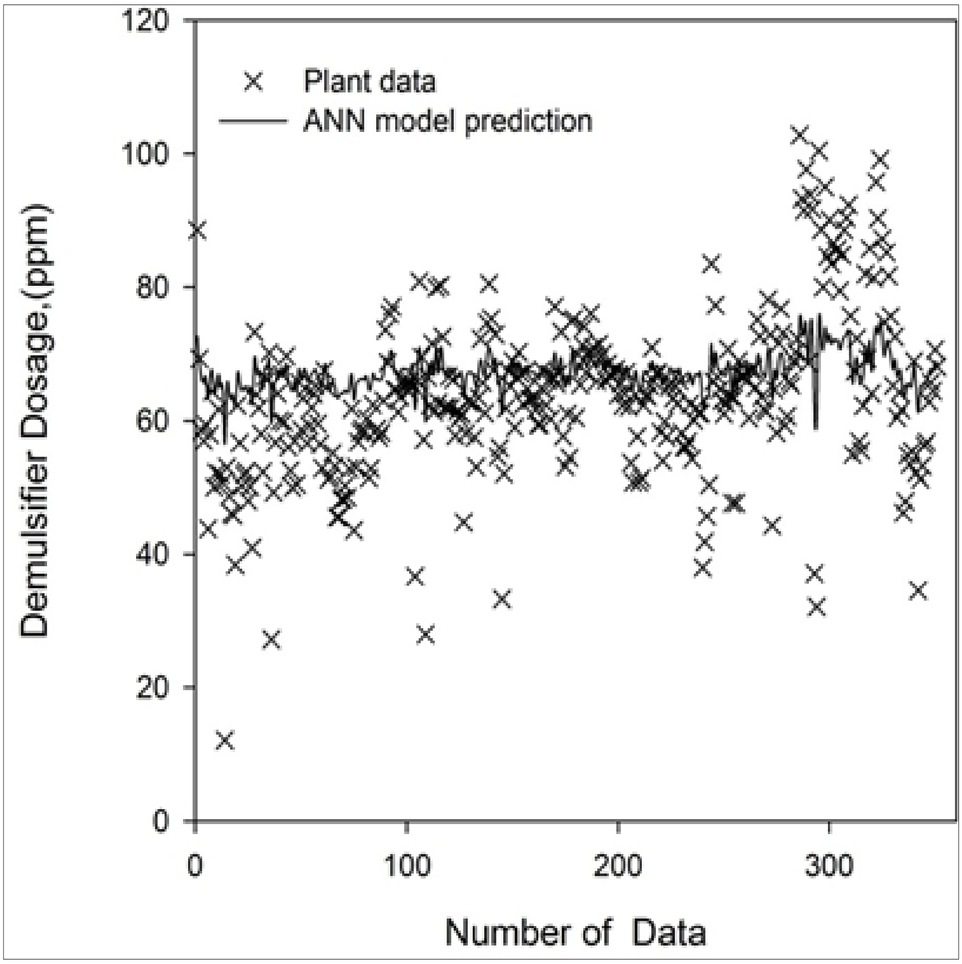

Figure 5.37. Demulsifier consumption rate model verification.

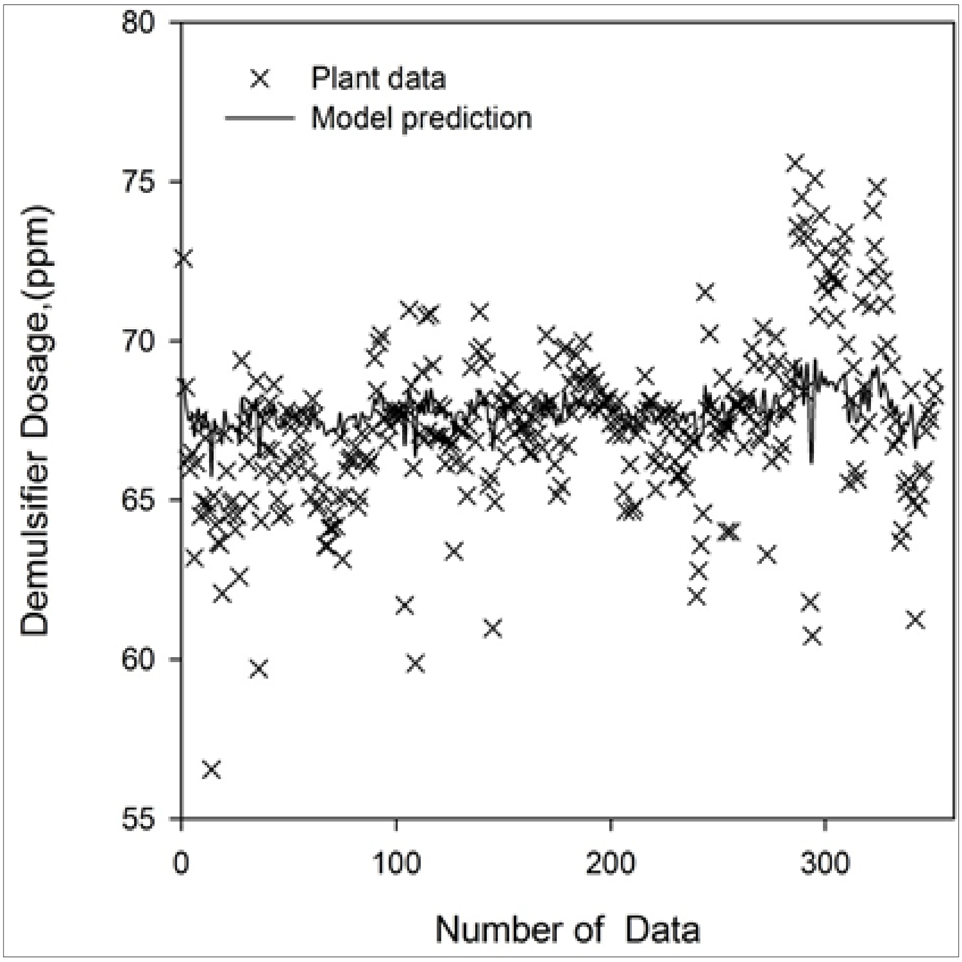

Figure 5.38. Demulsifier rate using the current control and the ANN controller.

The demulsifier rate measurements and the simulated demulsifier rates are shown in Figure 5.38. There is a significant reduction in the amount of demulsifier injection into the Desalting process when the proposed ANN is used as the algorithm to control the demulsifier consumption rate, assuming that the salt content is below 10 PTB with an optimal demulsifier dosage of about 69 ppm. Fresh water addition optimisation results are observed in Figures (5.39) to (5.40). The ANN model was not able to predict the fresh water addition rate when the range was between 5000 to 20000 barrels per day of fresh water addition as seen in Figure (5.39). However on optimising the process and getting a bound of 1000-1500 barrels per day of fresh water addition the model gave better predictions.

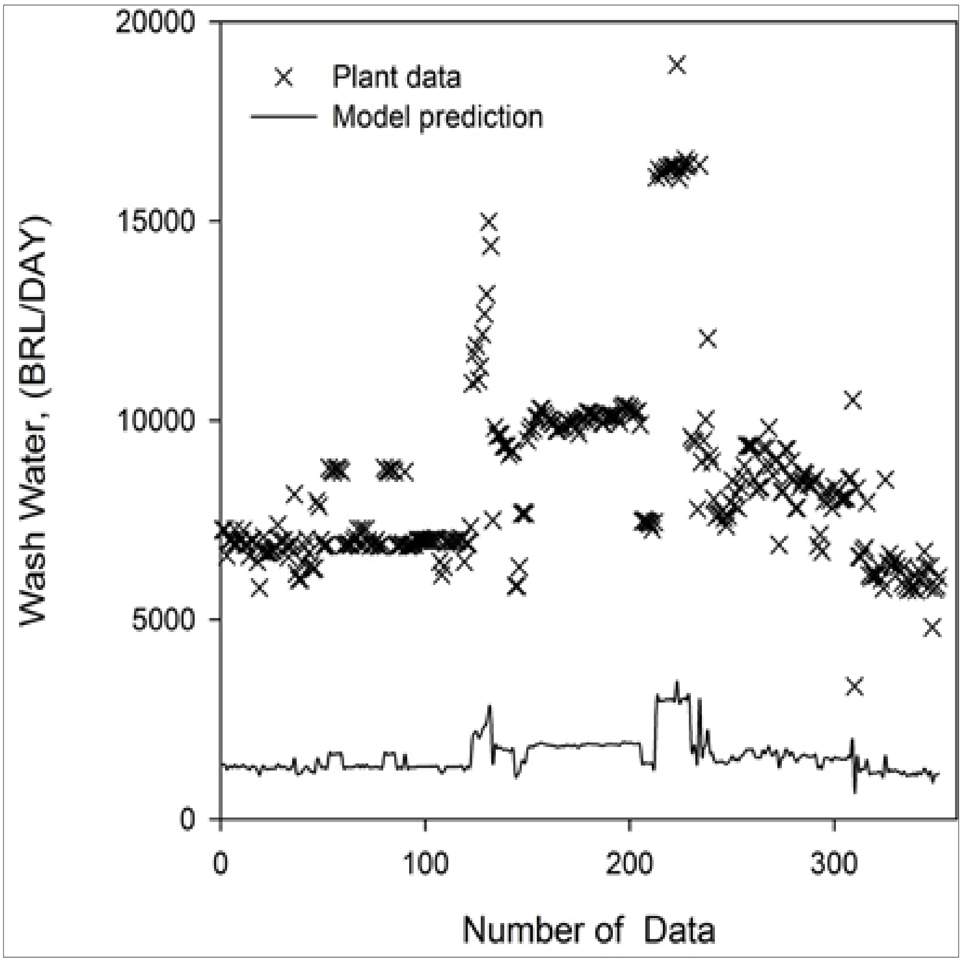

Figure 5.39. Wash Water Consumption rate :model verification.

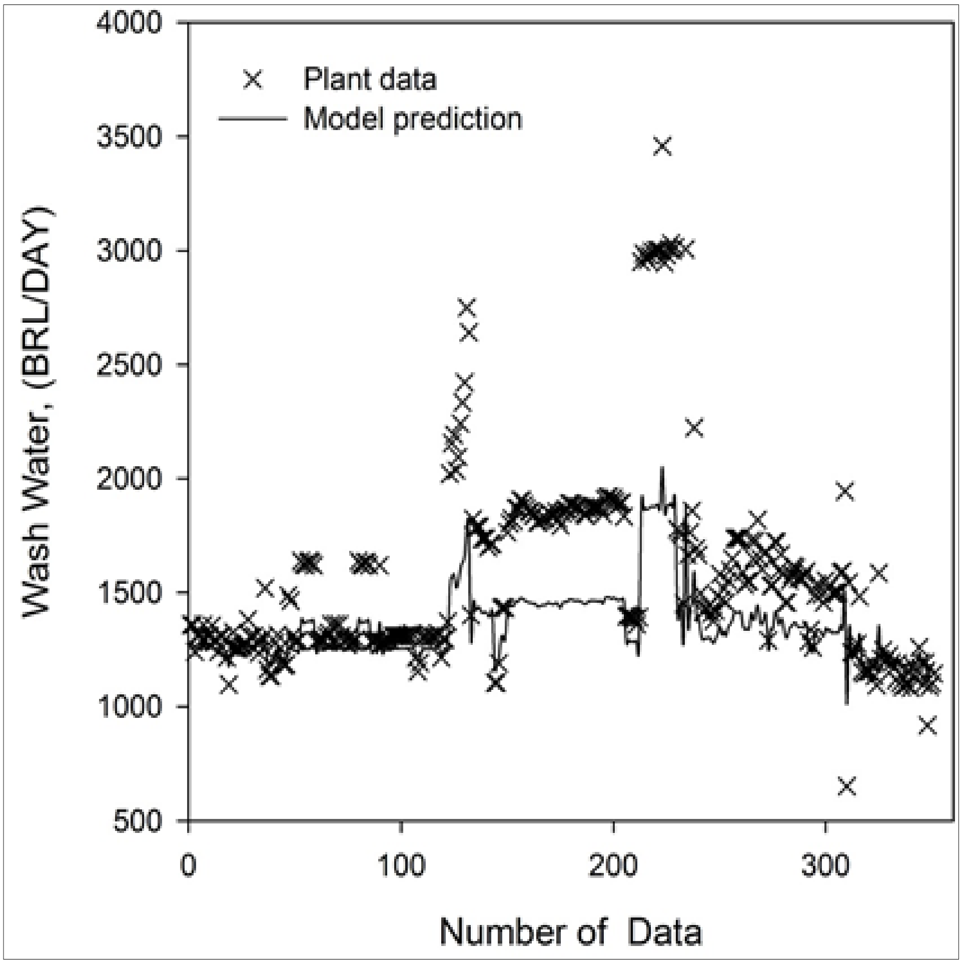

Figure 5.40. Wash Water rate using the current control and the ANN controller (Salt Content).

5.6 Closure

The preparation and analysis of input and model data was carried out. The importance of the correct technique of data filtering was highlighted with particular focus being emphasised on the removal of outliers in raw data. An important process in the use of ANN models was identified as being the selection of the right input variables. A comparison between using factor analysis and statistical analysis in the selection of inputs and it was observed that the former gave significantly better results. The training and testing phase of ANN model development was shown to be an important step in ANN model development. If this phase was wrongly done then the ANN model would not be accurate in its predictions. Optimisation of the ANN model architecture was carried out with the number of hidden layers, number of neurons in the hidden layers, the transfer function used and the learning rate identified as key elements in obtaining an ANN architecture that gave fast and accurate predictions. Fresh water addition and demulsifier addition were identified as key parameters in the economic performance of the desalting process. Due to a scarcity of water and the high cost of the demulsifier chemical it was important to try and optimise these two input variables thus reducing the cost of operations.

Chapter 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

It is quite clear that crude oil desalting is of paramount importance in ensuring the safe operations of a refinery as it prevents the corrosion of downstream equipment. In this work, data from Arabian Gulf Oil Company was analysed. What was quite astonishing was the amount of outlier data present in the raw data. As discussed Chapter 4, these outliers make it hard for the prediction of pattern recognition using ANN and were evident in initial findings. For Arabian Gulf oil company the significance of this is that plant operators need to improve the way data is recorded. Perhaps a more robust instrumentation and control scheme should be implemented thus reducing human error. Careful data analysis is also quite important in the preparation of data for use in ANN networks as was shown in Chapter 4. Many variables were obtained and choosing the right variables to use as input data would be quite difficult without the use of principal component analysis. This aided in the selection of the right inputs and led to the discarding of the least effective inputs. A total of seven inputs were determined to be the most important in the prediction of salt removal efficiency. These were total production, water in and water out, temperature in and temperature out, demulsifier rate and wash water rate.

The design of the optimum ANN network was done through trial and error, by adjusting various combinations of hidden layers and number of nodes in each layer, the best combination was found to be a network with two hidden layers with a 25 and 10 nodes in the hidden layers respectively. Initially 608 sets of data were used for each input variable, with 426 used for training and 184 used for testing and validation. What was quite clear from the onset was that the results obtained were poor with R2 oscillating between -0.1 to 0.6. One of the contributing factors to this was that a lot of the data contained outliers and thus once these outliers were identified, the new data then consisted of 351 sets of data for each input variable and the process was carried out again.

The ANN network model that was developed predicted the salt removal efficiency which could be described as perfect prediction based on the value of R^2 which was greater than 0.9, meaning it was a perfect fit. This would seem to suggest that for single output single input it was highly effective but this theory was not tested further due to unavailability of plant data. The use of plant data also severely limits the effectiveness of the model in trying to investigate different effects of input variables on the output. This is also quite significant owing to the fact that the plant is highly optimised thus further optimisation of input variables cannot be carried out. The amount of salt in crude oil in general from Libyan oil fields is very low, hence more often than not Libyan oil crude oil is highly desirable which would then suggest that perhaps instead of using desalters perhaps the use of hydro cyclones which in principle remove up to three times more water from washed crude oil. This would then mean that the use of demulsifiers would reduce significantly thus reducing costs assuming that the low levels of salt in the crude oil remained the same.

6.2 Future work

Neural networks are very attractive tools because of their simplicity, cost effectiveness, generic in nature and ease of use and would be particularly useful to plant operators. The results obtained have shown that neural networks have high potential in data analysis as they require less knowledge of the underlying physicochemical process, however this has its advantages and disadvantages as has been stated throughout the course of this research.
It has been shown that using plant data severely compromises investigations on various effects of different variables thus reducing the understanding of better performance of the desalter. Possible suggestion to overcome this limitation would be;

1. 1. To carry out several experiments by varying the amount of demulsifier and fresh water addition whilst keeping the other variables constant and collecting this data and running the model to analyse this data. This would be quite helpful to show whether in fact the reduction in demulsifier use would lead to less use of fresh water in the desalter thus significantly reducing cost

2. 2. With the advent of more advanced simulation tools, it would be interesting to model the desalter using Aspen Hysys and thus be able to use model predictive control algorithms to actually find the optimum demulsifier addition rate and comparing these findings with those of the experimental stage and combining this with the results of artificial neural network (ANN) prediction in order to compare the three methods.

Appendix A

Plant data

DATE	PROD. BRL/DAY	Salt In PPM	Salt-out PPM	Temp-In (Fº)	Temp Out (Fº)	Chemical PPM	Wash Water BRL/day	Salt Efficiency
1	210729	19817	5.7	143	140	88.58	7258	0.9997
2	206911	21925	8.55	143	139	69.33	7258	0.9996
3	211430	21100	14.3	144	140	58.46	6597	0.9993
4	212116	22200	14.3	143	140	57	6993	0.9994
5	215628	22100	17.1	143	139	59.4	6993	0.9992
6	214068	27100	17.1	142	140	43.74	6880	0.9994
7	211420	26000	19.95	144	140	57.96	7258	0.9992
8	212870	22100	25.65	143	140	64.37	6887	0.9988
9	212342	22200	11.4	142	140	50	6993	0.9995
10	212130	21200	11.4	143	140	52.19	6993	0.9995
11	216168	22000	17.1	142	139	61.7	7236	0.9992
12	215584	23100	19.95	143	140	51.93	6880	0.9991
13	105891	21450	22.3	140	137	50.7	6887	0.9990
14	173500	21400	28.5	132	129	12.09	6597	0.9987
15	207688	22100	25.65	137	134	52.98	6993	0.9988
16	215000	22200	22.5	141	138	48.7	6993	0.9990
17	212436	23400	14.3	142	139	46.07	6880	0.9994
18	170173	19500	14.3	134	130	45.8	6457	0.9993
19	194656	23400	17.1	140	137	38.4	5800	0.9993
20	198499	23400	14.3	140	137	62.31	6709	0.9994
21	206224	23400	14.3	138	135	56.73	7072	0.9994
22	204792	23400	14.3	140	138	50.19	6681	0.9994
23	206287	24350	17.1	142	139	51.88	6681	0.9993
24	203900	23400	17.1	143	140	52.3	6681	0.9993
25	206255	23400	17.1	142	140	47.99	6731	0.9993
26	208078	23400	14.3	142	140	50.07	6737	0.9994
27	209960	21350	11.4	140	136	40.93	6815	0.9995
28	207895	21350	11.4	141	138	73.28	7380	0.9995
29	213856	21350	11.4	143	139	63.91	6974	0.9995
30	211433	21350	11.4	144	140	61.91	6947	0.9995
31	214037	23400	17.1	141	138	58.04	6988	0.9993
32	212055	22000	11.4	142	139	52.3	6835	0.9995

33	205694	22000	11.4	142	139	66.56	6569	0.9995
34	206406	21350	11.4	142	139	66.1	6835	0.9995
35	183677	23400	14.3	143	140	70.21	6933	0.9994
36	137170	23400	11.4	133	129	27.2	8150	0.9995
37	214267	21350	11.4	140	137	49.25	6164	0.9995
38	207288	21450	11.4	141	139	56.78	6010	0.9995
39	209997	21200	11.4	141	139	64.06	6010	0.9995
40	209953	21300	11.4	144	142	59.98	6443	0.9995
41	208440	21200	14.3	143	141	66.91	6821	0.9993
42	210051	22200	14.3	143	141	59.81	7016	0.9994
43	214106	23400	17.1	140	138	69.69	6667	0.9993
44	214828	23300	17.1	142	139	56.04	6373	0.9993
45	218809	22200	11.4	144	141	52.46	6262	0.9995
46	149471	22300	11.4	139	135	49.94	6290	0.9995
47	210408	23100	14.3	142	139	57	7967	0.9994
48	216432	19500	11.4	143	140	50.41	7841	0.9994
49	217085	23000	14.3	144	143	65.78	6988	0.9994
50	215055	23700	17.1	145	142	58.64	6849	0.9993
51	215106	23500	22.8	143	141	63.34	6849	0.9990
52	206456	21000	19.95	144	142	64.78	6877	0.9991
53	214408	22500	17.1	145	143	56.6	8810	0.9992
54	214868	22500	14.3	145	142	59.24	8734	0.9994
55	212646	22200	14.3	145	141	61.95	8705	0.9994
56	213200	22000	14.3	145	142	63.99	8777	0.9994
57	213047	22000	14.3	145	142	65.25	8810	0.9994
58	214713	22000	11.4	145	142	59.57	8777	0.9995
59	216448	20000	11.4	145	142	56.5	8705	0.9994
60	215587	22300	11.4	147	145	52.84	6849	0.9995
61	215187	22300	14.3	144	140	67.54	6877	0.9994
62	213962	19500	11.4	145	140	64.96	6905	0.9994
63	212480	19500	11.4	143	139	51.19	6877	0.9994
64	215618	19500	11.4	144	139	51.59	6877	0.9994
65	216574	23000	11.4	144	140	55.17	6974	0.9995
66	216825	21350	11.4	144	141	53.11	7058	0.9995
67	217741	21400	11.4	145	142	45.52	7268	0.9995
68	217057	19500	8.55	145	142	45.54	6877	0.9996
69	217207	21450	14.3	146	144	48.17	7268	0.9993
70	218013	23000	14.3	147	144	48.25	6877	0.9994
71	208420	23000	14.3	145	142	50.2	7268	0.9994
72	216582	19500	11.4	146	144	48.47	6988	0.9994
73	217696	23000	17.1	145	142	52.75	6849	0.9993

74	218230	24350	17.1	146	144	61.77	6877	0.9993
75	219683	23400	17.1	147	144	43.51	6905	0.9993
76	218534	23400	14.3	147	145	52.98	6988	0.9994
77	219429	23000	11.4	146	144	56.84	6849	0.9995
78	219880	22100	17.1	147	145	58.29	6849	0.9992
79	218259	23100	11.4	146	144	58.79	6905	0.9995
80	216650	22100	14.3	146	144	58.29	8810	0.9994
81	217955	23100	17.1	146	143	60.32	8734	0.9993
82	218184	23100	19.95	146	143	51.4	8705	0.9991
83	218708	23000	14.3	146	144	52.78	8777	0.9994
84	218516	23100	17.1	145	141	62.41	8777	0.9993
85	218328	23500	17.1	145	143	58.38	8705	0.9993
86	218308	23250	17.1	145	142	58.78	6849	0.9993
87	217934	22000	14.3	147	144	57.53	6849	0.9994
88	218064	19500	17.1	149	146	58.23	6877	0.9991
89	219981	19500	8.55	149	147	62.98	6905	0.9996
90	210028	21000	8.55	150	147	73.63	8705	0.9996
91	208511	21000	8.55	150	146	68.75	6849	0.9996
92	217506	19500	11.4	150	145	75.96	6849	0.9994
93	215880	19500	14.3	148	143	77.06	6877	0.9993
94	211654	23000	14.3	148	143	64.66	6905	0.9994
95	210796	19500	14.3	151	144	64.63	6877	0.9993
96	215404	20450	14.3	150	144	61.28	6988	0.9993
97	215958	23450	17.1	148	144	63.55	6988	0.9993
98	216968	21000	17.1	148	143	65.94	6988	0.9992
99	218565	19500	19.95	148	143	65.04	6988	0.9990
100	212344	22300	19.95	149	144	65.78	6988	0.9991
101	216979	24100	34.2	148	143	64.35	6988	0.9986
102	212028	23100	25.65	149	144	65.79	6988	0.9989
103	184471	23100	42.75	149	145	65.22	7016	0.9981
104	200673	23100	42.75	148	143	36.68	6988	0.9981
105	202381	19500	71.25	148	143	65.92	7044	0.9963
106	201283	23500	57	148	143	80.86	7016	0.9976
107	158573	19600	28.5	137	131	69.52	6457	0.9985
108	132503	19500	14.3	137	133	57.2	6122	0.9993
109	139991	23200	11.4	138	134	28	6332	0.9995
110	207025	23400	19.95	149	146	66.5	6933	0.9991
111	212290	24800	14.3	151	149	62.32	6960	0.9994
112	212501	21450	17.1	152	149	71.56	6988	0.9992
113	199437	29300	22.8	152	149	61.35	6933	0.9992
114	203314	32500	14.3	150	146	79.95	6988	0.9996

115	174403	35000	19.95	139	134	62.69	6960	0.9994
116	196330	23500	11.4	150	145	80.25	6988	0.9995
117	200322	21350	11.4	149	146	72.57	7044	0.9995
118	207674	25350	11.4	150	148	61.94	7016	0.9996
119	211160	25350	14.3	151	148	61.94	6457	0.9994
120	214334	25350	17.1	151	148	66.63	6905	0.9993
121	211418	23550	17.1	151	149	61.95	6905	0.9993
122	213510	23550	11.4	152	151	66.16	7324	0.9995
123	212624	19500	11.4	150	147	57.8	10930	0.9994
124	210617	19500	11.4	150	148	61.41	11685	0.9994
125	210501	21000	11.4	153	151	60.36	11880	0.9995
126	173038	19500	8.55	153	151	60.98	11014	0.9996
127	188612	19500	8.55	150	144	44.76	11349	0.9996
128	208854	19500	8.55	151	149	58.09	12160	0.9996
129	209494	19500	8.55	154	152	62.83	12677	0.9996
130	207599	19500	8.55	154	152	63.13	13166	0.9996
131	205925	19500	8.55	156	154	62.54	14983	0.9996
132	210215	19500	8.55	153	151	57.52	14383	0.9996
133	207989	19500	8.55	154	152	53.01	7492	0.9996
134	210065	20500	8.55	155	153	63.43	9828	0.9996
135	210614	20500	8.55	202	200	72.25	9617	0.9996
136	211345	20100	8.55	154	152	65.7	9644	0.9996
137	210718	21100	11.4	155	153	61.16	9644	0.9995
138	215513	22100	14.3	197	195	74.63	9354	0.9994
139	213909	22100	14.3	197	195	80.56	9359	0.9994
140	211675	22100	11.4	207	205	75.28	9365	0.9995
141	195597	22100	11.4	272	270	67.63	9141	0.9995
142	213017	22150	19.95	272	270	72.91	9225	0.9991
143	211997	21200	17.1	146	144	54.62	9225	0.9992
144	170554	22150	14.3	227	225	55.9	5843	0.9994
145	144125	23500	14.3	149	147	33.23	5843	0.9994
146	199205	24350	17.1	151	149	52.04	6318	0.9993
147	212167	23550	14.3	149	147	61.87	7660	0.9994
148	212174	23550	14.3	149	147	67.49	7688	0.9994
149	212326	26350	19.95	150	148	65.11	7660	0.9992
150	214982	26300	17.1	150	148	68.93	9505	0.9993
151	214331	20500	17.1	150	148	59.01	9728	0.9992
152	216730	26500	17.1	187	185	66.57	9840	0.9994
153	210069	20920	19.95	187	185	70.27	9784	0.9990
154	205509	25500	19.95	149	146	67.09	10092	0.9992
155	206068	23500	22.8	151	148	62.47	10092	0.9990

156	217990	21350	17.1	152	148	67.29	10287	0.9992
157	214112	21350	14.3	153	148	64.77	10287	0.9993
158	213618	21350	17.1	153	149	63.2	10176	0.9992
159	213578	21350	19.95	153	150	63.2	10092	0.9991
160	216198	21350	17.1	154	150	63.41	10008	0.9992
161	215035	21350	17.1	154	150	61.62	10008	0.9992
162	217021	20350	14.3	154	149	59.42	9924	0.9993
163	214760	20450	14.3	154	149	59.5	9952	0.9993
164	216022	21550	17.1	154	149	67.6	9759	0.9992
165	217104	21350	17.1	153	150	64.46	9759	0.9992
166	215913	21500	17.1	153	149	62.33	9812	0.9992
167	216934	21600	17.1	154	151	66	9868	0.9992
168	216431	21600	17.1	155	152	60.24	9840	0.9992
169	217011	21600	17.1	154	151	66.56	10008	0.9992
170	216567	21600	17.1	155	152	77.1	9952	0.9992
171	216406	21600	17.1	155	152	65.52	9924	0.9992
172	216371	20450	17.1	155	152	67.1	9896	0.9992
173	214364	21600	14.3	155	152	73.32	10008	0.9993
174	216104	25450	17.1	155	152	57.7	9831	0.9993
175	214440	21600	19.95	154	152	53.12	9672	0.9991
176	215915	22500	25.65	154	152	61.02	9980	0.9989
177	214056	21600	19.95	155	151	54.4	10064	0.9991
178	215822	21600	17.1	154	149	74.87	10064	0.9992
179	210033	24350	19.95	153	150	75.24	10204	0.9992
180	211567	25300	17.1	155	150	60.49	10204	0.9993
181	214171	28500	31.35	154	150	69.92	10176	0.9989
182	213002	25350	17.1	154	150	65.36	10120	0.9993
183	213883	22350	17.1	154	150	71.32	10146	0.9992
184	211249	21350	19.95	155	151	74.09	10120	0.9991
185	206667	21450	14.3	155	151	67.24	10036	0.9993
186	210133	22425	17.1	155	151	69.73	9952	0.9992
187	210204	22425	19.95	155	149	76.08	9924	0.9991
188	211081	25460	22.8	155	150	71.02	10064	0.9991
189	210005	29640	19.95	153	151	69.81	10120	0.9993
190	208297	21450	17.1	154	151	65.92	10148	0.9992
191	210068	19816	14.3	154	151	71.49	10120	0.9993
192	208911	21126	17.1	154	151	69.79	10120	0.9992
193	211641	27360	22.8	154	151	70.12	10092	0.9992
194	211039	21126	17.1	154	152	66.03	10120	0.9992
195	209992	23500	14.3	154	152	68.54	9952	0.9994
196	212240	23700	14.3	154	151	67	10310	0.9994

197	211755	24500	14.3	154	150	66.56	10360	0.9994
198	213592	23300	17.1	154	149	67.36	10371	0.9993
199	211277	23500	19.95	153	148	67.75	10259	0.9992
200	212016	23500	22.8	153	149	63.89	10343	0.9990
201	210826	20300	19.95	153	148	65.55	10259	0.9990
202	212110	21600	31.35	152	149	62.28	10176	0.9985
203	209793	19500	28.5	153	151	64.08	10204	0.9985
204	209667	19500	19.95	154	152	67.28	10232	0.9990
205	196835	21000	19.95	153	151	62.1	9896	0.9991
206	205000	21500	19.95	137	134	53.62	7464	0.9991
207	206000	21500	17.1	137	134	50.75	7492	0.9992
208	206000	21500	14.3	137	134	63.91	7464	0.9993
209	204000	21500	17.1	137	134	57.63	7436	0.9992
210	205000	21500	14.3	137	134	50.74	7408	0.9993
211	205000	21500	14.3	138	135	51.34	7268	0.9993
212	217000	25450	31.4	138	135	62.29	7442	0.9988
213	202000	23450	19.95	137	134	63.81	16101	0.9991
214	213000	27350	14.3	136	133	63.61	16297	0.9995
215	208000	27350	11.4	137	134	65.24	16241	0.9996
216	211000	27350	17.1	140	137	70.99	16143	0.9994
217	200000	26450	19.95	140	137	65.9	16255	0.9992
218	201000	27550	11.4	140	137	67.16	16353	0.9996
219	209000	25050	17.1	139	136	67.16	16311	0.9993
220	213000	19500	14.3	139	136	58.3	16381	0.9993
221	178000	19500	11.4	139	136	53.96	16381	0.9994
222	209000	11700	14.3	139	136	59.85	16381	0.9988
223	215000	14500	17.1	139	136	57.56	18925	0.9988
224	199000	19500	14.3	138	135	65.08	16073	0.9993
225	199000	16012	14.3	135	132	65.8	16269	0.9991
226	199000	13650	14.3	134	131	63.36	16409	0.9990
227	200000	17450	14.3	135	132	65.07	16549	0.9992
228	202000	19500	14.3	137	134	62.52	16381	0.9993
229	201000	19500	14.3	138	135	65.97	16451	0.9993
230	204000	21450	14.3	137	134	58.2	9589	0.9993
231	206000	19500	14.3	137	134	56.08	9505	0.9993
232	201000	19500	14.3	137	134	56	9449	0.9993
233	201000	19500	14.3	137	134	56.88	7771	0.9993
234	192000	19500	14.3	138	135	62.46	16409	0.9993
235	195000	19500	14.3	138	135	54.25	8959	0.9993
236	196000	19500	14.3	139	136	60.07	9504	0.9993
237	193000	19500	11.4	140	137	61.89	10030	0.9994

238	194000	21450	11.4	140	137	61.11	12062	0.9995
239	198000	21450	14.3	140	137	61.11	9113	0.9993
240	171000	21450	14.3	140	137	38	8959	0.9993
241	154000	19500	14.3	135	132	41.82	8023	0.9993
242	174000	21450	17.1	131	128	45.66	7576	0.9992
243	199000	26450	14.3	132	129	50.36	7631	0.9995
244	206000	26325	11.4	137	134	83.5	7659	0.9996
245	200000	25450	19.95	138	135	65.9	7715	0.9992
246	205000	25350	17.1	138	135	77.3	7542	0.9993
247	209000	23400	19.95	137	133	66.62	7352	0.9991
248	211000	25350	19.95	138	135	64.67	7603	0.9992
249	204000	24375	19.95	138	135	63	7953	0.9992
250	231000	21937	17.1	139	136	61.05	8484	0.9992
251	229000	20962	19.95	140	137	62.55	7869	0.9990
252	215000	19500	14.3	140	137	70.7	8135	0.9993
253	188000	19500	17.1	141	138	63.64	7799	0.9991
254	208000	19500	17.1	138	135	47.64	8330	0.9991
255	210000	19500	17.1	138	133	63.35	8582	0.9991
256	210000	19500	14.3	137	134	47.64	8861	0.9993
257	192000	21500	14.3	139	136	68.95	9365	0.9993
258	197000	19500	17.1	141	138	66.68	9365	0.9991
259	195000	19975	14.3	143	140	66.68	9365	0.9993
260	196000	20060	22.8	143	140	66.68	9365	0.9989
261	193000	20800	19.95	143	140	66	8526	0.9990
262	194000	23400	19.95	141	138	60.39	8232	0.9991
263	198000	19500	19.95	139	135	67.58	8316	0.9990
264	78000	20150	19.95	139	139	67.83	8316	0.9990
265	154000	22912	19.95	143	140	64.97	9309	0.9991
266	174000	23400	17.1	144	141	75.13	8861	0.9993
267	199000	23097	22.8	143	140	72.65	9309	0.9990
268	206000	23400	22.8	141	138	63.53	9812	0.9990
269	200000	23400	19.95	143	140	61.76	8861	0.9991
270	201000	41535	28.5	142	139	61.36	8610	0.9993
271	209000	19500	22.8	140	137	78.16	9001	0.9988
272	211000	19500	19.95	139	136	72.9	9029	0.9990
273	204000	19500	22.8	133	130	44.25	6877	0.9988
274	231000	23425	31.35	136	133	64.65	8204	0.9987
275	229000	24425	45.6	139	135	58.19	8218	0.9981
276	217000	23100	48.45	139	135	71.66	9281	0.9979
277	215000	20712	37.05	139	135	76.76	9272	0.9982
278	188000	23400	19.95	141	138	73.15	8568	0.9991

279	210000	23400	14.25	144	141	59.28	8973	0.9994
280	210000	23400	17.1	143	140	60.68	8526	0.9993
281	204000	19500	17.1	143	140	65.87	7799	0.9991
282	208000	19500	14.3	142	139	65.3	7799	0.9993
283	205000	20400	14.3	143	140	69.01	8330	0.9993
284	193000	19987	14.3	143	140	70.25	8470	0.9993
285	200000	21460	17.1	144	141	72.3	8680	0.9992
286	208000	24425	17.1	144	141	102.82	8638	0.9993
287	211000	18720	14.3	142	139	93.26	8386	0.9992
288	218000	22340	14.3	143	140	91.49	8414	0.9994
289	219000	19500	19.95	142	139	97.68	8369	0.9990
290	220000	19500	14.3	142	139	68.7	8484	0.9993
291	220000	19500	14.3	142	139	93.85	8554	0.9993
292	177000	19500	14.3	142	139	91.7	6857	0.9993
293	126000	19500	14.3	138	133	37.11	7128	0.9993
294	126000	19500	11.4	136	133	32.1	6709	0.9994
295	177000	19500	11.4	138	135	100.44	7967	0.9994
296	199000	19500	11.4	141	138	88.61	8246	0.9994
297	193000	19500	11.4	141	138	80.02	8191	0.9994
298	207000	19500	11.4	140	137	95	7995	0.9994
299	205000	21500	11.4	139	136	84.6	7799	0.9995
300	208000	19500	14.3	140	137	90.1	8330	0.9993
301	214000	21250	17.1	141	138	83.51	8135	0.9992
302	218000	23400	17.1	141	138	86.59	8218	0.9993
303	219000	24057	17.1	141	138	85.47	8023	0.9993
304	206000	21450	11.4	143	140	85.76	8023	0.9995
305	217000	23400	11.4	142	139	79.47	8051	0.9995
306	216000	25300	11.4	143	140	84.78	8051	0.9995
307	218000	21890	14.3	142	139	88.57	8526	0.9993
308	219000	18730	11.4	144	141	90.39	8554	0.9994
309	216000	19186	11.4	143	140	92.32	10511	0.9994
310	135000	24057	11.4	143	140	75.68	3327	0.9995
311	169000	23400	11.4	142	139	54.92	8288	0.9995
312	157000	19500	11.4	140	137	67.46	6583	0.9994
313	158000	23400	11.4	139	136	72.32	6569	0.9995
314	158000	20656	11.4	140	137	56.87	6715	0.9994
315	155000	22340	14.25	142	139	55.53	6793	0.9994
316	174000	21450	14.3	142	139	62.23	7947	0.9993
317	210000	21450	14.3	141	138	81.98	6122	0.9993
318	222000	19500	14.3	144	141	69.32	6066	0.9993
319	223000	21450	14.3	145	142	85.77	6122	0.9993

320	219000	19500	14.3	145	142	64.06	6122	0.9993
321	219000	19500	11.4	145	142	81.4	6122	0.9994
322	220000	19500	14.3	145	142	95.76	6318	0.9993
323	218000	21450	14.3	144	141	90.31	6010	0.9993
324	201000	19500	14.3	145	142	99.16	5786	0.9993
325	182000	19500	14.3	142	139	87.27	8514	0.9993
326	219000	19500	14.3	142	139	74.77	6429	0.9993
327	218000	19500	11.4	144	141	85.19	6639	0.9994
328	218000	19500	11.4	144	141	81.68	6360	0.9994
329	221000	19500	8.55	145	142	75.66	6460	0.9996
330	218000	19500	8.55	146	143	65.24	6513	0.9996
331	217000	19500	11.4	146	143	72.57	6332	0.9994
332	215000	19500	11.4	147	144	60.51	6206	0.9994
333	220000	19500	11.4	147	144	64.23	5912	0.9994
334	221000	19500	11.4	147	144	61.62	6318	0.9994
335	222000	21450	8.55	147	144	46.18	5842	0.9996
336	217000	20150	8.55	148	145	47.86	5745	0.9996
337	222000	20656	11.4	150	147	54.84	5954	0.9994
338	221000	21450	11.4	150	147	53.46	5786	0.9995
339	222000	21450	8.55	150	147	55.4	6136	0.9996
340	221000	21450	8.55	149	146	68.9	5731	0.9996
341	176000	21400	11.4	146	143	52.14	6248	0.9995
342	213000	23400	11.4	146	143	34.52	5954	0.9995
343	220000	21450	11.4	148	145	51.2	6136	0.9995
344	223000	21450	8.55	149	146	53.2	6709	0.9996
345	224000	21450	11.4	150	147	56.3	6332	0.9995
346	220000	19500	11.4	149	146	56.8	5814	0.9994
347	224000	19500	11.4	148	145	62.8	6332	0.9994
348	219000	19500	11.4	148	145	65.76	4808	0.9994
349	212000	19500	11.4	147	144	64.43	5759	0.9994
350	226000	19500	11.4	148	145	70.63	5842	0.9994
351	225000	19500	14.3	149	146	68.08	6066	0.9993
352	218000	19500	14.3	150	147	66.17	5814	0.9993
353	220000	19500	14.3	150	147	67.3	5842	0.9993
354	222000	17940	11.4	150	147	71.7	6038	0.9994
355	220000	18530	14.3	148	145	73.89	5591	0.9992
356	214000	19640	14.3	147	144	68.6	5731	0.9993
357	218000	25350	11.4	148	145	61.66	5731	0.9996
358	210000	29250	11.4	149	146	64.27	5731	0.9996
359	213000	21450	11.4	149	145	48.64	6038	0.9995
360	190000	23400	17.1	146	143	54.78	6010	0.9993

361	215000	21450	14.3	147	144	54.02	5884	0.9993
362	216000	22460	11.4	148	145	58.07	6122	0.9995
363	221000	21450	11.4	149	146	63	5926	0.9995
364	220000	21450	14.3	148	145	64.59	5786	0.9993
365	218000	23400	14.3	148	145	70.46	5479	0.9994
366	219000	21450	11.4	149	146	65.09	5451	0.9995
367	217000	21450	14.3	150	147	60.89	5786	0.9993
368	213000	21450	14.3	150	147	67.44	5619	0.9993
369	220000	21450	14.3	150	147	68.88	5842	0.9993
370	217000	21450	14.3	151	148	65.31	5717	0.9993
371	216000	21450	14.3	152	149	67.1	5842	0.9993
372	211000	23450	14.3	149	146	69.72	5423	0.9994
373	218000	23450	28.5	147	144	73.6	5088	0.9988
374	219000	24500	19.95	150	147	62.95	5395	0.9992
375	224000	21450	25.65	150	147	63.4	5311	0.9988
376	224000	21450	14.3	149	146	74.62	5004	0.9993
377	220000	21450	17.1	149	146	67.65	5004	0.9992
378	220000	21500	14.3	149	146	71.3	4682	0.9993
379	221000	21500	17.1	148	145	77.1	5143	0.9992
380	219000	21450	11.4	147	144	58.8	5171	0.9995
381	215000	21500	14.3	147	144	72.88	4976	0.9993
382	220000	21550	11.4	147	144	70.46	5116	0.9995
383	218000	21450	11.4	148	145	65.57	4920	0.9995
384	214000	21450	14.3	149	146	63.45	4724	0.9993
385	199000	20050	14.3	149	146	61.62	4696	0.9993
386	218000	20450	14.3	146	143	67.54	4291	0.9993
387	219000	21450	17.1	147	144	62.52	4473	0.9992
388	217000	21450	11.4	148	145	71.64	4207	0.9995
389	217000	21400	11.4	148	145	71.82	4417	0.9995
390	218000	20450	11.4	148	145	64.51	3746	0.9994
391	218000	19500	11.4	148	145	62.27	4305	0.9994
392	218000	19500	8.55	148	145	58.75	4333	0.9996
393	219000	19500	11.4	149	146	65.15	4668	0.9994
394	221000	19500	11.4	149	146	62.91	4193	0.9994
395	220000	21450	14.3	150	147	57.76	4109	0.9993
396	217000	21450	17.1	148	145	60.81	4794	0.9992
397	221000	21450	17.1	148	145	57.24	5381	0.9992
398	223000	20656	11.4	148	145	59.29	4864	0.9994
399	223000	21450	14.3	148	145	60.93	5758	0.9993
400	222000	21450	17.1	149	146	55.13	5786	0.9992
401	224000	22530	11.4	150	147	59.03	5199	0.9995

402	224000	23800	11.4	150	147	68.9	5814	0.9995
403	221000	26150	11.4	148	145	66.04	6597	0.9996
404	219000	22783	11.4	148	145	67.02	6122	0.9995
405	218000	22780	8.55	149	146	80.76	6108	0.9996
406	216000	19500	8.55	150	147	98.46	6597	0.9996
407	217000	19500	8.55	150	147	66.65	5661	0.9996
408	207000	20000	8.55	149	146	90.83	7016	0.9996
409	215000	20000	8.55	150	147	93.45	5772	0.9996
410	219000	22400	8.55	150	147	89.04	5870	0.9996
411	212000	22000	8.55	149	146	105.3	5957	0.9996
412	214000	19500	8.55	149	146	88.99	5859	0.9996
413	216000	20100	8.55	150	147	78.13	5890	0.9996
414	218000	20100	8.55	150	147	73.43	5926	0.9996
415	217000	20100	8.55	151	148	60	6373	0.9996
416	217000	20100	11.4	150	147	82.58	5954	0.9994
417	216000	20100	8.55	150	147	74	5884	0.9996
418	217000	20100	8.55	149	146	92.98	5717	0.9996
419	218000	20000	11.4	149	146	77.79	6024	0.9994
420	217000	21800	11.4	150	147	79.29	5884	0.9995
421	217000	21770	11.4	151	148	86.82	5479	0.9995
422	217000	22820	11.4	151	148	100.68	5703	0.9995
423	216000	23485	11.4	150	147	88.62	5898	0.9995
424	216000	22641	11.4	151	148	93.17	5828	0.9995
425	216000	21701	8.55	151	148	89.92	5968	0.9996
426	217000	22640	14.3	148	145	90.19	6318	0.9994
427	215000	19500	11.4	148	148	62.99	6122	0.9994
428	214000	21773	11.4	152	149	61.92	6373	0.9995
429	212000	19500	14.3	151	148	65.11	6373	0.9993
430	203000	19751	11.4	153	150	59.95	5884	0.9994
431	210000	19500	11.4	153	150	60.97	6359	0.9994
432	223000	20560	11.4	153	150	65.4	5884	0.9994
433	226000	21600	14.3	151	148	63	5968	0.9993
434	225000	23400	14.3	151	148	61.48	6513	0.9994
435	225000	23400	14.3	150	147	59.24	6541	0.9994
436	225000	23400	17.1	149	146	67.08	6373	0.9993
437	222000	22000	11.4	149	146	59.89	6429	0.9995
438	223000	22100	17.1	150	147	58.36	6262	0.9992
439	221000	22200	14.3	150	147	58.23	6318	0.9994
440	222000	22100	14.3	151	148	54.41	6262	0.9994
441	221000	23000	14.3	150	147	52.43	5828	0.9994
442	220000	22100	14.3	149	146	52.82	5828	0.9994

443	221000	22200	14.3	150	147	54.21	5968	0.9994
444	221000	22100	14.3	150	147	61.41	6457	0.9994
445	219000	22100	14.3	149	146	57.84	6220	0.9994
446	218000	22500	14.3	151	148	55.41	6024	0.9994
447	185000	22500	14.3	150	147	57.26	6122	0.9994
448	188000	23100	14.3	145	142	48.06	5507	0.9994
449	231000	22900	11.4	147	144	69.54	4934	0.9995
450	233000	22900	11.4	148	145	61.66	4864	0.9995
451	225000	22100	14.3	150	147	56.4	6150	0.9994
452	222000	22100	14.3	149	146	54.5	5060	0.9994
453	217000	23000	14.3	149	146	62.89	5311	0.9994
454	223000	23300	11.4	147	144	61.45	5744	0.9995
455	222000	24300	11.4	148	145	67.97	5171	0.9995
456	223000	24300	14.3	148	145	65.5	5102	0.9994
457	224000	23400	11.4	148	145	68.1	5521	0.9995
458	224000	23400	14.3	148	145	67.77	5353	0.9994
459	224000	25350	17.1	146	143	70.14	4906	0.9993
460	223000	25350	17.1	146	143	69.58	4878	0.9993
461	224000	21350	17.1	145	142	69.83	5395	0.9992
462	225000	23400	17.1	147	144	68.1	5102	0.9993
463	226000	23400	14.3	146	143	72.56	5060	0.9994
464	225000	23400	11.4	146	143	73.65	5088	0.9995
465	222000	19500	11.4	147	144	74.08	5088	0.9994
466	225000	19500	8.55	147	144	78.9	5171	0.9996
467	215000	23400	11.4	146	143	70.52	5814	0.9995
468	223000	23400	11.4	145	142	70.5	5395	0.9995
469	222000	23400	11.4	144	141	72.5	5591	0.9995
470	226000	23400	11.4	145	142	71.17	5157	0.9995
471	226000	23400	11.4	145	142	72	5283	0.9995
472	229000	23400	14.3	145	142	73.39	5437	0.9994
473	231000	23400	14.3	144	141	74.6	5339	0.9994
474	228000	23400	11.4	147	144	74.42	4640	0.9995
475	223000	23600	11.4	144	141	96.8	5018	0.9995
476	225000	23750	11.4	143	140	81.07	5884	0.9995
477	218000	22400	11.4	146	143	87.79	5060	0.9995
478	213000	24200	11.4	145	142	90.73	4668	0.9995
479	216000	23400	11.4	143	140	91.11	5521	0.9995
480	217000	23400	8.55	145	142	88.59	5199	0.9996
481	223000	23400	11.4	144	141	85.89	5269	0.9995
482	224000	23400	14.3	144	141	86.14	5032	0.9994
483	225000	24300	17.1	144	141	73.97	5060	0.9993

484	224000	19500	17.1	144	141	75.54	5032	0.9991
485	218000	25000	17.1	145	142	67.76	4906	0.9993
486	221000	19500	17.1	145	142	68.67	4864	0.9991
487	221000	19500	17.1	143	140	72.7	5032	0.9991
488	219000	24250	17.1	143	140	79.7	5032	0.9993
489	222000	19500	17.1	142	139	71.7	5060	0.9991
490	222000	19500	17.1	143	140	73.9	5255	0.9991
491	221000	29400	14.3	143	140	79.59	5060	0.9995
492	219000	23650	11.4	143	140	82.88	5060	0.9995
493	219000	25500	11.4	143	140	79.99	5032	0.9996
494	223000	21500	11.4	143	140	79.81	4948	0.9995
495	221000	22300	11.4	143	140	72.78	4948	0.9995
496	218000	21300	11.4	142	139	76.74	5116	0.9995
497	224000	21300	11.4	143	138	76.62	5591	0.9995
498	224000	21300	11.4	140	137	76.91	5745	0.9995
499	196000	20100	14.3	143	140	56.52	5954	0.9993
500	218000	21000	11.4	140	137	71.99	6178	0.9995
501	218000	19500	11.4	144	141	75.95	5968	0.9994
502	217000	19500	8.55	145	142	72.34	6415	0.9996
503	219000	19500	8.55	147	144	76.18	6290	0.9996
504	220000	19880	11.4	146	143	77.3	6387	0.9994
505	221000	19500	11.4	144	141	77.82	6387	0.9994
506	226000	21000	11.4	143	140	77.66	6639	0.9995
507	220000	19500	11.4	142	139	83.28	5954	0.9994
508	223000	19500	11.4	142	139	83.58	6262	0.9994
509	194000	19500	8.55	143	138	69.97	6122	0.9996
510	189000	19500	11.4	137	134	81.82	6066	0.9994
511	206000	21000	8.55	139	136	73.87	6360	0.9996
512	203000	19500	8.55	140	137	71.78	6066	0.9996
513	212000	19500	8.55	142	139	76.09	6415	0.9996
514	217000	19500	8.55	143	140	68.63	6360	0.9996
515	215000	21000	8.55	144	141	73.83	5032	0.9996
516	212000	19500	8.55	143	140	73.56	6066	0.9996
517	197000	19500	8.55	143	140	82.82	5870	0.9996
518	213000	19500	8.55	143	140	66.57	5968	0.9996
519	215000	19975	8.55	141	138	60.32	6038	0.9996
520	209000	19500	8.55	141	138	64.19	5870	0.9996
521	211000	19500	8.55	143	140	71.93	6164	0.9996
522	204688	21800	11.4	142	138	57.45	6887	0.9995
523	211215	22400	19.95	142	139	50.74	7236	0.9991
524	207130	21000	19.95	143	139	49	6597	0.9991

525	213508	22100	19.95	142	140	52.91	7258	0.9991
526	213011	22200	17.1	143	140	51.83	7236	0.9992
527	204451	23400	17.1	138	134	53.68	6555	0.9993
528	203323	21350	11.4	141	138	47.55	6737	0.9995
529	212233	21350	17.1	140	137	59.57	7156	0.9992
530	153607	25400	11.4	140	137	47.51	6010	0.9996
531	209769	21200	14.3	144	142	55.02	6387	0.9993
532	197274	23100	14.3	137	134	56.77	7324	0.9994
533	213448	22000	22.8	144	142	49.72	6905	0.9990
534	214467	21500	11.4	144	142	54.29	6849	0.9995
535	217384	19500	11.4	143	140	50	7268	0.9994
536	210002	23000	14.3	145	143	52.71	6849	0.9994
537	218418	22100	19.95	146	143	50.61	6877	0.9991
538	214770	23100	14.3	147	144	54.48	8810	0.9994
539	215179	23000	8.55	149	148	56.8	6877	0.9996
540	213264	20450	14.3	148	145	57.6	6988	0.9993
541	206982	22400	57	148	144	64.79	6960	0.9975
542	151248	23000	14.3	138	134	43.05	6611	0.9994
543	181052	25450	17.1	139	135	81.82	7016	0.9993
544	211079	23000	11.4	152	149	57.37	7436	0.9995
545	194661	20500	11.4	153	150	62.08	11824	0.9994
546	211253	19500	14.3	154	152	71.7	9644	0.9993
547	211154	21450	17.1	277	275	54.32	9197	0.9992
548	213364	25350	17.1	150	148	64.85	6486	0.9993
549	199335	26600	17.1	157	155	60.95	9728	0.9994
550	217136	22550	22.8	152	149	61.54	10204	0.9990
551	216504	21350	17.1	154	149	55.6	9759	0.9992
552	216469	21600	17.1	155	152	71.18	10008	0.9992
553	214892	21600	17.1	155	152	67.66	9700	0.9992
554	215829	21600	17.1	153	148	74.87	10064	0.9992
555	209727	21350	17.1	154	148	63	10120	0.9992
556	210365	25433	17.1	154	151	68.8	10148	0.9993
557	209642	25700	14.3	154	152	67.74	10036	0.9994
558	213629	23000	17.1	152	148	65.15	10176	0.9993
559	207842	19500	17.1	153	150	65.04	10036	0.9991
560	211000	23500	17.1	138	135	65.39	12859	0.9993
561	206000	26350	14.3	139	136	60.55	19232	0.9995
562	194000	19500	14.3	138	135	65.7	16241	0.9993
563	203000	19500	14.3	137	134	66.82	16409	0.9993
564	197000	19500	14.3	137	134	59.91	16423	0.9993
565	78000	21450	14.3	137	134	36	7743	0.9993

566	201000	25350	22.8	139	136	61.95	7715	0.9991
567	217000	19500	19.95	139	136	67.2	7939	0.9990
568	201000	19500	14.3	137	134	47.64	8973	0.9993
569	171000	21450	14.3	139	135	67.83	8316	0.9993
570	205000	19500	28.5	142	139	65.74	8526	0.9985
571	208000	23400	17.1	142	139	56.42	9043	0.9993
572	204000	20656	25.65	143	140	89.79	8386	0.9988
573	107000	19500	17.1	139	136	45.92	6346	0.9991
574	202000	21500	11.4	140	137	91.39	7939	0.9995
575	219000	23400	17.1	142	139	89.55	8163	0.9993
576	216000	19500	11.4	144	141	88.26	10539	0.9994
577	223000	21450	14.3	141	138	72.49	6178	0.9993
578	216000	21450	14.3	145	142	92.64	6122	0.9993
579	213000	19500	11.4	147	144	61.08	6010	0.9994
580	222000	19500	11.4	147	144	58.98	4976	0.9994
581	219000	23400	11.4	149	146	68.21	6332	0.9995
582	220000	19500	8.55	148	145	70.6	6332	0.9996
583	223000	19500	14.3	150	147	68.8	6080	0.9993
584	214000	23540	11.4	148	145	54.23	5731	0.9995
585	217000	21160	14.3	149	146	61.14	5745	0.9993
586	218000	21500	25.65	148	145	68.86	5283	0.9988
587	221000	21450	14.3	147	144	68.14	4976	0.9993
588	217000	19500	11.4	148	145	64.51	4249	0.9994
589	222000	21160	11.4	148	145	56.64	5605	0.9995
590	221000	19500	8.55	150	147	84.75	6401	0.9996
591	218000	20100	8.55	150	147	84.79	5814	0.9996
592	216000	23820	11.4	151	148	87.35	6345	0.9995
593	216000	22640	11.4	148	145	72.31	6262	0.9995
594	226000	23400	11.4	152	149	69.53	5940	0.9995
595	222000	21100	14.3	150	147	59.68	5996	0.9993
596	222000	23400	11.4	146	143	67.21	5144	0.9995
597	222000	24300	11.4	148	145	61.45	5199	0.9995
598	223000	24300	17.1	145	142	67.7	4850	0.9993
599	227000	19500	11.4	146	143	71.7	5227	0.9994
600	225000	23400	11.4	146	143	91.09	5703	0.9995
601	220000	23400	11.4	146	143	86.66	5241	0.9995
602	219000	19500	17.1	144	141	74.68	4864	0.9991
603	220000	29400	11.4	144	141	76.09	5227	0.9996
604	224000	22100	11.4	143	140	72.06	5954	0.9995
605	216000	19500	11.4	144	141	77.75	6262	0.9994
606	204000	19580	8.55	138	135	80.31	6080	0.9996

Appendix B

Paper for Publication

MODELLING OF A LIBYAN CRUDE OIL DESALTER USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT :

Removal of salts from crude oil is important because at high temperatures they cause hydrolysis and form HCl which in turn causes corrosion in the downstream equipment. The likelihood of harmful and rapid corrosion increases as the pH level of crude drops lower. This paper presents a methodology based on the development of an Artificial Neural Networks (ANN)) for the investigation of salt removal efficiency of a crude oil de-salter. The ANN model's predictions can be utilized to investigate the effects of seven different input variables on the efficiency of salt removal. These variables are: salt intake and salt out from a de-salter, inlet and outlet temperatures of the crude, amount of chemical demulsifier and amount of fresh water added to the de-salter feed.

Keywords: Crude Oil; Desalting; Artificial Neural Networks; Optimisation

ARABIAN GULF OIL COMPANY

To whom it may concern

The Libyan oil company gave permission to Almahdi Salah Alhutmany to collect desalter data he needed to carry out his PhD research under a government scholarship. Theoretically his findings so far will be helpful in optimisation of the desalting process and as a result of that demulsifier costs will be reduced significantly.

The Arabian Gulf Oil company (AGOCo) is looking forward to meet Mr Almahdi Salah Alhutmany to discuss the possibility of implementing his programme on our operating system.

Kind Regards,

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