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Modeling of Sorkheh Reverse Osmosis (RO) Water Treatment Plant by Artificial Neural Network (ANN) with Genetic Algorithm (GA)

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ABSTRACT

The Reverse Osmosis (RO) process is one of the most widely used technologies in the water treatment industry to reduce water hardness. In this paper, the reverse osmosis treatment plant of Sorkheh city (Semnan province, Iran) was modeled by Artificial Neural Network (ANN) model. The ANN model parameters were optimized with the Genetic Algorithm (GA) method to increase ANN model accuracy. The optimization was done by updating the weight and bias, the number of layer neurons, activator functions, and the ANN training equation. The mean relative error of optimized ANN model results with respect to industrial data was obtained about 0.73% for water outlet flow rate and 0.47% for water pH. While the mean relative errors for water outlet flow rate and water pH in the non-optimized ANN model were evaluated 26.24% and 4.76%, respectively. Also, the results showed that the regression coefficient for the optimized neural network is equal to 0.995.

1. Introduction

Drinking water can be considered one of the most valuable components for maintaining human life on earth. An important point to note is that about 99% of the world's water resources are salty water or frozen, and only about 1% of it can be used [1]. Also, the world's growing population, industrialization, and climate change have put more pressure on water resources, and as a result, human societies face water supply problems. Over the past years, significant advances have been made in constructing seawater desalination plants and water treatment technologies. Multistage flash distillation, multi-effect evaporative distillation, vapor compression, and reverse osmosis (RO) are suitable to meet freshwater demand [2, 3]. Using membranes is an important desalination technology for water treatment among these technologies. The complexity of desalination systems by membrane technology led to the use

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of innovative methods in modeling and optimizing desalination systems [4-7]. The development of accurate theoretical models or experimental methods to predict the performance of membrane processes is a vital issue [8]. One of the most widely used theoretical models in the field of membrane science to study the performance of system behavior is the artificial neural network (ANN) [9].

It should be noted that the artificial neural network cannot be used to extract the results of other membrane systems, and is valid only for the range of operations in which it is calculated. The main advantage of this method is the appropriate prediction of the behavior of nonlinear processes with high accuracy. In addition, how the model is constructed allows the model to be updated with more empirical data to improve the predictions [8].

Yang *et al*. [10] modeled the artificial neural network in 36 different experiments using a vacuum membrane distillation system. They found that the artificial neural network model can achieve effective results for predicting the behavior of the hollow membrane module for the whole range of input variables. Mohammad *et al*. [11] considered a genetically optimized multilayer artificial neural network to construct a comprehensive mathematical model to predict the performance of a reverse osmosis process for removing chlorophenol from wastewater. The model response confirmed the success of the chlorophenol removal estimate for the proposed network structure based on a wide range of variables. Yaqub and Lee [12] modeled the ultrafiltration optimization of an aqueous solution using pyridinium chloride as a surfactant through an ANN model. The artificial neural network model achieved reliable training, validation, and testing data results. Al Aani *et al*. [13] used artificial intelligence tools in water purification and desalination. They used two different structures for this study. One for the permit flux, including an input layer with five neurons, two hidden layers with six and eight neurons, an output layer with one neuron, and a similar network with five neurons in the input layer and six neurons in both hidden layers for the membrane removal ability parameter. The results showed that using artificial intelligence tools leads to better utilization, process automation, and proper management of water resources.

Ahmad Yasmin *et al*. [14] used the ANN model to predict aerobic granule sludge performance (AGS). The input and output parameters used in predicting the model are chemical oxygen demand (COD), total nitrogen (TN), total phosphorus (TP), ammonia nitrogen (AN), and mixed liquid suspended solids (MLSS). Other feature analyses and predictions of system behavior were prepared and compared using Support Vector Forward Neural Network (SVM) and Feed-Forward Neural Network (FFNN). The modeling results showed that the neural network could be helpful in predicting effluent quality. Kim *et al*. [15] used two network models, one ANN and the other tree model (TM), to investigate the long-term performance of a full-scale reverse osmosis desalination plant. The artificial neural network and tree model application showed an appropriate regression coefficient between the measured and simulated output variables.

According to the studies conducted by the researchers, the use of ANN has been effective in modeling water purification processes by the membrane. But until now, the optimization of different ANN model parameters has not been investigated in detail. This study aims to develop a theoretical model based on an ANN model to accurately predict the performance of membrane modules in Sorkheh water treatment plant. Various adjustable parameters in the neural network, such as the number of neurons in different layers, the activation functions of each layer, and the neural network training equation, were optimized by the Genetic Algorithm (GA) to find the best ANN model.

Table 1. Sorkheh water treatment plant data

Inlet water flow rate (m^3/h)	Outlet water flow rate (m^3/h)	pH	Turbidity (NTU)	TDS (mg/lit)
1450.66	1359.13	6.50	0.38	402.46
1948.50	1813.50	6.50	0.38	349.26
2398.48	2294.37	6.50	0.38	345.94
2015.66	1937.38	6.50	0.38	305.70
1908.39	1798.50	6.50	0.38	336.73
1915.85	1802.62	6.50	0.38	309.44
1719.26	1598.63	6.50	0.38	362.53
1719.76	1623.13	6.15	0.30	354.40
1451.59	1382.00	6.15	0.30	386.01
1719.15	1667.62	6.15	0.30	341.17
1799.46	1697.25	6.15	0.30	314.72
1320.36	1167.50	6.15	0.30	377.29
1318.76	1203.13	6.15	0.30	433.38
1289.15	1132.12	6.15	0.30	516.41
1224.24	1151.25	6.15	0.20	595.16
2001.22	1940.63	6.22	0.20	621.39
2680.65	2566.75	6.22	0.20	584.00
2700.95	2586.76	6.22	0.20	571.89
2707.95	2571.74	6.22	0.20	563.59
1296.62	1208.26	6.22	0.20	513.21
2198.33	2068.87	6.22	0.20	476.43
22.9.12	2157.87	6.22	0.20	490.84
2212.22	2179.26	6.17	0.30	439.22
2608.95	2558.74	6.17	0.30	407.97
1745.75	1706.88	6.17	0.30	510.98
4098.66	1706.88	6.17	0.30	500.00
1645.22	1473.88	6.17	0.30	505.00
1523.26	1445.62	6.17	0.30	597.80
1709.12	1671.25	6.17	0.30	569.32
1923.22	1881.37	6.17	0.30	571.71

2. Material and methods

2.1. Industrial data collection

To model the membrane treatment unit of Sorkheh water treatment plant, the industrial data were collected in cooperation with the research and productivity improvement office of Semnan Province Water and Sewerage Department. This study uses four months of data to model the Sorkheh water treatment process, including inlet and outlet water flow rate, Total Soluble Solids (TDS), pH, and turbidity. About 504 industrial data were collected from Sorkheh water treatment plant. Table (1) shows some industrial data were used in the ANN modeling. Parameters such as inlet water flow rate, outlet water flow rate and TDS were measured online. The other parameters, including turbidity, pH, and EC were measured in the laboratory by experts. The collected data were entered into MATLAB software and analyzed to create an ANN model.

The water used for treatment in Sorkheh is supplied from two different wells. First, water was transferred to the pool in the treatment plant using pipelines and stored in five reservoir tanks. Then, water entered the sand filter's initial stage, which filters particles up to 6 microns. The filtered water entered the reverse osmosis membrane modules, Fig. 1. Some of the treated water was stored in a tank for membrane system daily washing with acid and anti-scalant. Finally, water was injected into the pipelines after confirming the water quality.

Fig. 1. Membrane system of Sorkheh city treatment plant

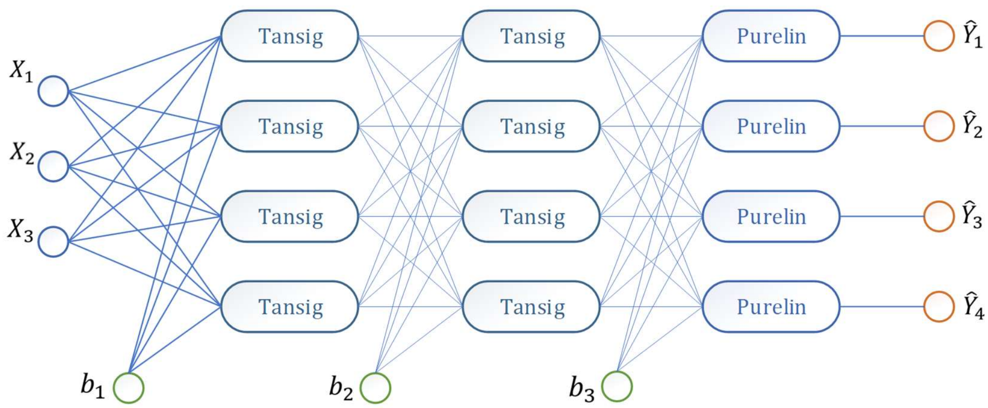

Fig. 2. Diagram of ANN structure

2.2. Modeling

In this work, the ANN model was used to model Sorkheh water treatment system. Since increasing the number of hidden layers of the neural network may lead to inadequate network training, only two hidden layers were selected in the ANN model, according to references [10, 14]. Fig. 2 shows the neural network structure in this study. Inputs (X) include input water flow rate (F_{in}), total solute of input solution (TDS_{in}), and diffusion coefficient (D). The outputs ($\hat{Y}$) include outlet water flow rate (F_{out}), total solutes at the outlet (TDS_{out}), turbidity, and pH. In the ANN model, four neurons and tan-sigmoid (Tansig) transmission functions were used for hidden layers (Eq. (1)), and the Purelin linear transfer function was used for the last layer, Eq. (2).

$$Tansig(\lambda) = \frac{1-\exp(-\lambda)}{1+\exp(-\lambda)} \tag{1}$$

$$Purline(\lambda) = \lambda \tag{2}$$

where λ is input data of ANN transfer function. To assign appropriate amounts of data to educational subsets (training, validation, and testing) 80% of data were used for training, 10% for validation, and 10% for testing. The selection of training, validation, and testing data were done by MATLAB ANN functions. The Levenberg-Marquardt algorithm, was used to teach the neural network, updating the weight and bias of the layers. According to the backpropagation algorithm in the ANN model, the Levenberg-Marquardt algorithm functions based on an approximation to Newton's method [16]. Eq. (3) presents the modification of the Levenberg-Marquardt algorithm to the Gauss-Newton method. This equation is used to evaluate changes in W during the ANN model training. The performance index parameter of ANN model is a function of the Mean Squared Error (MSE), Eq. (4). Also, the regression coefficient (Eq. (5)) is used to provide information about the goodness of fit by the ANN model.

$$W_{k+1} = W_k - [J^T J + \mu I]^{-1} J^T e \tag{3}$$

$$Mean\ Squared\ Error\ (MSE) = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y}_i) \tag{4}$$

$$R = \left(1 - \frac{\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)}{\sum_{i=1}^{N}\left(Y_i - \overline{Y}_i\right)}\right)^{0.5} \tag{5}$$

In Eq. (3) W, J, μ, I and e are the weight matrix, the Jacobin matrix that contains the first derivatives of network errors with respect to weight and bias, a parameter that is decreased after each successful step and is increased only when a tentative step would increase the performance function, the identity matrix and the vector of the network error, respectively. In Eqs. (4) and (5) N, Y_i, $\hat{Y}_i$ and $\overline{Y}_i$ are the number of data points, target values, predicted (output) values, and mean of predicted values, respectively.

3. Results and discussion

3.1. ANN model results

The ANN model was trained by 80% of all collected industrial data. These data were extract by MATLAB ANN functions and used for training of network. Table 1 shows some industrial data in this work. Fig. 3 depicts the ANN performance index diagram. According to this figure, 11 replications for the training data subset stopped the ANN training process. The appropriate value and the best case for the validation data of the current network were achieved in the fifth stage, but the network continued the training process to the next 6 stages.

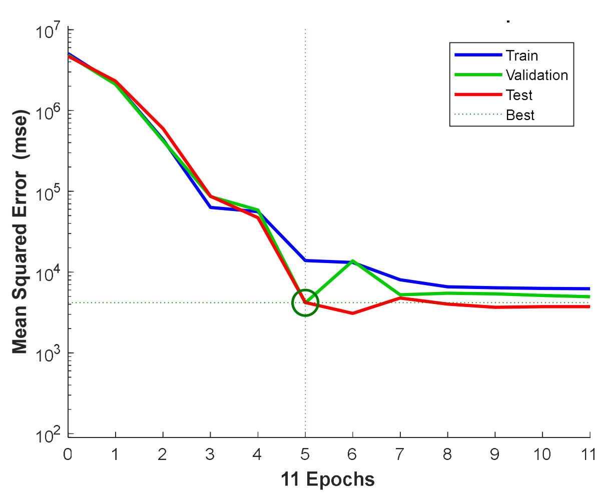

Fig. 3. Neural network performance indicator chart

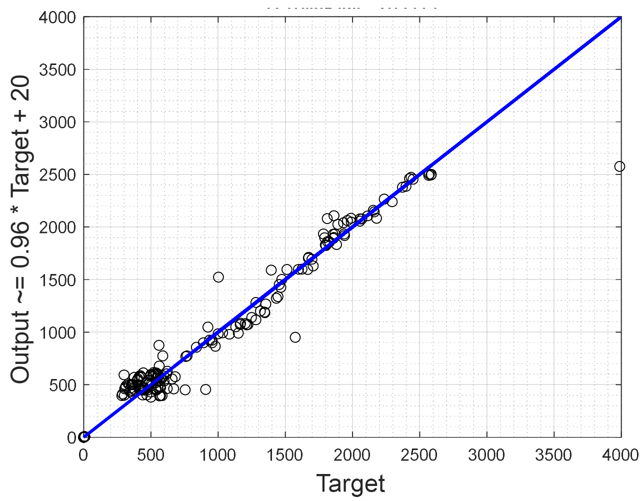

Fig. 4. Regression diagram of the training data set (R=0.987)

Fig. 4 shows a diagram of the training subset (Linear regression diagram). The target axis (x axis) is the outputs (values we need to reach, including outlet water flow rate, pH, NTU, and TDS.), and the outputs axis (y axis) is the predicted values by the ANN model. If the data on this figure were close to Y = X line (a line where the slope is equal to one and passes through the coordinate origin), the training is appropriate. By modeling the neural network using MATLAB software, the regression coefficient (R) was achieved at 0.987 for the training data set, which is the best coefficient for the network and the predictions made from the network. Also, the regression coefficient (R) was 0.996 for the test data set. Fig. 5 depicts the regression diagram of all data obtained from the ANN model with a total regression coefficient of R=0.989.

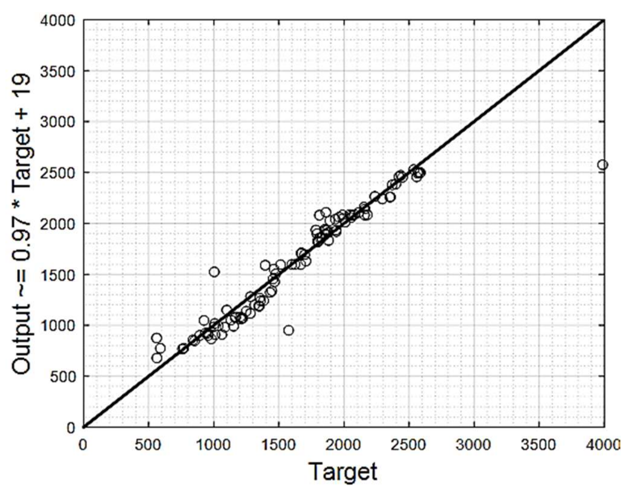

Fig. 5. Regression diagram of all data (R=0.989)

3.2. ANN model optimization with Genetic Algorithm (GA)

The ANN model is a powerful tool for predicting and modeling many complex linear and nonlinear relationships. According to research studies [11, 13], Genetic Algorithms (GA) can be implemented in the ANN model to optimize the neurons in each layer. In this study, in addition to the number of layer neurons, the activation function of the first and second hidden layers, the activation function of the output layer, and the network training equation were optimized by the GA method. It should be noted that the GA method's objective function was to minimize |1-R|. So, the regression value (R) approached close to 1 during the optimization process. Fig. 6 and Table 2 show the structure and the results of the optimized ANN model with the GA method, respectively.

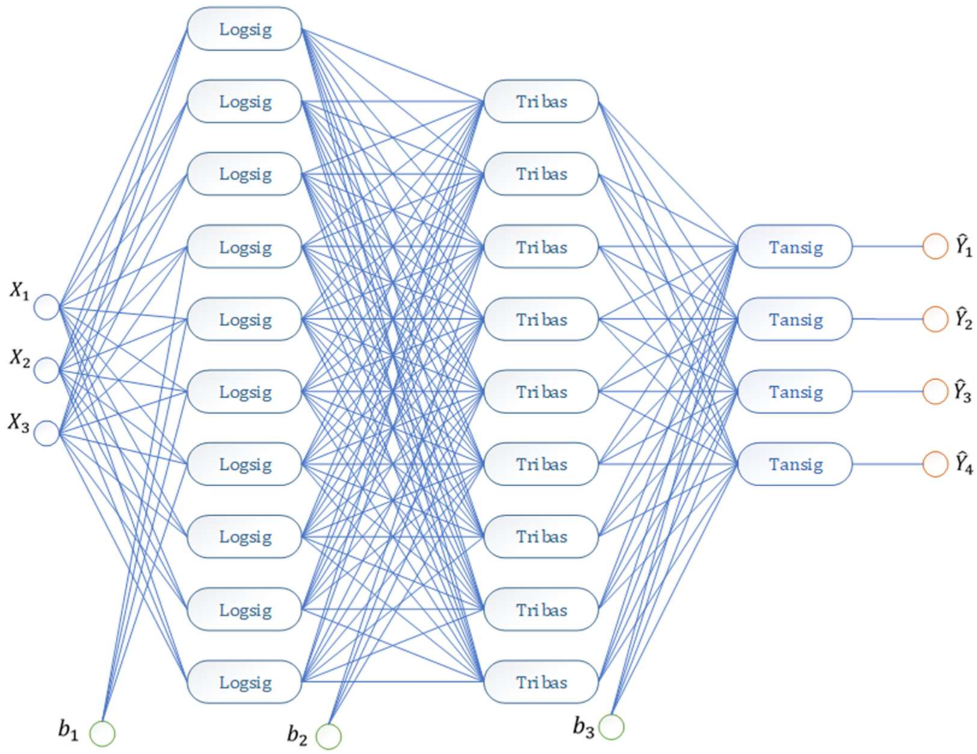

Fig. 6. Diagram of optimized ANN structure

Table 2. Optimized ANN model parameters

Optimized parameter	Optimized value
Number of the optimized first hidden layer of neurons	10
Number of the optimized second hidden layer of neurons	9
Neural network training equation	Trainlm (Levenberg-Marquardt)
Activation functions of the first hidden layer	Logsig (Eq. 6)
Activation functions of the second hidden layer	Tribas (Eq. 7)
Activation functions of the output layer	Tansig (Eq. 1)

$$Logsig(\lambda) = \frac{1}{1+\exp(-\lambda)} \tag{6}$$

$$Tribas(\lambda) = 1-|\lambda| \quad for \ |\lambda| \leq 1 \quad otherwise \quad Tribas(\lambda) = 0 \tag{7}$$

Fig. 7 depicts the optimized ANN performance index. According to the figure, the best state of network validation was achieved in stage 6 of the ANN training procedure. The best performance value for the validation data in the optimized ANN model was 3563, while for the model without optimization, this value was 4181.

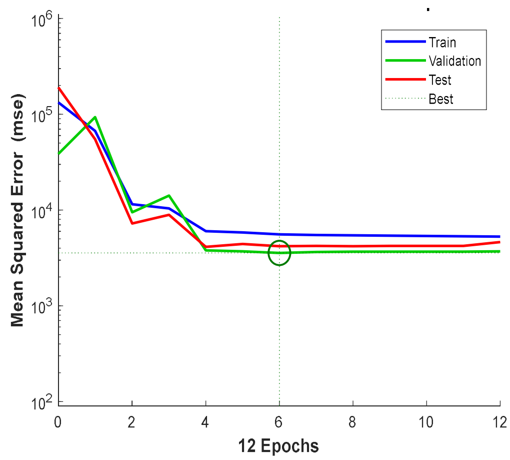

Fig. 7. Diagram of the optimized neural network performance index

Fig. 8 shows the regression coefficient diagram for the training data subset. The *R* value was obtained 0.994, showing the optimized network's better performance than the non-optimized network. Fig. 9 depicts the regression coefficient diagram for all data. Compared with the non-optimized neural network regression coefficient (*R*=0.989), the optimized neural network regression coefficient is 0.995.

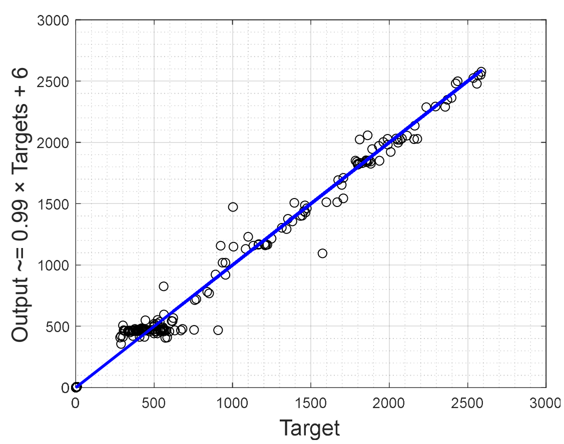

Fig. 8. Regression diagram of the training data set (R=0.995)

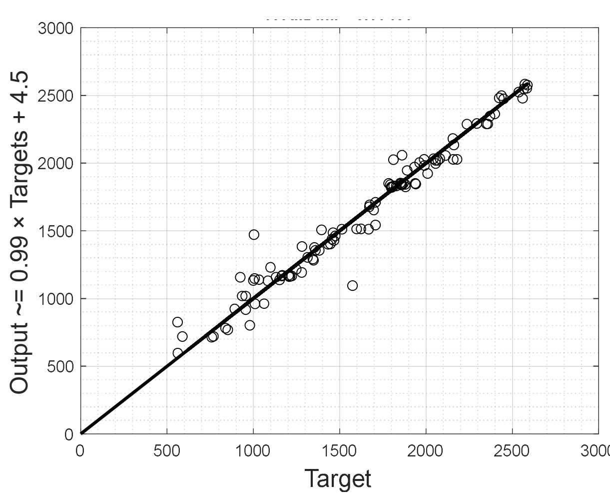

Fig. 9. Regression diagram of all data (R=0.995)

Table 3 shows some randomly selected data to compare neural network performance before and after optimization. As Table 3 depicts, the values calculated by the optimized ANN model have a better prediction of industrial data than the non-optimized network. The outlet water flow rate (F_{out}) mean relative error of the optimized ANN model with respect to industrial data prediction is 0.47%, while in the non-optimized ANN model, this error is about 4.76%. Also, the water pH mean relative error of the optimized ANN model concerning industrial data prediction is 0.73%, while in the non-optimized ANN model, this error is about 26.24%.

Table 3. Comparing industrial data by optimized and non-optimized ANN model

F_{out} (m^3/h) (Industrial data)	**F_{out} (m^3/h) (Non-optimized ANN)**	**F_{out} (m^3/h) (Optimized ANN)**	**pH (Industrial data)**	**pH (Non-optimized ANN)**	**pH (Optimized ANN)**
1813.5	1948.5	1832.27	6.5	6.66	6.5
2294.37	2398.48	2293.08	6.5	6.65	6.5
1798.5	1908.39	1818.75	6.5	6.66	6.5
1802.62	1915.85	1822.11	6.5	6.66	6.5
1167.5	1320.36	1171.05	6.15	6.59	6.15
1132.12	1889.15	1158.24	6.15	6.58	6.15
2586.76	2700.95	2575.92	6.22	6.58	6.22
2571.74	2707.95	2583.88	6.22	6.59	6.22
1706.88	4098.66	1710.22	6.34	6.73	6.17
1671.25	1809.12	1677.48	6.30	6.67	6.17
Mean relative error with respect to industrial data	26.24 %	0.73 %	-	4.76 %	0.47 %

4. Conclusion

This research used an optimized ANN model to model the Sorkheh city water treatment plant. The inputs of the ANN model include the inlet water flow rate, total solute, and brine permeability. The outputs include outlet water flow rate, pH, effluent turbidity, and total solute content (TDS). In the first step, the Levenberg-Marquardt equation was used to design the ANN model for network training. The network had two hidden layers, each layer containing four neurons and sigmoid transmission functions. By training the network, regression coefficient values for the training data subset were equal to 0.987, and for all data, the value was 0.989. In the second step, to increase the accuracy of the ANN model for the prediction of operating conditions, the GA method was used to optimize network parameters, including the number of hidden layer neurons, hidden layer functions, and the neural network training equation. According to the optimized ANN model results, the Levenberg-Marquardt equation was selected for ANN training. Also, ten neurons were evaluated for the first hidden layer, and nine neurons were obtained for the second hidden layer. The activator functions in the optimized ANN model were obtained Logsig function for the first layer, the Tribas function in the second layer, and the Tansig function for the output layer. The regression coefficient value for all data was equal to 0.995 in the optimized ANN model.

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