Asian Journal of Water, Environment and Pollution, Vol. 13, No. 3 (2016), pp. 95–102.
DOI 10.3233/AJW-160031

Reverse Osmosis Desalination Performance Using Artificial Neural Network Approach with Optimization

S. Virapan*, R. Saravanane[1] and V. Murugaiyan

Larsen and Toubro Limited, Mount Poonamalle Road, Manapakkam, Chennai – 600089, India
[1]Department of Civil Engineering, Pondicherry Engineering College, Puducherry, India
✉ virapans1816@gmail.com

Received January 29, 2016; revised and accepted May 13, 2016

Abstract: Reverse osmosis (RO) has found extensive usage in the fields of desalination and pollution control. The intention of the proposed work is to predict the thermal efficiency and average flux in RO process using Artificial Neural Network (ANN) with optimization process. These prediction processes initially optimize the network structure hidden layer and hidden neuron using different training algorithms and get the better network structure. For improving the prediction accuracy of RO in ANN process different optimization techniques are used. The optimal hidden layer and neuron attained in hybridization of GA and PSO technique based predict the parameters. From the results the ANN training algorithm predicts the error accuracy in LM and also in HA technique 75.2% and 89.25% respectively in this work compared to the GA and PSO techniques.

Key words: Reverse osmosis, efficiency, hidden layer and neuron, optimization technique and training algorithm.

Introduction

Of late, the water redeployment has been growing impressively on account of the zooming requirement for water caused by the unprecedented growth in population, rocketing urbanization, and tapering and ambiguous accessibility of the freshwater resources (Fujioka et al., 2012). The Seawater Reverse Osmosis (SWRO) technique, motivated by the exciting growth in the membrane materials, modules and procedure design, entails a total energy utilization of 3-4 kWh per m^3 of the desalted water, which is incredibly lesser than the other rival thermal mechanisms (Tufa et al., 2015).

One of the fascinating approaches for overwhelming the thorny issue of the osmotic pressure restriction is the deployment of the "loose" membranes wherein the surge in permeate concentration balances the enhancement in the feed osmotic pressure (Karode, 2001). The produced effluents were released into the river Palar by means of an unlined channel which paved the way for the surface and the groundwater pollution (Ranganathan and Kabadgi, 2011). The related solution is targeted at significantly scaling down the reject volume for clearance and simultaneously reclaiming further advantageous water from the corresponding unexploited water resource (Lee et al., 2009). Simply put, notionally a high water recovery for the sea water desalination to the tune of a whopping 80 per cent can be translated into reality, vis-à-vis a distinctive 35-40 per cent for the RO approach (Baskaran, 2014).

From the perspectives of the energy expenses and the ecology, cost-conscious and hygienic substitute power sources are highly essential to offer a reduced-cost desalination solution (Linares et al., 2006). The reduced energy utilization is unavoidable as and when the dilution rate perks up, though it inevitably results in an elevated capital expenditure for the membrane area (Linares et al., 2006).

The materials employed for the RO membranes are composed of the cellulose acetate, polyamides and other polymers (Kore et al., 2011). In such a scenario, the contaminants post the biggest threat in relation to that caused by the salts (Yang et al., 2016).

It is worth mentioning that the RSM effectively facilitates the performance of the polynomial empirical techniques for the approximation of process functioning. Further, the neural networks are termed as the global devices for the function approximation of the non-linear systems.

Literature Review

In the year 2016 Zou et al. (2016) convincingly suggested the seawater desalination as a vital method to lighten the deficiency of water resources in the coastal area. The competitive partial closed input–output model was effectively employed. The consequential outcomes illustrated the fact that the seawater desalination sector encompassed a huge investment multiplier 2.49 (ranked 9th in 18 sectors). Its influence coefficient and sensitivity coefficient were 1.09 (ranked 8th) and 1.14 (ranked 6th) separately, which established the fact that it exerted apparent demand pulling and supply pushing impacts on the national economy.

In the year 2015, Sahoo et al. significantly suggested the polygene ratio exhibiting exceptional integration of energy effectiveness and renewable energy. It represented the next generation energy creation method which was capable of overwhelming the intermittence of renewable energy, decreased expenses of the cost of power production and greenhouse gas discharges. In the long run, the multi effect dehumidification (MED) water desalination was generated by deploying restricted quantity of heat from water vapour (refrigerant; H_2O) by means of the HE1 of VAR cooling system.

The deployment of the nano filtration and reverse osmosis in reclaiming the micro-filtered biologically treated sewage effluent for irrigation was elegantly envisaged in Shanmuganathan et al. (2015). Moreover, the NF singly failed miserably to eliminate the essential extents of Na and Cl ions while RO came out successful in the attempt. Nevertheless, the integration of identical quantities of NF permeate and RO permeate achieved from a two-pronged hybrid management technique encompassing the NF accompanied by the RO paved the way for the formulation of a product quality ideal for the irrigation purposes, with regard to the captioned risk factors. Further, the deployment of the NF well ahead of the RO remarkably reduced the RO membrane fouling also. Both the NF and RO were competent enough to eliminate a large majority of the pharmaceutical and personal care products from the feed water, with the attendant prospects of protecting the soil and ground water from probable perils ultimately.

In 2015, Aish et al. admirably launched a novel technique employing the artificial neural network (ANN) technique to predict the reverse osmosis desalination plant's performance in the Gaza Strip by forecasting the succeeding week values of the total dissolved solids (TDS) and the permeate flow rate of the product water. The multilayer perceptron (MLP) and radial basis function (RBF) neural networks were trained and renovated in terms of the feed water constraints such as the pressure, pH and conductivity to forecast the permeate flow rate for the succeeding week values. The upshots of both developed networks were assessed and contrasted with those of the statistical model and it was established that the ANN forecasts were superior to those of the time-honoured techniques.

It is hoped that the up-and-coming investigators will be highly motivated and will leave no stone unturned in making fruitful efforts in the arena of the solar integrated mode of membrane distillation for the desalination of several water resources which will go a long way in effectively addressing the water crisis in the arid regions through the length and breadth of the cosmos. The current investigation also contributes its mite on the assessment and contrast of water quality scrutiny for well water employing both the desalination membrane techniques.

Proposed Methodology

The main objective of the proposed method is to develop the artificial model for predicting the RO performance parameters and the prediction of parameters using the Artificial Neural Network (ANN) structure with the optimization process. Here, an attempt is made to highlight the use of the ANN as a tool for better control and prediction for a chosen system. Their network model predicts water efficiency and average flux of the RO process. This work considers the input parameters such as the feed pressure, concentrate flow, and product flow rate, feed flow, total dissolved solids (TDS) and the recovery ratio. Initially for the prediction processes the Feed Forward Back Propagation (FFBP) structure with different training algorithms is used. For the analysis purposes, the hidden layers and neuron are varied with different training algorithms, and from the relative process the better ANN structure is attained in the Levenberg-Marquardt (LM) algorithm. For optimizing these hidden layers and hidden neurons to increase the efficiency of the neural network, different optimization technique such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and the hybridization of GA and PSO techniques are used. The number of layers and the number of processing elements per layer are the important decisions. Figure 1 shows the proposed method block diagram.

Artificial Neural Network (ANN)

The artificial neural network invariably encompasses a number of nodes (neurons) which possess several connections with other nodes. Each connection contains a weight related to it which can be modified in strength, in resemblance with the neurobiology synapses. The underlying principle in which the neural network functions is comparatively easy and straightforward. Figure 2 effectively exhibits the architecture model for the ANN structure, which contains three layers such as the input layer, output layer and hidden layer, and the hidden layer is in between the input and output layers. With a view to optimize the hidden layers and neurons of the neural network, a most modern and fruitful problem solving and optimization technique known as the hybridization algorithms (HA) is fascinatingly flagged off.

Structure Initialization

In initialization process, six inputs based the input layer weight α_j and the hidden layer weights β_{ij} are initialized input parameters B_i. Here consider, the five hidden layers and neuron varying (1 to 30) and output layer is one.

Input Layer

The input values such as β represents a weight of the input layer neuron, *N* denotes the number of data and *B* characterizes the input value. Based on these values, the basic function is evaluated.

$$B_f = \sum_{j=1}^{N} B_i \times \beta_{ij} \; (i = 1, 2, \dots 6) \qquad (1)$$

where B_f is a basic function, β_{ij} is an input layer weight and *i* is a number of input B_1 = feed pressure, B_2 = concentrate flow, B_3 = product flow rate, B_4 = feed flow, B_5 = total dissolved solids (TDS) and B_6 = recovery ratio.

Hidden Layer

A group of neurons are present in between the input layer and output layer. The outputs from the hidden layer are allocated to the output layer. The multi layer structure evaluates the outputs for each hidden layer procedure. The outputs of the hidden layer are represented by (i = 1, 2, … 5).

The network is competent to possess any number of hidden layers. The values on the output layer of neurons represent the outputs from the network. The ANN structure achieves the optimal hidden layer and neuron. In this regard, a feast of diverse training algorithms is effectively employed.

Different Training Algorithm

In ANN structure, different training algorithms are used to evaluate the minimum error value. In this process nine different training algorithms are used, which are Levenberg-Marquardt (LM), BFGS Quasi-Newton (BFG), Resilient Back Propagation (RP), Scaled Conjugate Gradient (SCG), Conjugate Gradient with Powell/Beale Restarts (CGB), Fletcher-Powell Conjugate Gradient (CGF), Polak-Ribiére Conjugate Gradient (CGP), One Step Secant (OSS) and Variable Learning Rate Back propagation (GDX). In ANN default structure these nine algorithms apply the process based on the hidden layer and neurons. Minimum error

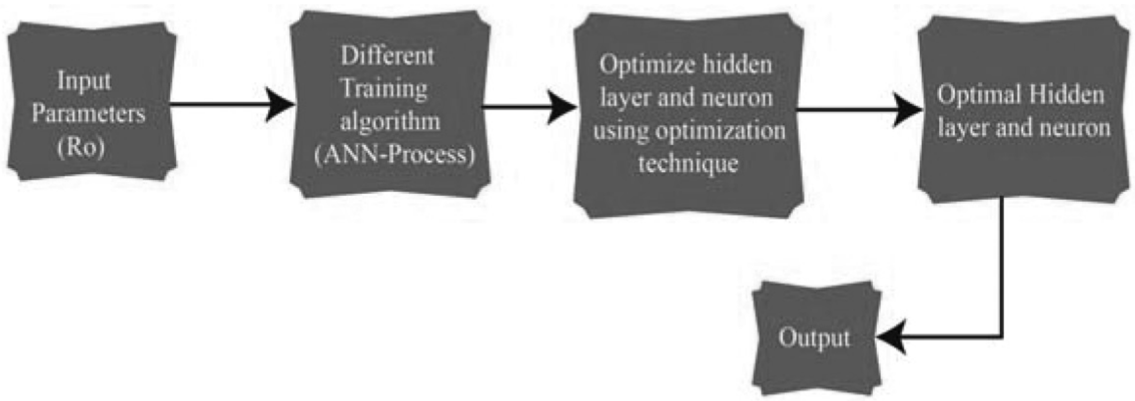


Figure 1: Block diagram for proposed method.

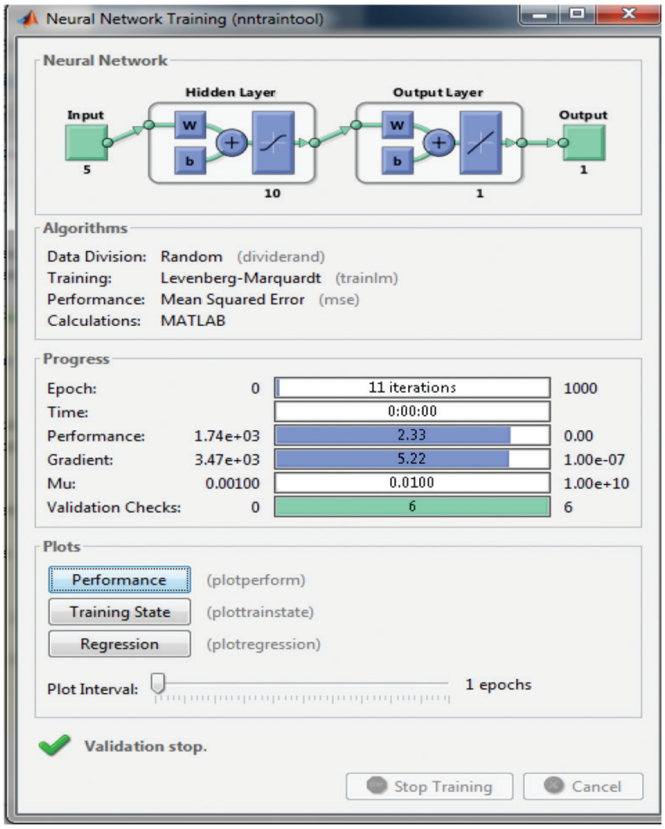


Figure 2: Architecture.

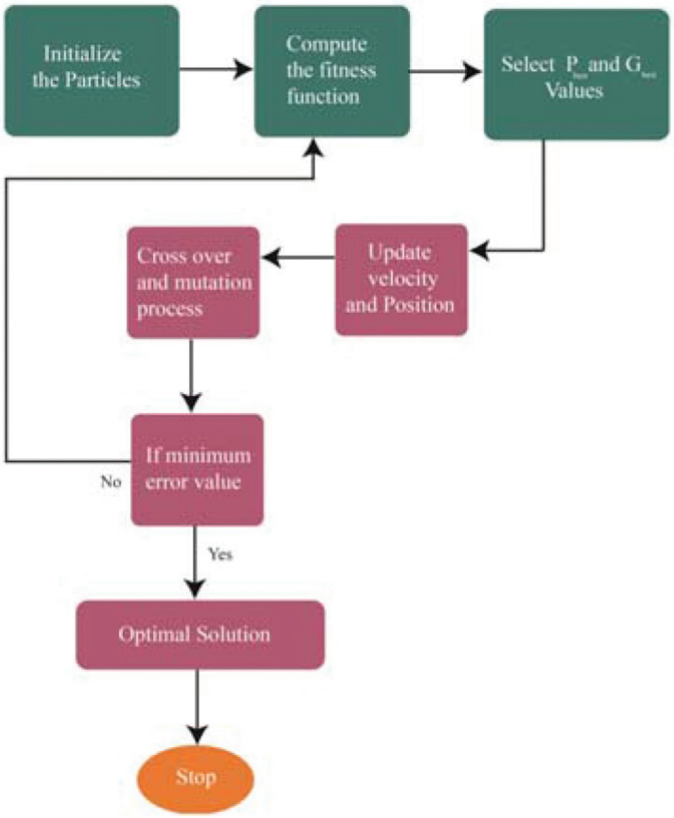


Figure 3: Flow chart for proposed method.

value is attained in the Levenberg-Marquardt (LM) algorithm in the ANN default structure.

Levenberg-Marquardt (LM) Algorith

The Levenberg-Marquardt (LM) algorithm has emerged as the most endearing technique which is offered a red carpet welcome these days. It is equipped with the excellent skills of outshining the simple gradient descent and other conjugate gradient technique in an extensive gamut of issues. Later on, another outlook on the novel technique is brought in by treating it as a trust-region technique.

The weight update vector ∇N is calculated as

$$\nabla N = [J^T(N) \times J(N) + \varepsilon I]^{-1} J^T(N) R \quad (2)$$

Below J^T (w) J (w) is referred to as the Hessian matrix. Pertaining to $\mu = 0$ the algorithm employs the Gauss-Newton approach. Pertaining to very large μ, the LM algorithm uses the steepest good or perhaps the error back propagation algorithm. The parameter is routinely altered at every iteration so as to safeguard the convergence.

Hybridization Algorithm

In the ANN structure optimization procedure, diverse optimization approach such as the GA, PSO and the hybrid process of GA and PSO techniques are effectively employed. From among the related methods, the optimal ANN structure is achieved in the hybrid approach. Here, two vital functions such as the crossover and mutation are brought in the genetic algorithm for enhancing the optimization. The general procedure is elegantly exhibited in the flowchart in Figure 3.

Initialization Process

Initialize the input parameters such as hidden layer and neuron in an initial solution and i is a number of solutions; this process is known as initialization process. The hidden layer and neuron is taken as the S_i that is

$$S_i = \{S_{0j}, S_{1j}, \ldots S_{nj}\}$$

where S_i defines an initial solution, i ε [1, 2 … 6] and j ε [1, 2 … 30] since, i^{th} value is considered as the number of solution and j^{th} value is considered as length of solution.

Fitness Function

Evaluate the fitness value of each solution and then calculate the best solution values.

$$F_i = \sum_{j=1}^{h} \alpha_j \times \left(\frac{1}{1+\exp(-\sum_{i=1}^{N} B_i \beta_{ij})} \right) \quad (3)$$

where, F_i is a fitness function, α and β are weights, B is the input parameters, i is the number of inputs; j is the number of weights and h is the number of hidden neurons. Find the fitness for each layer (i = 1, 2 … 5).

New Population Updation by Using Following Procedure

Finding the p_{best} and g_{best} value: In the start the fitness value is calculated approximately for every particle. The optimal one is considered as the p_{best} and g_{best} value among the fitness value. After that iteration, the current optimal fitness value chooses the p_{best} and the overall best fitness value chooses as the g_{best}.

Find the velocity V_k and position of the particles P_k: Now in PSO, equally the best velocity is initiated by all particles and the best positions established by every particle in the search method.

$$V_k^{y+1} = w.V_k^y + h_1 \times r_1 \times (P_{best\ k} - P_k^y) \quad (4)$$
$$+ h_2 \times r_2 \times (G_{best\ k} - P_k^y)$$
$$P_k^{y+1} = P_k^y + V_k^{y+1}$$

where V_k is the particle velocity, P_k is the current particle, h_1 and h_2 are the learning factor, r_1 and r_2 are the random values within the [0, 1].

In order to make the optimization more efficient crossover and mutation operations were prepared once the velocity and position are assessed.

Crossover

The reproduction contains the crossover and mutation operations. The crossover operation has many methods to produce the offspring such as the one point, two points, uniform, and the arithmetic crossover. In the process the single point crossover is used.

In parents 1 and 2 chromosomes, the green and brown colours are changed in their positions and the remaining gene of the chromosomes is exchanged between the parent chromosomes and these processes are shown in Figure 4.

Mutation

After the crossover, the child chromosome is mutated for increasing the efficiency of the solution and the bold letter shows the mutated gene on the chromosome. Mutation is the function of the generating new offspring from the single parent and it maintains the diversity of the each chromosome as shown in Figure 5.

Optimal Solution

Based on above mentioned processes, the optimal hidden layer and neuron are attained and the optimal fitness is also found which is defined as $F_{optimal}$. In this optimal fitness based the output is found out. The optimal values based predict the output water efficiency and the average flux in the reverse osmosis process.

$$F_{i(optimal)} = \sum_{j=1}^{h} \alpha_j \times \left(\frac{1}{1+\exp(-\sum_{i=1}^{N} B_i \beta_{ij})} \right) \quad (6)$$

Output Layer

The output layer contains a number of neurons. The hidden layer neurons are linked with the output layer by the neurons. The fundamental function of the output units is expressed by Equation O_1 and the output represents the water efficiency and average flux.

$$O_l = \sum_{i=1}^{n} \alpha_i \, \sigma(F_{i(optimal)}) \; l = 2, \; i \; \varepsilon \; 1 \quad (7)$$

Error value calculation using equation

$$E_i = \sqrt{\frac{\sum_{i=1}^{ND} (D_i - P_i)^2}{ND}} \quad (8)$$

where ND is the number of the data, D is the desired value and P is the predicted value, i = 1, 2, … n. By using this formula, the error value is determined from the difference between desired value and predicted value.

Result and Discussion

In the proposed work the results are taken in the working platform of MATLAB 2014 with the system configuration, i5 processors with 4GB RAM used in ANN with optimization process. This section discusses the results in the error value in the LM training algorithm and optimal structure with the output parameters in the reverse osmosis process.

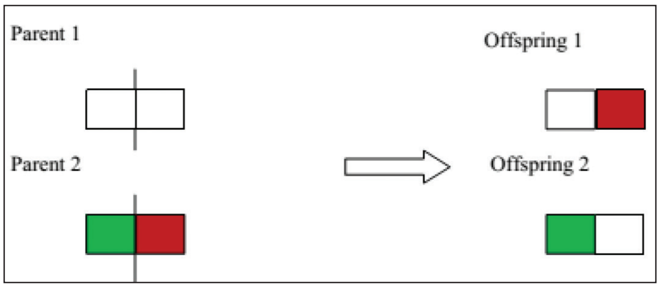


Figure 4: Single point crossover.

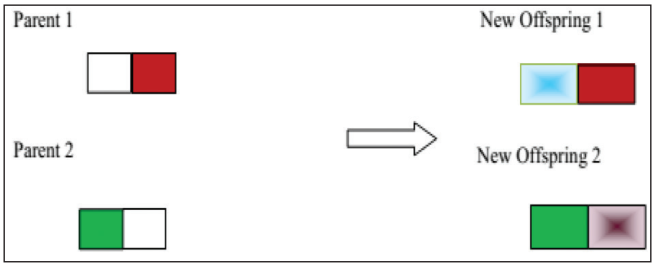


Figure 5: Mutations.

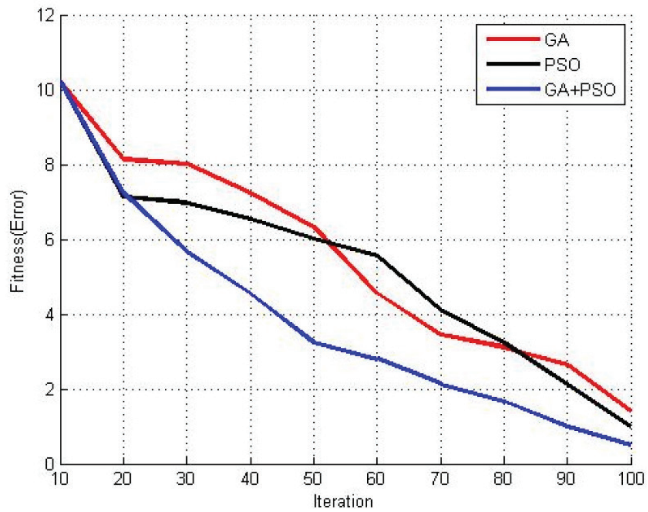
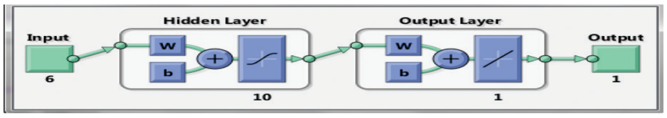
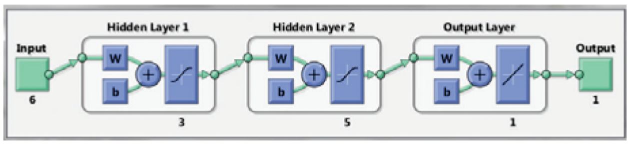
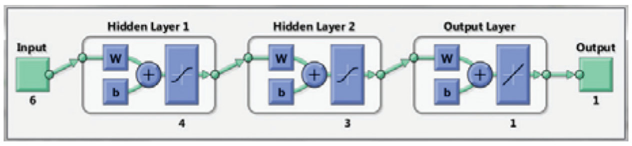


Figure 6: Convergence graph.

Table 1: Optimal structure and default structure of RO process

Technique		*Structure*	*Error accuracy (%)*
Default			90.2
Proposed technique (GA and PSO)	Water efficiency		97.7
	Average flux		81.5

Neural Network Structure for Optimization Technique

Different training and optimization algorithms are used to optimize the hidden layer and neuron of the artificial neural network structure.

Table 1 shows the optimal and default structures in the reverse osmosis in the ANN process. The neural network structure has five hidden layers and neuron varying from 1 to 30 and the optimal structure of HA has the hidden layer one and hidden layer two with 20 neurons to produce the maximum error accuracy of the water efficiency and average flux in the process. The proposed approach is compared to the default structure and the error difference is 7.56%. In the RO process the output parameters in the optimal hidden layers 1 and 2 the neurons are 4 and 3 respectively attained in the GA with the PSO process.

Convergence Graph

The graph appearing here (Figure 6) shows the average output error of the reverse osmosis process and the fitness graphs based on the iteration of the GA, PSO and hybrid techniques by altering the hidden layer and neuron and thus the error values are determined.

Figure 6 shows the convergence graphs for the ANN structure with optimization process average water efficiency and average flux values. In the proposed method initial iteration the average error value is 10.23 in the 7th iteration. When the iteration is varied the performance also changes in all techniques. The maximum fitness of the HA is 11.3 after 13 iterations. Through the graph the lion algorithm optimization strategy just specifies the ideal fitness value with the efficient results.

Experimental Results and Predicted Values for Proposed Method

The neural network process testing results and original values for the reverse osmosis process are shown in Table 2. In the ANN with optimization technique the nearby value occurs in the GA and PSO hybrid process.

Table 2 shows the water efficiency and average flux in the RO process and the ANN optimal structure results are discussed. If the input parameters are varied the output of water efficiency original value is 32 and the predicted value is 32.1 and the difference is minimum value; similarly all the water efficiency results are obtained.

Comparison Results

Different training algorithms are compared to obtain the minimum error value of water efficiency and average flux in the reverse osmosis process with the ANN structure. The error value is varied in each training algorithm and the minimum error value is attained in the hybrid GA and PSO techniques.

Figure 7 shows the water efficiency and average flux error values in different training algorithms such as the GA, PSO and the proposed GA with the PSO process. Various algorithms such as the LM, BFG, RP, SCG, CGB, CGF, CGP and OSS GDX are compared and then the minimum error value is attained. In Figure 7 (a) the minimum error value of proposed approach is 0.850 and when compared to the other training algorithms the difference is high. Figure 7(b) shows the average flux error graph in the training process and the minimum error value is attained in the LM algorithm. The minimum error value ranges from 0 to 1 and the

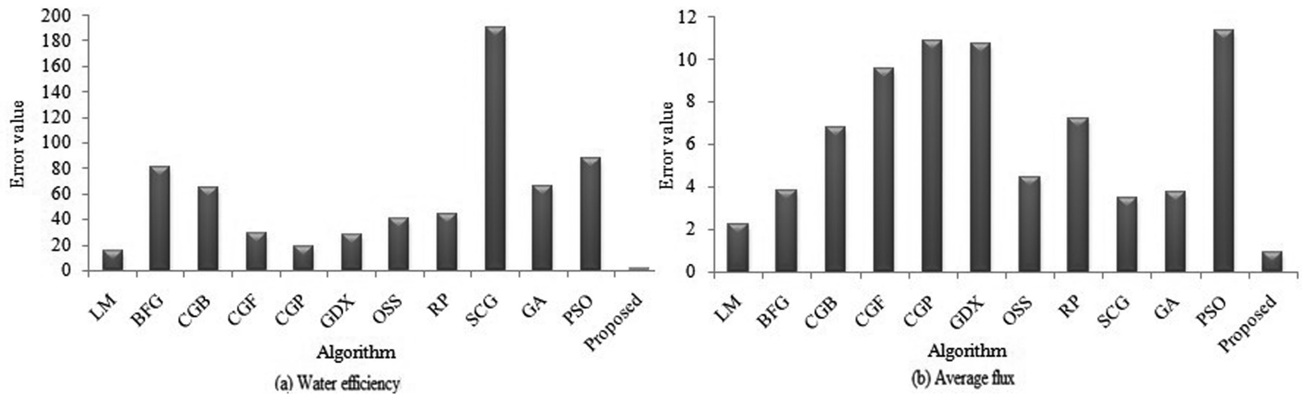


Figure 7: Comparison graph.

Table 2: Actual and predicted results

Sl. No	*Inputs*						*Outputs*			
	Feed Pressure	*Concentrate flow rate*	*Product flow rate*	*Feed flow rate*	*TDS*	*Recovery ratio*	*Water efficiency*		*Average flux*	
							Actual	*Predicted (proposed)*	*Actual*	*Predicted (proposed)*
1	4	105	16	121	9.18	0.132	13.2	13.2	1.9	1.90
2	5	90	20	110	8.93	0.182	18.2	18.2	2.2	1.98
3	5.5	80	23	103	8.37	0.223	22.3	22.80	3.4	3.39
4	6.5	72	26	98	7.9	0.26	27	27	4.2	4.28
5	7	64	30	94	7.81	0.319	32	32.1	4.4	4.40
6	7.5	59	33	92	7.7	0.359	36	36	5.5	5.03

minimum error value in the LM algorithm compared to the CGP minimized is 98% . In the ANN network, the LM training algorithm error value is 0.91 in all the specimens.

Conclusion

In the present work the neural network is applied to simulate the reverse osmosis. The developed ANN models in this study may be used as new predictive tools to improve the performance. The hybrid technique attains the optimal hidden layer and the neuron of the ANN structure based on this structure predicts the parameters. The convincing output results are observed to be nearly equal to the data set minimum error value achieved in the optimization method. In the proposed method the error percentage of the RO process for the water efficiency and average flux are 97.77% and 81.2% respectively. In future, the ANN investigators will look towards further unbelievable improvement methodologies for the production of diminished errors with their excellent techniques for the reverse osmosis process.

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