Prediction of Reverse Osmosis (RO) Membrane Properties Using One Year Real Operational Data

Dr. Kamal M. Sassi, Dr. Rajab. A. Atibeni, Dr. Mustafa T. Yagub

Department of Chemical Engineering - Faculty of Engineering

Zawia University

Abstract :

Modelling played an important role in simulation, optimisation, and control of reverse osmosis (RO) desalination processes. Water and salt permeability of the membrane are one of important membrane properties that affect optimal design and operation of RO processes. Therefore, estimation of membrane water and salt permeability is significant.

In this work, neural networks (NNs) based correlation has been developed based on the actual RO fouling data over one year of operation and used for estimating the membrane permeability decline factors. It is found that the NNs based correlations can predict the experimental water and salt permeability very closely.

Due to advancement in the microcomputer, plant automation becomes reliable means of plant maintenance. NNs based correlations (models) can be updated in terms of new sets of weights and biases for the same architecture or for a new architecture reliably with new plant data.

Keywords: Reverse osmosis; Spiral wound module; Seasonal changes; Fouling; Membrane permeability; Neural network techniques

1- Introduction :

The scarcity of fresh water resources and the growth of population, industry and agriculture have increased the reliance on water production using desalination technology. Some countries such as gulf areas rely completely on desalinated water [1]. Therefore, much attention is being paid to seawater and brackish water desalination technologies including Reverse Osmosis (RO) in attempts to improve the reliability and the performance of freshwater production processes.

Thermal and RO processes are, by far, the major desalination systems used now-a-days. RO process is less energy intensive and makes it most cost efficient [2]. For instance, energy consumption for seawater RO desalination is about one-half of that of multiple effect evaporator process [3].

Recently, seawater desalination by RO has been the main source of drinking water supply in many regions that have freshwater lake [4]. RO membranes used in sea water desalination are capable of producing good water quality by removing most of the salts and some other contaminants from water sources.

The cost of fresh water produced by membrane treatment has shown dramatic reduction trend. This remarkable progress has been made mainly through two aspects, huge improvements in membrane material and incorporation of the energy recovery devices in RO systems [4] which significantly reduce the energy requirements.

The mathematical modelling of RO systems plays an important role in operation and design of the RO process. Prediction of RO membrane performance under different operating conditions is necessary to optimize the design and operation of membrane separation process. The most costly design and operation problem in RO separation process are due to fouling formation on the membrane layer which significantly deteriorates the performance of the membrane separation process.

Neural networks (NNs) are modelling tools able to solve linear and non-linear multivariate regression problems with some desired accuracy [5]. Moreover, NNs methodology does not need any governing equations with assumptions to describe the process under study. A number of studies have been reported on the modelling, simulation and optimization of pressure-driven membrane systems using NNs tool [6,7,8]. Abbas and Al-Bastaki [9] developed NNs model to predict the performance of a RO experimental setup. The model considers ranges of operating conditions as input to the NNs model that include the feed pressure, temperature and salt concentration to predict the water permeate rate. A neural network-based modelling approach with back-propagation was investigated by Libotean et al. [10]. Operation data of normalized permeate flux and salt passage were used as input variables to develop NNs model for estimating RO plant performance.

Predictive models for simulation and optimization of RO desalination pilot plant based on both Response Surface Methodology (RSM) and Artificial Neural Network (ANN) models have been developed by Khayet et al. [11]. They found that RSM was unable to develop a global model to predict the RO performance while ANN approach provides a global model in a wide range of feed salt concentration.

Neural networks (NNs) tool also used in optimization of RO processes. For example, Lee et al. [5] have developed NNs models using one-year real operational data for the prediction of the performance of a Fujairah RO desalination plant. The input parameters of the NNs model consists of feed temperature, seawater salinity, operating pressure, feed flow rate, and operation time while the output parameters were permeate salinity and production. The NNs model then used to determine the temperature control to optimize the operation of RO plant.

NNs based correlation is developed in this work based on the actual water and salt permeability data to estimate the performance decline factors. Annual seawater temperature variation is considered in the NNs model.

2- Development of Neural Network Model

NNs based correlations are developed to estimate the water and salt permeability coefficients within one year of operation. Seawater temperature annual variation is also included in NN model.

2.1- Neural Network Architecture

The neural network topology in which the inputs and outputs of the neurons are organized is known as architecture of the neural network. A typical neural network consists of an input layer, one or more hidden layers; output layer and transfer functions. Multi-layer feed-forward neural network is the most common method of implementing NNs models as it is more able to deal effectively with the complex nonlinear problems [11].

Commonly neural networks are adjusted, or trained so that a particular input leads to a specific target output. The connections are made between the neurons of adjacent layers allowing the neuron to receive a signal from a neuron in the preceding layer and allow it to transmit signals to neurons in the immediately succeeding layers.

The processing neuron receives a number of inputs (a_i). A weighted sum of these signals is calculated, using the neuron's assigned weights (w_i), which is transferred by the transfer function to produce output signal, that is send to the neurons in the succeeding layer. Also a bias neuron (b) supplies an invariant output which is connected to each neuron in the hidden and output layers. The performance of NNs models are strongly influenced by the choice of the input-output function, transfer functions and the weights. Figure 1 shows the main categories of transfer functions.

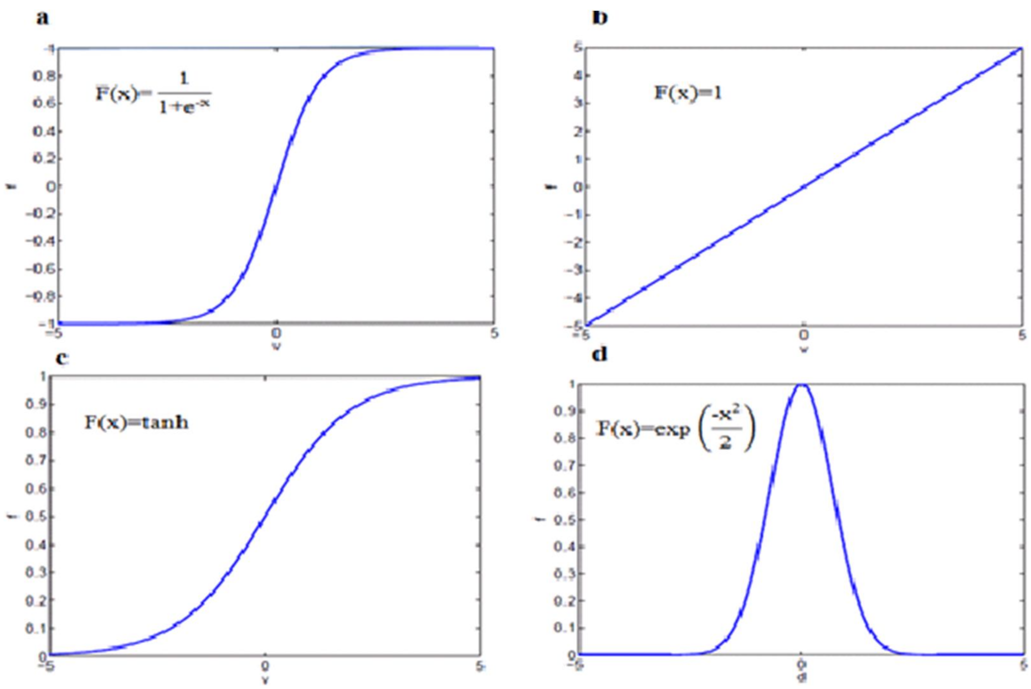

Figure 1 Different Neuron transfer Functions: (a) linear (b) Sigmoid (c) hyperbolic (d) Gaussian [6]

2.2Estimation of water and salt permeability coefficients:

Data collected from one stage RO desalination plant utilizing spiral wound modules was used in this study [12]. Data for one year were selected from the published data and used in neural network model.

Normalization the experimental data is required to avoid the effects of different operating conditions. The variables such as water fluxes and membrane permeability are commonly normalized with their initial values [13]. The experimental membrane permeability data obtained for spiral wound membranes [12] are normalized using their initial permeability coefficients. The resulting normalized membrane permeability decline factors of water and salt ($A_w^f ; A_s^f$) (Appendix I) are used to represent the membrane permeability decline.

NNs tool is used to develop two correlations for estimating water and salt permeability decline factors ($A_w^f ;\ A_s^f$) for a given seawater temperature profile and operation time. The seasonal variation of seawater temperature is embedded in the predicted permeability decline factors. A four layered NNs architecture shown in Figure 2 is used in this propose. In the proposed NNs based correlations, optimal network architecture (number of hidden layers and neurons in each layer) is chosen for each network by trial and error approach (multiple runs).

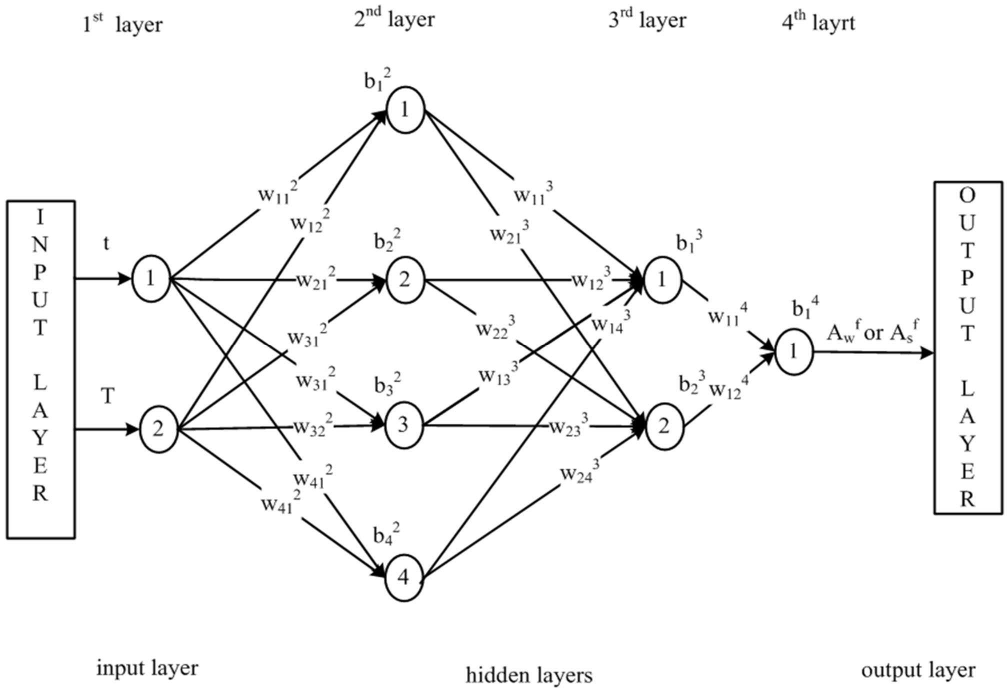

Figure 2 Four layer neural network

Two NNs models are developed to estimate water and salt permeability decline factors (A_w^f ; A_s^f), each model consists of two neurons in the input layer, two hidden layers containing four and two neurons respectively, and one neuron in the output layer. The outputs of hidden and output layers are determined as follow:

$$a_1^4 = f_1^4 \sum_{k=1}^{2} (w_{1k}^4 a_{1k}^3) + b_1^4 \tag{1}$$

Where a_k^3 is given as:

$$a_k^3 = f_i^3 \sum_{k=1}^{4} (w_{1k}^3 a_k^2) + b_j^3 \tag{2}$$

In general for the 3rd layer, the value of j th neuron can be given as:

$$a_j^3 = f_i^3 \sum_{k=1}^{4} (w_{1k}^3 a_k^2) + b_j^3 \tag{3}$$

Where a_k^2 is determined as:

$$a_k^2 = f_i^2 \sum_{k=1}^{2} (w_{1k}^2 a_k^1) + b_j^2 \tag{4}$$

In general for the 2nd layer, the value of j th neuron can be given as:

$$a_j^2 = f_j^2 \sum_{k=1}^{2} (w_{jk}^2 a_k^1) + b_j^2 \tag{5}$$

The transfer functions which describes the relationship between output layer and input layer of each neuron are hyperbolic tangent function (f_j^2, f_j^3=tanh) between the input and the first hidden and between the two hidden layers. While the linear function (f_j^4=1) is used between the last hidden layer and the output layer

The raw data collected from the field are normally scaled into an appropriate range (between zero and one or one and negative one) [14]. Appendix (I) shows experimental data collected from Pais et al. [12]. The data are scaled before used as input data. The relations used in data scale up are as follow:

Time

$$time_{scal} = \frac{time - time_{mean}}{time_{std}} \tag{6}$$

Temperature

$$T_{scal} = \frac{T - T_{mean}}{T_{std}} \tag{7}$$

Water permeability

$$A_{w\,scal}^f = \frac{A_w^f - A_{w\,mean}^f}{A_{w\,std}^f} \tag{8}$$

Salt permeability

$$A^f_{s\ scal} = \frac{A^f_s - A^f_{s\ mean}}{A^f_{s\ std}} \tag{9}$$

Where the subscripts mean, std and scal refer to average, standard deviation and scale up variables, respectively.

Two NNs models are solved in order to determine correlations which can be used to calculate water and salt permeability decline factors (A^f_w; A^f_s). The output values from the NNs are rescaled to find the value in original units. The experimental data was divided into three sets: a set of 50% of the data are selected for training , 25 % of the data for validation and last set (25 %) is selected for testing.

The back propagation algorithm is used for training a multilayer feed forward neural network [14]. The Neural Network Toolbox available in MATLAB software is implemented in this study to design and train the data.

The value of neurons (a_j) at the first, second or third layer can be expressed by the following equations:

$$a^2_1 = \tanh(w^2_{11} time_{scal} + w^2_{12} T_{scal} + b^2_1) \tag{10}$$

$$a^2_2 = \tanh(w^2_{21} time_{scal} + w^2_{22} T_{scal} + b^2_2) \tag{11}$$

$$a^2_3 = \tanh(w^2_{31} time_{scal} + w^2_{32} T_{scal} + b^2_3) \tag{12}$$

$$a^2_4 = \tanh(w^2_{41} time_{scal} + w^2_{42} T_{scal} + b^2_4) \tag{13}$$

$$a^3_1 = \tanh(w^3_{11} a^2_1 + w^3_{12} a^2_2 + w^3_{13} a^2_3 + w^3_{14} a^2_4 + b^3_1) \tag{14}$$

$$a^3_2 = \tanh(w^3_{11} a^2_1 + w^3_{22} a^2_2 + w^3_{13} a^2_3 + w^3_{14} a^2_4 + b^3_2) \tag{15}$$

Water and salt permeability decline factors $A^f_{w_{scal}}$ and $A^f_{s_{scal}}$ can be obtained from the output layer (a^4_1) which produces the final results of processing by the NNs model as:

$$a_1^4 = \tanh(w_{11}^4 a_1^3 + w_{12}^4 a_2^3 + b_1^4) \tag{16}$$

3- Results and discussion

The experimental input data for the NNs based correlations is shown in Appendix (I). The results of two NNs models of $A^f_{w_{scal}}$ and $A^f_{s_{scal}}$ are shown in Table 1 and Table 2. The weights and bias between the input layer, hidden and the output layer are included in the results.

The permeability decay factors predicted by the NNs are plotted versus their corresponding experimental values in Figures 3 and 4. The results illustrate good agreement between the predicted and experimental data. Also, it can be seen from the Figures 5, 6 that the experimental data of water and salt permeability decay factors are accurately predicted by the NNs model.

Table 1 NNs parameters for estimation water permeability factor

Weights		bias			Transfer function
2^{nd} layer					
w_{11}^2 =1.15622	w_{12}^2 =-1.72079	b_1^2 =3.09386			tanh
w_{21}^2 =-0.05138	w_{22}^2 =0.20847	b_2^2 =0.150153			tanh
w_{31}^2 =2.04809	w_{32}^2 =-3.43108	b_3^2 =-3.30951			tanh
w_{41}^2 =1.42777	w_{42}^2 =-0.96244	b_4^2 =-1.61448			tanh
3^{rd} layer				bias	
w_{11}^3 =1.76307	w_{12}^3 =-0.95896	w_{13}^3 = 2.15917	w_{14}^3 =2.20172	b_1^3=-3.03812	tanh
w_{21}^3 =0.28681	w_{22}^3 =1.96992	w_{23}^3 =-0.37512	w_{24}^3 =0.67162	b_2^3=0.29936	tanh
4^{th} layer		bias			
w_{11}^4 =0.58228	w_{12}^4 =3.76995	b_1^4 =-0.13469			1
time $_{mean}$	time $_{std}$	T $_{mean}$	T$_{std}$	$A^f_{w_{mean}}$	$A^f_{w_{std}}$
167.74	109.41	21.19	1.82	0.99	0.03

Table 2 NNs parameters for estimation salt permeability factor

Weights 2nd layer		bias			Transfer function
w^2_{11} =1.777414	w^2_{12} =-2.29036	b^2_1 =-4.52089			tanh
w^2_{21} =0.35902	w^2_{22} =-2.04543	b^2_2 =-1.60477			tanh
w^2_{31} =1.059634	w^2_{32} =-2.37573	b^2_3 =3.447281			tanh
w^2_{41} =-4.97533	w^2_{42} =-5.77942	b^2_4 =-14.6048			tanh
3rd layer				bias	
w^3_{11} =-1.39766	w^3_{12} =3.38951	w^3_{13} =3.07388	w^3_{14} =1.95439	b^3_1=0.80823	tanh
w^3_{21}=-1.84938	w^3_{22}=1.33817	w^3_{23} =-0.16574	w^3_{24} =-4.00229	b^3_2=-6.24591	tanh
4th layer		bias			
w^4_{11} =-1.34286	w^4_{12} =2.575753	b^4_1 =2.617429			1

time $_{mean}$	time $_{std}$	T $_{mean}$	T$_{std}$	$A^f_{s_{mean}}$	$A^f_{s_{std}}$
177.46	104.73	21.53	2.03	1.108	0.125

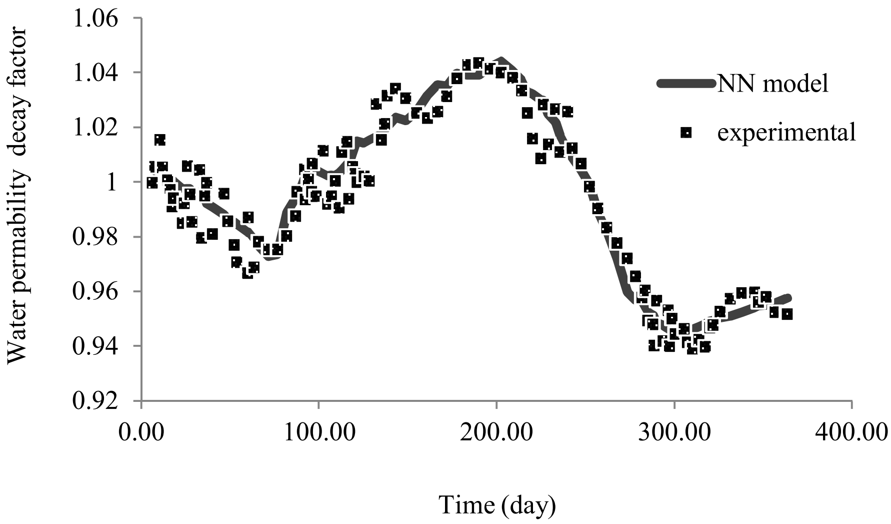

Figure 3 Actual water permeability decline factor and the predicted by NNs

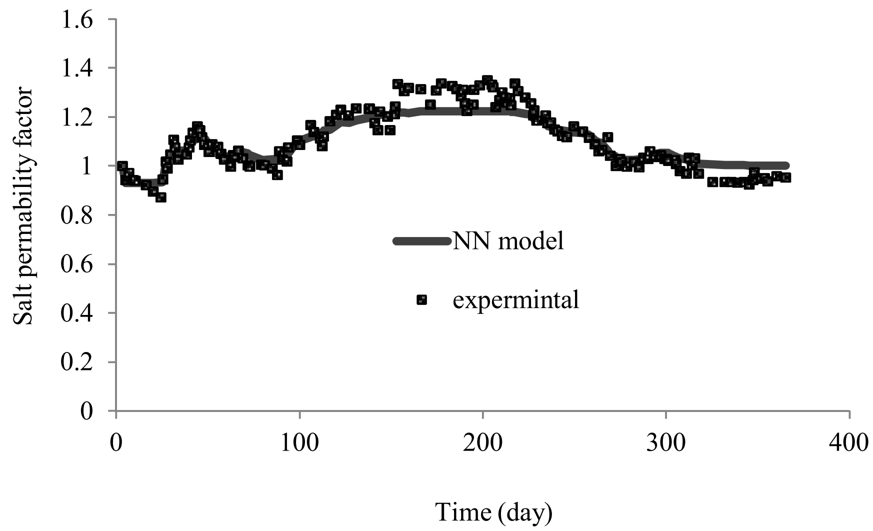

Figure 4 Actual salt permeability decline factor and the predicted by NNs

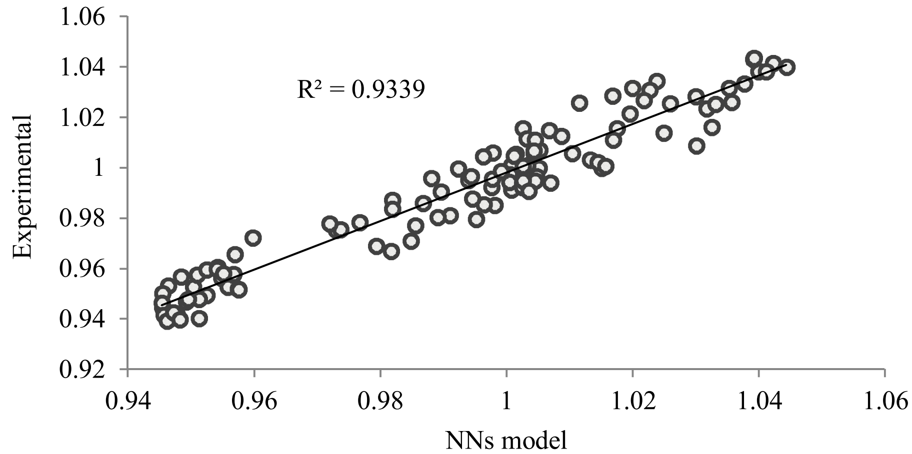

Figure 5 Actual and predicted water permeability decay factor

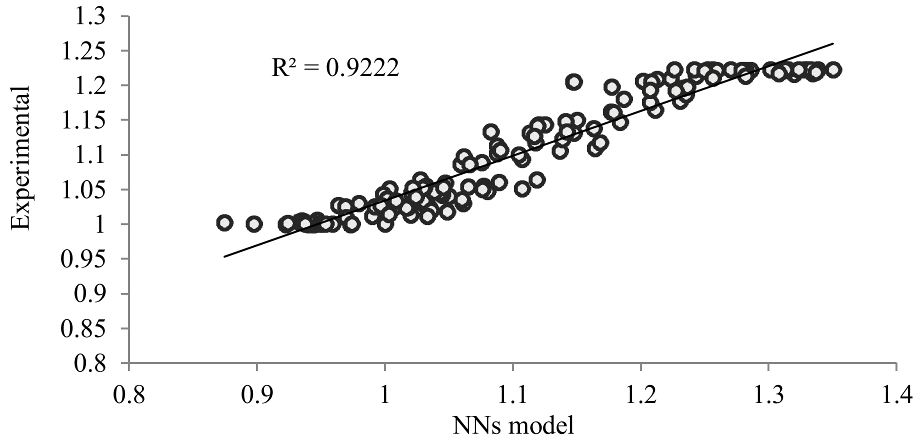

Figure 6 Actual and predicted salt permeability decay factor

4- Conclusion

In this work, NNs based correlation was developed for estimating the permeability decline factors over one year of operation for water and salt. For each correlation, a multi-layered feed forward network trained with back propagation method is used. The proposed NNs model structure (with one hidden layer and four neurons in hidden layer) is capable of predicting the experimental water and salt permeability decline factors very closely. For a given architecture, any correlation can be updated with new sets of experimental data.

The proposed model of membrane permeability decline factors could be embedded within the RO operation and design optimization model.

References:

[1] Abuzinada, A. H., Barth, H. J., Krupp, F. and Böer,B., Al Abdessalaam,T. Z. (2008) Protecting the Gulf's Marine Ecosystems from Pollution, Basel.

[2] Fritzmann, C., Lowenberg, J., Wintgens, T. and Melin, T. (2007) State-of-the-art of reverse osmosis desalination, Desalination 216, 1-76.

[3]Singh, R. (2008) Sustainable fuel cell integrated membrane desalination systems, Desalination 227, 14-33.

[4] Greenlee, L. F., Lawler, D. F., Freeman, B. D., Marrot, B. and Moulin, P. (2009) Reverse osmosis desalination: Water sources, technology, and today's challenges, Water Research 43, 2317-2348.

[5] Lee, Y. G., Lee, Y. S., Jeon, J. J., Lee, S., Yang, D. R., Kim, I. S. and Kim, J. H. (2009) Artificial neural network model for optimizing operation of a seawater reverse osmosis desalination plant, Desalination 247, 180-189.

[6] Niemi, H., Bulsari, A. and Palosaari, S. (1995) Simulation of membrane separation by neural networks, Journal of Membrane Science 102, 185-191

[7] Zhao, Y., Taylor, J. S. and Chellam, S. (2005) Predicting RO/NF water quality by modified solution diffusion model and artificial neural networks, Journal of Membrane Science 263, 38-46.

[8]Lu, J. and Lu, W. Q. (2010) A numerical simulation for mass transfer through the porous membrane of parallel straight channels, International Journal of Heat and Mass Transfer 53, 2404-2413.

[9] Abbas, A. and Al-Bastaki, M. (2005) Simulation and analysis of an industrial water desalination plant, Chemical Engineering and Processing 44, 999-1004.

[10] Libotean, D., Giralt, J., Giralt, F., Rallo, R., Wolfe, T. and Cohen, Y. (2009) Neural network approach for modeling the performance of reverse osmosis membrane desalting, Journal of Membrane Science 326, 408-419.

[11] Khayet, M., Cojocaru, C. and Essalhi, M. (2011) Artificial neural network modeling and response surface methodology of desalination by reverse osmosis, Journal of Membrane Science 368, 202-214.

[12] Pais, J. A. G. C. R. and Ferreira, L. M. G. A. (2007) Performance study of an industrial RO plant for seawater desalination, Desalination 208, 269-276.

[13] Song, L. F., Chen, K. L., Ong, S. L. and Ng, W. J. (2004) A new normalization method for determination of colloidal fouling potential in membrane processes, Journal of Colloid and Interface Science 271, 426-433.

[14] Tanvir, M. S. and Mujtaba, I. M. (2006) Neural network based correlations for estimating temperature elevation for seawater in MSF desalination process, Desalination 195, 251-272.

Appendix (I)

Water and salt permeability vs. seawater temperature throughout the year.

Water permeability

Time (days)	Temp (°C)	$(A_w)\ 10^7$ (m/s bar)	A^f_w (A_w/A_{wo})
6.06	19.28	2.31	1.000
7.51	19.25	2.32	1.004
10.3	*19.18*	*2.34*	*1.013*
11.84	**19.13**	**2.32**	**1.004**
13.76	19.13	2.31	1.000
14.73	19.14	2.31	1.000
15.98	*19.16*	*2.3*	*0.996*
17.33	**19.22**	**2.29**	**0.991**
18	19.22	2.29	0.991
22.91	19.16	2.27	0.983
24.16	*19.16*	*2.29*	*0.991*
25.8	**19.25**	**2.32**	**1.004**
27.14	19.31	2.3	0.996
28.49	19.22	2.27	0.983
32.63	*19.5*	*2.32*	*1.004*
33.78	**19.4**	**2.26**	**0.978**
35.52	19.34	2.29	0.991
36.48	19.16	2.3	0.996
39.94	*19.22*	*2.26*	*0.978*
46.39	**19.4**	**2.3**	**0.996**
48.51	19.37	2.27	0.983
52.07	19.74	2.25	0.974
53.52	*19.77*	*2.24*	*0.970*
59.77	**19.86**	**2.23**	**0.965**
60.16	19.89	2.28	0.987
63.33	19.86	2.23	0.965
65.84	*19.8*	*2.26*	*0.978*
71.42	**19.8**	**2.25**	**0.974**
76.62	19.95	2.25	0.974
81.72	20.29	2.26	0.978
86.82	*20.41*	*2.28*	*0.987*
87.49	**20.41**	**2.3**	**0.996**
91.63	20.63	2.32	1.004
92.21	20.69	2.29	0.991

cont'd next page

Salt permeability

Time (days)	Temp (°C)	$(A_s)\ 10^8$ (m/s)	A^f_s (A_s/A_{so})
3.37	19.41	2.62	1.000
6.75	19.28	2.55	0.973
9.28	*19.16*	*2.48*	*0.947*
10.5	**19.16**	**2.46**	**0.939**
16.12	19.13	2.42	0.924
20.06	19.19	2.35	0.897
24.46	*19.16*	*2.29*	*0.874*
25.3	**19.21**	**2.48**	**0.947**
26.99	19.25	2.67	1.019
27.74	19.22	2.59	0.989
29.61	*19.22*	*2.75*	*1.050*
31.3	**19.56**	**2.9**	**1.107**
32.05	19.53	2.82	1.076
33.74	19.47	2.69	1.027
38.42	*19.16*	*2.74*	*1.046*
39.83	**19.22**	**2.82**	**1.076**
40.39	19.22	2.9	1.107
41.7	19.22	2.98	1.137
44.33	*19.4*	*3.05*	*1.164*
45.64	**19.3**	**3.01**	**1.149**
46.58	19.4	2.93	1.118
59.04	19.86	2.69	1.027
62.42	*19.86*	*2.62*	*1.000*
63.73	**19.84**	**2.74**	**1.046**
64.1	19.8	2.72	1.038
66.73	19.77	2.79	1.065
69.16	*19.77*	*2.7*	*1.031*
71.69	**19.8**	**2.63**	**1.004**
72.82	19.86	2.62	1.000
79.28	20.2	2.64	1.008
80.97	*20.29*	*2.63*	*1.004*
85.19	**20.35**	**2.6**	**0.992**
87.72	20.41	2.52	0.962
88.94	20.47	2.78	1.061

cont'd next page

Water permeability

Time (days)	Temp (°C)	$(A_w)\ 10^7$ (m/s bar)	A_w^f (A_w/A_{wo})
96.15	21.18	2.32	1.004
98.18	21.27	2.29	0.991
102.31	*21.42*	*2.33*	*1.009*
104.62	**21.48**	**2.29**	**0.991**
106.74	21.6	2.29	0.991
108.96	21.69	2.31	1.000
111.17	*21.85*	*2.28*	*0.987*
112.81	**21.97**	**2.33**	**1.009**
115.6	22.18	2.34	1.013
116.75	22.21	2.29	0.991
118.68	*22.46*	*2.32*	*1.004*
120.12	**22.64**	**2.31**	**1.000**
121.28	22.76	2.31	1.000
125.13	22.76	2.31	1.000
128.21	*22.85*	*2.31*	*1.000*
132.06	**22.95**	**2.37**	**1.026**
134.85	23.01	2.34	1.013
136.87	23.13	2.35	1.017
138.12	*23.16*	*2.38*	*1.030*
143.03	**23.4**	**2.38**	**1.030**
148.8	23.37	2.38	1.030
154.67	23.59	2.36	1.022
160.74	*23.95*	*2.36*	*1.022*
166.51	**24.23**	**2.37**	**1.026**
171.9	24.23	2.38	1.030
177.49	24.56	2.39	1.035
183.45	*24.53*	*2.4*	*1.039*
189.81	**24.56**	**2.41**	**1.043**
196.16	24.81	2.4	1.039
202.51	24.99	2.4	1.039
208.67	*24.78*	*2.39*	*1.035*
213.77	**24.56**	**2.38**	**1.030**
217.04	24.29	2.36	1.022
219.93	24.26	2.34	1.013
224.74	*24.14*	*2.33*	*1.009*
226.09	**24.14**	**2.37**	**1.026**

cont'd next page

Salt permeability

Time (days)	Temp (°C)	$(A_s)\ 10^8$ (m/s)	A_s^f (A_s/A_{so})
93.9	20.75	2.82	1.076
103.9	21.27	2.98	1.143
105.9	*21.54*	*3.06*	*1.168*
107.68	**21.63**	**2.98**	**1.137**
111.34	21.85	2.92	1.115
112.18	21.88	2.84	1.084
122.3	*22.76*	*3.23*	*1.233*
126.61	**22.76**	**3.16**	**1.206**
130.83	22.95	3.24	1.237
137.76	23.13	3.23	1.233
138.33	*23.16*	*3.24*	*1.237*
140.86	**23.19**	**3.09**	**1.179**
142.64	23.31	3.01	1.149
143.86	23.4	3.21	1.225
147.98	*23.37*	*3.15*	*1.202*
149.39	**23.37**	**3.01**	**1.149**
151.82	23.47	3.18	1.214
152.01	23.56	3.26	1.244
153.51	*23.71*	*3.5*	*1.336*
159.51	**23.71**	**3.46**	**1.321**
166.16	24.23	3.45	1.317
171.22	24.29	3.28	1.252
174.5	*24.5*	*3.43*	*1.309*
177.13	**24.78**	**3.51**	**1.340**
183.4	24.53	3.48	1.328
185.84	24.5	3.45	1.317
188.09	*24.47*	*3.37*	*1.286*
189.31	**24.56**	**3.44**	**1.313**
191.28	24.9	3.21	1.225
194.74	24.81	3.28	1.252
195.21	*24.81*	*3.44*	*1.313*
205.71	**24.96**	**3.47**	**1.324**
226.14	24.14	3.29	1.256
227.64	24.05	3.17	1.210
228.11	*23.86*	*3.22*	*1.229*
229.33	**23.71**	**3.11**	**1.187**

cont'd next page

Water permeability

Time (days)	**Temp (°C)**	**$(A_w)\ 10^7$ (m/s bar)**	**A_w^f (A_w/A_{wo})**
228.98	23.86	2.34	1.013
233.02	23.71	2.37	1.026
235.62	*23.47*	*2.33*	*1.009*
239.95	**23.22**	**2.37**	**1.026**
242.45	23.1	2.33	1.009
247.56	22.92	2.32	1.004
252.08	*22.7*	*2.31*	*0.996*
256.7	**22.31**	**2.28**	**0.987**
261.9	22	2.27	0.983
267.67	21.6	2.25	0.974
273.35	*21.08*	*2.24*	*0.970*
281.53	**20.96**	**2.21**	**0.957**
283.55	20.84	2.21	0.957
285	20.75	2.19	0.948
287.88	*20.69*	*2.19*	*0.948*
288.27	**20.69**	**2.17**	**0.939**
290	20.5	2.21	0.957
293.56	20.44	2.17	0.939
296.55	*20.32*	*2.2*	*0.952*
297.03	**20.32**	**2.17**	**0.939**
298.47	20.2	2.19	0.948
300.3	20.17	2.18	0.944
307.13	*19.83*	*2.17*	*0.939*
310.21	**19.86**	**2.17**	**0.939**
313.78	19.74	2.17	0.939
317.14	19.65	2.17	0.939
321.57	*19.59*	*2.19*	*0.948*
325.52	**19.59**	**2.2**	**0.952**
331.49	19.71	2.21	0.957
337.93	19.68	2.21	0.957
344.86	*19.65*	*2.21*	*0.957*
347.27	**19.31**	**2.2**	**0.952**
351.6	19.25	2.21	0.957
356.7	19.28	2.2	0.952
362.96	*19.53*	*2.19*	*0.948*
363.54	**19.56**	**2.19**	**0.948**

Salt permeability

Time (days)	**Temp (°C)**	**$(A_s)\ 10^8$ (m/s)**	**A_s^f (A_s/A_{so})**
235.23	23.47	3.08	1.176
237.01	23.47	3.09	1.179
239.26	*23.22*	*3.01*	*1.149*
240.85	**23.19**	**2.99**	**1.141**
245.63	22.98	2.93	1.118
245.63	22.98	2.93	1.118
249.48	*22.82*	*3.05*	*1.164*
278.43	**20.96**	**2.62**	**1.000**
287.71	20.69	2.71	1.034
243.2	23.04	2.95	1.126
291.27	**20.5**	**2.78**	**1.061**
294.08	20.35	2.72	1.038
297.18	20.23	2.74	1.046
299.24	*20.2*	*2.7*	*1.031*
300.36	**20.17**	**2.7**	**1.031**
301.3	20.02	2.68	1.023
304.86	19.9	2.68	1.023
305.33	*19.83*	*2.64*	*1.008*
307.58	**19.83**	**2.57**	**0.981**
310.95	19.86	2.54	0.969
314.14	19.71	2.63	1.004
315.55	*19.68*	*2.71*	*1.034*
317.7	**19.65**	**2.54**	**0.969**
325.39	19.59	2.45	0.935
332.13	19.71	2.45	0.935
335.7	*19.71*	*2.45*	*0.935*
338.88	**19.71**	**2.44**	**0.931**
342.44	19.65	2.45	0.935
345.35	19.47	2.42	0.924
355.47	*19.25*	*2.46*	*0.939*
360.16	**19.44**	**2.51**	**0.958**
365.31	19.56	2.5	0.954

Note: Training data in plain, Validation data in *italic*, Test data in **bold**.