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Research Paper

Performance prediction of reverse osmosis in large Basra water desalination project using artificial neural networks

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ABSTRACT

This study evaluates the operational performance of the Large Basrah Water Project (LBWP) from February 1, 2023, to December 31, 2024, using an artificial neural network to predict reverse osmosis processes and analyze factors influencing permeability and concentration polarization. This trains and tests the Artificial Neural Network (ANN) model using a dataset comprised of 700 items and divides it into three groups: 80% for training, 10% for validation, and 10% for testing. The developed neural network model successfully predicts the output variables Q_p and C_p based on these six input variables: Feed Pressure, Temperature, Q_f, C_f, Turb, and PH. Using Bayesian regularization backpropagation, the model demonstrated excellent predictive performance for Q_p, with high correlation (R=0.98268) and low error metrics (RMSE =27.5389). While the prediction for C_p was slightly less accurate (R=0.95464 and RMSE=6.9029), the overall model performance remains robust and reliable. This approach provides a valuable predictive tool for understanding and optimizing the underlying system behavior based on the selected input parameters. Furthermore, the ANN model indicates that the related weights for temperature, pressure, feed water flow rates, feed water salinity, turbidity, and pH are 17%, 2.94%,42.94%, 28.23%, 6.72%, and 2.17%, respectively. These results imply that using the training datasets, the model fairly forecasts the concentration and flow of permeate.

1. Introduction

Artificial Neural Networks (ANN) are a form of computational models inspired by the human brain's networks of neurons [1]. A broad spectrum of scientific disciplines have recently benefited from the neural network approach. Environmental scientists and water engineers have been using ANNs since the dawn of the 1990s. The Artificial Neural Network (ANN) is a beneficial approach, having a flexible mathematical structure capable of detecting complicated nonlinear correlations among both the input and output data when compared with standard modeling methods [2]. They are used rather well to forecast the water quality of certain aquatic bodies. When John Holland initially proposed the fundamental idea of genetic algorithms in 1975, while presenting the Adaptive Systems Theory at Michigan University, a theory of adaptive systems. Inspired by concepts of natural selection and evolution, his creative work prepared the stage for a novel approach to optimization and problem-solving. Since then, this initial concept has evolved into a powerful tool in numerous fields like artificial intelligence, engineering, and economics [3,4]. The genetic algorithm is a searching method depending on Darwin's theory of evolution. This method replicates natural selection, in which the best-adapted individuals are selected for reproduction to generate the following generation's progeny. Genetic algorithms effectively search a large solution space to identify optimal or near-optimal outcomes for difficult problems by iteratively selecting, merging, and altering solutions [5]. ANNs in engineering are used as flexible function approximators that learn a complex nonlinear relationship from the data. Current uses of ANNs with RO systems include modeling the performance based on input parameters (flux, salt rejection, and fouling rates) to predict the performance, as well as to optimize the performance of RO processes, whether no analytical model exists or one is too cumbersome [1,6]. This section summarizes the application of ANNs for RO modelling or optimization. Al-Shayji [7] identified significant operational parameters that contribute to optimal performance and projected the large-scale effectiveness of spraying using the ANN model combined with statistical methods. Remlaoui et al.[8] This study presents a computational model for solar-powered desalination using photovoltaic/thermal collectors and membrane distillation. Rashida et al.[9] The study investigates the impact of operating conditions on the removal of heavy and radioactive elements from an aqueous solution containing Phosphogypsum using a Reverse Osmosis Membrane. Jafar, [10], proposed Ann's integration with an uncertain argument for creating an intelligent control system aimed at maximizing the performance of calm, continuous plants. This mix allows real-time changes to raise operational effectiveness.. Similarly, Ballello et al. [11] found that one can forecast membrane fouling and recovery after cleaning by using applied ANN models, an essential component for preserving system performance. Mjalli et al. [12] This study uses artificial neural network (ANN) black-box modeling to predict wastewater treatment plant performance. The model accurately captures plant operation characteristics, minimizing costs and assessing environmental balance. Lee et al. [13,14] studied an artificial neural network (ANN) model developed with flow rate for reverse osmosis (SWRO) and imitated developed water temperature and transmembrane pressure (TMP). To paint the mass flow in the diaphragm of the RO system, Zhao et al. [15] integrated ANN with a modified solution diffusion model; the predictions exceeded the pre-model. Additionally, Aish et al. [16,17] ANN were used to predict the performance of the RO system when saltwater treatment, active adjustment, and future maintenance are allowed, by predicting the performance of the system under different feed conditions. In addition, a more accurate procedure is produced at the RO system with simulation ANNs.

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Nomenclature

ANN	Artificial Neural Network	*LBWP*	Large Basrah Water Project
BP	Back Propagation	T	Temperature of feed
C_p	Permeate concentration	Turb.	Turbidity
C_f	Feed concentration	Trainbr	Bayesian regularization backpropagation.
RMSE	Root mean squared error	Traingda	Gradient descent algorithm
P	Pressure of feed	Trainoss	Algorithm for one-step backpropagation.
Purelin	Linear Function	Trainlm	Levenberg - Marquardt Algorithm
MSE	Mean square error	Trainrp	Resilient algorithm
Q_p	Permeate flow	Traingdx	Gradient Descent with Momentum and Adaptability.
Q_f	Feed flowrate	Trainscg	Backpropagation technique with a scaled conjugate gradient.
PH	Acidity/alkalinity of feed water	Turb	Feed turbidity
R	Regression	Tang-sig	Tangent hyperbolic function.
W	Weight	RO	Reverse osmosis, which is a water purification process.

To simulate calm uninterruptedness, Khayet et al. [18], for example, compared the efficacy of ANN with response surface methodology (RSM). Murthy and Vora [19] repeated the efficacy of ANNs in modeling dynamic RO systems. Moreover, K. Mohd et al. [20] projected membrane pore size with ANNs vital information for membrane filtration. Using geographical fouling data, Park et al. [21] developed a deep neural network (DNN) to model membrane fouling during nanofiltration and reverse osmosis filtration using in-situ fouling image data from optical coherence tomography (OCT). Abuwatfa et al. [22] using ANN models in RO systems marks significant progress in desalination that has at last extended the use of ANN by developing a deep neural network (DNN) to explain how organic fouling arises in RO membranes. D. Jumaah et al. [23] utilized the application of artificial neural networks (ANN) in building and forecasting the performance of home RO systems is investigated. Whereas the second case forecasts the weight percentage of ANN models depending on operating parameters such as feed pressure, feed temperature, and feed concentration. Abdulkareem et al. [24] studied the modeling of water pollution in Basra using an artificial neural network, a genetic algorithm, and an annealing simulation method. As the area evolves, the combination of ANNs with other machine learning techniques and optimization strategies will most likely produce even more sustainable and efficient desalination technologies, thus addressing problems of world water scarcity. In the present work, a neural network model was developed to predict two output variables based on six input variables. The network aims to establish a reliable predictive model that can accurately map the relationship between these inputs and outputs using a supervised learning approach.

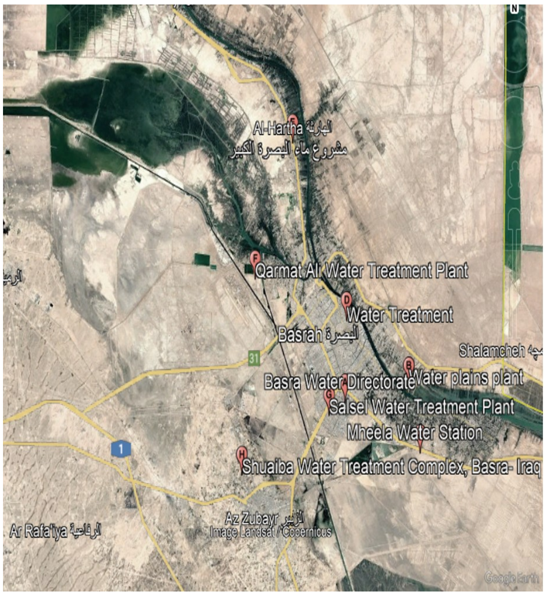


Figure 1. Shows the geographical location of the large Basra water desalination project.

2. Methodology

2.1 Study area

This study was conducted at the large Basra Water Project, located in the Al-Haritha district of the Basra Governorate in southern Iraq. The facility is positioned at coordinates 3064′95.00″ N and 4775′06.1″ E, Fig. 1, north of Basra city and west of the Shatt Al-Arab River. A group of firms, including JICA, OTV, VEOLIA, Hitachi, and Arab contractors, worked together to build the project on 80 dunums of land in the district. It serves more than two million people. The building of this factory started in 2014, and it opened for business in 2022. This plant can make 200,000 m^3 of product every day (8333.33 m^3/hr). The goal of the project is to improve the quality and quantity of water for the communities around it, which have been dealing with problems with dirty and scarce water for a long time. To make sure that water supplies in the area are managed in a way that lasts, it uses advanced filtration systems and regular monitoring. The operations team's job is to make sure that the UF and RO membranes work well by getting excellent pretreatment performance.

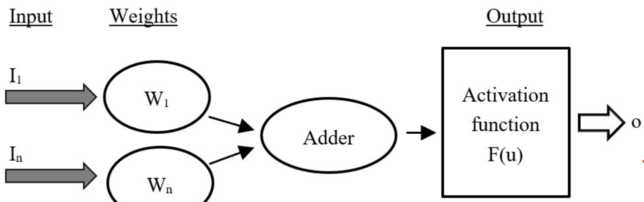


Figure 2. Essential elements of the Artificial Neural Network(ANN) [16, 17].

Table 1. ANN model input and output variables.

Item	Parameter	Symbol	Unit
Input variables	Pressure	P	Bar
	Temperature	T	C°
	Concentration	C_f	ppm
	Flow rate	Q_f	m^3/h
	Turbidity	Turb.	NTU
	PH	*PH*	—
Output variables	Permeate flow	Q_p	m^3/h
	Permeate concentration	C_p	ppm

2.2 Data description

This study used a neural network model to guess how much permeate will flow (m^3/h) and how concentrated it will be (ppm). The model looked at six factors: feed pressure (bar), input temperature (C°), flow rate (m^3/hr), concentration (ppm), feed turbidity (NTU), and pH. This research team collected the data from the major Basra water project, looked at it, and divided it into three groups: 80% for training, 10% for validation, and 10% for testing. The network employs supervised learning to build a reliable model that elucidates the connections between these inputs and outputs. This uses the nntool and nftool methods in the MathWorks MATLAB 2024 program to build the best artificial neural network model. The RO system's performance has led to the gathering of 700 days, from Feb. 2023 to Dec. 2024 data sets that show how things really work. Table 1 and Fig. 3 show this information. Drawn from the Large Basrah Water Project, Table 2 provides a synopsis of 700 sets of data regarding the operation of the reverse osmosis (RO) system in real-world conditions. Using the conditions of the large Basrah water project as what the model took in, the ANN model examined how well the reverse osmosis system operated by looking at the permeate flow (m^3/h) and concentration (ppm). Figure 4 illustrates the phases of a MATLAB 24 computer program that implements training, validation, and testing procedures for the effectiveness of training methods for reverse osmosis systems.

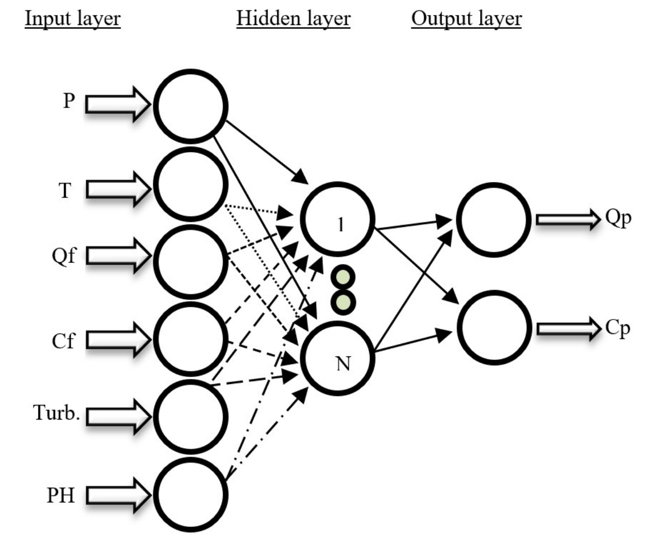


Figure 3. Shows the proposed network of the performance of reverse osmosis system training methods.

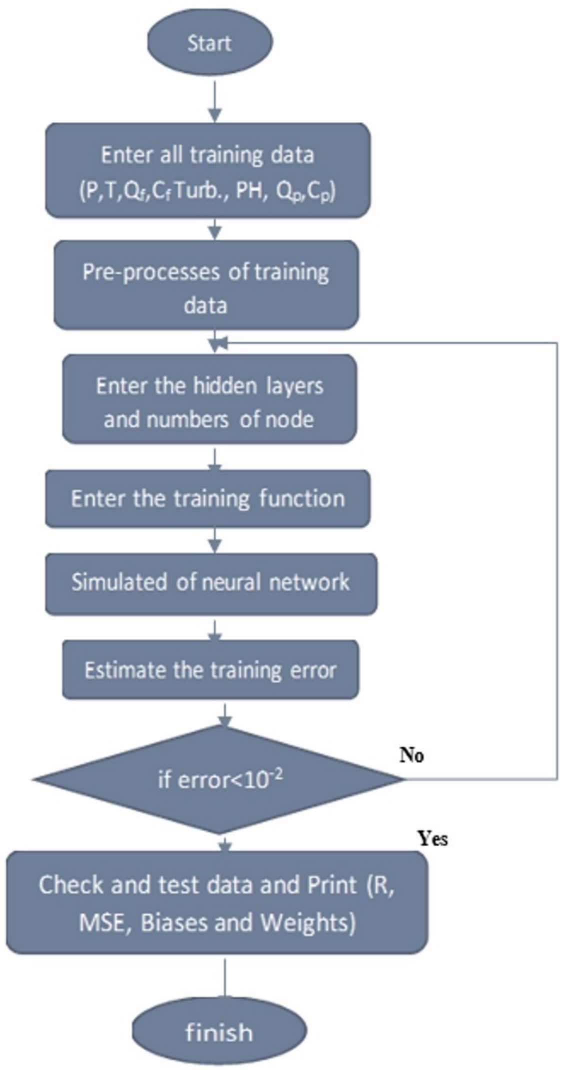


Figure 4. The flow chart shows the steps and the overview view the ANN model.

3. Artificial neural networks (ANN)

Artificial neural networks (ANNs) are mathematical computer models used in human brain activity identification. Artificial neural network (ANN) technology can solve problems even in the lack of data, absorb and learn from continuous data input, and preserve knowledge using up-to-date information. It can also perform brain activities. Because of their adaptability and development capability, ANNs are especially strong in a wide spectrum of uses, including image identification, natural language processing, and predictive analytics. By mimicking the neuronal connections in the brain, these models can quickly identify patterns and make informed judgments depending on the input they obtain. The capacity of a neural network to duplicate complex nonlinear relations without depending on any prior knowledge about the character of the relation is its fundamental benefit [25]. An ANN is made of many neurons expressed in many nodes. Whereas the input nodes reflect the independent variables, the output nodes [26] show the dependent factors. The learning process is largely aimed at identifying the ideal collection of weights that can generate the best output for the particular inputs. Calculating the error [2], helps us to match the network output to the intended reaction. Structures in neural networks abound. Feedforward and recurrent networks practically could be confused. From the input nodes through hidden nodes to the output nodes in feedforward networks, only forward-directed information flows. Recurrent networks offer connections whereby data can go backwards and forwards across network node connections. Another name for the recurrent networks is feedback networks [27]. When historical knowledge about the process or system model is absent, artificial neural networks (ANN) can map non-linear connections. Their capacity for ”learningänd modification by example, as well as their fast detection of structural elements, characterize their advantages over more conventional mathematical models. ANN modeling cannot substitute a complete knowledge of process behaviour, even if it helps to rapidly build models for complicated reactions. The choice of process elements, the acquired data, and the training area used primarily impact the efficacy of establishing a strong and reliable network. Comprehensive evaluation of these elements is essential for good model training to guarantee that the network can reach a suitable degree to fresh data. Furthermore, adjustments and continuous validation may be necessary to maintain the projections' quality and accuracy as new data becomes available. Recently, there has been a lot of interest in artificial neural networks (ANN). In the real world, it is used in a variety of fields, including oil drilling, engineering, industrial processes, mathematical models, and equations. Artificial neural networks help computers operate as they should. Usually, very non-linear model generations and estimations demand complex, large-scale environments. Thus, one can project the performance of the reverse osmosis system using an ANN. Three layers define artificial neural networks of the reverse osmosis process: an input layer, an output layer, and a hidden layer. Neurons at the input layer must first obtain outside data before sending it to the network's processors for study [28]. A neuron at the bottom gathers and processes the data sent from the input layer to the hidden layer before reacting [29]. Figure 2 depicts the essential elements of a neural network, including inputs and outputs, weighting variables, bias, and activation function [30].

4. Back propagation algorithm (BP)

Backpropagation (BP) is the most often used among the several learning techniques available for every neural network model. We apply this approach in supervised learning [25]. BP's main training concept modifies weights to lower mean square error (MSE) based on the gradient descent approach [31]. The BP algorithm is defined in two phases: forward and reverse phases. The algorithm distributes the network input data forward to the next level, and so on. The network fault is calculated following the forward phase. The network fault is spread backwards in the backward phase; hence, the weights undergo change [32]. Figure 2 shows three layers, each with n neurons, which make up the network architecture. The number of input variables determines the first layer, that of neurons. Receiving outside world input, this layer forwards it unaltered to the hidden layer. Usually referred to as hidden layers, intermediate layers have only weak ties to the outside world. The output layer's activation function carries summed individual values from the previous layer. The input layer receives the output and updates it with additional weight and bias, if necessary, within a specified error tolerance. Interestingly, nodes on the same layer do not have any connections to each other. This cycle will continue until all the limitations have been met. Once the limitations have been met, the model undergoes a final evaluation to ensure its accuracy and effectiveness in making predictions. Any necessary adjustments can be made during this phase, refining the weights and biases to enhance performance before deployment [33].

Table 2. Shows the actual data of the RO system used in the ANN model.

Date	Pressure (Bar)	Temperature (C°)	Q_f (m^3/h)	C_f (ppm)	Turb (NTU)	PH	Q_p (m^3/h)	C_p (ppm)
1-Feb-23	20.74	15.20	4208.48	2681	0.223	7.84	3308.82	37
2-Feb-23	15.33	15.20	5319.20	2220	0.089	7.94	4192.07	32
3-Feb-23	20.58	15.60	4255.36	1682	0.211	8.03	3348.21	21
4-Feb-23	20.92	15.55	3068.57	1720	0.201	7.93	3197.88	22
5-Feb-23	21.26	15.50	4326.65	1732	0.213	7.91	3408.50	20
6-Feb-23	21.64	15.80	4379.90	1789	0.235	8.09	3450.83	22
7-Feb-23	15.97	15.60	4390.39	1790	0.091	7.98	3452.67	24
8-Feb-23	21.25	15.80	4397.27	1934	0.108	8.05	3458.22	23
9-Feb-23	15.69	14.60	5425.77	1900	0.164	8.07	4280.04	23
10-Feb-23	21.32	15.20	5297.28	1789	0.166	8.05	4182.83	24
11-Feb-23	21.19	15.50	5368.92	1958	0.112	8.17	4240.05	36
12-Feb-23	21.21	15.40	5273.77	2028	0.143	8.11	4161.12	23

Table 3. Shows MSE, R, and Epoch for the one hidden layer of different ANN training algorithms.

No. of Neuron	Item	Trainlm	Trainbr	Trainrp	Traingdx	Traingda	Trainoss	Trainscg
15	R	0.96184	0.97265	0.94828	0.9202	0.84276	0.93668	0.92265
	MSE	0.14779	0.046283	0.14404	0.20906	0.34904	0.16482	0.19346
	Epoch	6	233	54	115	56	53	33
17	R	0.97055	0.97825	0.94104	0.90863	0.86366	0.92864	0.93471
	MSE	0.10702	0.039414	0.2072	0.18739	0.27171	0.14684	0.132
	Epoch	15	167	79	101	152	57	49
19	R	0.95865	0.97824	0.95319	0.90351	0.81926	0.93558	0.91954
	MSE	0.060104	0.03882	0.081722	0.18164	0.35304	0.11517	0.14735
	Epoch	4	146	118	89	97	59	49
21	R	0.97133	0.97527	0.94713	0.89767	0.84096	0.93959	0.94073
	MSE	0.069902	0.033935	0.1043	0.1963	0.30549	0.1008	0.10054
	Epoch	17	664	124	94	139	80	57
23	R	0.9699	0.97855	0.94413	0.88372	0.83023	0.92548	0.93921
	MSE	0.072116	0.033577	0.11525	0.27594	0.35964	0.16575	0.12774
	Epoch	8	524	126	85	196	58	78
25	R	0.97167	0.98268	0.94458	0.89678	0.82992	0.93753	0.94212
	MSE	0.085148	0.030188	0.1271	0.20939	0.28815	0.12331	0.10969
	Epoch	7	363	110	106	160	71	64
27	R	0.97262	0.97739	0.95099	0.42424	0.79523	0.93096	0.92305
	MSE	0.043659	0.028932	0.090101	2.1684	0.36407	0.1282	0.10966
	Epoch	24	327	137	16	168	58	36
29	R	0.96584	0.9799	0.94966	0.88578	0.79207	0.91342	0.94035
	MSE	0.087291	0.022342	0.10591	0.23676	0.48803	0.17154	0.11473
	Epoch	4	232	94	90	136	47	55

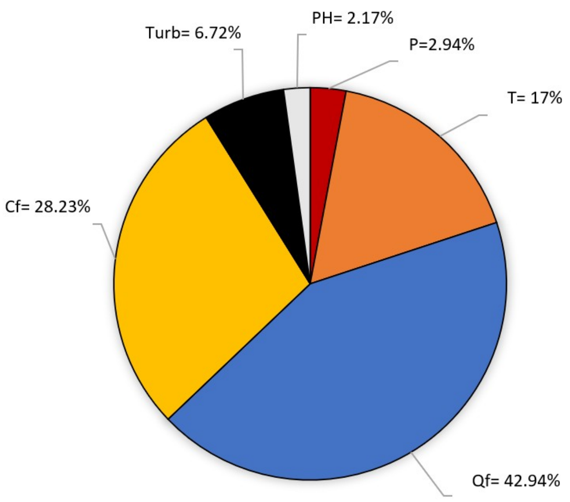


Figure 5. Shows the weight percentages of operating conditions.

5. Results and discussion

This part models the performance of the reverse osmosis system by means of neural networks with a single hidden layer. Seven training algorithms, Traingdx, Trianscg, Trainoss, Trainrp, Traingda, Trainbr, and Trainlm, have been investigated and tested to ascertain the optimal strategy for the performance of the reverse osmosis system network. That also probes different node counts for every method. We probe the performance of the artificial neural network(ANN) by increasing the number of hidden nodes, as indicated in Table 3. Bayesian regularization backpropagation with 25 nodes in the hidden layer outperforms other networks with varying node counts. The results of the Bayesian model show this is so because it attained a lower MSE of 0.030188 and a higher regression value of 0.98268 than in other models. Furthermore investigated are different numbers of nodes for different algorithms to determine the best approach for reverse osmosis system performance. The hidden and output layers are respectively set active by the hyperbolic tangent (tansig) and linear (purelin) functions. Following our investigation on the ideal activation functions (tansig, purelin) for showing data on the performance of the RO system, we then raised the number of neurons from 1 to 25 in increments of 2. This work intends to improve the correlation between the actual and expected values for Q_p and C_p as well as increase the accuracy of the artificial neural network model evaluating the RO system. This is thus in contrast to other regularization backpropagation outperforms networks with varying numbers of nodes in the hidden layer. When looking at the different methods used in ANN mode, the Bayesian regularization backpropagation (trainbr) method shows the smallest

Table 4. Training of ANN models with various neurons and transfer functions.

No. of Neuron	Item	(Tansig, Tansig)	Equation	(Tansig, Logsig)	Equation	(Tansig, Purelin)	Equation
15	R MSE Epoch	0.9764 0.044646 254	$0.95\times T+0.00067$	0.79291 0.54068 293	$0.51\times T+0.38$	0.97265 0.046283 233	$0.95\times T-2.5e^{-05}$
17	R MSE Epoch	0.9767 0.041223 227	$0.9\times T-0.0053$	0.79227 0.55664 293	$0.51\times T+0.38$	0.97825 0.039414 167	$0.96\times T-0.00071$
19	R MSE Epoch	0.97923 0.035495 179	$0.96\times T-0.0025$	0.79319 0.54617 767	$0.51\times T+0.38$	0.97824 0.03882 146	$0.96\times T-0.0019$
21	R MSE Epoch	0.97639 0.035209 275	$0.95\times T-0.0029$	0.79273 0.51221 255	$0.51\times T+0.38$	0.97527 0.033935 664	$0.96\times T-0.002$
23	R MSE Epoch	0.98193 0.030255 341	$0.96\times T+0.00052$	0.79295 0.54221 943	$0.51\times T+0.38$	0.97855 0.033577 524	$0.96\times T+0.0035$
25	R MSE Epoch	0.98135 0.031727 354	$0.96\times T-0.0062$	0.79271 0.55283 450	$0.51\times T+0.38$	0.98268 0.030188 363	$0.97\times T-0.0045$

mean square error (MSE) and the best correlation between the actual and predicted values of Q_p and C_p in the training data set. Moreover, we could show the favorable results of the (trainlm) method.

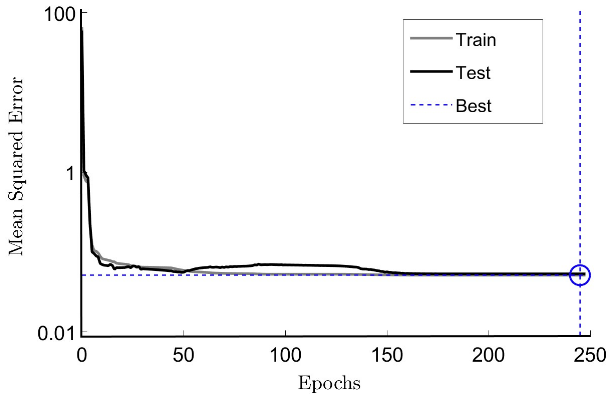


Figure 6. Displays the MSE for training and testing by a neural network with 11 hidden neurons for the (Tansig, Purelin) transfer function.

Furthermore, the many kinds of activation functions influence the performance of the neural network model in reverse osmosis since some of them do not reach the optimal MSE and regression. As such, we look into several output and hidden layer activation methods. Table 4 shows the MSE, R and Epoch values via different transfer functions. Among the activation function settings are(Tansig, Tansig); (Tansig, Logsig); (Tansig, Purelin). When one hidden layer in an artificial neural network is utilized, networks with a (Tansig, Purelin) structure can offer the best performance and regression as the shaded cell in Table 4 demonstrates.

Table 5. Shows comparison between the predicted and experimental data of Q_p and C_p.

Experimental Q_p	Predicted data of Q_p	Experimental C_p	Predicted data of C_p
3308.82	3277.02	37	40.890
2910.94	2961.60	68	62.770
3398.35	3368.96	73	69.669
2351.69	2327.45	65	68.810

With 25 hidden neurons and a transfer function of "Tansig, Purelin,"the findings show how a neural network may present better information display from the large Basrah water treatment plant. Perfect for simulating complex systems like water movement and quite successful at spotting minor, non-linear connections in enormous amounts of data are neural networks. These models' structure allows them to learn from a lot of data and create more accurate forecasts and insights than more outmoded modeling methods. Hidden neurons since the model generated a lower MSE (0.051527) show that in Fig. 6 and a higher regression value for Q_p and C_p (0.98268, 0.95464). The optimal equation for regassing real and expected data shows in Fig. 7 for Q_p and C_p are Eq. 1 and Eq. 2, respectively.

$$(Q_p)ANN = 1\times(Q_p)Actual + 14 \tag{1}$$

$$(C_p)ANN = 0.94\times(C_p)Actual + 1.7 \tag{2}$$

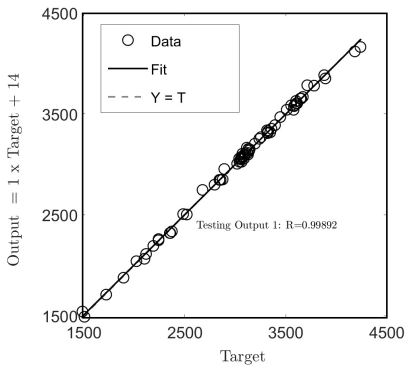
Table 6. Demonstrates how to train ANN models with No. of neuron to activation function (Tansig, Purelin).

No. of Neuron	Target	MSE	Epoch	Testing R	Equation
9	Q_p C_p	0.059649	138	0.99891 0.92693	$Output = 1.00\times Target + 00.58$ $Output = 0.95\times Target + 03.20$
11	Q_p C_p	0.051527	245	0.99892 0.95464	$Output = 1.00\times Target + 14.00$ $Output = 0.94\times Target + 01.70$
13	Q_p C_p	0.048733	325	0.99848 0.87006	$Output = 0.99\times Target + 14.00$ $Output = 0.85\times Target + 07.60$
15	Q_p C_p	0.046283	233	0.99862 0.85220	$Output = 0.99\times Target + 21.00$ $Output = 0.79\times Target + 14.00$
17	Q_p C_p	0.039414	167	0.99818 0.89180	$Output = 1.00\times Target - 13.00$ $Output = 0.91\times Target + 05.20$
19	Q_p C_p	0.03882	146	0.98275 0.89929	$Output = 1.00\times Target + 21.00$ $Output = 0.94\times Target + 02.30$

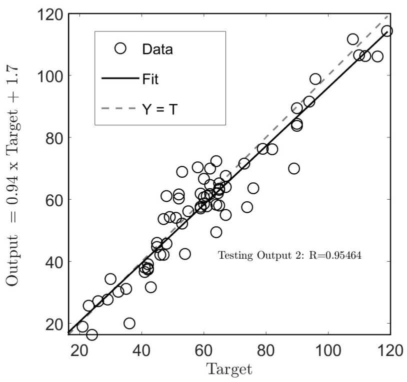
We trained the neural network on a dataset of 700 samples, dividing the data into training (80%), validation (10%), and testing (10%) sets. The results from the testing data show a strong correlation and a low root mean squared error (RMSE), which means the model is performing well. Specifically, the testing performance was:

$Q_P\ Output : R = 0.99892 \Rightarrow$ RMSE = 27.5389
$C_P\ Output : R = 0.95464 \Rightarrow$ RMSE = 06.9029

The high correlation for Q_P suggests that the model effectively captures the underlying relationships for this variable, whereas C_P, while still accurate, has a slightly lower correlation, indicating some complexity in prediction. Also, the results indicate that the weight percentages of the following operational conditions are, respectively, 2.94%, 17%, 42.94%, 28.23%, 6.72%, and 2.17%: pressure, temperature, feed flow, feed concentration, turbidity, and PH according to the data in Fig. 5. The findings indicate that the Ro intake feed flow has the greatest influence on the RO system's performance and the caliber of Q_p and C_p when compared to other factors. Table 5 comparison between the predicted and experimental data of Q_p and C_p. Table 6 presents the highest R test ratio for Q_p and C_p. Presenting data from the RO system proved that a neural network with 11 hidden neurons for the transfer function (Tansig, Purelin) was the best model.



(a) Output 01



(b) Output 02

Figure 7. Shows exact Q_P, C_p vs predicted Q_P, C_p.

6. Conclusions

This work runs the predictive model using the performance operating conditions of the reverse osmosis system from the large Basrah water project. Although feed pressure (bar), inlet temperature (C°), flow rate (m^3/h), concentration (ppm), feed turbidity (NTU), and pH are its input variables, the output variables of the ANN model are permeate flow (m^3/h) and concentration. This work made use of several feed-forward and feedback propagation layers in neural networks. Seven training strategies were analyzed in order to identify the most successful one. Projecting the performance of the reverse osmosis model seems to be optimal using Bayesian regularization backpropagation. While taking into account hidden layer count, hidden layer nodes, and transfer functions. Whereas Bayesian regularization backpropagation (Trainbr) delivers the lowest mean square error for the hidden layer, the transfer functions (Tansig, Purelin) produce the best results for the output layer, both during testing and training. This implies that the choice of the transfer function determines, most importantly, the maximum performance of the model. Future studies should look at other transfer functions and their likely impact on boosting general accuracy and dependability in reverse osmosis estimates. A neural network with 11 hidden neurons using the transfer functions (Tansig, Purelin) was found to be the best model for displaying data on the RO system's performance. Because in relation to other hidden neurons, the model produced a lower MSE (0.051527) and a higher regression value for Q_p and C_p (0.98268 and 0.95464, respectively). The ANN model also demonstrated the following weight percentages for various operational circumstances: 2.94% pressure, 17% temperature, 42.94% feed flow, 28.23% feed concentration, 6.72% turbidity, and 2.17% pH. Lower MSE and better regression values during ANN model training and testing indicate exceptionally high-quality data. This remarkable capability ensures that the model can adapt to new data efficiently and provide accurate estimates. Additionally, it highlights the importance of choosing the proper preprocessing methods and features to enhance model performance.

Authors' contribution

All authors contributed equally to the preparation of this article.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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