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Modeling of Reverse Osmosis Desalination Plants Performance in the Gaza Strip Using Artificial Neural Networks

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"نمذجة أداء التناضح العكسي لمحطات التحلية في قطاع غزة باستخدام الشبكات العصبية الاصطناعية"

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Thesis submitted to the Institute of Water and Environment (IWE),
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DEDICATION

I dedicate this work to:

My kind- hearted father and wonderful mother

The spirit of my brother, El Shaheed Samer Abdel-Jawad

My brothers and sisters

My friends and colleagues

Everyone contributed in the success of this work

Samaher M. Abdeljawad

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ABSTRACT

A rapidly growing technique for producing new water is desalination of seawater and brackish water, in which water with high dissolved solids content is converted to water with very low dissolved solids content. Desalination practice existing by desalination plants performance is a remarkable area in which scientists and researchers investigate and contribute to plant enhancement. In the Gaza strip maximum of the drinking water is produced through small private desalination facilities and RO housing units.

In view of understanding the status and performance of desalination plants in the Gaza strip, it was necessary to assess the feed and permeate water quality and develop several Artificial Neural Network (ANN) models to predict various water quality parameters. Hence, this study was undertaken with this objective. Although there have been a number of studies on the status of desalinated water quality pollution, however to the best of our knowledge this study is the first effort to use (ANN) technology for the prediction of desalination plants performance in the Gaza strip through predicting a number of water quality variables.

Five desalination plants were selected and monitored in terms of feed and permeate quality towards understanding the current status of the desalination plants and develop ANN models for predicting their performance.

All generated data were entered as Microsoft Excel sheets, uploaded to Minitab software and SPSS, and analysed using min, max, mean and standard deviation. In addition, the Pearson correlation coefficient and paired sample t-test were used to detect significant water quality variations at different desalination plants.

The feed water quality of selected plants was found to be noncompliant with WHO and Palestinian Standards Institute in furthermost samples which is in difference with the permeate values of all plants. The assessment made during this study may help in the better understanding of the current situation of desalination plants in the Gaza strip.

The collected samples were chemically analysed at the laboratories of the Ministry of National Economy and the Institute of Water and Environment at Al-Azhar University. At the initial stage of water quality variables prediction, water samples were collected from

five desalination plants, over a period of six months beginning from March to September 2013. The training and testing of the developed ANN models was carried out using neural network toolbox in the MATLAB. Two types of feedforward networks have been used including Multilayer Perceptron (MLP) and Radial Basis Function (RBF).

Several different MLP neural networks algorithms and RBF network have been trained and developed with reference to feed water parameters: pressure, pH and conductivity to predict permeate flowrate next week values. MLP and RBF neural networks have been used for predicting the next week TDS concentrations. Both networks are trained and developed with reference to permeate water quality variables including: water temperature, pH, conductivity and pressure. MLP and RBF neural networks have also been trained with the previous four parameters to predict chlorides and nitrates level. MLP and RBF neural networks have been trained and developed with reference to three water quality parameters including pressure, chloride and conductivity to predict magnesium concentrations.

Prediction results prove that both types of networks are highly satisfactory for predicting TDS and chloride water quality parameters and satisfactory for predicting permeate flowrate and nitrate concentrations. As compared with the TDS, chloride, flowrate, and nitrate developed models, magnesium model showed less accuracy prediction results. Results of the developed networks have also been compared with the statistical model and found that ANN predictions are better than the conventional methods.

الملخص

تعد تحلية المياه قليلة الملوحة و مياه البحر إحدى التقنيات السريعة النمو لإنتاج مياه جديدة حيث يتم تحويل المياه ذات المحتوى العالي من المواد الصلبة الذائبة إلى مياه ذات محتوى منخفض جداً من المواد الصلبة الذائبة. إن أداء محطات التحلية القائمة تعتبر مجال علمي فريد من نوعه عمل العلماء والباحثين من خلاله على التوسع في دراسة هذا المجال من أجل المساهمة في تطوير وتعزيز أداء عمل المحطات. إن ما يتم إنتاجه في قطاع غزة من الحد الأقصى لمياه الشرب يتم من خلال مرافق التحلية الصغيرة الخاصة وكذلك وحدات التناضح العكسي على المستوى المنزلي.

في ضوء فهم حالة وأداء محطات تحلية المياه في قطاع غزة فإنه كان من الضروري تقييم جودة مياه التغذية, والمياه المحلاة الناتجة من تلك المحطات المختارة لهذه الدراسة؛ ومن ثم تطوير العديد من نماذج الشبكات العصبية الاصطناعية للتنبؤ بقيم بعض العناصر المهمة في تحديد نوعية وجودة المياه وبالتالي أجريت هذه الدراسة تبعاً لهذا الهدف. على الرغم من وجود عدد من الدراسات والأبحاث المنشورة بخصوص حالة تلوث نوعية المياه المحلاة؛ ولكن لعلمنا فإن هذه الدراسة هي أول جهد لاستخدام تكنولوجيا التنبؤ بأداء محطات التحلية في قطاع غزة من خلال التنبؤ بعدد من المتغيرات لخصائص نوعية وجودة المياه.

لقد تم اختيار خمس محطات لتحلية المياه ومراقبة جودتها لكل من مياه التغذية والمياه المحلاة الناتجة باتجاه فهم الوضع الحالي لهذه المحطات ومن ثم تطوير عدد من نماذج الشبكات الاصطناعية العصبية للتنبؤ بأداء تلك المحطات.

لقد تم إدخال جميع البيانات المتولدة خلال هذه الدراسة عبر برنامج مايكروسوفت اكسل, Minitab , وبرنامج التحليل الاحصائي SPSS , حيث تم تحليل جميع البيانات وحساب الحد الأدنى والحد الأقصى والمتوسط الحسابي, وكذلك الانحراف المعياري بالإضافة الى حساب معامل ارتباط بيرسون واختبار الاقتران تي للكشف عن الاختلافات في نوعية المياه في محطات التحلية المختلفة.

إن جودة مياه التغذية لمحطات التحلية المختارة كانت غير متوافقة مع منظمة الصحة العالمية ومؤسسة المواصفات والمقاييس الفلسطينية في أغلب العينات, وذلك بخلاف المياه المحلاة الناتجة من تللك المحطات. وقد ساعد التقييم الذي قدم من خلال هذه الدراسة في فهم أفضل للوضع الحالي لمحطات التحلية في قطاع غزة.

إن العينات التي تم جمعها خلال هذه الدراسة حللت كيميائياً في مختبرات وزارة الاقتصاد الوطني و مختبرات معهد علوم المياه والبيئة في جامعة الأزهر. في المرحلة الأولية من التنبؤ بمتغيرات جودة المياه, جمعت عينات المياه من خمس محطات لتحلية المياه في قطاع غزة على مدى ستة أشهر بداية من مارس الى سبتمبر 2013م.

أُجريّ التدريب واختبار نماذج الشبكات العصبية الاصطناعية المطورة من خلال استخدام أدوات الشبكات العصبية في Matlab. وقد استخدم نوعين من الشبكات الأمامية (feedforward) و تشمل شبكة الادراك ذات الطبقات المتعددة MLP (Multilayer Perceptron) و شبكة وظائف الاشعاع الأساسي RBF (Radial Basis Function).وقد تم تدريب العديد من شبكات الخوارزميات MLP المختلفة وشبكة RBF وتطويرها بالرجوع الى عناصر مياه التغذية: ضغط المياه, والرقم الهيدروجيني, والموصلية الكهربية وذلك للتنبؤ بمعدل التدفق للمياه المحلاة

الناتجة لأسبوع مقبل. وقد استخدمت شبكات RBF , MLP للتنبؤ بتراكيز المواد الصلبة الذائبة لأسبوع مقبل, وذلك بتدريب تلك الشبكات وتطويرها بالرجوع الى متغيرات نوعية المياه الناتجة وتشمل كل من درجة حرارة الماء ودرجة الحموضة والموصلية والضغط. كما تم تدريب الشبكات العصبية بنوعيها MLP و RBF لنفس المتغيرات السابقة للتنبؤ بمستوى الكلوريدات والنترات. وكذلك تم تدريب الشبكات العصبية MLP و RBF وتطويرها بالرجوع إلى ثلاثة معايير لنوعية المياه وهي الضغط والكلوريد والموصلية الكهربية وذلك للتنبؤ بتراكيز الماغنيسيوم.

إن نتائج التنبؤ أثبتت أن كلا النوعين من الشبكات مرضية للغاية للتنبؤ بالمواد الصلبة الذائبة والكلوريد وكذلك مرضية للتنبؤ بتراكيز معدل التدفق والنترات؛ بالمقارنة بما سبق من النماذج المطورة لكل من المواد الصلبة الذائبة والكلوريد ومعدل التدفق والنترات, فقد أظهر نموذج الماغنيسيوم نتائج أقل دقة للتنبؤ. وبمقارنة نتائج نماذج الشبكات المطورة مع النموذج الإحصائي والتي أظهرت أن التنبؤات بالشبكة العصبية الاصطناعية هي أفضل من الطرق التقليدية.

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mg/l	Milligram per liter
MCM	million m^3 = Million cubic meter
MCM/yr.	million m^3/y = Million cubic meter per year
Mm^3	Million cubic meter
TDS	Total dissolved solids
pH	Potential of hydrogen
%	Percentage
R^2	Coefficient of determination
ºC	Degree centigrade
Q	Number of output units
P	Number of input units
wn	Vector of connection weights
γn	Step size
dn	Vector defining the direction of descent & n denotes the iteration number
min	Minimum
max	Maximum
w1	Weight connections between input layer and hidden layer
w2	Weight connections between hidden layer and output layer
b1	Biases between input layer and hidden layer
b2	Biases between hidden layer and output layer
Mg	Magnesium
Ca	Calcium
µs/cm	Micro semen's per centimeter
MW	Mega Watt
kWh	Kilowatt hour
ppm	Part per million
m^3/d	m^3/day = Cubic meter per day
mm	Millimeter
EC	Electrical conductivity
µm	Micrometer
S.D	Standard deviation
S.E	Standard error
m^3/h	Cubic meter per hour
NO_3^-	Nitrate
TH	Total hardness

NTU	Nephelometric turbidity units
P	Pressure
NaCl	Sodium chloride
$CaCl_2$	Calcium chloride
KCl	Potassium chloride
NaOH	Sodium hydroxide
CO_2	Carbon dioxide
HCO_3^-	Bicarbonate
CO_3^{2-}	Carbonates
$CaCO_3$	Calcium carbonate
Ca^{2+}	Calcium ion
Mg^{2+}	Magnesium ion

LIST OF ABBREVIATIONS

ASP	Actual state-of-the-plant
ADALINE	Adaptive linear neuron or later adaptive linear element
ANN	Artificial neural networks
BP	Back propagation
BPN	Back-propagation network
BFGS	Broydon fletcher goldfarb shanno (method)
IEEE	Institute of electrical and electronic engineers
IBM	International business machines
LM	Levenberg marquardt
MATLAB	Matrix laboratory (The language of technical computing)
MAE	Mean absolute error
MSE	Mean squared error
MED	Multi effect distillation
MLP	Multilayer perceptron
MADALINE	Multiple Adeline
MLR	Multiple linear regression
MSF	Multistage flash distillation
NF	Nano-filtration
NN	Neural network
OLS	Orthogonal least squares
PWA	Palestinian water authority
PFR	Permeate flowrate
RBF	Radial basis function
RBFNN	Radial basis function neural network
RO	Reverse osmosis
SWRO	Sea water reverse osmosis
SOM	Self-organized map
STM	Short-term memory
SDI	Silt density index
SPSS	Statistical package for the social science
SVR	Support vector regression
TECC	Technical engineering consulting company
TMP	Trans-membrane pressure
VC	Vapor compression
VQ	Vector quantization
WHO	World health organization

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CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Water is the most valued and important natural resource in the Middle East in broad-spectrum and in the Gaza strip in particular. It is fundamental for socioeconomic growth and environmental sustainability. The Gaza strip is mostly in calamitous situation that needs urgent and serious efforts to improve the water status on conditions of both quality and quantity.

The groundwater in the Gaza strip aquifer is approximately brackish excluding some fresh water in the appearance of shallow lenses. Consequently, the quantity of fresh groundwater is negligible and exists only in some areas in the Gaza strip for example Beit Lahia. Desalination of brackish and seawater appears to be promising, mainly in the absence of any other option in the Gaza strip. Though, utilizing desalination method as an alternative water supply entails many challenges such as energy cost and environmental characteristics (Hamdan, 2012). On one hand, confidence on desalination as a source of water supply can solve the increasing issue of water shortage in the vicinity and prevail over the deterioration problem of water quality. The securing of potable water for drinking purpose to the community in the Gaza strip is becoming an important goal to be implemented by the Palestinian Water Authority (PWA).

However, economic desalination of brackish and seawater is at the present a global ambition that has concerned extensive governmental and public awareness not only in arid areas but also in other regions in the world. Desalination entails the removal of salts and biological materials from seawater or brackish water to produce fresh water. There are a number of desalination techniques commercially are used. They are including: vapor compression distillation, electro-dialysis, multi-stage flash distillation; and reverse osmosis (Baalousha, 2006).

The Palestinian Water Authority identifies water desalination as the standard approach to alleviate the water problem and provide people in the Gaza strip with acceptable and potable water quality for drinking and other purpose (EL-Sheikh et al. 2003).

The important aspects of water quality modeling are the understanding, reporting and analysis of the results of physical, chemical and biological data for setting up measures and actions to control pollution. A neural network modelling is being used progressively to forecast and predict measurable characteristics of water bodies. The models must be developed according to the existing data and information about physical, chemical and biological parameters for numerous years of a particular part (Maier and Dandy, 2000).

The finding of this research is the first step in establishing ANN model for predicting the performance of Reverse Osmosis (RO) desalination plants through water quality indicators.

1.2 ARTIFICIAL NEURAL NETWORK MODELLING

Artificial Neural Network (ANN) is a computing system which its structure and process is driven from neurons in the brain of human being. Neurons are simple components working in parallel (Hinton, 1992). Neural networks can be well thought-out of various interconnected nodes as computational elements which can take inputs and convert them into outputs (Parthiban et al. 2005 and Arbib, 1995). ANN is capable to be trained for achieving a particular function by adjusting the values of the weights between units. In general, ANN is attuned, or trained, so that particular inputs go ahead to a number of objective outputs. Artificial neural network is superior at approximating functions. However, there is evidence that a comparatively simple neural network can robust any useful function (Hagan et al. 1996). One of the individual characteristics of the artificial neural network is its capability to be trained from experience and patterns and then to adjust with changing circumstances. An additional benefit of ANN is that it can present quick significant answers even when the statistics to be sequenced including errors or is partial (Lippmann, 1987).

1.3 STUDY AIM AND OBJECTIVES

The aim of this research work is to develop various models for predicting the permeate water quality indicators of the desalination plants in the Gaza strip through Artificial Neural Network (ANN). The main objectives of this study are:

1. To evaluate the current status of the desalination plants in the Gaza strip.

2. To monitor the water quality in the selected desalination plants.

3. To develop an indicator Artificial Neural Network models.

4. To suggest measures for controlling the water quality characteristics in the desalination plants.

1.4 SIGNIFICANCE OF THE STUDY

Desalination as non-conventional water resource offers the only rational option for meeting the rising demand for drinkable water for the inhabitants of Gaza strip. Water desalination also may play an immense role to diminish the adverse environmental impacts allied with lack of fresh water for at least drinking purposes and over pensiveness from the coastal aquifer as well.

There are already various existing and proposed projects in Gaza 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 reverse osmosis unit.

- This study is the first effort for desalinated water quality monitoring and modeling of reverse osmosis plants performance in the Gaza strip.

- The study will generate desalinated water characteristics data.

- The information and data will be helpful to the planners, decision-makers administrators, and environmentalist dealing with desalinated water environmental issues and their impacts.

- The implementation of this research work will provide various water quality prediction models for the Gaza desalination plants.

- The output of ANN developed models will help in designing a good monitoring and control plan for the water quality in the desalination plants.

1.5 ORGANIZATION OF THE THESIS

The thesis describes the results of desalinated drinking water quality monitoring parameters, environmental status of the desalination plants in the Gaza strip and development of various Artificial Neural Network models for predicting the important parameters of Reverse Osmosis i.e. total dissolved solids (TDS) and permeate flowrate.

The thesis comprises of six chapters including the conclusions and recommendations for future work. Chapter one details the general background of the current state of water quality and quantity in Gaza, general information about artificial neural network, aim and objectives of the study, and the significance of this work. Chapter two contains a detailed literature review on desalination and its various processes, understanding the way RO works and the factors that affect the RO operation performance, introduces the reader to artificial neural networks and the manner in which they function, and modelling of desalination plants performance using artificial neural network technology.

Chapter three presents the processes and analysis of water samples, and the artificial network models development approaches. Chapter four describes status of the existing desalination plants in the Gaza strip and their environmental impacts. Chapter five is dealing with the results of water quality monitoring and development of the artificial neural network models to predict the performance of RO system handling different feed-water sources and the validation of developed ANN models. Chapter six presents the conclusions obtained from the present study and the recommendations for future work to be conducted in order to improve and expand the developed ANN model to cover different feed and permeate-water samples.

CHAPTER 2

LITERATURE REVIEW

This chapter presents the information collected from different sources related to introduction and establishing the need for reverse osmosis, understanding desalination, and working of a reverse osmosis system, reverse osmosis performance, introduction to artificial neural network and ANN for modelling desalination plants performance. The basic core of this study is to monitor the desalinated drinking water for the purpose of developing a neural network models to predict some of water quality parameters for the purpose of desalinated water quality assessment in the Gaza strip. Conversely, modelling of the obtainable data over a period of time provides the key to the success of management measures in reducing pollution loads and improving the drinking water quality. As mentioned earlier, ANN models are developed for forecasting the desalinated drinking water quality parameters that can help to assess the load of pollutants causing public health risk and environmental problems. The information gathered from the literature reviews for this study is discussed in the following sections.

2.1 INTRODUCTION AND ESTABLISHING THE NEED FOR REVERSE OSMOSIS

Aish (2010) in his study investigated the chemical and bacteriological water qualities of different small scale of reverse osmosis (RO) desalination business units in the Gaza strip. The study results were compared with World Health Organization (WHO) standards. It was concluded that all chemical analyses of RO produced water are within the allowable limits. Microbiological analyses indicate that 25% of produced water samples exceeded the maximum allowable rate of the total coliform.

Al-Khatib and Arafat (2009) had studied the physical and chemical quality of desalinated water, groundwater and rain-fed cisterns in the Gaza strip. Their study revealed a clear superiority of quality for desalinated water, but also need to adopt better practices including maintenance and pre- and post-treatment in the desalination plants.

The major crisis associated with groundwater for future sustainability is the increase in the salinity. Generally groundwater is a chemically constant source of water over a long period of certain time. In areas close to the coast where pumping is undertaken the groundwater quality needs to be considered. The groundwater source quality (the aquifer) has to be tested in order to detect the changes in the water quality (Rengasamy, 2008).

Hairston (2006) stated that to meet up with future water demands it is fundamental to have in place sustainable water management all in excess of desalination technologies like reverse osmosis without concessions on water quality. The major sources for feed-water used for desalination processes including: seawater, brackish groundwater, domestic and industrial wastewater. The desalination of seawater could provide potable drinking water to about 1.2 billion people worldwide who do not have access to fresh drinking water.

El Sheikh et al. (2003) they prepared a strategy plan for water desalination in the Gaza Strip. They have discussed various types of desalination plants in their study. They concluded that the cost of desalination is still relatively expensive in the Gaza strip, reverse osmosis desalination is strongly recommended and considered as a strategic alternative in order to overcome the water shortage and meet the future needs of desalination.

2.2 UNDERSTANDING DESALINATION

Desalination is accepted worldwide and most of the plants are situated in the Middle East (50%), 20% in North America, 12-14% in Europe. According to the international desalination association a large number of these established desalination facilities mostly use Reverse Osmosis or Multistage flash distillation techniques for water treatment (Conway, 2008).

Green (2005) classified the techniques for desalination into three types based on the main process principle. (1) Membrane process like Reverse Osmosis and Electro dialysis employ membranes as a physical parting process where salts and unrequired minerals are separated from the feed-water. Membrane separation processes are commonly used in industry as compared to the thermal processes due to its low energy consumption, high product quality, bendy design and easy setting up. (2) Thermal Process like multistage flash distillation (MSF), multi effect distillation (MED) and vapor compression (VC) are based on the physical change in the condition of feed water. These processes need a large amount of energy in spite of the dissolved salts level in the water. (3) The process based on chemical relationship like Ion Exchange is mainly employed to produce high drinking water quality for industrial purposes. Such process would not be used to treat brackish or seawater as the feed-water.

Desalination can be defined as a process that removes dissolved mineral deposits from feed-water sources such as brackish groundwater, seawater or industrial wastewater. It can also be known as the process that eliminates excess salts and un-preferred minerals from water. It is necessary these un-preferred minerals and excess salts is eliminated from the water to make it healthy for human being consumption or industrial use (Betts, 2004).

Assaf (2001) has reviewed the existing and future planned desalination plants in the Gaza strip and their socio-economic and environmental impacts. He noted that the brine disposals from the desalination plants are a menacing and uncontrolled environmental problem in the Gaza strip.

El Bana (2000) defined the desalination process as a physical method that intends to take out the dissolved mineral deposits from either brackish groundwater or seawater. He showed that the desalination method would not be a good option for being used in industry or tourism activities. Also reported a number of researchers and scientists suggested many different biotechnology systems to be used in the desalination methods in the coming years.

In the Gaza strip preferred technology is reverse osmosis while most 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 feed water.

2.3 WORKING OF A REVERSE OSMOSIS SYSTEM

Bou-Hamad et al. (1997) showed that the reverse osmosis system consists of three major system components including: pretreatment, membrane separation and post treatment stabilization. Pretreatment of the feed-water is an important element of the RO system. This is a significant step and is made in order to prevent scaling of the membrane by scaling and fouling agents. Protecting the performance of the membrane during the operation is vital to maximize the efficiency and durability of the RO system. Pretreatment is important for good operation of RO equipment and may add major capital and operating cost to a desalination facility. However, the long term cost of not affording suitable pretreatment will far exceed the initial capital cost over the life time of the RO plant.

Safety measures should be taken to maintain suspended solids at a good enough level in the source feed-water. Contemporary high performance polymeric anti scaling has been successful in stabilizing solutions of economical soluble salts. Biological fouling can be circumvented through minimizing the time when the plant is not in operation. A number of different types of fouling, their cause and appropriate pretreatment techniques are found elsewhere (Ebrahim, et al. 2001).

2.4 REVERSE OSMOSIS PERFORMANCE

There are confident factors which significantly affect the performance of a reverse osmosis system. The most important variables which affect the performance of the RO system including: pretreatment, membrane performance and operating conditions.

Panicker et al. (2006) have observed that the feed-water quality has an enormous magnitude to the performance of RO system. Even though the feed-water is in general wastewater or water having 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. The objective of pretreatment processes is to reduce the pollutants that would damage the system major parts such as the membranes and the pressure pumps.

Kumar et al. (2006) have reported that fouling is a major hindrance that prevents competent operation of reverse osmosis systems pollute the quantity and quality of treated water, and thus increase the treatment cost. Fouling is mostly 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 crystallization. It is mainly caused by calcium salts such as calcium carbonate and calcium sulphate.

Durham and Walton (1999) along with membrane fouling the added major reasons for pretreatment are biological pollution and colloidal fouling. The fouling arising from dissolved ions found in the feed-water can be minimized by anti-scaling chemicals and controlling the system recovery. The problems related to fouling including: irreversible membrane damage, reduced flux rates and increase in the operating and capital costs. Thus, pretreatment promise the quality of feed water as good for preventing any drop in the RO system performance. The usual pretreatment technology was using deep bed filters, sand filters, cartridge filters, and chlorination as well as flocculation techniques. These conventional methods that used for pretreatment did not completely remove the suspended solids, bacteria and colloids. The traces of these impurities as soon as passing into the RO system will cause membrane fouling problem.

For the Doha Reverse Osmosis Plant in Kuwait, flocculation and dual media filtration are the pretreatment measures for treating the seawater before feeding it to the facility. The pretreatment process is designed to provide the RO system with good water quality and required amount by regularly monitoring and assessing the silt density index (SDI), turbidity, pH, temperature and chlorine (Ebrahim and Malik, 1987). These same factors were recognized as the key criteria after conducting different trials for determining the suitable feed-water characteristics (Teng, et al. 2003). As utilizing a RO system for treating wastewater it is suggested to have a microfiltration pretreatment process for protecting the RO membrane from the highly corrosive and fouling action of the wastewater (Durham and Walton 1999).

The conventional techniques use a mixture of sedimentation and diffusion to remove impurities. Though many particles are too small to be eliminated by sedimentation and some too large to be removed by diffusion. This showed the way for new technologies being developed for the pretreatment process. One of these is the use of continuous micro filtration technology. This is the most suitable 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 filtrate obtained is free from solid suspensions, bacteria and colloids (Chakravorty and Layson, 1997).

2.5 INTRODUCTION TO ARTIFICIAL NEURAL NETWORK

An artificial neural network (ANN) is a mathematical structure designed to mimic the information processing functions of a network of neurons in the brain (Hinton, 1992 and Jensen, 1994). ANNs are highly parallel systems that process information through many interconnected units that respond to inputs through modifiable weights, thresholds, and mathematical transfer functions. Each unit processes the pattern of activity it receives from other units, and then recordings its response to still other units. ANNs are mostly well-matched for problems in which large datasets comprise of complicated nonlinear relations among many different inputs. ANNs are intelligent to find and identify complex patterns in datasets that may not be well defined by a set of known processes or simple mathematical methods.

2.5.1 History of artificial neural network

The first artificial neuron model was introduced in 1943 by the neurophysiologist Warren McCulloch and the logician Walter Pits (McCulloch and Pitts, 1943). They have been modeled a simple neural network with electrical circuits.

Reinforcement this concept of neurons and how they work was a book written by Donald Hebb. The Organization of Behavior was written in 1949. It concluded that neural networks paths are strengthened each time when they are used as reported by Unar (1999).

Such as computers advanced into their infancy of the 1950s, it has become possible to begin to model the basics of these theories concerning human thought. Nathanial Rochester from the IBM research laboratories managed the first effort to simulate a neural network (Rochester, et al., 1955). At the first effort it was failed and then later efforts were successful. During this time the traditional computing began to blossom and, as it did, the importance in computing left the neural research in the background.

In 1956 the Dartmouth Summer Research Project on Artificial Intelligence provided an improvement to both artificial intelligence and neural networks (McCarthy, 1996). One of the good outcomes of this process was to motivate research in both the intelligent side, applied intelligence, as it is known through the industry, and in the much lower level neural processing part of the brain. In the years subsequent the Dartmouth Project, John von Neumann suggested duplicating simple neuron functions by using telegraph relays or vacuum tubes.

In 1958 Frank Rosenblatt, a neuron-biologist of Cornell, introduced a perceptron model (Olazaran, 1996). The Perceptron, which obtained from his research studies, was built in hardware. A single-layer perceptron was started to be suitable in classifying a continuous-valued set of inputs into one of two classes. The perceptron computes a weighted sum of the inputs, subtracts a threshold, and passes one of two possible values out as the helpful outcome (Haykin, 1998).

In 1959, Bernard Widrow and Marcian Hoff of Stanford have been developed models they named ADALINE and MADALINE (Widrow and Lehr, 1990). These models were named for their use of Multiple Adaptive Linear Elements. MADALINE was the first neural network being applied to a real world problem. It is an adaptive filter which eradicates echoes on phone lines. This neural network is still in practical use at present.

According to Unar (1999) from the late 1960s to the early 1980s, research on ANN was almost absent.

In 1982 several events caused a renewed interest. John Hopfield of Caltech presented a paper to the national Academy of Sciences (Hopfield, 1982). Hopfield's methodology was not to simply model brains but to build useful devices. With precision and mathematical analysis, he revealed how such networks could work and what they could do. At the same time, another affair occurred that a conference was held in Kyoto, Japan. The conference was named US-Japan Joint Conference on Cooperative/Competitive Neural Networks.

By 1985 the American Institute of Physics began what has become an annual meeting - Neural Networks for Computing. The work of Rumelhart et al. (1986a, 1986b) on feed-forward neural networks was a real innovation in the history of neural networks.

By the year (1987), the Institute of Electrical and Electronic Engineers (IEEE) first International Conference on Neural Networks depicted more than 1,800 attendees. In (1988) Broomhead and Lowe hosted Radial Basis Function (RBF) networks to the neural network subject. The concept of these networks was added by Poggio and Girosi in (1990). Now, neural network deliberations are arising everywhere. Their ability appears to be very optimistic as nature itself is the proof that this kind of thing works. So far, its future certainly is the key to the entire technology, lies in hardware development. Presently most neural network development is simply demonstrating that the principle works.

2.5.2 Artificial neural networks (ANNs)

The Artificial Neural Network is made with a methodical step-by-step method to enhance a performance norm or to monitor some implied internal limitation, which is generally signified as the learning imperative or process. The learning process comprises updating network architecture and connection weights so that a network can proficiently achieve a specific recognition task. In artificial neural networks, the designer selects the network topology, the performance function, the learning rule and the training algorithms, and the criterion to stop the training phase, but the system certainly adjusts the parameters (Adeoti and Osanaiye, 2013).

Many ANN architectures are available, but multilayer networks are commonly used for forecasting (Zhang et al. 1998; Maier and Dandy, 2000). An ANN adapts to learn the relationship or mapping between input and outputs during the training process (Mas and Ahlfeld, 2007).

2.5.3 Weight vector of an ANN

The weights are the connection strengths between neurons in the adjacent layers. A simple neuron is shown in (Fig.2.1) wi1, wi2, and wi3 are the weights associated with each of the connections between the inputs to a neuron and other neuron.

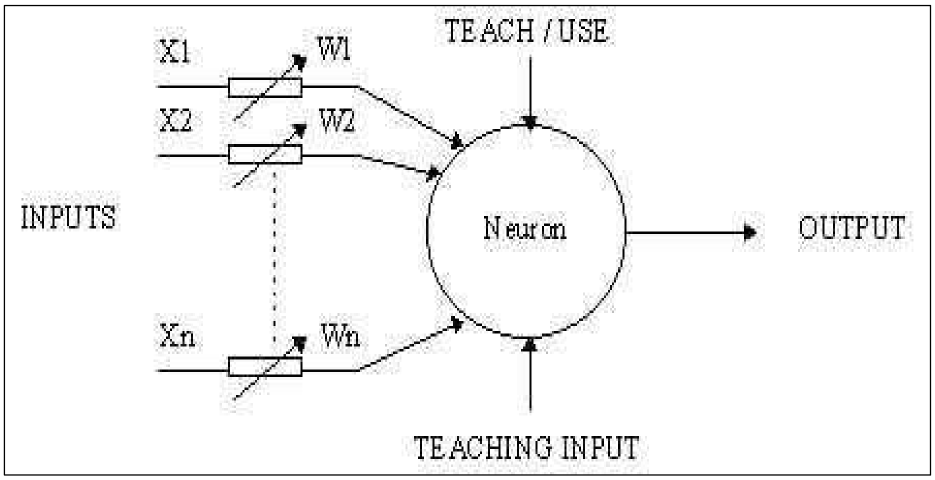

Fig.2.1: A simple neuron

The inputs to a neuron are weighted according to the type of the architecture of neural network. Supposing that there are 4 parameters applied as input data and that there are 7 hidden neurons in the neural network, then the weights between the input layer and hidden layer are given by a 4x7 weight matrix.

2.5.4 Architectures of artificial neural networks

The artificial neural network is normally composed of a set of matching parallel and distributed units, called neurons or nodes. The internal architecture of ANN provides dominant computational capabilities, allowing for the concurrent exploration of different competing hypotheses. Neural networks gather their knowledge through finding of patterns and relationships found in the data provided to them. There are two important architectures generally illustrate an ANN. These architectures are described below:

1. The feedforward topology

The feedforward topology is very popular due to its association with a quite dominant and comparatively robust learning algorithm named the back-propagation learning algorithm. The MLP network and RBF network are amongst the networks functioning by means of the feedforward topology.

2. The recurrent topology

The recurrent networks are designed in such a way as to allow the storage of information in their output neurons throughout dynamic states, for providing the network with some sort of memories. Whereas feedforward networks maping input into output and are fixed in the sense that output of a given pattern of inputs is independent of the prior state of the network. Recurrent networks are very advantageous for modelling and recognizing dynamic system. Several neural networks are designed based on the recurrent topology. Such networks include the Hopfield network and the Elman networks.

3. Activation functions

The basic computational tool for a neural network is the neurons. These are sorts of simple processors which take the weighted sum of their inputs from other neurons and put on them to linear or nonlinear mapping termed an activation function before taking the output to the next neuron. The activation functions can take different arrangements such as, sigmoid function, step function, hyperbolic tangent function, Gaussian function and linear function.

4. Neural network learning algorithms

In any neural network, the most important influence is the memory stored as values of the weights. During consecutive iterations of the ANN, it is the understanding (past experience or memory) that is being gathered to update the weights and train the ANN. Based on the method to modernize the weights; the ANN training is classified as supervised and unsupervised. The learning algorithms are used to update the weight at the interconnection level of the neurons throughout the network training procedure. There are three common types of learning algorithms (Saen, 2009). These algorithms are highlighted as bellow:

1. Supervised learning

It is the most common type in which a "teacher" runs information to the network to drive it to compete with the desired function. Suppose a set of input arrays (input data vectors) are applied to the network, then the output retort of the ANN is compared with the wanted response from "teacher". The teacher would notify the network whether the output decision is correct or incorrect. As well we could define an error criterion that would then be a basis to update the weights of the ANN so that the network will be trained with consecutive input arrays (Haykin,2007).

2. Unsupervised learning

The unsupervised networks also are called self-organizing networks. These networks do not have a "'teacher's" rules. The basis of unsupervised networks is clustering methods. They support in assemblage comparable patterns, where each cluster has patterns closer together. Some basic unsupervised models are Self-Organised Map (SOM) and the Vector Quantization ANN (VQ). The elementary idea in all of these networks is that the hidden layer of neurons should capture the statistical structures of the input data. The hidden neurons have an capability to extract the features of the data set (Haykin,2007).

3. Reinforcement learning

In the reinforcement learning, a direct supervisor is not available. However, a critic is available which encourages or discourages the network to produce a pattern (Haykin, 2007).

2.5.5 ANN types

Feedforward neural networks were introduced in the 1980s but govern the literature even in the present day. ANNs can be applied successfully in learning, relating, classification, generalization, characterization and optimization (Saen, 2009). They have found thousands of successful applications in almost every field of science and engineering. A feedforward network is trained by using the well known supervised learning. The most widely used supervised learning algorithm is the error back-propagation algorithm. The description and derivation of this algorithm can be found elsewhere (Haykin, 2007). The feedforward architecture is layered, that is it has an input layer, one or more hidden layers and output layer. The numbers of neurons in the input layer and the output layer are determined by the numbers of input and output parameters, respectively. The numbers of neurons in the output layer is equal to the number of actual outputs. However, the number of hidden layer neurons is found by trial and error method through extensive simulation studies. The activation function used in the hidden layer must be differentiable.

2.5.5.1 Multi-layered perceptron (MLP) networks

MLP is the most popular class of multilayer feedforward networks. The MLP is divided into three layers: the input layer, the hidden layer and the output layer, where each layer in this order gives the input to the next. The extra layers give the structure needed to recognise non-linearly separable classes. Based on the model architecture, an MLP network with m outputs, n_h hidden neurons and n_i input neurons can be articulated as:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w_{jk}^2 F\left\{\sum_{i=1}^{n_i} w_{ij}^1 x_i^0(t) + b_j^1\right\} for 1 \le k \le m \tag{2.1}$$

where, w^1_{ij} and w^2_{jk} represent the weights of the connection between input and hidden layer, and weights of the connection between hidden and output layer respectively. The b^1_j & x_i represent the thresholds in hidden neurons and inputs that are provided to the input layer respectively. F {•} is an activation function and is normally selected as sigmoid function. From equation (2.1), the values of w^1_{ij}, w^2_{jk} and b^1_j have to be determined by using the error back-propagation algorithm.

In general, MLP nueral network model has performed well in a number of hydrologic and water resources applications, such as (Maier and Dandy 2000; Tokar and Markus 2000; Anctil and Rat 2005; Schmid and Koskiaho 2006).

2.5.5.1.1 Back-propagation algorithm

The development of back-propagation algorithm denotes a landmark in ANNs which provides a computationally effective method for MLP networks training. This algorithm initially was introduced in 1974 by Paul Werbos and it was re-experienced by David Parker in 1985 and Romelhart et al. in 1986 (Unar, 1999).

In 1962 Rosenblatt also came close to determining the key for training perceptron when he anticipated a heuristic algorithm to adjust weights of the perceptron. See (Rosenblatt, 1962) to have more detailed description of this algorithm.

The back-propagation algorithm adjusts the weights and biases of an MLP neural network subsequently to minimize the sum of squared errors of the network. This is normally done by repeatedly adjusting the values of the network weights and biases in the direction of steepest descent with respect to error. This process is termed the steepest descent.

2.5.5.1.2 Improved back-propagation

To improve and upgrading as well using of the back-propagation algorithm, firstly the learning parameter η must be taken small to provide minimization of the total error indication. Though, for a small η the learning practice becomes very slow. On the other hand, large values of η correspond to fast learning, but lead to dependent oscillations which avoiding the algorithm from converging to the wanted solution. Furthermore, if the error function comprises of many local minima, the network might get stucked in some local minimum, or get stuck on a very flat topography. One of the possible ways to improve the standard back-propagation algorithm is to use adaptive learning rate and momentum.

2.5.5.1.3 Back-propagation with L-M algorithm

It has been perceived that the back-propagation is very slow in many applications even with adaptive learning rate and momentum. According to Hagan and Menhaj (1994) the training time can significantly be improved if the Levenberg-Marquardt is incorporated into the back-propagation algorithm.

Zhou and Si (1998) reported that the LM incorporation into the back-propagation algorithm not only improves the training time but also provides superior performance in terms of training accuracy and convergence properties.

2.5.5.1.4 Approximation capabilities of MLP networks

Mathematically it has been shown that a single hidden layer feedforward neural network is capable to approximate any continuous multivariable function to any wanted level of accuracy, providing that adequately many hidden layer neurons are existing (Cybenko, 1989; Hornik et al. 1989; Funahashi, 1989). The MLP neural networks typically use sigmodial non-linearity as their function.

The above mentioned works on the approximation capabilities of MLP network are very encouraging. These, though, guarantee only the presence of an approximating network and do not give any hints about how to build one. The subject of choosing an appropriate number of neurons in a hidden layer of an MLP network is almost unsolved. With limited hidden neurons, the network may not create outputs reasonably close to the goals. This consequence is named underfitting. In addition an unnecessary number of hidden layer neurons will increase the training time. This is termed overfitting. The network will have so much information processing capability that it will learn insignificant aspects of the training set, aspects that are irrelevant to the general population. If the performance of the network is evaluated with the training set, it will be good. However, when the network is called upon to work with general population, it will perform poorly. This is because it will consider trivial features unique to training set members, as well as important general features, and then become confused. Thus it is very important to choose an appropriate number of hidden layer neurons for satisfactory network performance.

A number of rough guidelines have been proposed to choose a suitable number of hidden layer neurons in a three layer MLP network. For example Lippmann, in the year 1987 has provided geometrical arguments and reasoning to justify why the number of neurons in the hidden layer of a three layer MLP network should be Q (P+1), where Q is the number of output units and P is the number of input units (Lippmann, 1987). A common approach is to start with a small number of hidden neurons e.g. with just two hidden neurons. Then slightly increase the number of hidden neurons, again train and test the network. Continue this procedure until satisfactory performance is achieved. This procedure is time consuming but usually results are good and successful. During this study such method was used to training the neural networks.

2.5.5.2 Radial Basis Function neural network (RBF-NN)

RBF network is a type of feedforward neural network that learns by using a supervised training technique. Zhang A. and Zhang L. (2004) reported that Broomhead and Lowe were the first researchers to exploit the use of radial basis functions in the design of neural networks. One characteristic feature of RBF is that response decreases, or increases, monotonically with distance from a centre point (Park and Sandberg, 1991). Moreover it has been perceived that RBF networks are able to approximate any practical continuous function mapping with a satisfactory degree of accuracy (Broomhead and Lowe, 1988).

The RBF network, which has three layers, can be appeared as a special class of multilayer feedforward networks. Each neuron in the hidden layer employs a radial basis function, such as Gaussian Kernel, as activation function. The output neurons implement a weighted sum of hidden neuron outputs. RBF network is centred at the point specified by the weight vector associated with the unit. Both the positions and the widths of these functions are learnt from training patterns. Each output unit implements a linear combination of these radial basis functions. Despite the topology similarity with MLP-NN, the RBF networks differ from MLP networks in several important points. According to Haykin (1994) these differences are given bellow:

1. In most applications an RBF-NN is a single hidden layer, whereas, MLP network may consist of one or more hidden layers.

2. The neurons in an output layer and in a hidden layer of MLP network share a common neuron model. On the other hand, the neurons in the output layer of RBF network are relatively different and assist altered purpose from those in the hidden layer.

3. The activation function of each hidden neuron in RBF networks calculates the distance between the input vector and the centre of that neuron. On the other hand, the activation function of each neuron in a hidden layer of MLP network calculates the inner product of the input vector and the synaptic weight of that neuron.

4. MLP neural network builds global approximation to nonlinear input-output mapping and then is capable of generalization in areas of the input space where little or no training data are obtainable. On the other hand RBF network build indigenous approximations to nonlinear input-output mappings and then are capable of fast learning and reduced sensitivity to the order of presentation of training data.

5. The hidden layer of MLP is nonlinear and the output layer can be linear or nonlinear. The hidden layer of RBF network is nonlinear and the output layer is always linear.

2.5.5.2.1 Training

The method for training radial basis function networks can be made in two stages. The first stage includes the determination of an proper set of RBF centres and widths. The second stage involves with the determination of the connection weights from the hidden layer to the output layer (Haykin, 1998). Certainly, the selection of RBF network centres is the most critical issue in designing the RBF network. These should be placed according to the demands of the system to be modeled (data to be predicted). A number of different methods have been proposed for the selection of appropriate RBF centres.

2.6 ANN FOR MODELLING DESALINATION UNITS PERFORMANCE

Mageshkumar et al. (2012) Artificial Neural Networks have been used for modeling hydrological parameters that are extremely nonlinear in both location and time-based levels. The input parameters selected for the model were turbidity, pH, hardness, sodium, calcium, chloride, potassium and sulphate. The testing of the predictive ANN model revealed good promise for predictions of the TDS levels between observed and predicted values. The coefficient of correlation during the validation process was found to be 0.951 and the mean squared error was 0.015.

Cordoba, (2011) presented a study of using ANN approach for the evaluation and prediction of some drinking water quality parameters within a water distribution system. The performance of ANN approach was analyzed on a 4-year database of water quality and hydraulic parameters. Two ANN models were constructed and one model was created using statistical approach multiple linear regression (MLR). From the results obtained in the study multilayer perceptron (MLP) models were found to be useful tools for prediction of free chlorine in water drinking supply.

Zaqoot et al. (2010) have constructed an ANN model to predict the acidity (pH) in the seawater along Gaza coast. They found that ANN is a promising model to predict and forecast pH level in the seawater.

Righton (2009) developed an Artificial Neural Network model for predicting the two important parameters of Reverse Osmosis including: salt rejection and permeate flowrate (flux). The neural network model successfully predicted the two important parameters. Using a neural network having two hidden layers and having a series of inputs of different concentrations, pressure and flowrates of the complex streams both two parameters were predicted. The developed artificial neural network model was tested using the experimental data obtained from pilot plant scale RO operations set up in Sharjah and Qatar.

Zaqoot et al. (2009) developed an artificial neural network for predicting dissolved oxygen concentrations in the Mediterranean Sea water along Gaza strip coast. The prediction results proved that ANN approach has good adaptability and extensive applicability for modelling the dissolved oxygen contents in the seawater along Gaza beach.

Lee et al. (2009) developed an artificial neural network (ANN) to predict the performance of a seawater reverse osmosis (SWRO) desalination plant, and then applied the model to forecast the feed water temperature. For developing the ANN model five input parameters were used including: feed temperature, feed total dissolved solids (TDS), trans-membrane pressure (TMP), feed flowrate, and time series and two output parameters were used including: permeate TDS and flowrate. The trained ANN model was successively found to produce good promise between the observed and predicted data (TDS: R^2 = 0.96; flowrate: R^2 = 0.75) in the test data set. The results showed that the variation of the feed water temperature and trans-membrane pressure (TMP) was found to be significantly affect both the permeate TDS and flowrate.

Najah et al. (2009) predicted water quality index at Johor River surface waters using ANN models. They developed various predictive models for total dissolved solids, electrical conductivity, and turbidity. The prediction results showed that the developed ANN models have an enormous potential for forecasting the water quality variables with total mean error of 10% for different water bodies.

Libotean et al. (2008) ANN modeling approach with back propagation (BP) and support vector regression (SVR) algorithms, introducing a short term memory (STM) time interval as an input parameter, was evaluated for describing and forecasting the time-variability of plant performance. An actual state of the plant (ASP) model and two types of forecasting models (sequential forecasting and matching forecast) for permeate flux and salt passage were investigated using real-time RO plant performance data.

Yesilnacar et al. (2008) had predicted nitrate level in groundwater by using four parameters as inputs for the model including: temperature, conductivity, pH and groundwater level. The Levenberg Marquardt (LM) algorithm was found to be the best one within 12 back propagation (BP) algorithms and best neuron number was determined as 25.

Diamantopoulou et al. (2005) had developed neural networks for predicting the values of three water quality parameters for one month ahead of the Strymon River at station located near the Greek-Bulgarian borders by utilizing the existing data of the monthly water quality as input variables. The monthly data of 13 collected parameters and the flow discharges at the selected stations during 1980-1990 were selected for the prediction purpose. The predictions result showed satisfactory of ANN models for predicting water quality parameters.

Abbas and Al-Bastaki (2005) used ANN technology to develop a model for predicting the performance of a reverse osmosis unit. The artificial neural network was fed with three inputs including: feed pressure, temperature and salt concentration to predict the water permeate rate. In their work the fast L-M optimization algorithm was employed for training the network. The developed network learned the input-output data mapping with accuracy.

Murthy and Mehul (2004) applied neural networks for prediction of RO desalination plants performance. The permeate flowrate and salts rejection at different conditions of the process were predicted using ANN based on the experimental water quality data. The model results were tested and compared with the observed data and the error percentage was calculated. The models showed that except the initial and final value of flowrates at low pressures the ANN model predictions values within the range of error (±1 %) except for sudden deviations. Such sudden deviations are not of much important because the predicted and experimental values are within the satisfactory range.

Al-Shayji and Liu (2002) have presented a methodology and practical guidelines for developing predictive models for large-scale commercial water desalination plants by (1) a data-based approach using neural networks based on the back-propagation algorithm and (2) a model-based approach using process simulation with advanced software tools ASPEN PLUS and SPEEDUP and compares the relative merits of the two approaches. The data was collected from the two largest multistage flash (MSF) and reverse osmosis (RO) desalination plants located in Kuwait and the kingdom of Saudi Arabia, respectively. Results showed that neural network and process simulation models are capable of accurately predicting the actual operating data from commercial MSF desalination plants, but the accuracy of a neural network model depends on both the proper selection of input variables and the broad range of data with which the network is trained.

Khuan et al. (2002) back-propagation neural networks, the modular neural network and the radial basis function model were used to model the water quality index for water bodies in Malaysia. The performance of the three developed models was satisfactory. On the other hand, the ANN simplified and accelerated the computation of the water quality index, as compared with the conventional method.

A1-Mutaz and A1-Sultan (1998) had described how a comprehensive mixing model can be used to predict Reverse Osmosis plant performance. Operating data for Manfouha desalination (RO) plants were used to investigate on the rationality of the values attained from the proposed model. Good promise was found. Whereas, the prediction values of productivity are 0.795 and 0.810 for Manfouha I and Manfouha II RO plants respectively. This showed a slightly increasing with time opposite to the field operated data that shows little decline of productivity with time in month for the period from 1414 to 1415 AH, with average values of 0.848 and 0.856 for Manfouha-I and Manfouha-II RO plants respectively.

CHAPTER 3

METHODOLOGY AND NEURAL NETWORK APPROACH

Five major desalination plants in the Gaza strip are selected for the research, to assess the water quality and develop ANN predictive models for the Gaza desalination plants. The water quality data were generated from five selected plants from southern, middle area, Gaza city and northern area. They are named Al-Salam desalination plant (Rafah), Al-Sharqia plant (Khan-Younis), Al-Balad plant (Dier-Al_Balah), Hanneaf desalination plant (Gaza) and Al-Radwan desalination plant (Beit-Lahya) see Fig.3.1.

In order to have a clear and better understanding of current status of the available desalination plants in the Gaza strip the data were collected from various available published reports, research papers and internet websites. In addition to that the selected desalination facilities were visited several times during the study. The selected plants are shown in Fig.3.1.

3.1 COLLECTION OF WATER SAMPLES

The water samples were collected and analyzed using the international protocols. A 500-ml and one liter polyethylene bottles were used for collecting samples. One liter sample was used for physical and chemical analysis. All samples were refrigerated at a temperature of 1 - 4 ºC during transit to the laboratory. The water samples were analyzed immediately after collection.

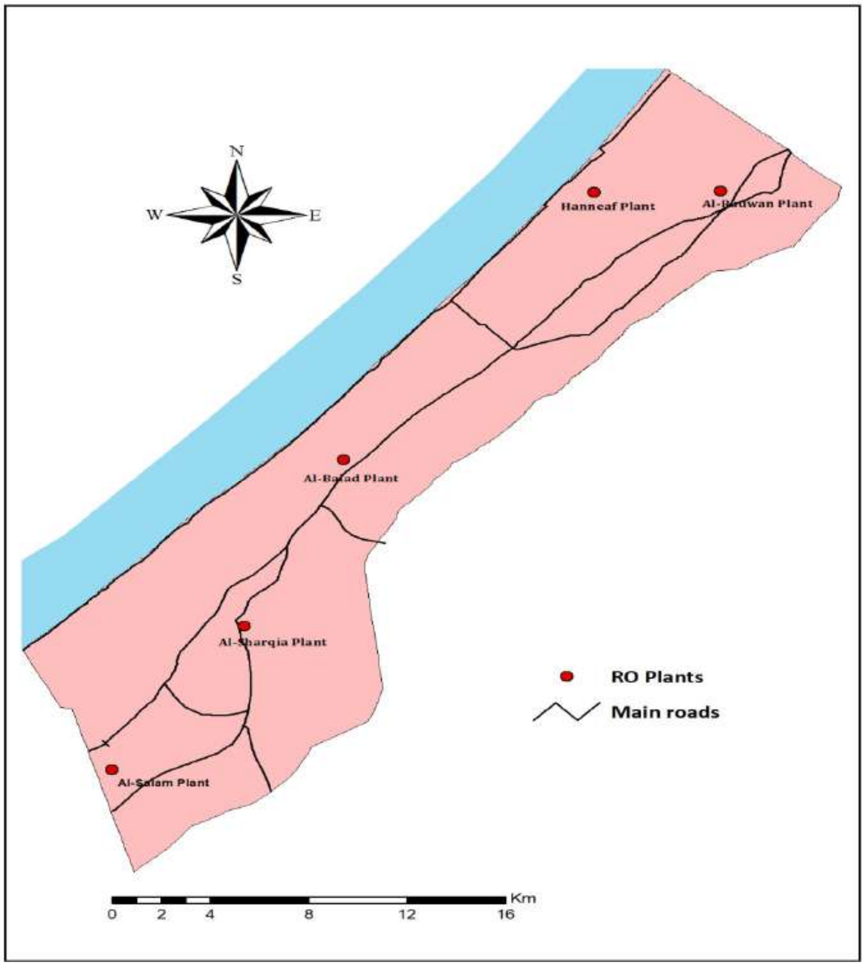

Fig. 3.1: Locations map of the selected desalination plants in the Gaza Strip

3.2 PROCESSING AND ANALYSIS OF WATER SAMPLES

The samples of water were collected once every week for a period of six months, the selected parameters including: temperature, pressure, water flowrate, TDS, hardness, pH, chloride, electrical conductivity, calcium, magnesium and nitrate. The samples were collected from the feeding wells and desalination plants (product desalinated water).

All analyses were carried out in the laboratories of the Palestinian Ministry of National Economy and Al-Azhar University. The collected water samples were analyzed according to the standard methods for the examination water and wastewater (APHA, 1998).

3.2.1 Water temperature

Temperature is measured in the stream with a thermometer or a meter. Alcohol-filled thermometers are preferred over mercury-filled because they are less hazardous if broken. The thermometer was placed in the water at least 4 inches below the surface. Enough time was allowed to reach a stable temperature (at least 1 minute). Then the final reading was recorded in the field data sheet. The temperature is measured in degrees Celsius (° C).

3.2.2 Pressure

Pressure is the force that pushes water through pipes. Water pressure determines the flow of water from the tap. Water pressure gauge was used to measure the water flow pressure in the desalination plants. The pressure unit is bar.

3.2.3 Water flowrate

Water flowrate is one of the most important process parameters in many areas, such as the chemical, pharmaceutical, petroleum, energy, power engineering industries and desalination units. The flow meter was used to measure the water flowrate. The flowrate unit is m^3/h.

3.2.4 Electrical conductivity

Electrical conductivity is a measure of the ability of water to pass an electrical current. Conductivity in water is affected by the presence of inorganic dissolved solids such as chloride, nitrate, sulfate, and phosphate anions (ions that carry a negative charge) or sodium, magnesium, calcium, iron, and aluminum cations (ions that carry a positive charge) (www.epa.gov, accessed on 26th March, 2013). During this work the conductivity meter was used to measure the conductivity. The conductivity unit which used in this study is (µs/cm).

3.2.5 pH

The pH is a measure of how acidic/basic water is. The range goes from 0-14, with 7 being neutral. The pH value of less than 7 indicates acidity, whereas a pH of greater than 7 indicates a base. The pH is a measure of the comparative amount of free hydrogen and hydroxyl ions in the water (www. water.usgs.gov accessed on 26th march 2013). The pH meter was used to measure pH values in the field during collecting the water samples.

3.2.6 Total dissolved solids (TDS)

TDS comprise inorganic salts (principally calcium, magnesium, potassium, sodium, bicarbonates, chlorides and sulfates…etc.) and small amounts of organic matter that are dissolved in water. TDS in drinking-water originate from natural sources, sewage, urban runoff and industrial wastewater (WHO, 2008). The TDS was measured by using the Oven method or conductivity meter. The general unit used for TDS concentration is mg/l.

3.2.7 Total hardness (TH)

Hardness in water is caused by dissolved calcium and, to a lesser extent, magnesium. It is usually expressed as the equivalent quantity of calcium carbonate (WHO, 2008). Titration method was used to measure the hardness during this work.

3.2.8 Chloride

Chloride in drinking-water originates from natural sources, sewage and industrial effluents, urban runoff containing de-icing salt and saline intrusion. Excessive chloride concentrations increase rates of corrosion of metals in the distribution system, depending on the alkalinity of the water. This can lead to increased concentrations of metals in the supply (WHO, 2008). Titration technique was used to measure the chloride in water. The common unit used for chloride is mg/l.

3.2.9 Calcium

The presence of calcium in water supplies results from passage over deposits of limestone, dolomite, gypsum, and gypsiferous shale. Calcium contributes to the total hardness of water (WHO, 2009). The titration method was used to measure the presence of calcium in the collected samples of drinking water.

3.2.10 Magnesium

Magnesium occurs commonly in the minerals magnesite and dolomite. Magnesium is important contributor to the hardness of a water, magnesium salts break down when heated, forming scale in boilers (WHO, 2009). The calculation method was used to measure the presence of magnesium in the collected samples of drinking water.

3.2.11 Nitrate

Nitrate can reach both surface water and groundwater as a consequence of agricultural activity (including excess application of inorganic nitrogenous fertilizers and manures), from wastewater disposal and from oxidation of nitrogenous waste products in human and animal excreta, including septic tanks. Some groundwater may also have nitrate contamination as a consequence of leaching from natural vegetation (WHO, 2008). UV-spectrophotometer method was used to calculate the nitrate concentration in water and the unit is mg/l.

3.3 ANN MODELS DEVELOPMENT APPROACHES

In the last few decades ANNs have become predominant for forecasting and predictions in a number of areas, including: medicine, finance, power generation, water resources and hydrology, ecological and environmental sciences as well as environmental engineering (Maier and Dandy, 2000; Rounds and Wood, 2001; Lee et al. 2003; Hatzikos et al. 2005; Muttil and Chau, 2006; Schmid and Koskiaho, 2006; El-Shafie et al. 2008; Esalmian et al. 2008; He, L.M and He, Z.L, 2008; and Al-Najah et al. 2009).

Maier and Dandy (1999) have been reported that it is very important to adopt a systematic approach in the development of neural network models, taking into account a number of factors such as data pre-processing, the determination of adequate model inputs and suitable network architecture, training and model tests.

In this study, for modelling purpose the feed-forward neural networks are considered and applied to model the water quality parameters which being performed for predictions purpose to test the performance of the five selected desalination plants in the Gaza strip.

This research work presented two types of techniques according to the different training algorithms. They are multi-layer perceptron (MLP) and Radial Basis Function Network (RBFN), both were trained on the obtained data to develop a method to predict the desalinated drinking water parameters .

Both of two neural networks belong to the feed-forward neural networks where there is no feedback connection between layers and no connections between units in the same layer. Moreover, both work in a supervised manner, are very good in classification and solving problems, easy to use, work as universal approximations, have very good nonlinearity capabilities and are widely used in the feedforward network family.

In this study for the training of MLP to predict water quality parameters the performance of the back-propagation algorithm has been enhanced by incorporating the Levenberg-Marquadrt (LM) algorithm into it. The LM algorithm which used in this work is a gradient based, deterministic local optimization algorithm. When it is employed to train the MLP model, the advantage of the Levenberg-Marquardt over the traditional back-propagation algorithm is that it can provide a faster (second-order) convergence rate and holds relative stability (Quilty, et al. 2004). Similar to the quasi-Newton methods, Levenberg-Marquardt algorithm was designed to approach second order training speed without having to calculate the Hessian matrix. The LM incorporation into the back-propagation algorithm not only improves the training time but also provides superior performance in terms of training accuracy and convergence properties.

In the other hand the Orthogonal Least Squares (OLS) algorithm is used for RBF network which was developed by (Chen et al. 1991).

The steps which are followed during the development of ANN models for predicting the performance of the selected desalination plants in the Gaza strip during this study are outlined below:

3.3.1 Data collection

As mentioned earlier, the water quality data are generated from the five selected desalination plants from the Gaza strip for a period of six months for the development of desalinated water quality models. The all generated data (120 reading) during this study are combined in one set to examine the posibility for developing various neural network models for predicting the water quality parameters including: TDS, chloride, permeate flowrate (flux) , nitrate and magnisum concentrations.

3.3.2 Data divisions

It is a common process to divide the obtainable data into two sub-sets; training and testing set. Neural networks may be incapable to generalize beyond the range of the used data for training resolution (Minns and Hall, 1996). It is imperative that the training and testing sets having the same population. In case the obtainable data are limited it might be very difficult to bring together a representative testing set.

Holdout method is one of the most practiced methods that maximize utilization of the obtainable data (Masters, 1993). The clue of this method is to standby a small subset of the data for testing and training the network with the remaining data. When generalization of the trained network is obtained with the help of testing set, a different subset of the data is used and the above process repeated. Maier (1995) and Maier and Dandy (1998a) recommended using a subset of the data as a testing set in an experimental phase to determine how long training should be carried out so that satisfactory generalization ability is attained. The subset used for testing is then added to the remaining training data, and the entire data set is used to train the network for a fixed number of epochs, based on the results from the experimental phase. In this study, about 70% of the obtainable data used for training and the remaining data used for validation and testing of the developed models.

3.3.3 Choice of performance criteria

It is significant to define the performance criteria for judging the model before development taking place. The performance criteria can have momentous influence on the model architecture and weight optimization procedures that already been selected. In most neural networks applications the performance criteria include one or more of the following: prediction accuracy, training speed and the time delay between the presentation of inputs and the response of outputs for the trained network. During the present work prediction accuracy was used as performance criteria in the process of ANN models development. A number of trials for the prediction accuracy have been recommended in the literature (Masters 1993; Lachtermacher and Fuller 1994; Maier and Dandy 1996b; Shukla et al. 1996; Xiao and Chandrasekar, 1997).

3.3.4 Data processing

At early stage of the water quality parameters prediction, inlet and outlet water quality data of selected desalination plants in the Gaza strip, over a period of six months beginning from March to September (2013) was generated. A total of five sampling locations in the Gaza strip are selected. The main obtainable selected water quality parameters including: water temperature, pressure, flowrate, turbidity, pH, EC, TDS, chloride, hardness, nitrate, calcium and magnisum. Because the input and output variables have very different orders of magnitude it is endorsed to rescale the data. In this way, more reliable predictions can be made. The normalisation of data is usually done with {0, 1} (Saen, 2009). Though, during this work the variables are rescaled to be included within the interval {0,1} which could cover all variations of the data sets used for the development of ANN prediction models.

3.3.5 Training

The goal of training stage is to obtain an accurate ANN model. In training stage, the selection of the transfer function, learning rate, momentum, exit condition setting, Mean Square Error (MSE) and verification of the model are needed. Network training can be conducted by using local or global methods. Local methods comprise of two categories: first-order and second-order methods. First-order methods are based on a linear model (gradient descent) while second-order methods are based on a quadratic model such as Newton's method (Battiti, 1992). In both cases, iterative approach is used to minimize the error function. The weight update equation formula is revealed by (Parisi et al. 1996):

$$w_{n+1} = w_n + \gamma_n d_n \tag{3.1}$$

Where w_n is the vector of connection weights, γ_n is the step size, d_n is a vector outlining the direction of descent and the subscript n represents the iteration number. The important difference between the various algorithms is the choice of d_n, which determines the convergence rate and computational difficulty. The global methods have capability to escape local minima in the error surface and also capable in finding optimal or near optimal weight arrangements. In the stochastic gradient algorithms, the error function does help the network to escape local minima in the error surface (Heskes and Kappen, 1993).

During the training developments, these helpful factors are gradually detached (Hassoun, 1995).

In this thesis, training, validation and testing of ANN models for the water quality parameters prediction were carried out using neural network toolbox in the MATLAB. The MLP network is trained by using the back-propagation incorporated with Levenberg-Marquardt algorithm. The tangent hyperbolic function is used as activation function in the hidden layer neurons. The linear activation function is used in the output layer neurons. The RBF network is trained by using the back-propagation incorporated with the Orthogonal Least Squares algorithm and the Gaussian radial basis function is used as activation function in the hidden layer. The linear activation function is used in the output layer.

3.3.6 Validation

The residual entropy of the trained network is a measure of its generalization. When the residual entropy increases, the performance of the generalization decreases, meaning that the model still needs modification. The residual entropy is monitored during training by means of MSE. It is the squared error between the output response of network and the training target. A network is said to be generalized well when the output is correct or close enough for an input. Then the model is ready for practice and use.

3.3.7 Testing

When the network training is completed, the trained network performance has to be tested by using unknown data set and the criteria recommended in (section 3.4.3). It is imperative that the testing data set should not have been used as a part during data sets training method. After testing the model with unknown data set and in case that there is a big difference in the error obtained when the tested set is used in comparison with the trained data set, it is likely that the two data sets are not representative of the same population or that the model is over fitted (Masters, 1993). Deprived testing can be owed to the network design, insufficient data preprocessing and rescaling of training and testing data sets. In this work the developmed network (models) performance is tested with different unknown data sets.

3.3.8 Developed ANN models procedure

The description and details of neural networks approach can be found elsewhere (Lek et al. 1996b), (Olden and Jackson, 2001) and (Haykin, 2007). Mostly, predictive models can be divided into statistical and physical based approaches. Statistical approaches determine relationships between historical data sets, whereas physically based approaches model the underlying processes directly. Multilayer perceptron neural network is closely related to statistical models (Rumelhart et al. 1986) and is the most appropriate type of ANN for prediction. When using ANNs for forecasting, the modeling idea employed is the same as the one used in traditional statistical approaches. In both cases the unknown model parameters (i.e., the connection weights in the case of ANNs) are adjusted in order to achieve the best match between a historical set of model inputs and wanted outputs.

According to kasabov (1996) the neural network generally consists of at least three or more layers, which comprise an input layer, an output layer and a number of hidden layers. Each neuron in one layer is connected to the neurons in the next layer, whereas there are no connections between the units of the same layer.

This work representing the application of ANNs to evaluate performance of the desalination plants in the Gaza strip through predicting some selected water quality parameters, having the dynamic and complex processes hidden in the obtained data itself. Addationally, the objective of this work is to investigate whether it is possible to predict one week ahead values of the water quality parameters measured during the monitoring activity at selected desalination plants in the Gaza strip.

Two types of feedforward networks are used to develop the ANN predictive models. They are MLP and RBF neural networks; both are trained on the generated data for developing predictive models for the water quality parameters predictions. The chosen MLP network was trained using the back-propagation incorporated with LM algorithm. The RBF network was trained using Orthogonal Least Squares algorithm. Before running the all models data sets were normalized to be included within the interval [0, 1]. The approach used to train and testing the ANNs models is briefly discussed as below**:**

Table 3.1: Methodology of the developed MLP and RBF NN models

Predictive Models	Models Structure	Explanation
Permeate flowrate	**MLP [3-6-1]** **RBF [3-87-1]** Three neurons in the input layer and one neuron in the output layer used for both MLP and RBF networks. Six neurons are optimized in the hidden layer for MLP and 87 for RBF networks.	Two ANN predictive models are developed including: MLP and RBF. The selected input variables for both networks are feed pressure, feed pH and feed conductivity. The data divided into two data sets: 87 readings used to train the network and 33 readings used for testing the network performance.
TDS	**MLP [4-6-1]** **RBF [4-87-1]** Four neurons in the input layer and one neuron in the output layer used for both MLP and RBF networks. Six neurons in the hidden layer are optimized for MLP and 87 for RBF networks.	Two ANN predictive models are developed including: MLP and RBF. The selected input variables for both networks are pressure, temperature, pH and conductivity. The data divided into two data sets: 87 readings used to train the network and 33 readings used for testing the network performance.
Chloride	**MLP [4-7-1]** **RBF [4-87-1]** Four neurons in the input layer and one neuron in the output layer used for both MLP and RBF networks. Seven neurons in the hidden layer are optimized for training MLP and 87 for RBF networks.	Two ANN predictive models are developed including: MLP and RBF. The selected input variables for both networks are pressure, temperature, pH and conductivity. The data divided into two data sets: 87 readings used to train the network and 33 readings used for testing the network performance.
Nitrate	**MLP [4-7-1]** **RBF [4-87-1]** Four neurons in the input	Two ANN predictive models are developed including: MLP and RBF. The selected input variables for both

	layer and one neuron in the output layer used for both MLP and RBF networks. Seven neurons in the hidden layer are optimized for MLP and 87 for RBF networks.	networks are pressure, temperature, pH and EC. The data divided into two data sets: 87 reading used to train the network and 33 readings used for testing the network performance.
Magnesium	**MLP [3-6-1]** **RBF [3-90-1]** Three neurons in the input layer and one neuron in the output layer used for both MLP and RBF networks. Six neurons are optimized in the hidden layer for MLP network training and 90 neurons for RBF networks.	Two ANN predictive models are developed including: MLP and RBF. The selected input variables for both networks are pressure, EC and chloride. The data divided into two data sets: 90 reading used to train the network and 30 reading used for testing the network performance. The selected data for training MLP and RBF networks was the readings of first 3 weeks while the fourth week readings was chosen for the developed model testing.

3.4 STATISTICAL ANALYSIS TOOLS

The water quality data is generated and being used to develop ANN predictive models to predict the water quality for assessing desalination plants performance in the Gaza strip. The generated data were entered as Microsoft Excel sheets, uploaded to Statistical Pakage for Social (SPSS) and to Minitab software, and analyzed using Min, Max, mean, standard deviation tools. In addition the Pearson correlation coefficient (a measure of linear association) and paired sample t-test are used to detect significant variations among parameters in different facilities. The training and testing of the developed ANN models were carried out using neural network toolbox in the MATLAB. Two types of feedforward networks are used. They are Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks.

CHAPTER 4

STATUS OF DESALINATION PLANTS IN THE GAZA STRIP

4.1 EXISTING DESALINATION PLANTS

The most major operated desalination plants in the Gaza strip are given in Table 4.1. The Palestinian Water Authority (PWA) built some other plants in cooperation with a number of different municipalities in addition to a large number of small private desalination units. Fig. 4.1 shows a map of desalination facilities in the Gaza strip.

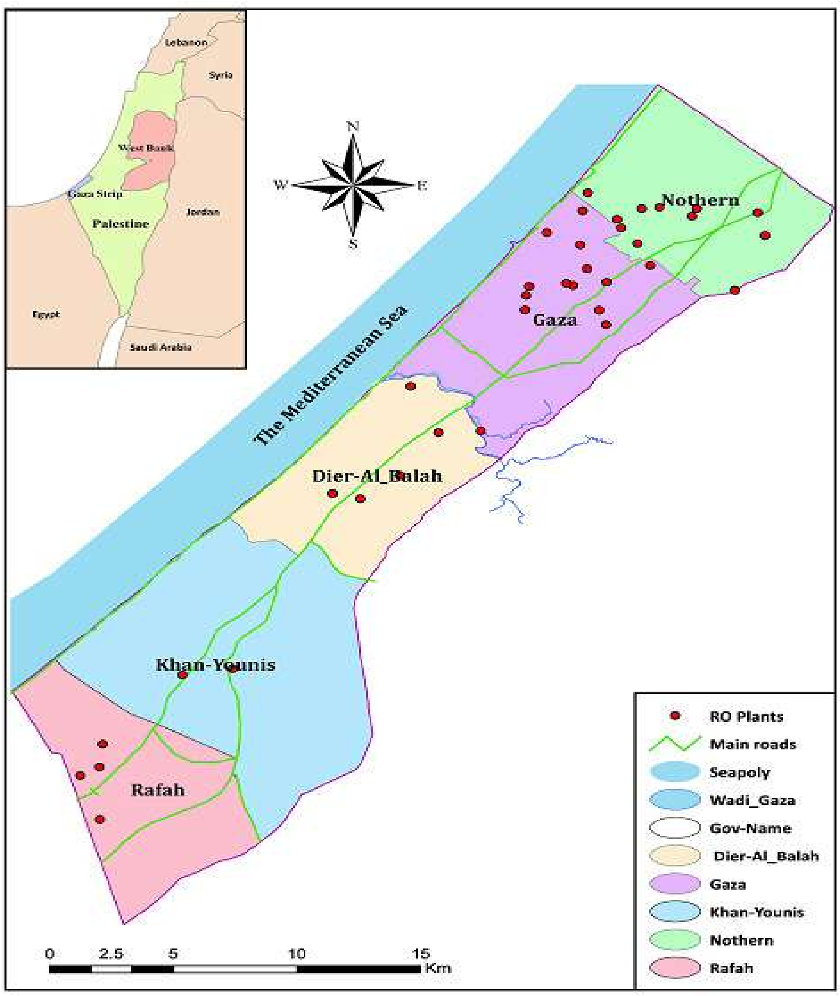

Fig.4.1: Locations map of the RO desalination plants in the Gaza Strip

The municipality of Dier-Al_Balah is operating the plant with a maximum capacity of about 1,872m^3/d. This Reverse Osmosis (RO) facility utilize brackish groundwater as feeding to produce about 1,080 m^3/d desalinated water along-with recovery rate of 75% (Baalousha, 2006). There are two large-scale RO desalination facilities placed in Khan-Younis city named Al-Sharqia, which was built in 1997 and Al-Saada which was built in 1998. Both plants are owned and functioned by the PWA and the municipality of Khan-Younis. The capacity of Al-Sharqia plant is about 1,200m^3/d and the capacity of Al-Saada plant is around 1,560m^3/d (El Sheikh, 2004). In 1998 RO desalination plant was constructed at the Gaza industrial zone. It was using brackish groundwater as an influent and had a capacity of 1,080m^3/d. It was planned that the produced desalinated water will be used for industrial purposes in the zone and partly for municipal use in the surrounding localities. Though, due to the difficult and hard political situation in the region work in this unit was disqualified (Metcalf and eddy, 2000).

Table 4.1: Large scale brackish water desalination plants in the Gaza Strip

Plant name	Location & construction date	Capacity (m^3/h)	Productivity (m^3/day)	Recovery rate %
Al-Balad	Dier-Al_Balah (1991)	60	420	75
Al-Sharqia	Khan-Younis (1997)	55	440	70
Al-Saada	Khan-Younis (1998)	80	640	70
Al-Bureij	Al-Bureij (2009)	60	480	83
Al-Nuwairy	Bani-Suhaila–Khan-Younis (2010)	50	400	75
Al-Salam	Rafah (2010)	60	480	80
Seawater	Dier-Al_Balah (2001)	30	200	80

Source: Personal communication, 2013

There are also two facilities that utilize seawater as influent. One is located in the northern part of Gaza strip near the beach and uses salt water from seashore well as feed water. The capacity of this facility was planned to be about 1,200m^3/d in the first stage and 5,000m^3/d in the final stage. This plant is not yet completed because of the fluctuation in the political situation. The second RO desalination plant is located in the middle area of the Gaza strip with a capacity of 600m^3/d in the first stage, and 1,200m^3/d in the second stage. The feeding water for this plant is salt water from wells drilled near the seashore. The second plant has been operated while the northern one is not in operation yet. There is a proposal for a regional desalination plant for the Gaza strip with a capacity of 60,000m^3/d in the first phase and 150,000m^3/d in the second phase (El Sheikh, et al. 2003 and El Sheiks, 2004). This plant will come across partially with the increasing demand of water supply in the region for various purposes. Seawater is planned to be used as a feed for this facility. In addition to the desalination plants in Table 4.1, there are many other small-scale units owned and operated by the private sector some of them under the control of the PWA and the Ministry of Health. All these units use RO technology to produce desalinated water from brackish groundwater and then treated water is sold to the community. Today, there are about 118 private desalination units owned and operated by private investors, almost 30 units are licensed by PWA (personal communication, 2013). According to Baalousha (2006) the capacity of private desalination facilities varies between 20 to 150 m^3/d and brine water rejection ranges from 30m^3/day to 240 m^3/day depending on the inlet quality. These private plants produce a total of about 2000 m^3/d of desalinated water.

4.2 WATER QUALITY

The PWA was reported that about 60% of the total amount of groundwater in the Gaza strip coastal aquifer is of poor quality and unfit for drinking purpose as compared with WHO standards (PWA, 2000). As water pumping rises, the aquifer becomes more brackish and deteriorated, and brine water intrudes the aquifer.

The level of chloride, for example, has lately reached more than 1,000 mg/l at several sites because of over-pumping. High chloride level has been observed in the Gaza city and southern area. In Khan-Younis governorate, seawater intrusion has been observed which cause rise in the level of chloride (Yakirevich et al. 1998).

Nitrate concentration (NO_3^-) has also been noticed at a high level, up to 400 mg/l, particularly in Khan-Younis governorate underground water wells. It is understood that the leached wastewater from septic tanks is accountable for this high level of nitrate. In the northern part of Gaza strip (Bait-Lahyia) where the wastewater treatment plant used to be overloaded and wastewater had been flooded in a wide region around, a high level of nitrate up to 500 mg/l had been observed (Baalousha, 2006).

4.3 WATER BALANCE AND ESTIMATED DEMAND

Precipitation is the most important source of groundwater recharge, as well as some other secondary components that contribute to groundwater recharge. There are some of non-fresh water sources that contributed to the aquifers feeding. These sources include: leakage of water and sewer systems, irrigation runoff, adjacent inflow to the aquifer, and seawater intrusion.

Water supply in the Gaza strip is almost totally based on groundwater abstraction. A small quantity about 4.7 MCM/y is imported from Israel and inconsequential quantities are currently produced by seven small desalination plants including: six brackish and one seawater plant. Table 4.2 presents the water balance for the Gaza Strip in the year of 2010 (PWA, 2012).

Table 4.2: Water balance in the Gaza Strip for 2010

Water balance	MCM/y
Groundwater abstraction for domestic supply	90
Groundwater abstraction for irrigation	80
Total groundwater abstraction	170
Sustainable yield of the aquifer, based on natural recharge	-55
Water deficit, resulting in 3.1 times overexploitation abstraction of the aquifer	115

Source: PWA, 2012

According to the PWA reports, the average yearly precipitation in the Gaza strip extents to about 320 mm based on a 20-year average data from (1980 to 1999). Several studies have been conducted to approximate the net groundwater recharge from precipitation (Baalousha, 2006). Based on these studies, it was noticed that the average annual net groundwater recharge from precipitation is about 43.29 million m^3 (Baalousha, 2004).

The overexploitation of the groundwater aquifer for a period of several decades has led to the lowering of the groundwater level which in turn has resulted in seawater intrusion from the Mediterranean Sea and to the rise (up-coning) of highly saline deep groundwater into the production wells. Another issue is the groundwater pollution by nitrates, primarily from untreated domestic wastewater discharges, and agricultural activities (PWA, 2012).

Table 4.3 presents the predictable water demand for the period from 2012 to 2035 which was prepared by (TECC, a local consultant) for the Palestinian Water Authority (PWA, 2012). It was reported by Baalousha (2006) that the annual shortfall in water resources raises annually additionally to the continuous deterioration of the coastal aquifer as a result of seawater intrusion and wastewater discharges. Annual water supply is projected to be increased due to the continual desalination projects, in addition to artificial recharge. The annual safe yield of the coastal aquifer is not more than 60 million m^3. Therefore, the available water in the aquifer covers only part of the demand, whereas the rest ought to be secured by other resources**.** According to the PWA (2000) strategy, the shortage in water may be reduced through the desalination of brackish water and seawater and wastewater reuse.

Table 4.3: Water demand forecast

year	2012	2015	2020	2025	2035
Population (million)	1.64	1.82	2.15	2.57	3.63
Per-capita production (l/c,d)	152	144	151	150	150
Domestic demand (MCM/y	91.10	95.34	118.48	140.72	198.50
Irrigation (MCM/y)	70	65	60	60	60
Total demand (MCM/y)	156	160	178	201	259

Source: PWA, 2012

The domestic water demand is estimated to be increased from currently 91 MCM to 118 MCM in 2020 and added to 199 MCM in 2035. The area of irrigable land is projected to be decreased due to the fast growing population and the existing limited land in the Gaza strip. The future use of more effectual irrigation techniques is expected to decrease the irrigation quantity of water from 70 to 60 MCM/y in the coming years. An irrigation water demand study done in 2011 by the Utah State University endorsed that utilizing more efficient irrigation techniques may reduce the current irrigation demand to 65 MCM/y (PWA, 2012).

4.4 UNCONVENTIONAL WATER RESOURCES

Understanding the critical water status in the Gaza strip in quality and quantity, finding out new sources of water supply is a necessity. Whichever new water source can ease the stress on the aquifer and help in the improvement of water quality.

Artificial recharge can increase the freshwater quantity of the aquifer when it is implemented. The PWA has implemented few projects for artificial recharge in Gaza. However, this choice is still under investigation and it can be a good alternative to overcome the water shortage problem and improve the water quality if it is implemented in large-scale projects (PWA, 2000). Meanwhile the agricultural activities consume about 60% of the total water demand; using treated wastewater for irrigation purpose can reduce depletion of groundwater importantly. Presently, the effluent of wastewater has not been utilized for agricultural purposes due to different reasons. Although Israel has been using treated wastewater for irrigation since long time, the PWA has recently planned to use recycled wastewater for irrigation (Metcalf & Eddy, 2000).

Desalination of seawater and brackish groundwater is the only alternative source of water supply. The first brackish water desalination plant was established by Israelis in 1991 and has been used in Gaza (Dier-Al_Balah) for municipal water supply. Many desalination plants have been set up and operated since then (Mogheir et al., 2013).

4.5 IMPACTS OF DESALINATION PLANTS

Desalination plants can have an indirect impact on the environment because of many plants receive energy from the local grid instead of producing their own. The potential contamination of groundwater aquifers in the proximity of desalination plants can be an environmental concern. There is a risk of polluting the groundwater from the drilling process when installing feed-water pumps. Leakage from pipes that carry feed-water into the desalination plant and highly concentrated brine out of the plant may percolate underground and cause damage to groundwater aquifers. The most important environmental aspects with respect to desalination plants in the Gaza strip are highlighted as below:

4.5.1 Energy utilization

Energy cost in desalination plants is about 30% to 50% of the total cost of the produced water based on the type of energy used. Fossil energy is the best type of energy for desalination from an economic point of view. To increase the efficiency of the desalination plant, it needs to be operated most of the day hours. Unfortunately, most of the RO plants in the Gaza strip are operating for about 8 hours per day, and thus the energy consumption is not optimal. Mixing different types of energy as heat and electricity can reduce the total cost of desalination. This method of mixing is termed a hybrid process, was reported by (Baalousha, 2006 and Al-Borsh, 2013). Hybrid desalination plants use both RO and distillation technologies for reducing energy requirements. The distillation unit draws waste steam from a thermal power station and utilizes the energy in the steam to heat seawater which is then distilled. The RO unit utilizes electricity from the power station and operates during periods of reduced power demand. Therefore mixing both systems leads to optimization of the total efficiency of the whole operation. Thus, the total cost of desalination can be reduced a lot through reducing the energy consumption which is about 50% of the total desalination cost.

Israel has provided energy for the Gaza strip since 1967. Additionally, a power plant was established in the Gaza strip comprising six turbines, with a total production capacity of 136 MW (when fully operated). In 2003, the first stage of this station was completed with a power output of 30 kWh which is about 40% of the Gaza strip needs. However, the cost of power produced locally in the Gaza plant is estimated at 0.125 $ per kWh. This is almost double the price of the electricity purchased from the Israeli grid. That means, if the desalination plants are fully based on the Gaza power plant, the cost of the desalination process is uncertain. Currently the power station does not operate with full capacity. This is due to the fuel shortage as a result of the critical situation in the Gaza strip arose since the last 14 years. On the other hand, if the desalination plants are dependent on Israel that would be a risky alternative since if Israel stops providing fuel and energy, these desalination plants could not operate.

4.5.2 Land precondition

Since the area of Gaza strip is very small, and the population density is very high as compared with other countries in the world, the land cost is high. Therefore, the land problem should be reviewed and assessed well if the desalination unit to be implemented near the beach or away from it. On one hand, locating the desalination unit near the beach is a good option as no transport of saline water or brine effluent is needed. On the other hand, constructing the desalination unit near the beach, which usually used for recreation purpose, is not a good option. Implementation of a desalination unit away from the seashore needs a pipeline to transport the feed seawater to the unit which means using pumps with more energy obligations. Moreover, construction of a pipeline to the sea will be needed to transport brine effluent into the sea. This definitely, increases the costs and implies the risk of pollution as a result of possible leakage. For a large desalination unit with a capacity of 150,000m^3/d, a considerable land area will be required. Large pumps required for RO, water pools, tanks, pipelines, and other facilities occupying a significant area. This may be as an important aspect in the case of the Gaza strip and should be considered. Hence, observant investigations should be conducted to reduce the impact of unit location (Baalousha, 2006).

4.5.3 Environmental aspects

The use of RO desalination facilities has the potential to negatively impact the environment. Effects on the environment can be caused by the discharge of chemicals used in the desalination process. Membranes used in the RO process have a short life and the cost of replacing these membranes can be accounted for nearly half the cost of desalination of seawater. The following sections discuss the impact of desalination plants in the Gaza strip on the environment.

4.5.3.1 Continuation impact

The maintenance of RO desalination plants is very important and essential duty. The pretreatment filters must be washed before processing the filtered seawater every few days to avoid clogging and maintain efficiency. This washing process produces chemical sludge. Sludge must be disposed suitably with either saline solution or by means of transport to the landfill. In addition, cleaning of the membrane, which must be done every 3 to 6 months, produces harmful components. In the cleaning process diluted acid or alkaline aqueous solution usually is used. Occasionally, sodium bisulphate is used to maintain chemical solution before any action. Such chemicals should be treated to free the membrane from toxicity. In addition to the environmental impact, there are some another problems. The maintenance needs trained and skilled people to do this job, and there is a doubt about such experienced people in the Gaza strip. Lacks in such experts may lead to rapid damage to the membranes and, therefore, increases the cost of desalination.

4.5.3.2 Groundwater pollution

Characteristics of saltwater discharged from the desalination facilities being dependent on the desalination method, the quality of feed water, permeate water, the pre-treatment, cleaning and the RO membrane storage methods used (Aish, 2010). Though, all the desalination facilities use chlorine, which is harmful on the environment, for cleaning the pipes in the treatment process. In general, the salt concentration of the discharged brine is nearly double than the seawater salts (seawater has about 35,000 ppm of salt concentration, whereas brine has 46,000 to 80,000 ppm) (Baalousha, 2006).

In the Gaza strip desalination units, RO is the most extensively technology used. And accordingly, the effluents from these units contain amounts of chemicals such as anti-scaling, ferric chloride, surfactants and acids, which may affect the environment if the process did not follow the appropriate mitigation (dilution process). Effluents from brackish water desalination units, which are also used in the Gaza strip, have properties quite different from that of groundwater. It has more calcium and magnesium in addition to some other components.

In the Gaza strip, the liquid waste of these units is not properly discharged. In all cases, the waste is dumped into the surrounding field, and therefore, it may lead to contamination of groundwater and leachate deposits may degrade productivity of the soil. This issue can be solved by using evaporation ponds for separating the water from the salt. Though, it is not efficient to do so in the Gaza strip due to the unavailability of land. Since desalination units are small and distributed in the whole area of Gaza, the existence of the economical solution would be transport of liquid wastes to the sea using tanks. This practice is not favored from an environmental point of view, since there may be a leak from the tanks. Another alternative could be by connecting the desalination discharge to the pipeline, which ends in the post- treatment unit on the beach before disposal of the brine (Baalousha, 2006).

In general, disposal of brine water in sewers or in wadi Gaza or to the sea by direct or indirect methods considered an important environmental issue besides the dealing with the impact of its disposal. There is very limited option to deal with brine water on site or to discharge into the sea or open areas (Aish, 2010).

In the lack of stabilization in the Gaza strip, there are no guidelines and rules for desalinated water thus there is no control of the desalinated water quality and the environmental effects of desalination facilities. As a result, the proprietors of commercial desalination facilities do not monitor the product water quality or environmental pollution level. There is also no public awareness of the produced water of poor quality by these commercial units. In this way, the PWA, which is the controlling authority, finds it enormously difficult to control the product water from desalination facilities and the environmental pollution level. Hence, the PWA should implement intensive monitoring program of these facilities and should not issue any permit for them without bearing in mind environmental impacts. Public awareness can be very supportive in this concern to demonstrate the thinkable pollution of the desalination product water. In addition to the commercial desalination facilities, using of small RO units at home is common practice in the Gaza strip. The product water from these units is mostly not controlled or tested. In the nonexistence of public awareness, people are using these RO units for long period without changing the membrane. As a result, the consumed water from the home units is somewhat unhealthy and might cause unlike diseases due to microbes and virus growths (Baalousha, 2006).

4.5.3.3 Effects on marine environment

The major impact of desalination plants on the surrounding environment is often reflected on marine life. The brine water discharged has the ability to alter the seawater salinity, temperature and the alkalinity and can cause alteration of marine habitats. Effluents from the desalination facility may also have severely affects on the marine environment and to damage the marine life in the region. However, the brine comprises of materials that originated in the sea, and its higher specific weight and possibly harmful chemicals may harm the marine environment around the discharge point. In general, the characteristics and the constituents of discharge brine water from desalination facilities which might contain all or some of the following constituents:

- High salt concentration. This may destroy organisms in the area of outfall. Besides, since brine might sink down due to its high density, this may cause severe damage of the marine environment underneath by preclusion of mixing and reducing oxygen level. The suitable solution would be by treatment of the brine and mixing with other seawater prior discharging into the sea.

- Brine has a temperature and turbidity higher than the seawater. Fish species are commonly very sensitive to any change in temperature. Therefore, this difference in temperature between the discharge and seawater may affect the flow pattern of migration of fish along the coast.

- Brine comprises of some chemicals such as biocide treatment, sulfur dioxide, coagulants, polymers, and in some cases may be combined with the waste flow comprising of chemicals from the treatment, flushing, cleaning, etc.

- High total alkalinity as a result of increasing the calcium carbonate, calcium sulfate and other elements in the seawater to nearly doubled.

- Toxic metals, which might be produced if the discharge brine has connection with metallic materials used in the plant units.

Appropriate brines dilution should be made far away from the seashore and the water quality in the area have to be monitored from time to time. In addition to the serious effects of desalination facilities brine discharge, intake has also effects on the surrounding coastal and marine environment. This intake may have different effects on marine species because of collision. These processes may arise when the species hit the intake or when these species are taken to the facility and destroyed throughout the desalination practice. Exceptional care must be taken to avoid or to decrease such effect to the lowermost possible extent (Baalousha, 2006 and Danoun, 2007). Table 4.4 shows the results of one sample of saline water (brine) was collected and analyzed for water quality parameters during the period of this study.

Table 4.4: Characteristics of discharged brine from desalination plants in Gaza Strip

Parameters	Values	Parameters	Values
pH	7.90	Turbidity	0.58NTU
Temp.	25.1(°C)	TDS	16331.34(mg/l)
Nitrate	382.25(mg/l)	Conductivity	21700(µs/cm)
Hardness	1710.72(mg/l)	Calcium	266.644(mg/l)
Chloride	6789.384(mg/l)	Magnesium	253.424(mg/l)

Note: Date of sample collection: 1/4/2013 (Al-Salam Plant).

4.5.3.4 Brackish water and seawater intrusion

Fresh water in the coastal aquifer of Gaza strip subsists in the form of lenses, which is located on more dense salt water. These lenses are recharged by way of rainwater infiltration and other secondary sources such as leakage from water network and sewer systems.

Over-pumping of freshwater causes up-coning of brackish and salt water underneath. Even though the desalination schemes using brackish water underneath the fresh lenses as intake, this may has an adverse effects on the environment. Extraction of brackish groundwater may add to imbalance in the groundwater scheme, which is by now very breakable. Continuous pumping of these dense layers of brackish groundwater might lead to lowering of water table above. The water table and transition zone between fresh and brackish/saline water is changeable by the time. This change causes drop in the water table level and consequently, may lead to considerable land subsiding with consequential destruction to structures, drainage and irrigation. In addition, several numbers of wells in the area are shallow, and they may become dry due to the lowering of groundwater table.

The agricultural activities may also be adversely affected since the root zone may be turned dry. In coastal aquifers, similar to the case of Gaza strip aquifer, there is a saline boundary between the fresh groundwater and the seawater. The length of that boundary is highly dependent on the inflow and outflow of groundwater. In normal situations, the length of the boundary is around tens to hundreds of meters. Withdrawal of groundwater may cause an internal alteration of this boundary, subsequently affecting the freshwater and saltwater balance. This balance is observably alarmed in the Gaza strip coastal aquifer. Given the high pumping rate, there is a strong evidence of seawater intrusion (Yakirevich et al. 1998).

From desalination viewpoint, any groundwater discharge irrespective to its quality, may lead to disruption of the balance. If the locations of shore wells which have been drilled for desalination purposes are not properly selected, they would severely affect the groundwater aquifer. It is recommended that beach wells to be located in the saline water zone behind the boundary to avoid any extension of the boundary inland. Alongside with its hydrogeological influence, beach wells have some other disadvantages. There is an immense doubt about the chance of water outflow in large amounts by the use of beach wells. Such wells may be not able to supply high amount of seawater due to many hydrogeological reasons. Moreover, clogging can take place in such wells. Thus, it must be carefully monitored if beach wells will be used as a seawater feeding source (Baalousha, 2006).

4.5.3.5 Quality of desalinated water

The quality of desalinated water differs on the basis of a desalination method. According to the World Health Organization (WHO) standards, potable water may have different minerals up to a certain extent. In commercial water desalination facilities in the Gaza strip, and in the lack of quality control, the desalinated water has very small amounts of almost minerals. It was reported that water produced from these plants have less than 20 mg/l calcium, 10 mg/l of magnesium and 100 mg/l hardness and 0 fluorides (Einav, et al. 2002). During this study the water produced from the selected desalination plants have less than 17 mg/l calcium, 6 mg/l and 70 mg/l hardness. Thus, the produced water contains very small amount of elements that are necessary for human being health.

4.6 Concluding remarks

Evidently, the desalination of seawater and brackish water is a necessity in Gaza strip. Utilizing desalination as a source of water supply has various benefits. It gives the impression that RO is the best choice in terms of produced water quality or the cost of treatment when it is compared with other technologies. On the other hand, the impact of these facilities is not well monitored.

Desalination has different aspects, including environmental, social, and economic effects. From the point of view, the environmental issue can be precisely studied before implementing the desalination projects, otherwise, In the Gaza strip, allowing for new sources of energy to be used in water desalination is very important for producing an independent source of electricity because it is a major issue by now in the Gaza strip. So, from the economic point of view, the cost of power consumption may be reduced by using natural resources such as natural gas to produce energy which can be supplied by the neighbors in Egypt.

Although RO is a promising technology, it requires a high degree of skilled people to run the desalination plants. If not, the membranes have to be replaced often which is very expensive. It should also be obtained to secure the supply of chemicals needed for water desalination in order to ensure the continuous operation of the units. An environmental issue should be considered before the implementation of any large-scale or regional desalination plants. The Palestinian Water Authority must strictly control the private sectors that constructing desalination facilities for commercial purposes to make sure that they consider the environmental themes.

At present, the brine of these national facilities is discharged into the surrounding environment, in the field or in the roads. Such brines must be appropriately disposed of under the control of Palestinian Water Authority. The product water quality has to be examined to confirm that it encounters with health necessities. An additional important concern is the pumping of brackish water from the aquifer. It is true that this water is not drinkable; however, it is situated in layers underneath the underground freshwater. Dropping of these layers of brackish water can cause reducing of the water table and interference of seawater disturbing the unsaturated area. The consequences of pumping such brackish water must be considered and examined to avoid any kind of damage to the aquifer.

CHAPTER 5
RESULTS AND DISCUSSION

5.1 STATISTICAL ANALYSIS OF WATER QUALITY DATA

The desalinated water quality data have been generated and used for the development of ANN predictive models for predicting the water quality of the desalination plants in Gaza strip. All generated data were entered as Microsoft Excel sheets, uploaded to SPSS and Minitab software, and analysed using Min, Max, mean and standard deviation tools. In addition the Pearson correlation coefficient (a measure of linear association) and paired sample t-test (p-value) were used to detect significant variations among the parameters at different desalination plants.

5.1.1 Water quality parameters

A total of 120 samples were collected from five major desalination plants in the Gaza strip and analysed for the evaluation purpose of water quality with respect to feed and permeate including: pressure, flowrate, temperature, pH, total dissolved solids, turbidity, conductivity, hardness, chloride, nitrate, magnesium and calcium. The sampling and laboratory analysis were carried out for a period of six months. The results on weekly trends along with results obtained from statistical analysis have been discussed as follow:

5.1.1.1 Water temperature

Temperature is one of the most important parameter in the environment, because almost all the physical, chemical and biological properties are governed by it. Temperature limits the saturation values of solids and gases that are dissolved in the water. The minimum, maximum, mean, standard deviation and standard error values of temperature measured during the period of this study are given in Table 5.1.

Table 5.1:Temperature statistical analysis among five desalination plants in the Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E
Al-Salam (Rafah)					
Feed water	**23.60**	**24.90**	**24.33**	**0.36**	**0.0685**
Product water	**24.10**	**25.40**	**24.69**	**0.32**	**0.0652**
Al-Sharqia (Khan-Younis)					
Feed water	**15.20**	**26.00**	**23.90**	**3.04**	**0.6223**
Product water	**21.90**	**26.70**	**24.90**	**1.24**	**0.2535**
Al-Balad (Deir-Al_ Balah)					
Feed water	**22.90**	**26.70**	**24.02**	**0.68**	**0.1388**
Product water	**22.50**	**26.70**	**24.55**	**1.05**	**0.2152**
Hanneaf (Gaza)					
Feed water	**22.80**	**23.40**	**23.18**	**0.16**	**0.0333**
Product water	**23.30**	**23.90**	**23.58**	**0.14**	**0.0305**
Al-Radwan (Bait-Lahyia)					
Feed water	**21.60**	**25.80**	**23.83**	**1.23**	**0.2519**
Product water	**21.80**	**25.80**	**24.07**	**1.05**	**0.2146**

From Table 5.1 it's clear that the water temperature differed little by plant as indicated by the overall mean and standard deviation analysis. Temperature varied from 15.2 to 26.7 ºC. Temperature exceeding the value of 26 ºC was relatively rare and was observed during summer season.

5.1.1.2 Pressure

Abou Rayan and Khaled (2002) presented a case study of the operation and maintenance of a 2000 m^3/d RO desalination plant over 6 years of operation. They found that the reverse osmosis system is sensible to changes in feed water temperature, and the product quality is sensitive to the change in feed water pressure. According to (Djebedjian et al. 2007) increasing the feed-water pressure increases the desalination facility productivity, but decreases the permeate salinity. The minimum, maximum, mean, standard deviation and standard error values of pressure during the period of this study are given in Table 5.2.

Table 5.2: Pressure statistical analysis among five desalination plants in the Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E
Al-Salam (Rafah)					
Feed water	**14**	**15.5**	**15.14**	**0.34**	**0.0686**
Permeate water	**13.5**	**14**	**13.92**	**0.17**	**0.0344**
Al-Sharqia (Khan-Younis)					
Feed water	**11**	**13**	**12.02**	**0.75**	**0.1548**
Permeate water	**9.5**	**12**	**10.63**	**0.70**	**0.1445**
Al-Balad (Deir-Al_ Balah)					
Feed water	**14.5**	**14.5**	**14.50**	**0**	**0**
Permeate water	**10.9**	**14.5**	**11.25**	**0.72**	**0.1484**
Hanneaf (Gaza)					
Feed water	**12.5**	**17.5**	**15.25**	**1.39**	**0.2843**
Permeate water	**11**	**17**	**13.64**	**1.44**	**0.2956**
Al-Radwan (Bait-Lahyia)					
Feed water	**15.5**	**19.5**	**17.46**	**1.29**	**0.2652**
Permeate water	**15.5**	**15.5**	**15.5**	**0**	**0**

From Table 5.2 it's clear that pressure extent differed little by plant as indicted by the overall mean and standard deviation analysis. Pressure extent for feed water varied from 11 to 19.5 bar and for product water ranged between 9.5 and 17 bar. Feed pressure measurement was found to be higher than permeate pressure for all desalination plants.

5.1.1.3 Water flowrate

The RO membranes are the core of RO system and specific data points need to be collected to determine the strength of the RO membranes. When the water temperature decreases it becomes more adhesive and the RO permeate flow will be dropped as it requires more pressure to push the water through the membrane. Similarly, when the water temperature increases the RO permeate flow will be increased. As a result, performance data for an RO system must be normalized so that flowrate variations are not interpreted as abnormal when no problem exists (http://puretecwater.com/what-is-reverse-osmosis.html). The minimum, maximum, mean, standard deviation and standard error values of pressure during the period of this study are given in Table 5.3.

Table 5.3: Flowrate statistical analysis among five desalination plants in the Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Recovery%
Al-Salam (Rafah)						**66.61**
Feed water	**72**	**78**	**73.77**	**2.06**	**0.4203**	
Permeate water	**36**	**60**	**49.14**	**6.36**	**1.2973**	
Al-Sharqia (Khan-Younis)						**77.88**
Feed water	**22**	**25.4**	**23.20**	**0.79**	**0.1624**	
Permeate water	**17**	**19**	**18.07**	**0.50**	**0.1023**	
Al-Balad (Deir-Al_ Balah)						**59.67**
Feed water	**60**	**96**	**80.05**	**13.79**	**2.815**	
Permeate water	**42**	**50**	**47.77**	**1.79**	**0.3657**	
Hanneaf (Gaza)						**70.17**
Feed water	**10.2**	**16.08**	**14.08**	**1.48**	**0.3028**	
Permeate water	**5.4**	**12**	**9.88**	**1.62**	**0.3314**	
Al-Radwan (Bait-Lahyia)						**51.45**
Feed water	**15.6**	**18.6**	**17.24**	**0.95**	**0.1942**	
Permeate water	**8.1**	**9.6**	**8.87**	**0.48**	**0.0990**	

From Table 5.3 it's clear that feed and permeate flow rate degree is differed by plant as observed from the overall mean and standard deviation analysis. Al-Salam plant was found to have the highest production rate of about 420 m^3/day at the highest flow rate (60 m^3/h) while Deir-Al_Balah plant were found to have nearly same production rate (350-400 m^3/day) at a flowrate of 50 m^3/day. In terms of recovery rate, the best performing plant is Al-Sharqia plant with about 77.88% while the weakest performing plant is Al-Radwan with 51.45%. Although the five plants have the same RO membrane type supplied by Koch, they have some slight differences in terms of performance.

5.1.1.4 pH

The test of pH is one of the most common analysis in water and great indicators of water quality. The pH is controlled by the amount of dissolved carbon dioxide CO_2, carbonates CO_3^{2-} and bicarbonate HCO_3^- (Domenico and Schwarts, 1990). Levels of pH are important to be known and controlled as lower and higher values of pH may lead to pipe corrosion and incrustation (WHO, 2003).

Generally, the desalination medium is acidic which is considered as a common trend for RO membranes applied for desalination. The minimum, maximum, mean, standard deviation and standard error values of all pH data are given in Table 5.4.

Table 5.4: pH statistical analysis among five desalination plants in the Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**18.91**
Feed water	**7.57**	**7.84**	**7.77**	**0.06**	**0.0121**	
Permeate water	**6.06**	**6.54**	**6.30**	**0.14**	**0.0286**	
Al-Sharqia (Khan-Younis)						**14.42**
Feed water	**7**	**7.83**	**7.35**	**0.22**	**0.0456**	
Permeate water	**5.75**	**6.87**	**6.29**	**0.30**	**0.0619**	
Al-Balad (Deir-Al_Balah)						**18.29**
Feed water	**6.96**	**7.12**	**7.05**	**0.04**	**0.0084**	
Permeate water	**5.33**	**6.32**	**5.76**	**0.24**	**0.0490**	
Hanneaf (Gaza)						**22.50**
Feed water	**7**	**7.24**	**7.11**	**0.05**	**0.0115**	
Permeate water	**5.3**	**5.70**	**5.51**	**0.10**	**0.0209**	
Al-Radwan (Bait-Lahyia)						**22.08%**
Feed water	**7.11**	**7.29**	**7.20**	**0.06**	**0.0129**	
Permeate water	**5.12**	**6.31**	**5.61**	**0.36**	**0.0750**	
WHO standard						**6.5-8**
Palestinian standard						**6.5-8.5**

As shown in Table.5.4 pH analytical data of inlet in all plants ranging within the acceptable WHO standards (6.5-8). While, pH of the permeate in most of the plants found to be less than WHO standards, as a result of lacking pH adjustment and clear control on desalination plants. Thus, after desalination, pH needs to be increased by adding NaOH. If this operation does not take place at RO plants, the pH of the water will be very low. The pH analytical data in the permeate water samples show that about 80% of the samples have pH lower than 6.5, the rest 20% of the samples have pH between 6.54–6.87 (Table 5.4).

5.1.1.5 Electrical conductivity (EC)

The ability of water to conduct an electric current is known as conductivity or specific conductance and depends on the concentration of ions in solution. Conductivity is measured in micro semen's per centimeter (µs/cm). The minimum, maximum, mean, standard deviation and standard error values of all conductivity data are given in Table 5.5.

Table 5.5: Water conductivity statistical analysis among five desalination plants in Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**96.94**
Feed water	**4620**	**5180**	**4841.66**	**137.64**	**28.09**	
Permeate water	**133.5**	**164.4**	**147.94**	**9.03**	**1.843**	
Al-Sharqia (Khan-Younis)						**85.81**
Feed water	**3790**	**4400**	**4029.16**	**151.02**	**30.82**	
Permeate water	**479**	**693**	**571.53**	**67.90**	**13.86**	
Deir-Al_Balah						**95.90**
Feed water	**5830**	**6900**	**6089.16**	**257.74**	**52.61**	
Permeate water	**232**	**275**	**249.07**	**11.97**	**2.44**	
Hanneaf (Gaza)						**97.88**
Feed water	**2470**	**4920**	**3423.12**	**785.94**	**160.43**	
Permeate water	**57.30**	**115.5**	**72.30**	**18.62**	**3.80**	
Al-Radwan (Bait-Lahyia)						**94.02**
Feed water	**861**	**943**	**900.41**	**21.75**	**4.43**	
Permeate water	**16.07**	**166**	**53.78**	**37.31**	**7.61**	
WHO standard (µs/cm)						**2000**
Palestinian standard						**2000**

From Table.5.5 it is clear that all feed readings were found to be higher than WHO and Palestinian standards except for Al-Radwan plant which had an ranging of EC readings (861-943 µs/cm). Therefore, about 80% of inlet samples are not complying with WHO and Palestinian drinking water standards. These relatively high EC readings of the inlets (2470–6900 µs/cm) were found to be significantly reduced in the produced water of all plants (less than 1000 µs/cm) and fit with WHO and Palestinian standards. This may indicates the high desalination efficiency and salt rejection of the RO membranes of these plants, however, the removal rate among the plants was found to be ranging between (85.81-97.88%).

As all feed concentrations of all plants were found to be higher than WHO and Palestinian standards, however, concentrations of the permeate of all plants reasonably dropped to reach around 100 µs/cm or less for Al-Radwan and Hanneaf plants and 150 µs/cm or less for Al-Salam plant and 250 µs/cm or less at Deir-Al_Balah plant. Such concentrations comply with both WHO and the Palestinian standards.

5.1.1.6 Turbidity

High levels of turbidity affect water taste negatively and indicate the presence of undesirable particles in the water. Principally, turbidity is a determining parameter for drinking water quality. Generally, some suspended matter or impurities such as clay, silt, sand, and other particles may cause water turbidity. The minimum, maximum, mean, standard deviation and standard error values of all turbidity data are given in Table 5.6.

Table 5.6: Water turbidity statistical analysis among five desalination plants in Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**46.87**
Feed water	**0.20**	**1.02**	**0.32**	**0.17**	**0.036**	
Permeate water	**0.08**	**0.31**	**0.17**	**0.06**	**0.011**	
Al-Sharqia (Khan-Younis)						**33.33**
Feed water	**0.11**	**0.31**	**0.21**	**0.05**	**0.012**	
Permeate water	**0.09**	**0.20**	**0.14**	**0.04**	**0.079**	
Deir-Al_Balah						**25**
Feed water	**0.13**	**0.36**	**0.20**	**0.06**	**0.012**	
Permeate water	**0.08**	**0.27**	**0.15**	**0.04**	**0.009**	
Hanneaf (Gaza)						**48.38**
Feed water	**0.14**	**0.96**	**0.31**	**0.18**	**0.036**	
Permeate water	**0.09**	**0.24**	**0.16**	**0.03**	**0.007**	
Al-Radwan (Bait-Lahyia)						**57.50**
Feed water	**0.19**	**0.70**	**0.40**	**0.17**	**0.035**	
Permeate water	**0.08**	**0.39**	**0.17**	**0.07**	**0.016**	
WHO standard (NTU)						**5**
Palestinian standard (NTU)						**1**

From Table.5.6 it is understood that the turbidity levels for both feed and permeate of all five plants are below WHO and Palestinian standards.

5.1.1.7 Total dissolved solids (TDS)

According to Al-Jamal and Al-Yaqubi (2000) the high levels of TDS and chloride in the groundwater may cause high salinity in the water supply (Hilles and Al-Najar, 2011). The desalination productivity is substantially measured by salts removal.

Mostly, conductivity, TDS, hardness, and the presence of ions like chloride, sodium, magnesium and calcium show how much the water is brackish. The minimum, maximum, mean, standard deviation and standard error values of all TDS generated data are given in Table 5.7.

Table 5.7: Water TDS statistical analysis among five desalination plants in the Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**97.06**
Feed water	**2860**	**6026**	**3123.08**	**624.09**	**127.39**	
Permeate water	**82.8**	**101.9**	**91.72**	**5.60**	**1.143**	
Al-Sharqia (Khan-Younis)						**85.81**
Feed water	**2350**	**2730**	**2497.83**	**93.78**	**19.14**	
Permeate water	**297**	**430**	**354.31**	**42.08**	**8.58**	
Deir-Al_Balah						**95.90**
Feed water	**3610**	**4280**	**3775.45**	**159.85**	**32.63**	
Permeate water	**143.7**	**170.7**	**154.45**	**7.42**	**1.51**	
Hanneaf (Gaza)						**97.88**
Feed water	**1531**	**3050**	**2122.16**	**487.43**	**99.49**	
Permeate water	**31.8**	**71.6**	**44.82**	**11.55**	**2.35**	
Al-Radwan (Bait-Lahyia)						**94.04**
Feed water	**534**	**590.72**	**559.83**	**14.44**	**2.94**	
Permeate water	**10**	**102.9**	**33.34**	**23.13**	**4.72**	
WHO standard (mg/l)						**1000**
Palestinian standard (mg/l)						**1000**

From Table.5.7 it is clear that all feed readings of TDS found to be higher than WHO and Palestinian standards except for Al-Radwan plant which had a ranging of TDS concentrations (534-590.72 mg/l). Hence, about 80% of inlet samples are not complying with WHO and Palestinian drinking water standards. These relatively high TDS values of the inlets (1531–6026 mg/l) found to be extremely reduced in the produced water of all plants. This may shows the high desalination efficiency and salt rejection of the RO membranes of the plants, as most of the high TDS measured in the plant feed is caused by the presence of salts at high concentrations. However, the removal rate among the plants was found to be ranging between (85.81-97.88%). As all feed concentrations of all plants were found to be higher than WHO and Palestinian standards, on the other hand, concentrations of the permeate of all plants reasonably dropped to reach around 100 mg/l or less for Al-Radwan, Hanneaf and Al-Salam plants, where as 200 mg/l or less for Deir-Al_Balah plant and 500 mg/l or less at Al-Sharqia plant. All of these concentrations found to be with the terms of both WHO and Palestinian standards. As shown in Table 5.7 the highest and lowest TDS removal was for Hanneaf plant (97.88%) and Al-Sharqia plant (85.81%) respectively.

5.1.1.8 Total hardness (TH)

According to Bruggen et al. (2001) water hardness is a key concern attendant with groundwater, as high levels of hardness adversely impact water quality. According to

WHO and Palestinian standards, the maximum allowable value for hardness as determined by $CaCO_3$ concentration should be 500 mg/l respectively. The minimum, maximum, mean, standard deviation and standard error values of all hardness generated data are given in Table 5.8.

Table 5.8: Water hardness statistical analysis among five desalination plants in Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**97.16**
Feed water	**310.59**	**386.45**	**367.45**	**17.99**	**3.67**	
Permeate water	**7.92**	**11.95**	**10.43**	**1.10**	**0.22**	
Al-Sharqia (Khan-Younis)						**95.62**
Feed water	**260.83**	**326.68**	**301.09**	**14.62**	**2.98**	
Permeate water	**11.15**	**15.93**	**13.16**	**1.39**	**0.28**	
Al-Balad Deir-Al_Balah						**98.25**
Feed water	**964.39**	**1203.84**	**1104.17**	**42.54**	**8.68**	
Permeate water	**15.84**	**23.90**	**19.30**	**2.00**	**0.41**	
Hanneaf (Gaza)						**98.88**
Feed water	**703.56**	**1446.19**	**1070.56**	**209.33**	**42.73**	
Permeate water	**7.92**	**17.82**	**11.89**	**2.29**	**0.47**	
Al-Radwan (Bait-Lahyia)						**92.07**
Feed water	**322.60**	**415.29**	**379.65**	**18.10**	**3.69**	
Permeate water	**7.92**	**65.73**	**17.99**	**2.40**	**2.53**	
WHO standard (mg/l)						**500**
Palestinian standard (mg/l)						**500**

As presented in Table 5.8 the feeds of Deir-Al_Balah and Hanneaf were found to have higher values of hardness as compared by WHO and Palestinian standards. On the other hands, feed water of Al-Radwan, Al-Salam and Al-Sharqia plants were found to be lower hardness values. The permeate hardness of all plants was found to be lower and acceptable levels that meet with both WHO and Palestinian standards. In addition, hardness removal percentages were found to vary from 92 % to 99%.

5.1.1.9 Chloride

The existence of chloride is well thought-out as one of the foremost causes for groundwater salinity in the Gaza strip, taking into account that levels of chloride concentrations found in the Gaza groundwater are considerably higher than those permitted by WHO and Palestinian standards. The minimum, maximum, mean, standard deviation and standard error values of all chloride generated data are given in Table 5.9. As shown in Table 5.9, about 80% of all investigated feed samples during this study were found to have high chloride concentrations, ranging from 649.58 mg/l to 1879.58 mg/l. The maximum chloride concentration was found in Al-Balad (Deir-Al_Balah) plant feed (more than 1800 mg/l) while the lower level of chloride concentrations was found at Al-Radwan plant feed (121.49 mg/l-147.75mg/l). The feed water of the other three plants was found to have chloride concentrations which range between (1058-1674 mg/l).

Table 5.9: Water chloride statistical analysis among five desalination plants in the Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**95.74**
Feed water	**1079.15**	**1165.80**	**1121.56**	**2.81**	**5.03**	
Permeate water	**39.31**	**57.57**	**47.69**	**4.37**	**0.89**	
Al-Sharqia (Khan-Younis)						**86.77**
Feed water	**923.47**	**1010.47**	**953.32**	**19.06**	**3.81**	
Permeate water	**107.12**	**153.65**	**126.05**	**13.75**	**2.81**	
Deir-Al_Balah						**95.76**
Feed water	**1622.3**	**1879.58**	**1674.51**	**51.70**	**10.55**	
Permeate water	**40.63**	**81.26**	**70.88**	**7.85**	**1.60**	
Hanneaf (Gaza)						**97.44**
Feed water	**649.58**	**1712.73**	**1058.14**	**322.26**	**65.78**	
Permeate water	**18.04**	**36.94**	**27.02**	**5.34**	**1.09**	
Al-Radwan (Bait- Lahyia)						**86.45**
Feed water	**121.49**	**147.75**	**135.54**	**6.60**	**1.34**	
Permeate water	**10.72**	**33.24**	**18.36**	**5.28**	**1.07**	
WHO standard (mg/l)						**250**
Palestinian standard (mg/l)						**250**

The permeate water of all plants was found to have lower chloride concentrations than what is allowed by WHO and Palestinian standards. The rejection percentage of chloride concentrations was found to be ranging between 86%–97%.

5.1.1.10 Nitrate

According to Levallois et al. (2005) nitrate is considered to be as the most predominant pollutant in the groundwater over all world. All organic and inorganic bases of nitrogen are commonly converted to nitrate. After decreasing, nitrate can be biologically transmuted to nitrogen gas. The increasing pollution of public and individual drinking water wells by nitrate is mostly due to the extensive use of fertilizers and waste (Khademikia et al. 2013). According to Bohdziewicz et al (1999) high levels of nitrates pollution, which are common occurrences in Gaza, are well thought-out as a health risk, as they are the reason of blue babies disease (Mogheir, et al. 2013). The minimum, maximum, mean, standard deviation and standard error values of all NO_3^- generated data are given in Table 5.10.

The nitrate levels over all plants (feed) are much higher than permitted level by WHO and PS standards. Conversely, the permeate water of all plants has lower and allowable concentration levels of nitrates by both WHO and Palestinian standards except for Al-Sharqia (Khan-Younis) plant, where the permeate water (99.32-145.81 mg/l) was found to be higher than the allowable WHO and Palestinian standards.

Table 5.10: Nitrate level statistical analysis among five desalination plants in the Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**87.45**
Feed water	**53.34**	**76.90**	**65.26**	**6.22**	**1.27**	
Permeate water	**5.31**	**10.36**	**8.19**	**1.21**	**0.24**	
Al-Sharqia (Khan-Younis)						**53.28**
Feed water	**133..22**	**404.75**	**272.73**	**65.43**	**13.35**	
Permeate water	**99.32**	**145.81**	**127.41**	**14.75**	**3.01**	
Al-Balad (Deir-Al_Balah)						**87.78**
Feed water	**116.36**	**154.26**	**138.10**	**10.83**	**2.21**	
Permeate water	**11.63**	**20.56**	**16.87**	**2.10**	**0.42**	
Hanneaf (Gaza)						**93.50**
Feed water	**122.85**	**203.94**	**169.69**	**20.51**	**4.18**	
Permeate water	**8.27**	**13.25**	**11.02**	**0.97**	**0.19**	
Al-Radwan (Bait-Lahyia)						**92.31**
Feed water	**113**	**142.60**	**128.02**	**8.11**	**1.65**	
Permeate water	**2.91**	**20.76**	**9.84**	**5.44**	**1.11**	
WHO standard (mg/l)						**50**
Palestinian standard (mg/l)						**50***

***Note: In the absence of alternative source of water, the ratio of nitrate (70 mg/l) is allowed to be as maximum value (According to Palestinian Standard - 2005).**

Significant nitrate removal was found in Hanneaf plant with nitrate levels reduced from nearly 170 mg/l for feed to 11 mg/l for permeate, where the removal percentage was found to be 93.5%.

5.1.1.11 Calcium

According to Kozisek (2003) a certain amount of Ca^{2+} is essential in drinking water not only because of inducing $CaCO_3$ precipitation, however, because of several health reasons. Calcium is very important element for human growth mainly for babies. About 20% of the suggested daily amount mostly comes from drinking water (Hills and al-Najar, 2011). The minimum, maximum, mean, standard deviation and standard error values of all Calcium generated data are given in Table 5.11.

Table 5.11: Water calcium statistical analysis among five desalination plants in Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**97.26**
Feed water	**52.95**	**63.87**	**59.98**	**2.81**	**0.573**	
Permeate water	**0.79**	**3.23**	**1.64**	**0.65**	**0.132**	
Al-Sharqia (Khan-Younis)						**95.53**
Feed water	**39.89**	**52.37**	**46.38**	**2.53**	**0.516**	
Permeate water	**1.37**	**3.23**	**2.07**	**0.53**	**0.109**	
Al-Balad (Deir-Al_Balah)						**98.02**
Feed water	**136.86**	**176.17**	**162.30**	**7.03**	**1.43**	
Permeate water	**2.36**	**7.92**	**3.21**	**1.15**	**0.235**	
Hanneaf (Gaza)						**99.16**
Feed water	**211.83**	**384.82**	**307.93**	**48.76**	**9.95**	
Permeate water	**1.58**	**4.84**	**2.57**	**0.94**	**0.193**	
Al-Radwan (Bait-Lahyia)						**96.23**
Feed water	**81.84**	**287.42**	**103.54**	**39.40**	**8.04**	
Permeate water	**1.37**	**16.76**	**3.90**	**3.32**	**0.678**	
WHO standard (mg/l)						**100**
Palestinian standard (mg/l)						**100**

Calcium concentration levels were investigated for the feed and permeate of all plants and compared with WHO and Palestinian standards maximum allowable values. As shown in Table 5.11, the feed water of Al-Balad (Deir-Al_Balah), Hanneaf (Gaza) and al-Radwan plants were found to have higher calcium concentration levels than WHO and Palestinian standards. While the feed water of Al-Salam and Al-Sharqia (Khan-Younis) plants were found to be lower than WHO and PS recommended levels. The calcium concentration in product water samples ranges from 0.79 mg/l to 16.76 mg/l, however, these concentrations level is lower than WHO and Palestinian standards.

5.1.1.12 Magnesium

Magnesium is the fourth supreme copious cation in the human-being bodies and the second greatest copious cation in intracellular runny liquid. It is a co-factor for about 350 cellular enzymes, some of which are intricate in driving metabolism. Furthermore, it is involved in protein and nucleic acid synthesis and is required for regular vascular tone and insulin sensitivity. Low magnesium extents are attendant with endothelial dysfunction, increased vascular reactions, raised circulating levels of C-reactive protein and decreased insulin sensitivity. Low magnesium status has been implicated in hypertension, coronary heart disease, type 2 diabetes mellitus and metabolic syndrome (WHO, 2009). The minimum, maximum, mean, standard deviation and standard error values of all magnesium generated data are given in Table 5.12.

From Table 5.12 it is clear that the concentration levels of Mg^{2+}, the feed water of Al-Salam, Al-Radwan and Al-Sharqia plants were found to have lower magnesium concentrations than what is allowed by WHO and Palestinian standards while the feed water of Al-Balad (Deir-Al_Balah) plants was found to be above the permitted standards. Unlike Hanneaf plant, which have the higher level than allowable in the WHO standards, while found to have lower than the allowable in the Palestinian standards. The permeate water of all plants, however, was found to have lower levels than what is permitted by both WHO and Palestinian standards. Magnesium removal percentage was found to be ranging from 94% to 98%.

Table 5.12: Water Mg^{2+} statistical analysis among five desalination plants in Gaza Strip

Desalination plants	Min.	Max.	Mean	S.D	S.E	Removal %
Al-Salam (Rafah)						**97.10**
Feed water	**43.25**	**57.40**	**52.78**	**3.16**	**0.064**	
Product water	**0.48**	**1.95**	**1.53**	**0.43**	**0.087**	
Al-Sharqia (Khan-Younis)						**96.26**
Feed water	**39.10**	**169.99**	**55.32**	**35.17**	**7.17**	
Product water	**0.97**	**2.89**	**2.06**	**0.46**	**0.094**	
Al-Balad (Deir El Balah)						**98.35**
Feed water	**151.02**	**187.23**	**169.47**	**7.52**	**1.53**	
Product water	**0.48**	**4.35**	**2.79**	**0.80**	**0.163**	
Hanneaf (Gaza)						**98.15**
Feed water	**9.13**	**117.50**	**71.06**	**26.07**	**5.32**	
Product water	**0.16**	**1.93**	**1.31**	**0.94**	**0.105**	
Al-Radwan (Bait-Lahyia)						**94.18**
Feed water	**5.62**	**40.98**	**32.85**	**6.36**	**1.29**	
Product water	**0.24**	**5.78**	**1.91**	**1.12**	**0.228**	
WHO standard (mg/l)						**60**
Palestinian standard						**100**

5.1.2 Water quality parameters Pearson's correlation

Correlation analysis is basically measures the relationship between two or more functionally independent variables. In water quality the correlation analysis is used to measure the strength and statistical significance of the relationship between two or more random water quality parameters. The strength of the relationship between two random parameters can be determined through calculation of a correlation coefficient r. The value of this coefficient ranges between -1 and 1. The value which is close to -1 shows a strong negative correlation.

When r is close to +1 is showing a strong positive correlation between the two parameters. The closer the value of r is to zero, it means the correlation is poorer (Armah et al. 2012). Correlation coefficient and paired t-test are calculated using SPSS and Minitab software's. The generated water data were analysed using paired t-test to detect variations in the measured parameters with location (desalination plant). Pearson's correlation was used to detect linear correlations between various parameters and locations. Table 5.13 shows the Pearson's correlation between permeate water quality parameters (temperature, pressure, flowrate, pH, EC, TDS, turbidity, hardness, chloride, calcium, magnesium and nitrate) for the values of the six months collected data to develop the water quality ANN models. From Table 5.13 it can be seen that pH is inversely correlated with pressure, turbidity and directly with the remaining parameters. Calcium also is correlated directly with temperature, pressure, turbidity, hardness, and magnesium, while it is inversely correlated with flowrate, pH, EC, TDS, chloride and nitrate. Flowrate is correlated inversely with pressure, turbidity, calcium, magnesium and nitrate as well as directly with pH, EC, TDS, hardness and chloride. TDS is correlated inversely with turbidity, pressure and calcium, but it is correlated directly with temperature, pH, EC, chloride, magnesium and nitrate.

Table 5.13: Pearson's correlation coefficient for values of permeate water parameters

Parameters	Temp	P	Flow	pH	EC	TDS	Turbidity	TH	Cl^-	Ca^{2+}	Mg^{2+}	NO_3^-
Temp	1											
P	-0.30	1										
Flow	0.27	-0.29	1									
pH	0.55	-0.31	0.37	1								
EC	0.37	-0.76	0.08	0.55	1							
TDS	0.37	-0.76	0.08	0.55	1	1						
Turbidity	-0.12	0.18	-0.06	-0.04	-0.15	-0.15	1					
TH	0.28	-0.07	0.05	0.02	0.08	0.08	0.06	1				
Cl^-	0.40	-0.81	0.19	0.56	0.99	0.99	-0.17	0.07	1			
Ca^{2+}	0.17	0.12	-0.15	-0.06	-0.08	-0.08	0.12	0.86	-0.11	1		
Mg^{2+}	-0.13	-0.13	-0.01	0.03	0.22	0.22	0.05	0.05	0.20	0.04	1	
NO_3^-	0.30	-0.62	-0.22	0.47	0.94	0.94	-0.13	-0.02	0.89	-0.09	0.22	1

Chloride is inversely correlated with turbidity, pressure and calcium where as it is directly correlated with temperature, pH, EC, TDS, magnesium and nitrate. Nitrate is inversely correlated with pressure, flowrate and turbidity as well as directly with temperature, pH, EC, TDS and chloride.

5.1.3 Spatial variations analysis

A major concern in managing water properties is whether or not water quality variables have changed over time or place. The two-sample student's t-test (*p-Value*) is most likely the utmost commonly used statistical test for this purpose. The t-test is robust for non-normal distributions if the distributions have the same shape (either symmetric or skewed) and sample sizes are equal. In addition t-test is appropriate for unequal variances if the sample sizes are equal (Montgomery and Loftis, 1987). Paired t-test was used to detect variations among the used parameters with location/desalination plants in the Gaza strip. Pearson's correlation was used to detect linear correlations between various desalination facilities.

Table 5.14 summarises the paired t test and the Pearson's correlations of temperature, pressure, flow rate, pH, EC and TDS in the permeate water quality data. All these results are obtained by using SPSS software program.

Table 5.14: Paired t test(*p-value*) & Pearson correlation (r) results for permeate water parameters including: (temperature, pressure, flowrate, pH, turbidity and EC)

Paired	Temp		Pressure		Flow rate		pH		Turbidity		EC	
locations	r	t-test(p)	r	t-test(p)	r	t-test(p)	r	t-test(p)	r	t-test(p)	r	t-test(p)
1&2 F*	0.74	0.461	0.13	<0.0001*	-0.24	<0.0001*	-0.53	<0.0001*	0.15	0.007*	0.93	<0.0001*
P**	0.75	0.222	0.47	<0.0001*	-0.04	<0.0001*	0.14	0.944	0.34	0.068	-0.15	<0.0001*
1&3 F	0.50	0.014*	0.00	<0.0001*	-0.54	0.052	0.29	<0.0001*	0.27	0.003*	0.68	<0.0001*
P	0.66	0.435	0.08	<0.0001*	-0.53	0.397	0.30	<0.0001*	0.30	0.120	0.58	<0.0001*
1&4 F	0.65	<0.0001*	-0.33	0.704	-0.41	<0.0001*	0.49	<0.0001*	-0.11	0.826	-0.24	<0.0001*
P	0.51	<0.0001*	-0.14	0.297	-0.56	<0.0001*	0.48	<0.0001*	0.32	0.727	0.26	<0.0001*
1&5 F	0.71	0.024*	-0.02	<0.0001*	0.37	<0.0001*	0.01	<0.0001*	0.29	0.049*	0.90	<0.0001*
P	0.59	0.004*	0.00	<0.0001*	0.50	<0.0001*	0.46	<0.0001*	0.31	0.732	0.55	<0.0001*
2&3 F	0.38	0.849	0.00	<0.0001*	0.17	<0.0001*	-0.40	<0.0001*	0.38	0.357	0.83	<0.0001*
P	0.68	0.045*	-0.31	0.045*	0.20	<0.0001*	0.01	<0.0001*	0.29	0.843	-0.39	<0.0001*
2&4 F	0.59	0.242	-0.49	<0.0001*	0.37	<0.0001*	-0.13	<0.0001*	-0.10	0.025*	-0.34	0.002*
P	0.73	<0.0001*	-0.13	<0.0001*	0.19	<0.0001*	0.13	<0.0001*	0.12	0.091	0.37	<0.0001*
2&5 F	0.62	0.883	-0.33	<0.0001*	0.01	<0.0001*	-0.20	0.009*	0.03	<0.0001*	0.93	<0.0001*
P	0.85	<0.0001*	0.00	<0.0001*	0.02	<0.0001*	-0.02	<0.0001*	0.061	0.123	0.11	<0.0001*
3&4 F	0.32	<0.0001*	0.00	0.013*	0.64	<0.0001*	0.13	<0.0001*	-0.06	0.012*	-0.27	<0.0001*
P	0.53	<0.0001*	0.22	<0.0001*	0.60	<0.0001*	-0.22	<0.0001*	0.32	0.119	0.01	<0.0001*
3&5 F	0.57	0.371	0.00	<0.0001*	-0.66	<0.0001*	0.29	<0.0001*	0.02	<0.0001*	0.76	<0.0001*
P	0.67	0.016*	0.00	<0.0001*	-0.43	<0.0001*	-0.43	0.110	-0.17	0.206	0.39	<0.0001*
4&5 F	0.75	0.009*	0.24	<0.0001*	-0.53	<0.0001*	0.14	<0.0001*	0.35	0.021*	-0.19	<0.0001*
p	0.68	0.014*	0.00	<0.0001*	-0.45	0.009*	0.33	0.238	0.41	0.508	0.30	0.010*

Note: F* (Feed water) and P (Permeate water)**

The results indicate that there are high significant differences in the pressure, flowrate, pH and EC for most of measured values at all locations, but no significant differences were noted for water temperature and turbidity at some locations. These significance differences justify the performance of water quality monitoring parameters over the Gaza strip desalination plants and prove that there is a real difference between the plants chosen for the water quality predictive models development. Pearson correlation in temperature found to be strong and moderate among all locations for feed and permeate water samples. Correlation in pressure, flowrate, pH, turbidity and EC among all plants is found to be weak. Table 5.15 illustrates the results of statistical analysis (paired t-test and Pearson correlation) of TDS, chloride, hardness, calcium, magnesium and nitrate in feed and permeate water samples.

Table 5.15: Paired t test(*p-value*) & Pearson correlation (r) results for permeate water parameters including: (TDS, Cl^- , hardness, nitrate, Ca^{2+} and Mg^{2+})

Paired	TDS		Chloride		Hardness		Nitrate		Calcium		Magnesium	
locations	**r**	**t-test(p)**	**r**	**t-test(p)**	**r**	**t-test(p)**	**r**	**t-test(p)**	**r**	**t-test(p)**	**r**	**t-test(p)**
1&2 F*	0.08	**<0.0001***	0.11	**<0.0001***	**0.69**	**<0.0001***	0.26	**<0.0001***	0.34	**<0.0001***	0.13	0.725
P**	-0.16	**<0.0001***	-0.16	**<0.0001***	0.45	**<0.0001***	0.07	**<0.0001***	0.58	**0.001***	-0.03	0.259
1&3 F	0.04	**<0.0001***	-0.12	**<0.0001***	**0.54**	**<0.0001***	**0.55**	**<0.0001***	0.38	**<0.0001***	0.47	**<0.0001***
P	**0.58**	**<0.0001***	0.20	**<0.0001***	0.12	**<0.0001***	**0.69**	**<0.0001***	0.23	**<0.0001***	0.38	**<0.0001***
1&4 F	-0.18	**<0.0001***	0.43	0.330	**0.52**	**<0.0001***	0.37	**<0.0001***	0.32	**<0.0001***	**0.50**	**0.001***
P	0.27	**<0.0001***	0.47	**<0.0001***	0.01	**0.016***	**-0.02**	**<0.0001***	0.02	**0.001***	**0.51**	**0.027***
1&5 F	0.16	**<0.0001***	**0.68**	**<0.0001***	0.49	**0.003***	0.16	**<0.0001***	0.33	**<0.0001***	0.03	**<0.0001***
P	**0.55**	**<0.0001***	0.48	**<0.0001***	0.32	**0.024***	0.31	0.182	0.10	**0.011***	0.29	0.238
2&3 F	**0.82**	**<0.0001***	-0.06	**<0.0001***	**0.58**	**<0.0001***	0.39	**<0.0001***	**0.57**	**<0.0001***	0.02	**<0.0001***
P	-0.39	**<0.0001***	-0.18	**<0.0001***	-0.01	**<0.0001***	0.21	**<0.0001***	0.40	**<0.0001***	0.03	0.459
2&4 F	-0.34	**0.002***	-0.30	0.139	0.32	**<0.0001***	0.01	**<0.0001***	0.34	**<0.0001***	0.13	0.072
P	0.36	**<0.0001***	0.21	**<0.0001***	-0.15	**0.035***	0.13	**<0.0001***	0.22	**0.028***	0.15	0.229
2&5 F	**0.84**	**<0.0001***	0.04	**<0.0001***	0.32	**<0.0001***	0.10	**<0.0001***	0.18	**<0.0001***	0.07	**0.005***
P	0.11	**<0.0001***	-0.07	**<0.0001***	0.21	0.198	0.05	**<0.0001***	0.33	**0.039***	-0.10	0.299
3&4 F	-0.28	**<0.0001***	-0.01	**<0.0001***	0.13	0.436	0.21	**<0.0001***	0.41	**<0.0001***	0.10	**<0.0001***
P	0.01	**<0.0001***	-0.08	**<0.0001***	0.15	**<0.0001***	-0.15	**<0.0001***	0.10	0.082	0.39	**<0.0001***
3&5 F	**0.67**	**<0.0001***	-0.26	**<0.0001***	0.26	**<0.0001***	0.10	**0.001***	0.16	**<0.0001***	0.16	**<0.0001***
P	0.39	**<0.0001***	-0.44	**<0.0001***	0.21	0.265	0.38	**<0.0001***	0.12	0.541	0.19	**0.001***
4&5 F	-0.09	**<0.0001***	0.21	**<0.0001***	**0.59**	**<0.0001***	0.05	**<0.0001***	-0.02	**<0.0001***	**0.61**	**<0.0001***
p	0.30	**0.010***	0.41	**<0.0001***	-0.01	0.087	0.18	0.226	0.04	0.184	0.23	**0.042***

Note: F* (Feed water) and P** (Permeate water)

From Table 5.15 the results show that high significant differences in the TDS measured values among all plants, but significant differences were recorded for chloride, hardness, nitrate, calcium and magnesium. For chloride no significant differences is found at Al-Salam (Rafah) & Hanneaf (Gaza) and Al-Sharqia (Khan-Younis) & Hanneaf plants in feed water samples. For hardness no significant differences is found at Al-Sharqia & Al-Radwan, Al-Balad (Deir-Al_Balah) & Al-Radwan and Hanneaf & Al-Radwan for permeate water samples and Al-Balad (Deir-Al_Balah) & Hanneaf plants for feed water samples. No significant differences found at Al-Salam & Al-Radwan and Hanneaf & Al-Radwan plants in permeate water samples for nitrate measured values. In calcium measured values no significant differences found to be at Al-Balad (Deir-Al_Balah) & Hanneaf, Al-Balad (Deir-Al_Balah) & Al-Radwan and Hanneaf & Al-Radwan plants for permeate water samples. In addition results showed that there is no significant in magnesium measured values among Al-Salam & Al-Sharqia, Al-Salam & Al-Radwan, Al-Sharqia & Al-Balad (Deir-Al_Balah), Al-Sharqia & Hanneaf and Al-Sharqia & Al-Radwan plants for permeate water samples and also the results shows that no significance in feed water values among Al-Salam & Al-Sharqia and Al-Sharqia & Hanneaf plants. These significance differences justify the performance of the water quality monitoring tests and prove that there is a real difference between the chosen desalination plants in the Gaza strip.

5.2 Developed ANN predictive models

ANN's technique was applied to develop predictive models to predict the performance of some selected desalination plants in the Gaza strip through predicting the water quality variables. Since the ANN approach will not assume any functional relationship between the dependent and independent variables, ANNs are suitable for capturing functional relationships between water quality variables in water quality. The ANN used was a fully connected feed-forward system RBF and MLP trained with a back-propagation algorithm using different techniques. The training and testing of ANN models for the water quality parameters prediction are carried out using neural network toolbox in the MATLAB. During this research several models have been developed to predict the water quality parameters including: permeate flowrate, TDS, Chloride, NO_3^- and Mg^{2+}. These predictive models are discussed in detail as follow:

5.2.1 Permeate flowrate (PFR) model

Permeate flowrate values are found to be ranged between 5.4 and 60m^3/h for training data set and ranged between 8.1 and 60m^3/h for testing data set. The mean value among all desalination plants for both training and testing data sets found to be 26.55m^3/h and 27.51m^3/h respectively. The statistical analysis reveals a positive strong correlation between permeate flowrate and feed electrical conductivity (EC) for both training and testing data sets whereas r values found to be 0.80 and 0.78 respectively. Negative correlation found to be between permeate flowrate and feed pressure for both training and testing data sets whereas the r values found to be -0.116 and -0.312 respectively. A positive moderate correlation is found to be between flowrate and pH for both training and testing data sets whereas the r values 0.268 and 0.59 respectively.

In this section we have investigated the ability of MLP and RBF neural networks to predict future values (one week a head) of permeate flowrate in the desalination plants of Gaza strip for the purpose of performance assessment. The neural network prediction results compared with the traditional statistical methods (multiple regression model). To develop MLP network several algorithms are used during training session including: Resilient back-propagation, Levenberg Marquardt, Variable learning rate back-propagation, BFGS Qusai-Newton, Bayesian rule and Gradient descent. The description of the permeate flow-rate developed network architecture is given in Table 3.1 chapter 3. The trained MLP and RBF networks performance is presented in Fig 5.1 and 5.2 respectively. The results of developed models during training and testing data sets as well as multiple regression model are given in Table 5.16. The parameters (i.e. weights and biases) of both trained MLP and RBF networks are given in annex 2.1. The results obtained from MLP used six different algorithms showed that the developed MLP network trained with back-propagation incorporated with LM algorithm is the most appropriate model for predicting permeate flow rate in the desalination plants of Gaza strip. There are many statistical tools for model validation, but the primary tools for most process modelling applications include MSE, correlation coefficient, standard error, standard deviation and error percentage. The performance of the developed ANN models obtained after training the data sets was tested using unknown data set. MSE, MAE, correlation coefficient, standard error and standard deviation tools are used for the models validation.

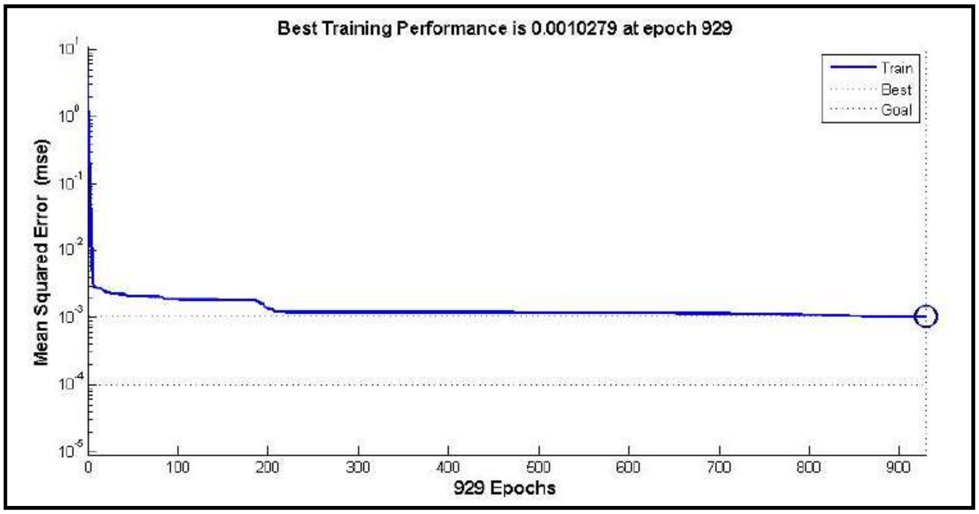

Fig.5.1: Permeate flowrate MLP Training Model performance

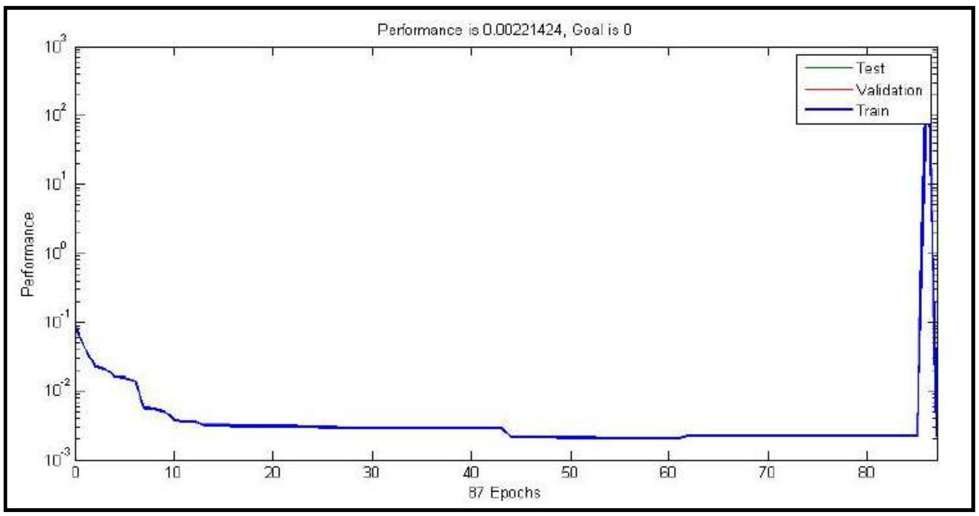

Fig.5.2: Permeate flowrate RBF Training Model performance

It can be seen from figures 5.1& 5.2 that the MLP network performance is slightly better than the RBF network. Also this result illustrated in Table-5.16 that shows the coefficient correlations between the predicted values of permeate flowrate using MLP, RBF and MLR for testing the developed model. The correlations between the predicted flowrate and actual values for MLP, RBF model testing is found to be strong and better than MLR model whereas coefficients correlation values are 0.9904, 0.9853 and 0.8976 respectively see (Figs.5.3, 5.6 and 5.9). The results obtained prove that the developed MLP and RBF neural network models are more accurate than MLR for predicting flowrate of product water in the desalination plants of the Gaza strip. The methodology used for the development of MLP and RBF predictive models may be extended to other water quality parameters belonging to underground water.

Table 5.16: Summary of developed ANN models and MLR results for predicting PFR

Models	Data set	MSE	R	S.D	MAE	S.E	Error Range (m^3/h)
MLP	Training	3.7004	0.9941	17.78	1.3644	1.90	0.001-6.53
	Testing	9.5218	0.9904	18.60	1.9145	3.23	0.061-8.91
RBF	Training	07.9713	0.9873	17.66	1.9170	1.89	0.017-8.85
	Testing	12.6450	0.9853	18.59	2.4382	3.23	0.026-9.81
MLR	Training	60.8297	0.9081	15.99	6.1412	1.71	0.08-23.05
	Testing	82-6492	0.8976	18.03	6.6217	3.13	0.04-22.68

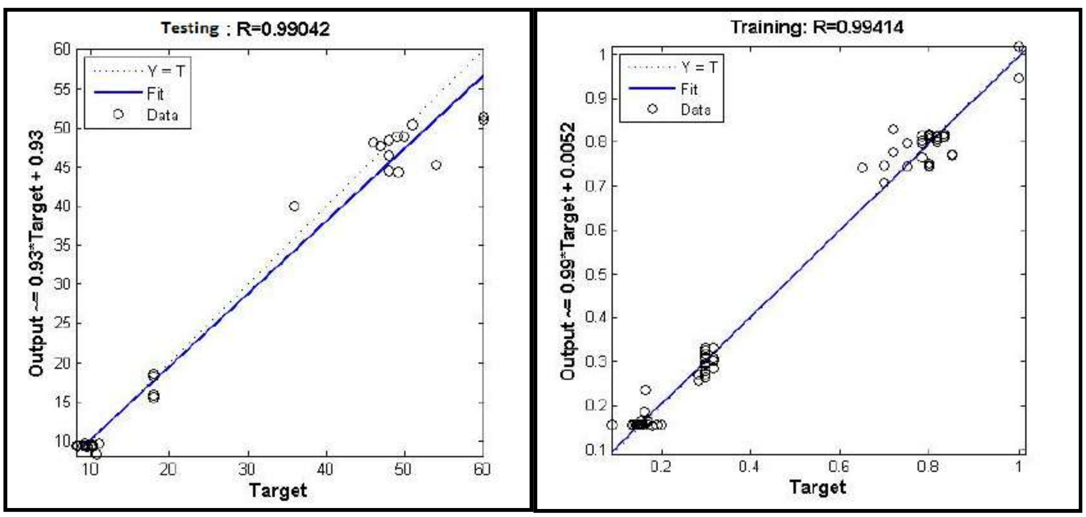

Fig.5.3: Permeate flowrate MLP Model regression for training and testing data sets

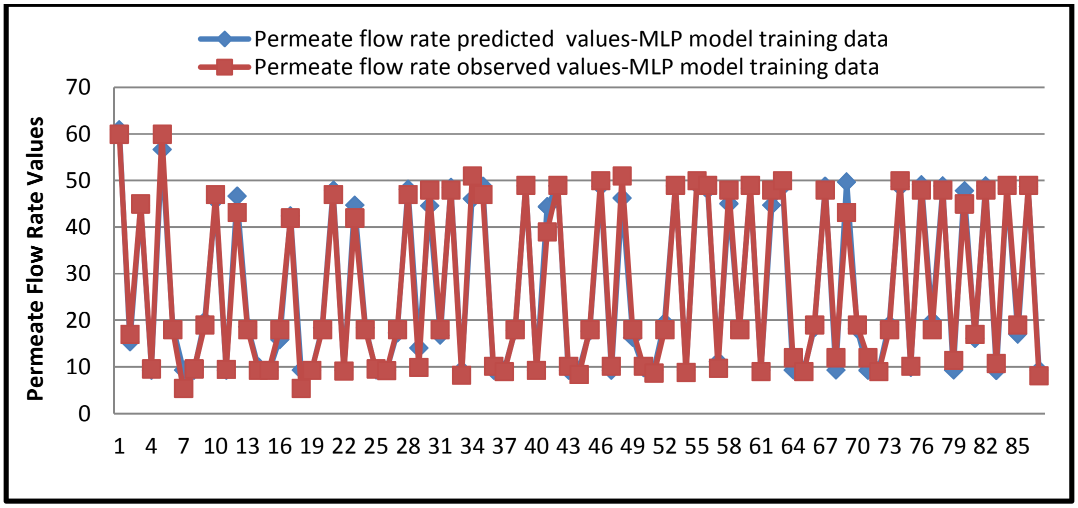

Fig.5.4: Comparison of permeate flowrate MLP Model-Training prediction results

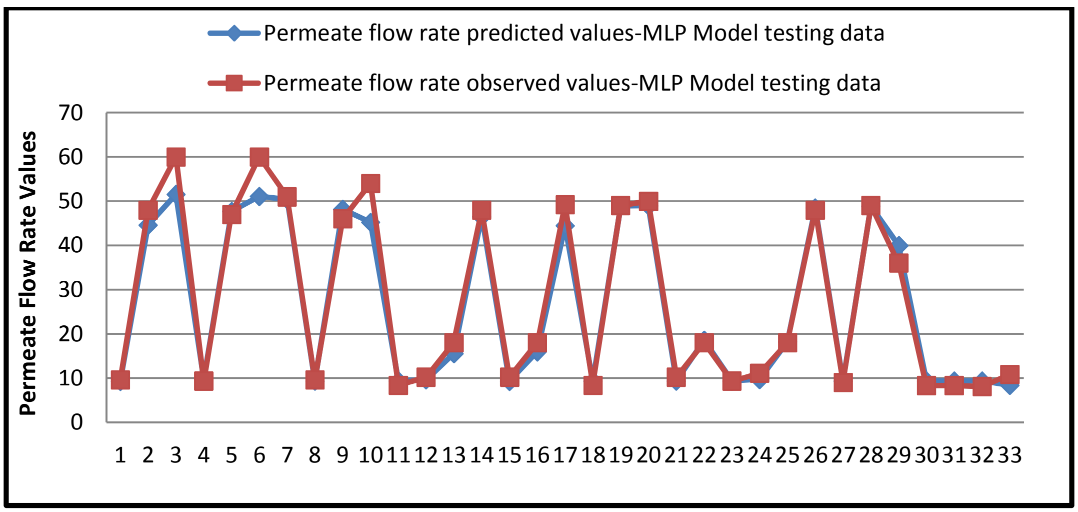

Fig.5.5: Comparison of permeate flowrate MLP Model-Testing prediction results

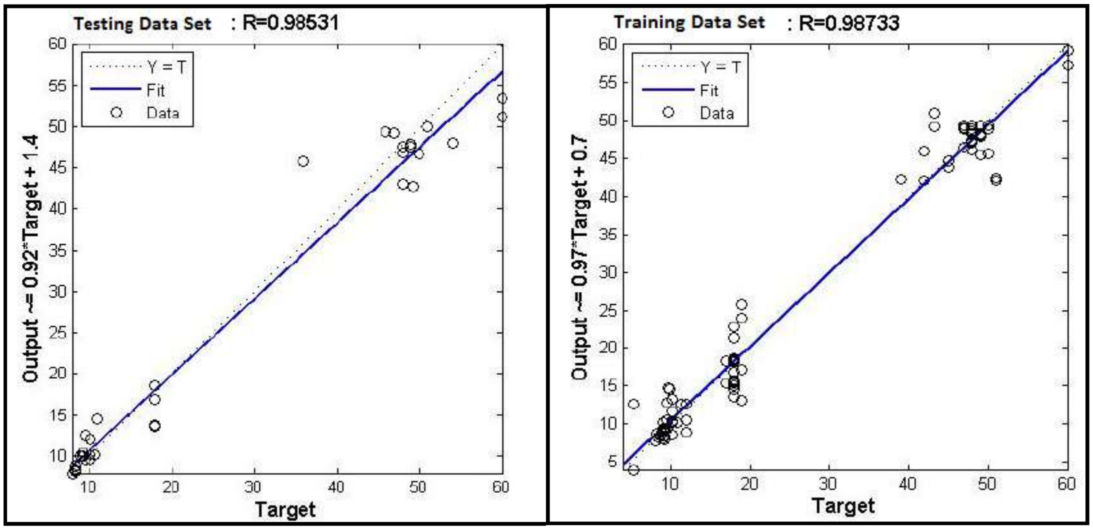

Fig. 5.6: Permeate flowrate RBF Model regression for training and testing data sets

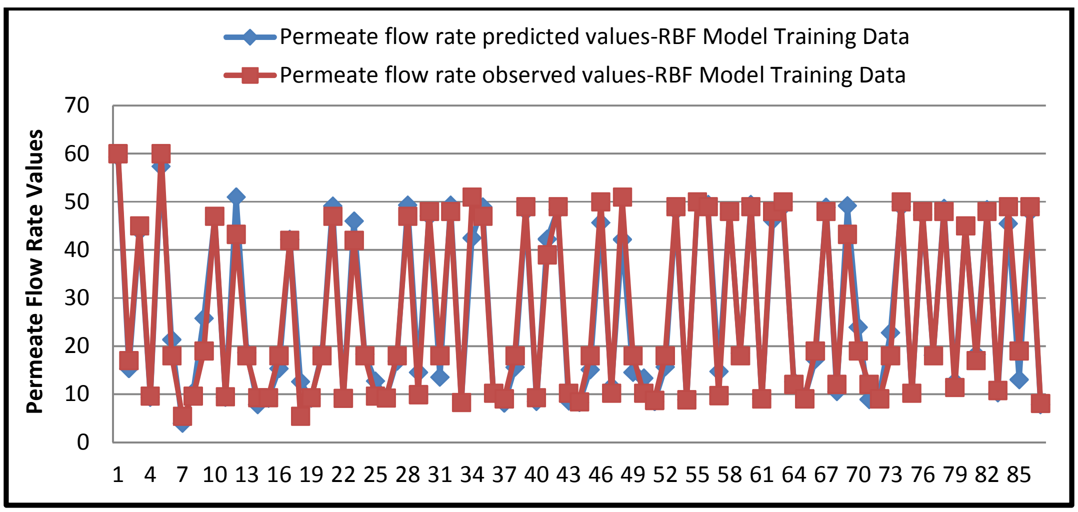

Fig. 5.7: Comparison of permeate flowrate RBF Model-Training prediction results

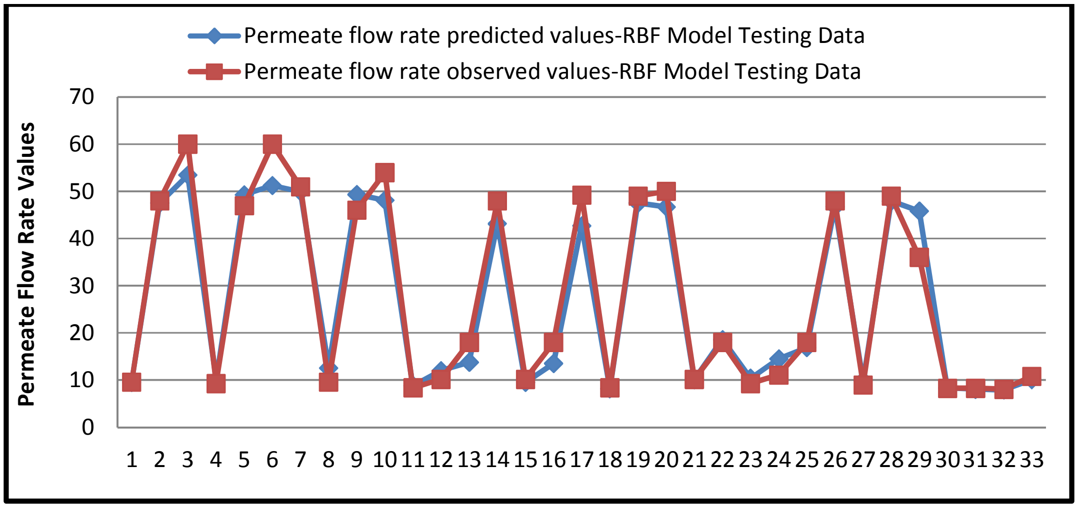

Fig. 5.8: Comparison of permeate flowrate RBF Model-Testing prediction results

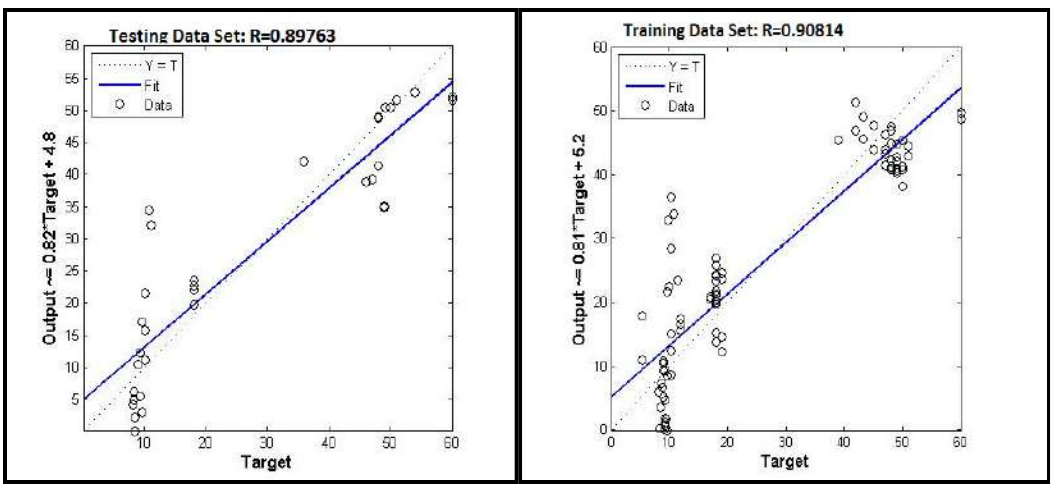

Fig. 5.9: Permeate flowrate MLR Model regression for training and testing data sets

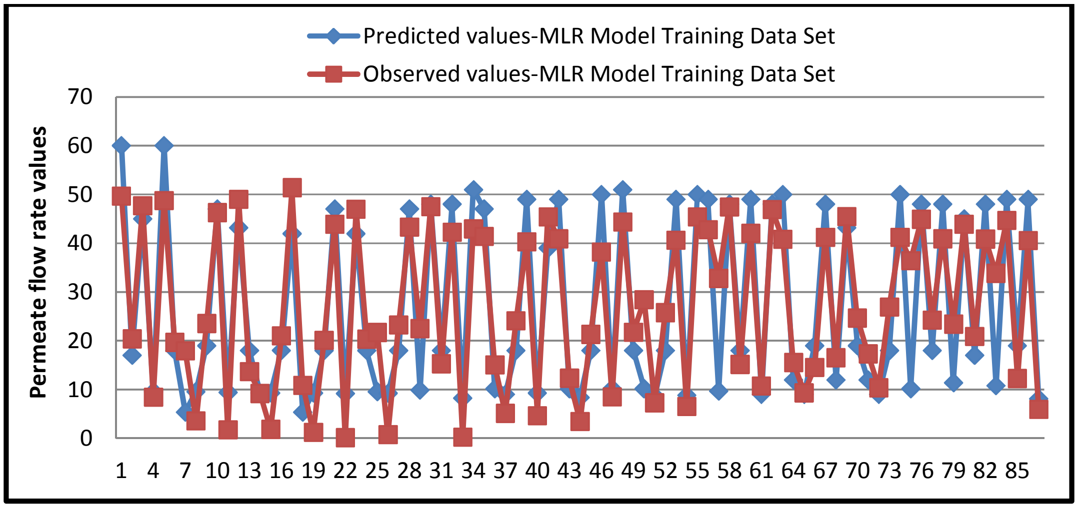

Fig.5.10: Comparison of permeate flowrate MLR Model-Training prediction results

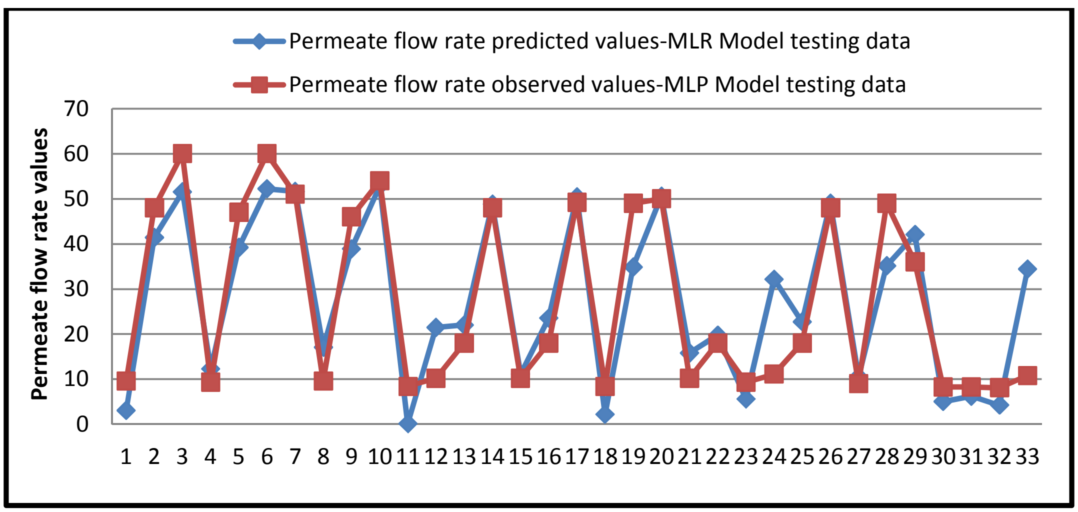

Fig.5.11: Comparison of permeate flowrate MLR Model-Testing prediction results

Figures 5.4 and 5.5 illustrate the comparison between permeate flowrate actual and predicted values of training and testing MLP model prediction results respectively. Figures 5.7 and 5.8 show the comparison between actual and predicted values of both training and testing data sets RBF predictive model results. The comparison results between permeate flowrate actual and predicted values for training and testing data sets of MLR statistical model are presented in Figs 5.10 and 5.11.

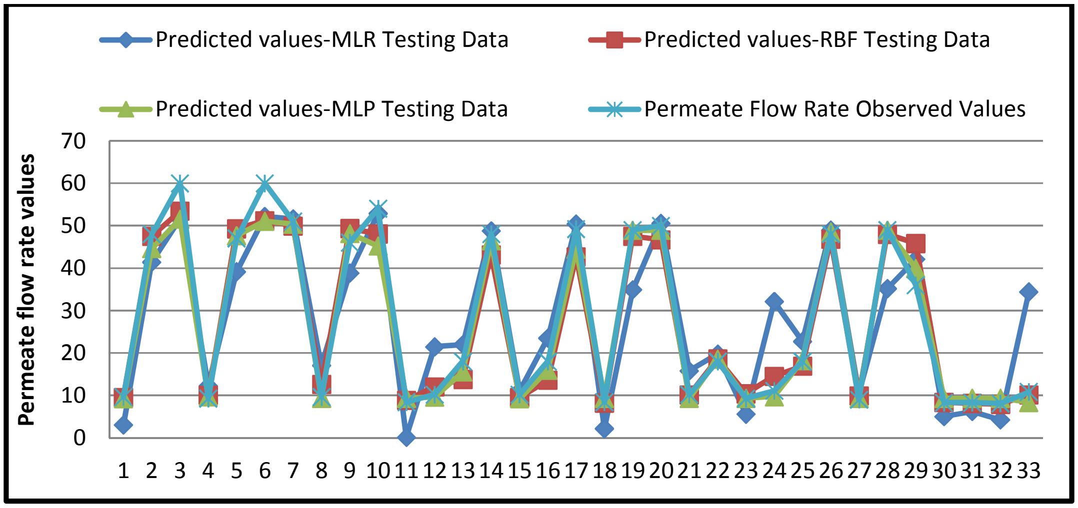

Fig.5.12: Comparison of flowrate MLP, RBF&MLR Model-Testing prediction results

Figure 5.12 presents comparison of MLP and RBF model prediction results with the conventional method predictions. From the above figure it can be understood that ANN predictions are better than conventional methods.

5.2.2 Total dissolved solids (TDS) model

Increased feed TDS or salt concentrations will decrease permeate flowrate and increase salt passage. This can also be a clue to surface coating or fouling by the salt. The TDS and EC are mostly affected by the feed composition of the impurities such as NaCl and applied pressure. Increasing the pressure will cause increase in the TDS and the EC rejection percentages (Righton, 2009). Total dissolved solids (TDS) values are ranged from 10 mg/l to 430 mg/l for training data set and from 11.8 mg/l to 340 mg/l for testing data set. The mean value among all desalination plants for both training and testing data sets is 146.01 mg/l and 106.04 mg/l respectively. The statistical analysis showed a positive very strong correlation between permeate TDS and permeate conductivity (EC) for both training and testing data sets whereas r values found to be 0.99 for both of them. Negative strong correlation found to be between TDS and feed pressure for both training and testing data sets whereas the r values found to be -0.77 and -0.71 respectively. A positive moderate correlation is found to be between TDS and pH for both training and testing data sets whereas the r values 0.59 and 0.42 respectively.

The correlation between TDS and permeate temperature is found to be positive and moderate for both training and testing data sets whereas the r values are 0.34 and 0.56 respectively.

To predict the future values (one week a head) of TDS concentrations in the desalination plants of the Gaza strip, feedforward MLP and RBF neural networks are employed. To create MLP network a number of algorithms are used in the training process including: Resilient back-propagation, Levenberg Marquardt, Variable learning rate back-propagation, BFGS Qusai-Newton, Bayesian rule and Gradient descent. The details of the TDS created network architecture are given in Table 3.1 chapter-3. The MLP and RBF neural network prediction results compared with the traditional statistical methods (multiple regression model). The trained MLP and RBF networks performance is presented in Fig 5.13 and 5.14 respectively. The summary of developed models results for training and testing data sets as well as multiple regression model are given in Table 5.17. The parameters (i.e. weights and biases) of both trained MLP and RBF networks are given in annex 2.2. The results obtained from MLP used several different algorithms revealed that the created MLP network which trained with back-propagation incorporated with LM algorithm is the most fitting model for predicting permeate TDS in the desalination plants of Gaza strip.

It can be seen from figures 5.13& 5.14 that the created RBF network performance is mostly similar to the MLP network. It is also understood from the results tabulated in Table 5.17 which show the coefficient correlations between the observed and predicted values of TDS using MLP, RBF and MLR for training and testing the developed models.

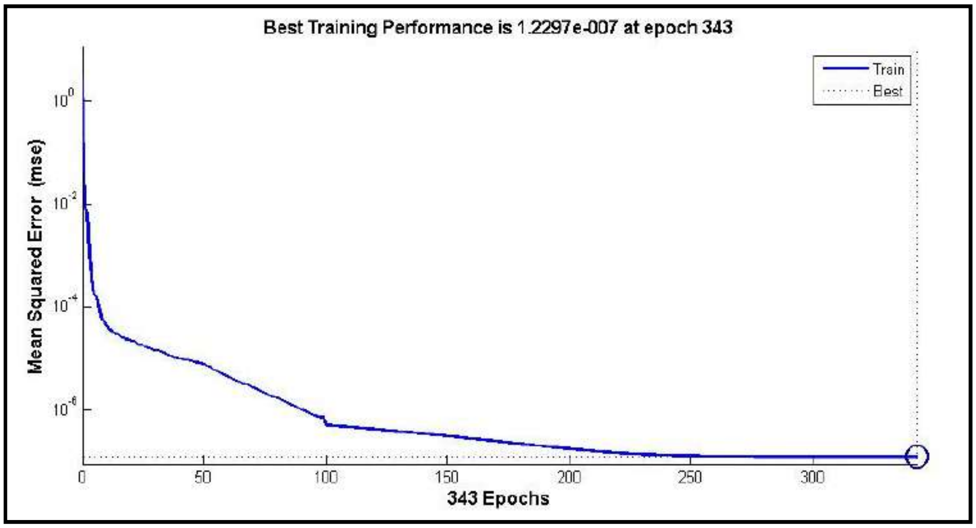

Fig.5.13: Permeate TDS MLP Training Model performance

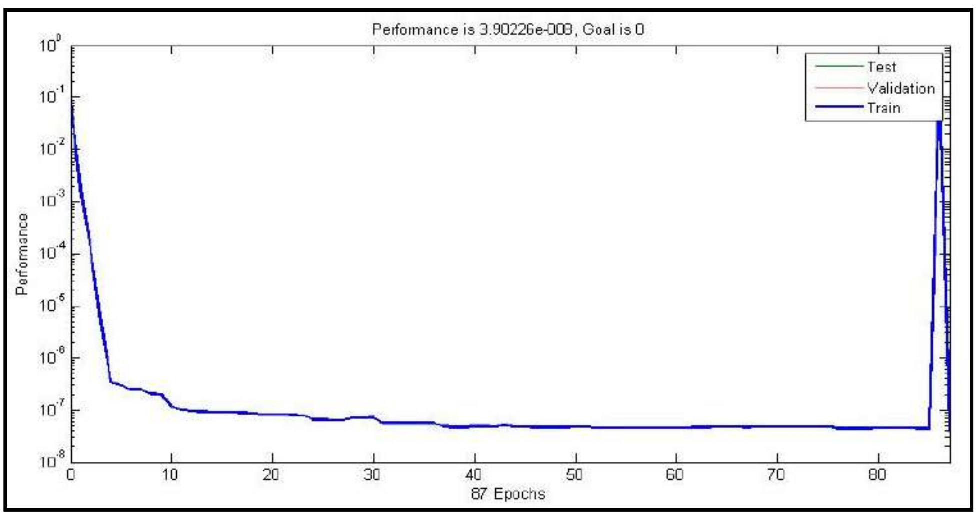

Fig.5.14: Permeate TDS RBF Training Model performance

Table 5.17: Summary of developed ANN models and MLR results for predicting TDS

Models	Data set	MSE	R	S.D	MAE	S.E	Error Range (mg/l)
MLP	**Training**	**0.0227**	**1**	**127.01**	**0.0994**	**13.70**	**0.0010-0.5285**
	Testing	**0.0233**	**1**	**91.92**	**0.1028**	**16**	**0.0026-0.5079**
RBF	**Training**	**0.0072**	**1**	**127.81**	**0.0585**	**13.70**	**0.0008-0.2467**
	Testing	**0.0810**	**1**	**91.89**	**0.1761**	**15.99**	**0.0057-0.9346**
MLR	**Training**	**0.0260**	**1**	**127.81**	**0.1153**	**13.70**	**0.0051-0.5860**
	Testing	**1.2810**	**0.9999**	**91.88**	**1.0885**	**15.99**	**0.0090-1.5871**

The correlations between the predicted TDS and actual values for MLP, RBF model training and testing is found to be very strong and slightly better than MLR model whereas coefficients correlation values are [1-1], [1-1] and [1-0.9999] respectively see (Figs.5.15, 5.16 and 5.17).

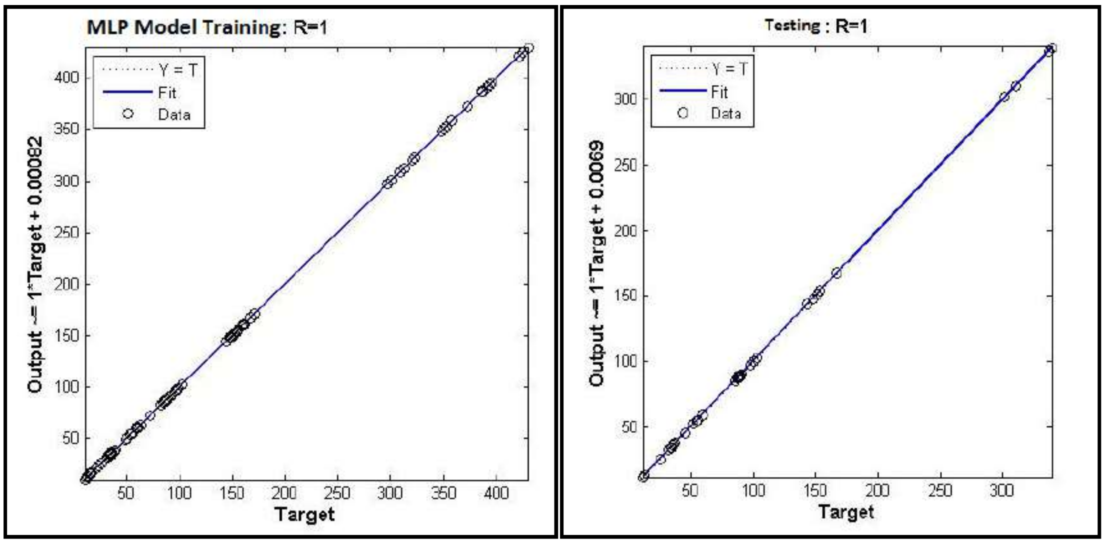

Fig 5.15: TDS MLP Model regression for training and testing data sets

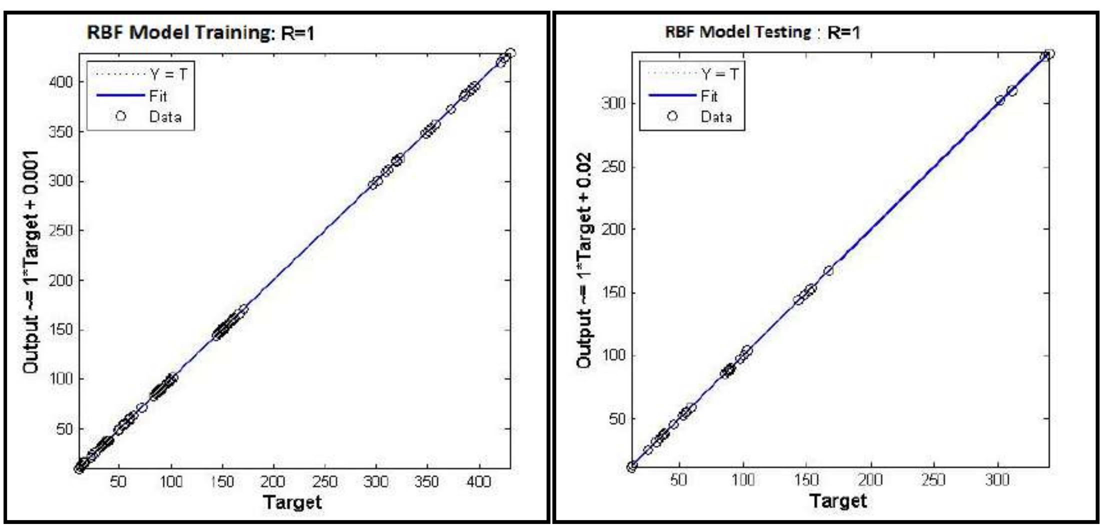

Fig.5.16: TDS RBF Model regression for training and testing data sets

The MLP and RBF networks and MLR performances have been tested with different data sets and the obtained results show very good performance. The results obtained prove that the developed RBF, MLP (neural network models) and MLR have high capability and accuracy in predicting TDS concentrations in the water quality of Gaza strip desalination plants.

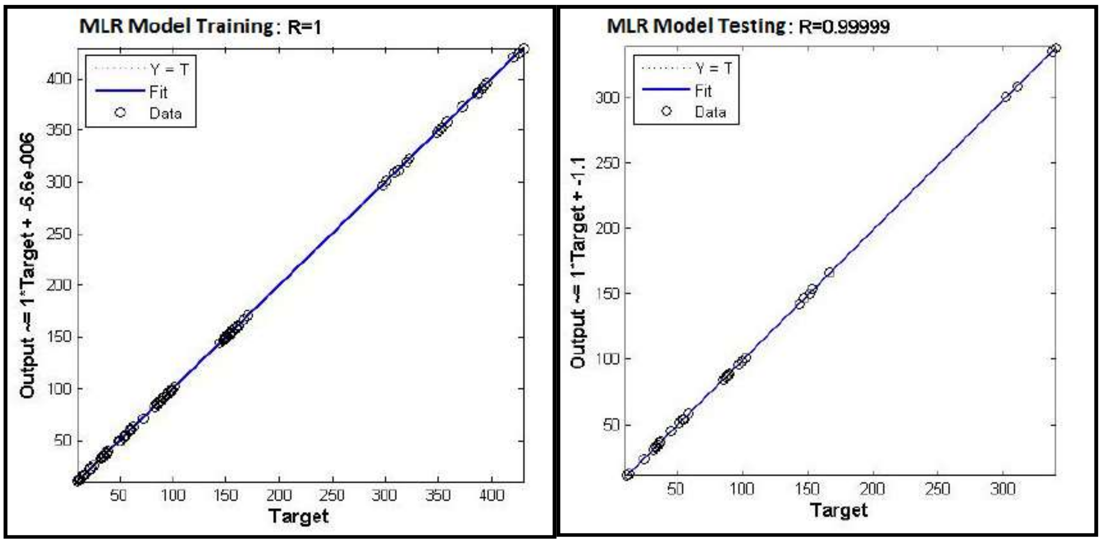

Fig.5.17: TDS MLR Model regression for training and testing data sets

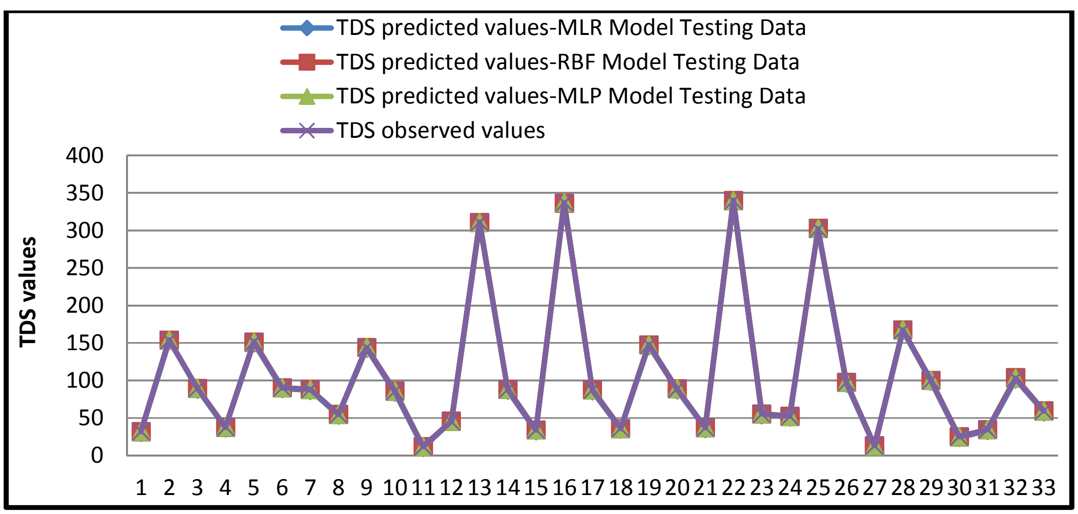

Fig.5.18: Comparison of TDS MLP, RBF&MLR Model-Testing prediction results

Figure 5.18 shows comparisons of MLP and RBF model prediction results with the conventional method predictions. From the above figure it can be understood that the performances of ANN models and conventional models for predicting TDS concentrations are almost same. This good prediction result obtained from the ANN and MLR models is due to the strong correlation between the selected input and output data. As a first case study for desalination plants TDS content modelling, the prediction results prove that the artificial neural networks and multiple linear regression models are suitable and robust for modelling the TDS level in the desalination plants water quality of Gaza strip.

5.2.3 Chloride model

Chlorides concentrations are ranged from 10.72 mg/l to 153.654 mg/l for training data set and from 10.826 mg/l to 121.898 mg/l for testing data set. The mean values for both training and testing data sets are found to be 61.56 mg/l and 48.62 mg/l respectively. The statistical analysis revealed a positive strong correlation between chloride and conductivity (EC) for both training and testing data sets whereas r values found to be 0.985 and 0.983 respectively. Negative strong correlation found to be between chlorides and pressure for both training and testing data sets whereas the r values found to be -0.819 and -0.753 respectively. A positive moderate correlation is found to be between chloride and temperature for both training and testing data sets whereas the r values 0.38 and 0.54 respectively. The correlation between Cl^- and pH is found to be positive and moderate for both training and testing data sets whereas the r values are 0.61 and 0.40 respectively.

For predicting the future concentration (one week a head) of chlorides in the product water quality of the Gaza strip desalination plants, feedforward MLP and RBF neural networks are employed. To develop MLP network several algorithms are used during training process including: Resilient back-propagation, Levenberg Marquardt, Variable learning rate back-propagation, BFGS Qusai-Newton, Bayesian rule and Gradient descent. Details of the developed neural network architectures are presented in Table.3.1 chapter-3. The MLP and RBF neural network prediction results are compared with the multiple regression model prediction results. The trained MLP and RBF networks performance is shown in Fig 5.19 and 5.20 respectively. The summary of developed models results for training and testing data sets as well as multiple regression model are presented in Table 5.18. The parameters (i.e. weights and biases) of both trained MLP and RBF networks are given in annex 2.3. The results obtained from MLP trained with several different algorithms showed that the developed MLP network trained with back-propagation incorporated with

LM algorithm is the most appropriate and fitting model to predict chlorides level in the water quality of desalination plants in the Gaza strip.

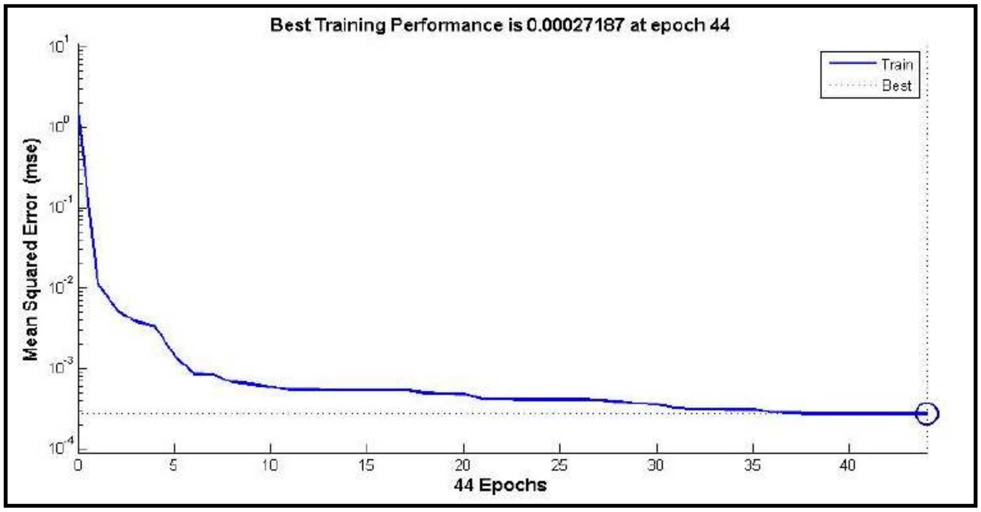

Fig.5.19: Product Chloride MLP Training Model performance

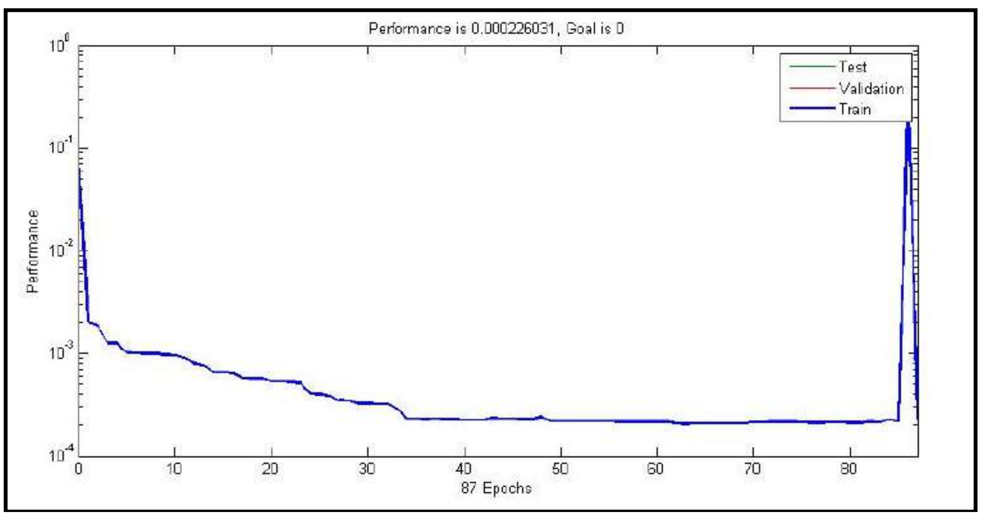

Fig.5.20: Product Chloride RBF Training Model performance

It can be seen from figures 5.19& 5.20 that the trained RBF network performance is slightly better than MLP network. It is also understood from the results tabulated in Table-5.18 which shows the coefficient correlations, performance (MSE), MAE and error range between the observed and predicted values of Cl^- using both MLP, RBF and MLR for training and testing the developed models.

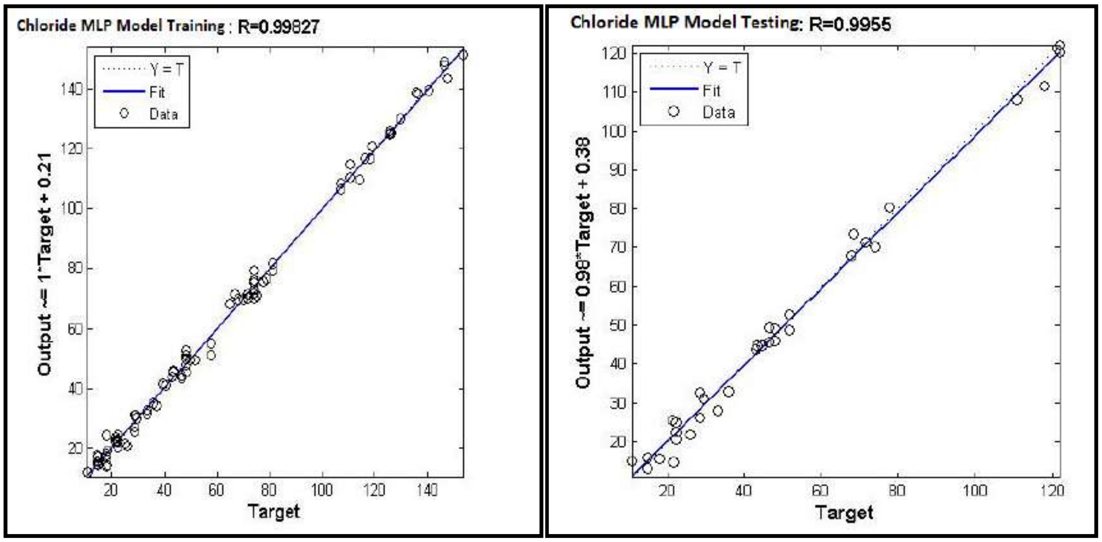

Fig 5.21: Chlorides MLP Model regression for training and testing data sets

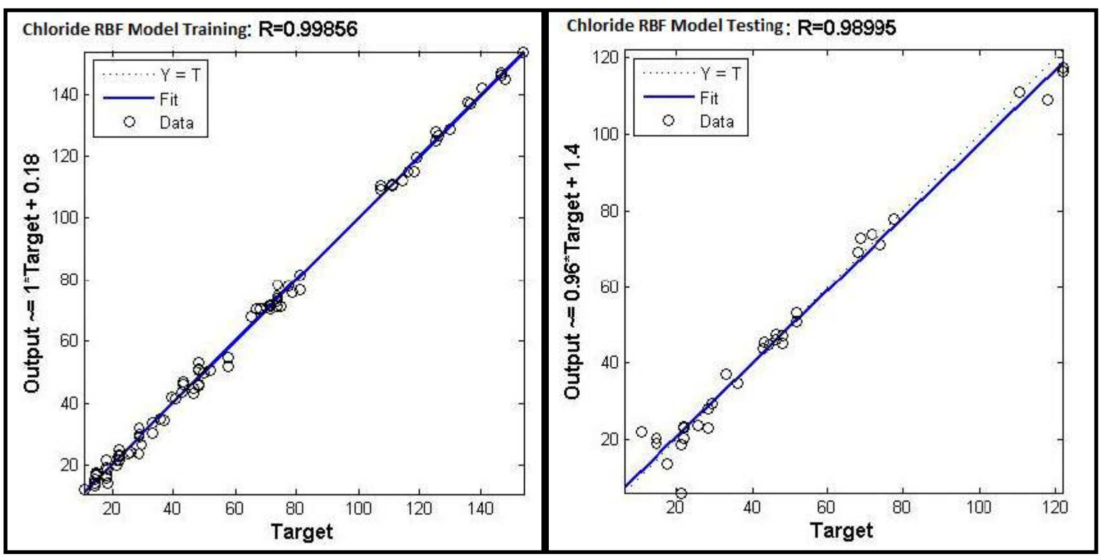

Fig 5.22: Chlorides RBF Model regression for training and testing data sets

The MLP and RBF networks and MLR performances have been validated with different data sets and the prediction results showed very good performance. The correlations between the actual and predicted values of chlorides for MLP, RBF model training and testing is found to be strong and slightly better than MLR model whereas coefficients correlation values are [0.9983-0.9955], [0.99856-0.98995] and [0.99122-0.98563] respectively see (Figs.5.21, 5.22 and 5.23).

The results achieved prove that the developed RBF, MLP (neural network models) and MLR have good competency and precision in predicting chlorides level in the water quality of Gaza strip desalination plants.

Table 5.18: Summary of developed ANN models and MLR results for predicting Chlorides

Models	Data set	MSE	R	S.D	MAE	S.E	Error Range (mg/l)
MLP	Training	5.9354	0.99827	41.60	1.9374	4.46	0.0231-6.4325
	Testing	8.5300	0.99550	31.53	2.3394	5.48	0.0064-6.9426
RBF	Training	04.9346	0.99856	41.61	1.7557	4.46	0.0241-6.4325
	Testing	20.3903	0.98995	30.99	3.0506	5.39	0.0446-11.125
MLR	Training	30.0259	0.99122	41.31	4.2918	4.42	0.2420-19.668
	Testing	27.8076	0.98563	30.24	4.1225	5.26	0.2770-11.781

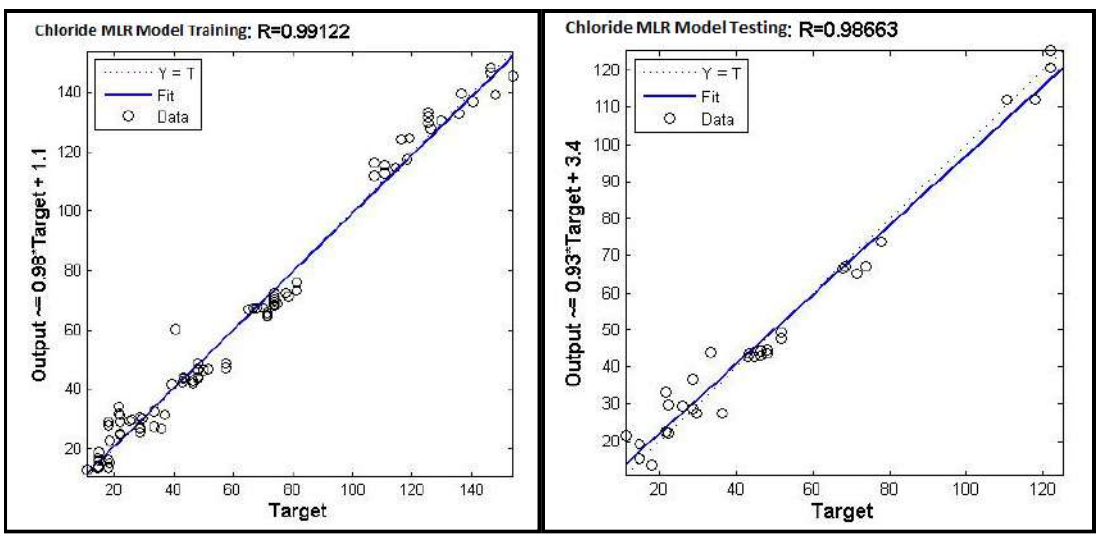

Fig 5.23: Chlorides MLR Model regression for training and testing data sets

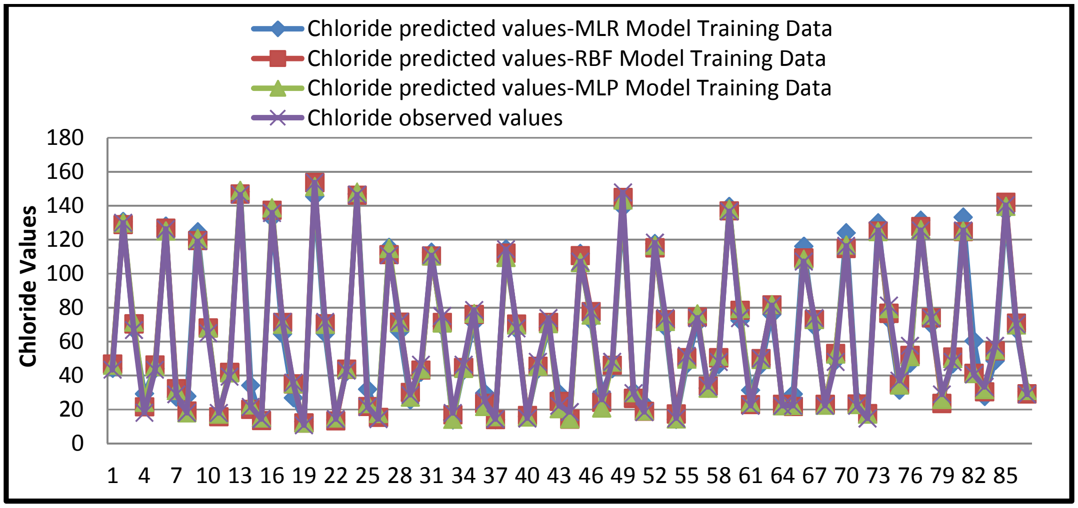

Fig 5.24: Comparison of Chloride MLP, RBF&MLR Model-Training prediction results

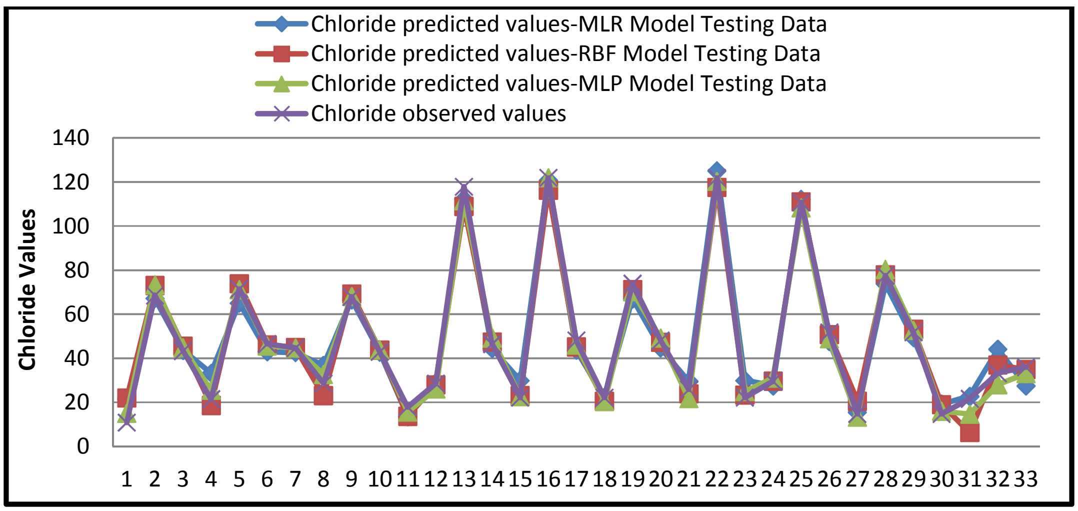

Fig 5.25: Comparison of Chloride MLP, RBF&MLR Model-Testing prediction results

Figures 5.24 and 5.25 show comparisons of MLP and RBF model predictions result of training and testing data sets with the MLR model predictions. From both figures it can be seen that the performances of ANN models are slightly better than MLR model for predicting chlorides level. This good predictions result obtained from the ANN and MLR models is due to the strong and moderate correlation between the selected input and output data. The good prediction results prove that the proposed approach is capable and suitable for modelling Cl^- in the water quality of desalination plants in the Gaza strip.

5.2.4 Nitrate model

Nitrate concentration in groundwater is a major problem in particular agricultural areas. Nitrates, being enormously soluble in water, move certainly through the soil and into the groundwater. Digestion of extreme amounts of nitrates causes ill health effects in infants less than six months old and vulnerable adults. It causes “blue baby syndrome” or Methemoglobinemia in infants, which can lead to brain damage and sometimes death (Ramasamy, et al. 2003). The objective of this section is to predict nitrate concentration in water quality of the desalination plants in the Gaza strip using neural networks and compare the prediction results with multiple regression model. In this study, we assumed that nitrate concentration in water quality depends on EC, pressure, pH and temperature of the product water.

Nitrate concentration NO_3^- values are ranged from 2.91 mg/l to 145.81 mg/l for training data set and from 3.72 mg/l to 141.92 mg/l for testing data set. The mean value among the selected five desalination plants for both training and testing data sets is 38.61 mg/l and 24.52 mg/l respectively. The statistical analysis revealed a positive strong correlation between NO_3^- and electrical conductivity (EC) for both training and testing data sets whereas r values found to be 0.94 and 0.91 respectively. Moderate negative correlation found to be between NO_3^- and pressure for both training and testing data sets whereas the r values found to be -0.64 and -0.53 respectively. A positive close to moderate correlation is found to be between NO_3^- and pH for both training and testing data sets whereas the r values 0.51 and 0.34 respectively. The correlation between NO_3^- and temperature is found to be positive and close to moderate for both training and testing data sets whereas the r values are 0.27 and 0.49 respectively.

For NO_3^- ANN model training and testing purpose, 87 observations (72 % of the data set) were used for training and 33 observations (28% of the data set) were used for testing the model performance. To predict the level of nitrates in water quality the feedforward MLP and RBF neural networks are employed. Then MLP and RBF neural network prediction results compared with the traditional statistical method (multiple regression model). The trained MLP and RBF networks performance is presented in Fig 5.26 and 5.27 respectively. The mean squared error (MSE) and mean absolute error (MAE) are calculated for the testing data set and then compared with the mean squared error of the training data set. The mean squared error, MAE, correlation coefficients, standard deviation, standard error and errors range for both the training and testing data sets are shown in Table 5.19. The mean squared for the testing data set found to closer to that of the training data set, implying that the predictions are similar for both the testing data set and the training data set. A paired t-test was done to check if any statistically significant difference existed between the actual NO_3^- and predicted NO_3^- for the validation data set. The probability of the calculated t-value and p-value for MLP, RBF and MLR training and testing data sets found to be [0.000005-0.057], [0.5-0.47709] and [0.001547-0.0272], [0.49938-0.489] and [0.000003-0.1763], [0.5-0.4302] respectively. Thus, no statistically significant difference exists at 0.05 confidence intervals between the actual NO_3^- and predicted NO_3^- for the testing data set of both MLP and RBF developed models.

The parameters (i.e. weights and biases) of both trained MLP and RBF networks are given in annex 2.4. The prediction results achieved by MLP used several different algorithms revealed that the developed MLP network which trained with back-propagation incorporated with LM algorithm is the most fitting model for predicting nitrate concentrations in the product water quality of desalination plants in the Gaza strip.

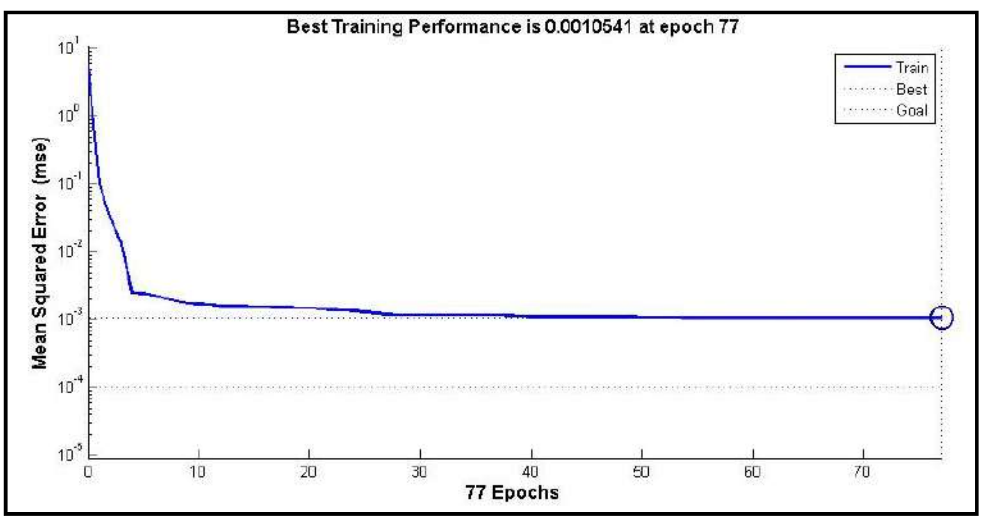

Fig.5.26: Product Nitrates MLP Training Model performance

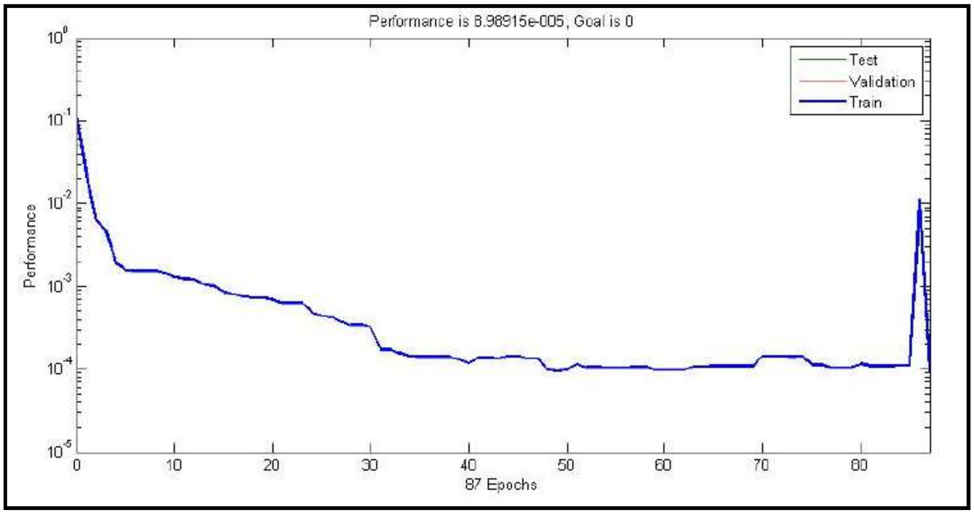

Fig.5.27: Product Nitrates RBF Training Model performance

Table 5.19: Summary of developed ANN models and MLR results for predicting Nitrates

Models	Data set	MSE	R	S.D	MAE	S.E	Error Range (mg/l)
MLP	Training	22.4116	0.99552	50.11	2.8759	5.37	0.0356-16.025
	Testing	27.7861	0.98972	37.15	3.4713	6.46	0.0831-15.373
RBF	Training	01.9113	0.99962	50.31	1.0118	5.39	0.0286-06.2404
	Testing	17.6708	0.99511	34.77	2.7143	6.05	0.1064-13.4489
MLR	Training	226.5559	0.95370	48.00	12.242	5.15	0.3977-40.4387
	Testing	173.9108	0.93386	33.90	11.159	5.90	0.9208-29.2750

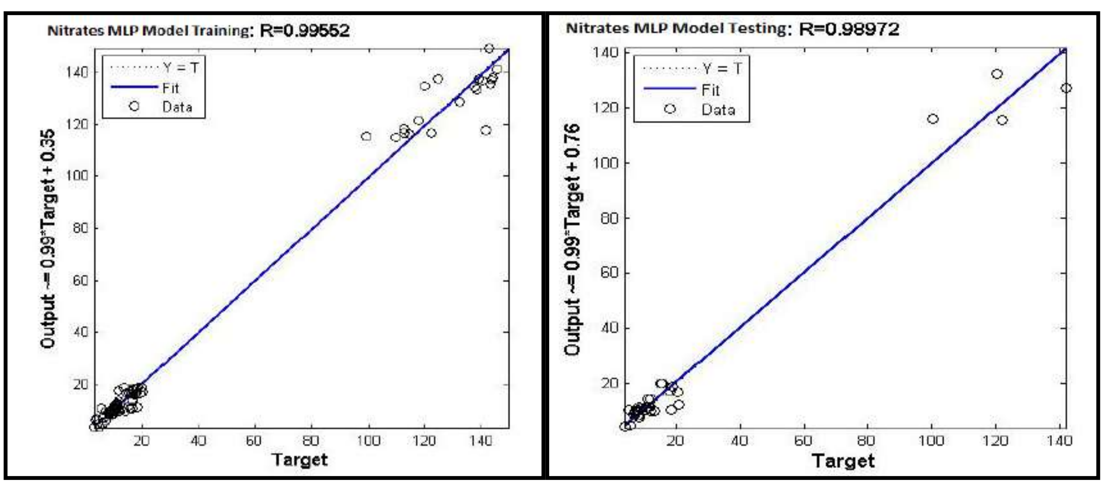

Fig.5.28: Nitrates MLP Model regression for training and testing data sets

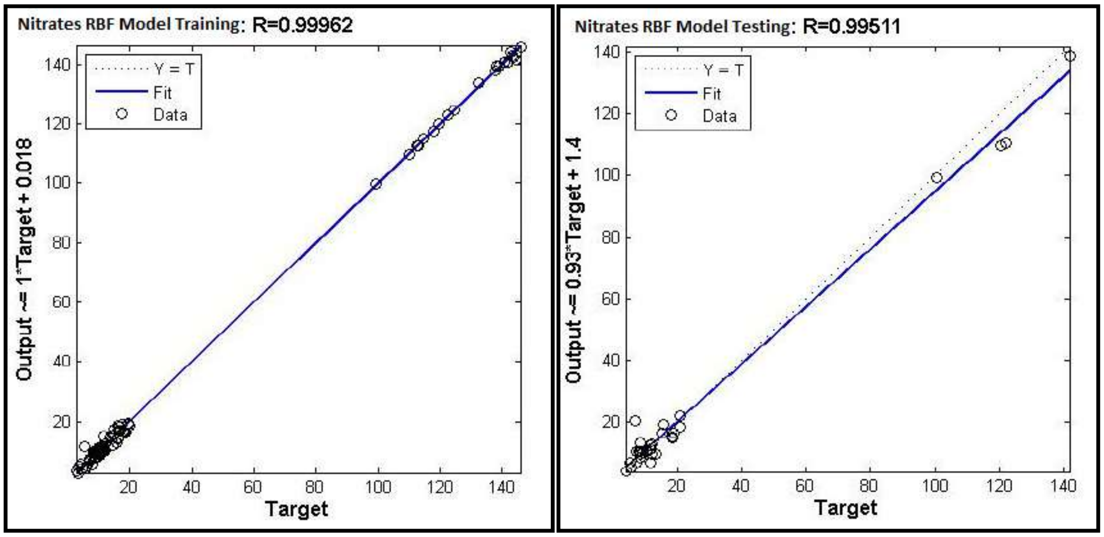

Fig.5.29: Nitrates RBF Model regression for training and testing data sets

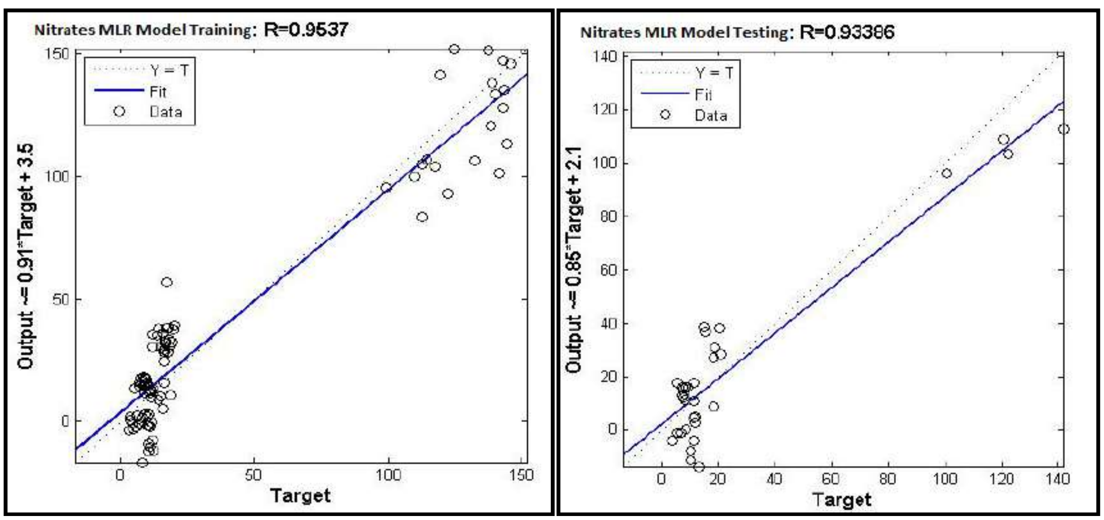

Fig.5.30: Nitrates MLR Model regression for training and testing data sets

The MLP and RBF networks performances have been tested with different data sets and the prediction results showed good performance. The correlations between the actual and predicted values of NO_3^- for MLP and RBF model training and testing is found to be strong and better than MLR model whereas coefficients correlation values are [0.99552-0.98972], [0.99962-0.99511] and [0.9537-0.93386] respectively see (Figs.5.28, 5.29 and 5.30). The prediction results of RBF model found to be slightly better than MLP in both training and testing data sets. The multiple linear regression statistical models could not predict about 20% of nitrate values in both training and testing data sets as several values obtained negatively. The achieved results demonstrate that the developed RBF and MLP (neural network models) have good capability and better than MLR in predicting nitrates level in the product of water quality in the desalination plants of Gaza strip.

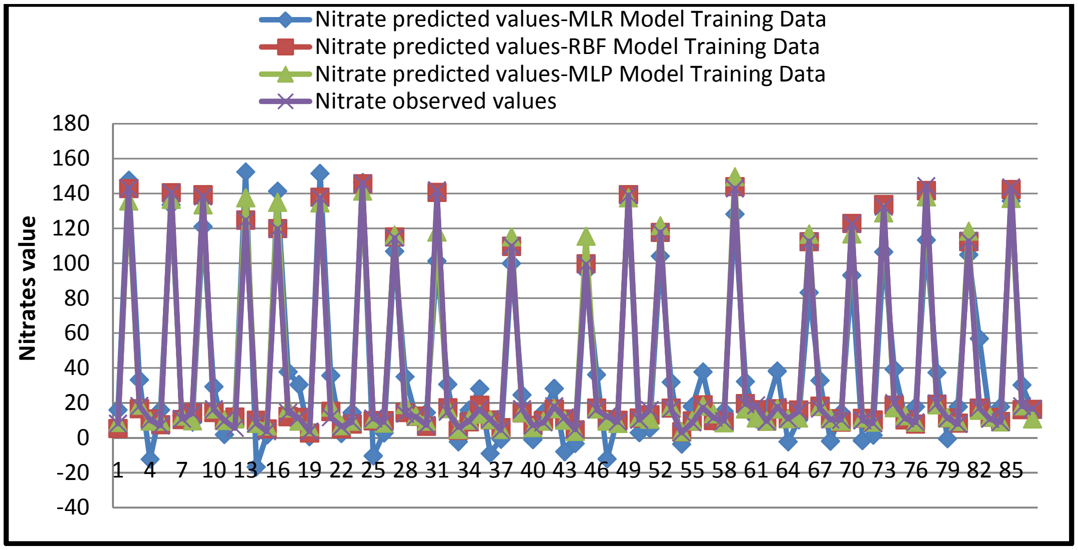

Fig 5.31: Comparison of Nitrates MLP, RBF&MLR Models-Training prediction results

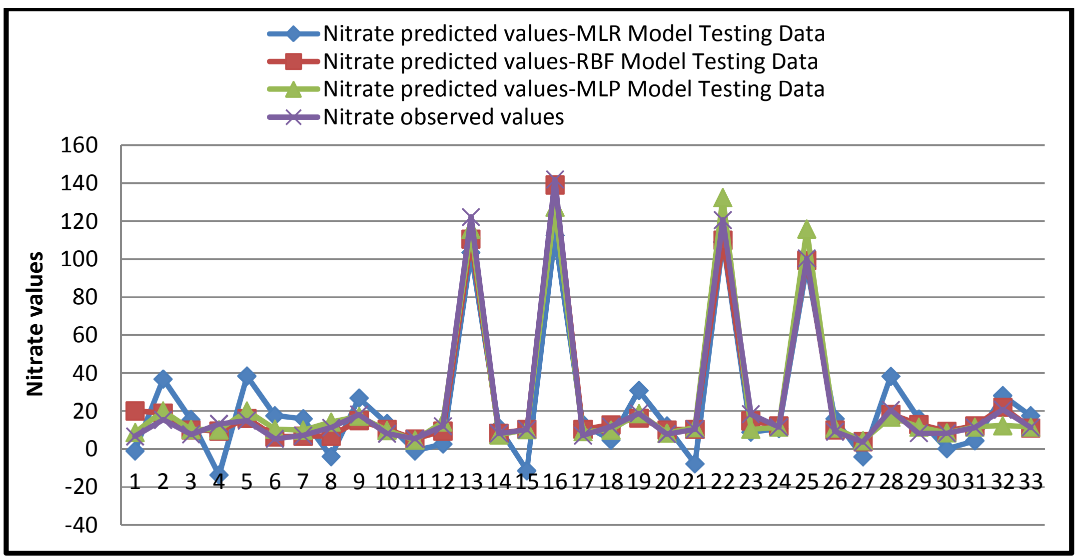

Fig 5.32: Comparison of Nitrates MLP, RBF&MLR Models-Testing prediction results

The prediction results of MLP and RBF models have been compared with statistical model by means of linear regression method in Minitab software and found that ANN predictions are better than conventional methods (Figs 5.31 and 5.32). From both figures it can be seen that the performances of ANN models are better than MLR model for predicting nitrates level. The good prediction results prove that the proposed approach is capable for modelling NO_3^- in the water quality of desalination plants in the Gaza strip.

5.2.5 Magnesium model

Based on the poor quality of what comes out of the municipal tap, health-conscious people often rely on bottled or home-filtered water for their drinking needs. While most desalinated, filtered and bottled waters are free of cancer-causing pollutants, they supply little or no magnesium. Even most tap water is bare of this very important mineral. The inferences of this prevalent magnesium deficiency are alarming, in as much as populations with low magnesium contented in drinking water show increased rates of sudden death. Magnesium plays hundreds of vital roles in the body, including: suppressing unstable heart rhythms, controlling blood pressure, maintaining insulin sensitivity, and regulating over 300 enzymes. Achieving best magnesium levels is an entire requirement for worthy health (Davis, 2007).

Magnesium (Mg^{2+}) values are ranged from 0.478 mg/l to 5.782 mg/l for training data set and from 0.1608 mg/l to 3.865 mg/l for testing data set. The mean value among all desalination plants for both training and testing data sets is 1.89 mg/l and 1.95 mg/l respectively. The statistical analysis showed a negative moderate correlation between Mg^{2+} and pressure whereas r values found to be (-0.29 & -0.38). A positive weak correlation observed between magnesium and chloride as well as conductivity for both training data and testing data sets whereas r values are found to be (0.31-0.34) and (0.29-0.29) respectively.

For predicting one week ahead Mg^{2+} concentrations in the desalination plants of the Gaza strip, feedforward MLP and RBF neural networks are employed. For constructing MLP network a number of algorithms are investigated during training process including: Resilient back-propagation, Levenberg Marquardt, Variable learning rate back-propagation, BFGS Qusai-Newton, Bayesian rule and Gradient descent. The methodology of Mg^{2+}constructed network architecture is given in Table 3.1 chapter-3. The results obtained from MLP trained with several different algorithms showed that the constructed MLP network which trained with back-propagation incorporated with LM algorithm is the most fitting model for predicting Mg^{2+} concentrations in the water quality of desalination plants in the Gaza strip. The MLP and RBF neural network prediction results were compared with the multiple linear regression model. The trained MLP and RBF networks performance is presented in Fig 5.33 and 5.34 respectively. The prediction results for ANN training and testing data sets as well as multiple linear regression model are given in Table 5.20. The parameters (i.e. weights and biases) of both trained MLP and RBF networks are given in annex 2.5.

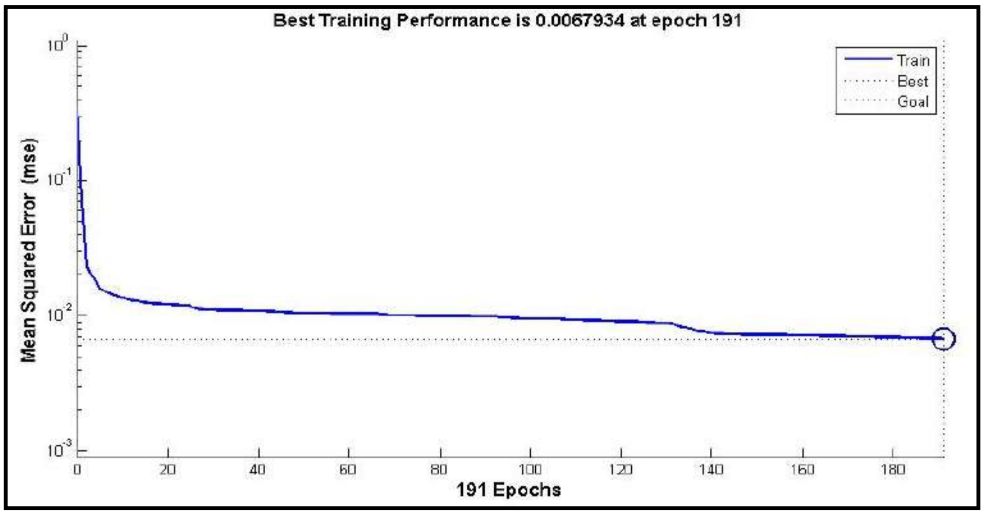

Fig.5.33: Product Magnesium MLP Training Model performance

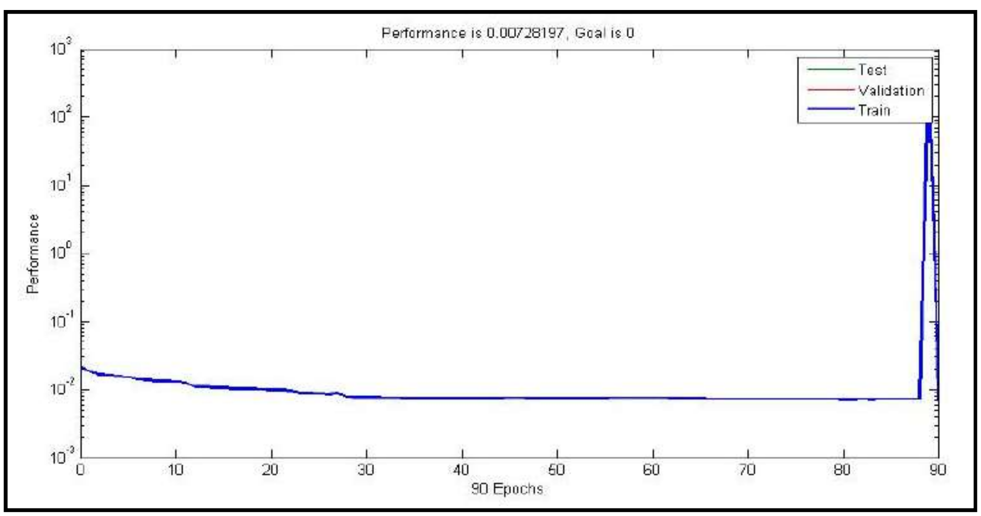

Fig.5.34: Product Magnesium RBF Training Model performance

It can be seen from figures 5.33& 5.34 that the constructed MLP network performance is slightly better than RBF network. Also it can be understood from the results shown in Table 5.20 which presents the coefficient correlations between the observed and predicted values of $Mg2^{+}$ using MLP and RBF as well as MLR for training and testing created models.

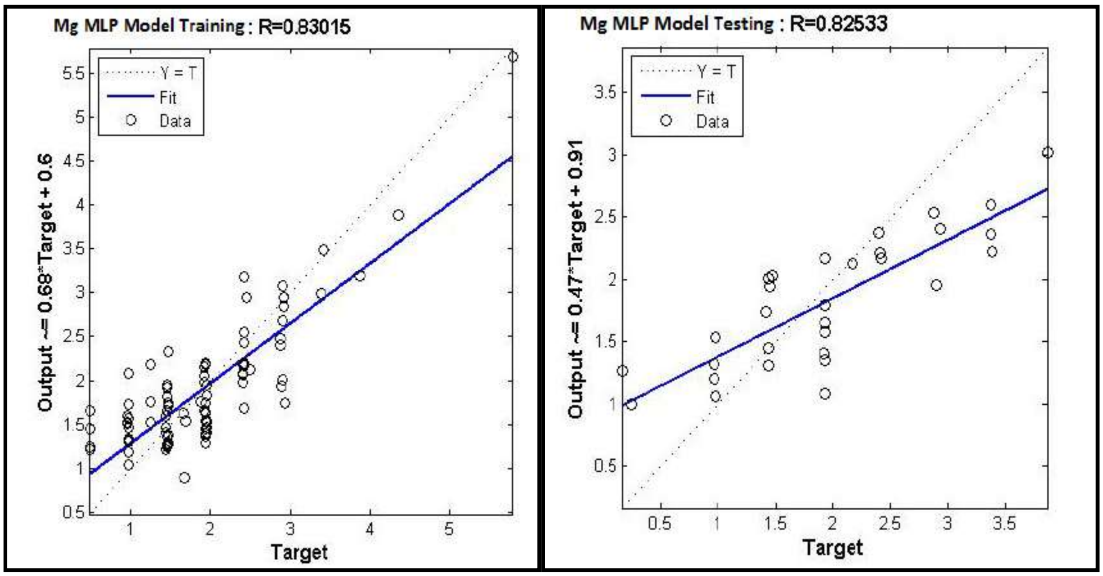

Fig.5.35: Magnesium MLP Model regression for training and testing data sets

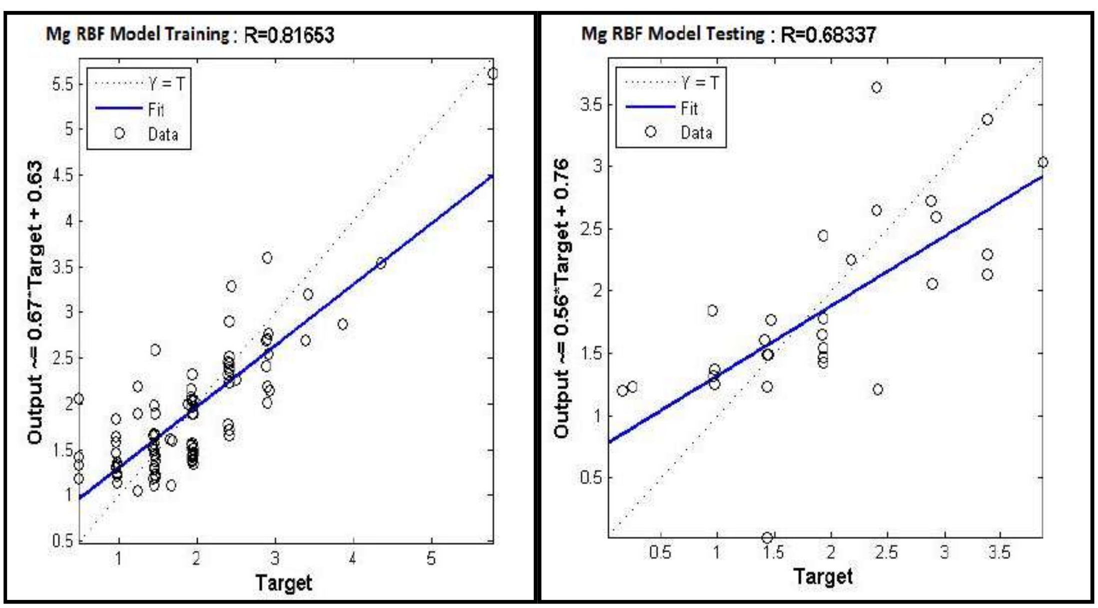

Fig.5.36: Magnesium RBF Model regression for training and testing data sets

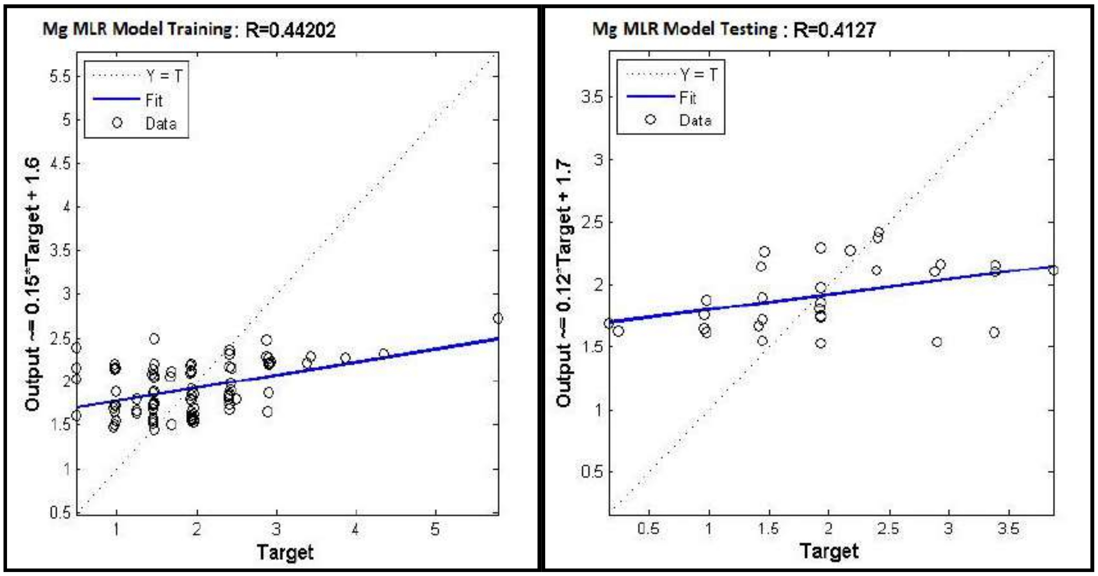

Fig.5.37: Magnesium MLR Model regression for training and testing data sets

Table 5.20: Summary of ANN models and MLR prediction results for Magnesium

Models	Data set	MSE	R	S.D	S.E	MAE	Error Range (mg/l)
MLP	Training	0.2271	0.83015	0.7068	0.0745	0.3833	0.0012-1.193
	Testing	0.3323	0.82533	0.5245	0.0957	0.4759	0.0132-1.155
RBF	Training	0.2437	0.81653	0.7017	0.0773	0.3871	0.0034-1.579
	Testing	0.4639	0.68337	0.7541	0.1376	0.5407	0.0003-1.411
MLR	Training	0.6666	0.44202	0.2920	0.0309	0.5658	0.0048-3.228
	Testing	0.6962	0.41270	0.2735	0.0499	0.6424	0.0249-1.753

The MLP and RBF networks performances have been validated with different unknown data sets and the prediction results showed acceptable performance as compared to the other developed models mentioned earlier. The correlations between the actual and predicted values of $Mg^{2+}$for MLP and RBF model training data set are found to be strong, and found to be strong for MLP model testing data set while found to be moderate for RBF model testing data set. Prediction results are also found to be better than MLR model whereas coefficients correlation values are [0.83015-0.82533], [0.81653-0.68337] and [0.44202-0.41270] respectively see (Figs.5.35, 5.36 and 5.37).

The prediction results of MLP model found to be slightly better than RBF in both training and testing data sets. The multiple linear regression statistical model could not predict about 30-50% of Mg^{2+}values in both training and testing data sets respectively. The achieved results demonstrate that the developed MLP and RBF (neural network models) have acceptable capability and better than MLR in predicting magnesium concentrations present in the product water of desalination plants in the Gaza strip.

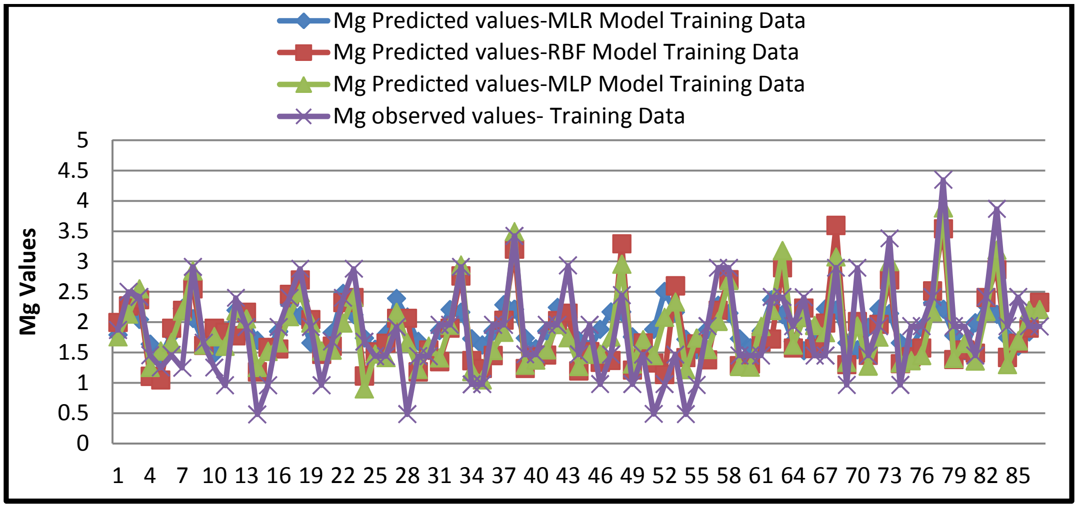

Fig 5.38: Comparison of Mg^{2+} MLP, RBF&MLR Models-Training prediction results

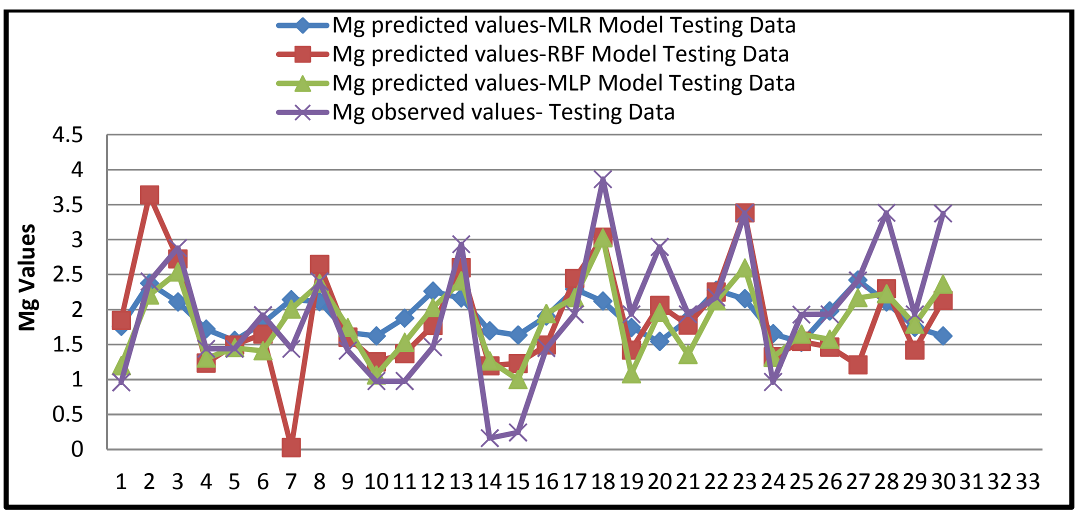

Fig 5.39: Comparison of Mg^{2+} MLP, RBF&MLR Models-Testing prediction results

Figures 5.38 and 5.39 show comparisons of MLP and RBF model predictions result of training and testing data sets with the MLR model predictions. From both figures it can be seen that the performances of ANN models are better than MLR model for predicting magnesium concentrations. As compared with the flowrate, TDS and chloride developed models Mg^{2+} model showed deprived prediction results. This is may be due to the weak correlation coefficients between the selected input and output data. Further improvement can be made to upgrade the performance of ANN and MLR for predicting Mg^{2+} level. This could be improved with selection of more appropriate water quality parameters.

5.2.6 ANN developed models verification

The training, testing and verification of ANN developed models for the desalinated water quality parameters prediction are carried out using neural network toolbox in the MATLAB. During this research five ANN models were developed to predict the performance of desalination plants in the Gaza strip including: permeate flowrate, TDS, chloride, nitrate and magnesium. All five developed models are discussed above in detail.

The performance of these developed ANN models obtained after training and testing is required to be verified by using other unknown data set. However, the required data for developed models verification purpose is collected from other four different desalination plants located in Gaza strip governorates. For verification purpose the MLP parameters (i.e. weights and biases) of the earlier developed ANN models are used to predict water quality parameters including: permeate flowrate, TDS, chloride, nitrate and magnesium for testing developed models performance.

The ANN developed models verification prediction results are tabulated in Table 5.21.The results showed that the ANN developed models have good capability and accuracy in predicting the performance of desalination plants in the Gaza strip. As a first case study for Gaza desalination plants performance modelling, the prediction results prove that the artificial neural network is suitable and capable for modelling the water quality in the desalination plants. Further improvement can be made to upgrade the performance of the network and increase the accuracy of prediction results. This can be done by adding more water quality parameters in the input data and increase the training data set size.

Table 5.21: The developed ANN models verification prediction results

ANN Models	Observed	Predicted	ANN Models	Observed	Predicted
Permeate Flowrate	20.0000	23.4028	**TDS**	145.700	134.452
	08.4000	09.2535		11.7430	10.6547
	08.3000	09.2712		11.4510	10.4897
	50.0000	49.9817		64.7000	59.8663
Chloride	46.9810	49.6287	**Nitrate**	08.1840	07.5160
	17.8660	16.3516		05.4270	04.2814
	17.8670	15.1262		07.0630	10.8693
	84.9590	82.9987		21.3880	17.7467
Magnesium	1.4570	1.4706			
	0.9770	1.0626			
	1.9560	1.3916			
	3.8650	4.2540			

CHAPTER 6
CONCLUSIONS AND RECOMMENDATIONS

In this work the assessment of feed and permeate water quality of five selected desalination plants in the Gaza strip was studied for understanding the current status of desalination plants performance and their environmental impacts. During this study the application of ANN approach was performed successfully for predicting various environmental parameters including: permeate flowrate, TDS, Cl^-, NO_3^- and Mg^{2+}. The developed models can be used for quick assessment of desalination plants performance for the management purpose. Also the models can be used for filling the gap of missing data in the database system. The following conclusions are prepared based on the analysis of this research work obtained results.

6.1 CONCLUSIONS

- Clearly, desalination of brackish water and seawater is a necessary alternative in the Gaza strip. Correlating with other desalination technology, it seems that RO is the best choice in terms of quality of produced water or the cost of treatment. However, the impact of these plants is not well investigated. Desalination has different effects including environmental, social, and economic. Because of the Israeli siege on the Gaza strip, looking for new sources of energy to be utilized for desalination purpose is very important to establish an autonomous source of electricity. Even though RO is auspicious technology, it needs highly professional people to operate and control the desalination facilities. Therefore, may be the membranes need replacing very often which is costly. Also a supply of chemicals needed for desalination process should be secured so as to ensure continuous operation of the facility. The environmental issue should be studied well before implementing the regional desalination plant if it is proposed. The PWA should strictly control the private sector that builds desalination units for commercial purposes to ensure that they consider environmental aspects. Presently, the brine of these inland units is disposed in the field or in the surrounding environment.

- An effort to evaluate and investigate performance of desalination plants in the Gaza strip in terms of feed and permeate quality and operational conditions was made. Operationally, all selected plants were found to have almost similar performance except for some slight differences in terms of capacity of desalinated water. From a quality point of view, turbidity, pH (except all plants in terms of permeate water), hardness and calcium (except for plants Deir-Al_Balah & Hanneaf in case of hardness and calcium for feed water) concentration levels for feed and permeate of all plants were found to be within WHO and Palestinian drinking water standards whereas nitrate concentration levels were found to be exceeding the maximum concentrations allowed by WHO and Palestinian standards for all plant feed. The chloride, TDS and conductivity concentrations of all plant feeds were higher than the WHO and Palestinian standards but the permeate water was found to be in compliance with those standards significantly. However, magnesium concentrations for the feeds and permeate of all plants (except for Deir-Al_Balah plant in terms of feed water and Hanneaf plant which found to be higher than the allowed concentrations in WHO in case of feed water) were found to be complying only with Palestinian standards. Generally, all plants are normally performing but the need to improve and increase their production without increasing their water resource abstraction and energy consumption is essential to meet the water demand of the Gaza strip inhabitants. In addition, pre-treatment of feed water with the application of some new technologies may significantly improve plant performance and potentially increase their water production.

- Initially, MLP and RBF neural networks were successfully developed to predict the one week ahead values of permeate flowrate, TDS, chlorides and nitrate in Gaza strip desalination plants. It was found that the MLP predictive model was slightly better than RBF models. The models were developed based on the data collected from five desalination plants in the Gaza strip. Another predictive MLP and RBF model was trained to predict magnesium concentration. In comparison with the flowrate, TDS, chloride and nitrate developed models; Mg^{2+} predictive model showed less accuracy prediction results. The developed models were compared with statistical models and it was found that the prediction results of ANN were better than the conventional methods.

- The developed ANN models in this study may be used as a new predictive tool to improve the performance and management practices of desalination plants in the Gaza strip.

6.2 SUGGESTIONS AND RECOMMENDATIONS

- It is suggested that generated saline water from desalination plants should be properly disposal under the control of PWA. In addition the quality of permeate water should be also monitored regularly to ensure that it meets health requirements.

- An important issue is the pumping of brackish water for desalination purpose from the coastal aquifer. It is factual that this water is not drinkable, but it is located in layers underneath the underground freshwater. Depletion of these layers of brackish water may cause dropping of the water table and intrusion of seawater affecting the unsaturated area. Hence, it is recommended that the effect of pumping this brackish water should be studied and investigated to prevent such damage to the aquifer.

- The multi criteria method commonly used to evaluate desalination plants performance it is recommended to be used as a guiding tool to prioritize the application for the improvements and developments of desalination plants efficiency.

- New technologies including Nano-filtration membrane (NF) application is recommended to be considered and experimentally investigated for measuring the possibility of enhancing the performance of the desalination plants and increasing production in the near future. In addition, effluent brine treatment technology prior to disposal may be studied and recommended.

- During this study it was observed that the TDS values of desalinated water in some of the selected desalination plants were in very low rate, which indicating that the rate of minerals in the water is very small. Hence, it is recommended to mix the desalinated water with brackish water by certain proportions that meeting with the WHO and Palestinian drinking water quality standard. This is required for maintaining access to the healthy water and keeping the level of total dissolved solids within the range.

- It was observed that some of the desalination plants (reverse osmosis) equipment's are not functioning properly. Therefore, it is recommended to conduct a periodic maintenance and cleaning process for all desalination plants in the Gaza strip.

- It is recommended to keep equivalency degree of acid and alkali in the desalinated water to maintain a moderate level of pH within the rate presented by the WHO and Palestinian drinking water quality standards (6.5-8.5).

- It is suggested to expand the scope of water desalination and constructing drinking water networks for distributing desalinated water to a large number of areas in the Gaza strip.

- An important issue suggested to be investigated in the future lies in establishing if the proposed ANN approach will prove robust and accurate enough even when applied to other water quality parameters such as (faecal indicator bacteria etc.).

- Further research efforts are to be suggested and directed towards an improved understanding of ANN performance in permeate flowrate, TDS, nitrate pollution level and magnesium modelling.

- It is suggested to investigate the systematic elimination of input parameters to further distinguish between critical and non-critical ANN inputs.

- It is suggested to simulate the desalination plants performance through membrane separation. This may be done by using ANN to predict the performance of a single unit then predicting a whole desalination plant.

- It is recommended to use ANN to predict the best membrane fabrication or membrane modification techniques.

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ANNEXES

Annex 1: Feed and Permeate Water Quality Parameters

ANNEX 1.A FEED WATER QUALITY PARAMETERS

Annex 1.1 – A (Al-Salam Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
18.03.2013	1S	23.6	15.0	75.60	7.83	5180	3210	0.28	384.380	1097.080	59.148	57.405	64.988
25.03.2013	6S	23.9	15.0	76.80	7.81	5120	3170	0.26	310.596	1097.078	52.958	43.252	55.475
01.04.2013	11S	24.3	15.0	76.80	7.75	5060	3130	0.29	360.360	1082.640	60.312	50.868	64.033
08.04.2013	16S	24.3	15.5	72.60	7.82	4960	3070	0.31	360.360	1100.059	58.725	51.832	56.540
18.04.2013	21S	23.9	15.0	75.00	7.83	4850	3010	0.26	340.560	1079.155	57.138	47.138	53.344
25.04.2013	26S	23.9	15.0	75.00	7.82	4820	2988	0.24	348.480	1086.302	57.138	49.911	61.139
29.04.2013	31S	23.9	15.5	78.00	7.8	4790	2970	0.21	356.400	1093.448	57.138	51.834	72.415
06.05.2013	36S	24.2	15.5	72.00	7.82	4840	3000	0.23	348.480	1107.742	53.964	51.837	64.776
15.05.2013	41S	23.9	15.5	72.00	7.84	4770	2960	0.23	379.008	1107.742	61.409	54.729	63.228
22.05.2013	46S	24.3	15.0	72.00	7.69	4750	2940	0.27	374.976	1157.768	61.409	53.751	73.991
27.05.2013	51S	24.3	15.2	73.20	7.74	4730	2930	0.23	358.848	1150.622	61.409	49.836	62.107
05.06.2013	56S	24.4	15.5	72.00	7.76	4710	2920	0.23	370.944	1137.718	59.793	53.753	69.731
10.06.2013	61S	24.4	15.5	72.00	7.78	4700	2910	0.35	358.848	1122.943	59.793	50.816	57.399
17.06.2013	66S	24.4	15.2	73.20	7.8	4620	2860	0.30	362.880	1130.330	59.793	51.795	68.834
26.06.2013	71S	24.8	15.0	73.20	7.81	4730	2930	0.29	378.480	1145.106	62.275	54.076	64.798
01.07.2013	76S	24.6	15.0	75.00	7.72	4950	3070	0.53	378.480	1145.106	60.678	55.045	65.919
08.07.2013	81S	24.6	15.5	72.00	7.76	4920	3050	1.02	378.480	1137.718	63.871	53.107	73.543
15.07.2013	86S	24.6	15.5	72.00	7.75	4880	6026	0.62	376.488	1137.720	62.275	53.592	72.197
22.07.2013	91S	24.5	15.0	72.00	7.73	4840	3000	0.21	374.496	1137.718	60.678	54.078	70.852
29.07.2013	96S	24.6	15.0	72.00	7.76	4880	2970	0.33	386.448	1115.555	63.871	55.041	76.905
19.08.2013	101S	24.9	14.0	72.00	7.57	4850	3000	0.23	386.448	1165.809	63.871	55.041	63.228
27.08.2013	106S	24.5	15.0	78.00	7.77	4800	2980	0.31	382.464	1122.631	62.275	55.043	65.919
02.09.2013	111S	24.6	15.0	75.00	7.73	4770	2960	0.20	382.464	1137.023	60.678	56.012	59.417
09.09.2013	116S	24.7	15.0	73.20	7.82	4680	2900	0.24	382.464	1122.631	59.081	56.981	65.471

Annex 1.2-A (Al-Sharqia Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
18.03.2013	2S	16.2	13.0	22.0	7.00	4400	2730	0.19	317.460	1010.47	43.330	50.760	274.750
25.03.2013	7S	15.2	12.0	23.0	7.17	4320	2680	0.23	260.832	952.725	39.891	39.103	382.250
01.04.2013	12S	23.9	12.0	24.0	7.41	4260	2640	0.23	295.020	934.682	52.376	39.825	262.250
08.04.2013	17S	23.4	11.0	23.0	7.09	4180	2590	0.29	297.000	957.66	49.202	42.232	138.593
15.04.2013	22S	17.6	13.0	23.0	7.15	4170	2580	0.25	289.080	957.66	49.202	40.309	133.407
25.04.2013	27S	23.7	12.0	23.0	7.31	4090	2540	0.20	300.960	936.22	44.441	46.082	320.179
29.04.2013	32S	24.9	12.0	23.0	7.34	4060	2520	0.12	297.000	957.66	46.027	44.158	244.750
06.05.2013	37S	24.6	13.0	23.0	7.32	4070	2520	0.15	289.080	943.367	46.028	42.235	133.222
15.05.2013	42S	23.3	12.0	23.0	7.11	3980	2470	0.28	290.304	957.66	45.248	43.006	404.750
20.05.2013	47S	24.8	13.0	23.0	7.24	3960	2460	0.20	294.336	971.954	46.865	43.003	282.063
27.05.2013	52S	24.6	13.0	23.0	7.44	3930	2440	0.22	294.336	979.101	45.248	43.984	286.995
05.06.2013	57S	25.2	13.0	23.0	7.31	3890	2410	0.11	294.336	938.248	45.248	43.984	310.762
10.06.2013	62S	25.0	12.5	23.0	7.38	3920	2430	0.20	322.560	967.799	46.865	49.854	245.291
17.06.2013	67S	24.7	11.5	23.0	7.64	3790	2350	0.26	290.304	923.473	46.865	42.025	281.166
26.06.2013	72S	25.9	13.0	23.0	7.55	3890	2410	0.18	298.800	953.024	46.307	168.055	263.677
01.07.2013	77S	25.7	11.5	23.0	7.23	4110	2550	0.31	314.736	960.411	47.904	47.324	266.816
08.07.2013	82S	25.6	11.0	23.0	7.23	4060	2510	0.17	302.784	975.187	47.904	169.995	327.354
15.07.2013	87S	26.0	12.0	23.0	7.32	4010	2480	0.31	306.768	945.636	44.710	47.328	273.094
22.07.2013	92S	25.3	11.0	25.4	7.23	4000	2480	0.17	314.736	967.799	46.307	48.293	288.789
29.07.2013	97S	25.6	11.0	25.4	7.78	3980	2468	0.20	320.712	966.055	47.904	48.775	286.995
19.08.2013	102S	25.9	11.5	23.0	7.83	3960	2460	0.23	326.688	964.311	49.500	49.256	285.202
26.08.2013	107S	25.9	12.0	23.0	7.62	3920	2430	0.14	294.816	935.525	43.113	45.397	311.211
02.09.2013	112S	25.7	11.0	22.0	7.63	3880	2400	0.23	294.816	935.525	44.710	44.427	245.739
09.09.2013	117S	25.1	11.5	24.0	7.09	3870	2400	0.24	318.720	935.525	47.904	48.291	296.413

Annex 1.3-A (Al-Balad Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
18.03.2013	3S	23.2	14.5	60.0	7.12	6520	4040	0.16	1177.170	1645.620	162.314	187.230	148.407
26.03.2013	8S	24.1	14.5	60.0	7.05	6480	4020	0.16	964.390	1652.834	136.866	151.025	132.481
01.04.2013	13S	23.9	14.5	60.0	7.11	6390	3960	0.16	1096.960	1645.617	161.891	167.046	146.926
09.04.2013	18S	23.5	14.5	60.0	7.06	6190	3840	0.31	1085.040	1650.892	155.542	168.977	122.852
15.04.2013	23S	23.4	14.5	66.0	7.12	6900	4280	0.29	1203.840	1879.587	176.175	185.291	116.370
23.04.2013	28S	22.9	14.5	63.0	7.10	6160	3820	0.17	1092.960	1700.919	165.065	165.121	139.341
30.04.2013	33S	24.1	14.5	61.2	7.07	6120	3790	0.15	1081.080	1643.745	163.478	163.200	147.678
06.05.2013	38S	23.6	14.5	76.2	7.09	6120	3800	0.15	1069.200	1622.305	163.478	160.317	144.619
15.05.2013	43S	23.6	14.5	90.0	7.07	6050	3751	0.15	1080.936	1672.332	160.925	164.714	143.722
20.05.2013	48S	23.7	14.5	90.0	7.06	5980	3710	0.14	1092.672	1722.359	158.371	169.113	142.601
27.05.2013	53S	24.1	14.5	90.0	7.03	5920	3670	0.13	1084.608	1693.773	163.218	164.214	147.481
05.06.2013	58S	24.1	14.5	90.0	7.10	5850	3630	0.18	1088.640	1647.475	163.218	165.193	145.739
10.60.2013	63S	24.1	14.5	96.0	6.96	5840	3620	0.20	1108.800	1640.087	161.603	171.066	116.367
17.06.2013	68S	24.0	14.5	62.0	7.00	5910	3670	0.26	1094.688	1699.189	161.603	167.641	128.251
26.06.2013	73S	24.3	14.5	90.0	7.08	5860	3630	0.20	1107.552	1662.251	166.066	168.055	134.753
01.07.2013	78S	24.1	14.5	90.0	7.05	6140	3800	0.36	1095.600	1647.475	162.872	167.092	132.735
08.07.2013	83S	24.4	14.5	90.0	7.03	6100	3780	0.23	1103.568	1640.087	161.275	169.995	144.618
15.07.2013	88S	26.7	14.5	90.0	7.00	6030	3740	0.16	1119.504	1662.251	164.469	171.925	128.027
23.07.2013	93S	24.1	14.5	90.0	7.05	5980	3710	0.20	1119.504	1640.087	161.275	173.863	134.753
29.07.2013	98S	24.2	14.5	88.8	7.00	5940	3680	0.19	1127.470	1654.863	166.066	172.889	154.260
19.08.2013	103S	24.1	14.5	90.0	7.04	6000	3720	0.20	1123.488	1712.731	174.049	167.079	151.121
26.08.2013	108S	24.3	14.5	89.4	7.05	5950	3690	0.24	1127.472	1712.731	156.485	178.704	147.982
03.09.2013	113S	24.1	14.5	90.0	7.08	5880	3650	0.13	1123.488	1655.161	162.872	173.861	125.785
09.09.2013	118S	23.9	14.5	88.8	7.09	5830	3610	0.29	1131.456	1683.946	166.066	173.857	137.668

Annex 1.4-A (Hanneaf Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
20.03.2013	4S	22.9	14.0	13.00	7.12	2590	1603	0.19	876.876	656.803	229.030	73.859	168.083
27.03.2013	9S	23.0	17.5	10.20	7.10	2470	1531	0.26	703.560	649.586	211.834	42.230	128.222
03.04.2013	14S	22.8	13.0	13.38	7.17	3090	1914	0.45	958.320	879.046	284.103	60.209	194.235
11.04.2013	19S	22.9	12.5	13.20	7.24	2930	1817	0.32	894.960	807.579	266.640	55.427	197.744
17.04.2013	24S	23.1	14.0	10.20	7.07	2940	1824	0.32	842.400	850.459	269.820	40.740	122.852
24.04.2013	29S	23.1	16.3	13.70	7.10	3070	1905	0.25	914.220	889.766	285.691	48.542	139.333
29.04.2013	34S	23.1	16.3	13.68	7.13	3200	1986	0.18	986.040	929.074	301.562	56.343	177.985
08.05.2013	39S	23.2	13.5	13.98	7.14	4180	2590	0.23	1255.320	1379.316	358.757	86.997	173.236
13.05.2013	44S	23.1	15.0	14.28	7.13	3790	2350	0.64	1165.248	1193.502	336.133	78.863	203.940
21.05.2013	49S	23.2	15.0	14.16	7.12	2950	1827	0.28	955.584	914.780	277.956	63.275	195.488
29.05.2013	54S	23.2	14.2	14.10	7.13	2800	1734	0.14	967.680	856.982	281.188	64.250	168.170
03.06.2013	59S	23.3	14.0	14.10	7.17	2900	1798	0.96	963.648	893.921	294.116	162.507	162.406
12.06.2013	64S	23.2	14.0	14.10	7.08	2680	1662	0.51	899.136	797.880	266.644	56.438	187.969
18.06.2013	69S	23.4	15.5	14.28	7.17	4080	2530	0.23	1398.384	1411.066	381.632	107.841	153.885
24.06.2013	74S	23.4	14.5	14.16	7.16	3160	1956	0.26	1051.776	967.799	316.164	63.438	177.193
02.07.2013	79S	23.4	15.5	13.80	7.01	4850	3010	0.30	1394.400	1566.209	381.632	106.874	163.158
10.07.2013	84S	23.4	16.5	15.30	7.17	4500	2790	0.23	1286.832	1448.005	356.084	96.267	173.183
18.07.2013	89S	23.2	16.0	16.08	7.04	2830	1755	0.24	964.128	820.044	284.228	61.543	184.712
24.07.2013	94S	23.2	16.0	16.08	7.09	2835	1758	0.26	972.096	820.044	285.825	62.508	178.446
30.07.2013	99S	23.2	16.0	16.08	7.13	2840	1762	0.28	980.064	820.043	287.422	63.473	171.929
20.08.2013	104S	23.3	16.5	14.40	7.00	4920	3050	0.30	1446.192	1712.731	384.826	117.506	161.905
27.08.2013	109S	23.3	16.0	15.48	7.17	3400	2110	0.17	1095.600	1065.059	311.374	76.982	176.441
04.09.2013	114S	23.3	17.0	15.06	7.05	4390	2720	0.20	1326.672	1468.055	365.664	100.124	155.388
10.09.2013	119S	23.2	17.5	15.12	7.10	4760	2950	0.18	1394.400	1597.589	372.051	112.687	156.892

Annex 1.5-A (Al-Radwan Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (μs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
20.03.2013	5S	22.9	16.0	18.60	7.27	936	580.00	0.31	352.370	132.850	90.124	30.839	125.547
28.03.2013	10S	22.4	15.5	18.50	7.26	943	585.00	0.27	322.608	129.917	81.844	28.640	124.704
03.04.2013	15S	22.5	16.0	18.48	7.28	929	576.00	0.19	382.140	135.787	98.404	33.041	142.152
10.04.2013	20S	21.9	16.0	18.48	7.29	921	571.00	0.32	368.280	128.641	95.230	31.603	117.667
17.04.2013	25S	21.7	16.0	18.54	7.26	914	567.00	0.24	372.240	121.494	92.055	34.491	125.785
24.04.2013	30S	21.6	16.0	18.30	7.20	912	565.00	0.30	368.280	128.641	95.230	31.603	138.341
29.04.2013	35S	24.3	16.0	18.12	7.23	918	569.00	0.20	364.320	128.641	95.230	30.642	128.129
09.05.2013	40S	22.9	16.5	17.70	7.15	901	558.00	0.48	395.136	135.787	100.193	35.110	131.463
13.05.2013	45S	22.9	16.5	17.58	7.13	898	557.00	0.47	395.136	128.641	103.425	33.148	126.093
21.05.2013	50S	23.4	17.5	17.04	7.23	887	550.00	0.43	370.944	142.934	93.729	33.161	142.601
29.05.2013	55S	23.7	18.0	17.10	7.12	881	547.00	0.53	415.296	140.367	98.577	40.984	115.471
04.06.2013	60S	24.3	17.7	16.02	7.11	880	546.00	0.67	374.976	132.980	93.729	68.264	128.924
11.06.2013	65S	24.8	18.0	16.20	7.12	873	541.00	0.70	374.976	147.756	95.345	33.158	136.771
18.06.2013	70S	25.0	18.5	15.60	7.19	861	534.00	0.67	394.416	132.980	99.001	35.658	140.358
24.06.2013	75S	25.5	18.5	15.72	7.14	880	563.20	0.70	386.448	140.367	100.597	32.756	124.664
02.07.2013	80S	25.8	19.5	17.10	7.11	923	590.72	0.54	402.384	140.368	100.597	36.624	125.784
10.07.2013	85S	24.6	19.0	17.28	7.26	916	568.00	0.58	386.448	132.980	95.807	35.663	138.789
16.07.2013	90S	25.0	19.0	17.34	7.19	908	563.00	0.47	382.464	140.368	95.807	34.696	113.004
24.07.2013	95S	23.9	19.5	17.28	7.28	890	552.00	0.26	386.448	132.980	92.614	37.600	125.560
30.07.2013	100S	25.3	19.5	17.28	7.17	892	553.00	0.23	386.448	132.980	287.422	32.756	122.645
20.08.2013	105S	24.3	17.5	16.56	7.24	901	559.00	0.41	390.432	143.927	95.807	36.629	125.561
27.08.2013	110S	24.2	17.5	16.56	7.28	894	554.00	0.19	378.480	143.927	92.614	35.666	127.354
04.09.2013	115S	24.9	17.5	16.20	7.22	878	545.00	0.38	386.448	143.927	95.807	35.663	121.300

ANNEX 1.B PERMEATE WATER QUALITY PARAMETERS

Annex 1.1-B (Al-Salam Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
18.03.2013	1D	24.2	14.0	60.0	6.28	147.60	91.500	0.14	10.290	43.310	1.032	1.871	8.094
25.03.2013	6D	24.4	14.0	60.0	6.22	145.50	90.200	0.17	8.580	43.305	1.032	1.456	7.040
01.04.2013	11D	24.7	14.0	60.0	6.19	144.00	89.300	0.18	11.880	43.305	3.174	0.957	7.757
08.04.2013	16D	24.8	14.0	43.2	6.12	133.50	82.800	0.21	7.920	39.306	1.587	0.959	5.605
18.04.2013	21D	24.2	14.0	60.0	6.06	145.60	90.300	0.13	11.880	46.454	1.587	1.921	5.314
25.04.2013	26D	24.2	14.0	51.0	6.12	141.95	88.009	0.12	10.890	44.667	1.587	1.680	7.152
29.04.2013	31D	24.3	14.0	42.0	6.18	138.30	85.700	0.11	9.900	42.880	1.587	1.440	9.013
06.05.2013	36D	24.7	14.0	54.0	6.22	138.20	85.700	0.16	11.880	42.880	1.587	1.921	8.139
15.05.2013	41D	24.1	14.0	48.0	6.15	137.30	85.100	0.17	10.080	46.454	0.808	1.956	7.309
22.05.2013	46D	24.5	14.0	51.0	6.14	142.00	88.000	0.24	10.080	46.454	0.808	1.956	9.417
27.05.2013	51D	24.6	14.0	48.0	6.54	142.30	88.200	0.09	10.080	46.454	0.808	1.956	8.184
05.06.2013	56D	24.7	14.0	39.0	6.28	142.80	88.500	0.15	10.080	48.021	2.424	0.976	8.744
10.06.2013	61D	24.8	14.0	49.2	6.34	140.80	87.300	0.31	10.080	48.021	2.424	0.976	7.175
17.06.2013	66D	24.8	14.0	51.0	6.46	140.00	86.800	0.17	10.080	48.021	3.232	0.485	9.036
26.06.2013	71D	24.9	14.0	50.0	6.47	143.30	88.900	0.20	9.960	48.021	0.798	1.933	7.847
01.07.2013	76D	24.9	14.0	50.0	6.34	157.50	97.700	0.26	9.960	51.714	1.597	1.448	8.677
08.07.2013	81D	24.9	14.0	48.0	6.48	153.00	94.900	0.22	9.960	48.021	1.597	1.448	9.641
15.07.2013	86D	24.9	14.0	48.0	6.36	155.05	96.150	0.22	9.960	49.867	1.597	1.448	9.462
22.07.2013	91D	24.9	13.5	48.0	6.23	157.10	97.400	0.20	9.960	51.714	1.597	1.448	9.260
29.07.2013	96D	24.9	13.5	43.2	6.43	158.70	98.400	0.10	11.952	48.020	1.596	1.932	10.358
19.08.2013	101D	25.4	13.5	36.0	6.34	161.80	100.300	0.13	11.952	51.714	1.597	1.932	8.369
27.08.2013	106D	24.8	14.0	48.0	6.42	159.70	99.000	0.08	9.960	57.571	1.597	1.448	8.879
02.09.2013	111D	24.8	14.0	45.0	6.37	158.20	98.100	0.10	11.952	48.021	1.597	1.932	7.825

Annex 1.2-B (Al-Sharqia Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
18.03.2013	2D	21.9	12.0	17	6.11	635	394	0.18	13.728	129.92	1.375	2.497	143.037
25.03.2013	7D	22.5	11.0	18	5.96	601	373	0.2	11.154	126.308	2.407	1.247	140.444
01.04.2013	12D	24.2	10.5	19	5.86	566	351	0.2	15.84	119.091	2.381	2.399	138.220
08.04.2013	17D	24.1	10.0	18	6.07	693	430	0.18	13.86	146.507	1.587	2.401	124.700
15.04.2013	22D	22.9	11.5	18	6.27	631	391	0.15	13.86	135.787	1.587	2.401	119.700
25.04.2013	27D	24.1	11.0	18	6.47	686	425	0.15	15.84	153.654	2.381	2.399	137.668
29.04.2013	32D	25.3	10.5	18	6.46	679	421	0.09	13.86	146.507	2.381	1.919	145.815
06.05.2013	37D	24.8	11.5	18	6.35	517	320	0.1	11.88	110.774	2.381	1.438	114.520
15.05.2013	42D	23.6	10.5	18	5.90	498	309	0.19	12.096	110.774	1.616	1.955	141.741
20.05.2013	47D	25.1	11.5	18	6.20	501	311	0.19	12.096	117.921	1.616	1.955	122.197
27.05.2013	52D	24.8	11.0	18	6.36	503	312	0.1	12.096	114.347	1.616	1.955	109.865
05.06.2013	57D	25.5	11.5	18	6.47	544	337	0.1	12.096	121.898	2.424	1.465	141.928
10.06.2013	62D	25.4	11.0	18	6.29	485	301	0.15	12.096	107.128	2.424	1.465	99.327
17.06.2013	67D	25.0	10.2	18	6.02	639	396	0.17	12.096	147.755	3.232	0.975	139.013
26.06.2013	72D	26.2	11.0	18	6.26	516	320	0.13	11.952	118.204	1.597	2.898	117.713
01.07.2013	77D	25.9	10.0	18	6.12	548	340	0.15	11.952	121.898	1.597	1.932	120.628
08.07.2013	82D	26.7	10.0	18	6.33	623	386	0.16	11.952	136.674	2.395	2.413	142.825
15.07.2013	87D	25.7	11.0	18	6.25	488	302	0.17	13.944	110.817	3.194	1.446	100.448
22.07.2013	92D	25.7	9.5	19	6.46	479	297	0.09	11.952	107.123	1.597	1.932	112.556
29.07.2013	97D	25.7	9.5	19	6.67	521	323	0.15	12.948	116.358	1.597	2.174	122.422
19.08.2013	102D	26.2	10.25	18	6.87	562	348	0.2	13.944	125.592	1.596	2.416	132.287
26.08.2013	107D	26.2	10.5	18	6.79	578	358	0.1	13.944	125.592	1.597	2.416	144.200
02.09.2013	112D	25.9	9.5	17	6.86	570	353	0.09	13.944	125.592	2.395	1.931	112.780

Annex 1.3-B (Al-Balad Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
18.03.2013	3D	23.8	10.9	45	5.64	243	150.66	0.16	17.358	66.763	2.963	2.415	18.251
26.03.2013	8D	23.9	10.9	48	5.41	248	153.60	0.16	18.876	68.567	2.751	2.912	15.430
01.04.2013	13D	23.6	10.9	47	5.86	237	147.10	0.15	15.840	64.958	3.174	1.918	16.390
09.04.2013	18D	23.6	11.2	47	5.33	244	151.60	0.27	17.820	71.467	2.381	2.880	14.977
15.04.2013	23D	22.5	11.2	42	5.44	243	150.40	0.24	17.820	71.467	2.381	2.880	14.349
23.04.2013	28D	22.6	10.9	47	5.40	240	149.10	0.11	17.820	71.467	2.381	2.880	11.637
30.04.2013	33D	24.3	10.9	46	5.90	232	143.70	0.16	21.780	67.894	7.920	0.481	18.161
06.05.2013	38D	24.0	11.2	47	5.58	241	149.30	0.14	17.820	71.467	3.174	2.399	13.699
15.05.2013	43D	24.0	10.9	48	5.95	246	152.60	0.14	18.990	75.041	2.799	2.911	15.022
20.05.2013	48D	24.1	10.9	47	6.32	251	155.80	0.13	20.160	78.614	2.424	3.422	16.345
27.05.2013	53D	24.2	11.0	49	6.18	232	144.00	0.08	18.144	67.894	2.424	2.933	16.390
05.06.2013	58D	24.4	10.9	49	5.98	239	148.00	0.11	20.160	73.878	3.232	2.932	17.982
10.60.2013	63D	26.6	11.2	50	5.85	260	161.30	0.12	18.144	77.572	3.232	2.443	16.076
17.06.2013	68D	24.6	10.9	49	5.67	238	147.60	0.17	16.128	73.878	4.040	1.463	18.825
26.06.2013	73D	24.9	11.0	49	5.79	244	151.30	0.12	17.928	73.878	2.395	2.898	16.704
01.07.2013	78D	25.1	11.0	49	5.65	259	160.80	0.23	21.912	73.878	2.395	3.865	17.287
08.07.2013	83D	25.5	10.9	49	6.03	257	159.00	0.12	17.928	73.878	3.194	2.413	19.327
15.07.2013	88D	26.7	11.0	50	5.94	275	170.70	0.15	19.920	81.266	3.194	2.897	17.713
23.07.2013	93D	24.7	10.9	48	5.76	248	154.00	0.15	19.920	73.878	2.395	3.382	16.682
29.07.2013	98D	25.9	11.0	49	5.83	270	167.20	0.14	21.912	77.572	3.194	3.380	20.561
19.08.2013	103D	25.7	11.0	50	5.74	269	166.80	0.12	23.904	81.265	2.395	4.348	19.910
26.08.2013	108D	24.9	10.9	48	5.56	256	158.60	0.11	21.912	73.878	2.395	3.865	19.552
03.09.2013	113D	25.1	14.5	48	5.67	259	160.70	0.09	19.920	40.633	3.992	2.413	17.152

Annex 1.4-B (Hanneaf Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
20.03.2013	4D	23.3	12.5	9.6	5.62	51.30	31.800	0.17	11.154	18.044	2.063	1.455	10.269
27.03.2013	9D	23.4	15.0	5.4	5.49	85.80	53.200	0.2	17.160	28.870	4.126	1.661	10.897
03.04.2013	14D	23.3	11.5	9.3	5.47	60.70	37.600	0.19	7.920	21.440	2.381	0.478	13.251
11.04.2013	19D	23.4	11.0	9.3	5.41	57.10	35.400	0.24	9.900	21.440	1.587	1.439	8.274
17.04.2013	24D	23.5	17.0	5.4	5.65	115.50	71.600	0.21	17.820	35.733	3.967	1.918	11.614
24.04.2013	29D	23.5	12.0	9.6	5.54	88.10	54.622	0.13	11.880	28.586	3.174	1.678	11.323
29.04.2013	34D	23.5	12.0	9.6	5.43	60.70	37.600	0.12	11.880	21.440	2.381	1.439	11.031
08.05.2013	39D	23.6	15.25	9.9	5.45	80.30	49.800	0.15	11.880	28.586	2.424	1.413	12.085
13.05.2013	44D	23.5	13.5	10.2	5.31	73.40	45.500	0.18	16.128	28.587	4.848	0.973	12.085
21.05.2013	49D	23.6	12.5	10.2	5.42	56.00	34.700	0.11	10.080	25.013	1.616	1.466	10.605
29.05.2013	54D	23.6	12.5	10.2	5.60	54.80	34.000	0.14	10.080	22.163	1.616	1.466	10.246
03.06.2013	59D	23.7	12.5	10.2	5.30	55.30	34.300	0.21	10.080	22.163	2.424	1.858	11.659
12.06.2013	64D	23.7	12.5	10.2	5.61	52.40	32.500	0.2	10.080	25.857	2.424	0.976	12.152
18.06.2013	69D	23.8	14.0	10.2	5.70	79.30	49.200	0.14	9.960	29.551	3.194	0.479	10.269
24.06.2013	74D	23.9	13.0	10.2	5.63	59.50	36.900	0.22	9.960	25.857	1.597	1.448	10.404
02.07.2013	79D	23.8	14.0	9.72	5.53	96.40	59.800	0.14	11.952	33.245	1.597	1.932	11.457
10.07.2013	84D	23.7	15.0	11.1	5.61	84.20	52.200	0.18	11.952	29.551	1.597	1.932	11.614
18.07.2013	89D	23.6	14.0	12.0	5.48	52.30	32.400	0.18	11.952	22.163	3.194	0.963	10.897
24.07.2013	94D	23.6	14.0	12.0	5.48	53.65	33.250	0.17	11.952	22.163	3.194	0.963	10.403
30.07.2013	99D	23.6	14.0	12.0	5.48	55.00	34.100	0.16	11.952	22.163	3.194	0.963	9.910
20.08.2013	104D	23.7	14.5	10.2	5.57	97.90	60.700	0.09	11.952	36.939	1.597	1.932	11.233
27.08.2013	109D	23.6	14.0	11.4	5.59	62.60	38.800	0.12	11.952	28.785	1.597	1.932	11.211
04.09.2013	114D	23.6	15.0	10.8	5.59	85.30	52.900	0.16	11.952	33.245	3.194	0.963	10.807

Annex 1.5-B (Al-Radwan Plant)

Date	Sample No.	Water Temp °C	Pressure (bar)	Flow rate (m^3/hr)	pH	EC (µs/cm)	TDS (mg/l)	Turbidity (NTU)	Hardness (mg/l)	Chloride (mg/l)	Calcium (mg/)	Magnesium (mg/l)	Nitrate (mg/l)
20.03.2013	5D	22.8	15.5	9.60	6.12	51.60	31.9	0.25	8.580	10.826	1.375	1.248	6.700
28.03.2013	10D	21.8	15.5	9.60	6.28	89.50	55.5	0.25	8.580	18.044	1.375	1.248	13.968
03.04.2013	15D	22.5	15.5	9.48	5.49	36.70	22.7	0.11	9.900	17.867	2.381	0.958	9.843
10.04.2013	20D	23.1	15.5	9.30	5.15	24.20	15.0	0.11	9.900	14.293	1.587	1.439	3.744
17.04.2013	25D	22.7	15.5	9.30	5.17	20.50	12.7	0.15	7.920	10.720	1.587	0.959	3.587
24.04.2013	30D	23.0	15.5	9.18	5.12	25.30	15.7	0.12	9.900	14.293	1.587	1.440	6.368
29.04.2013	35D	23.9	15.5	9.24	5.29	34.60	21.5	0.13	9.900	14.293	1.587	1.440	8.991
09.05.2013	40D	23.8	15.5	8.40	5.21	18.96	11.8	0.1	10.080	17.867	2.424	0.976	5.426
13.05.2013	45D	23.6	15.5	8.28	5.34	18.48	11.5	0.16	12.096	17.867	3.232	0.975	6.031
21.05.2013	50D	23.9	15.5	9.00	5.24	20.10	12.4	0.13	10.080	14.293	1.616	1.466	4.395
29.05.2013	55D	24.2	15.5	9.30	5.42	26.40	16.3	0.18	12.096	14.775	1.616	1.955	7.063
04.06.2013	60D	24.8	15.5	8.40	5.40	18.96	11.8	0.32	10.080	18.469	1.616	2.054	4.731
11.06.2013	65D	24.3	15.5	8.40	5.69	57.90	35.9	0.26	16.128	22.163	4.040	1.463	11.861
18.06.2013	70D	24.6	15.5	8.70	5.68	59.60	36.9	0.13	13.944	18.469	3.992	0.962	15.785
24.06.2013	75D	24.3	15.5	8.82	5.38	16.07	10.0	0.25	9.960	14.775	1.597	1.448	2.915
02.07.2013	80D	25.3	15.5	9.30	6.10	89.50	55.5	0.21	21.912	22.163	3.992	2.896	18.296
10.07.2013	85D	25.5	15.5	9.00	6.09	95.70	59.4	0.19	25.896	22.163	6.387	2.409	18.520
16.07.2013	90D	25.2	15.5	9.00	5.93	87.30	54.1	0.39	25.896	22.163	5.588	2.895	15.089
24.07.2013	95D	24.3	15.5	9.00	5.53	20.90	13.0	0.11	11.952	14.775	1.597	1.932	3.722
30.07.2013	100D	24.3	15.5	9.00	5.54	40.60	25.1	0.09	15.936	14.775	3.194	1.929	8.296
20.08.2013	105D	24.4	15.5	8.28	5.65	40.40	25.1	0.13	15.936	14.776	3.194	1.929	8.363
27.08.2013	110D	25.7	15.5	8.28	5.59	55.30	34.3	0.08	17.928	21.589	3.194	2.413	11.368
04.09.2013	115D	25.8	15.5	8.10	6.31	166.00	102.9	0.23	65.736	33.245	16.766	5.782	20.762

Annex 2: Weights and Biases of the developed ANN Models

Annex 2.1 Permeate Flowrate Model

A. MLP Model Weights and Biases Parameters

1. Weights

w1 =		
1.0e+004 *		
2.1020	0.0010	0.2902
3.9812	0.0006	0.1109
-2.2398	-0.0002	0.1350
2.2809	0.0012	-0.5013
1.4049	-0.0032	-0.0835
-2.2021	-0.0004	0.1404

w2 =					
-0.2687	0.3019	223.5272	0.0796	-0.2619	- 46.4168

2. Bias

b1 =	b2 =
-37.2086	-176.58
-50.3064	
27.0244	
-20.7759	
12.533	
26.6482	

B. RBF Model Weights and Biases Parameters

1. Weights

w1 =								
0.0010	1.0000	0.0021	0.0010	0.8478	0.0021	0.0011	0.6826	0.0022
0.0010	0.9449	0.0021	0.0010	0.1277	0.0026	0.0010	0.8667	0.0021
0.0010	0.1248	0.0027	0.0010	0.1301	0.0024	0.0011	0.6783	0.0022
0.0010	0.9261	0.0021	0.0011	0.1335	0.0023	0.0011	0.5899	0.0019
0.0010	0.1293	0.0028	0.0010	0.8464	0.0021	0.0011	0.5768	0.0016
0.0010	0.8841	0.0021	0.0010	0.8739	0.0021	0.0011	0.7174	0.0022
0.0010	0.8870	0.0021	0.0010	0.5913	0.0022	0.0011	0.6696	0.0022
0.0011	0.7188	0.0022	0.0010	0.8493	0.0021	0.0011	0.7072	0.0022
0.0010	0.6362	0.0025	0.0011	0.7072	0.0022	0.0010	0.6058	0.0020
0.0010	0.5609	0.0017	0.0011	0.6957	0.0022	0.0010	0.5884	0.0016
0.0011	0.5623	0.0016	0.0011	0.1346	0.0023	0.0010	0.6058	0.0016
0.0011	0.5696	0.0019	0.0011	0.1367	0.0022	0.0010	0.3884	0.0020
0.0010	0.7130	0.0024	0.0011	0.1267	0.0025	0.0010	0.3580	0.0025
0.0010	0.8928	0.0021	0.0011	0.1328	0.0028	0.0010	0.1286	0.0025
0.0011	0.7507	0.0022	0.0010	0.1316	0.0028	0.0011	0.6884	0.0022
0.0010	0.1275	0.0027	0.0010	0.1275	0.0026	0.0010	0.4246	0.0018
0.0010	0.8768	0.0021	0.0011	0.6913	0.0022	0.0011	0.7130	0.0022
0.0010	0.8667	0.0021	0.0011	0.1325	0.0023	0.0011	0.5493	0.0017

0.0010	0.8623	0.0021	0.0010	0.1322	0.0023	0.0011	0.6942	0.0022
0.0010	0.8580	0.0021	0.0011	0.5681	0.0017	0.0011	0.5884	0.0017
0.0010	0.4203	0.0020	0.0011	0.5681	0.0018	0.0010	0.7029	0.0022
0.0010	0.4101	0.0023	0.0011	0.5638	0.0019	0.0011	0.7420	0.0022
0.0010	0.4275	0.0022	0.0011	0.5928	0.0017	0.0010	0.4928	0.0023
0.0010	0.5797	0.0016	0.0010	0.6377	0.0019	0.0010	0.4261	0.0020
0.0010	0.4109	0.0023	0.0011	0.5739	0.0017	0.0010	0.6043	0.0019
0.0011	0.6174	0.0017	0.0010	0.4116	0.0023	0.0010	0.4638	0.0024
0.0010	0.8449	0.0021	0.0010	0.1330	0.0023	0.0010	0.8696	0.0021
0.0010	0.8522	0.0021	0.0011	0.6913	0.0022			
0.0010	0.6261	0.0017	0.0010	0.5768	0.0017			
0.0010	0.8899	0.0021	0.0010	0.3754	0.0020			

w2 =
1.0e+012 *
-0.0217 0 0 0 0.1650 0 0 0 -0.9301 0 0 0 0.4269 0.2069 -0.7532
0 0 0 0 0 0 0 -0.3001 0 -0.1884 0 0 0 0 0
0 0.2885 -0.1225 0 0 0 1.1036 0 0 0 0 0 0 0 0
0 0 0 0 0 0.3565 0.1367 -0.3290 0 0 0 0 -0.6192 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0.5800 0

2. **Bias**

b1 =	b2 =
0.8326*	4.49E+05

***Note: The same value of b1 (0.8326) is presented for all (87) hidden neurons.**

Annex 2.2 TDS Model

A. MLP Model Weights and Biases Parameters

1. Weights

w1 =			
1.0e+003 *			
0.2243	-0.0382	0.3152	-0.0040
0.0004	-0.0000	-0.0001	0.0001
1.1123	-0.2956	0.2323	-0.0003
-0.7483	-0.5581	-0.0198	0.0030
0.5801	-0.0173	-0.1304	-0.0020
1.0436	0.3117	-0.0161	0.0124

w2 =					
-0.0003	6.6286	0.0002	-0.1402	-0.0054	0.0004

2. Bias

b1 =	b2 =
-6.8833	0.6686
-0.0798	
-5.1412	
30.196	
-1.1147	
-20.135	

B. RBF Model Weights and Biases Parameters

1. Weights

w1=							
0.0088	0.0348	0.0144	1.0000	0.0086	0.0385	0.0159	0.3968
0.0089	0.0349	0.0159	0.3348	0.0086	0.0352	0.0157	0.3449
0.0093	0.0348	0.0159	0.9899	0.0087	0.0368	0.0157	0.3709
0.0082	0.0362	0.0209	0.3737	0.0083	0.0367	0.0144	0.9019
0.0078	0.0325	0.0162	0.3506	0.0082	0.0339	0.0245	0.1667
0.0078	0.0326	0.0157	0.3463	0.0084	0.0384	0.0162	0.3752
0.0078	0.0351	0.0224	0.0232	0.0091	0.0348	0.0157	0.3622
0.0093	0.0365	0.0152	0.9798	0.0091	0.0315	0.0224	0.1291
0.0090	0.0378	0.0159	0.7446	0.0085	0.0341	0.0152	0.7186
0.0078	0.0338	0.0159	0.0824	0.0083	0.0356	0.0157	0.3579
0.0093	0.0371	0.0137	0.6912	0.0085	0.0349	0.0152	0.8167
0.0079	0.0325	0.0224	0.0530	0.0096	0.0371	0.0137	0.7518
0.0091	0.0367	0.0159	0.6999	0.0080	0.0359	0.0157	0.3694
0.0081	0.0346	0.0162	0.3478	0.0092	0.0358	0.0166	0.7460
0.0076	0.0345	0.0224	0.0290	0.0076	0.0342	0.0180	0.0798
0.0083	0.0352	0.0157	0.3434	0.0078	0.0341	0.0180	0.0808
0.0085	0.0341	0.0157	0.3420	0.0088	0.0316	0.0173	0.9163
0.0084	0.0359	0.0159	0.3521	0.0099	0.0378	0.0148	0.8110
0.0086	0.0346	0.0157	0.3550	0.0084	0.0355	0.0224	0.1469

0.0094	0.0362	0.0202	0.2372	0.0086	0.0364	0.0224	0.1260
0.0078	0.0339	0.0173	0.0876	0.0093	0.0358	0.0202	0.2304
0.0091	0.0385	0.0144	0.8990	0.0078	0.0349	0.0224	0.0381
0.0079	0.0341	0.0220	0.1159	0.0087	0.0361	0.0147	0.9221
0.0078	0.0358	0.0224	0.0274	0.0092	0.0358	0.0159	0.7258
0.0081	0.0342	0.0180	0.0756	0.0080	0.0342	0.0209	0.1413
0.0098	0.0378	0.0152	0.8341	0.0091	0.0349	0.0202	0.2130
0.0082	0.0362	0.0159	0.3737	0.0089	0.0354	0.0202	0.2049
0.0083	0.0371	0.0159	0.3882	0.0080	0.0351	0.0224	0.0586
0.0081	0.0341	0.0216	0.1231	0.0079	0.0341	0.0202	0.0794
0.0081	0.0336	0.0180	0.0740	0.0089	0.0351	0.0202	0.1996
0.0082	0.0343	0.0202	0.1144	0.0092	0.0358	0.0202	0.2283
0.0082	0.0355	0.0224	0.0860	0.0086	0.0325	0.0159	0.8672
0.0081	0.0341	0.0202	0.0903	0.0090	0.0352	0.0202	0.2100
0.0077	0.0341	0.0224	0.0267	0.0074	0.0333	0.0224	0.0349
0.0099	0.0374	0.0137	0.8225	0.0092	0.0359	0.0202	0.2237
0.0081	0.0343	0.0157	0.3506	0.0088	0.0358	0.0202	0.1926
0.0079	0.0341	0.0202	0.0755	0.0093	0.0358	0.0202	0.2020
0.0079	0.0341	0.0202	0.0774	0.0094	0.0359	0.0202	0.2208
0.0079	0.0338	0.0216	0.1238	0.0091	0.0356	0.0202	0.2061
0.0075	0.0328	0.0224	0.0296	0.0074	0.0332	0.0224	0.0365
0.0076	0.0345	0.0224	0.0499	0.0093	0.0359	0.0195	0.2290
0.0088	0.0368	0.0224	0.1381	0.0091	0.0359	0.0202	0.2273
0.0089	0.0348	0.0202	0.1981	0.0090	0.0330	0.0166	0.9105

w2 =
1.0e+009 *
0.4109 0 -1.3389 0.3303 -4.1740 3.8274 -1.3559 1.4620 -0.9910 -0.6786 -1.8244 1.1498
3.6079 0 0 0 0 0 0 -1.0688 -0.1687 0 0 3.0546
0.2401 0 0.9829 -0.0591 0.8521 0 0.4888 0 -0.5746 -3.2856 0.7222 0
0.1107 1.8099 0 0 0 -0.8801 0 1.6097 1.7378 0 0 0
0 -1.4128 0 -2.3632 0 0 0.0378 0 0 0 0 0
0 0 1.0904 0 0 0 -4.2251 0 0 0 0 0
0 0 0 -1.3601 0 0 0 0.5266 0 0 0 -0.4108
0 0 2.1199

2. Bias

b1 =	b2 =
0.8326[*]	-2.16E+03

[*]**Note: The same value of b1 (0.8326) is presented for all (87) hidden neurons**

Annex 2.3 Chloride Model

A. MLP Model Weights and Biases Parameters

1. Weights

w1 =
1.0e+003 *
0.1132 -0.2100 -0.1956 0.0917
0.8314 -0.4342 0.1251 -0.0134
1.1807 0.2817 0.3183 0.0044
-1.3893 -0.1780 0.2245 0.0035
0.2390 0.0562 -0.0537 0.0021
-0.1417 -0.5648 -0.6475 -0.0145
-1.4970 0.3934 0.1054 -0.0066

w2 =
0.0152 -2.9991 0.0427 0.1036 0.5191 0.1357 -0.0996

2. Biases

b1 =	b2 =
-68.5994	-2.4704
3.2365	
-29.0893	
12.7849	
-4.2338	
39.9263	
-2.6808	

B. RBF Model Weights and Biases Parameters

1. Weights

w1 =	
0.0088 0.0348 0.0144 1.0000	0.0074 0.0333 0.0224 0.0349
0.0078 0.0351 0.0224 0.0232	0.0079 0.0341 0.0220 0.1159
0.0078 0.0358 0.0224 0.0274	0.0079 0.0338 0.0216 0.1238
0.0093 0.0348 0.0159 0.9899	0.0076 0.0345 0.0224 0.0499
0.0091 0.0385 0.0144 0.8990	0.0089 0.0354 0.0202 0.2049
0.0076 0.0345 0.0224 0.0290	0.0089 0.0351 0.0202 0.1996
0.0074 0.0332 0.0224 0.0365	0.0078 0.0349 0.0224 0.0381
0.0081 0.0342 0.0180 0.0756	0.0090 0.0352 0.0202 0.2100
0.0078 0.0338 0.0159 0.0824	0.0093 0.0358 0.0202 0.2304

0.0087	**0.0361**	**0.0147**	**0.9221**	**0.0077**	**0.0341**	**0.0224**	**0.0267**
0.0090	**0.0330**	**0.0166**	**0.9105**	**0.0093**	**0.0358**	**0.0202**	**0.2020**
0.0079	**0.0325**	**0.0224**	**0.0530**	**0.0088**	**0.0358**	**0.0202**	**0.1926**
0.0088	**0.0316**	**0.0173**	**0.9163**	**0.0089**	**0.0348**	**0.0202**	**0.1981**
0.0099	**0.0374**	**0.0137**	**0.8225**	**0.0080**	**0.0342**	**0.0209**	**0.1413**
0.0086	**0.0325**	**0.0159**	**0.8672**	**0.0080**	**0.0343**	**0.0202**	**0.1391**
0.0085	**0.0349**	**0.0152**	**0.8167**	**0.0084**	**0.0355**	**0.0224**	**0.1469**
0.0078	**0.0341**	**0.0180**	**0.0808**	**0.0092**	**0.0359**	**0.0202**	**0.2237**
0.0086	**0.0364**	**0.0224**	**0.1260**	**0.0083**	**0.0371**	**0.0159**	**0.3882**
0.0093	**0.0365**	**0.0152**	**0.9798**	**0.0092**	**0.0358**	**0.0202**	**0.2283**
0.0083	**0.0367**	**0.0144**	**0.9019**	**0.0086**	**0.0352**	**0.0157**	**0.3449**
0.0089	**0.0349**	**0.0159**	**0.3348**	**0.0080**	**0.0351**	**0.0224**	**0.0586**
0.0090	**0.0378**	**0.0159**	**0.7446**	**0.0091**	**0.0356**	**0.0202**	**0.2061**
0.0086	**0.0346**	**0.0157**	**0.3550**	**0.0084**	**0.0359**	**0.0159**	**0.3521**
0.0076	**0.0342**	**0.0180**	**0.0798**	**0.0091**	**0.0359**	**0.0202**	**0.2273**
0.0088	**0.0368**	**0.0224**	**0.1381**	**0.0082**	**0.0362**	**0.0159**	**0.3737**
0.0096	**0.0371**	**0.0137**	**0.7518**	**0.0078**	**0.0325**	**0.0162**	**0.3506**
0.0098	**0.0378**	**0.0152**	**0.8341**	**0.0081**	**0.0341**	**0.0202**	**0.0903**
0.0085	**0.0341**	**0.0152**	**0.7186**	**0.0084**	**0.0384**	**0.0162**	**0.3752**
0.0099	**0.0378**	**0.0148**	**0.8110**	**0.0081**	**0.0341**	**0.0216**	**0.1231**
0.0092	**0.0358**	**0.0166**	**0.7460**	**0.0083**	**0.0356**	**0.0157**	**0.3579**
0.0092	**0.0358**	**0.0159**	**0.7258**	**0.0080**	**0.0359**	**0.0157**	**0.3694**
0.0075	**0.0328**	**0.0224**	**0.0296**	**0.0087**	**0.0368**	**0.0157**	**0.3709**
0.0091	**0.0367**	**0.0159**	**0.6999**	**0.0081**	**0.0343**	**0.0157**	**0.3506**
0.0091	**0.0349**	**0.0202**	**0.2130**	**0.0086**	**0.0385**	**0.0159**	**0.3968**
0.0079	**0.0341**	**0.0202**	**0.0794**	**0.0083**	**0.0352**	**0.0157**	**0.3434**
0.0093	**0.0359**	**0.0195**	**0.2290**	**0.0082**	**0.0362**	**0.0209**	**0.3737**
0.0079	**0.0341**	**0.0202**	**0.0774**	**0.0078**	**0.0339**	**0.0173**	**0.0876**
0.0079	**0.0341**	**0.0202**	**0.0755**	**0.0091**	**0.0315**	**0.0224**	**0.1291**
0.0081	**0.0346**	**0.0162**	**0.3478**	**0.0082**	**0.0355**	**0.0224**	**0.0860**
0.0082	**0.0343**	**0.0202**	**0.1144**	**0.0078**	**0.0326**	**0.0157**	**0.3463**
0.0091	**0.0348**	**0.0157**	**0.3622**	**0.0082**	**0.0339**	**0.0245**	**0.1667**
0.0094	**0.0362**	**0.0202**	**0.2372**	**0.0081**	**0.0336**	**0.0180**	**0.0740**
0.0093	**0.0371**	**0.0137**	**0.6912**	**0.0085**	**0.0341**	**0.0157**	**0.3420**
0.0094	**0.0359**	**0.0202**	**0.2208**				

w2 =
1.0e+010 *
-0.9864 2.9951 -2.5181 -0.0754 -4.2132 0 -3.3422 -5.9523 -0.0055 1.3370 0.7911 1.3015 -0.2101 4.5857 -0.4297
-7.0812 0 0 1.0182 3.4933 0 6.8764 0 1.5633 -4.1042 0 0 4.7127 -3.1367 1.3322
0 0 -6.0216 0 0 0 0 0 0 0 -0.9960 4.1021 -2.1538 0 0
0 0 0 0 0 0 0 0 0 0 -2.5062 0 0 0 0
0 0 0 0 0 0 0 0 0 6.1626 0 0 0 0 -0.3576
0 0 1.5112 0 -1.6480 0 -1.6819 5.1374 -5.5283 1.2638 4.7649 0

2. **Biases**

b1 =	b2 =
0.8326*	4.66E+04

***Note: The same value of b1 (0.8326) is presented for all (87) hidden neurons.**

Annex 2.4 Nitrate Model

A. MLP Model Weights and Biases Parameters

1. Weights

w1 =			
1.0e+003 *			
0.8890	0.0437	0.1963	0.0338
0.9240	0.3649	-0.1935	0.0047
-0.9063	0.4088	-0.0330	0.0032
1.0625	-0.3131	0.2442	0.0259
0.3821	0.4854	0.1986	0.0015
-0.9067	0.3664	0.2413	0.0321
-1.3689	-0.0318	0.2256	-0.0030

w2 =						
0.3367	0.1058	0.0411	0.0430	-0.0215	0.0658	2.7185

2. Biases

b1 =	b2 =
-31.8077	-2.1609
-23.5919	
-6.6462	
-3.8449	
-24.1995	
-34.0338	
15.7466	

B. RBF Model Weights and Biases Parameters

1. Weights

w1 =							
0.0088	0.0348	0.0144	1.0000	0.0088	0.0316	0.0173	0.9163
0.0093	0.0348	0.0159	0.9899	0.0083	0.0367	0.0144	0.9019
0.0078	0.0351	0.0224	0.0232	0.0080	0.0342	0.0209	0.1413
0.0085	0.0349	0.0152	0.8167	0.0084	0.0384	0.0162	0.3752
0.0078	0.0338	0.0159	0.0824	0.0075	0.0328	0.0224	0.0296
0.0085	0.0341	0.0152	0.7186	0.0091	0.0359	0.0202	0.2273
0.0081	0.0336	0.0180	0.0740	0.0092	0.0358	0.0202	0.2283
0.0076	0.0345	0.0224	0.0499	0.0080	0.0359	0.0157	0.3694
0.0078	0.0325	0.0162	0.3506	0.0090	0.0352	0.0202	0.2100
0.0091	0.0315	0.0224	0.1291	0.0089	0.0348	0.0202	0.1981

0.0086	0.0385	0.0159	0.3968	0.0089	0.0351	0.0202	0.1996
0.0078	0.0349	0.0224	0.0381	0.0093	0.0359	0.0195	0.2290
0.0087	0.0361	0.0147	0.9221	0.0086	0.0325	0.0159	0.8672
0.0081	0.0346	0.0162	0.3478	0.0077	0.0341	0.0224	0.0267
0.0098	0.0378	0.0152	0.8341	0.0078	0.0341	0.0180	0.0808
0.0092	0.0358	0.0159	0.7258	0.0093	0.0358	0.0202	0.2304
0.0091	0.0348	0.0157	0.3622	0.0094	0.0359	0.0202	0.2208
0.0083	0.0371	0.0159	0.3882	0.0076	0.0345	0.0224	0.0290
0.0093	0.0365	0.0152	0.9798	0.0078	0.0358	0.0224	0.0274
0.0089	0.0349	0.0159	0.3348	0.0079	0.0341	0.0202	0.0755
0.0082	0.0362	0.0209	0.3737	0.0093	0.0371	0.0137	0.6912
0.0099	0.0374	0.0137	0.8225	0.0091	0.0349	0.0202	0.2130
0.0088	0.0368	0.0224	0.1381	0.0082	0.0343	0.0202	0.1144
0.0087	0.0368	0.0157	0.3709	0.0081	0.0341	0.0202	0.0903
0.0091	0.0367	0.0159	0.6999	0.0074	0.0333	0.0224	0.0349
0.0079	0.0341	0.0220	0.1159	0.0078	0.0326	0.0157	0.3463
0.0092	0.0358	0.0166	0.7460	0.0093	0.0358	0.0202	0.2020
0.0084	0.0359	0.0159	0.3521	0.0092	0.0359	0.0202	0.2237
0.0099	0.0378	0.0148	0.8110	0.0081	0.0341	0.0216	0.1231
0.0084	0.0355	0.0224	0.1469	0.0082	0.0339	0.0245	0.1667
0.0090	0.0378	0.0159	0.7446	0.0076	0.0342	0.0180	0.0798
0.0082	0.0362	0.0159	0.3737	0.0080	0.0351	0.0224	0.0586
0.0086	0.0364	0.0224	0.1260	0.0094	0.0362	0.0202	0.2372
0.0083	0.0352	0.0157	0.3434	0.0079	0.0341	0.0202	0.0794
0.0081	0.0343	0.0157	0.3506	0.0082	0.0355	0.0224	0.0860
0.0086	0.0346	0.0157	0.3550	0.0091	0.0385	0.0144	0.8990
0.0086	0.0352	0.0157	0.3449	0.0096	0.0371	0.0137	0.7518
0.0083	0.0356	0.0157	0.3579	0.0078	0.0339	0.0173	0.0876
0.0081	0.0342	0.0180	0.0756	0.0079	0.0341	0.0202	0.0774
0.0080	0.0343	0.0202	0.1391	0.0088	0.0358	0.0202	0.1926
0.0089	0.0354	0.0202	0.2049	0.0085	0.0341	0.0157	0.3420
0.0079	0.0338	0.0216	0.1238	0.0090	0.0330	0.0166	0.9105
0.0079	0.0325	0.0224	0.0530	0.0091	0.0356	0.0202	0.2061
0.0074	0.0332	0.0224	0.0365				

w2 =
1.0e+011 *
-0.1348 0.1092 0.3399 0.0524 0.0354 0.3374 0.4616 0 0.5246 0.0810 -0.0942 0 2.3173 0 0
0 0.1287 0 -0.1949 0 0.0319 -0.1424 -0.0445 0 -1.2600 0 0.3356 0 0.1175 0
0.7296 0 0 0 0 0 0 0 -0.9865 0 0 0 0.0351 - 0.2914 0.6134
-1.4904 0 0 0 0 0 0.2663 0 0 0 0 -0.0692 0 0 0
0 0 -0.1916 0 0.1385 0 0 0 0 -0.7667 0 0 0 -0.0560 0.4892
0 -0.0273 0 0.1763 -0.2062 0 0 0 -0.0601 0 -1.3048 0

2. Biases

b1 =	b2 =
0.8326*	7.00E+04

***Note: The same value of b1 (0.8326) is presented for all (87) hidden neurons.**

Annex 2.5 Magnesium Model

A. MLP Model Weights and Biases Parameters

1. Weights

w1 =		
82.9272	9.7024	21.1063
-232.4371	-12.0321	7.0021
291.8791	-6.4181	37.6395
-218.7847	-13.1210	9.6294
3.4579	8.8526	19.1872
265.9760	-24.4619	-0.2181

w2 =					
-11.6768	-6.3134	-10.5624	5.7000	18.8744	7.7390

2. Biases

b1 =	b2 =
-7.8271	-10.2442
6.6818	
-9.7438	
6.3631	
-6.2899	
6.7147	

B. RBF Model Weights and Biases Parameters

1. Weights

w1=								
0.0160	0.7522	0.1723	0.0168	0.7303	0.1719	0.0163	0.3790	0.1131
0.0226	0.0234	0.0215	0.0226	0.0806	0.0315	0.0175	0.1284	0.0417
0.0226	0.0299	0.0156	0.0226	0.0844	0.0323	0.0182	0.0816	0.0365
0.0226	0.0269	0.0260	0.0219	0.1243	0.0485	0.0204	0.0913	0.0420
0.0226	0.0752	0.0158	0.0182	0.0748	0.0263	0.0190	0.0867	0.0377
0.0248	0.1684	0.0521	0.0226	0.0869	0.0269	0.0153	0.7259	0.1615
0.0153	0.9898	0.2136	0.0226	0.1273	0.0323	0.0159	0.3732	0.1077
0.0160	0.7332	0.1667	0.0219	0.1251	0.0421	0.0159	0.3615	0.1000
0.0226	0.0293	0.0208	0.0182	0.0799	0.0323	0.0159	0.3499	0.1042
0.0226	0.0369	0.0208	0.0204	0.2121	0.0631	0.0153	0.8251	0.1736
0.0226	0.0504	0.0208	0.0204	0.2099	0.0631	0.0182	0.0764	0.0377
0.0211	0.3776	0.0592	0.0204	0.2041	0.0700	0.0159	0.3746	0.1077
0.0226	0.0535	0.0260	0.0204	0.2306	0.0700	0.0160	0.3557	0.1077

0.0138	0.6983	0.1562	0.0226	0.1395	0.0323	0.0159	0.3586	0.1094
0.0159	0.3455	0.0947	0.0204	0.1156	0.0431	0.0159	0.3542	0.0973
0.0226	0.0305	0.0215	0.0197	0.1070	0.0417	0.0159	0.3615	0.1077
0.0226	0.0385	0.0215	0.0204	0.2328	0.0839	0.0159	0.3469	0.1077
0.0226	0.0589	0.0215	0.0197	0.2359	0.0754	0.0160	0.8761	0.1841
0.0159	0.3382	0.0990	0.0226	0.1305	0.0263	0.0219	0.1227	0.0431
0.0197	0.2290	0.0754	0.0204	0.2070	0.0677	0.0146	0.9082	0.1992
0.0204	0.2152	0.0631	0.0204	0.2260	0.0727	0.0153	0.8426	0.1831
0.0149	0.9315	0.2154	0.0160	1.0000	0.2240	0.0149	0.8192	0.1831
0.0204	0.2089	0.0700	0.0204	0.2052	0.0700	0.0160	0.3921	0.1185
0.0175	0.9257	0.1894	0.0204	0.2016	0.0625	0.0138	0.8309	0.1831
0.0160	0.7114	0.1615	0.0204	0.2069	0.0651	0.0163	0.3542	0.1042
0.0168	0.9198	0.1979	0.0204	0.0782	0.0323	0.0204	0.2074	0.0677
0.0226	0.2420	0.0485	0.0204	0.0762	0.0323	0.0160	0.3382	0.0990
0.0204	0.2122	0.0677	0.0204	0.2230	0.0700	0.0175	0.0885	0.0313
0.0211	0.1427	0.0538	0.0204	0.2001	0.0677	0.0159	0.3659	0.1146
0.0160	0.7070	0.1562	0.0160	0.4009	0.1185	0.0168	0.0885	0.0313

w2 =
1.0e+010 *
0 0 3.0273 -1.7555 -0.9909 -1.3457 1.2792 0 0 0 0 -0.3577 0 1.2056 -4.5074
0 0 0 0 0 0 0.9644 0 -0.7865 0 0.7723 1.9082 0 0 -1.2202
-0.7277 0 0 6.8043 -2.5766 -2.5796 0 0 0 0 0 -6.4449 0 0 0
0 1.6339 0 0.0432 0 0 -1.0047 0 0 0 0 0 0 0 0
0 0.9539 0 0 0 0 0 0 0 1.6574 -1.2989 0 0 0 0
0 -2.1190 0 0 -1.8381 0 2.3638 -1.9405 -2.6840 9.1956 0 0 0 0 2.3689

2. Biases

b1 =	b2 =
0.8326*	9.35E+04

***Note: The same value of b1 (0.8326) is presented for all (90) hidden neurons.**