Department of Chemical Engineering

Development of an Artificial Neural Network Model for Predicting the Performance of a Reverse Osmosis (RO) Unit

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This thesis is presented for the Degree of
Master of Engineering
of
Curtin University of Technology

July 2009

DECLARATION

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Signature:

Date:

ACKNOWLEGMENTS

I would like to express my profound gratitude to A/Prof. Hari B. Vuthaluru for his support, guidance and invaluable technical advice during the course of my thesis. I would like to thank Professor H. Ming Ang for his constant guidance and support during the course of this project. I would like to thank my colleagues from the Chemical Engineering Department at Curtin University of Technology for their moral support and ideas generated during our constant discussions. I would also like to acknowledge the chemical engineering department staff for their assistance and help during the course of my project. Finally, I would like to thank my parents for their consistent support and encouragement through this period and I would like to dedicate this thesis to them. Without them this thesis would never have been possible.

List of Publications

1. R. Righton, H.B. Vuthaluru and H.M. Ang, "Artificial Neural Network Based Model for predicting the Membrane Performance of a Small Scale Reverse Osmosis Unit." Manuscript submitted to Desalination Journal (2009).

Summary

Desalination is one of the most widely used techniques to produce pure water from seawater, groundwater, wastewater or brackish water. This technique has gained wide spread acceptance throughout the world especially in arid and dry regions like the Middle East which possesses the largest capacity desalination plants in the world. On the other hand, Australia which is characterised by its arid regions does not utilise desalination as a source of providing pure water as compared to the Middle Eastern regions. The increasing population in the capital cities and the inhabitants of the isolated mining towns and smaller remote communities would benefit from using desalination. Reverse Osmosis (RO) is the one the widely used desalination technique in the world. It offers the distinct advantage over the other desalination techniques because it consumes low energy, provides a high quality final product, easy installation and flexible design. RO works on the principle of osmosis where the transfer of the solvent is done through a semi permeable membrane under the influence of a concentration gradient. The quality of the pure water that passes through the membrane during the RO process is a function of the difference between the applied pressure and the osmotic pressure of the solution.

This thesis presents the experimental results obtained from a small scale RO system conducted by Nasir (2005) and a method for the simulation of membrane performance by using artificial neural networks was developed. The experimental RO data obtained using synthetic water samples containing solutes ranging from sodium chloride, calcium carbonate, a combination of both, groundwater and industrial effluent was used to develop the neural network model. The neural network model successfully predicts the two important parameters on which the RO operation is based i.e. the solute rejection percentage and permeate flux. Using a neural network having two hidden layers and having a series of inputs of different concentrations, pressure and flow rates of the composite streams these two parameters were predicted. The artificial neural network model created was verified using the experimental data obtained from pilot plant scale RO operations set up in Sharjah and Qatar.

From the results obtained the simulated results for solute rejection and permeate flux are close to the analytical i.e. experimental obtained results. Traditionally membrane

performance has been predicted by polynomial correlations but the neural network model offers the advantage allowing the user to visualise the entire operation, capability of learning from the experimental results and obtaining highly accurate findings. The model generated in this study will provide the solid foundation for extending the ANN model applicability to cover several feedwater sources over a range of different pressures and concentrations.

The thesis describes the development of an Artificial Neural Network Model for predicting the two important parameters of Reverse Osmosis i.e. salt rejection and permeate flux. The thesis comprises of six sections including the conclusions and recommendations for future work.

Chapter details the general background of the current state of water supplies in Australia, looks at the existing RO plants that have been set up or being planned for the future and establishes the various uses of RO practices.

Chapter 2 contains a detailed literature review on desalination and its various processes, understanding the way RO works and the factors that affect the RO operation and performance.

Chapter 3 presents the modelling approach used during this study and introduces the reader to artificial neural networks and the manner in which they function.

Chapter 4 contains a brief description of the experimental procedures conducted by Nasir (2005) and this experimental data forms the basis for the model development.

Chapter 5 deals with the development of the artificial neural network model for predicting the performance of a RO system handling different feedwater sources and validation of the developed ANN model.

Chapter 6 presents the conclusions obtained from this study and the recommendations for future work to be conducted in order to expand the developed ANN code to cover different feedwater samples.

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A	Solvent permeability coefficient	$(kg.m^{-2}kPa^{-1}s^{-1})$
B	Solute permeability coefficient	$(m\ s^{-1})$
C	Concentration	(mg/L)
Cf	Feed Concentration	(mg/L)
Cm	Concentration in the membrane wall	(mg/L)
Cp	Permeate Concentration	(mg/L)
CP	Concentration Polarization	-
Cr	Concentration in the reject stream	(mg/L)
D	Solute diffusion coefficient	$(m^{-2}s^{-1})$
FL	Flow Rate	(l/min)
I	Ionic strength	(mol/kg)
Jp	Permeate volumetric flux	$(m\ s^{-1})$
Js	Solute mass flux	$(kg.m^{-2}s^{-1})$
Jw	Permeate Flux	(m/s)
K	Mass transfer Coefficient	(m/s)
L	Membrane thickness	(m)
LSI	Langelier Saturation Index	-
P	Pressure	(kPa)
Pf	Feed Pressure	(kPa)
Qc	Concentrate flowrate	$(m^3hr\ )$
Qf	Feedwater Flowrate	$(m^3hr\ )$
Qp	Permeate Flowrate	$(m^3hr\ )$
R	Ideal Gas constant	(joule/mol.k)
T	Temperature	(K)
ΔC	Concentration gradient	(mg/L)
ΔP	Membrane pressure gradient	(kPa)
$\Delta\Pi$	Osmotic pressure difference	(kPa)
ρ_ψ	Permeate density	$(kg\ m^{-3})$
σ	reflection coefficient	-

LIST OF ABBREVIATIONS

AAS	Atomic Absorption Spectroscopy
ABS	Australian Bureau of Statistics
ANN	Artificial Neural Network
DC	direct current
EC	Electrical Conductivity
ED	Electrodialysis
EDR	Electrodialysis Reversal
HSD	Homogenous solution model
MED	Multi effect distillation
MF	Micro Filtration
MSF	Multistage Flash Distillation
NAP	National Action Plan
NF	Nano Filtration
NN	Neural Networks
NOM	Natural Organic Matter
RO	Reverse Osmosis
RP	Rejection Percentages
SDI	Silt density index
SR	Solute Rejection
SWRO	Seawater Reverse Osmosis
TDS	Total Dissolved Solids
TOC	Total Organic Carbon
UF	Ultra Filtration
USP	United States Pharmacopeia
VC	Vapour Compression
WRP	Water Recovery Percentages

Chapter 1 Introduction

1.1 Background

The new millennium which dawned upon the world brought certain issues which mankind had to address. The issue of pollution, world hunger and climate change are just some of the problems facing the world in the coming decade. Among the worst is climate change which is affecting our natural water sources and creating drought and famine in various parts of the world. The problem of drought is a very serious issue in Australia and is badly affecting the farmers. In an arid continent like Australia, supplies of portable water are a very limited resource. Recent studies undertaken as part of the Murray Darling Basin Salinity Audit and the National Land and Water Resources Audit have highlighted the decline in the quality of the water sources (Quiggin, 2001).

Water is the most desired natural elements available to man. The uses of water are mainly for human consumption, to satisfy industry needs, agricultural purposes and recreational activities. Water can be obtained either naturally through rain water or created using artificial man made procedures like desalination. Most of the naturally available water lies in our oceans and 97.5% of our planet is covered with water. But the water available cannot be used for human consumption due to the presence of sea salt. The remaining water lies locked up in glaciers, ice caps and ground water. Another source of natural water is rainwater (Bidlack, et al. 2004). Some parts of the world achieve enough rain to satisfy their water demands but Australia due to its location and arid climate cannot rely on rainwater alone.

Fresh water is the most widely used natural resource available to man. Water is a renewable source but the sources of fresh water are rapidly decreasing. The demand for fresh water is increasing at an alarming rate. The current demand for water exceeds the supply in different parts of the world. Fresh water is a scarce resource in arid and dry regions like the Middle East, North Africa and Australia. It is of great importance that people have access to water which is free from impurities. Conservation of forests has assumed great importance because it balances the ecosystem. As per the United Nations Millennium Summit (2000) governments should be committed to environmental sustainability (Sachs and McArthur, 2005). Governments should aim to reduce the proportion of people without access to fresh water through technological advancements and scientific initiatives (Brown, 2006).

Australia is considered the driest inhabited continent on the planet. The rainfall and stream flow are naturally highly variable. Most lowland areas experience periods of barren and flood, and often have large floodplains with connected wetlands. Southern rivers have been extensively dammed to provide a reliable water source for agriculture and urban usage. The rivers in the northern topical regions are unmodified but they carry two thirds of Australia's surface water (Beeton, et al. 2006). The country is currently in its worst drought in recorded history and the consequences are disastrous. The results of this acute water shortage have been increasing food prices and severe water restrictions on farmers and house hold consumers.

The average house hold water consumption has increased by 13% in the last decade (Australian Bureau of Statistics, 2007). The current water demand is satisfied by existing ground water and surface water sources. The long term solution is not these existing water sources due to increasing population which leads to increased water demands. When the new millennium dawned upon the word, the issue of climate change took an extremely significant importance to human existence on planet earth.

Climate is the most essential component of the water cycle. Due to inevitable climate change projections of future warming and decrease in rainfall is likely to increase the water demand and further reduce water supply. Changes in the water supply over the city of Perth over the last decade represent the risks other major Australian capital cities are likely to encounter. Apart from Darwin all major Australian cities have water restrictions and face severe water shortage (Gallant, et al. 2007). The solution is to create a reliable water source which will constantly satisfy the society and industrial water demands. This can be achieved through Reverse Osmosis. Middle Eastern countries such as Saudi Arabia have the largest capacity and greatest number of desalination plants in operation. Although Australia has a large number of isolated communities and an arid region, desalination is not widely practiced. Isolated mining towns and communities require high quality water and these demands could be solved using Reverse Osmosis.

1.2 Groundwater and Surface Water Distribution in Australia

Australia relies on ground and surface water as a reliable source of fresh water. Groundwater is defined as water that is located in spaces and cracks between particles of soil, sand, gravel and rock. It can also be obtained from aquifers flowing below the water table. Groundwater results from water precipitation of rain and snow. Also the water that is not used by vegetation seeps below the surface of the ground to become groundwater. In this manner groundwater is constantly recharged. Groundwater is greatly reliant on the existing climatic conditions. Long term climatic changes due to pollution and other factors affect groundwater. In most areas groundwater getting recharged through precipitation and outflow from streams is sufficient to sustain the groundwater level. But in areas of low rainfall and dry climate groundwater cannot be recharged and groundwater levels drops (Murray, et al. 2003).

Around 21% of water used in Australia is obtained through groundwater resources. From the available ground water around 32% is used to meet urban and industrial demands, 51% for irrigation and 17% for stock watering and rural use. However South Australia, New South Wales and Victoria use groundwater primarily for irrigation while Western Australia uses its groundwater resources for urban and industrial purposes. Queensland utilises its groundwater resources mainly for rural stock and domestic use (Wantm, 2005).

Groundwater is found below most land in Australia but it is not equally distributed. The water quality and type of aquifer varies in different regions around the country. In some areas it forms a major part of the fresh water source while in some areas it is totally absent. As per Western Australia department of water, the Perth region and the Swan Coastal plain the superficial aquifer is around 50 metres. In the north of the city at Gnangara (located in between the Swan river, Ellenbrook, Moore River and Wanneroo) the superficial aquifer is 15 kilometres thick. Below the superficial aquifer there are a number of confined aquifers, the largest and most extensive of which are the Leederville, which is typically several hundred metres thick, and the Yarragadee, which is often greater than 1000 metres (Wantm, 2005).

1.3 Reverse Osmosis Plants Around Australia and Government Initiatives

Reverse osmosis allows undesired water to be converted into water which is free of bacterial or aesthetic containments. Reverse osmosis applications are utilised for providing pure treated water to the kitchen for human consumption or in industries for commercial and industrial usage. According to the International Desalination Association there are 13,080 desalination plants in operation around the world. Most of these plants are located in the Middle East because desalination requires a large amount of energy and oil is abundant in these nations (Buros, 2000). With climate change and severe drought affecting different parts of the world the use of desalination has increased.

The importance of desalination has been realised in Australia and various desalination plants have been constructed in the last decade. Desalination has been proposed by the Government for the number of the capital cities as a supplement to the existing sources of water. The very first desalination plant The Coolgardie Water Distiller which was thermal based was set up in Western Australia in 1896 (Urs, 2002). Reverse osmosis technologies are in place in different parts of Australia such as The Perth Seawater Desalination plant using sea water reverse osmosis (SWRO) located in Kwinana, Western Australia. The plant is located in Kwinana around 25 kilometres south of the main city centre and has a capacity of 140, 000m^3 and an annual output of 45GL of water supplying 17% of Perth's water needs. The Western Australian State Government has also proposed a $955 million desalination plant in Binningup near Bunbury that would deliver 45GL of water per year that would begin operation by 2011. In total there are 15 desalination plants set up in Western Australia with a combined capacity of 5-1800 m^3/day. Other examples include Ravensthorpe in Southern Western Australia, Denham north of Perth and Rottnest Island off the coast of Fremantle.

A $1.1 billion plant is currently being built at Tugun on the Gold Coast and will supply 46 Giga Litre of water a year. A Reverse Osmosis Filtration and Ozone Disinfection unit has been established in Goondiwindi Queensland since 1994 and handles 400kL/day with a TDS of 1800mg/L. The Victorian Government is building a 150GL plant in Gippsland, including interconnecting pipe work which is expected to cost about $3.1 billion and will be in operation by 2015. In New South Wales a 90G/L desalination plant is being built for Kurnell at a cost of about $1.76 billion. The RO plant at Penneshaw in South Australia provides portable water to the township of Penneshaw on Kangaroo Island, a few hours south of Adelaide. The plant uses RO technology to supplement its existing dam water supplies and uses seawater as the main feedwater source. The RO plant at Bayswater in New South Wales is the largest zero emission desalination plant in the world and provides 35ML/day of highly pure water to the adjacent power station (Baron, 2006).

Around the world desalination plants using reverse osmosis have been planned. Singapore has announced the construction of a large scale recycling plant using low fouling reverse osmosis membranes. The plants will have the capacity to produce 228,000 cubic meters of water per day and will be completed in phases by 2010.The Ashkelon seawater reverse osmosis (SWRO) plant the largest in the world located in Israel was voted 'Desalination Plant of the Year' in the Global Water Awards (Landers, 2006). With a capacity of 320,000m^3 per day, the plant produces around 13% of the country's domestic consumer demand – equivalent to 5–6% of Israel's total water needs at one of the world's lowest ever prices for desalinated water.

Individuals in power in local and international governments assume the supply of fresh water and its resources is inexhaustible. The per capita water supply worldwide is one third lower as compared to 25 years ago (Serageldin, 1999). The current population growth coupled with climate change paints a bleak future for fresh water and its resources. Due to the arid nature of Australia the sources of fresh portable water are scarce. The government of Australia has taken a note of this and put certain programs into action. The recent studies conducted on the Murray Darling Basin and the natural land and water resources have indicated the increase in salinity in the groundwater and surface water. This will result in decreased water quality and greatly affect Australia. Increase in salinity of ground and surface water will also result in damage to infrastructure and greatly reduce the productive potential of the region. Hence Australia has set up a National Action Plan (NAP) to address the salinity and water quality issues. The NAP has identified 21 priority regions where rising salinity is of major concern. The NAP has proposed better rainfall prediction techniques, using rain water efficiently and intercepting groundwater (Urs, 2002).

1.4 Potential Users of Reverse Osmosis Practices

The water available through desalination techniques like reverse osmosis can be used for domestic or industrial purposes. Reverse Osmosis has the potential to provide high quality drinking water and water for household applications. It can put into use to supply small towns or large cities. In Australia the isolated towns and mining communities have inadequate water resources and reverse osmosis plants on a small scale can provide water to the inhabitants of these communities (Robinson, et al. 1992).

Power plants, fertilizer plants and irrigation systems consume a large quantity of water for industrial purposes. The waste water resulting from their operations is termed as effluent and cannot be discharged directly into our waterways or sewage systems. Hence installing a reverse osmosis system for these industrial is essential. Reverse osmosis systems can be used to treat boiler feed water, industrial wastewater, process water and more. A few of the major uses for RO system applications are:

Boiler Feed Water Treatment: Reverse osmosis systems can be used to reduce the solids content of water before it is feed into the boilers for power generation.

Pharmaceutical: Reverse osmosis is an approved treatment process for the production of United States Pharmacopeia (USP) grade water for pharmaceutical applications.

Semiconductor: Reverse osmosis is an important component of a treatment process used to create ultrapure water which is a major constituent of the semiconductor industry (Betts, 2004).

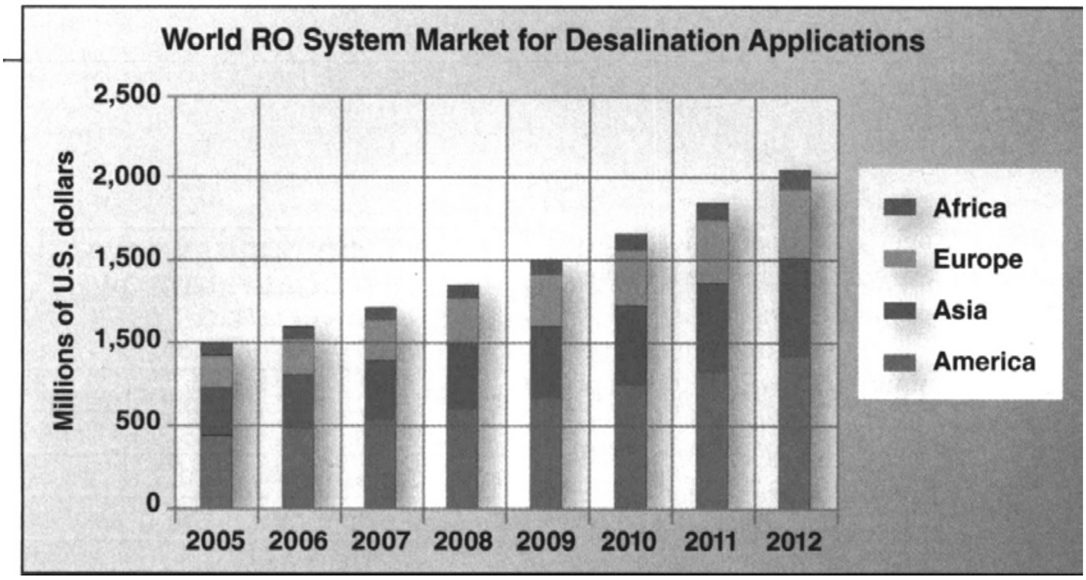

Figure 1.1 World Reverse Osmosis Market Distribution for Desalination Application (Boswell, 2005)

Reverse Osmosis represents the world's largest market for large-scale desalination systems with applications including desalination of both seawater and brackish water as shown in Figure 1.1. In 2007, worldwide sales of RO systems for desalination have been estimated to be approximately $1.7 billion. By 2012, this market is expected to reach $2.1 billion. In the Middle East, for example, the market for RO systems in desalination applications grew from $434 million in 2005 to $535 million in 2007. By 2012, this market is expected to grow to over $900 million representing 68% growth over the next five years. Ongoing industrialization and urbanization in China and South Korea continue to press water demands. There, the RO markets for desalination applications are forecast to reach $473 million and $248 million, respectively (Boswell, 2005). Thus the market for desalination has been established in the World and Australia needs to utilize this technology in order to meet the future industrial and community water requirements.

Desalination is not a new technology in Australia and various plants are currently in operation supplying water to supplement the existing water sources. The current status, future prospects and economics of these desalination technologies are well documented and there exists the potential to further increase the capacities of these existing plants as well as construction of new plants (Crisp, 2005).

1.5 Issues Associated with Reverse Osmosis Desalination

One of the main components of a Reverse Osmosis unit is the membrane. Since the RO technology is membrane based the performance of the system will depend on the membrane performance. The build up of solute on the membrane which leads to concentration polarization and cake formation, salt rejection and permeate flux are the important parameters which indicate membrane performance. RO membranes are expensive and have a life expectancy of 2-5 years. The main feed water source for most RO plants are seawater and industrial effluent or waste water. If the RO plant utilizes seawater as the feed water source, there can be interruptions to the service during stormy weather. This causes resuspension of the particles leading to increase in the amount of suspended solids in the seawater. The main contaminants present in seawater are sodium and calcium and the presence of these ions lead to increase solute build up on the membrane resulting in concentration polarization. This also reduces shell life of the membrane. If the feed water source is waste water, there is a possibility of bacterial contamination. Although this would be retained in the reject stream, bacterial growth on the membrane will result in bad taste and odour in the product water.

Most failures in RO systems are caused by the feed water not being pre treated satisfactorily. Pre treatment of the feed water is required in order to remove particulates so that the RO membrane lasts longer. Utilizing an effective pre treatment procedure for the feed water before it is fed into the RO system reduces the possibility of scaling and fouling and a higher quality final water product. Most RO plants operate at a high pressure and sometimes there are problems assoicated with the mechanical failure of the equipment in usage due to the high operating pressure. There is a need to operate the RO system at such an elevated pressure in order to reduce the energy consumption and operating pressure cannot be minimized because of osmotic pressure of the solution.

1.6 Objectives of the Study

The main objectives of this study is to predict the two important factors on which Reverse Osmosis performance is based i.e. the salt rejection and permeate flux. The study focuses on using feed water sources having sodium chloride and calcium carbonate impurities and also groundwater and industrial effluent which are potential water sources for Reverse Osmosis. Using Matlab an artificial neural network code is developed which successfully predicts these two parameters based on a series of inputs of different concentrations, pressure and flow rates of the composite streams. The developed neural network model will be validated using literature data obtained from RO operations set up in Sharjah and Qatar.

1.7 Significance of the Study

The significance of this project is to provide a clean water source for human as well and industry usage. With the natural water sources depleting and climate change on the horizon it is essential to establish a reliable water source to meet the future water needs. There are already various existing and proposed projects in Australia utilizing Reverse Osmosis desalination technology. An important aspect of this project is to create a realistic and reliable model which will effectively predict the performance of a RO unit. Using this model in such proposed locations will help to increase the quality of the final water product.

1.8 Organization of the Thesis

The thesis describes the development of an Artificial Neural Network Model for predicting the two important parameters of Reverse Osmosis i.e. salt rejection and permeate flux. The thesis comprises of six sections including the conclusions and recommendations for future work.

Chapter 1 details the general background of the current state of water supplies in Australia, looks at the existing RO plants that have been set up or being planned for the future and establishes the various uses of RO practices.

Chapter 2 contains a detailed literature review on desalination and its various processes, understanding the way RO works and the factors that affect the RO operation and performance.

Chapter 3 presents the modelling approach used during this study and introduces the reader to artificial neural networks and the manner in which they function.

Chapter 4 contains a brief description of the experimental procedures conducted by Nasir (2005) and this experimental data forms the basis for the neural network model development.

Chapter 5 deals with the development of the artificial neural network model for predicting the performance of a RO system handling different feedwater sources and validation of the developed ANN model.

Chapter 6 presents the conclusions obtained from this study and the recommendations for future work to be conducted in order to expand the developed ANN code to cover different feedwater samples.

Chapter 2 Literature Review

2.1 Introduction and Establishing the Need for Reverse Osmosis

Australia has relied on natural resources for fulfilling its domestic and industrial water demands. The main sources for centuries have been rainwater, groundwater and surface water. The water level in our rivers and lakes has dropped due to irregular rainfall and climate change. This has greatly affected the towns and cities depending on these water bodies for their water needs. These issues along with increasing urbanization will shape the future water demand for the major Australian cities. Water demand for the major Australian cities based on population growth alone is expected to increase by 31% for Brisbane, 48% for Perth, 33% for Sydney and Melbourne and 13% in Adelaide by 2031 (Birrell, et al. 2005). The local governments have temporary solutions in place like water cuts, water restrictions and better management of our water bodies along with recycling of domestic as well as industrial water.

The major problem associated with groundwater for future sustainability is the increase in the salinity. Normally groundwater is a chemically stable source of water over a long period of time. In regions close to the coast where pumping is undertaken the groundwater quality needs to be considered. The quality of the groundwater source i.e. the aquifer must be tested in order to observe the changes in the water quality. Under normal conditions where there are no contamination sources the aquifer produces a high quality of water over many years (Rengasamy, 2008).

Hence to meet future water demands it is essential to have in place sustainable water management through desalination technologies like reverse osmosis without compromising on water quality. The main sources for feedwater for desalination processes are seawater, brackish groundwater, domestic and industrial wastewater. Desalting seawater or industrial waste water could provide water to 1.2 billion people worldwide who do not have access to clean drinking water (Hairston, 2006). This chapter will look at the different types of desalination processes available and establish the fundamentals of reverse osmosis.

2.2 Understanding Desalination

Desalination can be defined as a process that removes dissolved minerals from feedwater sources such as brackish, seawater or industrial wastewater. It can also be referred to a process that eliminates excess salt and undesired minerals from water. It is essential these undesired minerals and excess salt is removed from the water to make it fit for human consumption or industrial use (Betts, 2004).

The techniques for desalination can be classified into three categories based on the main process principle.

1) Membrane process like Reverse Osmosis and Electro dialysis use membranes as a physical separation process where salt and undesired minerals are separated from the feedwater. Membrane separation processes are widely used in industry as compared to the thermal processes because of their low energy consumption, high product quality, flexible design and easy installation

2) Thermal Process like Multistage Flash Distillation, Multi effect Distillation, and Vapour compression are based on the physical change in the state of the feed water. These processes consume a large amount of energy regardless of the level of dissolved salts present in the water.

3) The process based on chemical bonds like Ion Exchange is mainly used to produce high quality water for industrial purposes. This process cannot treat brackish or seawater as the feedwater (Green, 2005).

Desalination is carried out world wide and most of the plants are located in the Middle East (50%), 20% in North America, 12-14% in Europe and less than 1% in Australia. As per the International Desalination Association most of these installed desalination plants around the wide use Reverse Osmosis or Multistage flash distillation as the preferred technique for water purification (Conway, 2008). In Australia as well the preferred technology is reverse osmosis with 64% of the plants using it. The major reason for using reverse osmosis is the simplicity of the process and the lowering of the salinity level while handling any type of feedwater.

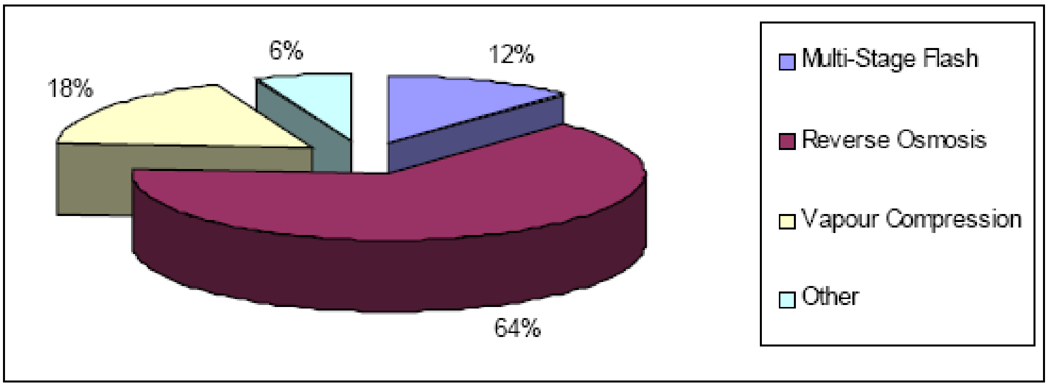

Figure 2.1 Installed Australian Desalination capacities (Conway, 2008)

2.3 Understanding Desalination Technologies

The desalination technologies are classified into thermal and membrane processes. This section will provide an overview of these processes and the main theoretical concepts associated with them.

2.3.1 Membrane Processes

Desalination through the use of membranes was introduced in the 1960s as an alternative to the thermal processes. The membrane process is a physical separation process where salt and undesired minerals are separated from the feedwater using a membrane to produce drinking water. The main membrane processes are Electrodialysis and Reverse Osmosis. The main features of these processes are the ability of the membrane to differentiate between salt and water (Bruggen and Vandecasteele, 2002). However the installed membrane works differently for each of these processes. This section will cover the Electrodialysis process while the Reverse Osmosis process is considered in detail in Chapter 2.6.

2.3.2 The Electrodialysis Process

Electrodialysis (ED) involves the movement of water through a filtering medium. The main principle of ED is the usage of a low voltage direct current (DC) electric field. The membrane resistance is overcome using this electrical field and the pre treated water is pumped through the electrodialysis cells. The main components of an ED cell are large number of narrow compartments through which feedwater is pumped. These compartments are separated using membranes that are permeable to either positive ions (cations) or negative ions (anions). The DC electrical field directs the cations and anions through the membrane to form two specific sections of water. These sections are the electrolyte enriched wastewater and the electrolyte depleted product water. Non ionic particles and bacteria will pass through the cell along with product water and this will require further treatment before it can be used domestically or for industry purposes (Xu and Huang, 2008).

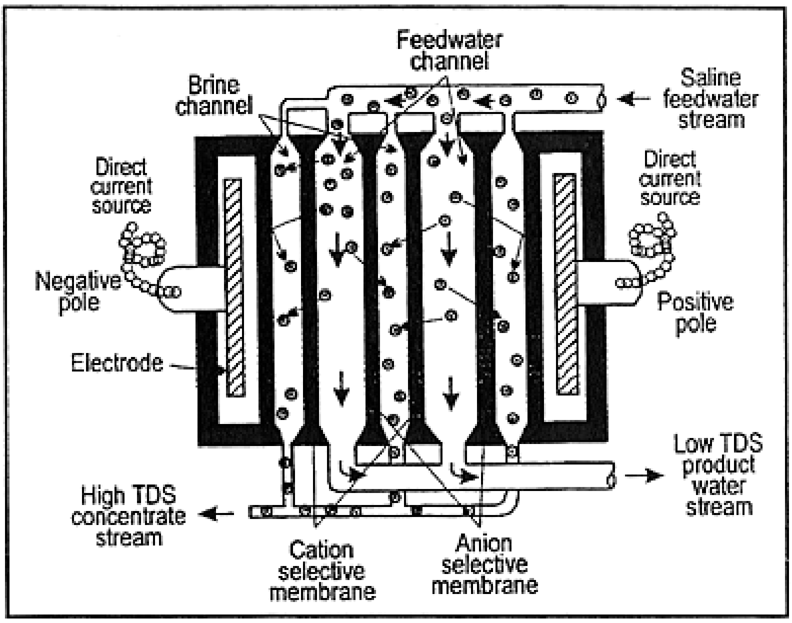

Figure 2.2 The Electrodialysis Process (Pilat, 2001)

The basic electrodialysis unit consist of cell pairs bound together with electrodes on the outside and are referred to as a membrane stack. The feedwater passes through all the cells in parallel paths to provide a continuous flow of desalinated water and a brine solution to emerge from the stack. Chemicals may be added to the streams in the stack to reduce the effects of scaling. Pre treatment of feedwater is essential as some minerals present in the feedwater could block the narrow channels in the cells (Pilat, 2001).

Recent developments have further enhanced the efficiency of the ED process. One such development is the Electrodialysis Reversal (EDR). This addition to the existing ED process involves a reversal stream of water flow to break up and flush out build up of scales and slime on the cells thus preventing scaling and fouling. This addition to the ED process allows the unit to operate with fewer pre treatment chemicals which are needed to prevent scaling (Veerman, et al. 2009).

The advantages of the ED process are as follows:

1) The ED process produces a high recovery ratio (85-94% for one stage)
2) The ED process can treat feedwater with a high level of suspended solids.
3) The energy used in the ED process is proportional to the salts removed and not the volume of water being treated.
4) The EDR membranes last 7-10 months longer as compared to the Reverse Osmosis membranes
5) The EDR membranes are immune to bacterial and silica scaling.
6) The EDR process can be operated at a low pressure.

The disadvantages of the ED process are as follows:

1) The ED cell membranes require periodic cleaning with specific chemicals.
2) It is common for leaks to occur during the operation from the membrane stacks.
3) Since bacteria and non ionic substance are not affected by the ED process, they remain undetected and pass into the product water. Hence further treatment is required before it can be used for domestic or industrial usage.

2.4 Thermal Processes

The thermal processes main used for commercial purposes are Multistage Flash Distillation (MSF), Multi effect distillation (MED) and Vapour Compression (VC). In recent years MSF and MED are used for large scale seawater desalination operations. These processes consume a large amount of energy regardless of the level of dissolved salts present in the water. These processes tend to use seawater as feedwater while brackish water is not an option for these processes.

2.4.1 Multistage Flash Distillation (MSF) Process

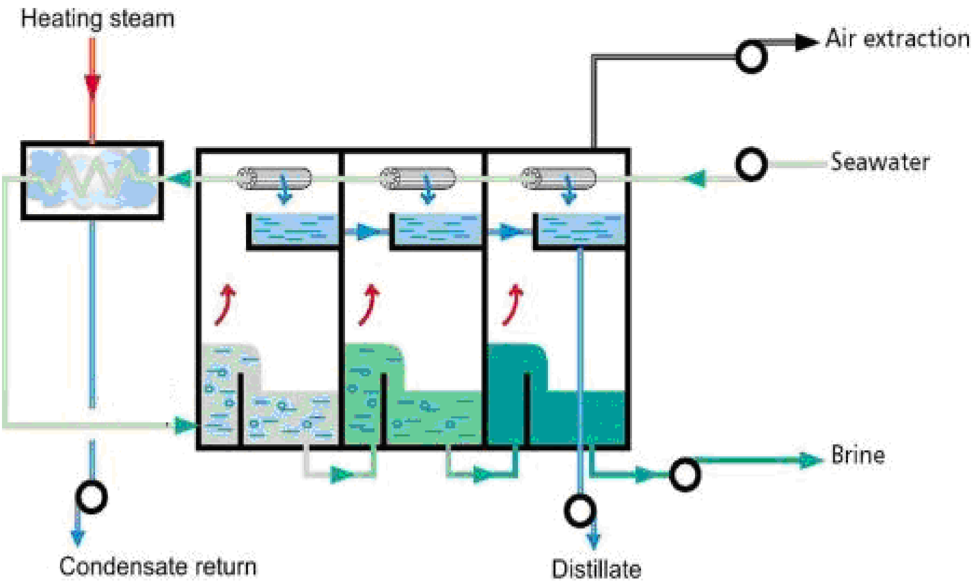

Figure 2.3 The Multistage Flash Distillation Process (El-Dessouky, et al. 1998)

The working principal of MSF involves seawater being pressurised and heated to the maximum allowable working temperature. When this heated liquid is introduced into a chamber maintained slightly below the saturation vapour pressure of the water, a fraction of the water content flashes into steam. This flashed stream is stripped off suspended brine as it passes through a mist eliminator. It condenses on the outer surface of the tubing. The condensed liquid drips into trays as fresh water.

The recirculating stream that flows through inside of the tubes condenses the vapour in each stage thus removing the latent heat of condensation. This cause the circulating brine to get preheated to the maximum operating temperature of the process which in turn recovers energy from the condensing vapour. This portion of the MSF plant is called the heat recovery section (El-Dessouky, et al. 1998).

The advantages of the MSF process are as follows:

1) Usually desalination plants use the MSF process if the plant will handle large capacities of feedwater.

2) The salinity of the feedwater does not affect the working of the MSF process nor does it add to the cost.
3) The MSF process produces a high quality final water product.
4) There is minimum need for pre treatment of the feedwater.
5) The process has flexible operational procedures and maintenance is not a major issue.
6) It can be coupled to another process where by the heat energy generated from an electricity generation plant can be used to run the MSF process.

The disadvantages of the MSF process are as follows:

1) It is extremely expensive to build a MSF plant and high level of expertise and technological knowledge is required to operate it.
2) Highly energy intensive due to the requirement of boiling the feedwater.
3) The recovery ratio is low and more feedwater is required to manufacture the same amount of product water as compared to other desalination techniques (El-Dessouky, et al. 1999).

2.4.2 Multiple Effect Distillation (MED) Process

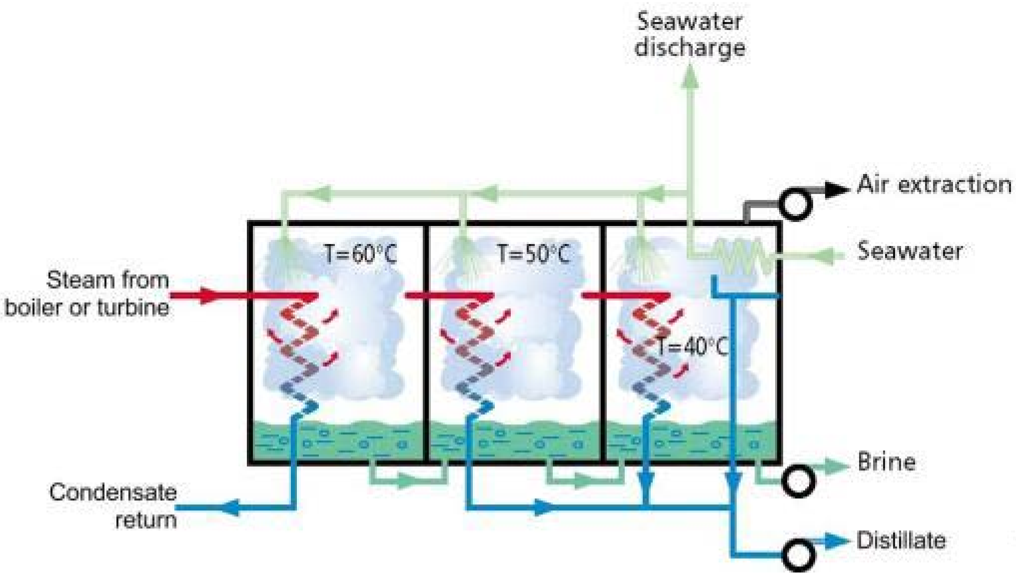

Figure 2.4 The Multiple Effect Distillation Process (Ophir and Lokiec, 2005)

The working principle of the MED process involves reducing the ambient pressure at each stage of the process thus allowing the feedwater to undergo multiple boiling without having to supply additional heat. In the MED process steam or vapour is used from a boiler and is fed into a series of tubes where it condenses and heats the surface of the tube. The surface area of the tubes act as a heat transfer surface and allows the saline water to evaporate on the other side of the tube. The energy used for evaporation of the saline water is the heat of condensation in the tube. The evaporated water now free of saline is fed in to the next lower pressure stage where it condenses again to form fresh pure water product (Wade, 2001). While the condensation process is taking place it gives out heat to evaporate a portion of the remaining feedwater. The typical arrangement of a MED process has condensation and evaporation taking place and they are termed as effects. This is continuously repeated from effect to effect at successively lower pressures and temperatures. The combined condensed vapour is the final pure water product (Ophir and Lokiec, 2005).

The major difference in the MED and the MSF process is the role of flashing steam in the MED process which is not as important as the condensing steam in the MSF. The condensing steam evaporates the feed seawater in each effect. In a MED process the steam produced in one effect is passed on to the next effect operating at a much lower pressure and temperature as compared to the previous effect. Hence the MED consumes less power in comparison to the MSF process (Green and Schwarz, 2002).

The advantages of the MED process are as follows:

1) The final water product is of an extremely high quality.
2) The MED plants can handle feedwater with biological and suspended matter.
3) The pre treatment requirements of the feedwater are minimum.

The disadvantages of the MED process are as follows:

1) The plants are expensive to construct and energy consumption is high.
2) The final product water is extremely hot and needs to be cooled before it can be used.
3) The recovery ratio is low but not lower than the MSF process.

2.4.3 The Vapour Compression (VC) Process

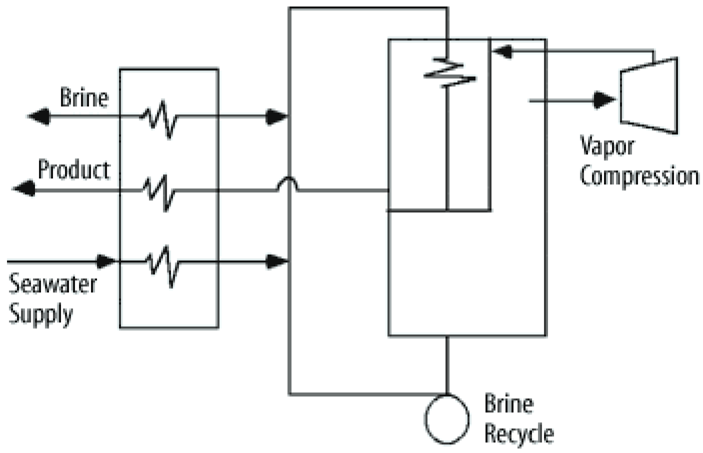

Figure 2.5 The Vapour Compression Process (Darwish and El-Dessouky, 1996)

The VC process utilized for desalination is a simple but efficient technology. The main working principle in the VC process is the continuous recycling of the latent heat in the evaporation condensation stages. The VC process is similar in process operation to the MED. The major difference is the vapour produced during the evaporation of the brine is not condensed separately. A compressor returns the condensate to the steam side of the same evaporator in which it originated. Thus forming a heat transfer surface on the steam side of the same evaporator and giving out latent heat to evaporate more brine solution. The energy required for the evaporation is not created from a steam source as in the other two thermal processes but from a vapour compressor. This unit raises the temperature of the vapour by its compressing action providing the driving force for the transfer of hear from vapour to brine (Darwish and El-Dessouky, 1996).

The advantages of the VC process are as follows:

1) The plants operating on the VC process are very compact and can be designed to be portable.
2) The VC process requires minimum treatment of feedwater.
3) The recovery ratio achieved using the VC process is high.
4) The final water product is of high quality.
5) The energy requirements needed for the VC process is low.

The disadvantages of the VC process are as follows:

1) The major component of the VC process is the steam compressors which are not easily available and highly expensive.
2) An auxiliary heater is required to raise the temperature of the feedwater to a point where some vapour is created.
3) The overall working of the plant is difficult and requires technical expertise and in depth knowledge.

2.5 Factors affecting Desalination Technology Selection

There are numerous factors to be considered before selecting the desired desalination technique. These factors have to be taken into account and some of them are summarized below.

Performance Ratio: The Performance Ratio is defined as the ratio of the amount of freshwater to the amount of energy consumed. In countries where the cost of energy (low fuel costs) is low a relatively lower performance ratio is accepted. Where as in countries with high fuel costs a higher performance ratio is essential (Stikker, 2002).

Plant Costs: It is essential to take into account the actual cost of the equipment for the different processes. The technical specifications of the plant and the cost of the equipment will have an overall effect on the cost of water production. For all types of desalination processes the cost of production of fresh water will reduce with increasing plant capacity. This is due to the costs being distributed over a larger capacity. The availability of skilled labour is essential for successfully operating the plant. The availability of local skilled labour is essential as it reduces reliance on foreign labour and keeps cost of plant operation in check (Ondrey, 2005).

Site Location: It is essential to consider an appropriate site for setting up the desalination facility. The cost of transporting water to the required point needs to be considered. If the final water product has to be transported over long distances this increases the unit cost of product water. It is best suited to have the facility as close to the feedwater source.

Feedwater: It is of prime importance to know the feedwater source for the desalination facility. The composition and salinity of the feedwater sources will affect the overall process and amount of pre treatment required. A large distance from the feedwater source and the desalination facility is undesirable. Pre treatment of feed water will add to the overall cost and in turn increase the cost of the final water product (Andrianne and Alardin, 2003).

Product and Reject Water: The reject obtained during the process i.e. brine needs to be disposed off in a correct manner. The brine disposal costs add to the freshwater cost because the brine needs to be treated before it can be rejected. If the location of the plant is near a coast the brine can be discharged into the sea in the form of a stream or salt ponds. Storing the freshwater product adds to the capital costs and pumping the product water to the consumer is taken as pumping costs (Dore, 2005).

2.6 Understanding Reverse Osmosis and Osmosis

Reverse Osmosis (RO) is a pressure driven process and this applied pressure is used to achieve solute separation. The water needed to be treated is allowed to pass through a membrane resulting in salts and minerals being retained on one side of the membrane and fresh water on the other side of the membrane. This section will closely look at osmosis and the manner in which reverse osmosis is achieved.

Osmosis is the main driving force by which reverse osmosis is achieved. It is the process in which the solvent i.e. water is transported through a semi permeable membrane under the influence of a concentration gradient. Nature uses osmosis to equalise the concentration of two fluids having different concentrations of dissolved substances (Sourirajan and Agrawal, 1969).

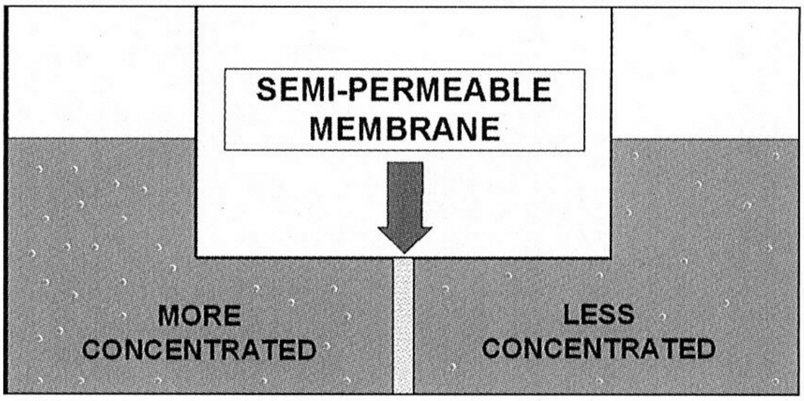

Figure 2.6 Representation of the Theory of Osmosis (Sourirajan and Agrawal, 1969)

Consider a system of two compartments where each compartments contains a different degree of salt concentration. In between these compartments a semi permeable membrane is placed. If this system is left unattended nature will try and equalise the salt concentration in the two compartments. Dilution of the more concentrated side will be achieved by movement of water through the semi permeable membrane until the compartments have equal salt concentrations. But when water is allowed to flow from one side to the other there will be change in the water level. The rise in the water level on one side will result in a differential pressure change from the original state. This is called the osmotic pressure. Hence the osmotic pressure of the difference in the water levels in the compartments will be able to counter the diffusion process causing the two compartments to have equal salt concentration (Rowzee, 2005).

Osmotic pressure can be calculated using the Van't Hoff equation which is given as:

$$\pi = RT\Sigma \sum Xi$$

Where:

π is the osmotic pressure (kPa)

T is the temperature (K)

R is the universal gas constant

$\sum Xi$ is the concentration of all the dissolved salts present in the solution.

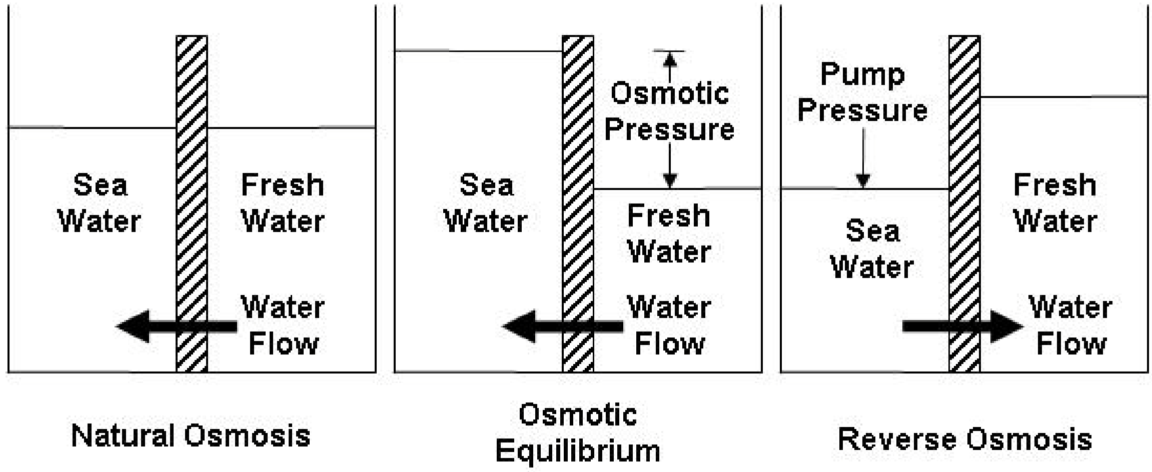

Figure 2.7 Representation of Natural Osmosis, Osmotic Equilibrium and Reverse Osmosis (Rowzee, 2005)

2.6.1 Generation of the Pore flow Model Equations to Understand RO

Reverse Osmosis can be achieved by simply reverse the natural phenomenon of osmosis by overcoming the osmotic pressure. When enough pressure is applied to the more concentrated salt compartment, water can be forced to flow in the opposite direction thus leaving a high percentage of impurities and salt behind. RO forces water with a greater concentration of impurities i.e. source water into a compartment or chamber with low concentration of impurities i.e. final product water. Thus by applying high pressure on the source side the natural osmotic process is reversed and RO is achieved. The semi permeable membrane plays an important role in the RO process since it allows the flow of pure water while rejecting the impurities and dissolved solids present in it. The recovered water is called permeate and the concentrated solution left behind is called the reject or brine. The quantity of pure water that passes through the semi permeable membrane during RO operation is a function of the difference between the applied pressure and the osmotic pressure of the salt solution (Harrison, 2006).

The solvent is driven through the membrane by pressure while the mass transfer of the solutes is diffusion controlled. Hence the permeation of the solvent through the membrane can be explained by the Pore Flow Model Equations (Wijmans and Baker, 1995).

$Jw = (\Delta p - \sigma.\Delta\Pi)$

Where

J_w is the solvent mass flux that passes through the membrane $kg.m^{-2}s^{-1}$

A is solvent permeability coefficient which is the characteristic for a given membrane $kg.m^{-2}kPa^{-1}s^{-1}$

ΔP is the membrane pressure gradient (kPa)

$\Delta \Pi$ is the osmotic pressure difference (kPa)

And σ is the reflection coefficient which is a reflection of the membrane selectivity

The solute mass flux can be described as per the solution diffusion model in which the solute dissolves in the membrane and then diffuses through the membrane down a concentration gradient. It is given as

$$Js = \frac{DsKs}{l}(Cf - Cp)$$

Where

J_s is the solute mass flux that passes the membrane $(kg.m^{-2}s^{-1})$

D_s is the solute diffusion coefficient in the membrane material $(m^{-2}s^{-1})$

K_s is the distribution or partition coefficient

l is the membrane thickness (m)

C_f and C_p are the concentrations in the feed and permeate solution $kg.m^3$

The solute permeability coefficient B $(m\ s^{-1})$ can be expressed as a function of diffusion and partition coefficients and membrane thickness, as

$$B = \frac{DsKs}{l}$$

The permeate volumetric flux J_p $(m\ s^{-1})$ can be calculated subsequently as the sum of the solute and solvent fluxes:

$$J_\psi = \frac{Jw + Js}{\rho_\psi}$$

Where ρ_ψ is the permeate density $(kg\ m^{-3})$

2.7 Working of a Reverse Osmosis System

A RO system consists of three major system components:

1) Pretreatment
2) Membrane Separation
3) Post treatment stabilisation.

Pretreatment of the feedwater is an essential component of the RO system. This is an important step and is carried out in order to prevent scaling of the membrane by scaling and fouling agents. Preserving the performance of the membrane throughout the operation is essential to maximise the efficiency and longevity of the RO system. Pretreatment is essential for proper operation of RO equipment and can add significant capital and operating cost to a project. However, the long term cost of not providing appropriate pretreatment will far exceed the initial capital cost over the life time of the RO facility (Bou-Hamad, et al. 1997).

Precautions should be taken to maintain suspended solids at an acceptable level in the source feedwater. Modern high performance polymeric anti scalants have been effective in stabilising solutions of sparingly soluble salts. Biological fouling can be avoided by minimising the time the plant is not in operation. Some of the various types of fouling, their cause and appropriate pretreatment techniques are summarised below. (Ebrahim, et al. 2001)

Fouling	Cause	Appropriate Pretreatment
Biological fouling	Bacteria, microorganisms, viruses, protozoan	Chlorination
Particle fouling	sand, clay (turbidity, suspended solids)	Filtration
Colloidal fouling	Organic and inorganic complexes, colloidal particles, micro-algae	Coagulation + Filtration Optional: Flocculation / sedimentation
Organic fouling	Natural Organic Matter (NOM) : humic and fulvic acids, biopolymers	Coagulation + Filtration + Activated carbon adsorption Coagulation+ Ultrafiltration
Mineral fouling	Calcium, Magnesium Barium or Strontium sulfates and carbonates	Antiscalant dosing Acidification
Oxidant fouling	Chlorine, Ozone, $KMnO_4$	Oxidant scavenger dosing: Sodium (meta) bilsulfite Granulated Activated Carbon

Table 2.1 Summarising the Different Types of Fouling, their Cause for Occurrence and the Appropriate Pretreatment Needed to Overcome the Concerned Fouling (Ebrahim, et al. 2001)

2.7.1 Membrane Separation

Membrane separation processes are widely used in industry as compared to the thermal processes because of their low energy consumption, high product quality and flexible design and installation. RO is one of the important membrane processes used for desalination of seawater, groundwater and brackish water.

The role of the semi permeable is off prime importance in the RO operation. The permeable membranes inhibit the passage of dissolved salts while permitting the desalinated product water to pass through. Applying pressure to the membrane assembly results in a freshwater product stream and a concentrated brine reject stream. Because no membrane is perfect in its rejection of dissolved salts, a small percentage of salt passes through the membrane and remains in the product water (Cheremisinoff, 2002)

Reverse osmosis membranes are made from cellulose acetate, cellulose triacetate and aromatic polyamide resins. The ability of the membrane to reject an ion is related to the ion size and also the charge on the ion. Ions of low charge are more difficult to reject as compared to higher charged ions. Flow through a semi permeable membrane is directly proportional to the net pressure across the membrane. The net pressure is the difference in the inlet pressure and the sum of the osmotic pressure and the pressure in the treated water storage container. The membrane is assumed to behave like a dense liquid layer. Ions and water are assumed to be soluble in the membrane material with pressure driving both of them though the membrane at their own unique rate.

The diffusion rate of water molecules through the membrane material is much higher than the ions through the solution. Some ions do dissolve through the membrane over time but a higher quantity of water molecules pass through the membrane (Rowzee, 2005). An efficient RO membrane must have a sufficiently large surface area to process a large amount of feedwater. This is reflected in the design of the RO membrane modules. The two most commonly used membrane modules used for desalination ad the hollow fibre membrane and the spiral wound membrane. These membranes along with the tubular membranes and the plat and frame membrane are described in detail below.

The Hollow Fibre Membrane

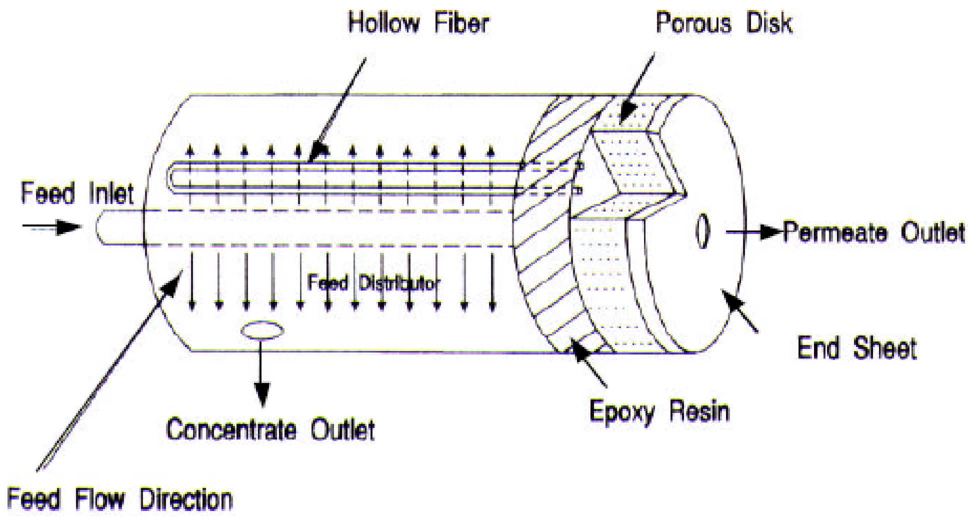

Figure 2.8 A Hollow Fibre Membrane (Noble and Stern, 1995)

The hollow fibre membrane is typically a bundle of several thousand 0.5-1.0mm diameter fibres spun into a membrane element. A hollow fibre membrane is spun with its own support structure. Hollow fibres as small as the size of a human hair and are produced with thickness making up approximately one half of the diameter. These fibres are bundled together as a U tube with the open ends potted in an epoxy tube sheet. The other end of the fibre bundle is also sealed in epoxy to prevent short circuiting of the feed stream to the concentrate stream.

The bundle is cased in a pressure vessel with the pressurised feedwater distributed from a tube in the centre of the bundle. As the water flows radially through the bundle and over the fibres some of the water penetrates the fibres flows down the bore and is collected at the tube sheet end of the vessel (Noble and Stern, 1995). The hollow fibre membranes have a high packing density, low pumping power and cleaning can be achieved using a backwash while the major problem is damage of a single fibre leads to replacement of the entire bundle which is expensive.

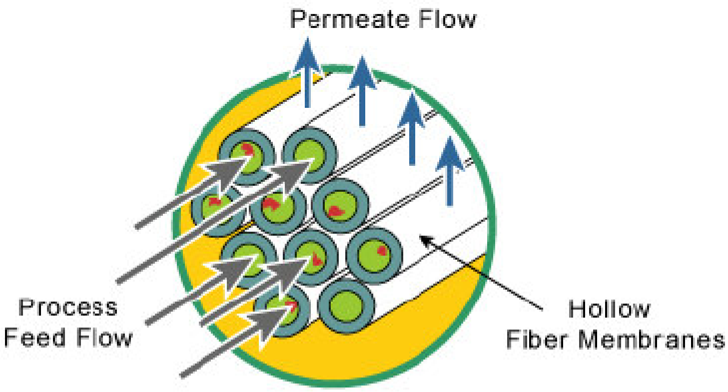

Figure 2.9 Cross Section of a Hollow Fibre Membrane (Noble and Stern, 1995)

Due to the membrane packaging density being so high this device has the highest ratio of water production to space occupied. The low flux offers the advantage of minimising the problem of concentration polarization. This high density packaging leaves very little space between the fibres thus making the size and amount of suspended solids more critical for operational performance (Awwa, 1999).

The Spiral Wound Membrane

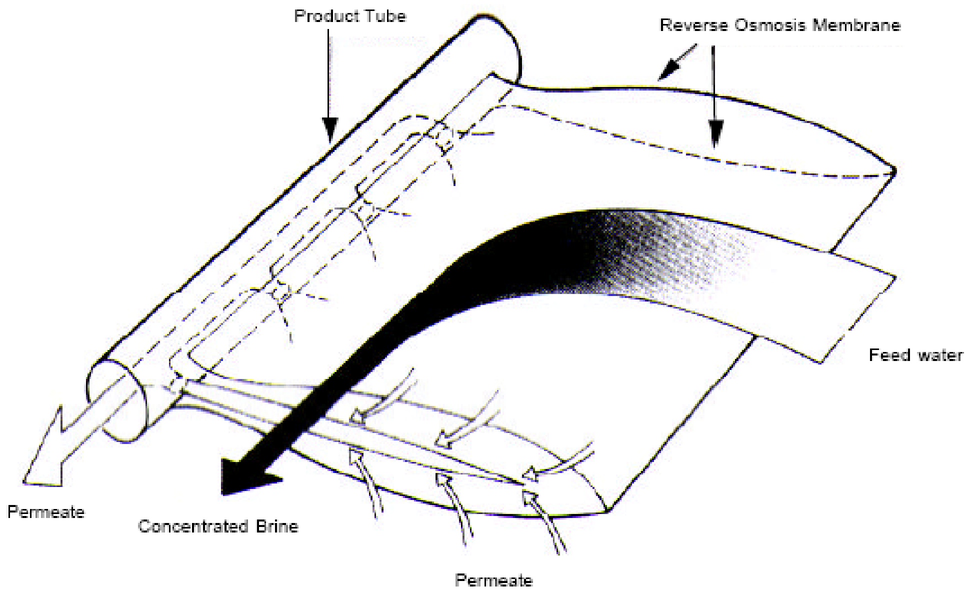

Figure 2.10 Spiral Wound Membrane (Nicolaisen, 2003)

The spiral wound membrane is cast in sheet form on a backing material such as sail cloth of cellulosic membranes and a non woven polyester web for the newer composite membranes. Two of these sheets are placed back to back and separated by a spacing fabric that acts as a permeate channel. Two sides and one end of this assembly are glued together to form an envelope. The open end of this envelope is connected to the permeate tube around which the envelope is wrapped to form the spiral. Additional plastic netting is wrapped to separate the membrane surfaces and maintain the feed stream channel height. This spiral assembly is fastened to prevent unravelling and a brine concentrate seal is fixed to one end (Nicolaisen, 2003).

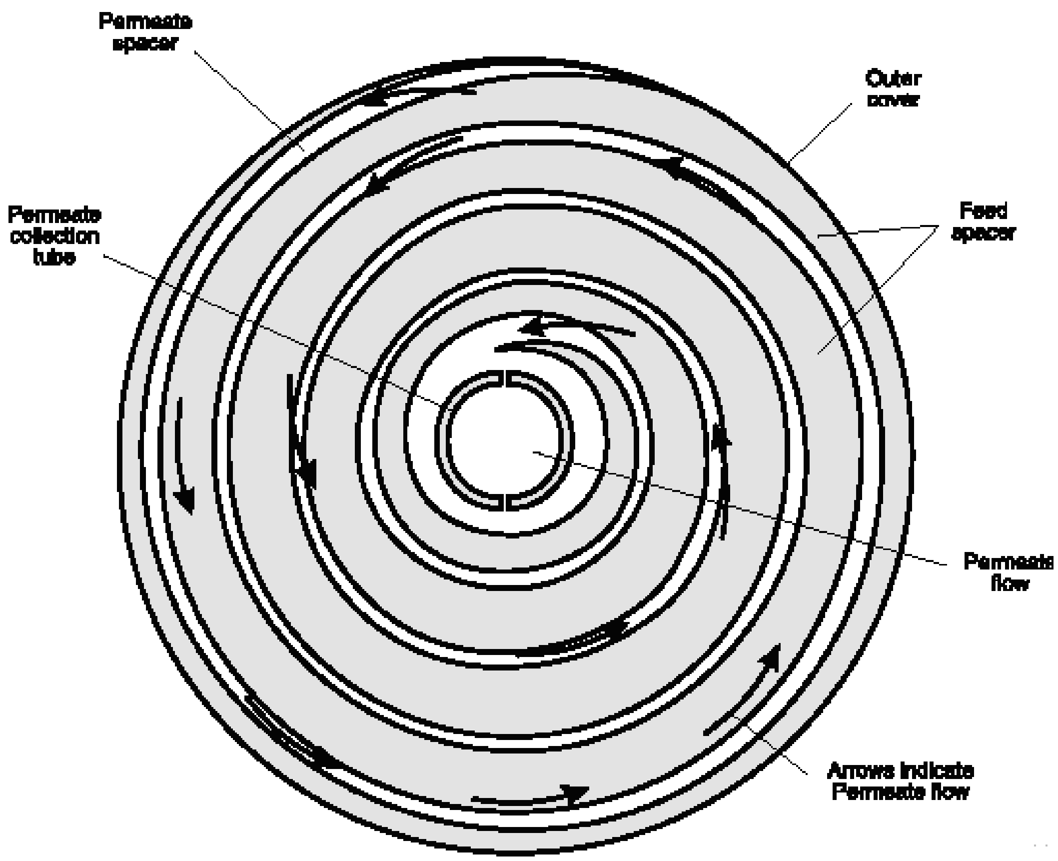

Figure 2.11 Cross Section of a Spiral Wound Membrane (Nicolaisen, 2003)

The elements are placed in a cylindrical vessel with the feed and the concentrate flowing through the feed side channels in a straight axial path parallel to the direction of the permeate collection tube. Some of the water penetrates the membrane and spirals its way to the centre collecting in the permeate tube. The remaining water passes from the element and out the concentrate end of the vessel. Several elements around six or seven are placed in series within the pressure vessel and the concentrate from one element serves as the feed for the next element in series

The Tubular Membranes

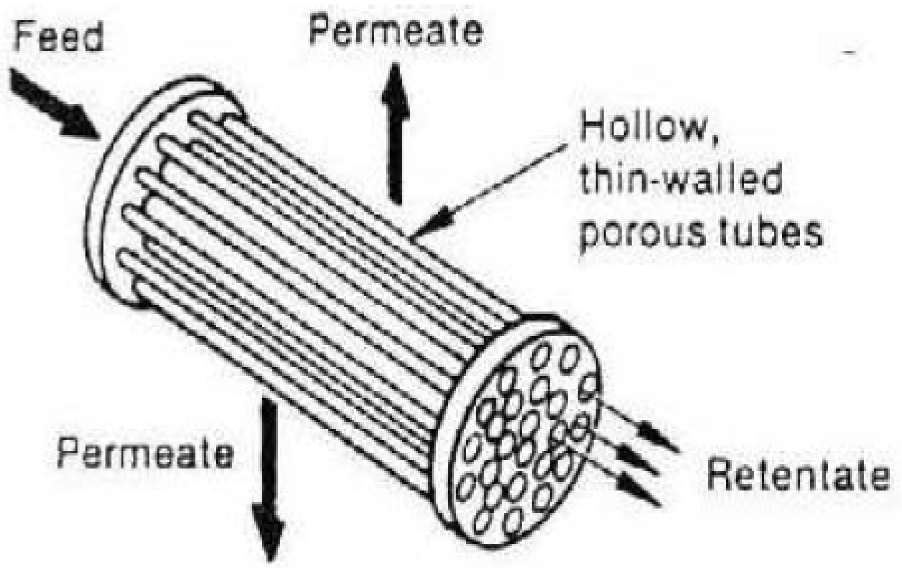

Figure 2.12 A tubular membrane (Lawson and Lloyd, 1997)

The tubular membranes date back toe the beginning of the membrane technology and are one of the earliest membranes used for desalination. It is primarily used in the food industry for concentrating tomato juice and cheese production. The tubular membrane is similar to the shell and tube filtration unit. The membrane is in a tubular form on the inside of a pressure tight porous support tube. The feed solution flows through the inside and the permeate flows through the tube wall into the shell side. Several membrane tubes are placed in a shell type container to from a unit. The main advantages of these membranes are easy cleaning and replacement techniques and less chances of membrane blockage. The drawbacks of tubular membrane are their high energy requirements for pumping large volumes of feedwater, high capital costs, and low membrane surface area per unit volume (Lawson and Lloyd, 1997).

The Plate and Frame Membranes

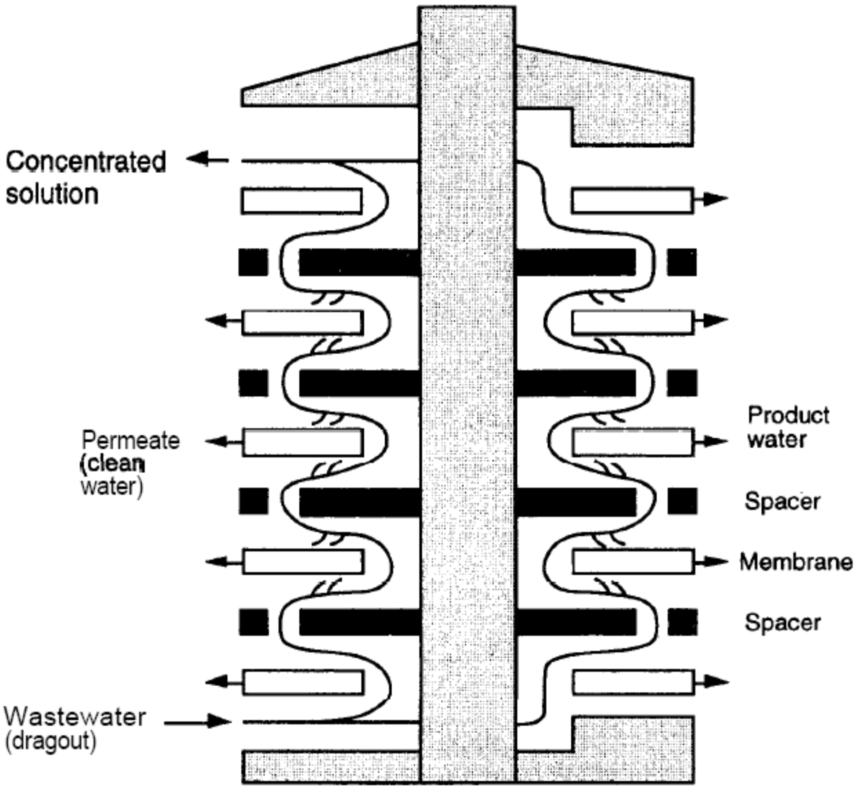

Figure 2.13 A plate and Frame Membrane (Nunes and Peinemann, 2001)

The plate and frame membrane is similar to the plate and frame filtration unit. In this membrane the membrane sheets, spacers and support plates are stacked alternately. The supports also form a flow channel for the permeate water. The feed solution flows in the modules inwards and outwards allowing the entire membrane surface to be covered by the feed stream and permeate is collected from each support plate. Recent innovations have increased the packing densities for new design of plate and frame membranes. Maintenance on plate and frame membranes is possible due to the nature of their assembly. They offer high recoveries with their long feed channels and are used to treat feed streams that often cause fouling problems (Nunes and Peinemann, 2001).

2.7.2 Post Treatment

The quality of the produced permeate is essential before it can be consumed by the community. If the quality of the produced final water product does not meet the desired requirements the need for additional pretreatment arises. RO produces corrosive finished water because they reduce pH and eliminate more calcium and alkanity than required. Typical post treatments are addition of certain chemical to adjust stability of the treated water, removal or addition of gases and the addition of chemicals to meet the national or international water quality standards. It is necessary to meet the required total dissolved solid requirements and concentration of certain ions and minerals.

Depending upon the level of dissolved solids removed the product water from a RO process will be corrosive to equipment and piping. As operation continues the membranes will be become less permeable and increasing amount of minerals are removed. It is likely that pH adjustments and methods of corrosion control will be required. The commonly used chemicals for the control of pH (neutralization) are calcium carbonate, calcium hydroxide, magnesium hydroxide and sodium carbonate. The chemicals used to lower pH are carbonic acid, hydrochloric acid, nitric acid and sulphuric acid (Redondo and Lomax, 1997).

Several indexes have been developed to assess whether the final water product is non scale forming, neutral or scale forming with respect to calcium carbonate. One of these scales is the Langelier Saturation Index (LSI). Positive LSI values indicate scale forming water and negative LSI values indicate non scale forming water. It may be calculated as follows:

$$LSI = pH - pHs$$

Where
ph = pH of the water being considered
pHs = pH of saturation

Actual corrosion rates are difficult to predict but maintaining a positive LSI index reduces general corrosion in most potable water. Alkanity and hardness are the two major factors in LSI calculation. The alkanity concentration provides an indication of a waters resistance to pH changes on the addition of an acid. The recommended value for alkanity is 40mg/l as calcium carbonate is maintained within the system to provide pH stability. Most alkanity in water is composed of hydroxide (OH), carbonates and bicarbonates. Major reactions affecting alkanity are dissolution of carbon dioxide and ionization of aqueous carbonic acid and bicarbonate. Most RO membranes do not remove dissolved gases. Carbon dioxide present in groundwater readily passes through the membrane and into the final product. RO systems using acid pretreatment will contain higher concentration of carbon dioxide in the feed and permeate because of the conversion of bicarbonate ion to carbon dioxide (Dudley and Darton, 1997).

Acidifying the feedwater during pretreatment is necessary because the alkanity in the feed water can be converted to carbon dioxide irrespective of the required pH for scale control. The carbon dioxide passing through the membrane then becomes a source of inorganic carbon for finished water alkanity. Hence it is an important part of producing noncorrosive product water. Low total dissolved solids (TDS) levels in the permeate increase resistivity but alkanity helps reduce the corrosion reaction. If gas stripping is done right after acid pretreatment carbon dioxide is given out into the atmosphere. Only a small percentage of the alkanity that gets converted into carbon dioxide during pretreatment remains in the water (Kim, et al. 2002).

Disinfection is required to destroy or reduce micro organisms present in the water before it is distributed to the consumers. The most common technique is chlorinating the water. When chlorine gas dissolves in water it reacts to form hydrochloric acid (which completely dissociates) and hypochlorous acid. The extent of the disassociation is dependent on the pH, temperature and concentration. The sum of the hypochlorous acid and hypochlorite ion in solution is the free available chlorine. Addition of chlorine increases the chlorides which in turn results in increase of the TDS in the finished water. In water where hydrogen sulphide is present chlorine will react with it to form elemental sulphur, hydrochloric acid and sulphuric acid. Elemental sulphur can be responsible for the increase in turbidity. The advantage of using chlorine to disinfect RO permeate water is that the membrane reject disinfected by product and other oxidisable substances from the feedwater. As a result this decreases the chlorine demand in the permeate water resulting in lowering cost for disinfection (Fritzmann, et al. 2007).

The common technique use to stabilize water is blending or chemical addition. The techniques that have been used to reduce corrosive characteristics of RO water are blending with less treated water or blending with brackish water from sub surface aquifers. Typical blend composition is 60-70 percent RO water. Remineralisation with suitable chemicals like sodium bicarbonate, calcium chloride and sodium hypochlorite can also aid in stabilizing the water. Lime is the least expensive chemical but its usage represents increased capital costs (Tularam and Ilahee, 2007).

2.8 Reverse Osmosis Performance

There are certain factors which greatly affect the performance of a reverse osmosis system. This section will look at the features which are responsible for RO performance. The most important variables which affect the performance of the RO system are pretreatment, membrane performance and operating conditions.

2.8.1 Pretreatment Process to Enhance RO Performance

The feedwater quality is of great importance to the performance of the RO system. Even though the feed water is generally wastewater or water containing impurities it still needs to be treated before it is allowed to pass through the membranes. All naturally occurring water contains some form of dissolved or suspended compounds. The typical inorganic compounds found in water are calcium, magnesium and sodium while the organic compounds include carbon, nitrogen, oxygen and chlorine. Pretreatment processes aim to reduce the contaminants that could damage the system components such as the membranes and the pressure pumps (Panicker, et al. 2006). Pretreatment of the initial feed water is always required and is generally the first step in the RO operation. The main reason for pretreatment is to ensure that during RO operation the impurities present in the feed water do not affect final water quality. A highly effective pretreatment process will lead to increase in membrane lifetime and prevention of membrane fouling and scaling (Isaias, 2001).

Along with membrane fouling the other major reasons for pretreatment are biological contamination and colloidal fouling. The fouling potential of dissolved ions present in the feed water can be minimised by anti scaling chemicals and controlling the system recovery. The problems associated with fouling are irreversible membrane damage, reduced flux rates and increase in the operating and capital costs. Hence pretreatment assures the quality of the feed water is good to prevent drop in performance of the RO system. The traditional pretreatment technology was using deep bed filters, sand filters, cartridge filters, chlorination and flocculation techniques. These traditional techniques used for pretreatment did not eliminate the suspended solids, bacteria and colloids. Traces of these impurities when passed into the RO system lead to membrane fouling (Durham and Walton, 1999). The traditional techniques use a combination of sedimentation and diffusion to eliminate impurities. However many particles are too small to be removed by sedimentation and some too large to removed by diffusion.

This led to new technologies been developed for the pretreatment process. One such technology is the use of continuous micro filtration technology. This is the most satisfactory pretreatment process capable of ensuring the highest quality of feed water fed to the system. A micro filtration system removes impurities as the feed water flows through the micro filtration membrane. The impurities are held on the surface of the membrane and are removed physically. The impurities cannot squeeze through the micro filtration membrane hence it is not dependent on the amount of impurities present in the feed water. The technology is simple where the feedwater passes through a barrier of 0.2 micron polypropylene membrane in a continuous mode and under a pressure gradient of 100kPa. The filtrate obtained is free from solid suspensions, bacteria and colloids (Chakravorty and Layson, 1997).

Nano filtration membranes can also be used for the pretreatment process due to its ability to remove calcium magnesium and sulphate ions. Another new technology used to pretreat wastewater and seawater is Ultra filtration. This technique provides a high quality filtrate which is free from suspended solids and microorganisms (Van-Hoof, et al. 2001).

Literature has reported various studies dedicated to studying affective pretreatment methods for RO operations. Ultra filtration is suggested as one of these techniques because it allows the removal of suspended solids and colloidal materials without the use of harmful chemicals. Using the ZeeWeed 1000 immersed membranes where filtration and backwashing is done in alternate steps where all the particulate material is rejected by the membrane and backwashing prevents membrane blockage from occurring (Cote, et al 2001).

Before the plant handling seawater desalination can be commercially set up it is essential to decide the adequate pretreatment process needed for handling the feed water. It is important to study the system parameters in order to enhance the RO operation. The open intake system optimises the quality of the water fed into the RO membrane which guarantees the highest salt rejection percentages and minimises the number of shut downs needed for membrane cleaning (Elguera and Perez-Baez, 2005). The open intake system along with micro filtration techniques for the seawater desalination is also suggested by Wilf and Klinko. These pretreatment techniques can be utilized to improve the quality of surface seawater feed to RO system. These new developments enable a more advanced RO system design, which should result in increased reliability and lower water cost (Wilf and Klinko, 1998).

For the Doha Reverse Osmosis Plant in Kuwait flocculation and dual media filtration are the pretreatment procedures in place for treating the seawater before it is sent to the RO plant. The pretreatment system is designed to provide the RO system with water of suitable quality and required quantity by constantly monitoring and measuring the silt density index (SDI), turbidity, pH, temperature, and chlorine content (Ebrahim and Malik, 1987). These same parameters were established as the main criteria after conduction various experiments in order to determine the appropriate feedwater characteristics (Teng, et al. 2003).When using a RO system to treat wastewater it is recommended to have a microfiltration pretreatment system in place to protect the RO membrane from the highly corrosive and fouling action of the waste water (Durham and Walton. 1999).

2.8.2 Membrane Performance

The different membranes used in the RO process reduce the dissolved impurities and suspended matter, organic pollutants thus making water consumable for society and industrial usage. The final product water quality depends on the manner in which the membranes can reject the impurities and allowing only water to pass through them.

But as operation continues there occurs a build up of the solute on the membrane surface resulting in fouling and scaling. The result of fouling and scaling are decrease in the overall performance of the RO plant, increase in maintenance cost and reduction in membrane life. Membrane scaling and fouling are considered as the major problems associated with affecting membrane performance (Malaiyandi, et al. 82).

Scaling refers to the deposition of the hard scale which will occur during operation due to the sparingly soluble salts present in the feedwater. Fouling refers to the deposition of suspended solids, colloids and bacteria on the membrane which occurs during operation. Reduction in water quality is the outcome of the scaling and fouling phenomenons. This result is higher energy consumption, decreased salt retention and increase in cleaning costs involved. The ability to prevent formation of scale on the membrane is critical for optimum membrane performance.

The current techniques used to control scaling are softening to remove low solubility solutes like calcium and silica, acidification to prevent calcium carbonate scale and addition of antiscalant chemicals. The antiscalant chemicals are added to the feed water to prevent precipitation and scaling on the membranes. They work by increasing the induction till until precipitation occurs or changing the crystal habits to prevent scale from attaching itself to the membrane. Although these antiscalants are successful to a certain extent it is difficult to predict the concentrations of the sparingly soluble solutes. The common forms of mineral scale are calcium carbonate, calcium sulphate, barium sulphate and iron hydroxide.

Ion exchange methods remove scale forming species from the RO feedwater, while chemical techniques change the characteristics of the RO feedwater so that crystal formation is not favoured. An example of a chemical technique to prevent fouling is lime softening, which involves chemical processes that reduce the hardness of the wastewater, essentially preventing material from precipitating out. Lime, soda, ash, and NaOH are used to convert soluble calcium and magnesium to insoluble calcium carbonate and magnesium hydroxide. Magnesium hydroxide tends to absorb silica, another scalant. These solids are then collected as sludge from the bottom of the softener.

Fouling is a major obstacle that prevents efficient operation of reverse osmosis systems, causing deterioration of both the quantity and quality of treated water, and consequently resulting in higher treatment cost. Fouling is mainly caused by the inorganic matter, colloidal or organic matter and bacterial matter. Inorganic fouling is the deposit of sparingly soluble salt on the membrane surface as a result of crystallisation. It is mainly caused by calcium salts such as calcium carbonate and calcium sulphate (Kumar et al. 2006).

Colloidal and organic fouling is the accumulation of suspended and colloidal particles in the feed water that contain high concentration of colloidal species such as iron, aluminium and silica. It is mainly caused by organic matter in feedwater that accumulates on the membrane surface. The outcomes of organic fouling are reduced water production and decreased membrane life (Zhu and Elimelech, 1997).

Biological fouling refers to the bacterial or algal matter attaching itself to the membrane and subsequent growth with the release of biopolymers as a result of microbial activity. It may also result due to sulphates and anaerobic bacteria present in the feedwater source. The growth of the bacteria is helped by light and microorganisms embedded in the membrane multiply. The degradation of the membrane material provides a source of carbon and energy and increase biological fouling activity. This fouling activity can be reduced by periodic membrane cleaning.

2.9 Fouling and Scaling in Reverse Osmosis

Many studies have been conducted on the prediction, quantification and control of fouling for the pressure driven membrane processes but also for biological waste water treatment technology. Several approaches were proposed for fouling diagnosis in membrane filtration processes, like quantitative models for explaining the organic fouling based on solute properties (Kimura, et al. 2004) and also development of neural networks predictive models to describe the adverse impact of fouling occurrence over the process performance (Abbas and Al-Bastaki, 2005).

More recently studies were conducted to mathematically develop modelling of a submerged membrane reactor and the occurrence of fouling for such a system (Ho and Zydney, 2006). A neural network based specialized tool was developed to classify and diagnose the functioning mode of water circulation electrical controllers used for detection of simulated fouling in this system (Lalot, 2006).

Studies on organic fouling of RO membranes have shown that the rejection of organic substances is governed by their physicochemical properties (e.g., molecular size, solubility, diffusivity, polarity, hydrophobicity, charge), membrane properties (e.g., permeability, pore size, surface roughness, hydrophobicity, charge), process operating conditions (e.g., flux, trans membrane pressure, temperature, feed pH) and feed water composition (Ozaki and Li, 2002).

The early work of Matsuura and Sourirajan investigated the correlation of cellulose acetate rejection of 54 organic compounds (32 alcohols and phenols and 22 mono carboxylic acids) as a function of the relative acidity of the molecule, estimated by the shift in the OH-band maximum in the IR spectra and of the Taft Number which accounted for the effect of substituent's on the polar effect of the molecule. (Matsuura and Sourirajan, 1971)

Schutte investigated the performance characteristics of two commercially available RO membranes (one cellulose acetate and one composite polyamide) with respect to rejection of 20 organic compounds including benzene, toluene, acetone, cyclohexane, 11 alkyl alcohols (methanol, ethanol, 1 - propanol, 2 - propanol, 1 - butanol, 2 - butanol, 2 - methyl - 1 - propanol, 2 - methyl - 2 - propanol, 1 - pentanol, 1 - hexanol and 1 - heptanol), 7 alkyl phenols (phenol, 4 - methyl phenol, 4 - ethyl phenol, 2,6 - dimethyl phenol, 4 - n - propyl phenol, 4 - isopropyl phenol and 4 - nbutyl phenol). Reverse osmosis experiments were performed at three different operating pressures ranging from 1405 to 5620kPa.

The polyamide membrane rejection of linear alkyl alcohols increased with increasing molecular weight. The rejection of branched isomers was observed to be higher compared with the rejection of linear isomers of equal molecular mass. The polyamide membrane rejection of alkyl phenols, benzene and toluene increased linearly with molecular weight. In the case of cellulose acetate membrane no correlation was observed between the molecular weight of the considered compounds and their rejection. Moreover, cellulose acetate membrane showed lower rejection compared with the polyamide membrane. Since the organics passage through RO membranes depends on both sorption and diffusion, the solute flux was correlated with the adjusted total surface area of the molecules (Schutte, 2003).

More recently Bellona, Drewes, Xu and Amy carried out a comprehensive literature review regarding factors affecting organics rejection and rejection mechanisms for NF and RO water treatment. The solute parameters identified to determine the organic rejection were molecular weight, molecular size (length and width), molecular structure (e.g., number of methyl groups in the molecule), acid dissociation constant, hydrophobicity or hydrophilicity, polarity and diffusion coefficient. Membrane properties that affect rejection were found to be molecular weight cut off, porosity, morphology (i.e. hardness) and surface charge. Also feedwater composition such as hardness, ionic strength and presence of organic matter influenced the rejection (Bellona, et al. 2004).

2.9.1 Concentration Polarization

During the normal operation of RO the feed water along with the suspended solids and dissolved impurities are allowed to pass through a semi permeable membrane. The feed water comes in contact with the membrane and most water diffuses through the membrane leaving behind the suspended solids and impurities.

As the procedure continues the continuous action of leaving behind suspended solids and impurities starts to build up on the surface of the membrane. The solids accumulate to concentrations that exceed their concentrations in the feedwater and this phenomenon is known as concentration polarization (Kim and Hoek, 2005).

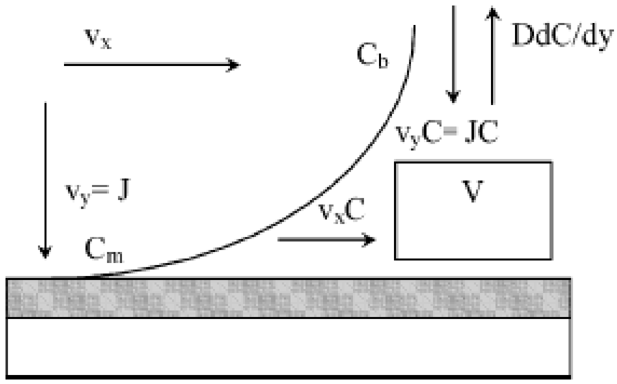

Figure 2.14 Concentration Polarization in the RO Membrane (Kumar, et al. 2006)

The phenomenon of concentration polarization occurs at a membrane surface due to the transport and accumulation of foulants close to the membrane surface i.e. a boundary layer is created. The thickness of the boundary layer depends on the turbulence of the feedwater flow. Increase in the turbulence will reduce the thickness of the boundary layer and reduce concentration polarization (Kumar et al. 2006).

Formation of a boundary layer leads to a concentration gradient at the membrane surface with back transport of the foulant occurring due to diffusion. The larger the boundary layer the slower is the back diffusion of the suspended solids. The concentration polarization is given as:

$$Cp = \frac{Cm - Cp}{Cb - Cp} = \frac{Jw}{k}$$

where

C_m = Solute concentration in the membrane wall

C_p = Permeate concentration

J_w = Solvent Water flux

k = Mass transfer coefficient.

The techniques used to reduce the concentration polarization are increasing flow rate, assembling an intensifier for turbulent flow, impulse and agitating methods, periodic depressurization of membrane tube, flow reversal, precoating of membrane surfaces and modification of membrane polymeric structure. Besides the use of all these methods for limiting the concentration polarization, fouling and scaling can be controlled by feed pretreatments and regular membrane cleaning (Kosutic and Kunst, 2002).

Literature has also noted some techniques to measure the concentration polarization build up during operation. A simple technique was proposed by Sutzkover, Hasson and Semiat for determining the mass transfer coefficient and concentration polarization in a RO system. The technique is based on evaluation of the permeate flux decline induced by the addition of a salt solution to an initially salt-free water feed. Since the net pressure driving force is influenced by the level of the osmotic pressure prevailing on the membrane surface, the magnitude of flux decline enables the evaluation of membrane surface concentration, and hence the determination of the mass transfer coefficient k. Hence, the value of k can be simply determined from the osmotic pressures of the saline feed and the permeate respectively by measuring the permeate flux of the salt-free water, and the permeate flux of the saline solution (Sutzkover, et al. 2000).

Kim and Hoek compared analytical concentration polarization models to a rigorous concentration polarization model and experimental concentration polarization data. A numerical concentration polarization model was developed to enable local description of permeate flux and solute rejection in cross flow reverse osmosis separations. They concluded that the predictions of local concentration polarization, permeate flux and solute rejection by film theory and the numerical model also agreed well for realistic ranges of RO process operating conditions (Kim and Hoek, 2005).

2.9.2 Cake Formation Theory

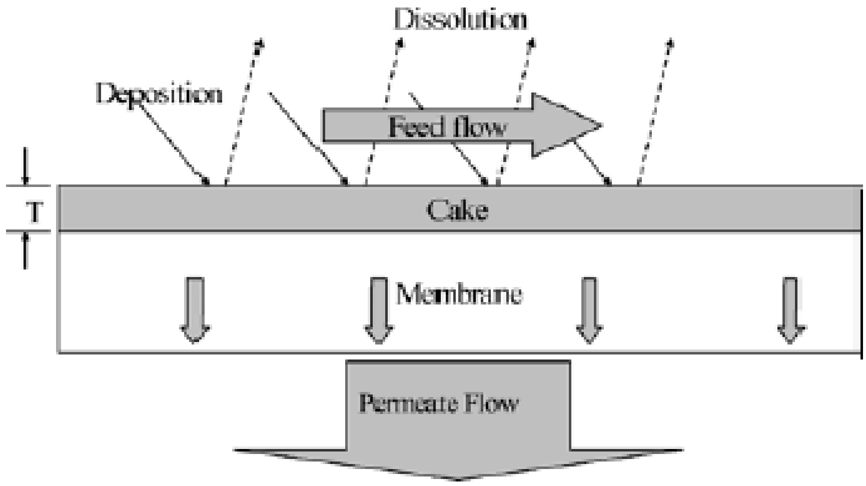

Figure 2.15 Cake Formation Theory (Rao, et al. 2005)

The cake formation theory is also used to describe the fouling and scaling phenomenon that occurs during reverse osmosis operation. The results of various studies and experiments conducted have led to the conclusion for a new source of decline in salt rejection. This is attributed to the formation of a cake enhanced osmotic pressure. The reason for this occurrence is a combination of a back diffusion of salt ions and altered cross flow hydrodynamics within colloidal deposit layers. This results in an increase in osmotic pressure and a greater salt concentration polarized layer (Hoek and Elimelech, 2003).

Lin, Rao and Shirazi (2005) explain the cake formation theory by focussing on decline in permeate flux in cross flow membrane filtration. Consider the schematic diagram of cross flow filtration (Figure 2.15) where the feed water flows along the surface of the membrane from one end to the other. The concentrate is collected at the other end and the filtrate passes through the membrane as permeate. It was observed that the permeate flux declined during the early stages of cake formation and then gradually levelled off as time progress and finally reaching a steady stage ultimate flux when the rate of solid deposition is balanced by back dissolution.

The initial studies in this area were conducted by Micheals and a group of researches in 1970. They studied the transition from the pressure dependent flux region to the pressure independent flux region and limiting flux region. They concluded that the transition occurs at lower pressure when low resistance membranes, lower mass transfer coefficients and high feed concentrations are used (Blatt, et al. 1970). This paved the way for further studies to be conducted regarding fouling and scaling during membrane operation. Studies conducted by Chen, Fane, Madaeni and Wenten explain the cake formation theory by measuring the critical flux (Jcrit) and measuring the transmembrane pressure drop. Above Jcrit the operating pressure has a period of instability for increasing and decreasing flux. Once Jcrit has been exceeded by the system the colloids in the polarized layer form a consolidated cake across the membrane (Chen, et al. 1996).

2.9.3 Factors Affecting Reverse Osmosis Performance

Most RO systems operate normally over a long period of time and can withstand the effect of fouling and scaling. However with continued operation fouling and scaling will affect the RO performance. The feed water characteristics, type of membrane used and the pretreatment procedures carried out all influence the performance of the membrane. The performance of a RO system can be explained used key terms. This section will look at these terms.

Rejection: It is defined as the percentage of solid concentration removed from the system feedwater by the membrane in use. Ion rejection is the effectiveness of the membrane to eliminate a single ion in the feed water. It is calculated as follows:

$$\text{Ion Rejection} = 1 - \frac{Cp}{Cf}$$

Where C_p is the ion concentration in the permeate
And C_f is the ion concentration in the feed water.

The build up of solute on the membrane also affects the performance of the membrane. The increase of the salt concentration on the membrane surface can be estimated by the percentage of the build up of salts along the membrane surface. It is calculated as follows:

$$\text{Percent Build up} \equiv \frac{\text{Ions remaining in product water}}{\textit{Ionsremaining} \inf \textit{eedwater}} \times 100$$

Water Recovery: The water recovery is calculated using the following equation:

$$\textit{PercentWater}\,\mathrm{Re}\,\mathrm{cov}\,\textit{ery} = \frac{Pf}{Pf + Rf} \times 100$$

Where P_f is the permeate flow rate

And R_f is the rejection flow rate

Chapter 3 Modelling Approach

3.1 Introduction

Mathematically modelling a real world system can aid in predicting a system's behaviour and performance in responding to various input parameters. When a system is accurately modelled, system refinement and system performance optimisation can be achieved using softwares reducing computation time and over dependence on trial and error style approaches of computation. This type of mathematical modelling can be facilitated using specialised software. Matlab is one such mathematical modelling software which is widely used in engineering research projects across different industries. System models are created using Matlab and simulated using Simulink, a model simulation application included in the Matlab suite. This section will closely look at the approach taken for developing the Artificial Neural Network code and the theory of neural networks and rejection mechanisms.

3.2 Understanding Artificial Neural Networks

Neural Networks are composed of simple elements operating in parallel. These networks are inspired by biological nervous systems. The network function is determined by the connections between elements and it can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Neural networks ate adjusted or trained so that a particular input leads to a specific target output. The network is adjusted based on a comparison with the desired output and the weights are adjusted. It is represented below in Figure 3.1.

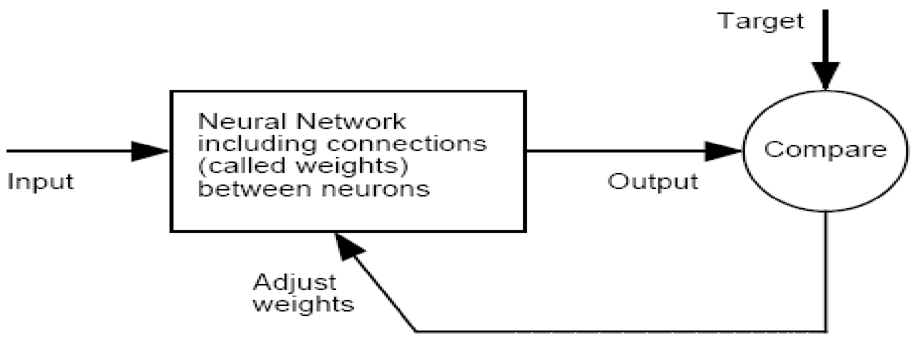

Figure 3.1 Representation of a Neural Network (Bhagat, 1990)

During the last 15 years, neural networks (NN) have gained significance in process modelling due to their wide range of application and ease with which they handle complex and highly non linear problems. NN were successfully applied to problems from various areas including the business, medical and industrial fields. The first theory of learning using neurons was given by Donald O Hebb in 1949. Hebb suggested that a neuron's efficiency in contributing to the firing of another neuron increases as the other neuron fires. This theory is based on observing biological behaviour in the conductivity of connections between neurons and their synapses. The weight of connections between neurons is changed analogously to the changing of conductance of neural neurons synapses. Thus networks internal parameters called weights are directly dependent on the learning that the neural network experiences just as the conductivity of biological synapses change as a biological neural network learns (Hebb, 1949).

Neural networks can predict any continuous relationship between inputs and the target. Similar to linear or non-linear regression, artificial neural networks (ANN) develop a gain term that allows prediction of target variables for a given set of input variables. Physical chemical relationships between input variables and target variables may or may not be built into the association of target and input variables. The origins of artificial neural networks can be contributed to Frank Rosenblatt and the development of a Perceptron. The Perceptron consisted of two layers of neurons and a simple learning algorithm that could recognize certain patterns of input. The ability to recognize similar patterns is powerful because it reduced the amount of explicit programming (Rosenblatt, 1962).

Artificial neural networks are numeric techniques able to capture and represent complex input output relationships. They have the ability to learn linear as well as non linear correlative patterns between sets of input data and corresponding target values, directly from the data set that is modelled. They can also be successfully used in classification problems, since there are specific algorithms available to group the input patterns in different clusters based on similarities and dissimilarities between them. The ANN is characterized by processing units (neurons) and adjustable parameters i.e. weights (Bhagat, 1990).

In the ANN approaches, data normalization is necessary before starting the training process, to ensure that the influence of the input variable in the course of model building is not based by the magnitude of their native values, or their range of variation (El-Hawary, 1993). The normalization technique used consist in a linear transformation of the input/output variables to the range [0,1] using the following expression:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max(X_j - \min(X_j)}$$

Where

X'_{ij} = normalized variable for j for pattern i

Min (Xj) and max (Xj) = minimum and maximum values of that variable in a particular data set.

Back propagation is a neural network training method based on a forward flowing of information, and back propagated error corrections. The back propagation networks are usually organized in layers of neurons, as the architecture presented below in Figure 3.2

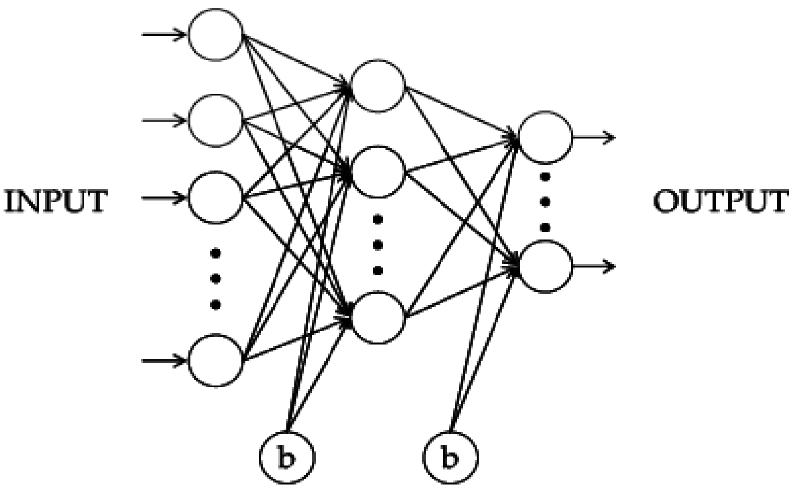

Figure 3.2 Multilayer Neuron Architecture (Bhagat, 1990)

The connections are made between the neurons of adjacent layers allowing the neuron to receive a signal from a neuron in the preceding layer and allow it to transmit signals to neurons in the immediately succeeding layers. Normally there are at least three neuron layers: an input layer which receives the input data, one or more hidden layer and an output layer. Also a bias neuron (b) supplies an invariant output is connected to each neuron in the hidden and output layers.

Each processing element (neuron) receives a number of inputs, (Xi). A weighted sum of these signals is calculated, using the neuron's assigned weights (Wi) , which is transformed by an activation function (f) to produce a single output signal (Y) , that is send to the neurons in the succeeding layer. It can be calculated as follows

$$Y = f(\sum_i XiWi + b) .$$

It is can also be explained using the representation below in Figure 3.3:

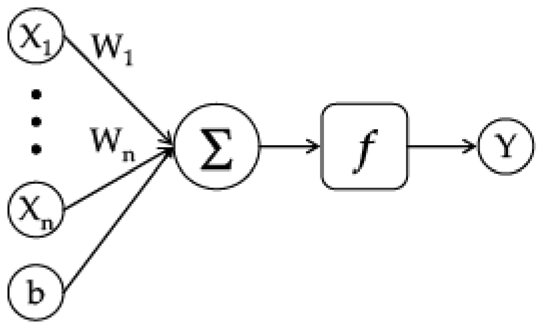

Figure 3.3 Single Neuron Model (Bhagat, 1990)

The activation function defines the output of the neuron in terms of the activity level at its input. Different expressions can be used for the neuron's activation function, like a step, sigmoid, tangent sigmoid or linear function as shown in Figure 3.4

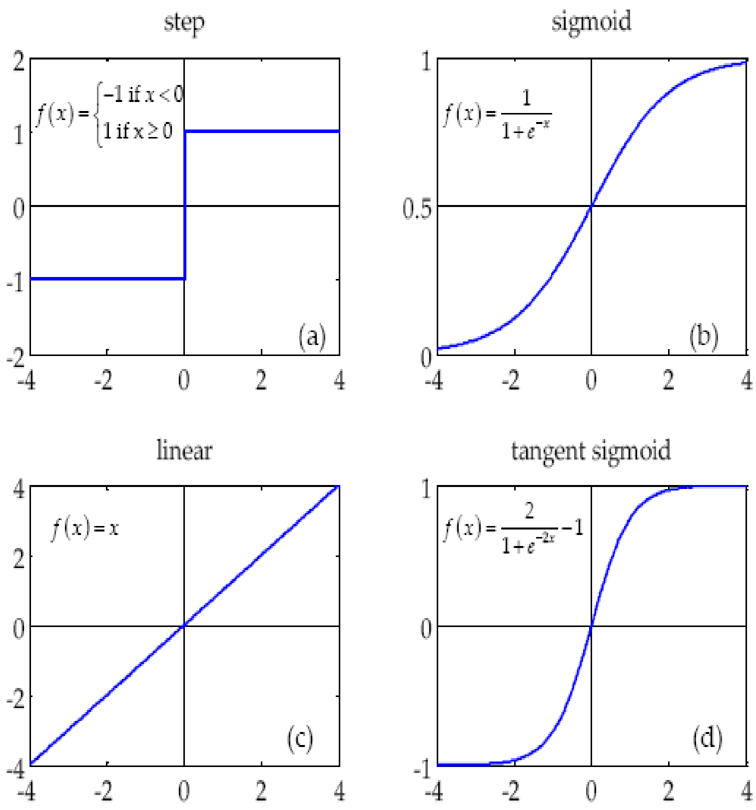

Figure 3.4 Different Neuron Activation Functions: a) Step function b) Sigmoid function c) Linear function d) Tangent Sigmoid function (Niemi, et al. 1995)

The back propagation training consists of two passes of computation: a forward pass and a backward pass. In the forward pass an input pattern vector is applied to the neurons in the input layer. The signals from the input layer propagate to the units in the first hidden layer, each one producing an output as described above. The outputs of these neurons are propagated using the same algorithm to units in subsequent layers until the signals reach the output layer where the actual response of the network to the input vector is obtained (Niemi, et al. 1995).

A more efficient method used for weights adaptation is the Levenberg - Marquardt algorithm which is a combination between the gradient descent rule and the Gauss - Newton method. This algorithm uses a parameter to decide the step size, which takes large values in the first iterations and small values in the later stages (Levenberg, 1944). For the learning phase, the data must be divided in two sets: the training data set, which is used to calculate the error gradients and to update the weights, and the validation data set, which allows to select the optimum number of iterations in which the networks learns general information from the training set. As the number of iterations increases, the training error drops whereas the validation data set error begins to drop, then reaches a minimum and finally increases.

Continuing the learning process after the point when the validation error arrives to a minimum leads to a process called over fitting, when the network became specific to the pattern vectors that form the training data set. After finishing the learning process, another data set (test set) is used to validate and confirm the prediction accuracy (Delgrange, et al. 1998).

3.3 Studies Conducted on Operations Using ANN Techniques

In recent years the trend has been to develop RO process models based on the dynamics of the process and direct analysis of experimental data. Hence artificial neural network (ANN) based models have been provided an option to model the plant performance variations using easy and inexpensive techniques to measure process parameters. Previous studies conducted in this area of using artificial neural networks to describe filtration processes focused on modelling the permeate flux decline and equivalent increase in the total membrane resistance.

The available approach for modelling membranes separation processes by means of ANN considers a steady state procedure to identify the influence of different process variables on the separation performance. Studies to simulate the RO of aqueous ethanol and acetic acid solution were conduced by Niemi, Bulsari and Palosaari. They conducted different laboratory experiments considering different process parameters like feed flow velocity, temperature, concentration and rejection. These parameters were used as the basis of an ANN model to estimate the permeate flux and the rejection percentage (Niemi, et al. 1995). The Neural Network predictions were better than the ones obtained with a finely porous mass transfer model conducted by the same researchers (Niemi and Palosaari, 1993).

Several studies also addressed the problem of system performance during the process operation. A study was conducted by Dornier, Declox, Trystram and Lebert for a raw cane sugar syrup plant using microfiltration. Using a NN architecture with three inputs (time, trans membrane pressure and cross flow velocity), two hidden layers (with 5 and 3 neurons, respectively, as resulting from an optimization process) and one output (total membrane resistance), it was showed that the best results were obtained when experiments in the centre and periphery of the parametric range were used in training a model based on constant operating conditions. The capacity of neural networks models to represent the evolution of process performance under variable operation conditions was also investigated.

In this case, the network was trained with four different experimental runs with filtration time ranging from 140 to 180 hours, and tested using three other sets when the filtration time varied from 100 to 180 hours. Acceptable values were obtained for the variation coefficient and the coefficient of determination between the experimental and predicted membrane resistance on the whole data base (16.1% and 0.874, respectively). However, the total membrane resistance could not be well reproduced for one experimental run with a dynamic different from the ones used in training. Also, it is expected that the model can not be applied beyond the time range considered in training i.e. maximum of 180 hours (Dornier, et al.1995).

A study was conducted to study the ability of a neural network approach for the simulation of cross flow milk ultra filtration under constant feed quality. A series of laboratory experiments were conducted and the permeate flux and the total hydraulic resistance were predicted as a function of operational time, pH and fat percent of the feed. Using a set of processing conditions a single curve simulation was created in order to enable the selection of optimum number and arrangement of training points. Similarly 6 experimental points for each set of feed quality conditions including data corresponding to the beginning and end of the filtration period were chosen to train the neural network model. A higher accuracy model was created using only 10% of the experimental data and with a lower relative error (Razavi, et al. 2004).

A neural network model was used to predict the hydraulic resistance and the trans membrane pressure of an ultra filtration drinking water pilot plant at the end and beginning of each filtration cycle. The best combination of input parameters were the turbidity of raw water, temperature and the permeate flow rate. The longer the process is continued the more impact it has on the membrane performance and this was also taken into consideration. Prediction errors lower than 5% were obtained when modelling both cases of reversible and irreversible fouling (Delgrange, et al. 1998).

In a subsequent study (2000) a model was developed for predicting the productivity of an ultra filtration plant based on the two feed forward neural networks interconnected in a recurrent way. The evolution of the total membrane resistance at the end of each cycle and the beginning of the next cycle after backwashing was predicted based on filtration operating parameters such as permeate flow, filtration time, water quality (i.e. turbidity, dissolved oxygen and pH) and backwash operating parameters (i.e., backwash pressure and chlorine concentration). The model allowed good predictions even in the case of changing water quality and operating conditions for both reversible and irreversible fouling, with 90% of the experimental points predicted with less than 10% of error (Delgrange, et al. 2000).

Investigations into the use of a neural network model for predicting the time evolution of the membrane resistance in a drinking water nano filtration process was also carried out. The process uses several configurations like flat membrane sheets, single and multiple spiral wound elements for bench and full scale operations. Models based on back propagation architecture, implementing a Levenberg Marquardt learning algorithm were developed to relate influent flow rate (sum of feed water and recovery water flow rates), permeate flux, total dissolved solids (TDS) index, pH and temperature of the feedwater and operational time with the evolution of the total membrane resistance. The model allowed good predictions using only 10% of the experimental points for training with a relative error below 5% (Shetty and Chellam, 2003).

Chellam also investigated the use of ANN in simulation of transient permeate flux decline caused by poly dispersed colloids during constant feed quality cross flow microfiltration. Fouling caused by three different types of rigid and stable particles with different size distribution under a wide range of hydrodynamic conditions were analysed. The instantaneous permeate flux was modelled as a function of initial feed concentration, initial feed flux, entrance shear rate, trans membrane pressure and filtration time. For each one of the colloidal suspensions, an individual ANN model was trained using extreme values of input parameters. Using about 23% of the experimental data for training phase, accurate models were created with a relative error of less than 10% (Chellam, 2005).

The performance of a cross flow membrane filtration of a colloidal suspension using a radial basis function and a feed forward back propagation neural network was studied by Chen and Kim. The model was used to predict the permeate flux during the filtration operation under constant feed quality. The particle size of the suspended solids (SiO2), solution pH and ionic strength, trans-membrane pressure and filtration time were used as input parameters. The model accurately predicted the permeate flux using 17% of the data with a relative error of less than 10% (Chen and Kim, 2006).

Sahoo and Ray used the same input data as Chen and Kim to develop a genetic algorithm based method for obtaining the desired geometry of a back propagation neural network and a radial basis function network. The influence of training data set size and the importance of scaling the data were also taken into consideration. The results confirmed that the models performance enhance when using a larger training dataset, and also, the use of scaled data slightly improve the performance of the models. Comparing their results with the ones obtained by Chen and Kim it was concluded that the genetic algorithm optimized the artificial neural network model for a back propagation neural network model (Sahoo and Ray, 2006).

3.4 Terminology and Equations Considering a Single Membrane

Initial investigation into reverse osmosis performance was explained with the help of the diffusion solution model. This model describes permeation through a dense membrane where the active layer us permeable but non porous. Water and solutes dissolve into the membrane material, diffuse through the membrane and reliquefy on the permeate side of the membrane. Dissolution of water and solutes into a solid material occurs if the solid is loose enough to allow individual water and solute molecules to travel along the interstices between polymer molecules of the membrane (Wijmans and Baker, 1995).

This model assumes the mass transfer coefficients are constant through the process. However it is well known that the mass transfer coefficients (K) vary with feedwater quality, operating conditions and the physical and chemical properties which vary with time of operation and effectiveness of pretreated feed water. The mass transfer coefficients vary with time and have to be taken into consideration (Paul, 2004).

An investigation on pesticide removal by reverse osmosis was carried out by Taylor (1998) concluded that the mass transfer coefficients could be derived using flux and recovery of the system. Hence the solution diffusion model was modified and the flux and recovery of the system also taken into consideration. This modified model predicted permeate concentrations more affectively than the initial solution diffusion model and came to be known as the homogenous solution model (HSD). The HSD model considers the operational parameters like water quality, water recovery and membrane specific coefficients to determine the system performance.

Consider a single membrane element as shown in Figure 3.5 The HSD developed considers a mass balance around the membrane element and concentration pressure gradient solute mass and recovery. All mass transfer coefficients are overall Ks and consider solute diffusivity and membrane thickness (Zhao, et al. 2005).

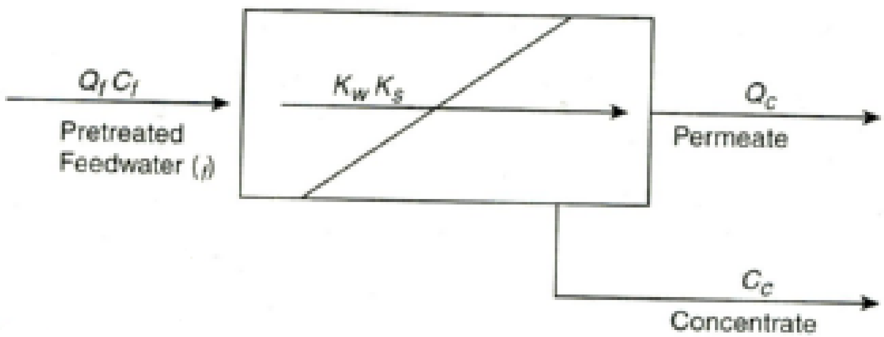

Figure 3.5 Cross Section of a Single Membrane Element (Zhao, et al. 2005)

Mass balance for water flow:

$$Q_f = Q_p + Q_c$$

Where:

Q_f = feedwater flow rate

Q_p = permeate flow rate

Q_c = concentrate flow rate.

Mass balance for the solute flux is given as

$$Qf \times Cf = QpCp + QcCc$$

Where:

C_f = Feedwater solute concentration

C_p = Permeate solute concentration

C_c = Concentrate solute concentration

The product recovery rate is given as

$$R = \frac{Qp}{Qf}$$

Where:

R = product water recovered from the feed water.

Water flux is given as:

$$Fw = Kw(\Delta P - \Delta \Pi) = \frac{Qp}{A}$$

Where:

K_w = water mass transfer coefficient

Δ P = trans membrane pressure difference

$\Delta \Pi$ = trans membrane osmotic pressure difference

A = effective membrane area

The dissolved solute flux is given as

$$Fs = Ks(Cm - Cp)$$

$$Fs = Ks\left[(\frac{Cf + Cp}{2}) - Cp \right]$$

$$Fs = \frac{QpCp}{A}$$

Where:

K_s = Solute mass transfer coefficient

C_m = concentration at the membrane surface.

The water mass transfer coefficient is given as:

$$Kw = \frac{Qp}{A(\Delta P - \Delta \Pi)}$$

$$Kw = \frac{Qp}{A \times NAP}$$

Where:

NAP is the Net area Pressure and is calculated as $\Delta P - \Delta \Pi$

The solute mass transfer coefficient is given as:

$$Ks = \frac{QpCp}{A\Delta C}$$

Where:

ΔC is the concentration difference.

This concentration difference is calculated as:

$$\Delta C = (Cm - Cp)$$

$$\Delta C = \frac{(Cf + Cc)}{2} - Cp$$

Finally all these variables are used to derive the final permeate concentration. It is given as:

$$Cp = \frac{KsCf}{Kw\Delta P + \Delta \Pi \left(\frac{2 - 2R}{R} \right) + Ks}$$

The linear approximation of the non linear concentration profile of the feedwater stream induced an error in the MSD model. This was corrected by developing a differential equation relating the feedwater stream concentration into the HSM model. It was given as:

$$Cp = \frac{KsCf}{-RFw}\ln\left(1-\frac{Rfw}{Fw+Ks}\right)$$

$$Cp = \frac{KsCf}{-RFwFwekb}\ln\left(1-\frac{RFw}{Kse^{Fw/kb}}\right)$$

3.5 Solute Rejection Mechanisms

The basic mechanisms of rejection are electrostatic precipitation at the membrane surface, solubility and diffusivity through the membrane material due to chemical effects or straining due to the size and other chemical properties of molecules. RO membranes are often negatively charged because of the presence of ionized functional groups such as carboxylates in the membrane material. Negatively charged ions may be rejected at the membrane surface due to electrostatic repulsion and positively charged ions may be rejected to maintain electro neutrality in the feed and permeate solutions. The presence of polar and hydrogen bondable functional groups in the membrane increases the solubility of polar compounds such as water over non polar compounds providing a mechanism for greater flux of water through the membrane. Large molecules would be expected to have lower diffusivity through the membrane material or be unable to pass through the membrane at all.

The rejection capabilities of a RO membrane are related with percent salt rejection.
The salt rejection for a RO membrane is calculated as:

$$\text{Rej} = 1-\frac{Cp}{Cf}$$

Where:

C_p = concentration in the permeate

C_f = concentration in the feed water.

3.5.1 Generation of Water and Solute Flux Equations

A variety of equations have been developed for the rate of water and solute mass transfer through a RO membrane. This model expresses the flux as the product of a mass transfer coefficient and a driving force. The driving force for water flux through a RO membrane is the net differential pressure or the difference between the applied and osmotic pressure differentials and is given as follows:

$$\Delta P_{NET} = \Delta P - \Delta \Pi$$
$$\Delta P_{NET} = (P_F - P_P) - (\Pi_F - \Pi_{P})$$

Where:

ΔP_{net} = net trans-membrane pressure (bars)

P_f = feed pressure

P_p = permeate pressure.

The water flux through the RO membranes is given by the following equation:

$$Jw = kw(\Delta P - \Delta \Pi)$$

Where:

J_w = Volumetric flux of water (L/m^2h)

K_w = mass transfer coefficient for water flux (L/m^2h.bar)

The equation for water flux is valid at any point on the membrane surface between the feedwater entrance and concentrate discharge in a membrane element but the applied and osmotic pressure changes continuously along the length of the membrane due to continuously changing solute concentration. As a result the overall flux is determined by integrating the above equation along the length of the membrane element.

The driving force for solute flux is the concentration gradient and the flux of solutes through the RO membranes is given as:

$J_s = k_s(\Delta C)$

Where:

J_s = Mass flux of solute $mg/m^2.h$

K_s = mass transfer coefficient for solute flux L/m^2h or m/h

ΔC = concentration gradient across the membrane mg/l

The flux of solutes through the membrane is equal to the flux of water multiplied by the solute concentration in the permeate as described by:

$$\mathrm{Js} = \mathrm{Cp.Jw}$$

The ratio of permeate flow to feedwater flow or recovery is calculated as:

$$r = \frac{Qp}{Qf}$$

Using flow and mass balance principles the solute concentration in the concentrate stream can be calculated from the recovery and solute rejection. The flow and mass balances using flow and concentration principles is given as:

$$FlowBalance: Qf = Qp + Qc$$
$$MassBalance: CfQf = CpQp + CcQc$$

Where:

Q = flow m^3/s

C = concentration, mole/L or mg/l

Combining the mass and flow balances with the rejection equation and recovery yields the following expression for the solute concentration in the concentrate stream:

$$Cc = Cf\left[\frac{1-(1-rej)r}{1-r}\right]$$

Where:

rej = rejection (dimensionless expressed as a fraction)

C_c = concentration in the concentrate moles/L or mg/L

C_f = concentration in the feed water, moles/L or mg/L

For a well function RO membrane rejection is close to 100 percent then the equation is simplified as follows:

$$Cc = Cf\left[\frac{1}{1-r}\right]$$

The main focus of this study is predicting the membrane performance of a RO system. For this purpose a modelling software called MATLAB is used. In the simulation of a RO process it is essential to assess the permeate, concentrate and reject streams for the given water condition in order to calculate the permeate flux and solute rejection percentage. The data sets needed are pressure, various feed concentrations, flow rates and concentration of the permeate and reject streams and the predicted outputs are permeate flux and Solute Rejection percentages. A precise estimation of the flow area can be made considering its dependence on the permeate flux and rejection.

For a given sample of feedwater, groundwater and effluent the solute rejection and permeate flux in the bulk phase will be calculated. Also using the neural network toolbox the general simulink system for the given water samples will be created along with prediction of output performance. A simple block diagram illustration will help understand the creation of the ANN code.

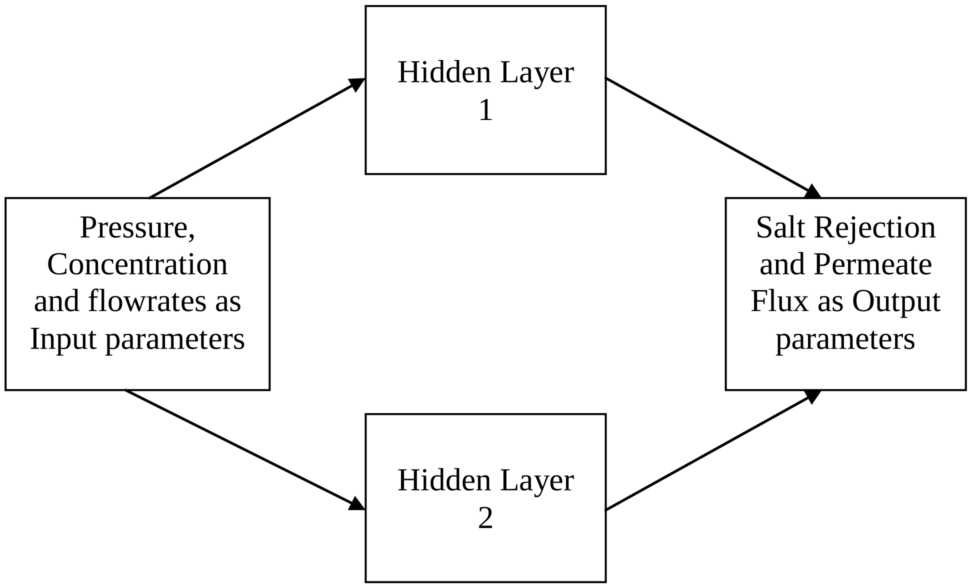

Figure 3.6 Block Diagram of the Developed ANN Code

Chapter 4 Sources of Data Used for Model Development

4.1 Introduction

In order to predict RO performance certain experimental procedures have been carried out by Nasir (2005) and the data collected using these experimental procedures have been used to develop the final Neural Network model. This chapter will look at the various experimental procedures conducted. It will also look at the experimental design, experimental procedures along with material and chemicals used for the experiments. The initial feedwater experiments carried out have sodium and calcium as the predominant minerals that may contribute to scaling and fouling.

4.2 Preparation of NaCl and $CaCO_3$ Samples

Before the experiments were carried out the dissolved impurities containing varying amount of sodium, calcium and combination of sodium and calcium solutions were created. Sodium and calcium solutions in these experiments are referred as simulated feedwater samples. Sodium solutions are prepared by diluting sodium chloride at concentrations ranging from 100mg/l to 5000mg/l into demineralised water with electrical conductivity of 20 ± 5µS/cm. The usage of demineralised water minimises the effect of other ions which may be present in the water. The use of distilled water is undesirable because of the need for large water samples required for feed sample preparation.

Similar procedures are carried out for preparation of calcium solution. It is prepared by mixing $NaHCO_3$ (between 0.005 and 0.02 M) with $CaCl_2$ (between 0.005 and 0.02 M). The various reactions taking place during the preparation are given below.

$$
\begin{aligned}
&2NaHCO_3 + CaCl_2 \rightarrow Ca(HCO_3)_2 + 2NaCl \\
&Ca(HCO_3)_2 \rightarrow CaCO_3 + H_2CO_3 \\
&H_2CO_3 \rightarrow H_2O + CO_2
\end{aligned}
$$

The variables considered in the experiments are the applied pressure (1250-4750), sodium chloride concentration (from 100 to 5000 mg/l), calcium carbonate concentration (from 50 to 100 mg/l) and combination of the two mixtures. The simulated feedwater samples are created by diluting sodium chloride and calcium carbonate mixtures with demineralised water in a polyethylene tank. Atomic Absorption Spectroscopy is used to determine the sodium and calcium concentrations in the permeate and reject streams. Samples are taken every 15 minutes and analysed by the Atomic Absorption Spectroscopy using Natrium and Calcium lamp at wavelength of 489 and 422.7 nm respectively. Lanthanum Oxide solution (10%) was added to the calcium carbonate solution samples to prevent the interference by other minerals and compounds. Total dissolved solids (TDS) and pH where measured by a Hanna pH-EC-TDS meter. The electrical conductivity is measured using a Yokogawa SC 82 conductivity meter. All experimental runs were performed at ambient conditions and typical operational time was one hour.

4.3 Preparation of Wastewater and Groundwater Samples

For the experiments concerned with secondary effluent, samples were taken from Kwinana Water Reclamation Plant situated 35 km from Perth. The samples were placed in a 1000L tank and operating pressure of the experiments ranged from 1250 to 3250kPa. The characteristics of the secondary treated effluents are summarised below in Table 4.1.

Parameter	Unit	Values
pH	-	6.6-6.7
Total Dissolved Solids	mg/l	350-400
Electrical Conductivity	µS/cm	768-1113
Turbidity	NTU	4.89
Total Organic Carbon	mg/l	6.03
Sodium	mg/l	114.6
Calcium	mg/l	22.19
Iron	mg/l	0.60
NH_4 as N	mg/l	4.74

Table 4.1 Characteristics of the Wastewater Experimental Samples

For the groundwater experiments operating pressure ranged from 1000-3250kPa with three hours of operation time. The samples were placed in a 5600L tank and the permeate and concentrated were collected and analysed every 15minutes for the first one hour and every 30minutes for the next two hours. The characteristics of the groundwater samples used for the experiments are given below in Table 4.2.

Parameter	**Unit**	**Values**
pH	-	6.0-6.1
Total Dissolved Solids	mg/l	200-290
Electrical Conductivity	µS/cm	410-450
Turbidity	NTU	<1
Sodium	mg/l	74.84
Calcium	mg/l	19.14
Iron	mg/l	0.36

Table 4.2 Characteristics of the Groundwater Experimental Samples

Chapter 5 Artificial Neural Network Model Development

5.1 Introduction

The basic fundamentals of Reverse Osmosis and its working have already been established in Chapter 2. RO is used to purify brackish water, industrial wastewater and groundwater thereby rejecting ions and contaminants from passing through. This chapter will focus on the key parameters that affect the performance of a RO system. The chapter will be split into five sections and look at the various scenarios which been considered i.e. working of the RO system handling sodium chloride, the system handling calcium carbonate and a combination of the two, the system handling groundwater and the system handling secondary effluent. Thus in general the whole system is affected by the performance of the membrane. This section will look at the performance of the RO system considering certain parameters and using Artificial Neural Networks (ANN) these parameters will be predicted. The basic fundamentals of ANN and its working mechanisms have been discussed in Chapter 3.2.

The mathematical modelling of real world industry scenarios and situations is of extreme importance in innovation and technological advancement. When such a model can be created using mathematical tools and software it allows the user to accurately model, optimise and predict performance of the system handling various different parameters. This can also be time saving and economically advantageous to create such a mathematical model before setting up or extending an existing process.

Artificial neural networks are used for modelling the RO and determining the effect of different parameters and how they affect the RO performance. It is widely used in different engineering research projects and is not just limited to the chemical industry. A general System model will be created and simulated using Simulink a model simulation application which is available in the MATLAB software. Simulink will help create a dynamic system that work for the considered data. It has its limitations for testing data and is satisfactory within the given scope of this work.

Permeate flux and salt rejection are the key performance parameters of a RO process. They are mainly influenced by the variable parameters given below:

Pressure: Increased feed water pressure will increase permeate flux and decrease the permeate TDS. With excessive pressure the membrane may become deformed or compacted which will result in decrease of the product flow.

Temperature: Increased temperature will increase permeate flux, which increases salt passage. It is also important to note that every unit is rated for a product flow temperature of 25°C. With a temperature decrease, the product flow will decrease. On average the membranes lose about 2% production for every degree below 25°C. During the entire operation the RO system is kept at ambient conditions hence the effect of temperature is not considered and assumed to not affect this particular design.

Recovery: The recovery is the ratio of the permeate flow to the feed flow. When recovery is increased, the permeate flux will decrease and the salt passage will increase.

Feedwater Concentration: Increased TDS or salt concentrations will decrease permeate flux and increase salt passage. This can also lead to surface coating or fouling by the salt.

5.2 RO Performance with Feedwater Samples containing Sodium Chloride

5.2.1 Effect of Pressure on TDS, EC, WRP and Permeate Flux

The system handles the total dissolved solids (TDS) and electrical conductivity (EC) of the solution fairly well. The TDS and the EC are generally affected by the feed composition of the impurity i.e. NaCl and applied pressure. Increasing the pressure will lead to increase in the TDS and the EC rejection percentages. However in practice this is not observed as per the findings noted in Appendix A and Table 5.1.

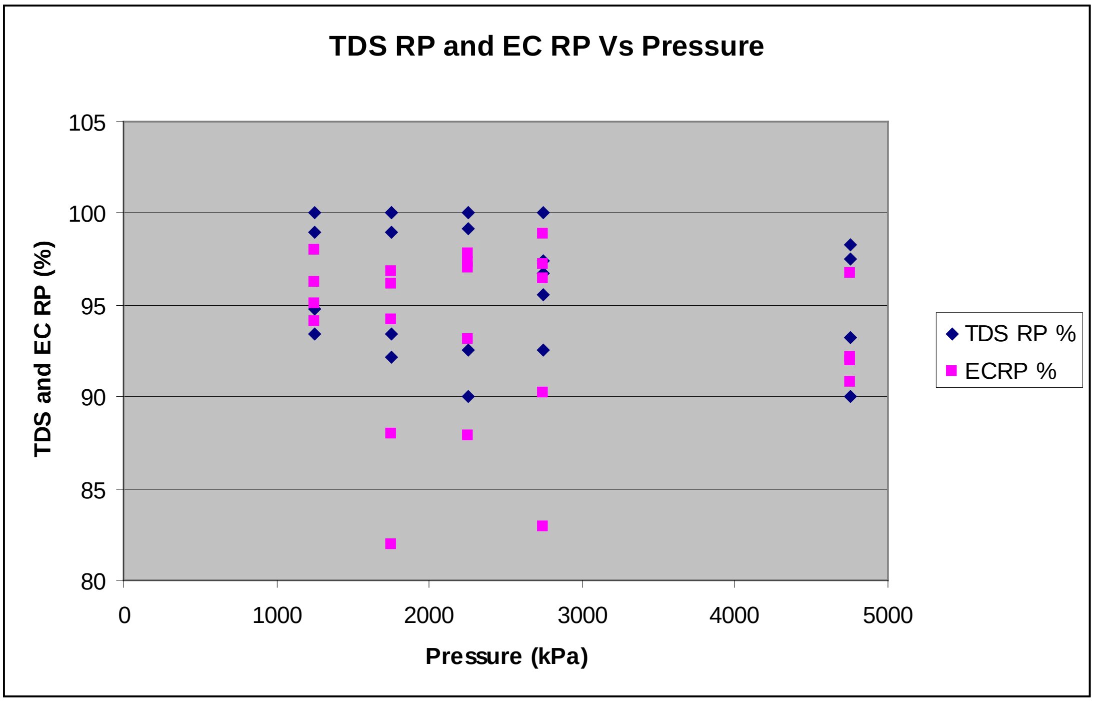

Figure 5.1 TDS and EC Rejection Percentages for the NaCl Solution

It can be clearly seen from Table 5.1 and Figure 5.1 as operation of the RO continues the TDS rejection percentage (RP) gradually decreases. This can be attributed to the build up of the sodium chloride on the membrane being used in the system which in turn affects the quality of the final water product.

For an initial feed solution of 100 mg/l of NaCl and operating pressure of 1250kPa the TDS RP is 99% and EC RP is 96.20% and for the same feed concentration but an elevated pressure of 4750kPa the TDS and EC RP drops down to 97.55% and 96.78%. As from Figure 5.1 the linear reduction in the value of the percentages are noted with gradual decrease in the value with passage of time. These values are not inter dependent but greatly dependent on the operating pressure.

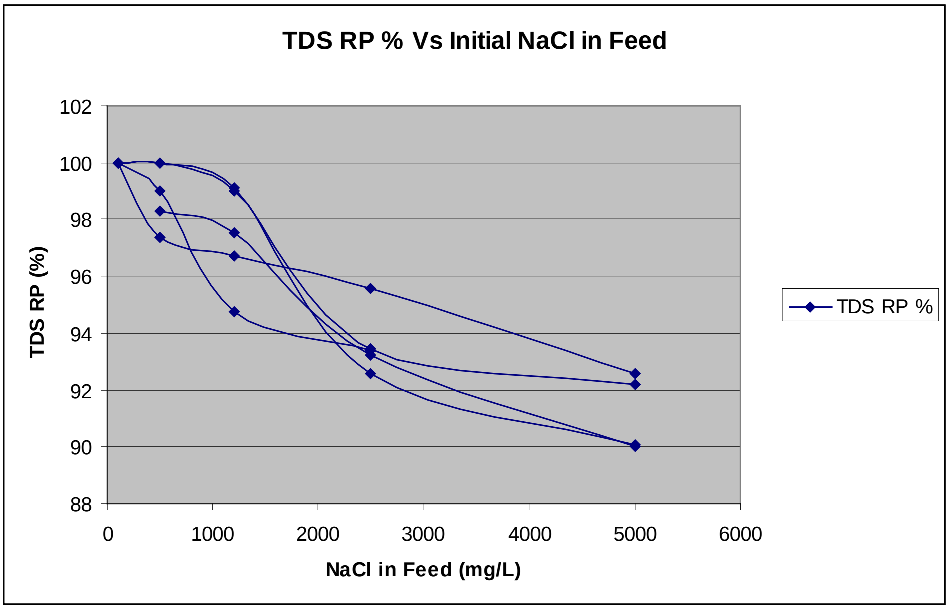

Figure 5.2 TDS RP for the NaCl Solution as a Function of the Initial NaCl Feed Concentration

When the TDS rejection percentage is plotted against the initial feed concentration (Figure 5.2) there is a gradual decline in the amount of NaCl rejected as the operation continues. The performance of the RO system will decline due to various factors the main being decline in the membrane rejecting the salt impurities due to fouling and pore blockage. The initial high values of the TDS RP are attributed to the high operating pressure and this high pressure also has an effect on the acidity of the permeate. Higher operating pressures increase the diffusivity of CO_2 in the product water and the final product water requires pH adjustment. Similar results are noted with the EC rejection percentages when plotted as a function of the initial NaCl feed as illustrated in Figure 5.3.

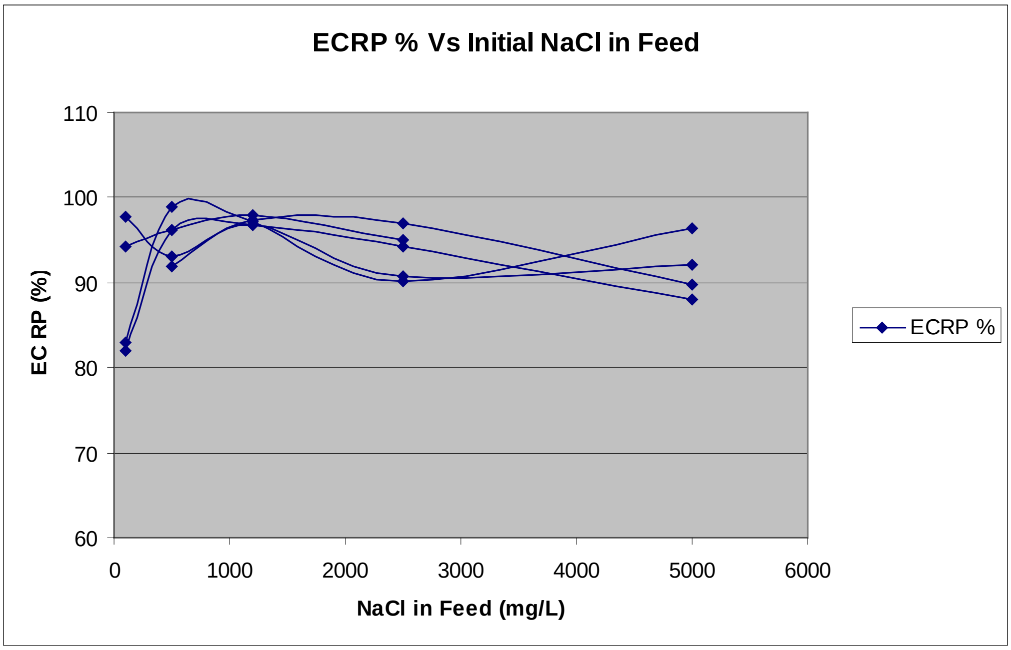

Figure 5.3 EC rejection percentages for the NaCl Solution as a Function of the Initial NaCl Feed Concentration

After observing the change in the TDS and EC RP with respect to pressure and feed concentration we now have a look at how the water recovery percentages (WRP) are affected during the operation. Table 5.2 (Appendix A) and Figure 5.4 depict the linearity of the WRP and flow rates for the permeate and reject streams. A maximum WRP of 71.1538 was noted while the system operated at a pressure of 4750kPa and was handling 2500 mg/l of NaCl feed solution. The lowest value of WRP was 11.11% for the system handling 2500 mg/l of NaCl with operating pressure of 1250Kpa. It can be clearly observed that increasing operating pressure will increase the WRP and the permeate flow rate which increases from 1.5l/min to 9.25l/min while the reject flow rate decreases from 12l/min to 3.75l/min.

Also on close observation for operating pressure of 2750kPa and with a feed NaCl concentration of 2500 mg/l the permeate and reject flow rates are equal. This can be attributed to the stage of achieving equilibrium. At this equilibrium stage the osmotic pressure of the solution becomes equal to the applied pressure i.e. 2750kPa. Higher osmotic pressure of solution will result in diffusion of ions into the membrane. As a result the concentration of ions in the permeate will decrease otherwise high concentrations of ions will remain in the bulk phase and reject streams.

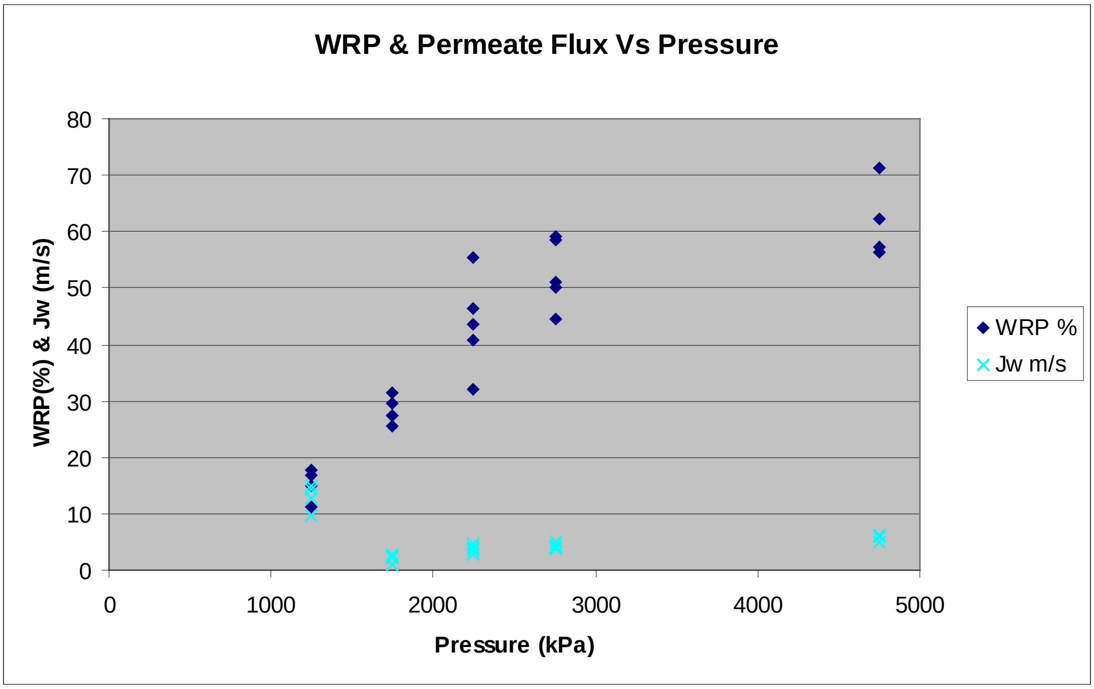

Figure 5.4 WRP and Permeate Flux for the NaCl Solution at Different Pressures

From figure 5.4 it can be observed that the water recovery percentage (WRP) increase linearly with the increase in pressure and sodium chloride concentration in the feed water. The lowest WRP recorded was 11.11% and the highest WRP recorded was 71.1538% for the investigated pressures of 1250 to 4750kPa. The WRP however reduced right away the maximum value of the WRP was recorded due to the increase in the NaCl concentration in the feed water solution and the osmotic pressure.

The increase in the NaCl concentration leads to increase in the osmotic pressure of the solution. In theory as reported by Avlonitis, Hanbury and Boudinar the operating permeate flux will be zero (Avlonitis, et al. 1993). Thus it is concluded that the osmotic pressure of the solution is the net driving pressure which was reported in Lee's experimental work in as early as 1975 (Lee, 1975). In our experimental findings the value of the permeate flux does not reach zero but drops down to as low as 1.06256m/s. thus it is concluded that the permeate quality decreases with continued operation and increasing NaCl concentration.

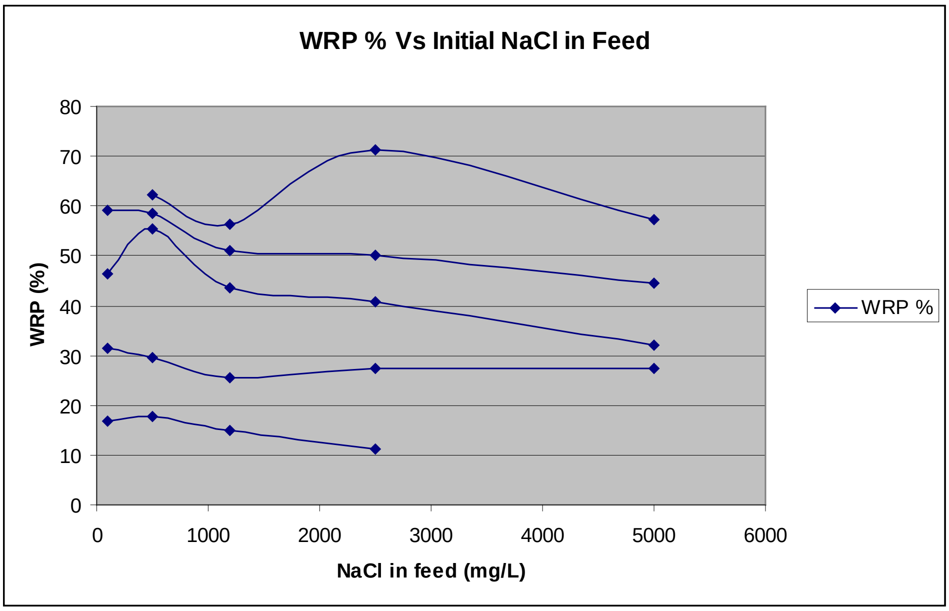

Figure 5.5 WRP for the NaCl Solution as a Function of the Initial Nacl Feed Concentrations

As soon as the osmotic pressure equals the net driving pressure the reported values of WRP when plotted as a function of the initial NaCl in feed start fluctuating with increasing pressure as illustrated in Figure 5.5. Although in order to overcome the osmotic pressure the operating pressure must be increased. This is when the maximum WRP is recorded at an elevated pressure of 4750kPa. The inconsistency of the WRP can also be a result of the increase in concentration polarization and membrane blockage due to continued operation.

The Figure 5.6 indicates the affect of the operating pressure on the permeate flux. The salt rejection percentages predicted by the model from the MATLAB codes are also indicated in the figure. The average Salt rejection percentages for the feed concentrations of NaCl of 100mg/l, 1200mg/l, 2500mg/l and 5000mg/l are 0.811, 0.89932, 0.93227, 0.99899 and 1 .0 respectively. As clearly seen from Table 5.3 and the profiles in Figure 5.4 the permeate flux decreases with the increase in the NaCl concentration.

Increasing the TDS or the NaCl concentration results in decrease of the permeate flux and increase in salt passage. This is attributed to increase in the osmotic pressure difference across the membrane. A higher driving force is required to overcome the osmotic pressure for the same salt concentration is required. The higher feed concentration also leads to fouling by salt and membrane blockage. Similar results were also noted in the study on the desalination of seawater from Telok Kalong Beach in Malaysia (Shamel and Chung, 2006).

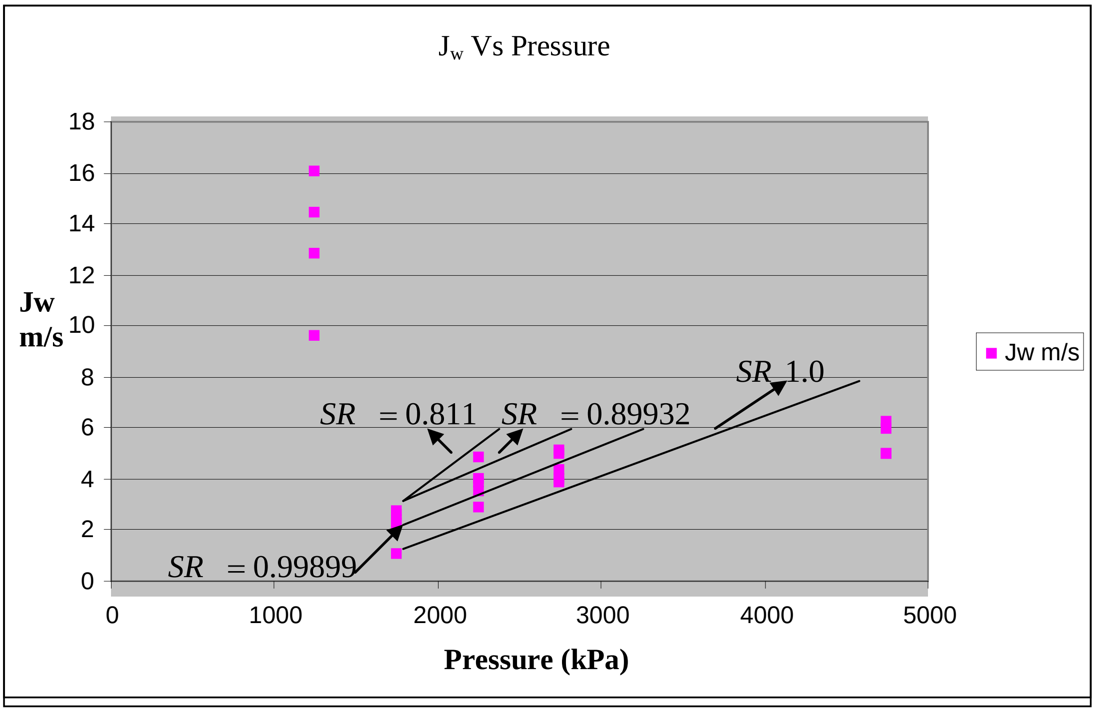

Figure 5.6 Permeate flux (J_w) for the Sodium Chloride Solution at Different Operating Pressures along with the SR values obtained from Simulation

5.2.2 Sodium Rejection Percentages Achieved by the RO system

The effect of the pressure on the rejection of NaCl impurity is given in Figure 5.7 and the values noted in Table 5.4. With increase in pressure the rejection (SR) of the NaCl impurity also increases. The highest value of the SR was noted for operating pressure of 4750kPa and feed concentration of 5000 mg/l as 98.6 and the lowest value of SR was 93.27 for operating pressure of 1250kPa and 100mg/L of initial feed concentration. The lower rejection values for NaCl are observed at the lower operating pressures of 1250kPa and 1750kPa and 100mg/L of initial feed concentration. Thus it can be concluded that when pressure is increased the SR percentages thus increasing permeate quality.

These values are similar to the ones found in other studies conducted on RO operations handling seawater with extremely high NaCl concentration. In their study on the desalination plant over six years of operation Rayana and Khaled found that the RO system worked fine when handling such large concentrations of NaCl and the rejection percentages were in the range of 95-98%. Although this system has an extreme pretreatment process and uses cartridge filters for screening the initial feedwater (Rayana and Khaled, 2003). Also reported by Al-Enezi and Fawzi considering a single stage RO unit, two stage systems and a two pass system was that product salinity will increase with the feed salinity and strong dependence on the system recovery (Al-Enezi and Fawzi, 2003).

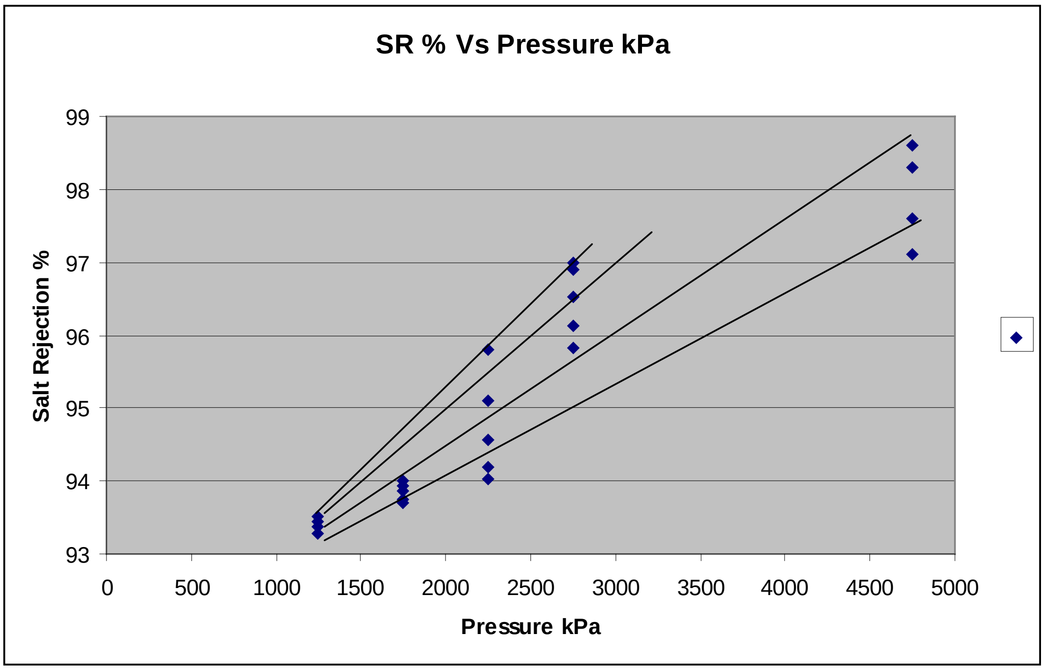

Figure 5.7 Sodium Rejection Percentages Obtained by the RO system for the NaCl Solution at Different Operating Pressures

5.2.3 Predictions Derived from the ANN model

The above experimental results established the performance of the RO system and its main function in rejecting impurities and having a good permeate flux throughout the operation. The ANN model created will verify these results and predict the salt rejection and the permeate flux for the same system conditions and parameters.

With the help of MATLAB and a neural network toolbox a code is written which will predict the salt rejection and the permeate flux of the system. In developing the model certain assumptions are used which are summarised below.

- The neural network model assumes a steady state operation for the RO system. The model also assumes an isothermal operation thus the temperature of the feed, permeate and reject streams are equal.
- The feed pressure is dependent on the feed salinity and it accounts for the osmotic pressure generated by the salinity on the feed side.
- The feed pressure also accounts for the module friction losses and membrane resistance of the RO operation.
- The membrane selectivity is constant and is equal for all types of considered salts in this study.
- The membranes used during the RO operation and model type of the equipment are always fixed.
- The neural network model assumes a constant permeability coefficient for water and salt permeation during the RO operation.
- The neural network model assumes complete mixing conditions during the operation.

For this model creation simple laboratory experiments were carried out and the data obtained from Nasir (2005) will be used to model the system. From this data collected the permeate flux and rejection of the RO system will be predicted. Using MATLAB simulation these values will be determined. The theory of ANN and neural network modelling has already been covered in 3.2. The values of the weight parameters are determined based on the experimental data and the permeate flux and SR will be calculated based on different input variables. The input variables used for this model development are the pressure, various feed concentrations, flow rates and concentration of the permeate and reject streams and the predicted outputs are permeate flux and Solute Rejection percentages.

The ANN created has two hidden layers, input layer which will simply transmit the input variable without any processing to the next layer. The nodes in the hidden layer receive weighted inputs and these weighted inputs are added to get the net input and output of the node using an activation function.

The weight parameters are found so that they are the variables in the numerical method which finds such values for the weight parameters that produce the best fit of the output of the network to the experimental data. This is called network training and it aims at minimising the sum of square of errors i.e. the differences between the calculated outputs and the desired outputs. The Levenberg-Marquardt method is used to determine the weights in the ANN simulation. Similarly the remaining salt rejection values and permeate flux values are simulated using the ANN code. These values are noted in the Table 5.5.

NaCl Feed mg/l	**J_w Experimental**	**SR Experimental**	**SR Simulated**	**J_w Simulated**
100	14.42	93.27	**92.95**	**9.85**
500	15.02	93.37	**92.17**	**12.67**
1200	12.820	93.44	**93.78**	**11.11**
2500	9.615	93.51	**94.12**	**8.71**
100	2.724	93.69	**92.77**	**2.87**
500	2.564	93.74	**93.87**	**2.75**
1200	2.24	93.87	**93.11**	**1.78**
2500	2.40	93.94	**93.37**	**1.74**
5000	1.06	94	**94.57**	**1.04**
100	4.00	94.02	**93.38**	**4.51**
500	4.80	94.19	**93.47**	**3.97**
1200	3.84	94.57	**93.71**	**3.10**
2500	3.52	95.11	**95.49**	**3.12**
5000	2.88	95.81	**95.87**	**2.97**
100	5.12	95.82	**94.16**	**5.96**
500	4.96	96.12	**94.88**	**5.78**
1200	4.32	96.52	**95.77**	**4.17**
2500	4.00	96.89	**95.87**	**3.81**

5000	3.84	97	**97.47**	**3.51**
500	6.25	97.1	**96.14**	**6.34**
1200	5.96	97.6	**98.73**	**6.19**
2500	5.92	98.3	**99.11**	**5.87**
5000	4.96	98.6	**99.89**	**5.97**

Table 5.5 The Simulated Results for Salt Rejection Percentages and Permeate Flux for the NaCl Feedwater Samples

The simulated results for SR and permeate flux are close to the analytical i.e. experimental obtained results shown in Table 5.5. The system profiles predicted by the ANN model are shown below in Figures 5.8 and 5.9. The model results agree well with the experimental data and model predictions. For the validation of the results i.e. for the permeate flux prediction the number of epochs used for the first data set was 18 and the total number of data sets was 25.An example of the simulated permeate and salt rejection values are shown in the Figure 5.6 and 5.7 for P = 4750kPa the rejection is 99.899 % and the permeate flux with 18 epochs is 5.97714.

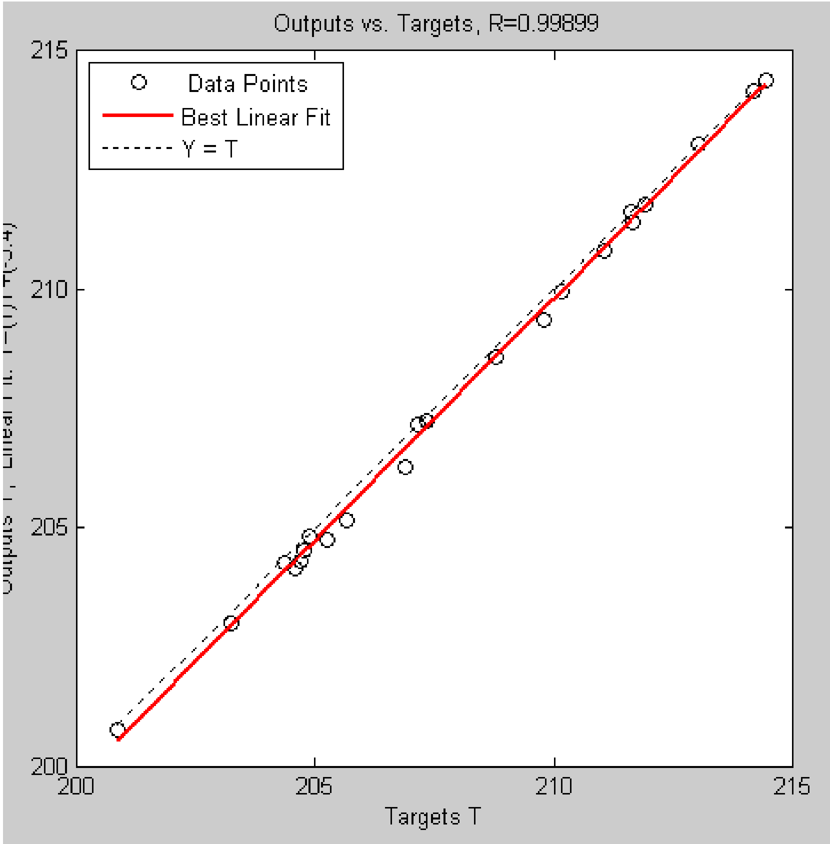

Figure 5.8 Predicted Salt Rejection Percentage of 99.89 by the ANN for P = 4750kPa and Initial Feed Concentration of 5000mg/L

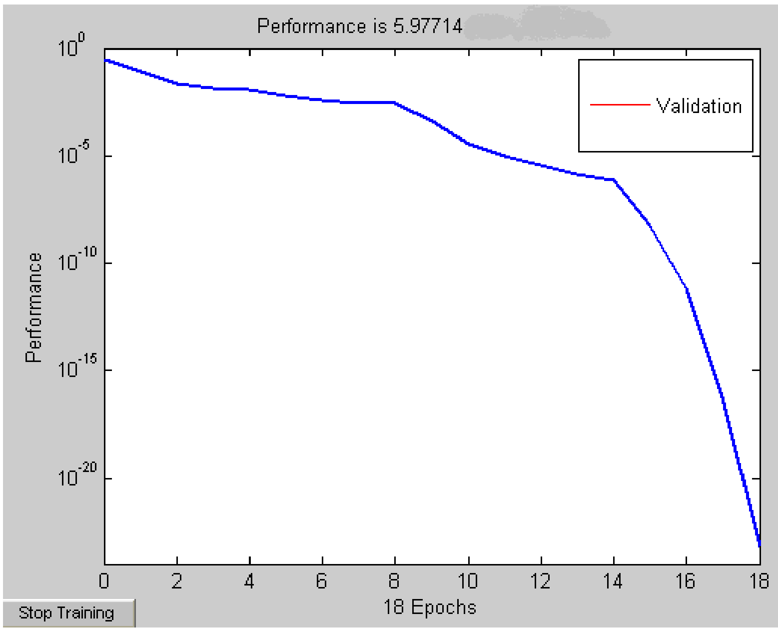

Figure 5.9 Predicted Permeate Flux of 5.97714 by the ANN for P = 4750kPa and Initial Feed Concentration of 5000mg/L with 18 Epochs

Similarly the SR and permeate flux is predicted by the ANN model for P=1200kPa and initial feed concentration of 100mg/L which is 92.952 and 9.85956 respectively

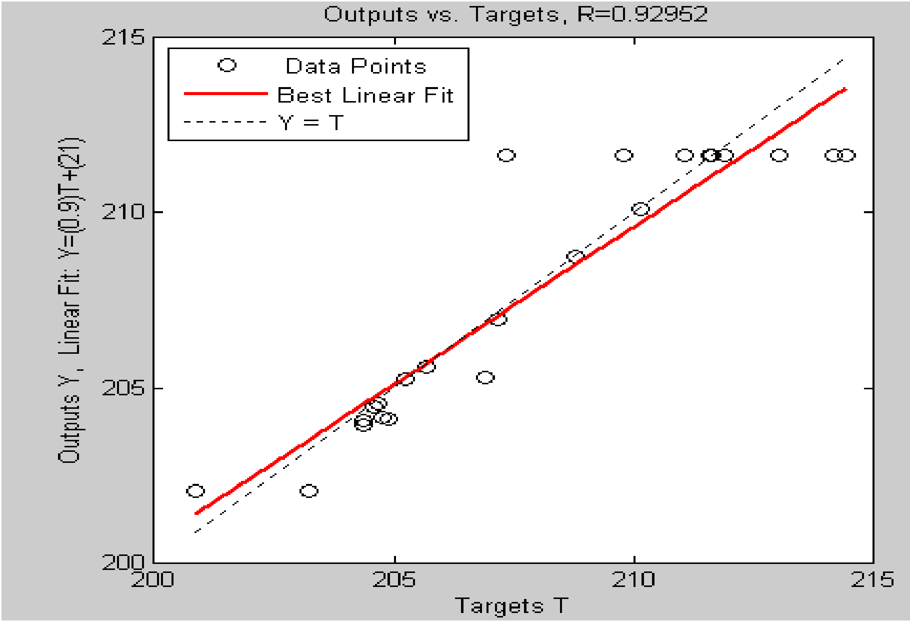

Figure 5.10 Predicted Salt Rejection Percentage of 92.2952 by the ANN for P = 1200kPa and Initial Feed Concentration of 100mg/L

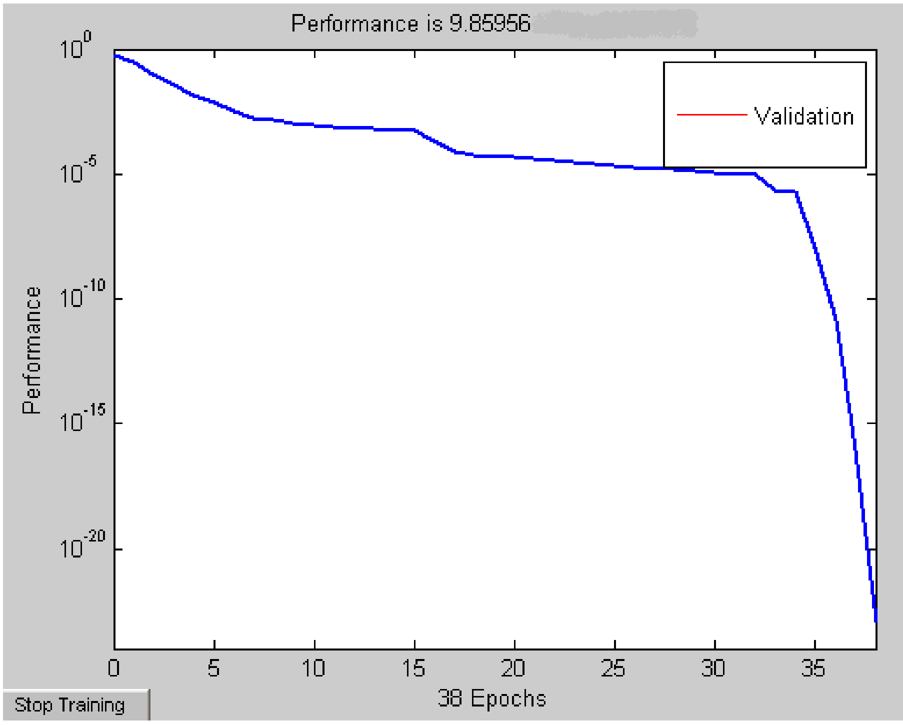

Figure 5.11 Predicted Permeate Flux of 9.85956 by the ANN for P = 1200kPa and Initial Feed Concentration of 100mg/L with 38 Epochs

The real prediction power of the ANN model is observed when the simulated and experimental values of the predicted parameters are plotted as a function of the initial NaCl in feed. The simulated and experimental values of the parameters are greatly affected by the increasing pressure which results in steadily increasing Salt Rejection values but decreasing Permeate Flux values due to the effect of scaling. The Figure 5.12 and 5.13 show the experimental results and the simulated results obtained from the ANN model. This shows the predictive power of the network in determining accurate results. The percent deviation of the simulated results from the original experimental values for SR is 1.31% and for J_w is 2.3%.

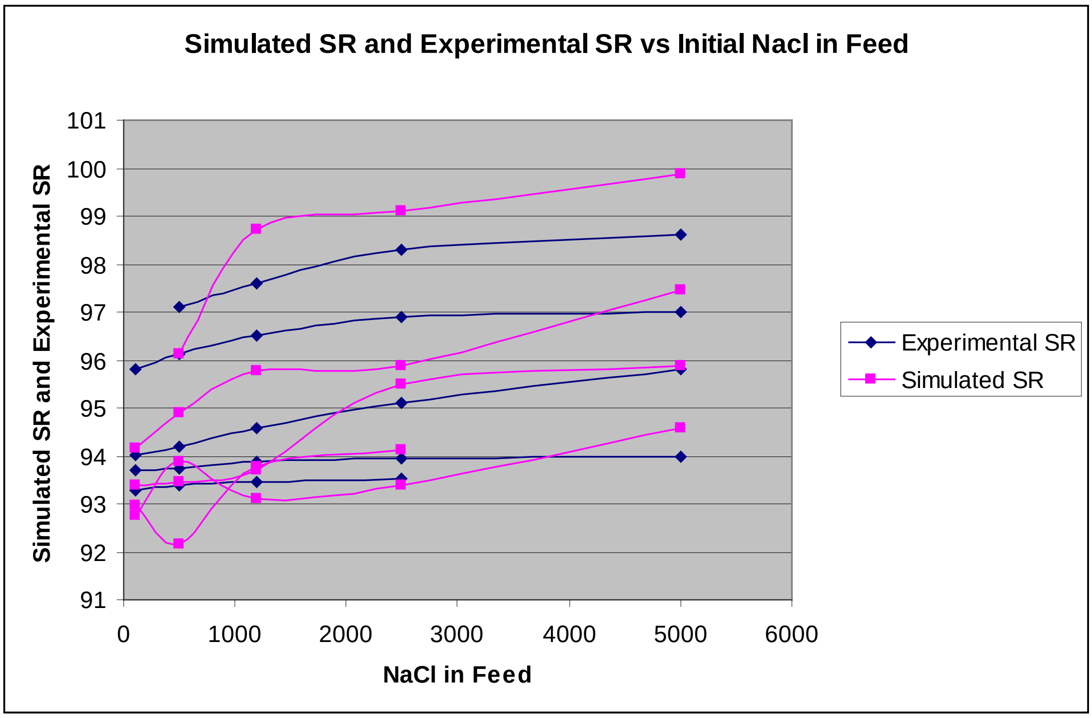

Figure 5.12 Simulated and Experimental SR Values as a Function of the Initial Feed

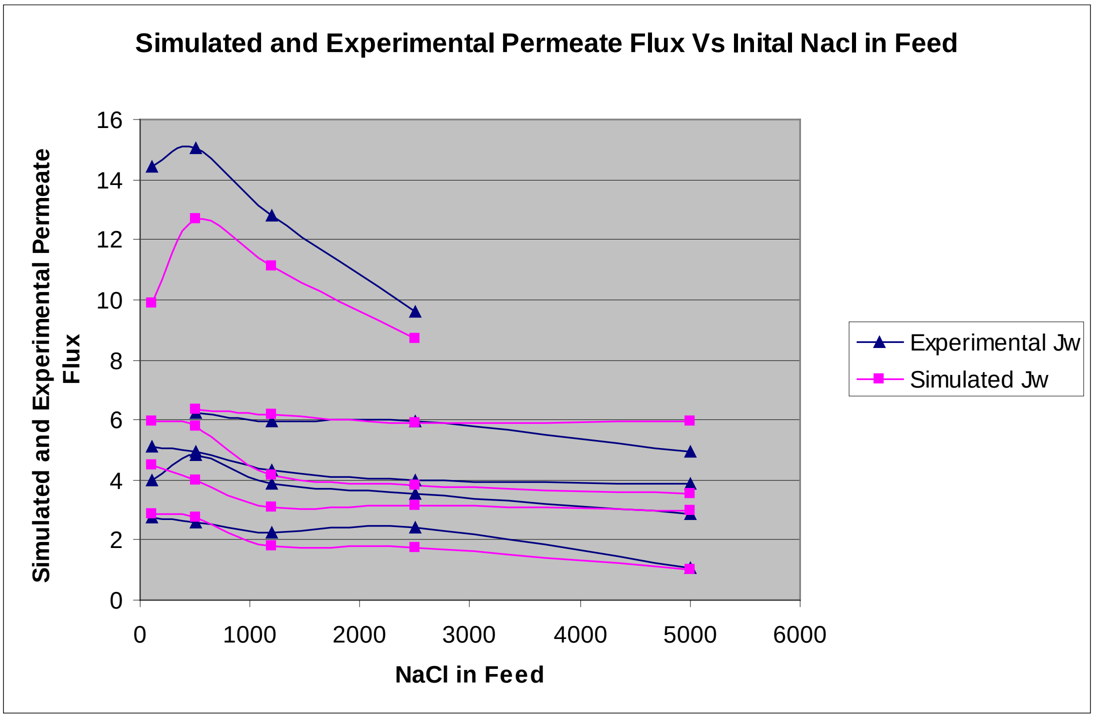

Figure 5.13 Simulated and Experimental Permeate Flux Values as a Function of the Initial Feed

The residuals i.e. the differences between the experimental values and those obtained by the artificial neural network models are shown in Figure 5.14 and 5.15 for rejection and permeate flux, respectively. The figures show that the residuals by the artificial neural network model behave approximately in the same way, and that the residuals can be considered sufficiently random, independent and uncorrelated. The percent deviation from the experimental values is 1.31% for SR values and 2.1% for J_w values.

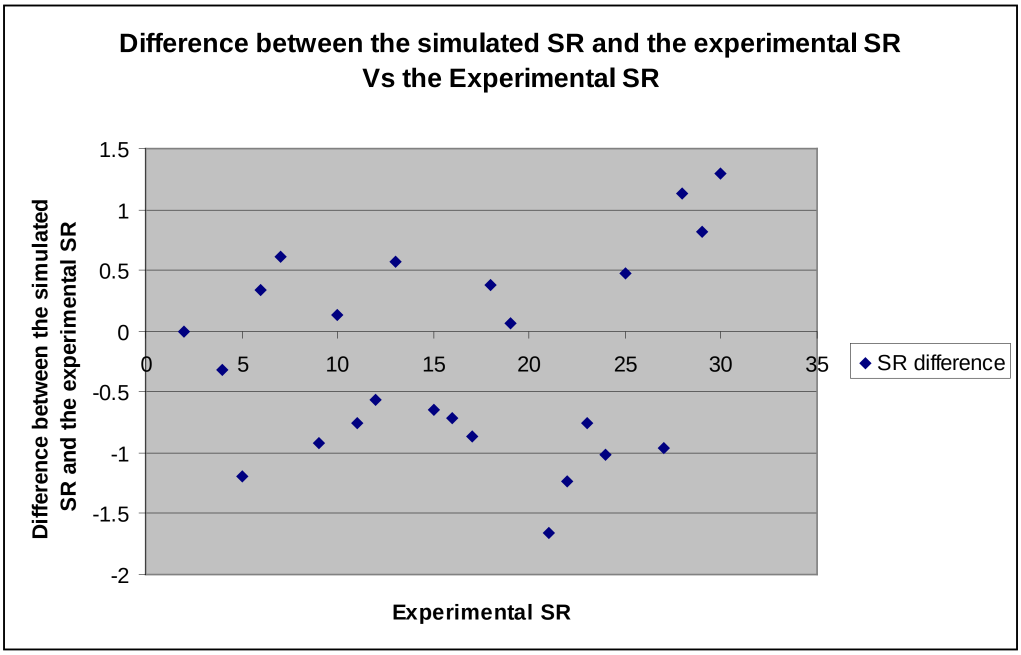

Figure 5.14 Difference Between the Experimental Values and Simulated Values of SR

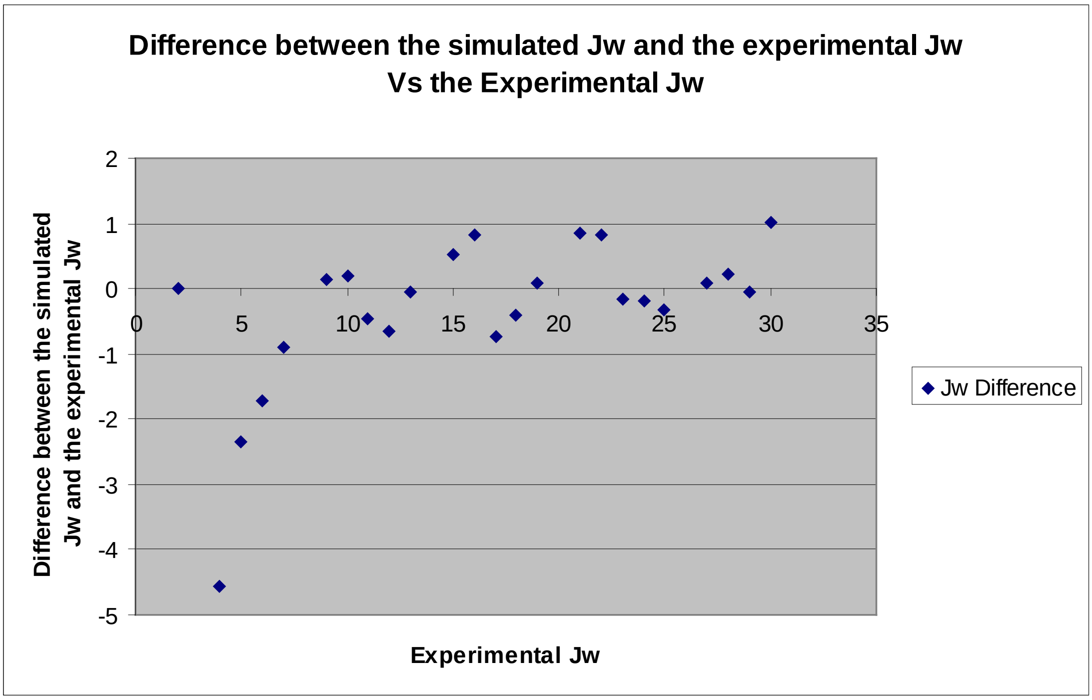

Figure 5.15 Difference Between the Experimental Values and Simulated Values of Permeate Flux

5.2.4 Creation of the Simulink System for the RO

The Simulink system is tightly integrated with the Matlab environment. It requires Matalab to define and evaluate the model and block parameters. Simulink enables to have access to mathematical functions inorder to imitate the data and provides a platform for arriving at the minimum and maximum deviations with respect to the data. The simulink system created using the neural network toolbox is shown below. The simple neural network with the input layer the output layer and the two hidden layers i.e. layer 1 and layer 2 is in figure 5.16 The simulink for the first hidden layer and the simulink for the weighted bias is shown in figure 5.17 and 5.18 while the simulink for the second hidden layer is 5.19 in Appendix A.

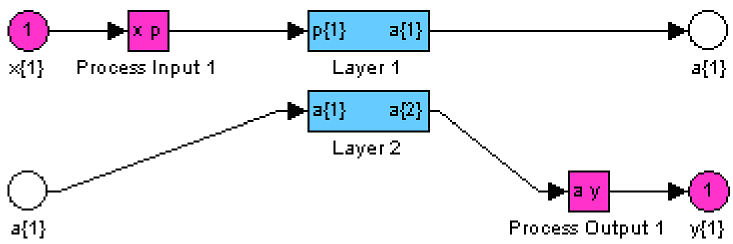

Figure 5.16 Simulink System for the ANN Model Along with the Hidden Layers

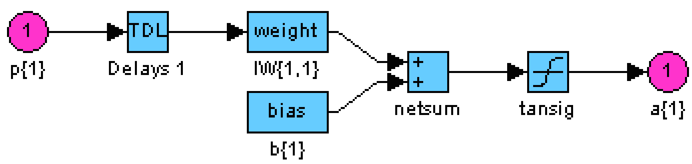

Figure 5.17 Simulink System for the ANN Model for the First Hidden Layer

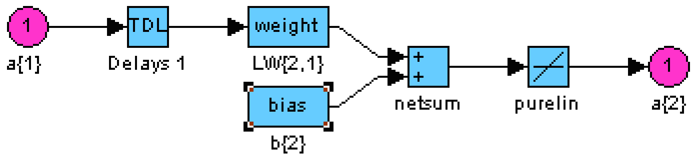

Figure 5.18 Simulink System for the ANN Model with the Second Hidden Layer

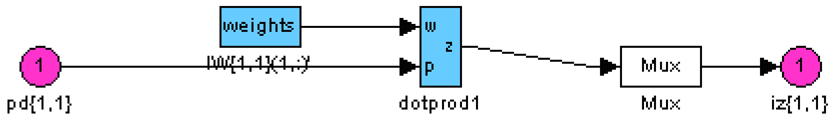

Figure 5.19 Simulink System for the ANN Model using the Weighted Values

5.3 RO Performance with Feedwater Samples containing Calcium Carbonate

5.3.1 Effect of Pressure on TDS, EC, WRP and Permeate Flux

On examining the data on Total dissolved solids (TDS) and Electrical Conductivity (EC) rejection percentages for the $CaCO_3$ samples of concentration range ranging from 50mg/L to 5000mg/L the RO system shows good performance in handling these samples. It can be clearly seen from Table 5.7 and Figure 5.20 as operation of the RO continues the TDS rejection percentage gradually decreases. This can be attributed to the build up of the calcium carbonate on the membrane being used in the system which in turn affects the quality of the final water product.

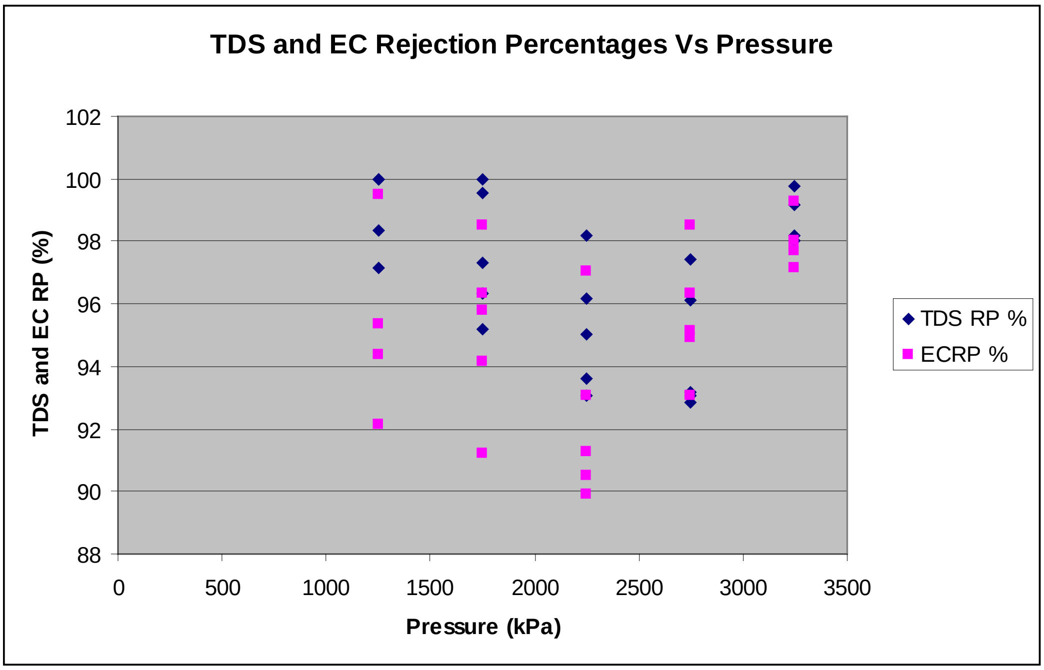

Figure 5.20 TDS RP for the $CaCO_3$ Solution Vs Pressure

For an initial feed solution of 50 mg/l of $CaCO_3$ and operating pressure of 1250kPa the TDS RP is 100% and EC RP is 99.49% respectively and for the same feed concentration but an elevated pressure of 3250kPa the TDS and EC RP drops down to 99.76% and 99.27%. As from Figure 5.21 the linear reduction in the value of the percentages are noted with gradual decrease in the value with passage of time.

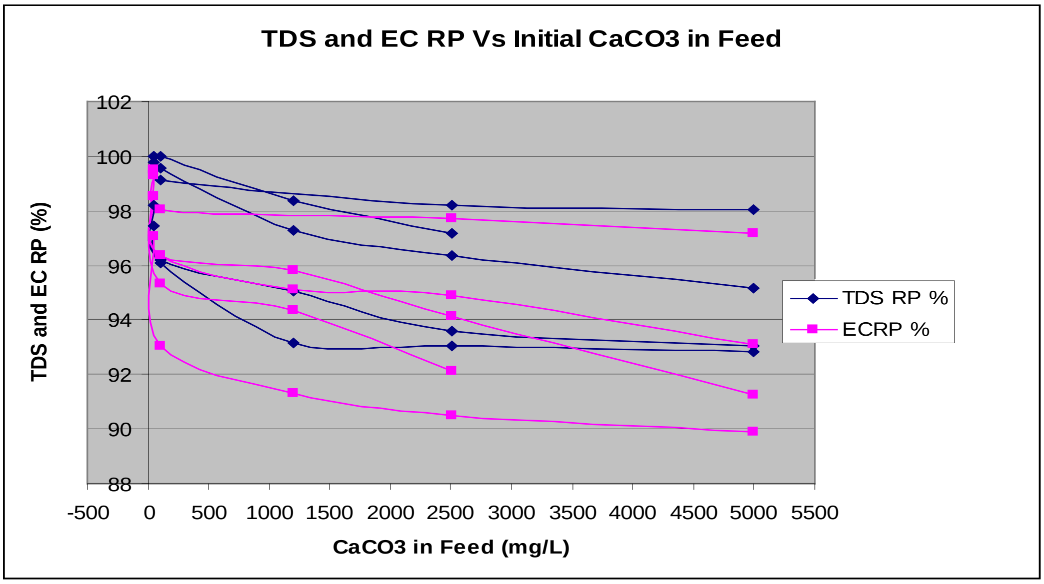

Figure 5.21 TDS and EC RP for the $CaCO_3$ Solution as a Function of the Initial $CaCO_3$ Feed Concentration

When the TDS and EC rejection percentage is plotted against the initial feed concentration (Figure 5.21) there is a gradual decline in the amount of $CaCO_3$ rejected as the operation continues. The performance of the RO system will decline due to various factors the main being decline in the membrane rejecting the salt impurities due to fouling and pore blockage. Similar results were noted with the same parameters for the NaCl feed samples as indicated in figures 5.1 and 5.2

After observing the change in the TDS and EC RP with respect to pressure and feed concentration we now have a look at how the water recovery percentages (WRP) are affected during the operation. Table 5.7 and Figure 5.22 depict the linearity of the WRP and flow rates for the permeate and reject streams. A maximum WRP of 74.076% was noted while the system operated at a pressure of 3250kPa and was handling 50 mg/l of $CaCO_3$ feed solution. The lowest value of WRP was 14.176% for the system handling 2500 mg/l of $CaCO_3$ with operating pressure of 1250kPa. It can be clearly observed that increasing operating pressure will increase the WRP and the permeate flow rate which increases from 2.75/min to 10.25/min while the reject flow rate decreases from 11l/min to 2.85/min.

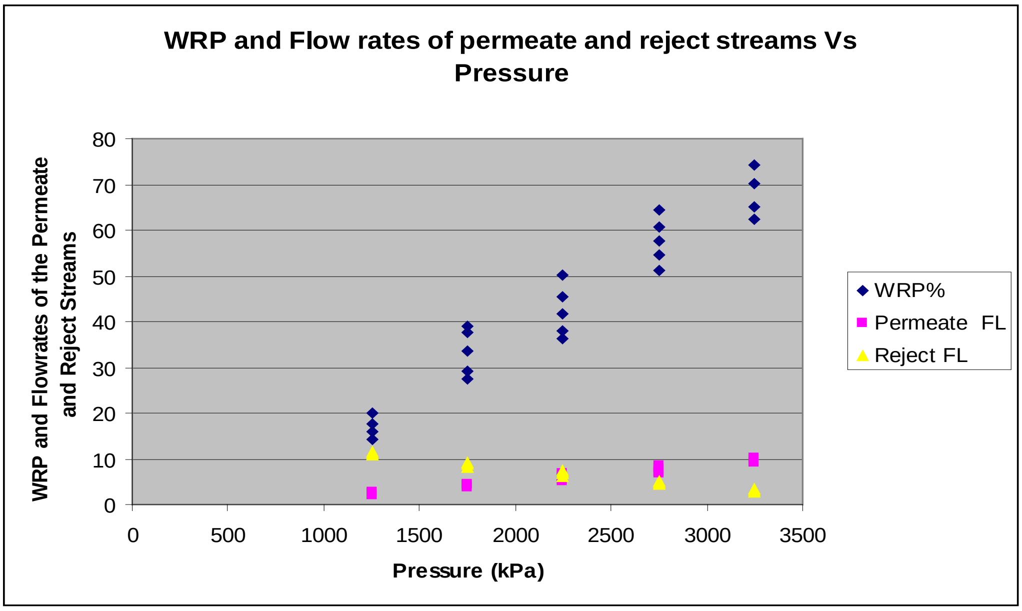

Figure 5.22 WRP and flow rates for the Permeate and Reject Streams for the $CaCO_3$ Solution at Different Operating Pressures

As expected the increase of the pressure will lead to an increase in the permeate flow rate and calcium rejection percentages. It is also observed that reducing calcium concentration in feedwater may enhance the permeate flux and the percentages of the calcium rejections. However there are no significant deviations in the WRP for the different feed concentrations of $CaCO_3$ and different pressure ranges. Similar trends for permeate flux were observed as shown in figure 5.23.

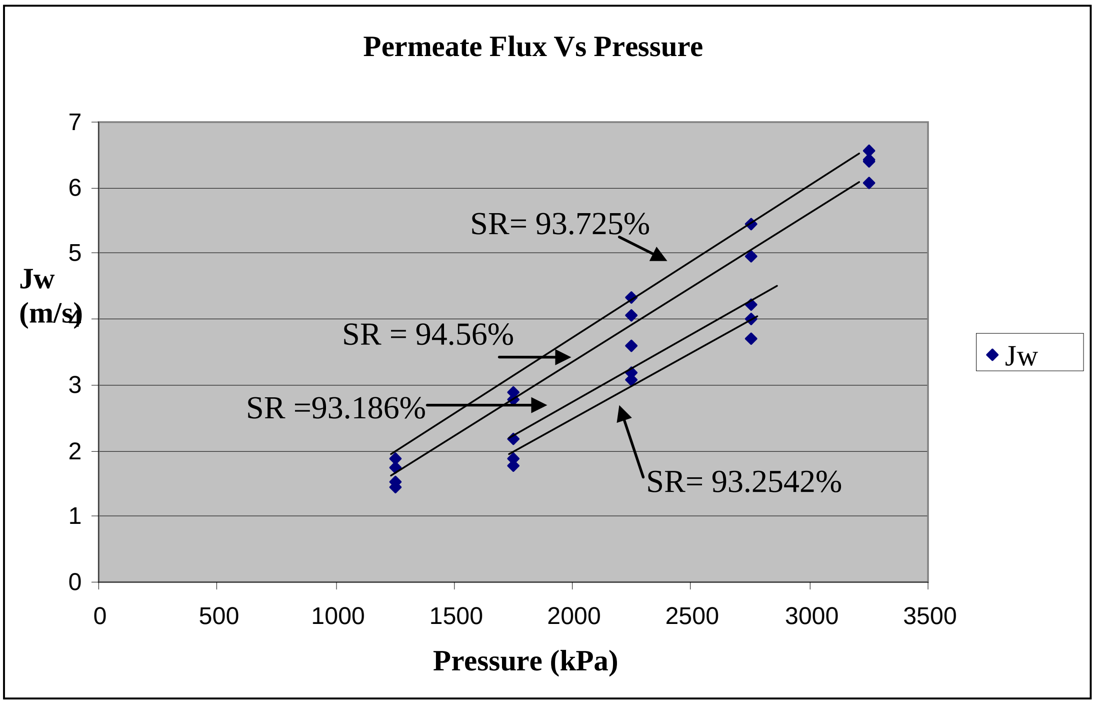

Figure 5.23 Permeate Flux (J_w) for the $CaCO_3$ Solution at Different Operating Pressures

The above figure 5.25 indicates the affect of the operating pressure on the permeate flux. The salt rejection percentages predicted by the ANN model from the MATLAB codes are also indicated in the figure. The average Salt rejection (SR) percentages for the feed concentrations of $CaCO_3$ of 50mg/l, 1200mg/l, 2500mg/l and 5000mg/l are 93.725%, 94.56%, 93.186% and 93.2542% respectively. As clearly seen from table 5.7 and the profiles in figure 5.23 the permeate flux decreases with the increase in the $CaCO_3$ concentration.

5.3.2 Calcium Rejection Percentages Achieved by the RO system

The effect of the pressure on the rejection of $CaCO_3$ impurity is given in Figure 5.24 and the values noted in Table 5.8. With increase in pressure the rejection of the

$CaCO_3$ impurity also increases. The highest value of the SR was noted for operating pressure of 3250kPa and feed concentration of 5000 mg/l as 98.753 and the lowest value of SR was 90.078 for operating pressure of 1250kPa and concentration of 2500mg/L of initial feed. The lower rejection values for NaCl observed were also at the lower operating pressures of 1250kPa and 1750kPa and 100mg/L of initial feed concentration. Thus it can be concluded that when pressure is increased the SR percentages thus increasing permeate quality.

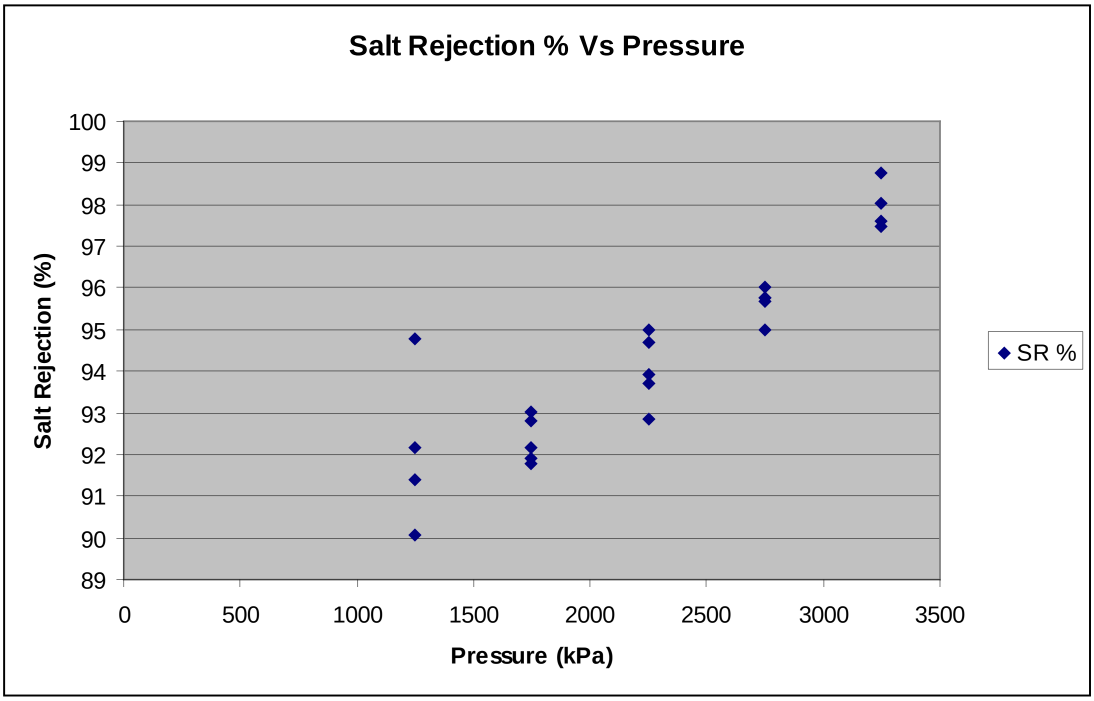

Figure 5.24 Calcium Rejection Percentages Obtained by the RO System for the $CaCO_3$ Solution at Different Operating Pressures.

However the calcium rejection percentages tend to decrease with an increase in the initial feed concentration of calcium carbonate. Calcium rejection percentages declined at a higher feed concentration indicating build up on the calcium side of the membrane surface. This occurs due to concentration polarisation and a simultaneous deposit of calcium on the membrane surface.

Previous studies conducted in this area attribute this rapid build up of calcium due to the several polymorphic crystalline structures of calcium carbonate. This solute has several polymorphic crystalline structures such as calcite and vaterite (Dallas and Koutsoukos, 1990). The more commonly occurring form is calcite which has a rhombohedron structure and low solubility in water. This study says that calcite will react with the resulting carbonic acid formed by the reaction between water and carbon dioxide to form calcium bicarbonate. This calcium bicarbonate will precipitate during the RO operation and it will be converted to calcium carbonate on the membrane wall due to the existing carbon dioxide in the solution.

Another form of crystalline calcium carbonate structure is Aragonite which changes to calcite in the presence of water. This change also leads to increase in the calcium ions on the membrane surface. This was confirmed by a study by Pahiadaki, Andritsos, Yiantsios and Karabelas when they observed that calcite and aragonite the two forms of calcium carbonate will precipitate on the membrane surface during RO operation leading to increased scaling and concentration polarisation (Pahiadaki, et al. 2005).

5.3.3 Predictions Derived from the ANN Model

We have so far established the various performance parameters and functions. The above experimental results established the performance of the RO system and its main function in rejecting impurities and having a good permeate flux throughout the operation. The ANN model created will verify these results and predict the salt rejection and the permeate flux for the same system conditions and parameters. The model assumptions remain the same as covered in 5.2.4.The simulated results for SR and permeate flux are close to the analytical i.e. experimental obtained results shown in Table 5.9. The system profiles predicted by the ANN model are shown above in Figures 5.27 and 5.28 respectively. An example of the simulated permeate and salt rejection values are shown in the Figure 5.25 and 5.26 for P = 1250kPa the solute rejection is 93.725% and the permeate flux with 28 epochs is 1.73815.

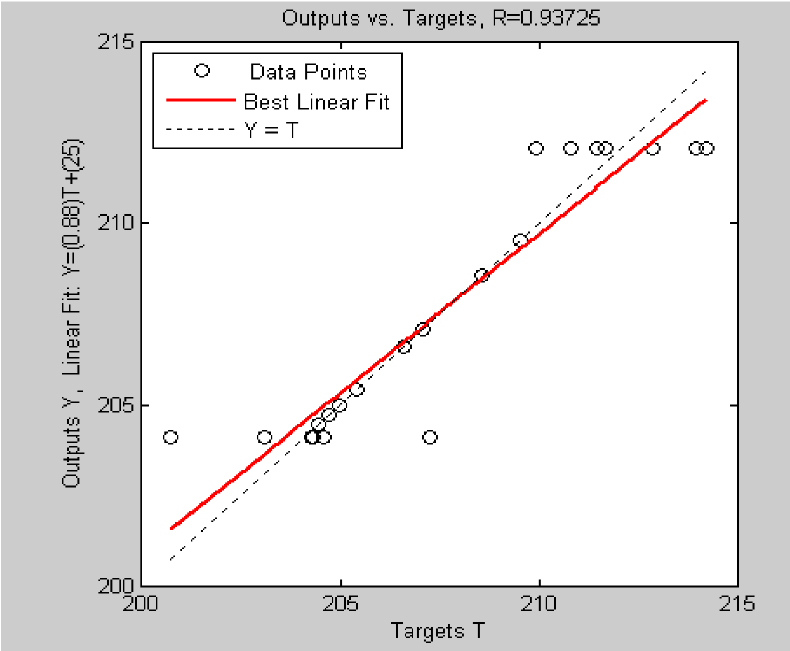

Figure 5.25 Predicted Calcium Rejection Percentage of 93.725% by the ANN for P = 1250kPa and Initial Feed Concentration of 50mg/L

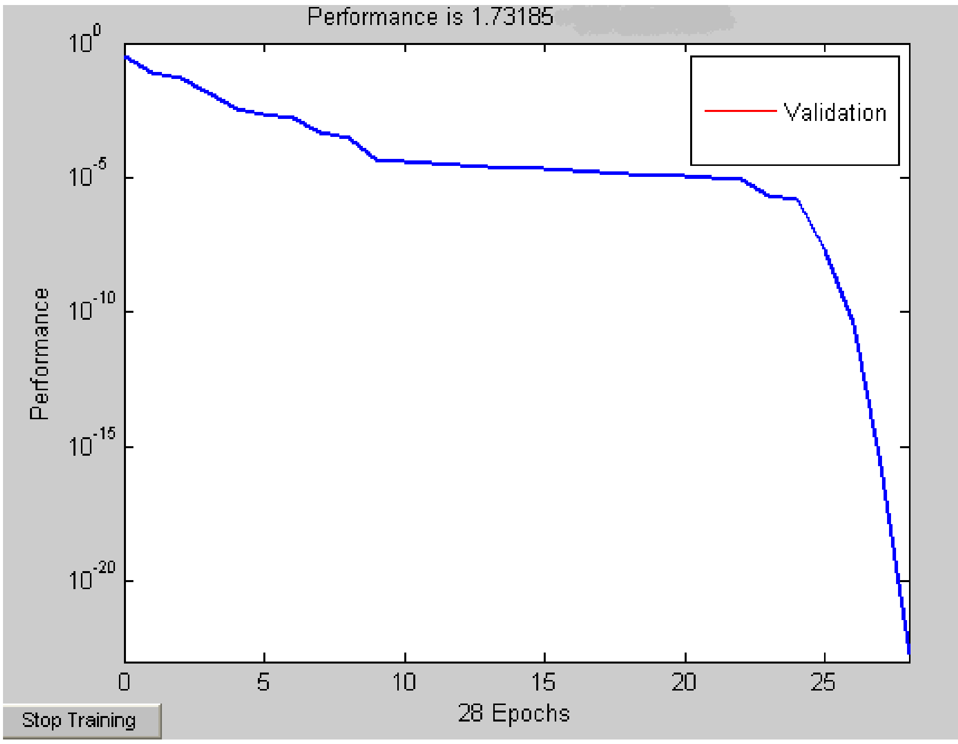

Figure 5.26 Predicted Permeate Flux of 1.73185 by the ANN for P = 1250kPa and Initial Feed Concentration of 50mg/L with 28 Epochs

Similarly the SR and permeate flux is predicted by the ANN model for P=3250kPa and initial feed concentration of 100mg/L which is 99.899 and 6.78134 respectively for 32 epochs shown in figure 5.27 and figure 5.28.

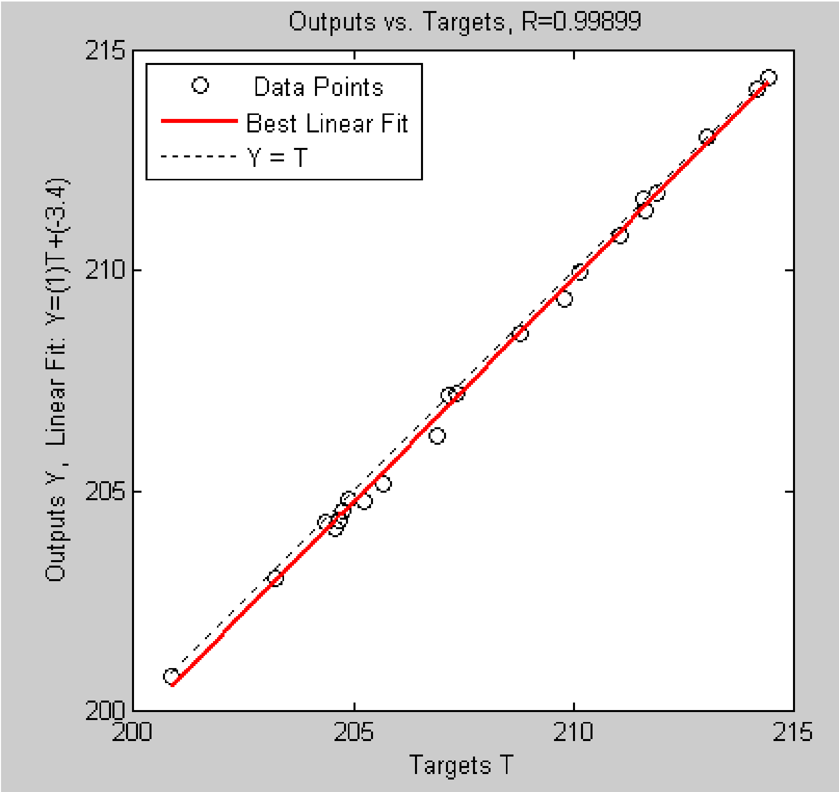

Figure 5.27 Predicted Calcium Rejection Percentage of 99.899% by the ANN for P = 3250kPa and Initial Feed Concentration of 5000mg/L

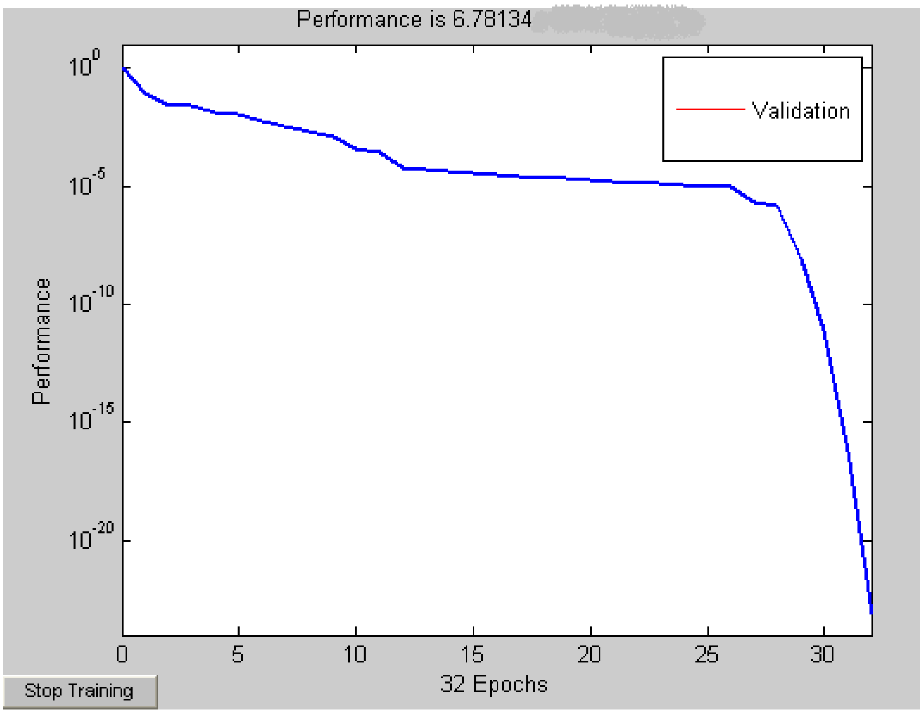

Figure 5.28 Predicted Permeate Flux of 6.78134 by the ANN for P = 3250kPa and Initial Feed Concentration of 5000mg/L with 32 Epochs

$CaCO_3$ Feed mg/L	J_w m/s	SR %	SR simulated	J_w simulated
50	1.44	94.78	**93.72**	**1.73**
100	1.89	92.17	**93.94**	**1.95**
1200	1.75	91.4	**92.05**	**1.25**
2500	1.52	90.07	**91.21**	**1.34**
50	2.88	93.02	**94.56**	**2.96**
100	2.77	92.79	**94.13**	**2.64**
1200	2.17	92.17	**91.15**	**2.84**
2500	1.87	91.78	**90.16**	**2.06**
5000	1.77	91.89	**91.34**	**1.67**
50	4.32	94.98	**93.18**	**4.15**

100	4.05	94.67	**92.18**	**4.54**
1200	3.58	93.94	**94.26**	**3.31**
2500	3.18	93.71	**94.68**	**3.015**
5000	3.08	92.84	**91.51**	**3.15**
50	5.44	95.74	**96.15**	**5.06**
100	4.96	95.68	**96.79**	**5.13**
1200	4.21	95.75	**94.15**	**4.61**
2500	4.00	94.97	**93.05**	**4.18**
5000	3.71	96.04	**92.19**	**3.49**
50	6.41	97.46	**96.25**	**6.19**
100	6.57	97.58	**97.85**	**6.31**
2500	6.44	98.04	**99.89**	**6.781**
5000	6.07	98.75	**98.58**	**6.16**

Table 5.9 The Simulated Results for Salt Rejection Percentages and Permeate Flux for the $CaCO_3$ Feedwater Samples

The real prediction power of the ANN model is observed when the simulated and experimental values of the predicted parameters are plotted as a function of the initial $CaCO_3$ in feed. The Figure 5.31 and 5.32 show the experimental results and the simulated results obtained from the ANN model. This shows the predictive power of the network in determining accurate results.

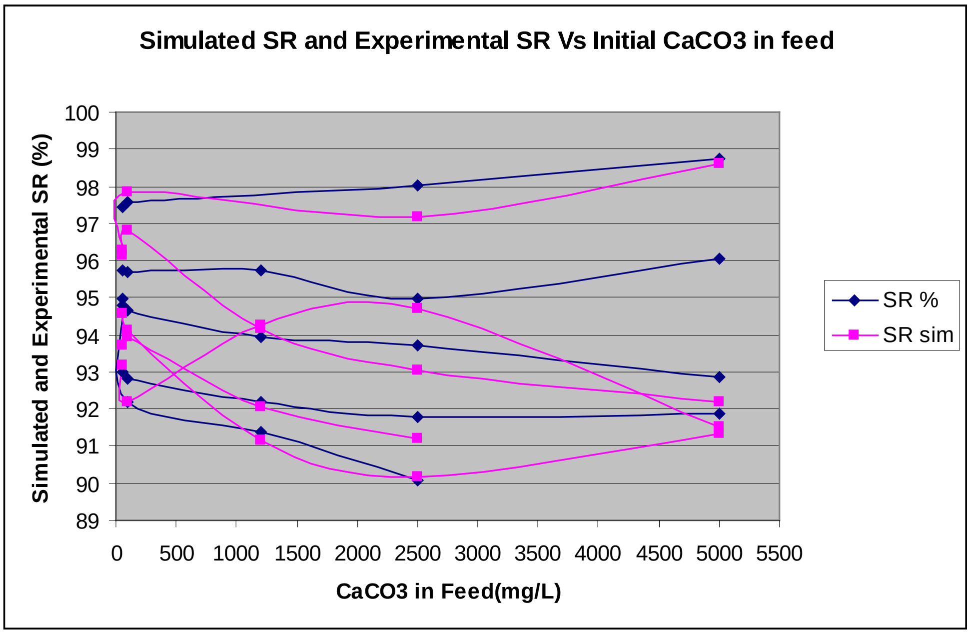

Figure 5.29 Experimental SR and the Simulated SR Values as a Function of the Initial $CaCO_3$ Feed

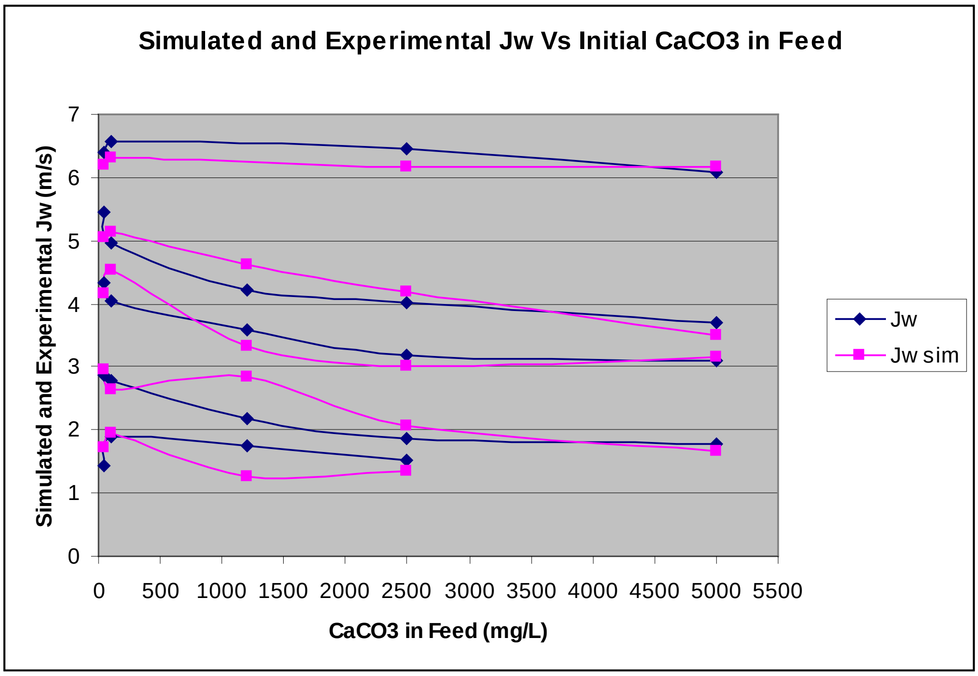

Figure 5.30 Experimental Permeate Flux and the Simulated Permeate Flux Values as a Function of the Initial $CaCO_3$ Feed

The residuals i.e. the differences between the experimental values and those obtained by the artificial neural network models are shown in Figure 5.31 and 5.32 for rejection and permeate flux, respectively. The figures show that the residuals by the artificial neural network model behave approximately in the same way, and that the residuals can be considered sufficiently random, independent and uncorrelated. The percent deviation from the experimental values is 1.83% for SR values and 2.78% for J_w values. Similar findings were noted for the NaCl samples as shown in Figures 5.14 and 5.15 and Table 5.8

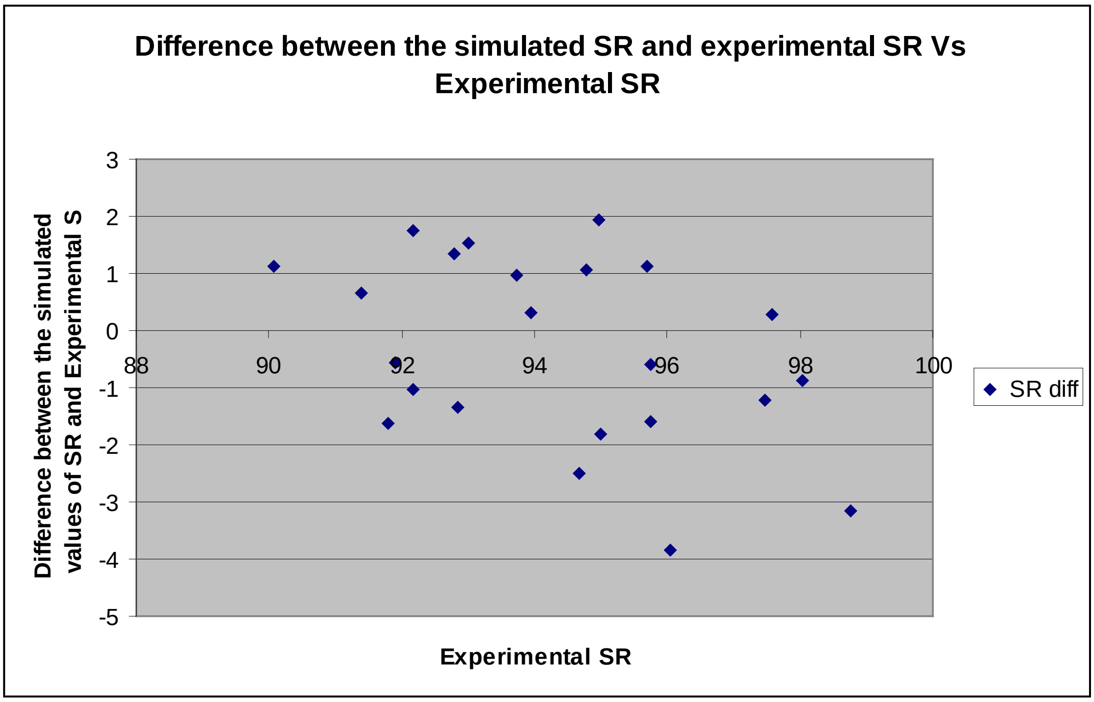

Figure 5.31 Difference Between the Experimental and Simulated Values of SR

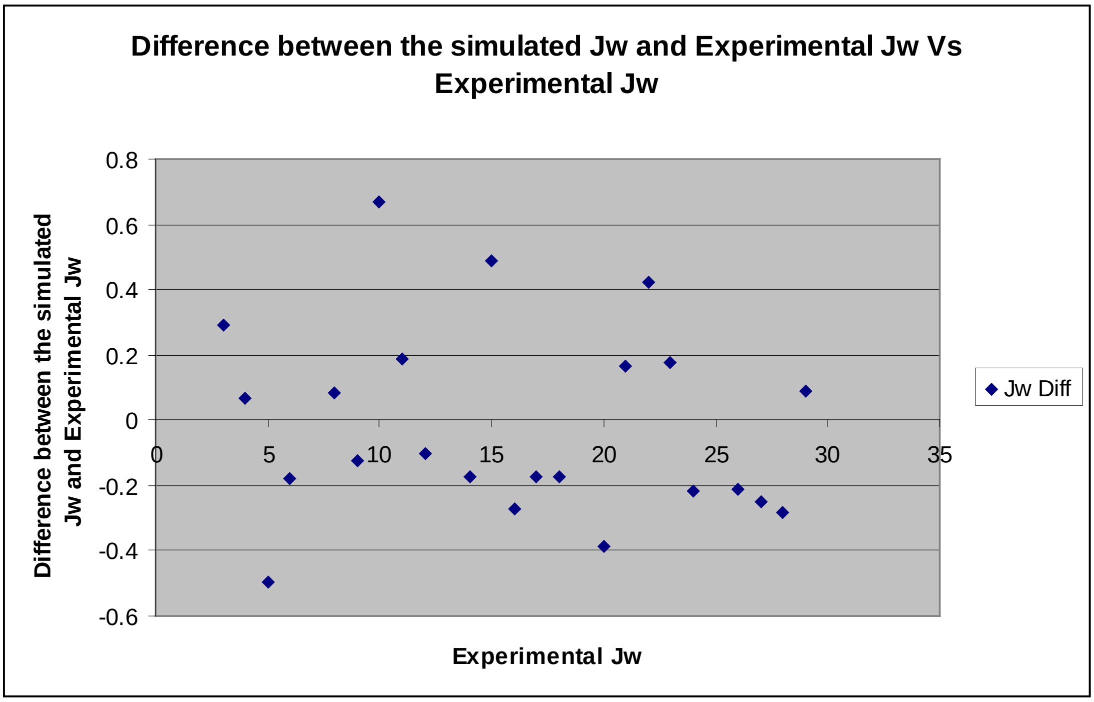

Figure 5.32 Difference Between the Experimental Values and Simulated Values of Permeate Flux

5.4 RO Performance with Feedwater Samples containing NaCl and $CaCO_3$

5.4.1 Effect of Pressure on TDS, EC, WRP and Permeate Flux

The Figure 5.33 and Table 5.10 show's the effect of the Total Dissolved Solids (TDS) and Electrical Conductivity (EC) rejection percentages for the combined NaCl and $CaCO_3$ solution over a range experimental pressure. It is observed that the low concentrations of the solutes in feedwater have less effect on the TDS and EC rejection percentages. Both these parameters remain fairly constant over the range of experimental pressure i.e. 1250kPa to 3750kPa. However increase in the applied pressure will slightly decrease the rejection percentages of the TDS and EC. Thus it signifies that the effect of ionic strength has to be taken into consideration for high solute concentrations. For seawater and brackish water this factor needs to be taken into consideration while predicting the salt rejection of the RO system.

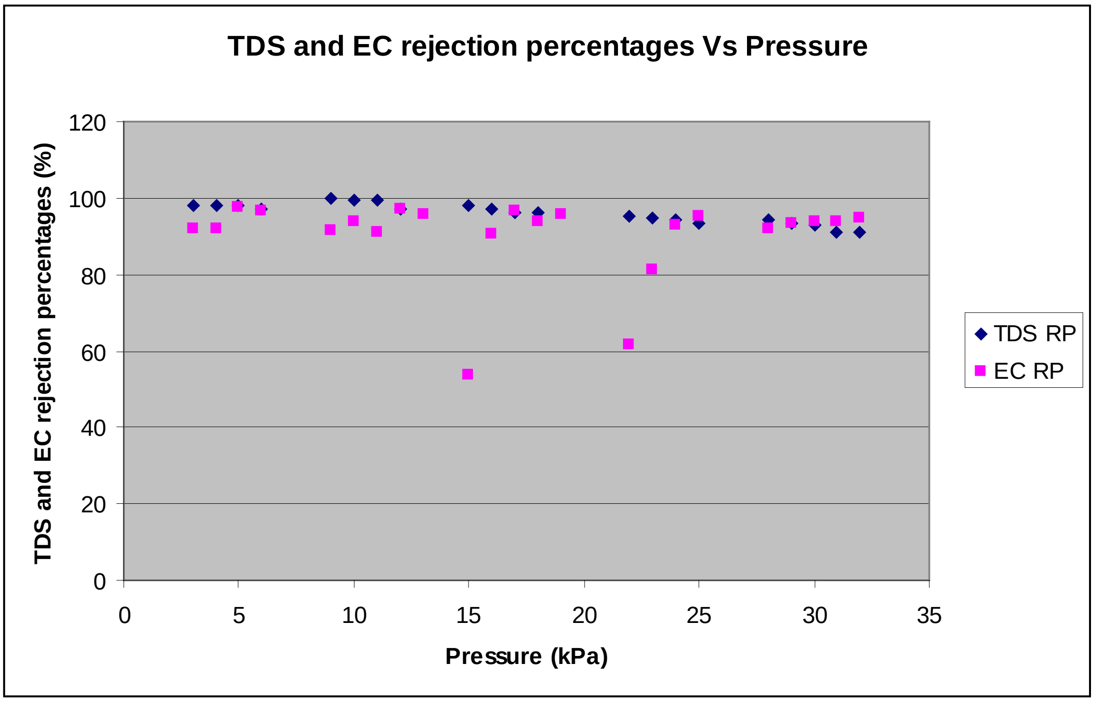

Figure 5.33 TDS and EC Rejection Percentages for the Combined NaCl and $CaCO_3$ Solution at Different Operating Pressures

Figure 5.34 and Table 5.10 shows the effect of the applied pressure to the water recovery percentages (WRP) and permeate flux handling the combined Sodium chloride and Calcium Carbonate solution at different operating pressures. It can be clearly observed both the WRP and permeate flux decline due to the build up of calcium carbonate on the membrane surface. Deposits of calcium carbonate on the membrane surface followed by dissolution of calcium carbonate in the bulk phase will increase the calcium concentration in the bulk solution at lower operating pressure. Also turbulence in the small scale RO unit will minimise the effect of solute build up on the membrane surface. Similar findings were noted by Yang in his experiments carried out on RO membranes to investigate the scaling caused by $CaCO_3$ during RO operation. It is a well known fact that scaling can be prevented using anti scalants but these are expensive and sometimes result in environmental problems. The method suggested to reduce scaling is by using Zinc as a scale suppressant. The results indicted that the dosage of trace amounts of Zinc can suppress scale formation within a certain range of water compositions (Yang, 2006).

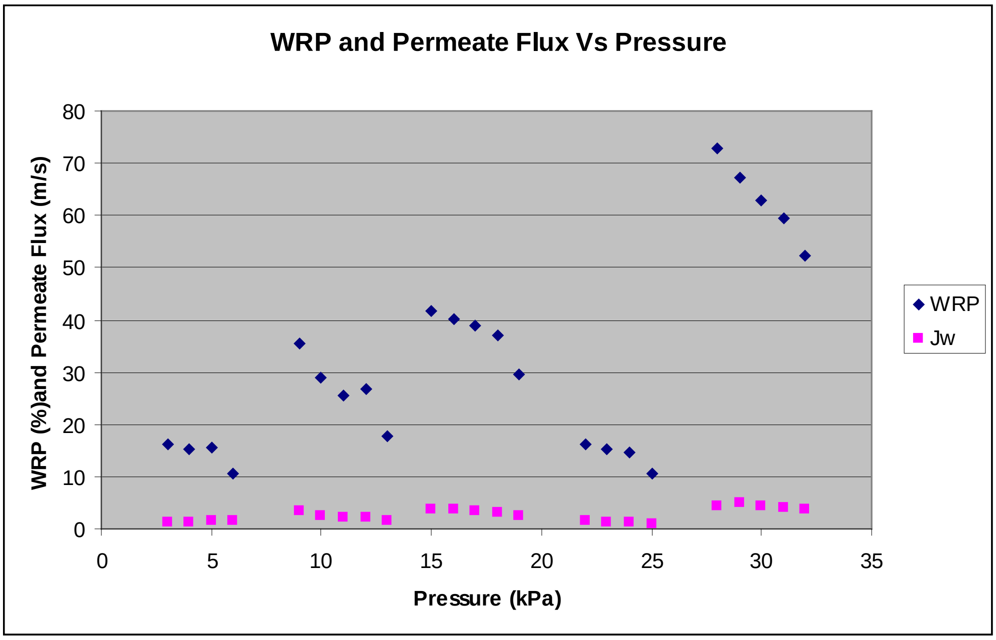

Figure 5.34 WRP and Permeate Flux (J_w) for the Combined NaCl and $CaCO_3$ Solution

Also deposits of sodium chloride rapidly occur when the sodium chloride in the membrane surface exceeds the saturation concentration and cause pore blockage. Build up of the two solutes will lead to increase in the mass transfer coefficient (k), reduce the permeate flux and WRP. This occurrence is common in RO operations and is commonly known as scaling.

5.4.2 Effect of Concentration on WRP and Permeate Flux

Figure 5.35 and Table 5.10 shows the WRP depend on the sodium concentration in the feed water samples because it is present in a larger concentration in the feedwater and thus it is the domination solute. At low concentrations of sodium in the feedwater the WRP is higher and tends to decrease with the increasing solute concentration. For P=1250kPa and feed sodium concentration of 100mg/L the WRP is 16.0714% and for 2500mg/L the WRP drops to 10.714%. An increase in the sodium concentration not only decreases the WRP but also affects the osmotic pressure of the solution.

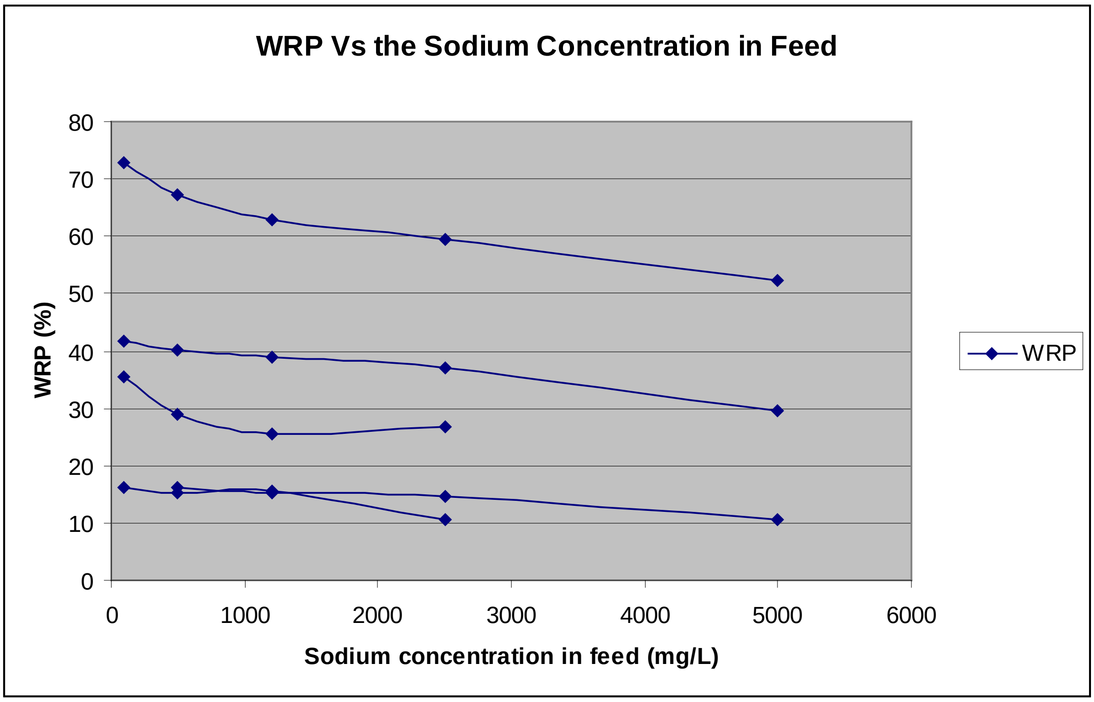

Figure 5.35 WRP and Permeate Flux (J_w) for the Combined NaCl and $CaCO_3$ Solution

5.4.3 Solute Rejection Percentages Achieved by the RO System

The salt rejection percentages achieved by the RO system is shown in Table 5.11 and Figure 5.36 over experimental pressure and concentration ranges. The solute rejection percentages remain constant over the given experimental pressure ranges. The results indicate that the solute rejection percentages below 90% are obtained for very low concentration of the combined solutes in the feedwater even after increasing the applied pressure. This suggests that the osmotic pressure has pronounced effect for high concentration of the combined sodium chloride and calcium carbonate samples. Therefore the build up of solute in the membrane surface is mainly due to the differences in the ionic strengths of the two samples.

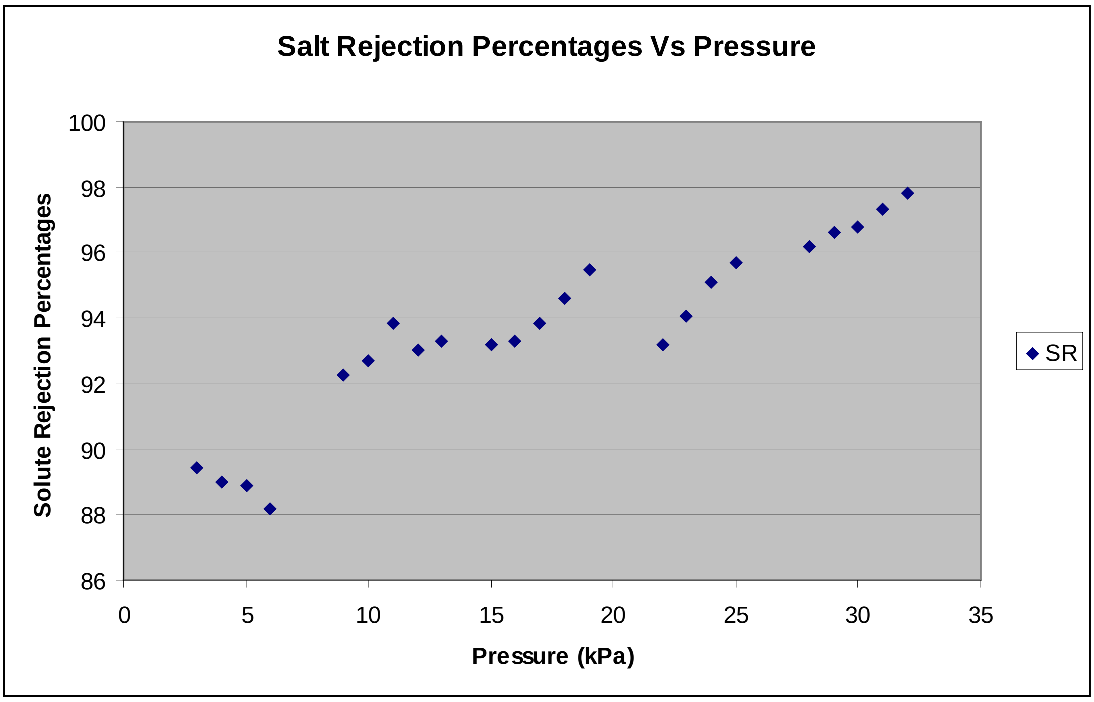

Figure 5.36 Solute Rejection Percentages for the Combined NaCl and $CaCO_3$ Solution

The presence of the sodium ion in the feedwater increase the solubility of the calcium in the bulk solution for the given pressure range. The reason for this can be attributed to the polyamide membrane which is primarily negatively charged and it easily rejects the divalent cations more compared to the monovalent ions. For the feedwater used in this experiment contains cations and anions which make contact with the membrane and leads to increase in the cation concentration at the membrane surface. Therefore concentration of the cations on the membrane surface is greater than the anions in the bulk solution.

The difference in the concentrations of cations and anions will create an electrical potential which is known as the Donnan potential. The Donnan potential attracts cations to the membrane surface and repels the anions. This effect is most prominent for low to mid salinity solutions and can be completed neglected for the very low salinity solutions i.e. TDS < 300mg/L. also the Donnan potential is weak for solutions with high divalent ion concentration (Bartels, et al. 2005).

5.4.4 Predictions Derived from the ANN Model

We have so far established the various performance parameters and functions. The above experimental results established the performance of the RO system and its main function in rejecting impurities and having a good permeate flux throughout the operation. The ANN model created will verify these results and predict the salt rejection and the permeate flux for the same system conditions and parameters. The model assumptions remain the same as covered in 5.2.3.

The simulated results for SR and permeate flux are close to the analytical i.e. experimental obtained results shown in Table 5.11. The system profiles predicted by the ANN model are shown above in Figures 5.37 and 5.38 respectively. An example of the simulated permeate and solute rejection values are shown in the figure 5.40 and 5.41 for P = 1750kPa initial NaCl is 100mg/L and CaCO3 is 50mg/L the rejection is 94.83 and the permeate flux with 39 epochs is 2.95261.

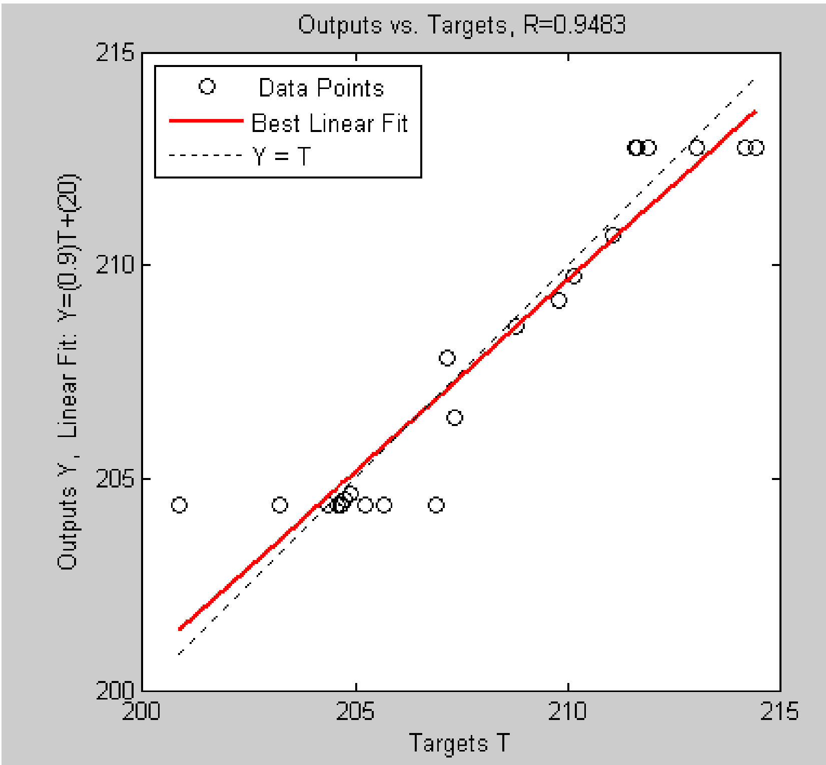

Figure 5.37 Predicted Solute Rejection Percentage of 94.83 Achieved by the ANN for P=1750kPa and Initial Sodium Concentration of 100mg/L and Calcium Concentration of 50mg/L

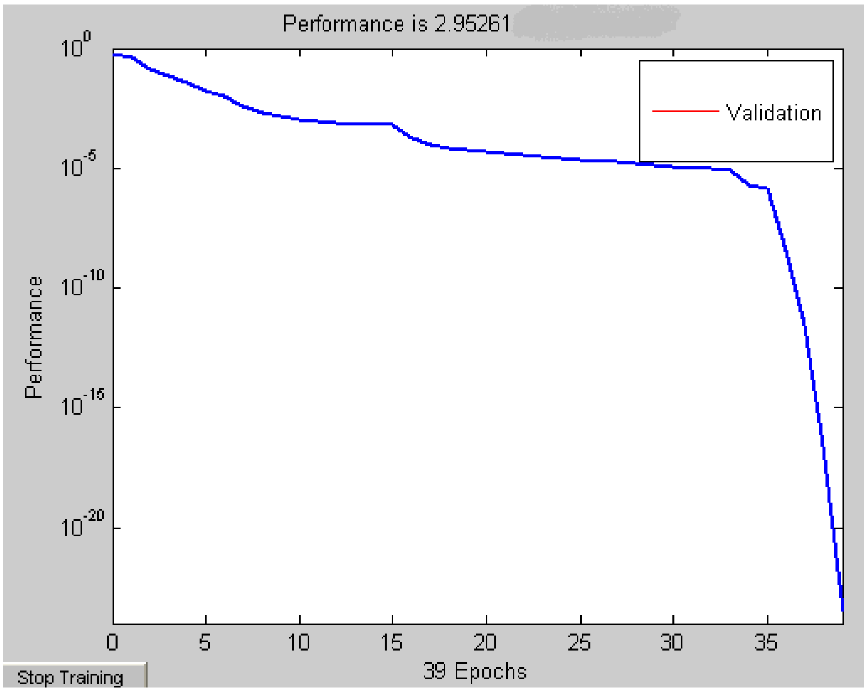

Figure 5.38 Predicted Permeate Flux of 2.95261 by the ANN for P = 1750kPa and Initial Sodium Concentration of 100mg/L and Calcium Concentration of 50mg/L

Similarly the Solute Rejection percentages and permeate flux is predicted by the ANN model for P=2750kPa and initial sodium feed concentration of 500mg/L and calcium concentration of 100mg/L is 91.847 and 1.29451 respectively with 17 epochs as shown in Figure 5.39 and 5.40.

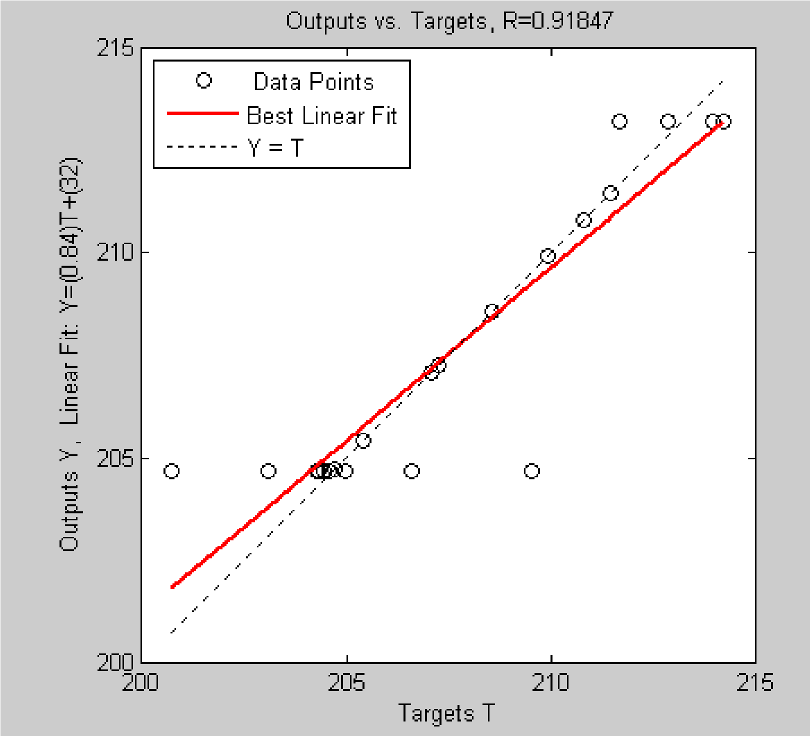

Figure 5.39 Predicted Solute Rejection Percentage of 91.847 by the ANN for P=2750kPa and Initial Sodium Concentration of 500mg/L and Calcium Concentration of 100mg/L

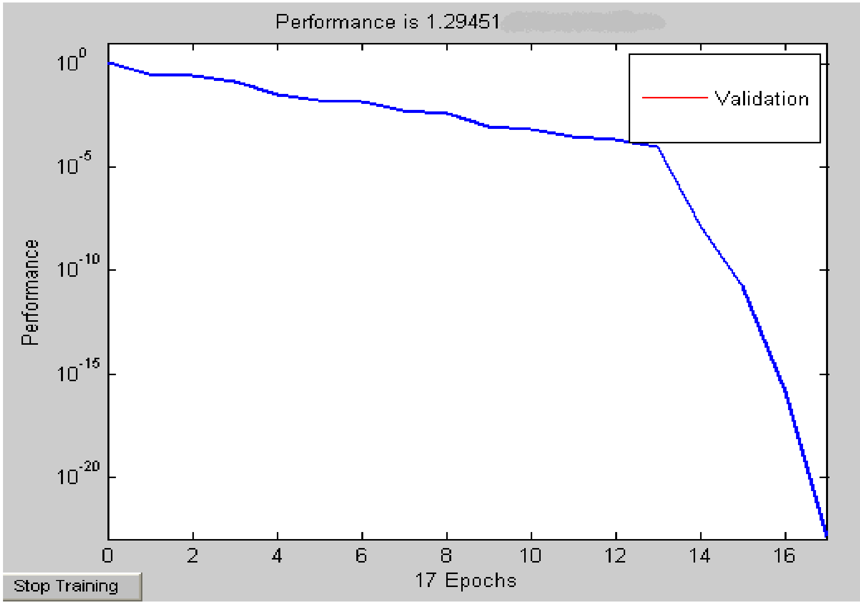

Figure 5.40 Predicted Permeate Flux of 1.29451 by the ANN for P=2750kPa and Initial Sodium Concentration of 500mg/L and Calcium Concentration of 100mg/L

5.4.5 Concluding Remarks

The effect of sodium chloride, calcium carbonate and the combination of the two solutes on the RO performance was investigated. It was evident that the low concentration of the solutes below 2000mg/L and pressure of 2250kPa had no significant effect on the RO system performance. Increasing the operating pressure of the system has a considerable affect on the build up of the solutes on the membrane surface. The results also indicated that the phenomenon of scaling and fouling is prevalent and could be a potential problem in the small scale RO operation.

5.5 RO Performance with Feedwater Samples containing Wastewater

5.5.1 Introduction

Every community and industry produces solid and liquid waste and the liquid waste is termed as wastewater. It is essentially the water produced by the community and industry after it has been used for a range of applications. In general wastewater can be defined as the combination of the liquid or water carried waste produced from housing communities and commercial or industrial establishments along with groundwater and surface water. Wastewater recycling and treatment through Reverse Osmosis has gained significant importance in the last twenty five years. It has become an alternative source of water supply for non domestic, agricultural and industrial usage (Into, et al. 2004).

Reclaiming wastewater by treating it to remove the solids and impurities and using it to recharge aquifers is a more prominent technique as compared to simply discharging it in to sewer. This reclaimed wastewater cane be used for agricultural, industrial and domestic purposes (Asano, 1986). Various pilot plants and commercial facilities across the world have demonstrated the technical and economic feasibility of reclaiming municipal wastewater effluents through membrane processes (Pino and Durham, 1999). Recycling wastewater in order to fulfil our water demands is not yet a popular method in Australia. Less than 10% of the wastewater created is recycled for domestic or industrial usage. This wastewater generated provides an abundant source of feedwater and if treated successfully can be used in the near future (Anderson, 1996).

5.5.2 Studies Devoted to Wastewater Treatment Using RO

RO has been used for treating wastewater by removing certain dissolved salts and organics from the effluents and numerous studies have been devoted to this application. A study on a spiral wound membrane RO system handling industrial effluents was carried out to determine the effectiveness of the technique. In the main objective of the study was to recover products and reduce the concentration of the pollutants in the wastewater steam by using a spiral wound membrane. The study concluded that pH value of the solution plays an important role in the ionization of the different species and subsequently their retention in the solution (Bodalo-Santoyo, et al. 2004).

RO using four different polyamide membranes was tested to reduce the concentrations of pollutants in a synthetic effluent stream containing acrylnitrile and three inorganic species (sulphate, ammonium and cyanide). The rejection percentage of sulphate ion was high in all the membranes tested (96% to 99.4%) regardless of the working pressure. Ammonium rejection values were between 72.3% and 83.9%, while acrylnitrile rejection was low (10.5% to 28.8%) compared with the results obtained for the other pollutants. Cyanide rejection was negative for all membranes tested**.** The study concluded that cyanide and ammonium could not be eliminated in a single step operation when they are simultaneously present in industrial wastewater. The results pointed to the need to carry out several steps at different pH values to reduce the level of both pollutants in the wastewater (Bodalo-Santoyo, et al. 2003).

Studies have also been devoted to recharging the groundwater table by treating effluents. The objective of the study undertaken by Ramirez, Oviedo and Alonso was to define the optimum conditions of secondary effluents for successful operation of RO to recharge the groundwater. The system used a cellulose acetate membrane as well as two thin film composite membranes and the performance of the system was noted. It concluded that high recoveries of the pollutants lead to irreversible fouling in the membrane but can be overcome by increasing membrane area. Also importance of pretreatment is established as this would lead to reduction in fouling (Lopez-Ramirez, et al. 2006).

The wastewater produced in the tanning industry has a high level of salts and organic material. Before this wastewater can be eliminated it needs to be treated to reduce the concentration of these elements. A comparative study of six different RO membranes was conducted to test their ability to reduce the concentration of salts and organic matter to an acceptable level before they can be disposed. The most suitable membrane was chosen on the basis of the permeate flux, conductivity of the permeate stream and the rejection coefficient conductivity (Bodalo, et al. 2005). In order to reduce the amount of water and chemicals used for the tanning operation RO was suggested as the most desired technique to reduce the salt content in the wastewater stream (Cassanoa, et al. 1999). Gauwbergen and Baeyens have predicted the flux and solute concentration in different flows for RO spiral wound membranes by outlining the important factors such as osmotic pressure, hydrodynamic flow profile and separation characteristics of the membrane material (Gauwbergen and Baeyens, 1999).

A combination of filtration, ultra filtration along with RO for treatment of tannery wastewater was evaluated after conventional physical and chemical treatment of the wastewater. Filtration was carried out using micro filters as a previous stage to ultra filtration process. Ultra filtration tests were performed in a laboratory plant and the reverse osmosis step was carried out using an ESPA-1 membrane from Hydranautics. No fouling was observed but it concluded that decline in permeate flux should be expected by scaling if high conversions are required. (Fababuj-Roger, et al., 2007).

A combination of RO along with other filtration techniques are also used to eliminate effluents from textile based wastewater. This combination technique was tested on a pilot plant handling textile wastewater. The pilot plant uses sand filtration and ultra filtration as pretreatments for the membrane process which could be RO or nano filtration. The efficiency of the various treatments in removing pollutants from textile wastewater from an activated sludge plant was tested on the reduced scale to optimize the industrial plant design. The permeate obtained can be reused in the dyeing process for the textile operation. The removal of the effluents using nano filtration was 75% and 90% using RO (Marcucci, et al. 2001).

A feasibility study was conducted on a combined physiochemical treatment with nano filtration and RO for water reuse. Tests from filtration techniques such as microfiltration and ultra filtration showed that a primary physicochemical treatment (i.e. coagulation or flocculation) was necessary to limit membrane fouling. Two coagulants (organic polyelectrolyte or ferric chloride) were tested by using different chemical concentrations at pH 6.8. Then, Nano Filtration and RO experiments were performed and investigated at different operating pressures. It was concluded that the percent production rate increased with the trans membrane pressure allowing a higher yield for allowed a higher yield for nano filtration 22.6% as compared to RO 18.3% (Suksaroj, et al. 2005).

Similarly post treatment of the secondary textile wastewater was tested at pilot scale on membrane modules for the direct reuse of polished effluent within the dyeing processes. It was concluded that waste water an organic compound content less than 10mg/l, conductivity less than 40µS/cm and negligible residual colour can be recycled to the textile dyeing industry (Rozzi, et al. 1999).

For the meat industry the treatment of wastewater was done by applying three hybrid processes in the following combinations ultra filtration–reverse osmosis, coagulation–reverse osmosis and coagulation–ultra filtration–reverse osmosis. Neither coagulation nor ultra filtration enabled a sufficient removal of pollutants from the wastewater resulting in non disposal of the wastewater into the sewage system. The system combining ultra filtration and reverse osmosis was found to be the most favourable. The treatment effectiveness and the volume permeate flux obtained during RO were similar to the effectiveness and filtration velocity obtained in RO in the hybrid system of coagulation, ultra filtration and reverse osmosis (Bohdziewicz and Sroka, 2005).

An integrated membrane process consisting of a membrane bioreactor, continuous membrane filtration and reverse osmosis was used to treat the wastewater generated from a paper-mill. The recovery of water achieved by the integrated system was over 65% and the permeate generated met the standards for reusing as feedwater for the paper manufacturing process (Zhang, et al. 2009). A similar integrated membrane system was used to treat the industrial wastewater generated from a cooling tower. This system was found to be effective in reducing the turbidity and silt density index of the wastewater enabling product water to be reused (Wang, et al. 2006).

5.5.3 Effect of Pressure on Total Organic Carbon, TDS, WRP, Permeate Flux and Solute Rejection

The percentages of Total Organic Carbon (TOC) and Total Dissolved Solids (TDS) for the range of operating pressures are shown in Table 5.12. The performance of the RO membrane achieved by the small scale RO system is better than those achieved by Pino and Durham (1999) and Kim and Jang (2006) during their experimental work. The results obtained by Pino and Durham for TOC rejection was 91% and 70-80% for Kim and Nang reported during their pilot plant experiments of secondary treated sewage effluent (Kim and Jang, 2006).

Pressure	TOC	TDS
1250	87.25	91.71
1500	93.77	94.29
2000	94.01	97.14
2500	94.18	97.35
2750	94.27	97.56
3250	95.13	97.78

Table 5.12 TOC and EC Rejection Percentages for the Wastewater at Different Operating Pressures

For the current experiments carried out with the effluent samples both the TDS and TOC increase with the applied pressure. For an applied pressure of 1500kPa the TOC and TDS was 93.77% and 94.29% while it increased to 95.13% for TOC and 97.78%

for TDS at an elevated pressure of 3250kPa. These results obtained are low compared to the results obtained with NaCl and $CaCO_3$ samples suggesting presence of dissolved metal ions such as iron and silica that attach themselves to the membrane wall and high turbidity. Higher TOC and TDS rejection percentages can be achieved for effluents having high presence of dissolved iron and fluctuating turbidity by using alum during the pretreatment process which significantly reduces the affect of organic foulants and scalants (Qin, et al. 2006).

The Figures 5.41 and 5.42 show the effect of the pressure on the water recovery percentages (WRP) and permeate flux at different operating pressure. As expected (Table 5.13) the WRP and permeate flux increase with an increase in the operating pressure and the highest value recorded for WRP was 41.5094% at P=3250kPa while the lowest value was 16.0714% for 1250kPa. For permeate flux the highest values was also at the same high pressure recorded for WRP as 2.5m/s and 0.8653m/s as the lowest value at 1250kPa. The low values of WRP and permeate flux are caused by the presence of the suspended solids, organic carbon and dissolved metal ions in the effluent. Presence of these contaminates prevents a higher WRP than obtained.

Figure 5.43 shows the solute rejection percentages achieved by the RO unit. The solute rejection percentages are fairly constant over the pressure range and tend to increase with the increase in operating pressure. The solute rejection percentages obtained were similar to the ones obtained in a pilot study for the reclamation of treated sewage effluent in Singapore using a micro filtration and a RO system. The plant used six spiral wound RO membranes and the operation was carried out continuously during the study. The average rejection percentages achieved by the same was 90-96% (Qin, et al. 2005).

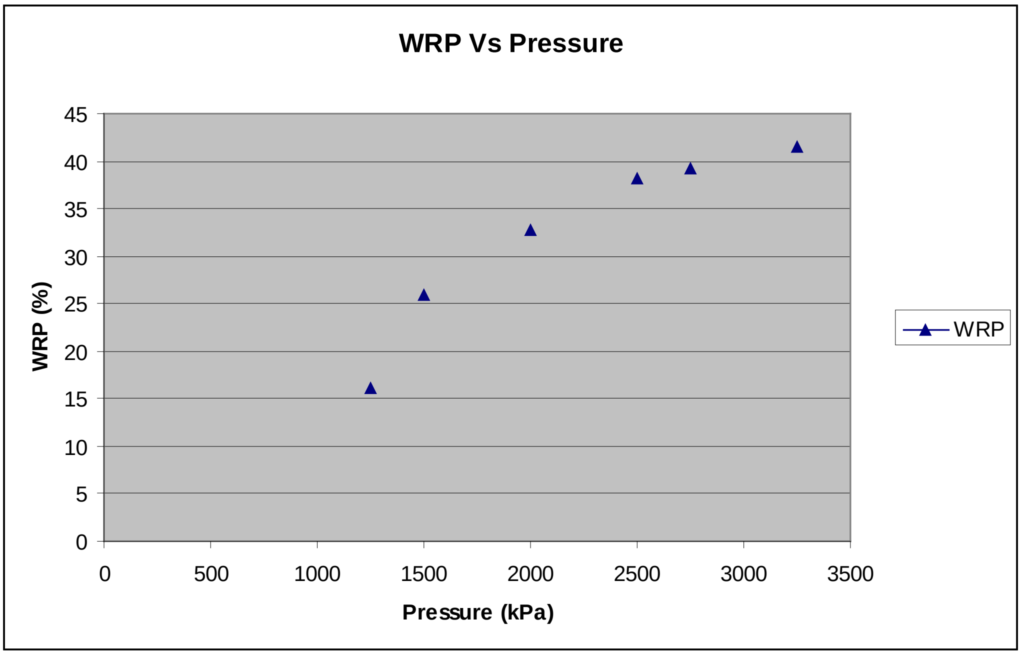

Figure 5.41 WRP for the System Handling Wastewater at Different Pressures

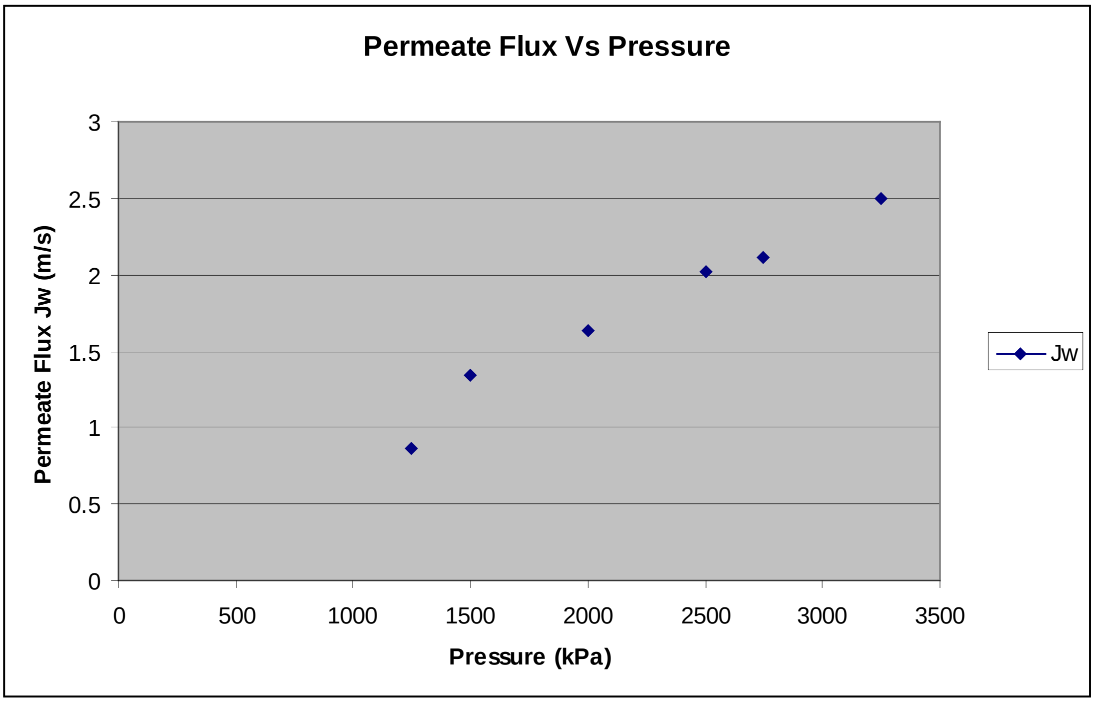

Figure 5.42 Permeate Flux for the RO System Handling Wastewater at Different Operating Pressures

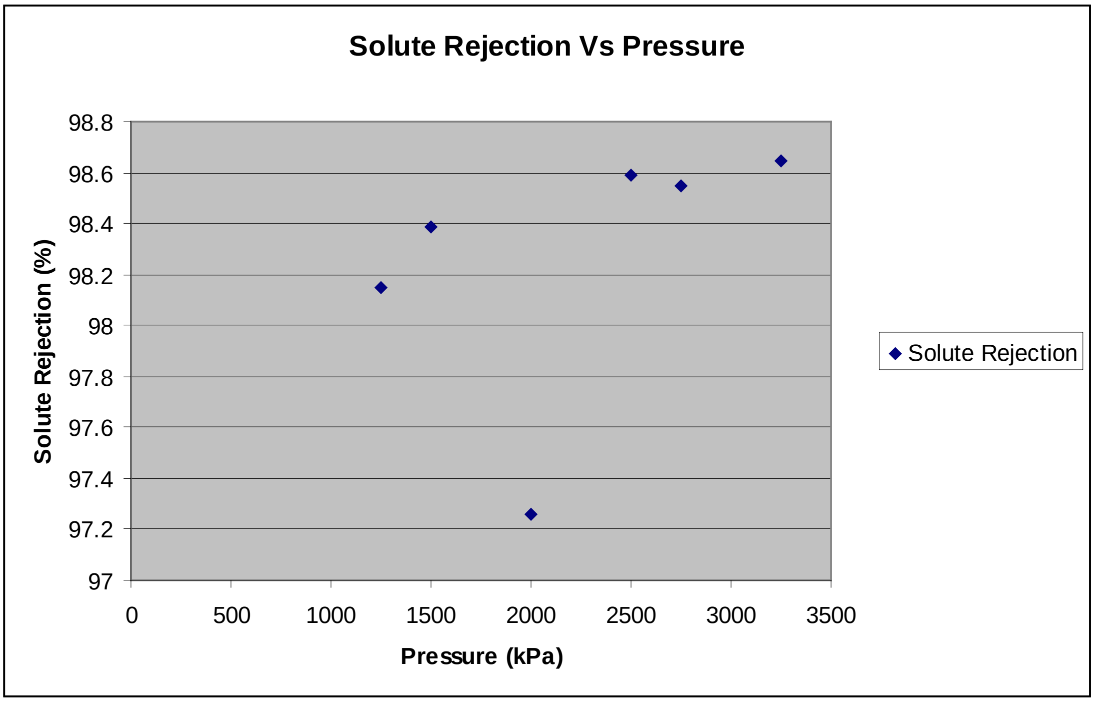

Figure 5.43 Solute Rejection Percentages for the RO System Handling Wastewater at Different Operating Pressures

5.5.4 Predictions Derived from the ANN Model

We have so far established the various performance parameters and functions. The above experimental results established the performance of the RO system and its main function in rejecting impurities and having a good permeate flux throughout the operation. The ANN model created will verify these results and predict the salt rejection and the permeate flux for the same system conditions and parameters. The model assumptions remain the same as covered in 5.2.4.

The simulated results for SR and permeate flux are close to the analytical i.e. experimental obtained results shown in Table 5.13. The system profiles predicted by the ANN model are shown above in Figures 5.44 and 5.45 respectively. An example of the simulated permeate and solute rejection values are shown in the Figure 5.44 and 5.45 for P = 3250kPa the rejection is 99.899 and the permeate flux with 19 epochs is 2.9662.

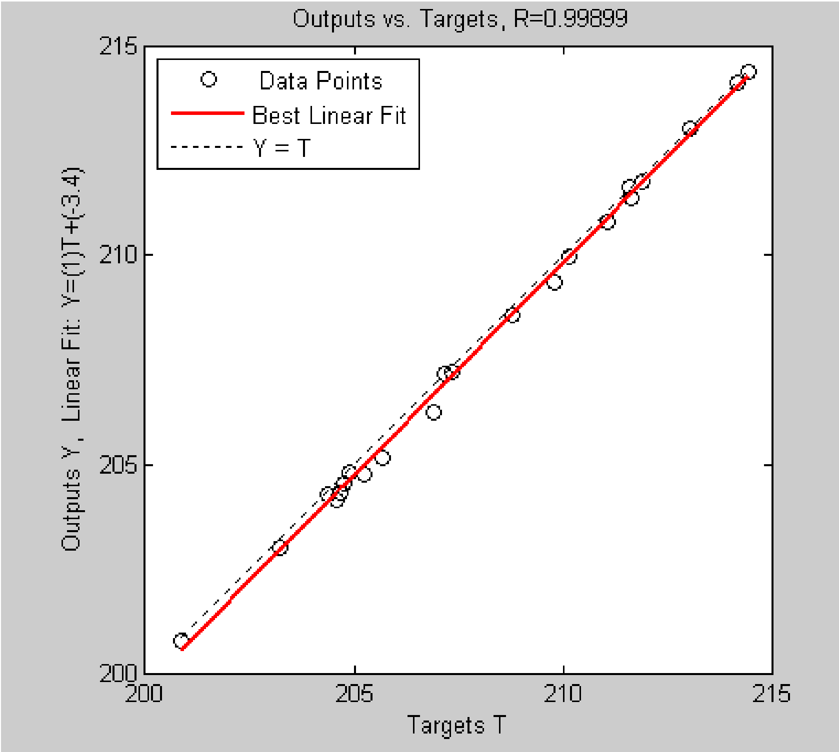

Figure 5.44 Predicted Solute Rejection Percentage of 99.899 by the ANN for P=3250kPa for the Wastewater Sample

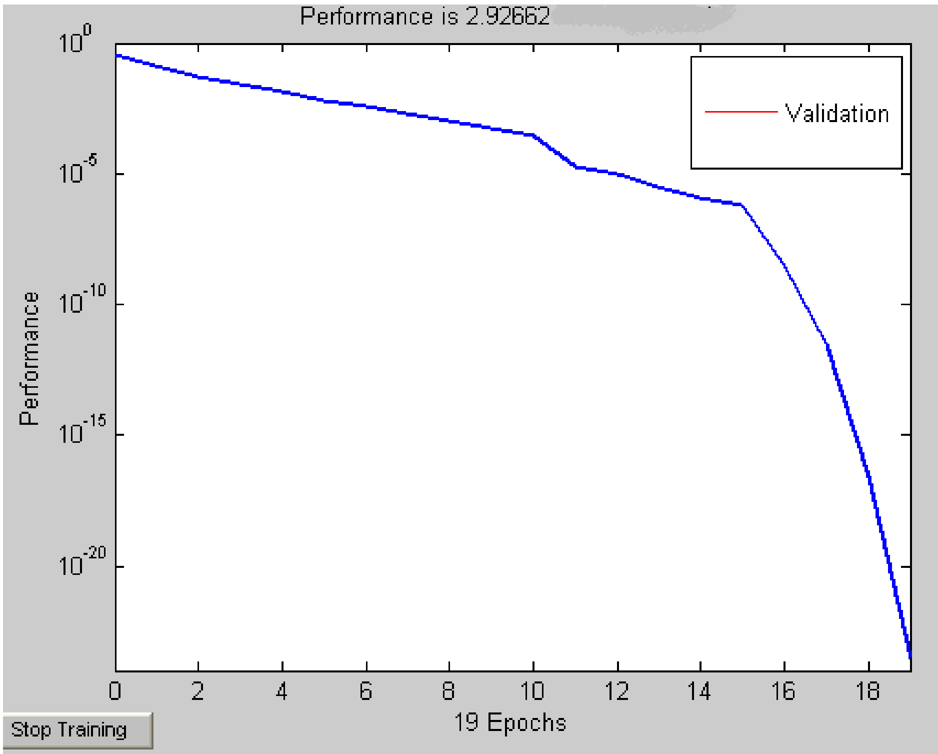

Figure 5.45 Predicted Permeate Flux of 2.9662 by the ANN for P=3250kPa for the Wastewater sample with 19 Epochs

5.5.5 Concluding Remarks

The RO performance while handling secondary effluent as the feedwater was investigated. The findings showed that the water recovery percentages, solute rejection and permeate flux increased with applied pressure. The percentages of the solute rejection are not as high as expected because of solute build up which tends to increase as the operation is continued over a period of time. The lower values of the WRP and permeate flux obtained are caused by the characteristics of the secondary effluent that have high suspended solids, minerals and organic matter. It is desirable to have a suitable pretreatment procedure in place before treating secondary effluent wastewater to prevent membrane blockage and low quality permeate.

5.6 RO Performance with Feedwater Samples containing Groundwater

5.6.1 Introduction

Groundwater is the water that fills the space and cracks between particles of soil, sand, gravel and rock that lay beneath the surface of the earth. Geological formations composed of permeable materials that are capable of storing and yielding large quantities of water are called aquifers. Groundwater is characterised by having high concentrations of dissolved salts and is too saline for direct human usage. In Australia groundwater is mainly used for irrigation and human consumption and up to four million people depend totally or partially on groundwater for their domestic water supply. Around 21% of water used in Australia is derived from groundwater sources and 55% of this derived water is used for public drinking water purposes.

Groundwater has a low level of particles, colloids and natural organic matter (NOM) but an extremely high level of hardness and alkalinity. The NOM species found in groundwater are humic and non-humic substances which are the major fouling agents in groundwater treatment through RO systems. The humic substances have a great impact on the water quality die to its hydrophobic properties while the non humic substances do not affect water quality as much as the humic substances. Reverse Osmosis will aid in treating groundwater to obtain a more pure source of water for domestic as well as industrial use.

5.6.2 Studies Devoted to Groundwater Treatment Using RO

Various studies have been conducted with RO operations dealing with groundwater. Early studies have been done by Odegaarda and Koottatep to remove humic substance from natural water. Using RO the removal of humic substances in order to remove colour and haloform precursors in small waterworks were carried out using three different laboratory setups and different membranes. They concluded that pressure had no influence on the permeate quality but membrane pore size was the significant factor affecting permeate flux as well as product water flux. The concentration of humic substances in the influent was not found to affect product water flux but the transport of humics across the membrane was found to be dependent upon influent concentration. For the selected membranes, the removal of humic substances amounted to 80–100% in terms of colour removal, and 50–99% in terms of permanganate value reduction (Odegaarda and Koottatep, 1982).

A study was conducted on the water of the Suwannee River in Georgia using RO in order to isolate the dissolved organic matter from the river water. A portable RO system was constructed and this system handled 150-180 litres of river water. The recovery of the dissolved organic matter was 90% without exposure to harsh chemical reagents or extreme temperature (Serkiz and Perdue, 1990).

The portable RO system set up Sun. Perdue and McCarthy processes 15-200 litres of water per hour with 90% recovery of organic carbon. RO was used to remove organic mater from surface and ground water without exposing the water to harsh chemical reagents. The performance of the RO system was not affected because of the use of a cation exchange resin (Na^+ form) and using an in-line 0.4µm filter to remove suspended particles and precipitates formed by polyvalent cations (Sun. et al.1995).

A combination of RO and nano filtration was used to remove the nitrates from the groundwater due to contamination from fertilizer usage in agriculture. This had led to the contamination of natural water reservoirs and aquifers with nitrates. This combination technique removed the nitrates but the performance was reduced because of the formation of membrane scale from $CaSO_4$ and $CaCO_3$ (Bohdziewicz, et al. 1999). Such a combination technique also reduces the landfill leachate which greatly affects the groundwater quality (Peters, 1998).

The technical economic feasibility of desalination of brackish groundwater by RO was undertaken in great detail to determine if this source of water can fulfil the water demands of Jordan. The brackish groundwater samples were collected from the Zarqa basin and had high levels of TDS, total suspended solids and volatile solids. The RO operation used a Film Tec RO membrane and the system was operated at 20-30bar and $40^0 C$ with a WRP of 77.5% and rejection rates of 98.5%. This study contributes to the development of efficient technologies to produce affordable potable water in Mediterranean countries where the threat of water shortages is a severe problem (Afonso, et al. 2004).

The problems of formation of polarised films and by-products which generate bacteria and fouling were tackled at a pilot plant equipped with RO and nano filtration membranes. The main objective of this experiment was to evaluate the effectiveness of Nano Filtration and RO membranes on quality of final water product. Samples of brackish water were filtered through filtrate cartridges in order to get rid of the suspended matter. A pilot plant equipped with composite RO and NF membranes was operated at 6bar, ambient temperature and neutral pH. This pilot plant shows the ease with which the combination of both processes is carried out. The recovery ratio in the combined nano filtration and RO operation was higher compared to that obtained in RO alone. This may be due to the decrease in the osmotic pressure of the RO membrane. This combined operation also improves salt rejection and thus leads to a decrease in the salinity of water product (M'nif, et al. 2007).

5.6.3 Effect of Pressure on TDS, EC, WRP, Permeate Flux and Solute Rejection

The effect of pressure on the Total Dissolved Solids (TDS) and Electrical Conductivity (EC) rejection percentages is shown in Figure 5.46. As expected the RO system shows good performance in handling the groundwater samples. For low pressure range of 1000kPa to 1500kPa the highest TDS rejection percentage achieved is 87.9472. Higher TDS rejection percentages are obtained when the operating pressure is increased to 2750kPa and the highest value recorded was 94.06% as shown in Figure 5.46. RO systems cannot be employed on a low pressure system and low pressures are not capable of overcoming the osmotic pressure of the solution. For the higher pressures the TDS and EC rejection percentages remain fairly constant. Thus higher quality of permeate can be achieved when a higher operating pressure greater than 1500kPa is used. These results were consistent with the previous findings obtained from the effluent samples and the NaCl and $CaCO_3$ samples.

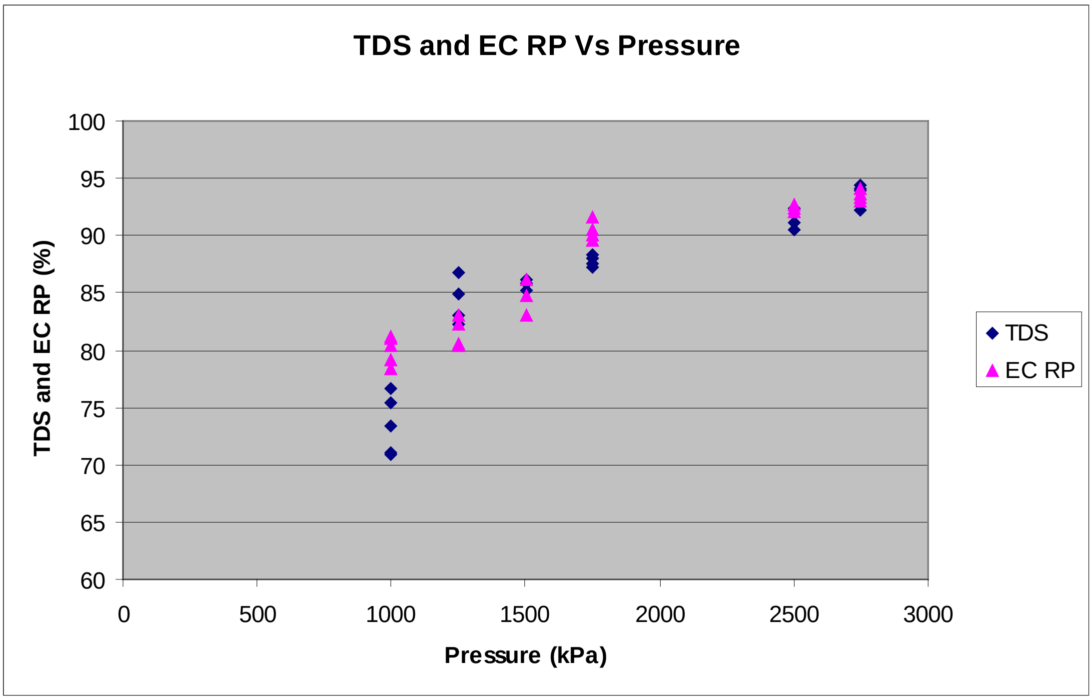

Figure 5.46 TDS and EC RP for the System Handling Groundwater

The effect of pressure on the WRP rejection percentages is shown in Figure 5.47. For low operating pressure of 1000kPa the percentage of groundwater recovered was only 26.415 but increasing the operating pressure to 2750kPa the WRP recorded was 73.178. Similar trends were observed with the permeate flux for the groundwater samples. The WRP and permeate flux for the groundwater experiments are similar to the ones obtained in the earlier experiments with effluents, NaCl and $CaCO_3$ samples These values obtained are close to the values obtained in a similar study conducted by Schafer and Richards while testing a hybrid membrane system handing brackish bore water in an Australian national park site (Schafer and Richards, 2005).

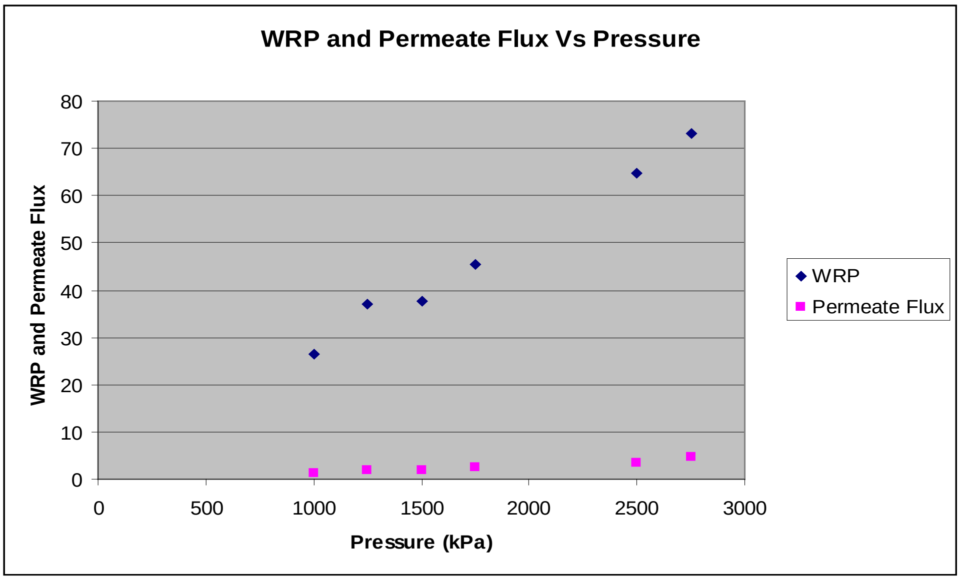

Figure 5.47 WRP and Permeate Flux for the RO System Handling Groundwater

Figure 5.48 illustrates the solute rejection percentages achieved by the RO unit while handling groundwater. As expected the solute rejection percentages increase with the increase in the operating pressure. The highest value recorded is 98.6948% for the P=2750kPa and 91.047% for the lower pressure of 1000kPa. From the Figure 5.48 it is clear that the solute rejection percentages are low at the start and increase as operating pressure is increased. The solute rejection percentages remain constant throughout the operation and similar findings were reported with the effluent samples, NaCl and $CaCO_3$ experimental runs.

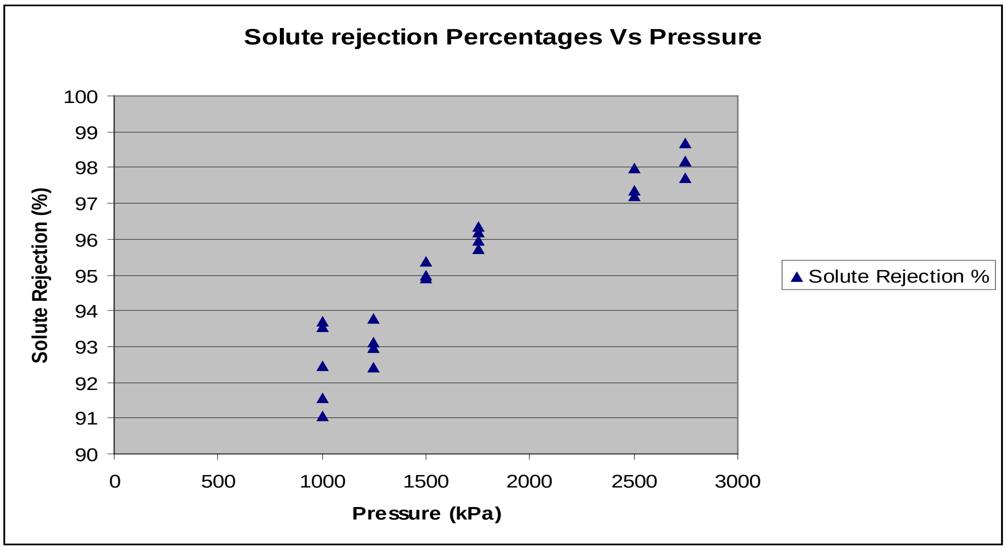

Figure 5.48 Solute Rejection Percentages for the RO System Handling Groundwater

5.6.4 The Predictions Derived from the ANN Model

We have so far established the various performance parameters and functions. The above experimental results established the performance of the RO system and its main function in rejecting impurities and having a good permeate flux throughout the operation. The ANN model created will verify these results and predict the salt rejection and the permeate flux for the same system conditions and parameters. The model assumptions remain the same as covered in 5.2.4.

The simulated results for SR and permeate flux are close to the analytical i.e. experimental obtained results. The system profiles predicted by the ANN model are shown above in Figures 5.49 and 5.50 respectively.

An example of the simulated permeate and solute rejection values are shown in the figure 5.49 and 5.50 for P = 1000kPa the rejection is 93.47 and the permeate flux with 31 epochs is 1.20169.

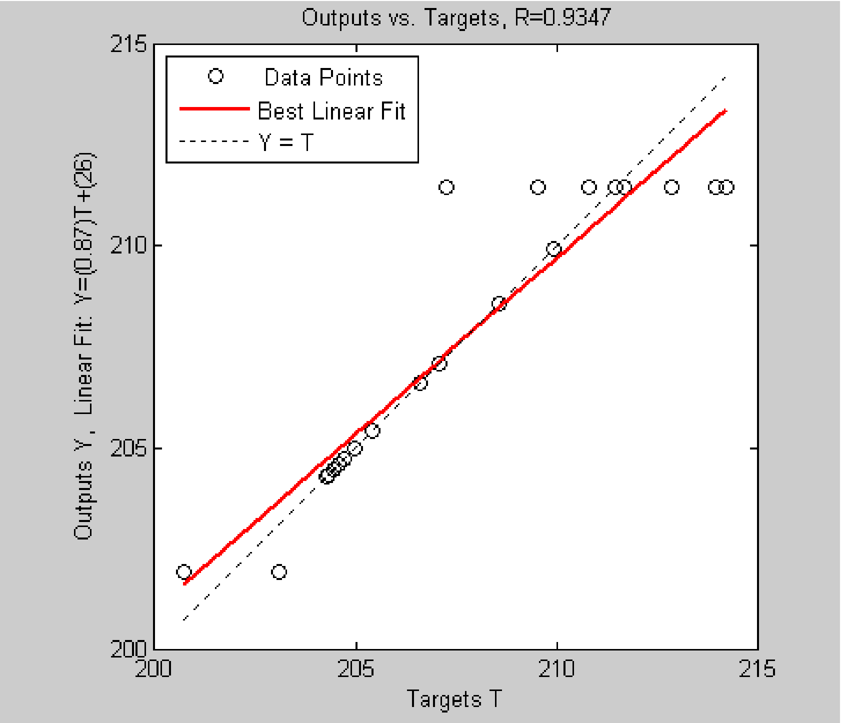

Figure 5.49 Predicted Solute Rejection Percentage of 93.47 by the ANN for P=1000kPa for the Groundwater Sample

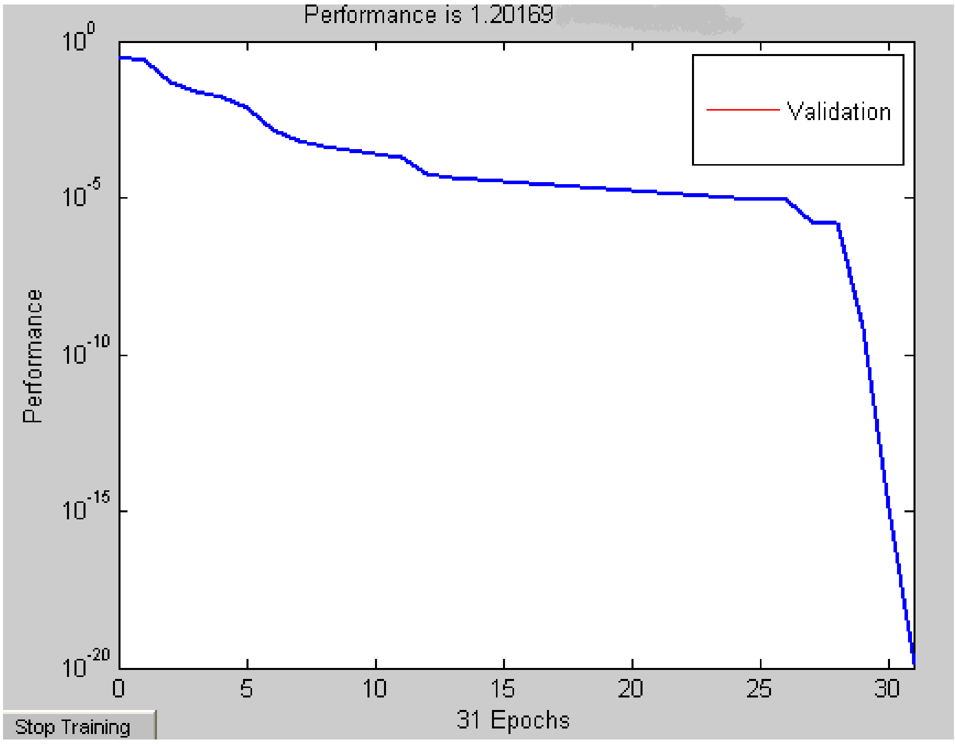

Figure 5.50 Predicted Permeate Flux of 1.20169 by the ANN for P=1000kPa for the Groundwater Sample with 31 Epochs

5.6.5 Concluding Remarks

The RO performance while handling groundwater as the feedwater was investigated. From the findings it was evident that the water recovery percentages and permeate flux increase linearly with applied pressure. However in practise a suitable pretreatment system is needed to achieve to these results due to the presence of the humic and dissolved minerals present in the groundwater. Higher solute rejection percentages have been noted for groundwater because of its characteristic features of having a low TDS and EC.

5.7 Artificial Neural Network Model Validation

The accuracy of the proposed neural network model has been validated by comparing with the selected data from Majali, Ettouney, Abdel-Jabbar and Qiblawey from their experimental work on RO plants. The experimental data obtained is different from the data used for modelling the neural network i.e. high concentration of sodium chloride in the feedwater samples. The concentration range is 3000 to 90000mg/L and pressure ranges from 2000 to 7500kPa which is similar to the pressure range of the earlier experimental work.

There are two sets of data obtained from this study which analyses the design and operating characteristics of two small scale reverse osmosis plants set up in Sharjah and Qatar. The plant located in Sharjah operates on low salinity brackish water while the plant located in Qatar operates on high salinity seawater. Table 5.14 shows the predicted profiles of the semi empirical model for the plant at Sharjah. The plant at Sharjah has a small capacity and has two stages to maximize the salt rejection.

Pressure kPa	**NaCl in Feed mg/L**	**Flowrate Permeate l/min**	**Flowrate Reject l/min**	**SR %**	**NaCl Permeate mg/l**	**NaCl Reject mg/l**
2200	3500	1.03	9.54	**94.55**	210	3855.81
2176	3855.81	0.93	8.6	**95.04**	231.38	4247.79
2152	4247.73	0.84	7.77	**94.55**	254.86	4679.62
2128	4679.62	0.76	7.1	**94.55**	280.77	5155.35
2104	5155.35	0.68	6.32	**94.56**	309.32	5679.45
2080	5679.45	0.62	5.71	**94.63**	340.76	6256.82
1800	6256.82	1.71	12.55	**93.9**	375.41	6256.82
1776	7058.83	1.51	11.05	**93.94**	423.53	7058.83
1752	7963.64	1.33	9.72	**93.66**	477.82	7963.64
1728	8984.44	1.17	8.55	**93**	539.07	8984.44
1704	10136.08	1.03	7.53	**93.1**	608.16	10136.08
1680	11435.35	0.9	6.62	**93.94**	686.12	11435.34

Table 5.14 Predicted Profiles for the Plant at Sharjah

The neural network generated using the ANN code predicts the average salt rejection (SR) for the above data. Figure 5.51 shows the predicted salt rejection as 92.642%. There is a good agreement between the predicted model results and the results obtained from literature (Majali, et al. 2008). The model shows agreement with low level feed concentrations of sodium chloride and low pressure ranges as well as the higher ranges.

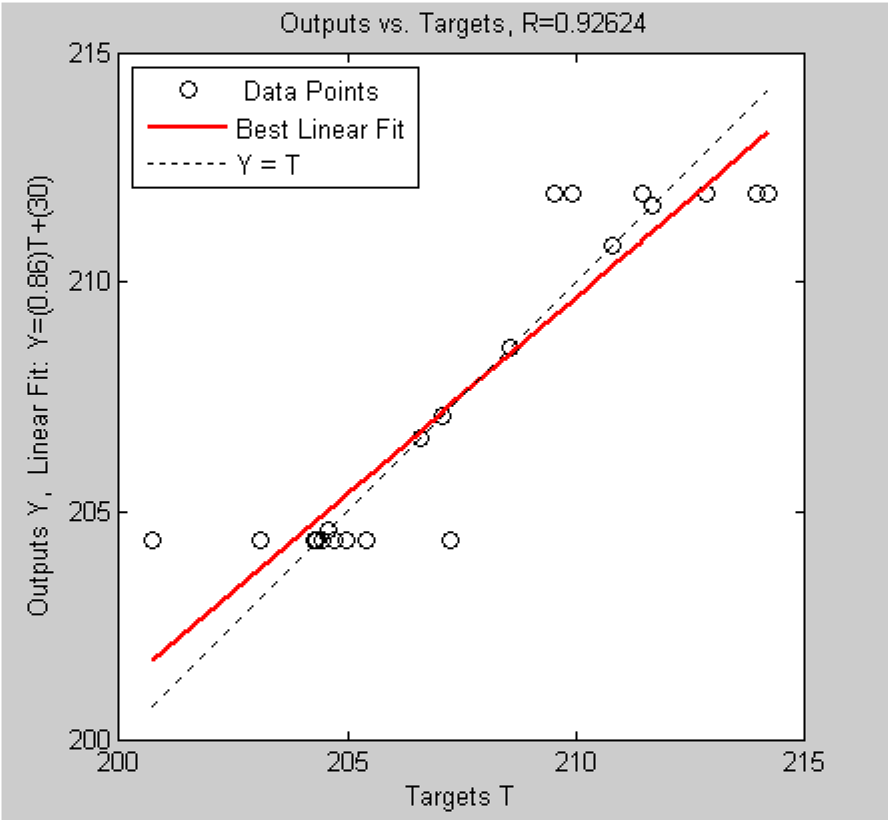

Figure 5.51 Predicted Salt Rejection Percentage as 92.624% from the ANN Code

Table 5.15 shows the predicted profiles of the semi empirical model for the plant at Qatar. The plant at Qataris built to test the feasibility of handling high salinity seawater as the feed. The plant has three RO modules in series. The plant has two stages to maximize the salt rejection.

Pressure kPa	NaCl in Feed mg/l	Flowrate Permeate l/min	Flowrate Reject l/min	SR %	NaCl Permeate mg/l	NaCl Reject mg/l
7500	580000	8.91	113.49	**99**	580	580000
7476	62509.95	8.26	105.22	**99.31**	625.09	62509.95
7452	63370.58	7.66	97.56	**99.14**	673.70	67370.58
7428	72609.16	7.1	90.45	**98.98**	726.09	72609.16
7404	78255.09	6.59	83.87	**98.34**	782.55	78255.09
7380	84340.02	6.11	77.76	**99.17**	843.40	84340.02
7500	580000	8.91	113.49	**99.63**	230.9	63101.2
7476	62509.95	8.26	105.22	**99.57**	292.4	68225.7
7452	63370.58	7.66	97.56	**99.48**	376.6	73216.3
7428	72609.16	7.1	90.45	**99.36**	490.7	77860
7404	78255.09	6.59	83.87	**99.20**	655.2	82060.8
7380	84340.02	6.11	77.76	**98.96**	882	85596.3

Table 5.15 Predicted Profiles for the Plant at Qatar

The neural network generated using the ANN code accurately predicts the average salt rejection (SR) for the above data. Figure 5.52 shows the predicted salt rejection as 95.25%. There is an excellent agreement between the model predictions and the collected literature data. As shown with the low level concentrations of brackish water the model shows agreement with high level feed concentrations of sodium chloride and higher pressure ranges.

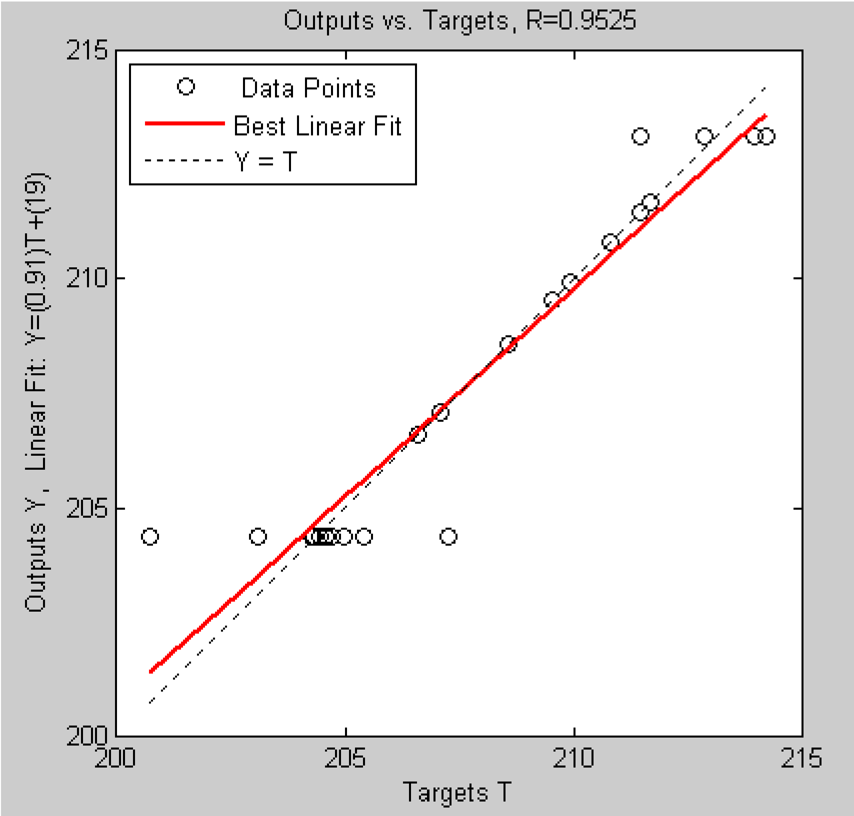

Figure 5.52 Predicted Salt Rejection Percentage as 95.25 % from the ANN Code

The Artificial neural network model for the prediction of salt rejection and permeate flux was developed using the available experimental data runs of the simulated feedwater, wastewater and groundwater (Nasir, 2005). The key RO parameters like operating pressure and feedwater characteristics affecting the system have also been considered in the model development. Additionally, the artificial neural network model has also been validated with the existing data obtained from literature. Overall neural network models proposed in the thesis will be beneficial in predicting the RO performance.

Chapter 6 Conclusions and Recommendations

6.1 Conclusions

Reverse Osmosis is one of the most widely used desalination techniques and it is widely established throughout the world. Desalination facilities have been established throughout the world where the expected water demand has exceeded the available resources. This thesis has presented the key performance parameters and a method of predicting these parameters have been provided. Literature data has been used to develop a neural network model to predict the key RO parameters. Using an artificial neural network (ANN) model the solute rejection percentages and permeate flux has been successfully predicted. Several conclusions have been drawn from the study and are summarised below.

6.2 Model for Simulated Feedwater Samples

The proposed neural network model successfully predicts the key RO performance parameters i.e. salt rejection and permeate flux for the simulated feedwater samples. The simulated results generated from the ANN code are similar to the experimental obtained results and the neural network model shows good accuracy in predicting these parameters. The real prediction power of the ANN model is observed when the simulated and experimental values of the predicted parameters are plotted as a function of the initial solute in feedwater. This shows the predictive power of the network in determining accurate results.

The residuals i.e. the differences between the experimental values and those obtained by the artificial neural network models show that the residuals by the artificial neural network model behave approximately in the same way, and that the residuals can be considered sufficiently random, independent and uncorrelated. The percent deviation from the experimental values for the NaCl samples are 1.31% for SR values and 2.1% for J_w values while the percent deviation for the $CaCO_3$ samples are 1.83% for SR values and 2.78% for J_w values.

6.3 Model for Wastewater and Groundwater Samples

The developed ANN code successfully predicts the solute rejection and permeate flux for these two feedwater samples. However the ANN model suggested in this thesis has some limitations because it was used to predict the performance of RO unit handling feedwater samples with low salt concentration and only two ions were taken into consideration for this study.

While investigating groundwater as the feedwater it was evident that the water recovery percentages and permeate flux increase linearly with applied pressure. However in practise a suitable pretreatment system is needed to achieve these results due to the presence of the humic and dissolved minerals present in the groundwater. Higher solute rejection percentages have been noted for groundwater because of its characteristic features of having a low TDS and EC. Similarly when secondary effluent was utilised as the feedwater the findings showed that the water recovery percentages, solute rejection and permeate flux increased with applied pressure. The percentages of the solute rejection are not as high as expected because of solute build up which tends to increase as the operation is continued over a period of time. The lower values of the WRP and permeate flux obtained are caused by the characteristics of the secondary effluent that have high suspended solids, minerals and organic matter. It is desirable to have a suitable pretreatment procedure in place before treating secondary effluent wastewater and groundwater to prevent membrane blockage and low quality permeate. Hence the ANN model is recommended for groundwater and secondary treated wastewater for low solute concentrations. The percent deviation from the experimental values for the groundwater samples are 2.17% for SR values and 2.95% for J_w values while the percent deviation for the industrial effluent samples are 2.67% for SR values and 2.83% for J_w values.

The practical implications of this project is to provide a reliable water source for human as well and industry usage. Experimental investigations can be optimized with the help of this prediction tool in not only assessing the suitability of such techniques but also in planning for various water facilities. There are already various existing and proposed projects in Australia utilizing Reverse Osmosis desalination technology.

Using this ANN model in such proposed locations will provide a platform for future projects in this area.

6.4 Recommendations for Future Work

Although these developed ANN models are not mechanistically based, it did not encounter any drastic change in the permeate flux and SR percentages for different concentrations of the investigated feedwater samples. Such changes can be further investigated at extended pressure ranges and varying concentrations to give new insight into mechanisms affecting RO performance. More rigorous ANN models can be developed and could significantly improve overall performance of the RO system. The present study focused on performance variability that was of short duration and for a limited data range. The results of the present study suggest that there is merit in applying the present approach to plant operations that may involve longer time scales of operation and performance degradation. The present study has its limitations and the following recommendations are proposed to be carried out in the future.

1) To study the effect of operating time on the performance of the RO unit. The present study has been conducted without considering operating time as a factor for build up of solute on the membrane wall in scaling and fouling operations. Research into this area considering the effect of time would be of great significance in commercial RO plants.

2) An experimental setup to study the effect of pre treatment on the given feedwater samples used in the existing RO unit. The pretreatment of feedwater samples with high salinity and suspended is highly recommended before treating with the existing RO unit. This minimizes the effect of scaling and fouling which is prevalent during the operation. The effectiveness of the pretreatment process will lead to higher overall membrane performance and longer membrane life. It is also suggested to experimentally investigate a combination of pretreatment processes like micro filtration, ultra filtration and nano filtration for the existing RO unit to affectively reduce scaling and forming during the operation.

3) An experimental setup to study various types of groundwater and wastewater feed samples. Even though these types of feedwater have been investigated it is recommended to study the performance of the existing RO unit in handling groundwater and treated wastewater of varying concentrations along with the presence of heavy metals and minerals in the feedwater.

4) To study the production costs of Reverse osmosis desalination for producing pure drinking water. Although the importance of Reverse Osmosis has been established in this study, the cost of production of pure water has not been investigated. It is recommended to analyse cost of water production by RO and do a cost comparison for similar desalination techniques producing same quantity and quality of final water product. This statistical approach could be taken by comparing already established desalination facilities using different desalination technologies.

5) To further develop the model by investigating various ions and higher pressure range through extensive modelling of the investigated feedwater. The ANN code developed had two hidden layers which predicted the solute rejection and permeate flux for the system. Further research could be conducted by extending the ANN code to include three or more hidden layers for more accurate modelling of the system for the given feedwater. The study conducted mainly considered sodium and calcium as the two main ions that affect the performance of the RO unit. It is recommended to expand the modelling approach to include the effect of other ions in the feedwater such as iron, silica and magnesium.

6) An experimental setup to study the performance of the RO unit while handling seawater samples. The RO unit has not been investigated for handling seawater feed samples. Seawater is characterised by having a high level of salinity and research into the effect of high concentration of dissolved solids in seawater would further strengthen the generated ANN model. It is recommend testing the developed ANN model for predicting the performance of the RO unit while handling seawater and if similar accurate predictions are obtained while considering the feedwater samples considered in the study.

References

Abbas. A. and N. Al‐Bastaki (2005). “Modelling of an Reverse Osmosis water desalination unit using neural networks.” Chemical Engineering Journal **114**(1-3): 139‐143.

Afonso, M.D., J.O. Jaber and M.S. Mohsen (2004). “Brackish groundwater treatment by reverse osmosis in Jordan.” Desalination **164**(2): 157-171.

Al-Enezi, G. and N. Fawzi (2003). “Design consideration of RO units: Case studies.” Desalination **153**(1-3): 281-286.

Anderson, J.M. (1996). “A possible regulatory framework for water recycling in Australia.” Desalination **106**(1-3): 331-333.

Andrianne, J. and F. Alardin (2003). “Thermal and membrane process economics: Optimized selection for seawater desalination.” Desalination **153**(1-3): 305-311.

Asano, T. (1986). “Wastewater Reclamation and Reuse.” Water Pollution Control Federation. **58**(6): 529-532.

Australian Bureau of Statistics, 2007.

Avlonitis, S., W. T. Hanbury and M.B. Boudinar (1991). “Spiral wound modules performance. An analytical solution: Part I.” Desalination **81**(1-3): 191-208.

AWWA: American Water Works Association (1999). “Manual of Water Supply Practices- Reverse Osmosis and Nanofiltration.” Denver Colorado: 1-71.

Baron, O. (2006). “Desalination options and their possible implementation in Western Australia: Potential role for CSIRO Land and Water.” CSIRO: Water for a Healthy Country National Research Flagship Canberra.

Bartels, C., R. Franks, S. Rybar, M. Schierach and M. Wilf (2005). "The effect of feed ionic strength on salt passage through reverse osmosis membranes." Desalination **184**(1-3): 185-195.

Beeton, R.J.S., Buckley, K.I., Jones, G.J., Morgan, D., Reichelt, R.E., Trewin, D. (2006 Australian State of the Environment Committee) (2006) Australia State of the Environment 2006, Independent report to the Australian Government Minister for the Environment and Heritage, Department of the Environment and Heritage, Canberra .

Bellona, C., J.E. Drewes, P. Xu and G. Amy (2004). "Factors affecting the rejection of organic solutes during NF/RO treatment ‐ a literature review." Water Research **38**(12): 2795 ‐ 2809.

Betts, K. (2004). "Desalination, desalination everywhere." Environmental Science and Technology." **38**(13): 246-247.

Bhagat, P. (1990). "An Introduction to Neural Networks." Chemical Engineering Progress **86**(8): 55 ‐ 60.

Bidlack, W.R., W. Wang, R. Clemens and J.S. Rhee (2004). "The worlds most precious resource." Journal of Food Science **69**(2): 55.

Birrel, B., V. Rapson and F. Smith (2005). "Impact of Demographic change and urban consolidation on Domestic Water Use." Water Services Association of Australia Inc Melbourne.

Blatt, W., A. Dravid, A.S. Michaels and L. Nelsen (1970). "Solute polarization and cake formation in membrane ultrafiltration: causes, consequences and control techniques." Membrane Science and Technology J.E Flinn Edition Plenum, New York 47-91.

Bodalo, A., J.L. Gomez, E. Gomez, A.M. Hidalgo and A. Aleman (2005). “Viability study of different reverse osmosis membranes for application in the tertiary treatment of wastes from the tanning industry.” Desalination **180**(1-3): 277-284.

Bodalo-Santoyo, A., J. L. Gomez-Carrasco, E. Gomez-Gomez, F. Maximo-Martin and A. M. Hidalgo-Montesinos (2003). “Application of reverse osmosis to reduce pollutants present in industrial wastewater.” Desalination **155**(2): 101-108.

Bodalo-Santoyo. A., J. L. Gomez-Carrasco, E. Gomez-Gomez , M. F. Maximo-Martin and A. M. Hidalgo-Montesinos (2004). “Spiral-wound membrane reverse osmosis and the treatment of industrial effluents.” Desalination **160**(2) 151-158.

Bohdziewicz, J. and E. Sroka (2005). “Treatment of wastewater from the meat industry applying integrated membrane systems.” Process Biochemistry **40**(3-4): 1339–1346.

Bohdziewicz, J., M. Bodzek and E.W. Sik (1999). “The application of reverse osmosis and nanofiltration for the removal of nitrates from groundwater.” Desalination **121**(2): 139-147.

Boswell, C. (2005). “A market with an unquenchable thirst.” Chemical Market Reporter **268**(8): 19.

Bou-Hamad, S., M. Abdel-Jawad, S. Ebrahim, M. Al-Mansour and A. Al-Hijji (1997). “A Performance evaluation of three different pretreatment systems for seawater reverse osmosis technique.” Desalination **110**(1-2): 85-91.

Brown, E.V. (2006). “Water: A Human Right for all.” Global Watch **1**(2): 91-98.

Bruggen, B.V. and C. Vandecasteele (2002). “Distillation vs. Membrane filtration: overview of process evolutions in seawater.” Desalination **143**(3): 207-218.

Buros, O.K. (2000), The ABC's of Desalting. Second Edition Produced by the saline water conversion council for the international desalination association, Riyadh, Saudi Arabia.

Cassanoa, A., R. Molinari and E. Driolia (1999). "Saving of Water and Chemicals in Tanning Industry by Membrane Processes." Water Science and Technology **40**(4-5): 443-450.

Chakravortya, B. and A. Layson (1997). "Ideal feed preteatment for reverse osmosis by continuous microfiltration." Desalination **110**(1-2): 143-149.

Chellam, S. (2005). " Artificial Neural Network model for transient crossflow of microfiltration of polydispersed suspensions." Journal of Membrane Science **258**(1-2): 35-42.

Chen, H.Q. and A.S. Kim (2006). "Prediction of permeate flux decline in crossflow membrane filtration of colloidal suspension: a radial basis function neural network approach." Desalination **192**(1 – 3): 415 – 428.

Chen, V., A.G. Fane, S Madaeni and I.G. Wenten (1997). "Particle deposition during membrane filtration of colloids: transition between concentration polarization and cake formation." Journal of Membrane Science **125**(1): 109-112.

Cheremisinoff, N.P. (2002). "Membrane Separation Technologies Handbook of Water and Wastewater Treatment Technologies." 335-371.

Conway, M. (2008). "The desalination Solution." The Futurist **42**(3): 23-25.

Cote, P., J.C. Cadera, J.C. and A. Munro (2001). "A new immersed membrane for pretreatment to reverse osmosis." Desalination **139**(1-3): 229-236.

Crase. Lin (2008). "Water Policy in Australia: The impact of change and Uncertainty." Washington USA.

Crisp, G. (2005). “Desalination and Water Reuse: Forging Ahead in Western Australia.” International Desalination Association (IDA) World Congress on Desalination and Water Reuse, September, 11-16, Singapore.

Dallas, E. and P. G. Koutsoukos (1990). “Calcium Carbonate scale formation and prevention in a flow through system at various temperatures.” Desalination **78**(3): 403-416.

Darwish M.A. and H. El-Dessousky (1996). “The Heat recovery thermal vapour compression desalting system: A comparison with other thermal desalination processes. Journal of Heat Recovery Systems **16**(6): 523-537.

Delgrange, N.C., C. Cabassud, M. Cabassud, L. Durand-Bourlier and J.M. Laine (2000). “Neural networks for long term prediction of fouling and backwash efficiency in ultrafiltration for drinking water production.” Desalination **131**(1-3): 353-362.

Delgrange, N.C., C. Cabassud, M. Cabassud, L. Durand-Bourlier and J.M. Laine (1998).“Modelling of ultrafiltration fouling by neural network.” Desalination **118**(1-3): 213-227.

Dore, M.H.I. (2005). “Forecasting the economic costs of desalination technology.” Desalination **172**(1-3): 207-214.

Dornier, M., M. Decloux, G. Trystram and A. Lebert (1995). “Dynamic Modelling of Cross - Flow Microfiltration Using Neural Networks.” Journal of Membrane Science **98**(3): 263 - 273.

Dudley, L.Y. and E. G. Darton (1997). “Pretreatment procedures to control bio-growth and scale formation in membrane systems.” Desalination **110**(1-2): 11-20.

Durham, B. and A.Walton (1999). Membrane pretreatment of reverse osmosis: long term experience on difficult waters.” Desalination **122**(2-3): 157-170.

Ebrahim, S. and A. Malik (1987). “Pretreatment of surface seawater feed at DROP.” Desalination **63**: 95-107.

Ebrahim, S., M. Abdel-Jawad, S. Bou-Hamad and M. Safar (2001). “Fifteen years of R&D programs at KISR. Part I. Pretreatment technologies for RO systems.” Desalination **135**(1-3): 141-153.

El-Dessouky, H.T., H.M. Ettouney and Y.A-Rouni (1999). “Multistage flash desalination: Present and future outlook.” Desalination **73**(2): 173-190.

El-Dessouky, H.T., I. Alatiqi and H. Ettoney (1998). “ Process synthesis: The multistage flash desalination system.” Desalination **115**(2): 155-179.

Elguera, A.M. and S.O. Perez-Baez (2005). “Development of the most adequate pre-treatment for high capacity seawater desalination plants with open intake.” Desalination **184**(1-3): 173-183.

El-Hawary, M.E. (1993). “Artificial neural networks and possible applications to desalination.” Desalination **92**(1-3): 125-147.

Fababuj-Roger, M., J.A. Mendoza-Roca, M.V. Galiana-Aleixandre, A. Bes-Pia, B. Cuartas-Uribe and A. Iborra-Clar (2007). “Reuse of tannery wastewaters by combination of ultrafiltration and reverse osmosis after a conventional physical-chemical treatment.” Desalination **204**(1-3): 219-226.

Fritzmann, C., J. Lowenberg, T. Wintgens and T. Melin (2007). “State of the art of reverse osmosis desalination.” Desalination **216**(1-3): 1-76.

Gallant, A.J.E., K.J. Hennessy and J. Risbey (2007). “Australian Meteorological Magazine.” **56**(4): 223-239.

Gauwbergen, D.V. and J. Baeyens (1999). “Assessment of the Design Parameters for Wastewater Treatment by Reverse Osmosis.” Water Science and Technology **40**(4-5): 269-276.

Green, M.G. and D. Schwarz. (2002). "Extracting drinking water from salt water." Appropriate Technology **29**(3): 56-59.

Green, S. (2005). "Quenching a Thirst." Power Engineering International **13**(12): 33.

Hairston, D. (2006). "The desalination challenge: Making water abundantly available." Chemical Engineering Progress **102**(9): 6.

Harrison, J.F. (2006). "What is Reverse Osmosis." PM Engineer **12**(3): 22

Hebb, D.O. (1949). "Organization of Behaviour." Wiley New York.

Ho, C.C. and A.L. Zydney (2006). "Overview of fouling phenomena and modelling approaches for membrane bioreactors." Separation Science and Technology **41**(7): 1231-1251.

Hoek, E.M.V. and M. Elimelech (2003). "Cake-enhanced concentration polarization: A new fouling mechanism for salt-rejecting membranes." Environmental. Science and. Technology. **37**(24): 5581-5588.

Into, M., A.S. Jonsson and G. Lengden (2004). "Reuse of industrial wastewater following treatment with reverse osmosis." Journal of Membrane Science **242**(1-2): 21-25.

Isaias, N.P. (2001). "Experience in reverse osmosis pretreatment." Desalination **139**(1-3): 57-64.

Kim, S. and M.V. Hoek (2005)."Modelling concentration polarization in reverse osmosis processes." Desalination **186**(1-3): 111-128.

Kim, I.S. and N. Jang (2006). "The effect of calcium on the membrane biofouling in the membrane bioreactor." Water Research **40**(14): 2756-2764.

Kim, S.L., J.P. Chen and Y.P.Ting (2002). "Study on feed pre treatment for membrane filtration of secondary effluent." Separation and Purification Technology **29**(2): 171-179.

Kimura, K., S. Toshima, G. Amy and Y. Watanabe (2004). "Rejection of neutral endocrine disrupting compounds (EDCs) and pharmaceutical active compounds (PhACs) by RO membranes." Journal of Membrane Science **245**(1-2): 71-78.

Kosutic, K. and B. Kunst (2002). "RO and NF membrane fouling and cleaning and pore size distribution variations." Desalination **150**(2): 113-120.

Kumar, M., S.S. Adham and W.R. Pearce (2006). "Investigation of Seawater Reverse Osmosis Fouling and Its Relationship to Pretreatment type." Environmental Science and Technology **40**(6): 2037 – 2044.

Lalot, S.(2006). "On-line detection of fouling in a water circulating temperature controller (WCTC) used in injection moulding: Part 1: Principles." Applied Thermal Engineering **26**(11-12): 1087-1094.

Landers, J. (2006). "Israel builds World's largest Reverse Osmosis Desalination plant." Civil Engineering **76**(2): 22.

Lawson, K.W. and D.R. Lloyd (1997). "Membrane Distillation." Journal of Membrane Science **124**(1): 1-25

Lee, C.H. (1975). "Theory of reverse osmosis and some other membrane permeation operations." Journal of applied polymer science **19**(1):.83-95.

Levenberg, K. (1944). "A Method for the solution of Certain Non-Linear Problems in Least Squares." Quarterly of Applied Mathematics **2**(2): 164-168.

Lin, C.J., P. Rao and S. Shirazi (2005). "Effect of operating parameters on permeate flux decline cause by cake formation: A model study." Desalination **171**(1): 95-105.

Lopez-Ramirez, A.J., M.D. Coello Oviedo and J.M. Quiroga Alonso (2006). “Comparative studies of reverse osmosis membranes for wastewater reclamation.” Desalination **191**(1-3): 137-147.

Lopez-Ramirez, J.A., S. Sahuquillo, D. Sales and J.M. Quiroga (2003). “Optimization studies for secondary effluent reclamation.” Water Research **37**(5): 1177-1184.

Lu, Y.Y. and Y.D. Hu (2005). “Optimum design of reverse osmosis seawater desalination system technology.” Water Treatment. **3**: 9–16.

M’nif, A., S. Bouguecha, B. Hamrouni and M. Dhahbi (2007). “Coupling of membrane processes for brackish water desalination.” Desalination **203**(1-3): 331-336.

Majali, F., H. Ettouney, N. Abdel-Jabbar and H. Qiblawey (2008). “Design and operating characteristics of pilot scale reverse osmosis plants.” Desalination **222**(1-3): 441-450.

Malaiyandi, P., T. Matsuura and S. Sourirajan (1982). “Predicitability of membrane performance for mixed solute reverse osmosis system: system cellulose acetate membrane D-glucose-D, L-malic acid water.” Industrial. Engineering. Chemistry. Process Design and. Development **21**(2): 277–282.

Marcucci, M., G. Nosenzo, G. Capannelli, I. Ciabattia, D. Corrieri and G. Ciardelli (2001). “Treatment and reuse of textile effluents based on new ultrafiltration and other membrane technologies.” Desalination **138**(1-3): 75-82.

Matsuura, T. and S. Sourirajan (1971). “Reverse Osmosis Separation of Some Organic Solutes in Aqueous Solution Using Porous Cellulose Acetate Membranes.” Industrial and Engineering Chemistry Process Design and Development **10**(1): 102 – 108.

McIvaine, R. (2008). “Reverse Osmosis.” Chemical Engineering **115**(8): 20-24.

Mohammadi, T., M.. Kazemimoghadam and M. Saadabadi (2003) “Modelling of membrane fouling and flux decline in reverse osmosis during separation of oil in water emulsions.” Desalination **157**(1-3): 369-375.

Murray, B.R., M.J.B. Zeppel, G.C. Hose and D. Eamus (2003). “Groundwater dependent ecosystems in Australia: It’s more than just water for rivers.” Ecological Management and Restoration **4**(2): 110-113.

Nasir, S. (2005). “Effect of sodium chloride and calcium carbonate concentration on spiral wound membrane performance.” International Desalination Association (IDA) World Congress on Desalination and Water Reuse, September, 11-16, Singapore.

Nicolaisen, B. (2003). “Developments in membrane technology for water treatment.” Desalination **153**(1-3): 355-360.

Niemi, H. A. and S. Palosaari (1993). “Calculation of permeate flux and rejection in simulation of ultrafiltration and reverse osmosis processes.” Journal of Membrane Science **84**(1-2): 123-137.

Niemi, H., A. Bulsari and S. Palosaari (1995). “Simulation of membrane separation by neural networks.” Journal of membrane separation **102**: 185-191.

Noble, R.D. and S.A. Stern (1995). “Membrane separations and technology: principles and applications.”Amsterdam New York.

Nunes, S.P. and K.V. Peinemann (2001). “Membrane technology in the chemical industry.” Weinheim Chichester.

Odegaarda, H. and S. Koottatep (1982). “Removal of humic substance from natural waters by reverse osmosis.” Water Research **16**(5): 613-620.

Ondrey,G. (2005). “Membrane technology enhancements make water more affordable at world's largest desalination plant.” Chemical Engineering **112**(12): 15-16.

Ophir, A. and F. Lokiec (2005). “Advanced MED process for most economical seawater desalination.” Desalination **182**(1-3): 187-198.

Ozaki, H. and H.F. Li (2006). “Rejection of organic compounds by ultra‑low pressure reverse osmosis membrane.” Water Research **36**(1): 123‑130.

Pahiadaki, T.T., C. H. Andritsos, N. Yiantsios and A.J. Karabelas (2005). An experimental study of CaCO3 Scaling of RO and NF Membranes. International Desalination Association (IDA) Word Congress on Desalination and Water Reuse, September, 11-16, Singapore.

Panicker, S.T., S. Prabhakar, P.K. Tewari (2006). “Influence of feed quality on seawater reverse osmosis performance.” International Journal of Nuclear Desalination **2**(2): 166 – 171.

Parekh, B. S. (1988). “Reverse Osmosis Technology: An Application for High-Purity Water Production. New York, Marcel Dekker, Inc.

Paul, D.R. (2004). “Reformulation of the solution-diffusion theory of reverse osmosis.” Journal of Membrane Science **241**(2): 371-386.

Peters, T.A. (1998). “Purification of landfill leachate with reverse osmosis and nanofiltration.” Desalination **119**(1-3): 289-293.

Pilat, B. (2001). “Practice of water desalination by electrodialysis.” Desalination **139**(1-3): 385-392.

Pino, M.P.D. and B. Durham (1999). “Wastewater resue through dual membrane processes: opportunities for sustainable water resources.” Desalination **124**(1-3): 271-277.

Qin, J.J., M.H. Oo, M.N. Wai, H. Lee, S.P. Hong, J.E. Kim, Y. Xing and M. Zhanga (2005). "Pilot study for reclamation of secondary treated sewage effluent." Desalination **171**(3): 299-305.

Qin, J.J., M.N. Wai, M.H. Oo, K.A. Kekre and H. Seah (2006). "Feasibility study for reclamation of a secondary treated sewage effluent mainly from industrial sources using a dual membrane process." Separation and Purification Technology **50**(3): 380-387.

Quiggin, J. (2001). "Environmental economics and the Murray-Darling river system." Australian Journal of Agricultural and Resource Economics **45**(1): 67-95.

Rayana, M.A. and I. Khaled (2003). "Seawater desalination by reverse osmosis: A case study." Desalination **153**(1-3): 245-251.

Razavi, M.A., A. Mortazavi and M. Mousavi (2004). "Application of neural networks for crossflow milk ultrafiltration simulation." International Dairy Journal **14**(1): 69 – 80.

Redondo, J.A. and I. Lomax (1997). "Experiences with the pretreatment of raw water with high fouling potential for reverse osmosis plant using FLIMTEC membranes." **110**(1-2): 167-182.

Rengasamy, P. (2008). "Salinity in the Landscape: A Growing problem in Australia." Geotimes **53**(3): 34.

Robinson, R., G. Ho and K. Mathew (1992). "Development of a reliable low cost reverse osmosis desalination unit for remote communities." Desalination **86**(1): 9-26.

Rosenblatt, F (1962). "Principles of Neurodynamics, Perceptrons and The Theory of Brain Mechanisms." Spartan Books.

Rowzee, M.V. (2005). "Understanding Reverse Osmosis." PM Engineer **11**(2): 15.

Rozzi, A., M. Antonelli and M. Arcari (1999). “Membrane Treatment of Secondary Textile Effluents for Direct Reuse.” Water Science and Technology Volume **40**(4-5): 409-416.

Sahoo, G.B. and C. Ray (2006). “Predicting flux decline in crossflow membranes using artificial neural networks and genetic algorithms.” Journal of Membrane Science **283**(1-2): 147-157.

Sachs, J. and J. McArthur (2005). “The Millennium Project: A plan for meeting the Millennium Development Goals.” The Lancet **365**(9456): 347-353.

Schafer, A.I. and B.S. Richards (2005). “Testing of a hybrid membrane system for groundwater desalination in an Australian national park.” Desalination **183**(1-3): 55-62.

Schutte, C.F. (2003). “The rejection of specific organic compounds by reverse osmosis Membranes.” Desalination **158**(1 ‑ 3): 285 ‑ 294.

Serageldin, I (1999). “Looking ahead: water, life and the environment in the twenty first century.” International Journal of Water Resources Development **15(**1-2) :17-28.

Serkiz, S.M.and E.M. Perdue (1990). “Isolation of dissolved organic matter from the Suwannee River using reverse osmosis.” Water Research **24**(7): 911–916.

Shamel, M.M. and O.T. Chung (2006). “Drinking water from desalination of sweater: Optimization of reverse osmosis system operation parameters.” Journal of Engineering Science and Technology **1**(2): 203- 211.

Shetty, G.R. and S. Chellam (2003). “Predicting membrane fouling during municipal drinking water nanofiltration using artificial neural networks.” Journal of Membrane Science **217**(1-2): 69-86.

Sourirajan, S. and J. P. Agrawal (1969). “Reverse Osmosis.” Industrial and Engineering. Chemistry **61**(11): 62–89.

Stikker, A. (2002). “Desal technology can help quench the world's thirst.” Water Policy **4**(1): 47-55.

Suksaroj, C., M. Heran, C. Allegre and F. Persin (2005). “Treatment of textile plant effluent by nanofiltration and/or reverse osmosis for water reuse.” Desalination **178**(1-3): 333-341.

Sun, L., E. M. Perdue and J. F. McCarthy (1995). “Using reverse osmosis to obtain organic matter from surface and ground waters.” Water Research **29**(6): 1471-1477.

Sutzkover, I., D. Hasson and R. Semiat (2000). “Simple technique for measuring the concentration polarization level in a reverse osmosis system.” Desalination **131**(1-3): 117-127.

Taylor, J. (1998). “Flat sheet, Bench and Pilot Testing for Pesticide Removal Using Reverse Osmosis.” American water Works association Research Foundation.

Teng, C.K., M.N.A. Hawlader, and A. Malek (2003). “An experiment with different pretreatment methods.” Desalination **156**(1-3): 51-58.

Tularam. A.G. and M. Ilahee (2007). “Environmental concerns of desalinating seawater using reverse osmosis.” Journal of Environmental Monitoring **9**(8): 805 -813

Urs, A. (2002). Economic and Technical Assessment of Desalination Technologies in Australia: with Particular Reference to National Action Plan Priority Regions, Department of Agriculture, Fisheries and Forestry- Australia.

Van-Hoof, S.C.J.M., J.G. Minnery and B. Mack (2001). “Dead-end ultrafiltration as alternative pre-treatment to reverse osmosis in seawater desalination: a case study.” Desalination **139**(1-3): 161-168.

Veerman, J., M. Saakes, S.J. Metz and G.J. Harmsen (2009). "Reverse electrodialysis: Performance of a stack with 50 cells on the mixing of sea and river water." Journal of Membrane Science **327**(1-2): 136-144.

Wade, N.M. (2001). "Distillation plant development and cost update." Desalination **136**(1-3): 3-12.

Wang, Z., Z. Fan, L. Xie and S. Wang (2006). "Study of integrated membrane systems for the treatment of wastewater from cooling towers." Desalination **191**(1-3): 117-124.

WANTM: Waterwatch Australia National Technical Manual (2005) Groundwater Monitoring Department of the Environment and Heritage- Australia.

Wijmans, J.G. and R. W. Baker (1995). "The solution-diffusion model: a review." Journal of Membrane Science **107**(1-2): 1-21.

Wilf, M. and K. Klinko (1998). "Effective new pretreatment for seawater reverse osmosis systems." Desalination **117**(1-3): 323-331.

Xu, T.and C. Huang (2008). "Electrodialysis based separation technologies: A critical review." AICHE Journal **54**(12): 3147.

Yang, Q. (2006). "Inhibition of $CaCO_3$ Scaling in Reverse Osmosis System by Zinc Ion." Chinese Journal of Chemical Engineering **14**(2): 178-183.

Zhang, Y., C. Ma, F.Ye, Y. Kong and H. Li (2009). " The treatment of wastewater of paper mill with integrated membrane process." Desalination **236**(1-3): 349-356.

Zhao, Y., J. Taylor and S. Chellam (2005). "Predicting RO/NF water quality by modified solution diffusion model and artificial neural networks." Journal of membrane science **263**(1-2): 38-46.

Zhu, X and M. Elimelech (1997). “Colloidal Fouling of Reverse Osmosis Membranes: Measurements and Fouling Mechanisms.” Environmental science and technology **31**(12): 3654-3662.

Appendices

Appendix A

Table 5.1 TDS RPP and EC RP for the Sodium Chloride Solution at Different Operating Pressures

Pressure kPa	**NaCl Feed mg/l**	**TDS RP %**	**EC RP %**
1250	100	100	98.14
1250	500	99	96.2
1250	1200	94.78	95.02
1250	2500	93.39	95.03
1750	100	100	98.91
1750	500	100	96.1
1750	1200	99	96.83
1750	2500	93.44	94.24
1750	5000	92.18	88.02
2250	100	100	97.76
2250	500	100	93.1
2250	1200	99.12	97.35
2250	2500	92.57	97.05
2250	5000	90.05	89.83
2750	100	100	98.91
2750	500	97.37	98.88
2750	1200	96.69	97.19
2750	2500	95.58	95.20
2750	5000	92.57	96.42
4750	500	98.29	92
4750	1200	97.55	96.78
4750	2500	93.24	90.75
4750	500	90.02	92.11

Table 5.2 WRP and Flow Rates for the Permeate and Reject Streams for the Sodium Chloride Solution at Different Operating Pressure

Pressure kPa	**NaCl mg/l**	**WRP %**	**Permeate FL**	**Reject FL**
1250	100	16.67	2.25	11.25
1250	500	17.85	2.5	11.5
1250	1200	14.81	2	11.5
1250	2500	11.11	1.5	12
1750	100	31.48	4.25	9.25
1750	500	29.62	4	9.5
1750	1200	25.62	3.5	10
1750	2500	27.27	3.75	10
1750	5000	27.24	2.5	12
2250	100	46.29	6.25	7.25
2250	500	55.55	7.5	6
2250	1200	43.63	6	7.75
2250	2500	40.74	5.5	8
2250	5000	32.14	4.5	9.5
2750	100	59.25	8	5.5
2750	500	58.49	7.75	5.5
2750	1200	50.943	6.75	6.5
2750	2500	50	6.25	6.25
2750	5000	44.44	6	7.5
4750	500	62.22	9.75	3.75
4750	1200	56.36	7.75	6
4750	2500	71.15	9.25	3.75
4750	5000	57.40	7.75	5.75

Table 5.3 Permeate Flux for the Sodium Chloride Solution at Different Operating Pressures

Pressure kPa	**NaCl Feed mg/l**	**J_w m/s**
1250	100	14.42
1250	500	16.02
1250	1200	12.82
1250	2500	9.61
1750	100	2.72
1750	500	2.56
1750	1200	2.24
1750	2500	2.40
1750	5000	1.06
2250	100	4.00
2250	500	4.80
2250	1200	3.84
2250	2500	3.52
2250	5000	2.88
2750	100	5.12
2750	500	4.96
2750	1200	4.32
2750	2500	4.00
2750	5000	3.84
4750	500	6.25
4750	1200	4.96
4750	2500	5.92
4750	500	4.96

Table 5.4 Sodium Rejection Percentages Achieved by the RO System

Pressure kPa	**NaCl Feed mg/l**	**SR %**
1250	100	93.27
1250	500	93.37
1250	1200	93.44
1250	2500	93.51
1750	100	93.69
1750	500	93.74
1750	1200	93.87
1750	2500	93.94
1750	5000	94
2250	100	94.02
2250	500	94.19
2250	1200	94.57
2250	2500	95.11
2250	5000	95.81
2750	100	95.82
2750	500	96.12
2750	1200	96.52
2750	2500	96.89
2750	5000	97
4750	500	97.1
4750	1200	97.6
4750	2500	98.3
4750	500	98.6

Table 5.6 Simulated SR and J_w Values and Residual Differences Between the Simulated and Experimental Values of SR and J_w

NaCl Feed mg/l	J_w m/s	SR	SR Simulated	J_w Simulated	SR Diff	J_w Diff
100	14.42	93.27	92.95	9.85	-0.318	-4.56
500	15.02	93.37	92.17	12.67	-1.2	-2.35
1200	12.82	93.44	93.78	11.11	0.34	-1.71
2500	9.615	93.51	94.12	8.71	0.61	-0.90
100	2.72	93.69	92.77	2.87	-0.92	0.15
500	2.56	93.74	93.87	2.75	0.13	0.19
1200	2.24	93.87	93.11	1.78	-0.76	-0.45
2500	2.40	93.94	93.37	1.74	-0.57	-0.65
5000	1.06	94	94.57	1.01	0.57	-0.04
100	4.00	94.02	93.38	4.51	-0.64	0.51
500	4.80	94.19	93.47	3.97	-0.72	0.83
1200	3.84	94.57	93.71	3.10	-0.86	-0.74
2500	3.52	95.11	95.49	3.12	0.38	-0.40
5000	2.88	95.81	95.87	2.97	0.06	0.08
100	5.12	95.82	94.16	5.96	-1.66	0.83
500	4.97	96.12	94.88	5.78	-1.24	0.81
1200	4.32	96.52	95.77	4.17	-0.75	-0.14
2500	4.00	96.89	95.87	3.81	-1.02	-0.19
5000	3.846	97	97.47	3.51	0.47	-0.32
500	6.25	97.1	96.14	6.34	-0.96	0.09
1200	5.967	97.6	98.73	6.19	1.13	0.22
2500	5.92	98.3	99.11	5.87	0.81	-0.05
5000	4.96	98.6	99.89	5.97	1.29	1.0

Table 5.7 WRP, TDS RP and Flow Rates for the Permeate and Reject Streams for the Calcium Carbonate Solution at Different Operating Pressure

Pressure kPa	CaCO3 Feed mg/l	TDS RP %	ECRP %	WRP %	Permeate FL	Reject FL
1250	50	100	99.49	20.01	2.75	11
1250	100	100	95.35	17.58	2.5	11.5
1250	1200	98.34	94.37	15.84	2.17	11.25
1250	2500	97.14	92.14	14.17	2.07	10.75
1750	50	100	98.51	39.14	4.5	9

1750	100	99.53	96.35	37.54	4.5	9.25
1750	1200	97.29	95.79	33.47	4.31	8.7
1750	2500	96.34	94.15	29.17	4.17	8.29
1750	5000	95.17	91.23	27.47	3.87	8.05
2250	50	98.17	97.04	50.09	6.75	6.75
2250	100	96.17	93.04	45.28	6.25	7.5
2250	1200	95.04	91.28	41.54	5.73	7
2250	2500	93.58	90.51	38.07	5.51	6.8
2250	5000	93.04	89.89	36.18	5.15	6.25
2750	50	97.44	98.51	64.39	8.5	4.7
2750	100	96.10	96.36	60.78	7.75	5
2750	1200	93.17	95.12	57.54	7.25	5.12
2750	2500	93.04	94.91	54.51	7	4.85
2750	5000	92.84	93.07	51.07	6.66	4.31
3250	50	99.76	99.27	74.07	10	3.5
3250	100	99.14	98.04	70.04	10.25	3.5
3250	2500	98.17	97.69	64.97	9.55	3
3250	5000	98.04	97.145	62.22	9.31	2.85

Table 5.8 Simulated SR and J_w Values and Residual Differences Between the Simulated and Experimental Values of SR and J_w for the $CaCO_3$ Feedwater Samples

CaCO3 Feed mg/l	**J_w m/s**	**SR %**	**SR simulated**	**J_w simulated**	**SR Diff**	**J_w Diff**
50	1.44	94.78	93.72	1.73	1.05	0.29
100	1.89	92.17	93.94	1.95	1.76	0.06
1200	1.75	91.4	92.05	1.25	0.65	-0.49
2500	1.52	90.07	91.21	1.34	1.14	-0.18
50	2.88	93.01	94.56	2.96	1.54	0.08
100	2.77	92.79	94.13	2.64	1.34	-0.12
1200	2.17	92.17	91.15	2.84	-1.01	0.66
2500	1.87	91.78	90.16	2.06	-1.61	0.18
5000	1.77	91.89	91.34	1.67	-0.54	-0.10
50	4.32	94.98	93.18	4.15	-1.80	-0.17

100	4.05	94.67	92.18	4.54	-2.48	0.48
1200	3.58	93.94	94.26	3.31	0.32	-0.27
2500	3.18	93.71	94.68	3.01	0.97	-0.17
5000	3.08	92.84	91.51	3.15	-1.33	-0.17
50	5.44	95.74	96.15	5.06	-0.59	-0.38
100	4.96	95.68	96.79	5.13	1.12	0.16
1200	4.21	95.75	94.15	4.61	-1.60	0.42
2500	4.00	94.97	93.05	4.18	1.92	0.17
5000	3.71	96.04	92.19	3.49	-3.84	-0.21
50	6.41	97.46	96.25	6.19	-1.20	-0.21
100	6.57	97.58	97.85	6.31	0.27	-0.25
2500	6.44	98.04	97.18	6.15	-0.86	-0.28
5000	6.07	98.75	98.58	6.16	-3.16	0.08

Table 5.10 TDS EC RP, WRP and Permeate Flux for the Combined NaCl Solution and $CaCO_3$ Feedwater at Different Operating Pressures

Pressure kPa	**NaCl in Feed mg/L**	**TDS RP %**	**EC RP %**	**$CaCO_3$ in Feed mg/L**	**WRP %**
1250	100	98.1	92.13	50	16.07
1250	500	98.26	92.05	50	15.20
1250	1200	98.18	97.68	50	15.54
1250	2500	97.16	96.53	50	10.71
1750	100	100	91.73	50	35.54
1750	500	99.48	93.92	50	29.09
1750	1200	99.34	90.97	50	25.45
1750	2500	97.19	97.19	50	26.63
1750	5000	97.76	95.66	50	17.85
2250	100	98.11	53.69	50	41.81
2250	500	97.18	90.58	50	40.28
2250	1200	96.18	96.46	50	38.88
2250	2500	96.15	93.74	50	37.03
2250	5000		95.66	50	29.62
2750	500	95.48	61.73	100	16.07
2750	1200	94.84	81.37	100	15.20
2750	2500	94.31	93.08	100	14.54

2750	5000	93.17	95.14	100	10.71
3750	100	94.51	92.14	100	72.89
3750	500	93.16	93.18	100	67.39
3750	1200	92.87	93.71	100	62.79
3750	2500	91.04	93.87	100	59.52
3750	5000	91.01	94.98	100	52.27

Table 5.11 Simulated SR and J_w Values for the Combined NaCl and $CaCO_3$ Feedwater Samples

Pressure kPa	**NaCl in Feed mg/L**	**$CaCO_3$ in Feed mg/L**	**J_w m/s**	**SR %**	**SR simulated %**	**J_w simulated m/s**
1250	100	50	1.28	89.44	90.16	1.98
1250	500	50	1.37	89	90.64	2.65
1250	1200	50	1.43	88.89	89.54	2.64
1250	2500	50	1.49	88.17	89.65	1.87
1750	100	50	3.44	92.26	91.05	3.67
1750	500	50	2.56	92.69	92.16	3.17
1750	1200	50	2.24	93.84	92.561	2.97
1750	2500	50	2.08	93.05	93.461	2.61
1750	5000	50	1.60	93.31	93.851	1.97
2250	100	50	3.68	93.17	93.15	2.97
2250	500	50	3.84	93.31	92.18	2.90
2250	1200	50	3.36	93.84	91.54	3.67
2250	2500	50	3.20	94.61	90.54	3.17
2250	5000	50	2.56	95.47	92.64	3.07
2750	500	100	1.44	93.18	91.84	1.29
2750	1200	100	1.36	94.07	91.64	2.24
2750	2500	100	1.28	95.08	90.54	2.07
2750	5000	100	0.96	95.71	94.54	1.56
3750	100	100	4.48	96.18	92.66	3.97
3750	500	100	4.96	96.61	93.56	4.45
3750	1200	100	4.32	96.79	94.54	4.31
3750	2500	100	4.00	97.31	95.54	4.01
3750	5000	100	3.68	97.81	96.78	3.91

Table 5.13 Total Organic Carbon Percentages, Total Dissolved Solids Percentage, WRP Percentages, Experimental SR and Permeate Flux (J_w) Values, Simulated SR and J_w Values for the Wastewater Sample

Pressure kPa	**TOC %**	**TDS %**	**WRP %**	**J_w m/s**	**SR %**	**SR simulated %**	**J_w Simulated %**
1250	87.25	91.71	16.07	0.86	98.14	96.18	1.31
1500	93.77	94.29	25.92	1.34	98.38	97.64	1.04
2000	94.01	97.14	32.69	1.63	97.26	97.61	1.16
2500	94.18	97.35	38.18	2.01	98.59	98.17	1.36
2750	94.27	97.56	39.28	2.11	98.55	98.69	2.94
3250	95.13	97.78	41.50	2.5	98.64	99.89	2.96

Appendix B

The Developed Artificial Neural Network (ANN) Code Using for Modelling the Reverse Osmosis Unit Handling the Different Feedwater Samples.

```
% These codes are training, validation and testing program for NN modeling using
% batch gradient descent without pre-processing data
% The transfer function in the hidden layer are log-sigmoid and the output
% layer transfer function is linear
% training and test data

load wastetreatmenttrainingdata
load wastetreatmenttestingdata

ptrain=wastetreatmenttrain(1:23,1:20);
ttrain=wastetreatmenttrain(1:23,21);
ptest=wastetreatmenttest(1:23,1:20);
ttest=wastetreatmenttest(1:23,21);

ptr=ptrain';ptt=ptest';
ttr=ttrain';ttt=ttest';

% pre-processing data
[ptrn,ptrs]=mapminmax(ptr);
[ttrn,ttrs]=mapminmax(ttr);
[pttn,ptts]=mapminmax(ptt);
[tttn,ttts]=mapminmax(ttt);

% developing the ANNs model
j=1
n1=j
n2=1
net=newff(minmax(ptrn),[n1 n2],{'tansig','purelin'},'trainlm');
```

```
% training the network
startTime = clock;
[net,tr]=train(net,ptrn,ttrn);
currentTime = etime(clock,startTime);

% simulation
atr=sim(net,ptrn);
atrain=mapminmax('reverse',atr,ttrs);
meas=atrain';
msetr=mse(ttr-atrain)   % % determine the mean square error for training data

att=sim(net,pttn);
attest=mapminmax('reverse',att,ttts);
pred=attest';
msetest=mse(ttt-attest)  % determine the mean square error for test data

%finding coeficient correlation
for i=1:1
   figure (i)
   [m(i),b(i),r(i)]=postreg(atrain(i,:),ttr(i,:)) % figure for training data
end
for i=1:1
figure(i+1)
   [m(i),b(i),r(i)]=postreg(attest(i,:),ttt(i,:))    % figure for test data
end
gensim(net,-1)
```