# Optimization of desalination wastewater treatment unit performance; Experimental investigation accompanied with artificial neural network and adaptive neural fuzzy interferences modeling

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## ABSTRACT

Almost high salinity effluent stream of desalination units is drained into the sea or dispersed on soil breaking the aqua salt concentration balance and also increase salt content of sea ecosystem or soil. So it is concerned with environmental engineering, corrosion engineering, control engineering, chemical engineering and etc. So zero discharge desalination (ZDD) plants have been proposed with a view of reaching salt and water instead of hazardous saline wastewater. Predicting wastewater pretreatment performance (effluent total hardness, $CO_2$ content and electrical conductivity) as the first step in ZDD plants is considered in this work both experimentally (on a pilot plant) and mathematically (modeling with artificial neural network and adaptive neuro fuzzy inference system). So, optimum operating conditions (150 cc $Al_2(SO_4)_3$ as coagulant, mixing rate in first pretreatment reactor= 110 rpm, 600 cc NaOH and 450 cc $Na_2CO_3$ as additives) are recognized, then optimal NN architecture (three layer feed forward back propagation network with 10 neurons in hidden layer, Levenberg-Marquardt algorithm is as network training function, tangent sigmoid transfer function) and also optimal ANFIS architecture (five layers with six neurons in two hidden layers, two *Bell* membership functions and four rules) are determined. The results confirm predictive modeling by ANN is most efficient comparing with ANFIS in prediction of performance.
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## INTRODUCTION

Direct drainage of the concentrated brine wastewater of desalination units into sea, could cause salinity and thermal shocks to aqua environment as mentioned[28]. But if the concentrated brine wastewater is pretreated in basic softening process, it can be used in order to production of salt and potable water. Total hardness which is caused by $Mg^{2+}$ salts and $Ca^{2+}$ salts, are removed and production of Sodium Chloride becomes possible during pretreatment process[10]. Usage of Sodium Carbonate and Sodium Hydroxide or Calcium Hydroxide in wastewater, vanishes the temporary and permanent hardness as Magnesium Hydroxide and Calcium Carbonate compounds. These particles are small and time is needed for the sedimentation as demonstrated[32,38]. Required time for coagulation, flocculation and sedimentation steps will be short enough and also the turbidity of the product is

minimized By using mineral coagulants in special conditions. Determination of the optimized amounts of Sodium Carbonate, Sodium Hydroxide, suitable conditions of the pretreatment process, type and dosage of coagulant, have to be studied and evaluated to reach the higher yield and minimize total hardness.

Published papers in the field of pretreatment process of wastewater from a desalination unit are scarce in the literature and there is not enough information about this to predict the performance of pretreatment units. In the other hand wastewater pretreatment process is one of unit in zero discharge desalination plants.

In recent years, neural networks have been used as a powerful modeling tool in various pretreatment processes to predict the unit performance; some features of previous studies are summarized in TABLE 1. These are obtained from TABLE 1;

1) Most popular form of neural network in use is feed forward neural network.
2) No record for modeling of pretreatment of desalination wastewater unit by neural network is found in the literature.
3) Back propagation algorithm is also efficient in prediction networks.

**TABLE 1: Researchers' studies in modeling of pretreatment process of wastewater by neural network**

|    | Reference | Year | Model type | Application |
|----|-----------|------|-----------|-------------|
| 1 | Zvi Boger [5] | (1992) | Back propagation feed forward neural network | Wastewater Treatment Plant Operation |
| 3 | Spall et al.[33] | (1997) | Network model. | Wastewater quality predication system |
| 4 | Zhu et al. [47] | (1998) | Fuzzy systems and neural networks | Wastewater treatment |
| 5 | Tay et al. [35, 36] | (1999, 2000) | Fuzzy modeling, Back propagation neural network | Anaerobic biological wastewater pretreatment |
| 6 | Belanche et al. [3] | (2000) | Feed-forward net time-delay neural networks | Wastewater treatment plants |
| 7 | Gontarski et al.[14] | (2000) | Feed-forward back propagation neural network | Industrial treatment plant |
| 8 | Lee et al.[17] | (2002) | Hybrid neural network | Industrial waste water treatment |
| 9 | Timothy et al.[37] | (2003) | Kohonen Self-Organising Feature Maps (KSOFM) neural network | Municipal wastewater treatment plant |
| 10 | Zeng G.M. et al. [45] | (2003) | Back-propagation neural network | Paper mill wastewater treatment |
| 11 | Hamed et al. [15] | (2004) | Feed forward neural network | Waste water treatment plan |
| 12 | Onkal-Engin et al. [25] | (2005) | Artificial Neural Network (ANN) trained with a back-propagation algorithm | Biochemical Oxygen Demand (BOD) values of samples from wastewater treatment plant |
| 13 | Ozer Cinar [8] | (2005) | Kohonen self-organizing feature maps | Pelham wastewater biological oxygen demand (BOD), total suspended solids (TSS) and fecal coliform |
| 14 | Lee et al. [18] | (2005) | Feedforward back-propagation neural network | Cokes wastewater treatment plant |
| 15 | Cinar et al. [9] | (2006) | Cascade-forward back-propagation | Treating cheese whey wastewater |
| 16 | Chen et al. [6] | (2007) | Back propagation neural networks (BPN) algorithm | Wastewater Treatment Process |
| 17 | Majlli et al.[23] | (2007) | Back propagation, artificial neural network (ANN) | Wastewater treatment plants performance |
| 18 | Parthinban et al.[28] | (2007) | Feed-forward neural network | Starch wastewater treatment |
| 19 | Rangassamy et al. [31] | (2007) | Multi layer feed forward perceptron | Starch wastewater treatment |
| 20 | Macho´n et al. [19] | (2007) | Feed-forward neural network | Coke wastewater nitrification |
| 21 | Yu et al.[43] | (2008) | Back propagation artificial neural network models | Wastewater reuse applying ORP/pH monitoring |

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| | Reference | Year | Model type | Application |
|---|---|---|---|---|
| 22 | Torrecilla et al. [38, 39] | (2007, 2008) | Feed-forward back propagation neural network | Olive oil mill wastewater |
| 23 | Suh et al. [34] | (2009) | Back propagation learning algorithm | Scale activated-sludge wastewater treatment plant |
| 24 | Aber et al. [1] | (2009) | Feed forward back propagation network | Removal of Cr(VI) from synthetic and real wastewater |
| 25 | Mingzhi et al. [21] | (2009) | Fuzzy neural networks | Biofilm wastewater treatment Process |
| 26 | Mingzhi et al. [22] | (2009) | Feed-forward back propagation algorithm | Paper mill wastewater treatment |
| 27 | Purkait et al. [30] | (2009) | Feed-forward network | Leather plant effluent |
| 28 | Pai et al. [26] | (2009) | Neuron fuzzy inference system (ANFIS) | Hospital wastewater treatment plant effluent |
| 29 | Chen z. et al. [7] | (2009) | Back propagation neural network | Wastewater treatment and reuse in submarine cabin for long voyage |
| 30 | Sadrzadeh et al. [32] | (2009) | Feed-forward back propagation neural network | Pb2+ removal from wastewater using electrodialysis |
| 31 | Basha et al. [3] | (2010) | Feed-forward back propagation neural network | Chemical industry effluent |
| 32 | Fang et al. [13] | (2010) | Feed-forward back-propagation NN | Municipal wastewater treatment plant |
| 33 | Waewsak et al. [41] | (2010) | Neural-fuzzy control system, neural network with back propagation algorithm | Wastewater treatment and biogas production, |
| 34 | Nandi et al. [24] | (2010) | Back propagation-based multi-layer feed forward artificial neural network (ANN) model | Treatment of oily wastewater using low cost ceramic Membrane |
| 35 | Turan et al. [40] | (2011) | Feed forward back propagation network with | Cu(II) from industrial leach ate by pumice |
| 36 | . Silvia Curteanu et al. [10] | (2011) | Feed-forward back propagation neural network | Electrolysis process in wastewater treatment |
| 37 | Pendashteh et al [29] | (2011) | A feed-forward neural network trained by batch back propagation algorithm | Treating hyper saline oily wastewater |
| 38 | Pai et al. [27] | (2011) | Adaptive neuron fuzzy inference system (ANFIS) | Wastewater treatment plant of industrial Park |
| 39 | Bhatti et al. [4] | (2011) | RSM and ANN modeling | Removal of copper from synthetic wastewater |

Although, ANFIS is a powerful modeling tool to predict the performance of nonlinear process, but this has not been considered as much as artificial neural network.

This work focused on the prediction of performance of one step in zero discharge desalination plant which is desalination waste water pretreatment. The goal of this step is softening high salinity wastewater from a petrochemical desalination plant and preparing it to produce salt and water instead of drainage into sea. So, natural salt concentration of sea and soil doesn't be increased by desalination wastewater. This subject can be interesting as a view of sciences related to corrosion, control, environmental, chemical and etc sciences. Both experimental work and modeling are applied to optimize the performance prediction of pretreatment process.

Modeling is done by ANN and ANFIS which are powerful adaptive models in prediction and optimization of processes, based on experimental data.

## MATERIALS AND METHOD

Optimum amounts of each coagulant, and also the type of mixture and the best speed of the first pretreatment reactor are investigated experimentally. Three commercial mineral coagulants, Aluminum Sulfate, $Al_2(SO_4)_3$, Ferric Sulfate, $Fe_2(SO_4)$ and Ferric Chloride, $FeCl_3$, are used in the pretreatment process

of concentrated brine wastewater. Moreover in softening process Sodium Carbonate and Sodium Hydroxide must be added to the brine wastewater. So the appropriate fraction of these additives to coagulant is considered. Experiments are held in two PVC series tanks equipped by adjustable agitator. Optimum values of speed, coagulant and additives are gained when total hardness of produced wastewater reaches to minimum amount. Figure 1 shows this setup.



**Figure 1 : Basic structure of an two layer neural network model, (IW (input weights), LW (layer weights), 10 neuron, 3 input, 1 target and two transition function)**

Optimum results of experiments are used in an ANN program and also in ANFIS program to train and simulate networks for predicting the amounts of total hardness, $CO_2$ content and electrical conductivity.

## Practical desalination unit of mobin petrochemical complex

Mobin petrochemical complex is located in south of Iran and works as a utility unit for whole petrochemical companies. Five MED practical desalination units in Mobin petrochemical complex provide the water supply. About $1030 \, ton/hr$ flow rate of sea water is fed to each of desalination unit although each unit has designed for $1100 \, ton/hr$ of sea water. About 28% of the feed is produced as sweet water and high saline water is drained to the sea as brine wastewater. So, the total flow rate of brine wastewater is $3700 \, ton/hr$, approximately. Salinity of the brine wastewater is 54500ppm and the to-

**TABLE 2 : The properties of Wastewater before treatment process**

| Composition | Unit | Brine outlet line |
|---|---|---|
| Ca++ | ppm as $CaCO_3$ | 14616.3 |
| Mg++ | ppm as $CaCO_3$ | 36080 |
| Total hardness | ppm as $CaCO_3$ | 50696.3 |
| Fe++ | ppm | Trace |
| Ba++ | ppm | Trace |
| SO$_4$ -- | g/l | 5.25 |
| HCO$_3$ - | g/l | 0.185 |
| Salinity | ppm | 54500 |
| Silica | ppm | 0.1 |
| Specific Gravity at 15 c | | 1.04 |
| pH | | 8.2 |
| Viscosity (Kinematic) | Mm2/s | 0.7 |
| TSS | g/l | Trace |
| Total Dissolved Solids | g/l | 63.8 |
| Conductivity | ms/cm | 77100 |

tal hardness is about 50696.3 ppm as $CaCO_3$. Some of specifications of brine wastewater are in TABLE 2.

## Artificial neural network

Artificial neural network (ANN) has been adopted in many areas of science. Neural networks are adjusted, or trained, so that a particular input leads to a specific target output as demonstrated[36]. The term backpropagation refers to the manner in which the gradient is computed for nonlinear multilayer network as mentioned[2,3,9] and is commonly used in many ANN

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applications as demonstrated[22,29,41].

Structure of a multi layers neural network model is shown in Figure 2. In this work Back propagation feed forward type is selected to be optimized. This neural network consists of two layers (hidden and output), neurons in hidden layer, network training functions and layer's learning function. Experimental input data are normalized and then divided into training (40%), testing (30%) and validation data (30%).

Optimization of this network includes finding appropriate network training function among Levenberg-Marquardt back propagation, *trainlm*, Gradient descent with momentum back propagation, *traingdm* and BFGS quasi-Newton back propagation, *trainbfg*, network architecture using hyperbolic tangent sigmoid transfer function, *tansig*, Log-sigmoid transfer function, *logsig* and Linear transfer function, *purelin*, in each layer of network and determining optimum number of neurons in hidden layer using trial- and- error approach. A number of steps are during the model development process which is shown schematically in Figure 3.

Reasonable results are obtained when the *rmse* is small and the validation and test correlation coefficient gets close to one. Since the used transfer function in the hidden layer is sigmoid, all samples must be normalized. So any samples ($X_i$) from the training, validation and test sets are scaled to a new value ($X_{newi}$) as follows:

$$Y = (X - X_{mean}) \times \left( \frac{Y_{std}}{X_{std}} \right) + Y_{mean} \qquad (1)$$

Where $X_{mean}$ and $Y_{mean}$ are mean values of each row of input and each row of output, $X_{std}$ and $Y_{std}$ are standard deviation for each row of input and each row of output, respectively.

Training aims at estimating the parameters ($IWij, LW_j$, $b_j$, and $b_2$) by minimizing an error function, such as the root mean square error (RMSE) which is expressed as:

$$RMSE = \left( \frac{\sum_{i=0}^{i=N} (Ytar_i - Yout_i)^2}{N} \right)^{0.5} \qquad (2)$$

Where data is the number of data points and targets are experimental outputs and output shows program results. Also correlation coefficient *(R)* and mean abso-
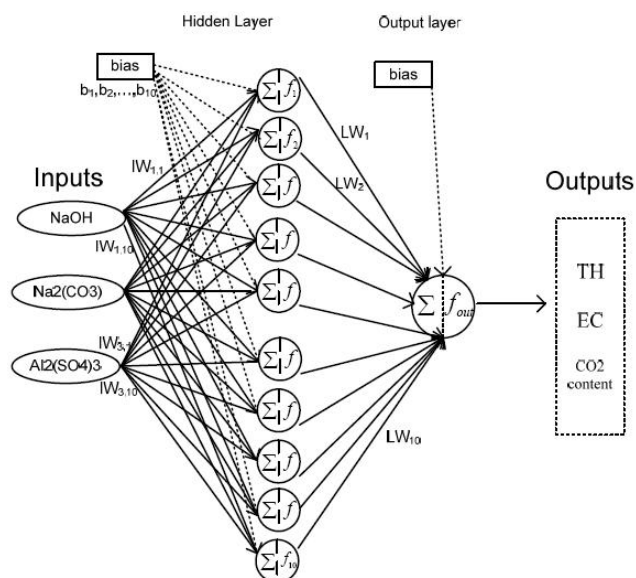


**Figure 2 : Steps of the neural network model development process**
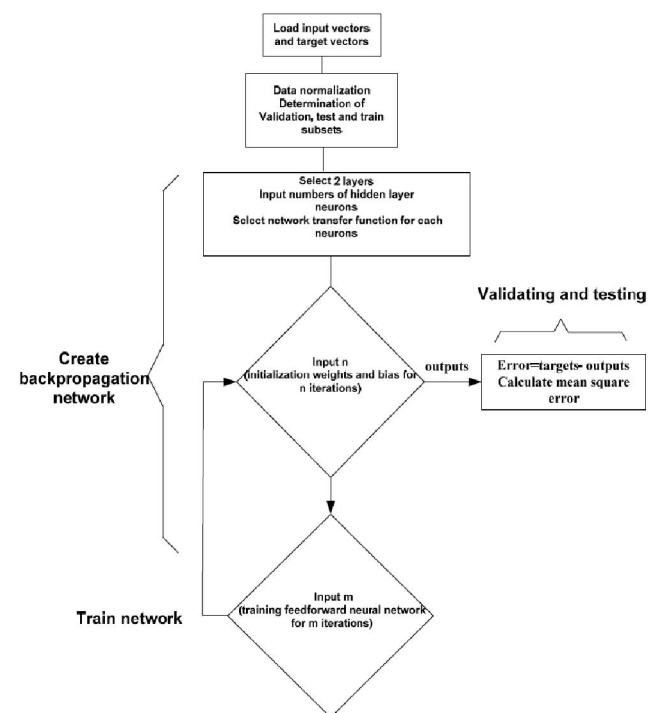


**Figure 3 : Experimental apparatus**

lute error *(MAE)* are two statistical criteria which are employed to show the modeling performance and described as:

$$MAE = \frac{\sum_{i=1}^{N} |(Ytar_i - Yout_i)|}{N} \qquad (3)$$

$$R = \frac{\sum_{i=1}^{N}(Ytar_i - \overline{Ytar})(Yout_i - \overline{Yout})}{\sqrt{\sum_{i=1}^{N}(Ytar_i - \overline{Ytar})^2 \sum_{i=1}^{N}(Yout_i - \overline{Yout})^2}} \qquad (4)$$

### Fuzzy interference system

Experiments show that there are various variables affect on TH, EC and $CO_2$ content and nonlinear relations between desalination effluent wastewater indices

and characteristics of pretreatment effluent stream. Fuzzy system is a powerful tool to predict outputs in nonlinear systems fast and precisely. Neuro-fuzzy inference system (ANFIS) using a given input/output data set. This function constructs a fuzzy inference system (FIS) whose membership function (MFs) parameters are adjusted using either a BP algorithm alone or in combination with a least squares type of method. This adjustment allows the fuzzy systems to learn from the data they are modeling. The process of fuzzy inference involves Membership

**TABLE 3 : Categories of experiments are done in this study**

| Parameters | unit | Value |
|---|---|---|
| Mixing rate in first pretreatment reactor | rpm | 50, 70, 90, 120, 140, 160, 180, 200, 220 |
| Coagulant ($Al_2(SO_4)_3$, $FeCl_3$, $Fe_2(SO_4)_3$) | cc | 10, 20, 30, 40, 50, 70, 110, 150, 115, 130, 140, 100, 85, 160, 180 |
| NaOH/4000 cc coagulant | | 1.5, 3, 4 |
| $Na_2CO_3$/4000 cc coagulant | | 1,2, 3 |

**TABLE 4 : Experimental data for $Al_2(SO_4)_3$, (Mixing rate in coagulation step= 70 rpm; mixing rate in flocculation step=50rpm; wastewater sample=4lit)**

| Run | NaOH cc | Na₂CO₃ cc | Al₂(SO₄)₃ Cc | Wastewater pH | Temperature C | Total Alkalinity ppm as CaCO3 | Total Hardness ppm as CaCO3 | Clarified water PH | CO₂ ppm as CaCO3 | EC μΩ/cm |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 150 | 100 | 100 | 8.99 | 19.6 | 933.3333 | 5100 | 9.9 | 0.267265 | 62921.35 |
| 2 | 40 | 30 | 10 | 8.93 | 19.5 | 1200 | 6573.3333 | 10.4 | 0.108664 | 71161.05 |
| 3 | 15 | 20 | 10 | 8.4 | 19 | 3333.333 | 7140 | 10.65 | 0.16974 | 73408.24 |
| 4 | 15 | 10 | 10 | 8.6 | 19.1 | 3466.667 | 7933.333 | 10.8 | 0.124973 | 75655.43 |
| 5 | 150 | 200 | 100 | 9.14 | 19.5 | 1600 | 4306.667 | 10.4 | 0.778081 | 71910.11 |
| 6 | 160 | 120 | 40 | 8.99 | 19.8 | 1733.333 | 4533.333 | 10.75 | 0.070111 | 68164.79 |
| 7 | 60 | 80 | 40 | 8.99 | 19.6 | 933.333 | 4873.333 | 9.44 | 0.770799 | 73408.23 |
| 8 | 60 | 40 | 40 | 8.93 | 19.8 | 333.333 | 5893.333 | 9.39 | 0.308875 | 73408.24 |
| 9 | 225 | 150 | 150 | 8.84 | 19.9 | 666.6667 | 3740 | 10.1 | 0.120452 | 68164.79 |
| 10 | 225 | 300 | 150 | 8.81 | 19.7 | 1200 | 1773.3333 | 10.55 | 0.076928 | 666666.7 |
| 11 | 600 | 450 | 150 | 8.82 | 19.7 | 2133.33 | 453.33 | 11.44 | 0.00374 | 62921.30 |
| 12 | 400 | 300 | 100 | 7.7 | 20 | 2933.3333 | 2040 | 11.99 | 0.004748 | 65168.54 |
| 13 | 127.5 | 85 | 85 | 8.6 | 18 | 933.333 | 2720 | 10.4 | 0.084517 | 66666.67 |
| 14 | 127.5 | 170 | 85 | 8.7 | 17.8 | 800 | 2606.667 | 10.4 | 0.072443 | 65917.6 |
| 15 | 340 | 255 | 85 | 8.57 | 18 | 1066.667 | 2266.667 | 10.75 | 0.043145 | 64423.22 |
| 16 | 560 | 420 | 140 | 8.12 | 19.2 | 2366.66 | 643.333 | 9.52 | 0.076231 | 62353.21 |
| 17 | 80 | 60 | 20 | 8.23 | 19.5 | 1133.333 | 6014.6667 | 10.6 | 0.058623 | 70362.61 |
| 18 | 200 | 150 | 50 | 8.88 | 18.9 | 1566.6667 | 3566.666 | 10.32 | 0.031562 | 63223.44 |
| 19 | 280 | 210 | 70 | 8.69 | 19.42 | 1233.333 | 3055.3333 | 11 | 0.099532 | 66022.05 |
| 20 | 440 | 330 | 110 | 9.45 | 18.6 | 2766.6667 | 1856 | 11.2 | 0.084123 | 63223.44 |
| 21 | 460 | 345 | 115 | 9.42 | 19.94 | 2526.333 | 1243.6667 | 10.36 | 0.083175 | 63012.11 |
| 22 | 520 | 390 | 130 | 8.54 | 18.68 | 2166.6667 | 755 | 11.33 | 0.063213 | 63112.23 |
| 23 | 640 | 480 | 160 | 8.88 | 17.9 | 2033.333 | 575.2223 | 9.68 | 0.075845 | 60123.01 |
| 24 | 720 | 540 | 180 | 8.65 | 18.5 | 1800 | 721.333 | 10.2 | 0.0469523 | 59754.21 |

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Functions, Logical Operations, and If-Then Rules. A network type structure is similar to that of a neural network, which leads inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map.

## RESULTS AND DISCUSSION

### Experimental results

Total hardness removal of effluent stream from desalination unit is conveyed in two pretreatment reactors. Major parameters which decrease the amount of TH, $CO_2$ content and EC are mixer speed in first pretreatment step, type of coagulant and amount of coagulant. Also, experiments performed to find the optimum ratio of Sodium Carbonate to coagulant and Sodium Hydroxide to coagulant and these ratios are investigated by experiments. 405 experiments are done for three mineral coagulants and TABLE 3 summarizes types of experiments also TABLE 4 shows some obtained data for $Al_2(SO_4)_3$ just in 70 rpm mixing rate of first pretreatment reactor. Results are visualized in Figure 4 and Figure 5.
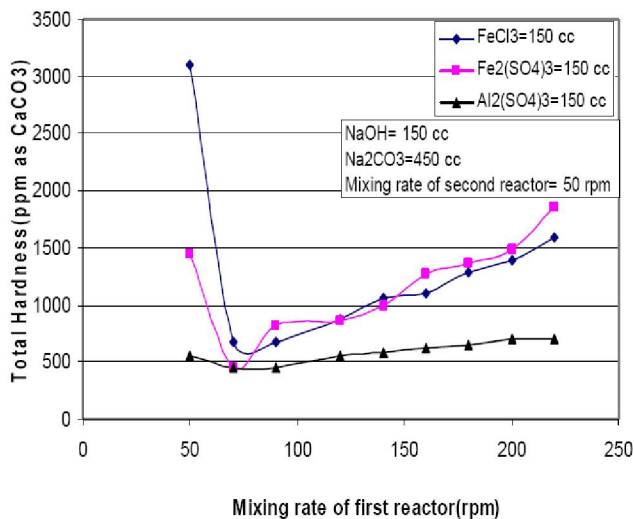


**Figure 4 : Effluence of mixing rate of first pretreatment reactor on TH for three coagulants**

Data analyzing reveals that decreasing total hardness, eliminating ions effectively so electrical conductivity decreases, it seems when appropriate amounts of NaOH, $Na_2CO_3$ and coagulant are used, $HCO3^-$ is consumed to form sediments so TH and $CO_2$ content decrease and consequently EC decreases.

Figure 4 visualizes that $Al_2(SO_4)_3$ is the most effective coagulant comparing with $Fe_2(SO_4)$ and $FeCl_3$. Also total hardness minimizes when mixing rate in first
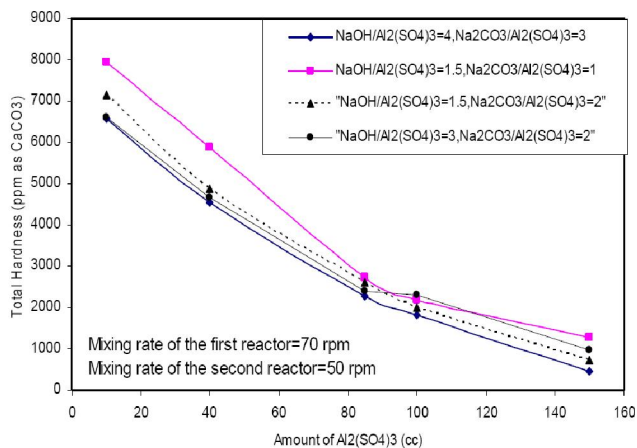


**Figure 5 : Influence of amounts of NaOH and $Na_2CO_3$ on TH**

pretreatment reactor is 70 rpm. Mixing rate in the first pretreatment reactor causes direct effect on coagulation step, it must be adjusted in such value to improve breaking connections in coagulant compound and also improve proper ions conjunctions to perform coagulation.

Using $Al_2(SO_4)_3$ as coagulant, optimum values of NaOH and $Na_2CO_3$ which are added into the solution are considered in Figure 5.

Optimum characteristics resulted in these experiments to meet minimum levels of TH, $CO_2$ content and EC are as followed.

a) Mixing rate in the first pretreatment reactor is equal to 70 rpm, lower mixing rate doesn't make enough turbulences in the solution to breaks connections while higher mixing rate than 70 rpm refuses forming effective connections to coagulate so prevent sedimentation.

b) Effective type of coagulant is $Al_2(SO_4)_3$.

c) 150 cc of coagulant is added to 4000 cc of wastewater.

d) Ratio of NaOH to coagulant is equal to 4 and for $Na_2CO_3$ is equal to 3.

e) Decreasing TH leads decreasing $CO_2$ content and also decreasing EC so monitoring TH can be criteria to predict EC value and $CO_2$ content of effluent wastewater. These are important to control corrosion damages.

So optimum data (influent values and effluent values) are carried out to optimize the artificial neural network,

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**TABLE 5 : Experimental data is used to optimize neural network**

| Parameter | Unit | Value |
|---|---|---|
| Type of coagulant | ----- | $Al_2(SO_4)_3$ |
| Amount of coagulant in each 4000 cc of wastewater sample | cc | 10, 20, 30, 40, 50, 70, 110, 150, 115, 130, 140, 100, 85, 160, 180 |
| Amount of NaOH in each 1000 cc of wastewater sample | cc | 40, 80, 120, 160, 200  280, 440, 600, 460, 520, 560, 400, 340, 640, 720 |
| Amount of $NA_2CO_3$ in each 1000 cc of wastewater sample | cc | 30, 60, 90, 120, 150 210, 330, 450, 345, 390, 420, 300, 255, 480, 540 |
| Mixing rate in coagulation step | rpm | 70 |

this is explained in next section. TABLE 5 shows data that is used to optimize the artificial neural network.

### Neural network modeling results

In this case study, gained experimental data are normalized and randomized and then divided into training (40%), testing (30%) and validation data (30%). First the effect of each input on each output is monitored by training networks. Then 12 different types of neural network are created and verified then the optimal performance is revealed by

a) Minimum *rmse*.
b) Factor of correlation coefficient, $R^2$, gets close to one.

### Sensitivity analyzing

Three layers network with 10 neurons in hidden layer and *tansig* transfer function and *trainlm* training function is trained to investigate sensitivity analyzing.

TABLE 6 shows the sensitivity of each output variables to inputs, each input shows the same effect and has highest effect on TH. For $CO_2$ content $R^2_{NaOH}=$ $R^2_{Na2CO3}$ (1)> $R^2_{AL2 (SO4)3}$ (0.9997) is visualized and for

**TABLE 6 : Sensitivity analyzing**

| | | (1) NaOH | (2) Na₂CO₃ | (3) Alum | 1;2 | 1;2;3 |
|---|---|---|---|---|---|---|
| TH | R2 | 1 | 1 | 1 | 0.9996 | 0.99988 |
| | rmse | 0.0024 | 0.0078 | 0.0053 | 0.0210 | 0.0339 |
| EC | R2 | 0.9998 | 0.9998 | 0.9996 | 0.999 | 0.999 |
| | rmse | 0.0132 | 0.0170 | 0.0190 | 0.0456 | 0.0298 |
| CO2 | R2 | 1 | 1 | 0.9994 | 0.9966 | 0.9968 |
| | rmse | 0.0021 | 0.0046 | 0.0229 | 0.0567 | 0.00587 |

EC, $R^2_{NaOH}= R^2_{Na2CO3}$ (0.9998) > $R^2_{AL2 (SO4)3}$ (0.9996) is obtained. Higher amount of $R^2$ indicate higher sensitivity.

The effect of additives on each output also investi-

gated by the same network and concluded that $R^2_{TH}$(0.9996) > $R^2_{CO2\ content}$ (0.999) > $R^2_{EC}$(0.9966).

Also, effects of three influent indices on each effluent parameter are shown in TABLE 6 and again this is shown that they predict TH, precisely. So predicting TH values of effluent stream is dependant strongly on three influent indices and experimental results also indicate this.

### Network optimization

According to the contributed algorithm the optimum architecture and training function of neural network is determined.

1) A multi layers feed forward back propagation network with three neurons in input layer and three neurons in output layer is used.
2) Three training functions are examined for faster optimization and *trainlm* finds better optima and decreases value of *rmse* much more rapidly with time than *traingdm* and *trainbfg* functions. TABLE 7 shows the performance of the training functions according to the amount of *rmse*.
3) Using *trailm* with fixed number of neurons in hidden layer, three possible transfer functions in hidden layer and output layer are analyzed in five types of networks architectures. TABLE 8 shows that *tansig* function in both hidden and output layer has minimum *rmse* and maximum $R^2$.
4) The last step in network optimization is fixing the number of neurons in hidden layer to reach lowest *rmse* and also gain proper performance without time consumption. TABLE 9 contains results of modeling of 6 types of neural networks.

Figure 6 and Figure 7 show a comparison between calculated and experimental values of the output variable (TH) for test and validation sets, using the optimized neural network model with number of hidden layer

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**TABLE 7 : Performance of network training functions**

| Neuron in hidden layer | Network training function | Hidden transfer function | Output transfer function | RMSE | $R^2$ |
|---|---|---|---|---|---|
| 10 | traingdm | Tansig | tansig | $8.54 \times 10^{-8}$ | 0.93211 |
| 10 | Trainbfg | Tansig | tansig | $2.25 \times 10^{-14}$ | 0.88614 |
| 10 | Trainlm | Tansig | tansig | $9.23 \times 10^{-11}$ | 0.99791 |

**TABLE 8 : Architecture of neural network**

| Neuron in hidden layer | Network training function | Hidden transfer function | Output transfer function | RMSE | $R^2$ |
|---|---|---|---|---|---|
| 10 | trainlm | Tansig | tansig | $9.23 \times 10^{-11}$ | 0.99791 |
| 10 | trainlm | Logsig | logsig | 0.1220798 | 0.91262 |
| 10 | trainlm | Tansig | logsig | 0.1320765 | 0.87387 |
| 10 | trainlm | Tansig | purelin | $5.15 \times 10^{-7}$ | 0.97362 |
| 10 | trainlm | Logsig | purelin | $3.21 \times 10^{-8}$ | 0.99002 |

**TABLE 9 : Optimization of number of neurons in hidden layer**

| Neuron in hidden layer | Network training function | Hidden transfer function | Output transfer function | RMSE | $R^2$ |
|---|---|---|---|---|---|
| 8 | trainlm | Tansig | tansig | $1 \times 10^{-8}$ | 0.99510 |
| 10 | trainlm | Tansig | tansig | $9.23 \times 10^{-11}$ | 0.99791 |
| 12 | trainlm | Tansig | tansig | $1.31 \times 10^{-11}$ | 0.95988 |
| 15 | trainlm | Tansig | tansig | $2.46 \times 10^{-10}$ | 0.99641 |
| 18 | trainlm | Tansig | tansig | $3.602 \times 10^{-6}$ | 0.99456 |
| 20 | trainlm | Tansig | tansig | $1.10 \times 10^{-7}$ | 0.99320 |



**Figure 6 : Comparison of the experimental test data with those predicted via neural network modeling**
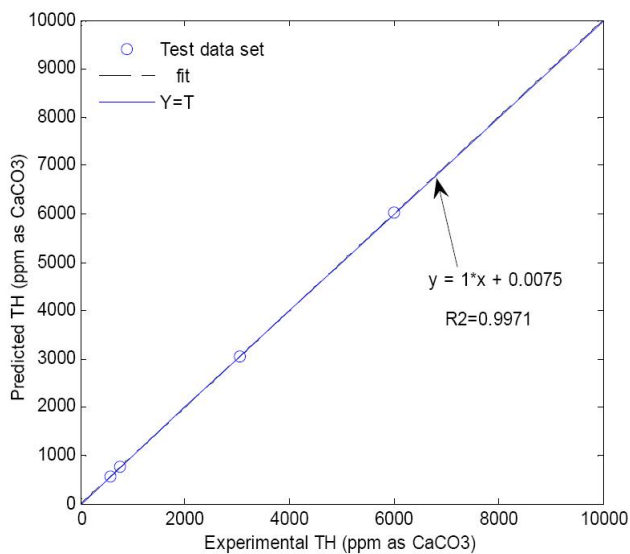


**Figure 7 : Comparison of the experimental validation data with those predicted via neural network modeling**

equal to ten, respectively. Obviously, calculated data tracks experimental ones very well and correlation coefficient, $R^2$, is close enough to one. Figure 8 shows $CO_2$ experimental values and the precise prediction of optimized network for $CO_2$ content. Also, Figure 9 and
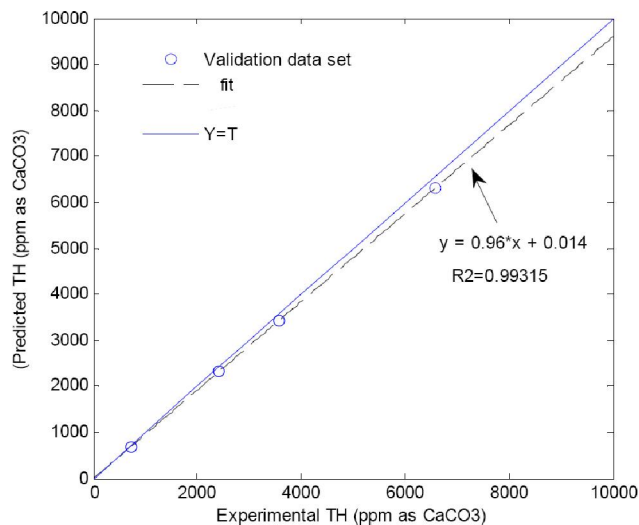
Figure 10 compare experimental and predicted values of EC and TH, respectively.

The suitable architecture for prediction of effluent performance is determined to consist of a hidden layer with 10 neurons with *tansig* transfer function. Also *trainlm* shows the best performance in this investiga-
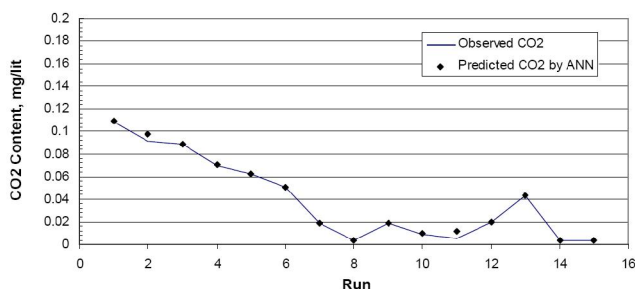
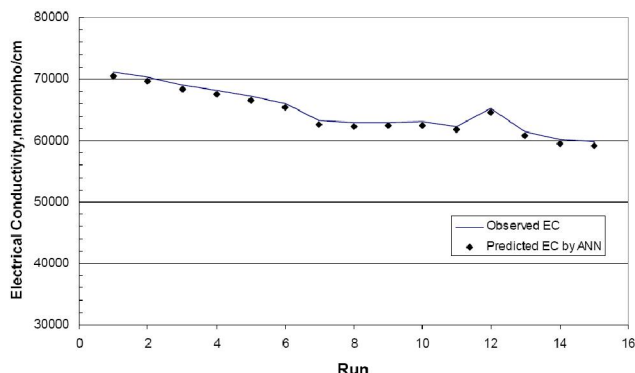**Figure 8 : Predicted TH data versus experimental**



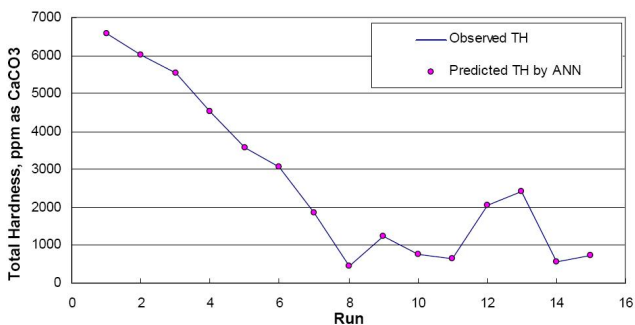**Figure 9 : Predicted EC data versus experimental**



**Figure 10 : Predicted $CO_2$ content vs. experimental**
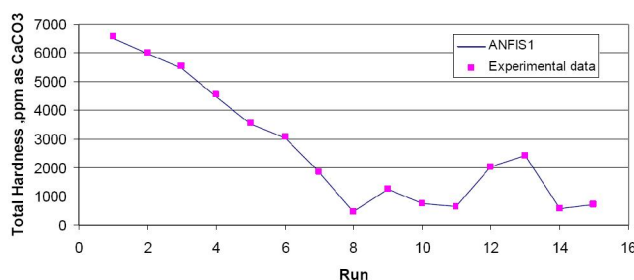


**Figure 11 : Comparison between TH prediction data by ANFIS1 and experimental data**
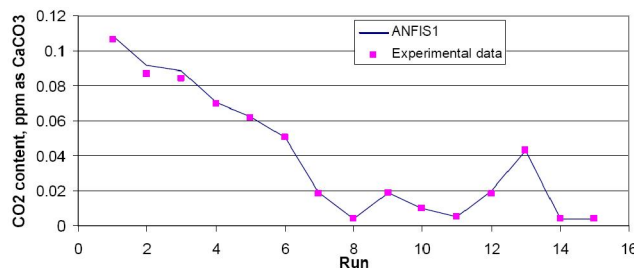


**Figure 12 : Comparison between predicted $CO_2$ content by ANFIS1 and experimental data**

tion when initial data divided into 40% (training), 30% (testing) and 30% (validating). TABLE 10 reports *Weight* and *Bias* values which are obtained with the optimized neural network.

**Fuzzy interference results**

TABLE 11 shows types of ANFIS models which are examined to predict treatment unit effluent qualities. Number of layers and MFs and rules are determined for optimal model.

Statistics criteria which are used to show the model

**TABLE 10 : Matrices of weights, IW: weights between input and hidden layers; LW: weights between hidden and output layers**

| Neuron | IW | | | Bias | Neuron | LW |
|---|---|---|---|---|---|---|
| | Variable | | | | | |
| | NaOH | Na2(CO3) | Al2(SO4)3 | | | |
| 1 | -1.3345 | 2.6985 | -0.4639 | 2.9339 | 1 | -1.2281 |
| 2 | -0.1190 | 3.2331 | -0.6928 | 1.5836 | 2 | -1.8267 |
| 3 | -1.3486 | 0.5628 | 0.4592 | 4.0818 | 3 | 6.2114 |
| 4 | 1.3974 | 1.3603 | 2.2730 | 5.1039 | 4 | -2.8053 |
| 5 | -0.8324 | 1.9868 | -2.1414 | -1.2313 | 5 | 0.2601 |
| 6 | -0.8403 | -1.8547 | -3.7155 | 2.6674 | 6 | 1.0171 |
| 7 | 0.7875 | -0.6412 | -3.3781 | 2.6697 | 7 | -0.8059 |
| 8 | -0.7134 | -2.5426 | -2.0331 | -2.8525 | 8 | -0.8042 |
| 9 | -0.6422 | -1.7614 | 2.3629 | -2.2570 | 9 | 0.0424 |
| 10 | 0.1735 | -1.4767 | 2.6963 | 2.8603 | 10 | -0.8283 |
| | | | | | bias | -0.9125 |

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**TABLE 11 : Architecture of ANFIS models**

| Item | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Basic structure | | | | | | |
| No. of total layers | 5 | 5 | 5 | 5 | 3 | 3 |
| No. of input and output layers | 3 | 3 | 3 | 3 | 2 | 2 |
| No. of nodes in hidden layers | 6 | 6 | 6 | 6 | 6 | 6 |
| No. of nodes in input layer | 4 | 4 | 4 | 4 | 4 | 4 |
| No. of neurons in output layer | 3 | 3 | 3 | 3 | 3 | 3 |
| **MFs** | **Bell** | **Bell** | **Gaussian** | **Gaussian** | **Gaussian** | **Bell** |
| No. of MFs | 2 | 4 | 2 | 4 | 2 | 4 |
| No. of fuzzy rules | $2^2$ | $4^2$ | $2^2$ | $4^2$ | $2^2$ | $4^2$ |

**TABLE 12: Statistical indices for ANFIS models**

| Effluent indices | Statistical criteria | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|
| | R | 0.9669 | 0.9593 | 0.9664 | 0.9447 | 0.9072 | 0.9195 |
| TH | MAE | 0.0473 | 0.0572 | 0.0583 | 0.0599 | 0.0726 | 0.0626 |
| | RMSE | 0.0332 | 0.0358 | 0.0372 | 0.0396 | 0.0446 | 0.0416 |
| | R | 0.9860 | 0.9800 | 0.9771 | 0.9773 | 0.8695 | 0.8999 |
| CO2 | MAE | 0.01321 | 0.0142 | 0.0181 | 0.0210 | 0.1103 | 0.1030 |
| | RMSE | 0.2216 | 0.2235 | 0.2241 | 0.2258 | 0.2363 | 0.2213 |
| | R | 0.7969 | 0.7424 | 0.7152 | 0.7011 | 0.5869 | 0.6690 |
| EC | MAE | 0.0412 | 0.0441 | 0.0487 | 0.0511 | 0.1320 | 0.1011 |
| | RMSE | 0.0946 | 0.0944 | 0.0924 | 0.0954 | 0.1912 | 0.1506 |
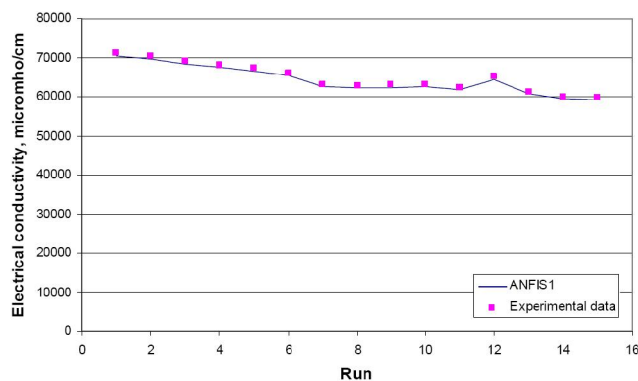


**Figure 13 : Comparison between predicted EC by ANFIS1 and experimental data**

performance are reported in TABLE 12. Comparison between criteria for ANFIS 3 and ANFIS 5 also between NAFIS 2 and ANFIS 6 concludes increasing numbers of hidden layers increases the accuracy of ANFIS prediction so amounts of *mae* and *rmse* between experimental data and model results gets lowest. Also Bell membership function acts better than Gaussian and increases amount of correlation coefficient. Comparing obtained results between ANFIS1 and ANFIS2 shows increasing membership rules doesn't show posi-

tive effect in predicting precisely. Finally ANFIS1 is selected as an optimal model to predict treatment performance.

Figure 11 shows ANFIS1 results versus experimental amounts of TH and indicates the excellent agreement, Figure 12 shows comparison between ANFIS1 predicted values of $CO_2$ content and experimental data and they show somehow a good agreement. Good agreement is obtained between experimental amounts of EC and predicted ones shown in Figure 13.

## CONCLUSIONS

The influence of the main parameters of the pretreatment process on the final values of total hardness is evaluated experimentally. On the other hand, the predictions of the main system outputs of a treated waste as a function of initial characteristics (optimized amount of NaOH to coagulant, $Na_2CO_3$ to coagulant and $Al_2(SO_4)_3$), are performed using neural networks. According to this investigation bellow results are obtained:
1) The best of coagulant is $Al_2(SO_4)_3$ and the best mix-

ing rate in first pretreatment reactor is 70 rpm, lower speed can't break coagulant connections properly and higher speed can't make effective collision to form sediments and remove total hardness.

2) This is beneficial to use amounts of additives considering the amount of coagulant so the optimum value for NaOH to coagulant and $Na_2CO_3$ to co-agulant is 4 and 3, respectively.

3) In optimum operating conditions, total hardness decreases to 453.33 ppm as $CaCO_3$, Also electrical conductivity and $CO_2$ content reaches minimum levels and 62921.3 and 0.00374, respectively.

4) The optimized Multilayer neural network consists of tangent sigmoid transfer function in hidden layer, and also in output layer. The number of optimized neurons is 10 in the hidden layer and Levenberg-Marquardt algorithm as network training function. Obtained mean squared error is $9.61 \times 10^{-6}$ and correlation coefficient is 0.99791 so this neural network modeling could give excellent agreement with experimental results.

5) The optimized Multilayer ANFIS consists of five layers with six neurons in two hidden layers, two *Bell* type membership functions with four rules.

6) Optimized ANN predictions are more precise than optimized ANFIS results. ANN shows lower *rmse* with experimental data.

7) The optimized neural network can be used to predict the efficiency of pretreatment process of desalination effluent, generally.

8) Predictions of optimized neural network can be applied for optimization purposes for pretreatment units and also for forecasting performance of zero discharge desalination plants.

9) Results are applicable for control engineers, corrosion engineers and process engineers, chemical and environmental engineers.

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