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RESEARCH ARTICLE

UTALIZATION OF ARTIFICIAL NEURAL NETWORKS (ANNS) FOR PREDICTION THE REVERSE OSMOSIS DESALINATION PLANT PERFORMANCE OF ARAB POTASH COMPANY

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ABSTRACT

Freshwater resources are being rapidly exhausted as a result of both natural and anthropogenic activities. In recent years, there has been considerable interest in the potential and opportunities presented by the desalination technology for brackish and seawater. especially reverse osmosis desalination to mitigate the increasing of water scarcity and supplying fresh water. In this research, the performance prediction of a multistage with two passes of medium-sized spiral wound brackish water RO (BWRO) desalination plant with capacity (1200m3/day) for Arab Potash Company (APC) placed in Jordan is developed and forecasted for one month by utilizing an artificial neural network (ANN) model as a smart manufacturing system. For predicting the next one-month values of permeate flowrate, recovery, and rejection of product water plant, a neural network such as Multilayer perceptron (MLP) and radial basis function (RBF) were developed and trained based on the feed water parameters which include pH, pressure, conductivity and Temperature to predict the values of permeate flowrate, plant recovery, and plant rejection for one-month. The results have been predicted and indicated that both forms of neural networks are extremely reasonable for forecasting permeate flowrate, plant recovery, and plant rejection. Forecasting of plant performance, with both Multilayer perceptron (MLP) and radial basis function (RBF) neural networks models, generated predictive results with good accuracy for long-term memory time intervals extended to 725 hr for permeate flowrate, recovery, and rejection of the product water plant for forecasting times up to one month. Up to this, this research would be an effective tool used for predicting the good desalination plant performance, which contribute to saving the cost and energy.

KEYWORDS

Artificial neural network (ANN), Process performance forecasting, brackish water RO Desalination, performance indicators prediction, MLP and RBF neural networks.

1. INTRODUCTION

As a result of the constrained accessibility of clean water sources, desalination has become a gradually dependable process for water sources worldwide, with demonstrated advantages and accessibility of technical and economic side (Elsaid et al. 2020). However, to ensure efficient and reliable water supply in Jordan, where fresh water is limited, reverse osmosis desalination plants present a viable solution (Mohsen et al., 2010). Reverse osmosis (RO) is a physical technique that utilizes phenomenon principle of osmosis, precisely the difference of osmotic pressure among the saline and clean water to flush out salts from brackish and seawater. In this process, pressure greater than osmotic pressure is applied to the feed raw water and led to reverse the flow of water, which consequences in pushing freshwater to pass through the pores of membrane and separated from the salt, while the brine is disposed (Ghernaout, 2017). The RO process can be employed to purify both brackish water and seawater, and it is applicable for mitigating the concentrations of (total dissolved solids_ TDS) with up to 45×103 mg/L. The energy is needed to operate the pumps in the reverse osmosis, which in turn increase the pressure employed to feed water. The pressure value needed being directly related to the concentration of TDS in the feed raw water. For brackish water (500 - 30,000 ppm), the pump pressure necessity is about (140 – 400) psi. Therefore, the concentration of TDS in feed water has a significant impact on the consumption of energy and on the product water cost (Voutchkov, 2017).

Artificial neural networks ANN is one of the most efficient tools utilised in artificial intelligence and machine learning especially for Smart manufacturing systems. The primary aim of ANN is to obtain a correlation for independent (input) dependent (output) variables. This correlation is formed from a machine learning process in which a data set is given to a network. Accordingly, it is set as data driven from a model. The most commonly used ANN is a Multi-layer Perceptron (MLPNN), and Radial Basis Function Neural Network (RBFNN) (Jawad et al. 2021).

In current years, there several efforts to develop the employment of artificial neural networks (ANN) as a feasible method to advance data-driven from models in order to improve the brackish water reverse osmosis processes performance (Dornier et al., 1995; Delgrange-Vincent et al., 2000; Razavi et al., 2004; Chen et al., 2006; Khayet et al., 2011; Salgado-Reyna et al., 2015; Yao et al., 2022). This study, applied ANN method to improve a model for forecasting reverse osmosis plant performance with reference to the experimental water quality data

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(Murthy and Vora, 2004). They predicted the salt rejection and permeate flowrate at different operating conditions and the predicted results compared with the practical data and showed strong correlation.

In previous work, ANN models of RO plant performance employed training data sets in which the training and testing data points were interspersed to the complete data time-series (Abbas and Al-Bastaki, 2005). These models demonstrated reasonable effectiveness in data interpolation, which refers to forecasting for input value ranges (variable) for which the model of ANN was tested and trained. However, they exhibited limitations in their forecasting capabilities, specifically in predicting performance for time periods not included in the training dataset. The researchers improved ANN models to assess and forecast the performance of membrane processes by characterizing flux decline and rejection variation over time in relation to changes in feed quality (Abbas and Al-Bastaki, 2005). In this context, the ability to forecast the reverse osmosis (RO) membrane plants performance, even for short-term future intervals, would enhance the flexibility to formulate an incorporated process approach for controlling the process and establish a prompt warning system to indicate the necessity for maintenance actions, such as adjustments to process variables like pressure and flow rates, as well as membrane cleaning (Delgrange et al., 1998; Libotean et al., 2009).

An artificial neural network model developed for forecasting the salt rejection (saline) and permeate flowrate parameters of brackish water RO desalination plants (Righton, 2009). This study, predicted these two parameters by utilizing an ANN consuming hidden layers (two) and inputs contained a series with various concentrations, flow rates and pressure of the composite streams (Righton, 2009). Additionally, two RO desalination plants utilizing the ANN technique were also modeled for salt rejection and permeate flux forecasting (Libotean et al., 2009). According to this study, investigated the capability to predict the performance of a reverse osmosis (RO) plant using real-time performance data from the plant (Libotean et al., 2009). They assessed three distinct forecasting models: the standard time-series-correlation (STSC) method, the sequential- forecast (SF) method, and the marching-forecast (MF) method. Additionally, they compared the support vector regression (SVR) model with a multilayer perceptron (MLP) model. The findings suggest that these models can effectively forecast standardized performance parameters with practical accuracy over short time intervals, extending up to 24 hours.

This study demonstrated the possibility of using artificial neural network (ANN) technique for predicting the large- and small-scale BWRO desalination plant performance located in Gaza Strip (Aish et al., 2015). They are forecasting the rates of total dissolved solids concentrations (TDS) and the flowrate of permeate in produced water for the next week from the data obtained. The researchers developed a Multilayer perceptron (MLP) and radial basis function (RBF) neural networks for forecasting permeate flowrate based on feed water parameters such as the pressure, the pH and the conductivity (Aish et al., 2015). Furthermore, for forecasting TDS concentrations based on quality variables of product water such as; temperature, pressure, pH and conductivity. The results confirmed that both artificial neural networks are extremely reasonable for forecasting permeate flowrate and TDS concentrations in the treated product water.

According to this study, explored and developed neural networks (NNs) for a brackish water reverse osmosis (RO) desalination plant to investigate the antifouling properties of membranes designed using a combination of polypyrrole (PPy) and coated with multiwalled carbon nanotubes (MWCNTs) (Farahbakhsh et al., 2019). They created two neural networks to analyze both raw and oxidized membranes. The prediction results indicated that the oxidized membrane achieved a higher water flux with a consistent curve. Additionally, as a result of decreasing salt rejection and water flux the accumulation of particles on the surface of the membrane was also forecasted by developed model.

In this work, the viability of constructing artificial neural network models of a multistage, two passes medium-scale spiral wound (BWRO) desalination plant performance is demonstrated to predict the next one-month values of permeate flowrate, plant recovery, and plant rejection of the product water. To the authors' best knowledge, the performance forecasting of (BWRO) desalination plant of Arab Potash Company (APC) located in Jordan with capacity (1200m3/day) based artificial neural network (ANN) technique has not yet been utilised. Therefore, the objective of this study is to develop Multilayer Perceptron (MLP) and Radial Basis Function (RBF) neural networks to predict the performance indicators of the brackish water reverse osmosis (BWRO) desalination method. This prediction will be based on feed water operating conditions, including temperature, pressure, pH, and the conductivity, to estimate permeate flowrate, plant recovery, plant rejection, and values over a one-month period.

The predicted outcomes achieved from both improved neural networks are compared with reliable experimental data collected over one month provided from Arab Potash Company desalination unit. This serves as the initial case study for assessing the desalination plant performance used by the Arab Potash Company (APC).

2. Description Of Brackish Water Ro Desalination Process And Feed Characteristics

2.1 Case Study Description

The flowsheet for a BWRO desalination plant designed for the APC plant, with flow rate about 1200 m^3/day, is illustrated in figure 1. This system consists of (20) pressure vessels and (120) membranes. The arrangement of the BWRO plant features a 2-pass design that includes both retentate (saline water) and permeate (fresh water) reprocessing. The 1st pass comprises 2 parallel stages of 6 pressure vessels arranged in a (4:2) configuration, while the 2nd pass consists of three stages of four pressure vessels arranged in a (2:1:1) configuration. The permeate from the first pass, which contains low-concentration streams, is collected and directed into the second pass for further processing. Conversely, the retentate from the first pass, characterized as a high-concentration stream, is discharged. The permeate from the second pass is collected to produce high-quality product water with a salinity of 2 ppm, while the retentate from the 2nd is recycled back to the 1st pass and combined with raw feed water.

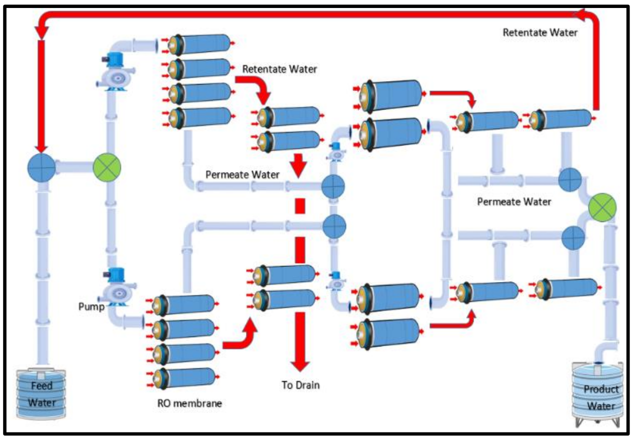

Figure 1: BWRO desalination plant of APC schematic diagram (Adapted from Al-Obaidi et al., 2018).

2.2 Plant feed characteristics

The feed characteristics of the brackish water reverse osmosis (BWRO) plant are as follows: feed concentration of 1098.62 ppm, feed temperature of 25 °C, feed flow rate of 74 m^3/h, and feed pressure of 9.22 atm. Table 1 gives the membrane and plant feed water specifications of an industrial BWRO plant of APC.

Table 1: Features of membrane and inlet operating conditions of BWRO plant of APC

Parameter	Unit	Value
Membrane provider, brand, configuration, and area $\boldsymbol{A}$	(m^2)	Toray Membrane; USA Inc, TMG20D-400, spiral wound, 37.2
Constant of Water permeability ($\boldsymbol{A_w}$)(m/atm s) at 25 °C	°C	9.6203x10-7
Constant of Salt permeability ($\boldsymbol{B_s}$) (m/s) at 25 °C	°C	1.61277x10-7

Table 1 (Cont.): Features of membrane and inlet operating conditions of BWRO plant of APC		
Pump efficiency	(η)	85%
Feed water salinity	(ppm)	1098
Daily production capacity	(m^3/day)	1200
Average product salinity	(ppm)	1.96

3. Methodology

The data of BWRO desalination plant performance (output variables) including the values of permeate flowrate, plant recovery, and plant rejection for one-month with reference to the feed water operating conditions (input variables) including inlet temperature, inlet pressure, feed water pH and feed water conductivity were provided from the Arab Potash Company. The forecasted results obtained from both developed Multilayer perceptron (MLP) and radial basis function (RBF) neural network models are compared against reliable experimental data for one month provided from Arab Potash Company. The performance parameter data is generated and utilized to improve (ANN) models for forecasting the desalination plant performance.

4. Model Development Of Artificial Neural Network (Ann)

Artificial neural networks (ANNs) are powerful tools being employed to predict the output variables which represent the performance of BWRO desalination plant. The neural network models are often generated based on the obtainable and available data for quality parameters of water desalination plant for short or long term of time (Jadhav et al., 2023). ANN forms a nonlinear correlation between input variable and output variable in order for modeling desalination plants performance during the training process (Jawad et al., 2021). In general, MLP and RBF are popular types of feedforward neural networks used for forecasting. However, for building ANN model, three phases are required: (training the data, validation data, and prediction the desired data). Therefore, the dataset must be classified into three different sets that are training dataset, validation dataset, and forecasting dataset. The largest number of data points used as training data with about (70–80%), while the outstanding data is utilised for validation and forecasting.

The most conventional statistical indicators used to estimate the performance of the ANN are (Mean Square Error (MSE), Mean Square Error (MSE), mean absolute error (MAE), and the coefficient of correlation (R2)). Eq. (1), represent a statistical criterion used in this research to assess if the model is fitted and able to justify the variability in the response.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i^t - y_i^p)^2}{\sum_{i=1}^{n}(y_i^t - \bar{y})^2} \quad (1)$$

Whereas, y_i^t,is the targeted output result, y_i^p is the predicted output result and $\bar{y}$ is the average of target outputs over number of data points.

4.1 Multi-layer Perceptron neural network

The MLPNN model has significantly demonstrated well in a number of performance applications such as hydrologic, management of water resources and desalination plants. The MLP is comprised of 3 layers (Input result layer, one or more hidden result layers, and an output layer), and each result layer in order serving as the input for the following layer. In MLP, the training method aims to determine the weight values that will generate the expected result from the NNs, assisting a comparison with the real objective values. Through the training process, the weights connected with each neuron are reorganized after each period utilizing one type of the training algorithms model until a significantly precise network is attained since the training depend on minimizing the errors between the wanted outputs and the networks outputs.

4.2 Radial basis function neural network

Both RBF and MLP neural network models are structured with three distinct layers. In the hidden layer, each neuron works as a radial basis function (the Gaussian kernel) which acts as the activation function. Neurons output from model generated a weighted summation of outputs from the hidden neuron layer. The network is placed at the center specified point stated by the weight vector correlated with the unit. In this regard the, both widths and the sites of these functions are discovered from training dataset. A linear pattern of these radial basis functions employed for each unit of output. The process for training RBF networks consists of two steps. The first step involves identifying a suitable set of center and width points. The second step includes determining the linking weights from the hidden layer to the output layer. A distinctive characteristic of RBF networks is that their response varies inversely or directly with the distance from a central point. Furthermore, RBF networks have been shown to effectively estimate any applied incessant function mapping with a reasonable level of accuracy. The output of the network is generated in a manner analogous to that of the MLP, utilizing the weighted sum the outputs of hidden neurons. The quantity of neurons hidden is established through the training process, where one RBF neuron is counted to the network at each iteration, continuing until the error objective is achieved or the upper limit number of neurons is attained.

5. Model Evaluation

The established ANN models were training and testing by employing NN toolbox in the MATLAB which is one of the language of technical computing. During the training session there are several algorithms utilised to build MLP network, such as: Broydein-Fletcheir-Goldfareb-Shannio (BFGS) Qusai-Newton, Levenbeirg-Marquardt, Variable-learning-rate backpropagation, Resilient backpropagation, Bayesian rule and Gradient descent.

The RBF network is tested and trained as the activation function in the hidden layer based on the backpropagation integrated with the algorithm of orthogonal-least-squares (OLS) and, the Gaussian-radial-basis-function (GRBF) is utilised. Moreover, the linear activation function is used in the output result layer. The data set was separated into two different data sets before the ANN models been running; (70%) of data-set employed for training determination and (30%) data-set employed for testing and trying the performance of networks and then the data continued built-in the interval {0,1} after normalized. In designing the RBF network selection of center points is the most vital issue, theses selections depend on data to be predicted.

A typical neural network consists of 3 layers: an input result layer, at least 1 hidden result layer, and an output result layer. The most commonly used networks typically feature only 1 hidden layer. Each layer contains a specific number of neurons or nodes that corresponds to the number of input parameters, with the number of output parameters matching the number of neurons in the output layer. One or more hidden layers can contain multiple neurons, determined by the optimum design of the ANN model. The value of each neuron in both the hidden result and output result layers is influenced by weights that are evaluated and determined during the training process. Additionally, each neuron in the hidden and output layers receives a constant value known as the threshold value or bias, which acts as a weighted input. The ideal number of hidden layers and nodes within each layer is specific to the problem at hand, and there is no existing method to determine this in advance. As a result, a trial-and-error approach involving multiple runs was employed to identify the best network design, which included configurations with 1 or 2 hidden layers and 3, 5, 10, or 15 nodes in each hidden result layer.

The training procedure of MLP network started with trailing 1 or 2 neurons in the hidden result layer, then the number of neurons stayed constant ore gradually increased until the developed network reached a high targeted performance.

In this work, for predicting the permeate flow rate, the used inputs to the network model were the inlet operating pressure, inlet operating temperature and conductivity, and the output was the permeate flow rate. Moreover, for predicting the plant recovery rate, the inputs were the inlet operating pressure, inlet operating temperature, PH, and conductivity, and the output was the plant recovery rate. Furthermore, for predicting the plant rejection rate, the inputs were the inlet operating pressure, conductivity, and the feed flowrate, and the output was the plant rejection rate.

The procedure of MLP network testing and training in progress with applying (2 neurons) in the hidden result layer, then the number of neurons grown steadily until reach a very good performance with about 6 neurons for the developed network BWRO plant. The developed design of MLP neural network for forecasting plant performance indicators given in table 2

Table 2: Characteristics of MLPNN developed models for forecasting BWRO desalination plant performance of APC						
Performance Indicator	**Network Architecture**	**Input**	**Value**	**Output**	**Value**	**Coefficient of Correlation (R^2)**
Permeate Flow Rate	3-6-1	Operating pressure	9.220 (atm)	Permeate Flow Rate	0.0235 m^3/s	R^2 = 0.998
		Operating temperature	25 (°C)			
		Conductivity	1983.06 µs/cm			
Plant Recovery Rate	4-6-1	Operating pressure	9.220 (atm)	Plant Recovery Rate	56.902 %	R^2 = 0.997
		Operating temperature	25 (°C)			
		PH of feed water	7.45 – 7.55			
		Conductivity	1983.06 µs/cm			
Plant Rejection Rate	3-6-1	Operating pressure	9.220 (atm)	Plant Rejection Rate	99.799 %	R^2 = 0.998
		Conductivity	1983.06 µs/cm			
		Feed water flowrate	0.020555556 m^3/s			

The same input neurons in RBF neural network which used for training was used for MLP model network. During the process of training, the RBF model neural network effectively managed steady-state neurons in the hidden result layer. In summary, the current design comprised 1 input layer (with the necessary number of inputs for each tested model), 1 output layer (representing a single output target variable), and a hidden layer where varying numbers of neurons were applied across various models to evaluate the various design configurations performance.

The model performance is evaluated by the coefficient of correlation (R2), which is one of the statistical metrics used for evaluation. Hence, the forecasted results obtained from both developed neural networks are validated with a reliable experimental data for one month provided from Arab Potash Company. In validation process including how you will test the model on unseen data from the APC plant. The validation results show high correlation between the predicted and reliable experimental results for all of the plant performance indicators (permeate flow rate, plant recovery rate, and plant rejection rate.

It is anticipated that the established method may demonstrate useful in developing plants performance and theoretically enhance their water producing. Furthermore, it may be employed as a good tool to enhance present freshwater quality management performs in any brackish water desalination plant. Additionally, using ANN modeling technique for RO process control identification.

6. Results And Discussion

The forecasted outcomes attained from both developed neural networks were compared with reliable experimental data collected from APC desalination plant and found that ANN predictions for one month were consistent with data collected from APC plant.

6.1 Permeate Flow Rate predictive model

To forecast the future flow rates (one month ahead with about 725 hr) of permeate in the desalination plant of APC, feed forward MLP and RBF models of neural networks are utilized. The MLP and RBF neural network forecasting outputs were consistent and contrasted with original data collected for APC desalination plant for permeate flow rate and showed high agreement. As presented in figure 2. It is clear that the value of predictive permeate flow varied steadily with about 8.1987 m3/hr among period of time with range of 48 hours. However, this value achieved by both MLP_ANN and RBF_ANN model used.

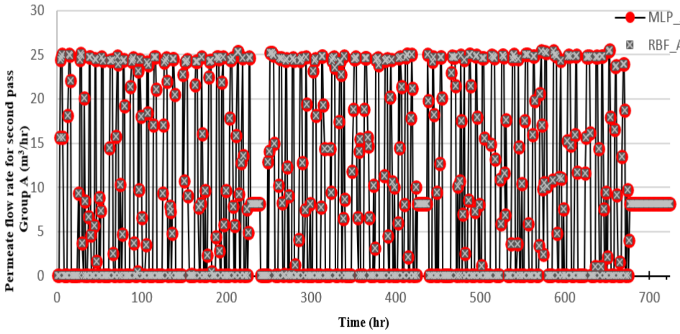

Figure 3: MLP ana RBF Artificial Neural Network training performance for predicting plant recovery rate of APC desalination plant.

6.3 Plant Rejection Rate predictive model

To predicting the future rates (one month ahead with about 725 hr) of rejection in the plant of APC, feed forward MLP and RBF models of neural networks are utilised, and given in figure 4. The MLP and RBF models of neural network forecasting outcomes were consistent and contrasted with original data collected for APC desalination plant for rejection rate and showed high agreement. It is clear that the value of predictive plant recovery rate varied steadily with about 88.267 % among period of time with range of 47 hours. However, this value achieved by both MLP_ANN and RBF_ANN model used.

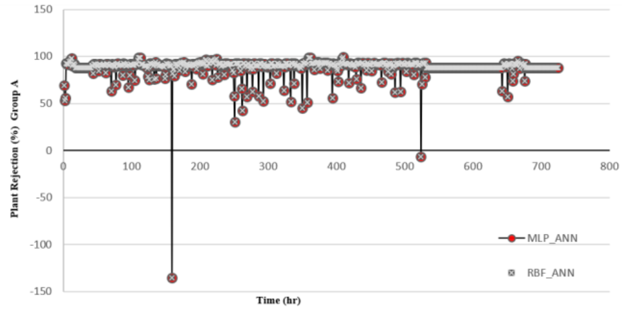

Figure 4: MLP ana RBF Artificial Neural Network training performance for predicting plant rejection rate of APC desalination plant.

The predictive outcomes obtained from both developed networks of MLP and RBF, were compared with the reliable experimental data collected from APC desalination plant and demonstrated good agreement with acceptable error, table 3 shows summary the predictive ANN models verification prediction results generated from developed Artificial Neral networks models for BWRO desalination plant performance of APC, and the tested observed reliable data provided from APC plant.

Table 3: The predictive ANN models verification for plant performance forecasting results.

ANN model	Predicted Result for group A	Value	Observed result range (Min-Max)
MLP_ANN	Permeate flow rate Average from 1st pass group A (m3/hr)	8.1987	Permeate flow rate range (m3/hr): 24.6–26.6
	Recovery rate Average (%)	27.33	Recovery rate Average (%): 84–86
	Rejection rate Average (%)	88.267	Rejection rate Average (%): 0–95
RBF_ANN	Permeate flow rate Average (m3/hr)	8.1987	Permeate flow rate range (m3/hr): 24.6–26.6
	Recovery rate Average (%)	27.33	Recovery rate Average (%): 84–86
	Rejection rate Average (%)	88.267	Rejection rate Average (%): 0–95

The outcomes of the established MLP and RBF models of neural network show that the plant performance indicators can be forecasted by considering parameters related to the quality of water. In this regard, artificial neural networks investigating the correlation relating the input parameters and output performance indicators. Since the comparison of ANN predictions outcomes with assigned values of performance indicator showing high accuracy of performance. Consequently, it can be affirmed that applying artificial neural network model which used for predicting performance by forecasting the output indicators is consider as appropriate tool can be used in performance predicting of desalination plant.

7. Conclusion

It is important to study and predict the RO desalination plant performance over time which aids in improving product quality and process optimisation. As well as performance predictive can be considered as an early warning technique for the deterioration of RO plant performance. Moreover, improving the desalination plant performance would save energy consumption. In this work, permeate flowrate, recovery rate, and rejection rate as performance indicators of desalination plant have been forecasted up to one month based on developed MLP and RBF neural network models as smart manufacturing system. By comparing, the predictive results showed that all the performance indicators achieved have a high agreement with reliable experimental data collected from BWRO desalination plant of APC.

References

Abbas, A. and Al-Bastaki, N., 2005. Modeling of an RO water desalination unit using neural networks. Chemical Engineering Journal, 114(1–3), Pp. 139–143.

Aish, A.M., Zaqoot, H.A. and Abdeljawad, S.M., 2015. Artificial neural network approach for predicting reverse osmosis desalination plants performance in the Gaza Strip. Desalination, 367, Pp. 240–247.

Al-Obaidi, M.A., Alsarayreh, A.A., Al-Hroub, A.M., Alsadaie, S. and Mujtaba, I.M., 2018. Performance analysis of a medium-sized industrial reverse osmosis brackish water desalination plant. Desalination, 443, Pp. 272–284.

Chen, H. and Kim, A.S., 2006. Prediction of permeate flux decline in crossflow membrane filtration of colloidal suspension: A radial basis function neural network approach. Desalination, 192(1–3), Pp. 415–428.

Delgrange-Vincent, N., Cabassud, C., Cabassud, M., Durand-Bourlier, L. and Laine, J., 2000. Neural networks for long term prediction of fouling and backwash efficiency in ultrafiltration for drinking water production. Desalination, 131(1–3), Pp. 353–362.

Delgrange, N., Cabassud, C., Cabassud, M., Durand-Bourlier, L. and Laine, J., 1998. Modelling of ultrafiltration fouling by neural network. Desalination, 118(1–3), Pp. 213–227.

Dornier, M., Decloux, M., Trystram, G. and Lebert, A., 1995. Dynamic modeling of crossflow microfiltration using neural networks. Journal of Membrane Science, 98(3), Pp. 263–273.

Elsaid, K., Kamil, M., Sayed, E.T., Abdelkareem, M.A. and Wilberforce, T.O., 2020. Environmental impact of desalination technologies: A review. Science of the Total Environment, 748, 141528.

Farahbakhsh, J., Delnavaz, M. and Vatanpour, V., 2019. Simulation and characterization of novel reverse osmosis membrane prepared by blending polypyrrole coated multiwalled carbon nanotubes for brackish water desalination and antifouling properties using artificial neural networks. Journal of Membrane Science, 581, Pp. 123–138.

Ghernaout, D., 2017. Reverse Osmosis Process Membranes Modeling—A Historical Overview. Journal of Civil, Construction and Environmental Engineering, 2(4), Pp. 112–122.

Jadhav, A.R., Pathak, P.D. and Raut, R.Y., 2023. Water and wastewater quality prediction: Current trends and challenges in the implementation of artificial neural network. Environmental Monitoring and Assessment, 195(2), 321.

Jawad, J., Hawari, A.H. and Zaidi, S.J., 2021. Artificial neural network modeling of wastewater treatment and desalination using membrane processes: A review. Chemical Engineering Journal, 419, 129540.

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(1–2), Pp. 202–214.

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(2), Pp. 408–419.

Mohsen, M.S. and Gammoh, S., 2010. Performance evaluation of reverse osmosis desalination plant: A case study of Wadi Ma'in, Zara and Mujib plant. Desalination and Water Treatment, 14(1–3), Pp. 265–272.

Murthy, Z. and Vora, M.M., 2004. Prediction of reverse osmosis performance using artificial neural network. Desalination. [Volume and page numbers needed]

Razavi, M.A., Mortazavi, A. and Mousavi, M., 2004. Application of neural networks for crossflow milk ultrafiltration simulation. International Dairy Journal, 14(1), Pp. 69–80.

Righton, R., 2009. Development of an artificial neural network model for predicting the performance of a reverse osmosis (RO) unit [Master's thesis, Curtin University].

Salgado-Reyna, A., Soto-Regalado, E., Gómez-González, R., Cerino-Córdova, F., García-Reyes, R., Garza-González, M. and Alcalá-Rodríguez, M., 2015. Artificial neural networks for modeling the reverse osmosis unit in a wastewater pilot treatment plant. Desalination and Water Treatment, 53(5), Pp. 1177–1187.

Voutchkov, N., 2017. Pretreatment for reverse osmosis desalination. Elsevier.

Yao, L., Li, Y., Cheng, Q., Chen, Z. and Song, J., 2022. Modeling and optimization of metal-organic frameworks membranes for reverse osmosis with artificial neural networks. Desalination, 532, 115729.