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A review of the artificial neural network based modelling and simulation approaches applied to optimize reverse osmosis desalination techniques

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ABSTRACT

The current global issue of water scarcity has demanded for over-abstraction of conventional freshwater resources. The states of water scarcity are anticipated to worsen, as by 2050 the population is estimated to reach 9 billion worldwide. Desalination is considered a solution to solve the water scarcity issues, as it is considered a drought-proof water source, which does not depend on climate change, river flows or reservoir levels. Moreover, membrane fouling is still the main "Achilles heel" for the effective operation of desalination systems. This makes the technology chemically, energetically and operationally intensive and requires a considerable infusion of capital. The application of an artificial neural network (ANN), the computing model inspired by the human brain, and its variants, have been developed that can optimize the operation of membrane-based desalination system through analyzing the complex experimental and real-time data. This review paper presents the recent trends and developments focussed primarily on the modelling and simulation of reverse osmosis (RO) plant using ANN to solve the challenging problem in membrane-based desalination systems. The literature review suggested that ANN has a potential application in predicting linear, nonlinear, complicated complex systems with high accuracy and with better control, prediction of membrane fouling, cost analysis. Therefore, ANN considered a strong basis to attract and motivate the researchers to work in this field in the future.

Keywords: Desalination; Modelling and simulation; Reverse osmosis; Artificial neural network

1. Introduction

The worldwide demand for fresh and usable water has increased over the past decades due to population growth, economic development as well as expanded irrigation schemes, etc., [1,2]. Around 2 billion people are expected to suffer from water scarcity, of which, 95% (1.9 billion) may live in developing countries [3]. Among the various alternative solution of water scarcity, desalination is an ideal solution to fulfill the requirements of human, animals, and plants. Various desalination techniques such as multistage flash (MSF), multi-effect distillation (MED), reverse osmosis (RO),vapor compression (VC), and electrodialysis (ED), etc., and their hybrids are being increasingly used for treating and converting saline water to freshwater. Alkaisi et al., 2017 [4] standards of living, and the rapid development of the agricultural and industrial sectors. Desalination seems to be one of the most promising solutions to the water problem; however, it is an intensive energy process. The integration of the renewable energy into water desalination systems has become increasingly attractive due to the growing

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demand for the water and energy, and the reduction of the contributions to the carbon footprint. The intensive investigations on the conventional desalination systems, especially in the oil-rich countries have somewhat overshadowed the progress and implementation of the renewable energy desalination (RED) recently highlighted RO as the major technology used for water treatment in desalination plants. There is about 10% average growth in capacity of desalination plants per year worldwide, out of which membrane desalination accounts for 2/3 of total installed capacity [3]. The total desalination capacity is about 80 Mm^3/d, of which 75 % (~60 Mm^3/d) is using RO (installed and projected 2018) [5].

Membrane fouling is still the main "Achilles heel" for the effective working of the membrane-related desalination plants [6]. Thus this technology is intensified energetically, chemically, and operationally and demands a considerable infusion of infrastructure, engineering expertise etc. [7]. The consequences of membrane fouling are increased operating pressure, decreased membrane permeability, increased frequency of chemical cleaning and membrane deterioration [8]. Modelling and simulation of such techniques is an important key for improving water quality as well as optimization of the process parameters.

During the last two decades, various soft computing methodologies have been used by researchers to modify the desalination process through modelling and simulation. Among several soft computing methodologies, probabilistic reasoning (PR), genetic algorithm (GA), artificial neural network (ANN), fuzzy logic control (FLC), etc., assume tremendous significance to optimize the operation as well as the design of the desalination plant. The optimization of the plant performance using these tools can significantly reduce the overall chemical consumption, and thereby, lower the operational cost of the desalination plant. Furthermore, these tools or methods also support in controlling the various critical issues such as prediction of water quality parameters, implementation of the online automation monitoring system, optimization, product recovery as well as salt reduction [9].

ANN is the most vibrant tool that attracts the attention of machine learning due to its capability in predicting linear, nonlinear and complex systems with high precision and accuracy. ANN can be also be used to support operations of diverse engineering as well as medical applications at optimum conditions. It can help to operate the plant with high profitability with efficiency to govern almost every aspect of the desalination plant.

El-Hawary [10] presented the possible applications in desalination using ANN. It efficiently supports fault detection, alarm processing, control applications, load forecasting, operations, security assessment, and operational optimization. Special advantages offered by ANN include the ability to work with incomplete knowledge, its information storing capability, fault tolerance, decision making, parallel processing, etc. However, it does present some disadvantages such as long training time, hardware dependence, unexplained behavior, difficulty in locating the problems in the network, etc.

The exhaustive aim and objective of this review article are to understand the possibilities of design and implementation of various perspectives of RO using ANN. RO is most efficient in terms of separation performance as well as salt rejection and has lower energy consumption per unit of treated water. The RO applications in desalination further involve sub-technologies such as seawater RO (SWRO), brackish water RO (BWRO), low-pressure RO (LPRO), RO electrodeionization (RO-EDI) and RO demineralizer (RO-DM). Hybrid technologies based on RO such as RO-MSF, RO-FO, NF-RO-MED, UF-SWRO, etc. have been also developed for further enhancing the productivity of freshwater productivity. ANN provides an appropriate controlling strategy and simulates the controlled process. Hence, significant outcomes of its utilization in modeling and simulation are: increased high impact research, useful simulation results to enable the industry to avail benefits of effective decision making for process optimization and control, reduced labor and maintenance, and thereby, increased operational time of the RO based desalination plants and their productivity.

The organization of this review article is as follows: Section 2 details the theory of ANN and RO used in desalination processes; Section 3 presents the extensive survey of literature and sketches the efforts in modelling of RO based desalination processes using ANN from 1995–2018 to highlight its increasing significance in the area. The future aspects and perspective work methodology are discussed in Section 4, and finally, in Section 5 we summarize and provide conclusions.

2. Theory

2.1. Artificial Neural Network

ANN mimics the behavior of biological neurons in the human brain. It can learn from datasets (patterns of data), test the trained network using new sets of data, corrects the error in prediction followed by a final validation. In line with this, the three phases of ANN are called training or learning (learning period of the network), recall (testing of new data by training phase) and generalization (subject to minor change or error corrections). Its basic foundation lies in the artificial neuron, also called node. Murthy et al. [11] presented the anatomy of a processing element (PE) of a single neuron which is shown in Fig. 1. It has four basic components: inputs and outputs, internal thresholds, weight factors, and functional forms.

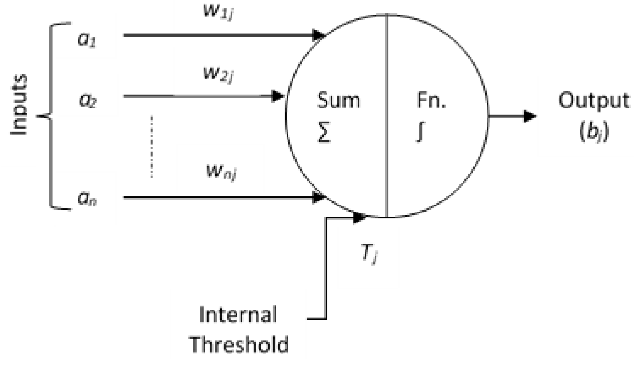

Fig. 1. Anatomy of a processing element (PE) of a single neuron.

Where

Inputs and outputs:	Inputs: $a_1, a_2, \ldots a_i, \ldots, a_n$. (the first element of the j^{th} PE is an input vector ā) Output: b_j
Weight factors:	w_{ij} (for the i^{th} input, a_i, corresponding to j^{th} node), $a_i w_{ij}$ (product component ā and w̄ as the actual input). (to provide the weighted input).
Internal threshold:	T_j (the internal threshold for the j^{th} PE, The node calculates all the $a_i w_{ij}$, s, sums the terms together, and then calculates the total activation as:

$$Total\ activation = \left(\sum_{i=1}^{n}\left(a_i w_{ij}\right) - T_j\right) \quad (1)$$

Threshold values (T_j) are also called 'Bias'.

Functional forms:

$$Functional\ form = f\left(\sum_{i=1}^{n}\left(a_i w_{ij}\right) - T_j\right) \quad (2)$$

It is a function of the difference between the input function and the internal threshold. Such a function may be chosen from the root, log or sigmoidal form. A sigmoid function as:

$$f(x) = \frac{1}{1 - \exp(-x)} \quad (3)$$

Various method/algorithms are used for training of ANN such as error correction learning, Back propagation (BP) algorithm, etc. BP algorithm frequently employed a method to train the networks in desalination and chemical engineering fields. It predicts RO performance by defining the three layers; input, hidden, output, for ANN. The evolution of such a BP network is presented in Fig. 2.

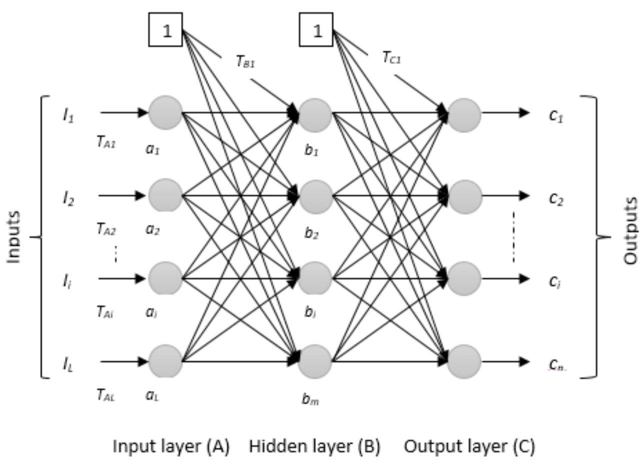

Fig. 2. Three-layered back propagation network.

Where

Layers:	Input (A), hidden (B) and output layer (C)
Input vector:	$I_1, I_2, \ldots, I_i, \ldots, I_L$. (Feeding into the input layer A to at the i^{th} node)
Input layer A with l-nodes:	$a_1, a_2, \ldots, a_i, \ldots, a_l$
Hidden layer B with m-nodes:	$b_1, b_2, \ldots, b_i, \ldots, b_m$
Output layer C with n-nodes:	$c_1, c_2, \ldots, c_i, \ldots, c_n$,
v_{ij}	Weights that relates the i^{th} node of A and j^{th} node of B
w_{ij}	Weights that relates the i^{th} node of B and j^{th} node of C
T_{Ai}, T_{Bj}, T_{Ck}	Internal threshold or bias for A, B and C respectively. Here, $i = 1, 2, \ldots l$, $j = 1, 2, \ldots m$, and $k = 1, 2, \ldots n$, where l, m and n are the number of nodes in layer A, B and C.
$E = \sum e_n^2$	Sum-of-squares-error (SSE) or total error function. (to adjust the weights v_{ij}, s, and w_{ij}, s to minimize E, called training).
$e_n = d_n - c_n$	Output error vector (from n^{th} node of the output layer), c_n is the predicted output and d_n is the desired output.

BP algorithm requires an ANN such as 'Perceptron' which has feed forward interlayer connections and each layer feeds sequentially into the next layers. It has no intra-layer, recurrent or feedback connections. Nodes may have any value depending upon the applications. It attempts to map the system properly to set inputs with expected outputs through minimization of SSE chosen as the error function. Various steps are shown in Fig. 3 and subsequently, the BP algorithm to perform particular applications has been presented.

Backpropagation Algorithm (BP):

1. Start BP algorithm with initially specify weight factors (v_{ij}, s, and w_{ij}, s) and threshold values (T_{Ai}, T_{Bj}, T_{Ck}) randomly within the interval *[-1, +1]* for every node.

2. Give input I_i into ANN, All outputs from the 1[st] layer are calculated, using the standard sigmoid function.
   Let, $x_i = I_i - T_{Ai}$ then output from node $a_i = f(x_i)$

3. The output from layer B is then estimated using:

$$b_j = f\left(\sum_{i=1}^{l}\left(v_{ij} a_i\right) - T_{Bj}\right) \quad (4)$$

   where, $f(\ )$ is the sigmoid function

4. The output from layer C is estimated using:

$$c_k = f\left(\sum_{i=1}^{m}\left(w_{jk} b_j\right) - T_{ck}\right) \quad (5)$$

   where, $f(\ )$ is another sigmoid function

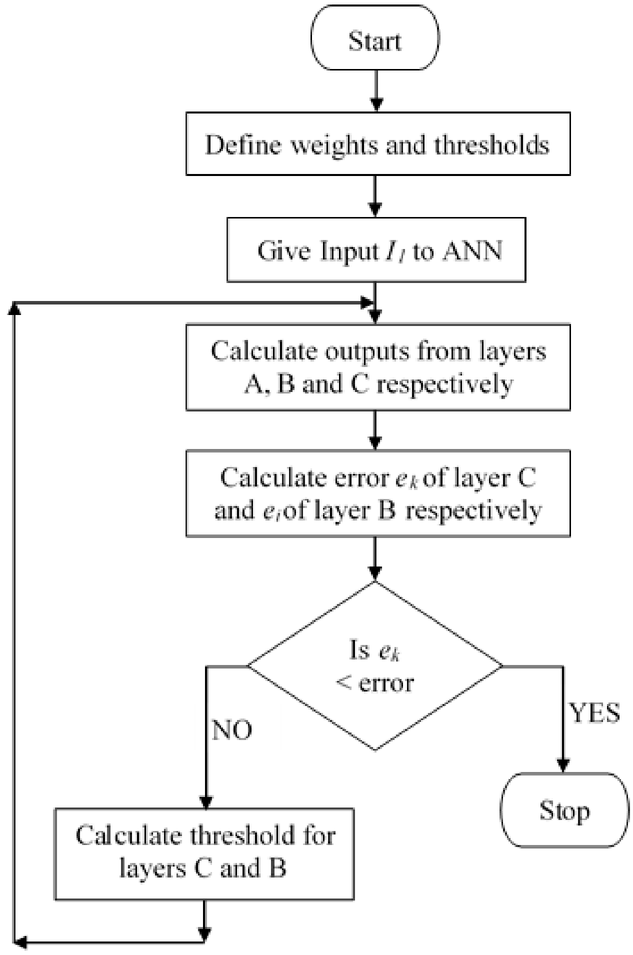

Fig. 3. A flow diagram showing the implementation of back-propagation technique.

5. k^{th} component of the output error, e_k, for each node in layer C is calculated using:

$$e_k = f'(c_k)(d_k - c_k) \tag{6}$$

Here, $f'(c_k)$ is the differential form of the sigmoidal function, d_k is the desired result.

The j^{th} component of error vector e_j for each node in layer B is then calculated using:

$$e_j = f'(b_j)\sum_{k=1}^{n}\left(w_{jk}e_k\right) \tag{7}$$

Calculate internal threshold values for layers B and C:

$$T_{Bj'}new = T_{Bj'}old + \beta_B e_j \tag{8}$$

$$T_{Ck'}new = T_{CK'}old + \beta_C e_k \tag{9}$$

Here, β_B and β_C are positive constants that control the learning rate.

6 The weights of inputs layer B are then adjusted as:

$$v_{ij'}new = v_{ij'}old + \beta_B\, a_i e_j \tag{10}$$

likewise, the weights of layer C inputs are adjusted as:

$$w_{jk'}new = w_{jK'}old + \beta_C b_j e_k \tag{11}$$

The convergence may be if a momentum term is included and weight changed are smoothed by:

$$v_{ij'n+1} = v_{ij'n} + \beta_B\, b_j e_j + \alpha\,(v_{ij'n} - v_{ij'n-1}) \tag{12}$$

Where, α is the momentum term ($0 < \alpha < 1$) and n represents the iterative step.

7. At the last repeat steps, 2 to 6 until the SSE is appropriately small or zero.

2.2: Reverse osmosis

RO is the most versatile membrane-based desalination technology used across the world. It has assumed this popularity because of its collective advantages, such as operation at very high pressure, ease of installation, clean, flexibility to use several membrane types, easy to troubleshoot and high recovery. Fig. 4 illustrates the basic principle of osmosis and reverse osmosis. Osmosis is the targeted diffusion of water through a semipermeable membrane, which permits water molecules passage while the larger molecules such as salt particles and others are not permitted. This movement of molecules is inevitable and creates the natural known as osmotic pressure. RO is a pressure driven processes, that forces solvent from a region of more solute concentration through a semi-permeable membrane to another region with less solute concentration by applying a higher pressure (excess of osmosis pressure). Therefore, the direction of water flow reversed, and hence, called reverse osmosis, presented by Fritzmann et al. [12] water scarcity is being recognised as a present or future threat to human activity and as a consequence, a definite trend to develop alternative water resources such as desalination can be observed. The most commonly used desalination technologies are reverse osmosis (RO).

Mahadeva et al. [9] presented a generalized block diagram of RO desalination plants as shown in Fig. 5. In such a desalination plant, primarily seawater is stored in a storing chamber using an external low-pressure pump. A core RO system is made up of 4 basic components: pre-treatment, external pressure, membrane, and post-treatment. Initially, pre-treatment removes the excess turbidity and suspended solids followed by filtration. Then, the high-pressure pump applies the osmotic pressure to remove the brine at the membrane outlet. Further, membrane assemblies such as fine hollow-fiber, spiral-wound and tubular are used to resist high temperature, for high permeability, for high salt rejection and to ensure long and reliable life. Finally, the product water requires post-treatment prior to storage and transmission to the customer.

When the RO desalination plant has been installed, the most vital point for the RO system is that its parameters (fluxes, salt rejection, recovery, etc.) must be tested well before transmission of purified water to the user. Therefore, some basic transport equations and operational variables used in the plants generally and also used elsewhere [13] are:

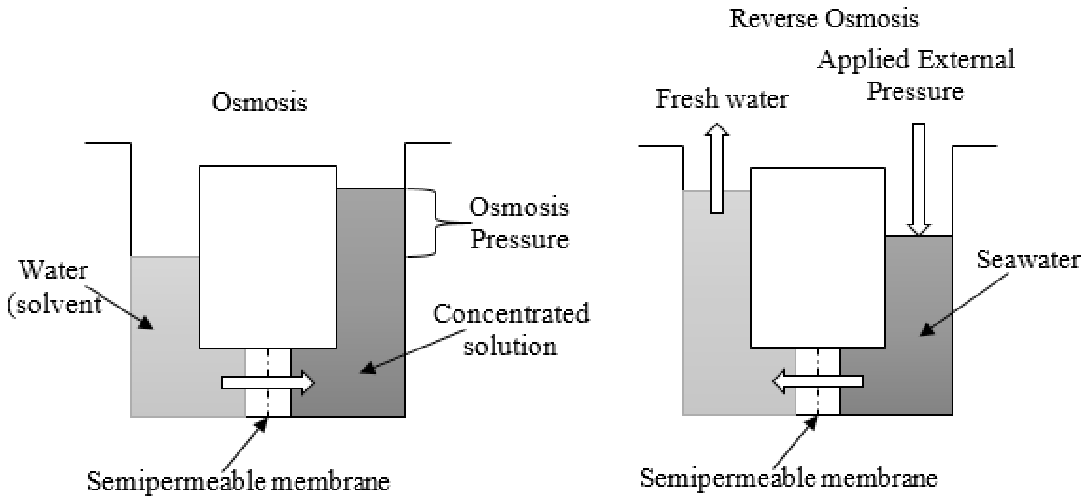

Fig. 4. The basic principle of osmosis and reverse osmosis.

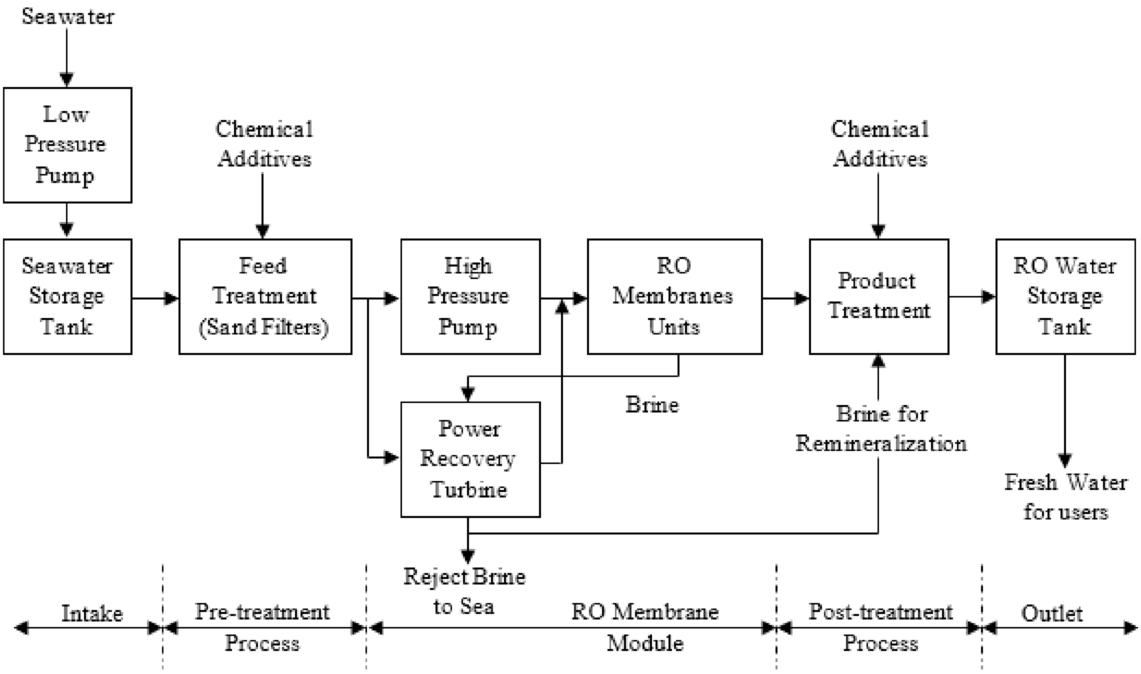

Fig. 5. Generalized reverse osmosis (RO) desalination plant. (Source: Mahadeva et al., Modelling and simulation of desalination process using artificial neural network : a review [9]).

2.2.1. Basic transport equations

Water flux, J_1 (m³/m²/s), through membrane is given by-

$$J_1 = K_1(\Delta P - \Delta\pi) \tag{13}$$

where Δπ and ΔP are the osmotic and hydraulic pressure differential across the membrane (atm). K_1 is the pure water transport coefficient, defined as water flux through the membrane per unit driving force. It is dependent on membrane properties, temperature of the system and chemical composition of salt solution.

$$K_1 = K_W \frac{A}{\tau} \tag{14}$$

where K_w is the membrane permeability coefficient of water, A and τ are the membrane area and thickness (m).

$$\pi = MRT \tag{15}$$

where M is the molarity of solution (mol/L), R is universal gas constant (0.08206 L atm mol^{-1} K^{-1}) and T is the feed water temperature (K).

However, salt flux, J_2 (*kg/m²/sec*), an indicator of the membrane effectiveness in removing salts, is proportional to the concentration difference, ΔC, across the membrane and given by:

$$J_2 = K_2 \Delta C \tag{16}$$

where K_2 is coefficient of salt transport (*m/s*) and $\Delta C = Cf - Cp$ (where, C_f and C_p are the salt concentration of feed and product respectively (kg/m³)).

The ability of membrane towards salt rejection is expressed as

$$Salt\ rejection\ (\%) = \left(1 - \frac{Product\ concentration}{Feed\ concentration}\right) \times 100\% \tag{17}$$

Product water recovery is expressed in terms of flow rates of product and feed as follows:

$$Recovery(R) = \frac{Q_p}{Q_f} * 100\% \tag{18}$$

where Q_p and Q_f are the product and feed flow rates (*m³/day*).

2.2.2. Operational variables

Monitoring of the operational variables and data are an important step in the RO plant used to check its performance periodically. The variable, permeate flux, is the volume flowing through the membrane per unit area per unit time. Since it is important to maintain constant and controlled during operation. Another variable, permeate conductivity is essentially used in RO plant to estimate the quality of the produced water but is affected by changes in pH, temperature, pressure, etc. The major requirement in such a plant is to maintain mentioned parameters so as to ensure good control of quality as well as the quantity of the product water.

A basic step by step algorithm of modelling and simulation of RO desalination technique using ANN is illustrated in Fig. 6. In the presented algorithm, BP method is proposed as a useful ANN learning technique. This is the generalized algorithm for RO desalination plants.

In this section, we have summarized ANN theory including its advantages, main component of PE and learning BP algorithm in detail. Furthermore, basic principles of RO and step by step algorithm to employ ANN for modelling a generalized desalination plant has been presented.

3. Progress in ANN applications to RO modelling in literature

The basic elements of ANN utilized in RO desalination are the prediction and adaptation which can decrease the degradation of the membrane to enhance overall plant's efficiency. ANN is the most effective machine learning tool in prediction and optimization problems associated with small as well as large-scale desalination plants. The modelling and simulation of desalination plants using ANN have been exhaustively explored and analyzed by various scientists and academicians. Initially, Niemi et al. [14] developed a feed-forward neural network system for the separation of acetic acid and ethyl alcohol from water by using RO. It involves input variables such as; flow velocity, solute concentration, temperature, and pressure, as well as output variables such as; rejection and permeates flux. Levenberg-Marquardt (L-M) method is used to determine the weights in the network, as it was found easy to use and required less computational time for processing. The results were compared with conventional mass transfer method (as a finely porous model). It observed that the permeate flux and rejection of ANN model were better than the finely porous model.

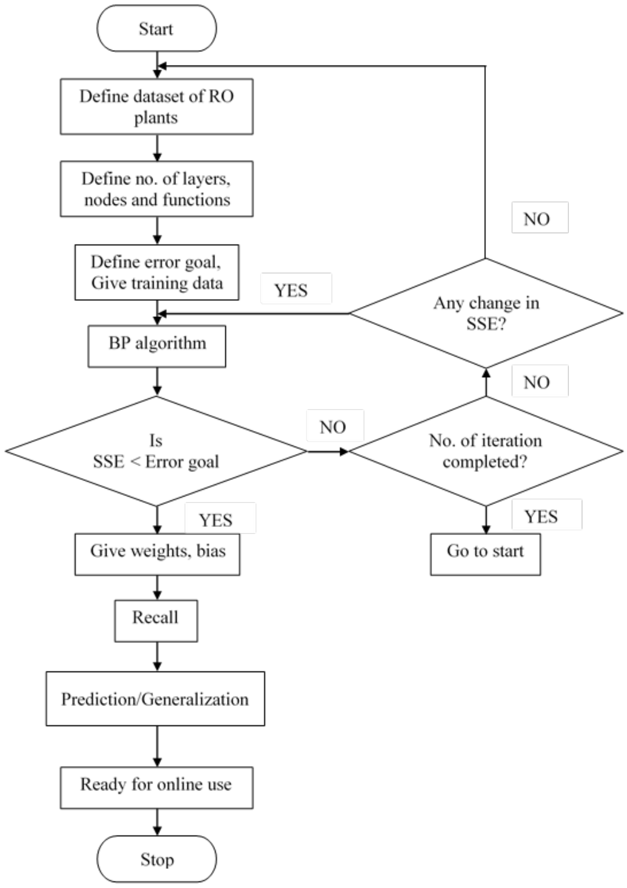

Fig. 6. Algorithm followed during ANN modelling of an RO process.

Jafar et al. [15] proposed a neural network model based on adaptive radial basis function (Adaptive RBF) algorithm for RO plants. An adaptive RBF produced better error norms of permeate prediction (1.73) than BP algorithms (2.084) but required more computational effort. The error norms of total dissolved solids (TDS) prediction of adaptive RBF model (2.32) was also better than BP algorithms (3.41). Al-Shayji et al. [16] modeled of large-scale commercial (MSF (1,81,760 m³/d) and RO (56,800 m³/d)) desalination plants located in Kuwait and Saudi Arabia through two methods: model-based process simulation and data-based neural network. The authors found a close match between the simulated and actual plant results. Murthy et al. [11] developed a model for the separation of sodium chloride using ANN through L-M method. The system involves input parameters of feed concentration (1,000–30,000 ppm), pressure (20–

100 atm), and feed rates (300–1500 mL/min). The predicted error range was within ±1%.

Abbas et al. [17] attempted a feed forward neural network model using the L-M algorithm to predict the permeate rate of RO plants. They used a FilmTech SW30 membrane, where the permeate rate increased with increasing temperature and pressure and decreased with increasing concentration of feed. Zhao et al. [18] proposed a model for calculating NF/RO water quality through a modified solution-diffusion model and two ANN models. The first model was multilayer perceptron (MLP) based which was a feed-forward neural network employs a sigmoid function. The second ANN model used was normal RBF composed of a feed-forward neural network by a single hidden layer using a softmax function. These models predicted the permeate *TDS* more accurately than existing models. They have also compensated the effects of system flux, recovery and feed water quality on solute mass transfer coefficient. Al-Alawi et al. [19] developed an ANN-based prototype controller for the optimum use of power supply and photovoltaic diesel system. It consisted of a diesel generator (DG), photovoltaic modules and battery bank for RO desalination plant. It was able to control DG On/Off status, maintain minimum loading levels with high accuracy, reduced fuel dependency, engine wear, tear and helped cut down greenhouse gas emissions.

Lee et al. [20] and was then applied to the simulation of feed water temperature. The model consists of five input parameters (i.e., feed temperature, feed total dissolved solids (TDS presented an ANN model to predict the performance parameters of SWRO desalination plant. It involved of 5 input parameters (trans-membrane pressure, feed temperature, feed flow, feed TDS and time) and 2 output parameters (flow rate and permeate TDS). Fujairah SWRO plant located in the United Arab Emirates producing 454,000 m^3/d of drinking water in one year is a hybrid plant consisting of MSF and SWRO ensuring 62.5% + 37.5% fraction of water production. A variant of the feed water temperature and trans-membrane pressure created to have a significant effect on permeate TDS and flow rate. Libotean et al. [21] developed a model with BP and support vector regression (SVR) algorithms for forecasting RO performance and possible use for operational diagnostics located at Port Hueneme, California. It includes the concept of the short-term memory time interval to capture the time-variability of plant performances. An actual state of the plant and 2 types of forecasting models (sequential and matching) have been developed for real-time RO performance. The models show noble predictive accuracy for short-term memory time intervals in ranged 8–24 h. The ability of forecasting of plant performance would provide additional flexibility to process control approach and an early warning scheme for membrane cleaning, adjustment of pressure and flow rates, etc.

Khayet et al. [22] proposed an analytical model for simulation and optimization of RO using response surface methodology (RSM) and ANN. RSM model was valid for a specific range of feed salt concentration while the latter was valid over the complete range. RSM model was carried out for low brackish and seawater high salt feed concentrations. RSM and ANN models have the ability to solve linear and nonlinear multivariate problems. To test the significance of both models they have been analyzed by analysis of variance (ANOVA) method. All objective functions given by ANN and RSM have been optimized by Monte Carlo simulation methods. Moradi et al. [23] presented an ANN model using BP feed-forward network and modified surface force pore flow model for RO membrane performance. Prediction parameters are: total flux, separation factor and pure solvent flux which are predicted well than the others. The predicted values have been compared with experimental data and achieved mean square error < 0.0007 and correlation coefficient of 0.99.

Garg et al. [24] developed a small-scale BWRO plant using RSM (with center composite design) and ANN (using BP) methodology. The results were compared and found to be optimal inside the acceptable range with a water recovery of 19.18%, TDS rejection of 89.21% and specific energy consumption of 17.60 kWh/m^3. It was also observed that the energy consumption of the plant was significantly minimized. Barello et al. [25] expressed through a model that the water permeability constant (K_w) carries high significance in any desalination plant. The authors developed a time-dependent ANN model based on correlation to predict K_w in desalination process under fouling conditions and observed that, the model was competent to predict K_w values for any operating pressure, any membrane type and any feed salinity within a wide range. Aish et al. [26] developed a forecast RO desalination plant performance model (at 5 small and large-scale BWRO plants in Gaza strip) to predict the next week values (TDS and permeate flow rate) using ANN. The MLP and RBF based networks were trained with the given performance parameters. Both networks showed highly satisfactory and better results compared to conventional methods. It was found that MLP based results were better than RBF. In adding, multiple linear regression model was also used to compare the predicted results (using MLP and RBF). Salgado-Reyna et al. [27] presented a membrane-based can-manufacturing waste-water treatment plant using 4-layer feed forward ANN through BP algorithms. It included pre-treatment processes such as filters, settling tank, coagulation and flocculation reactor, sand activated carbon, and polishing filters. The results showed a 96.1% acceptable removal of TDS and 72% effluent recovery. The predicted and experimental flow data were nobly correlated. Madaeni et al. [28] developed an optimized data-driven system for predicting the performances of 3 RO plants (located at Fars Province, Iran), finding control strategies using ANN (using BP algorithms) and long-term forecasting (next 5,000 h) of process performance. GA was used to find feed flow rate, TMP and control process in a specific period of time.

Salami et al. [29] proposed a simple mathematical equation and ANN model (using BP) to simulate 8 types of SWRO membranes (SW30-2540, SW30HRLE-4040, SW30-4040, SW30-3031, SW30HR-380, SW30HRLE-440i, SW30 HRLE-400i, SW30 HRLE-1725). ROSA software was used to generate feed data. Both models were found to be highly reliable, accurate and provided optimized results. The correlation coefficients of the ANN model (0.97) were found to be better than the mathematical equation (0.96). Iranmanesh et al. [30] implemented the RBF model for the estimation of RO membrane performance based on the modified surface force pore flow model. It includes total flux, separation factor, and pure solvent flux. The predictive ability of the

RBF technique and experimental data were evaluated. The mean square error for total flux (0.00009 and 0.00012), for separation factor (0.00009 and 0.00016) and for pure solvent flux (0.00013 and 0.00013) were observed. Cabrera et al. [31] presented models for handling the process of a small-scale prototype SWRO desalination plant (using ANNs as control strategy) located at Gran Canaria, Spain. The work helps them manage varying available electrical power. Cabrera et al. [32] again used the three machine learning techniques (ANN, SVM, and RF) to the study the performance of wind-powered SWRO desalination plant. The work highlighted two outcomes: first, SVM and random forest (RF) had a better prediction than ANN, and second, variable pressure and flow rate operate more continuously than the constant pressure and flow rate.

In this section, we have reviewed extensively recent trends and developments in the modelling and simulation of RO related plants using ANN that help solve the challenging problem of increasing productivity, improving water quality and enhancing process efficiency. A short summary of relevant research contributions around RO desalination technologies using ANN/Hybrid ANN techniques by researchers is presented in Table A1 (Appendix).

Fig. 7 illustrates the research contributions of researchers based on modelling and simulation of RO desalination processes using ANN from 1995 to 2018. The analysis of recent trends shows that research contributions using ANN have increased significantly in the last six years from 2013 to 2018.

The description in section 3 enables the understanding that ANN machine learning tool is very effective in predicting the parameters and proficient of managing the linear, nonlinear and complicated complex problems. However, the accuracy of an ANN model depends on the suitable selection of input variables and methodology. It also depends on the wide range of available datasets from desalination plants. It can manage noisy data more efficiently than others. However, the 'overtraining' of the network may lead to an incorrect prediction.

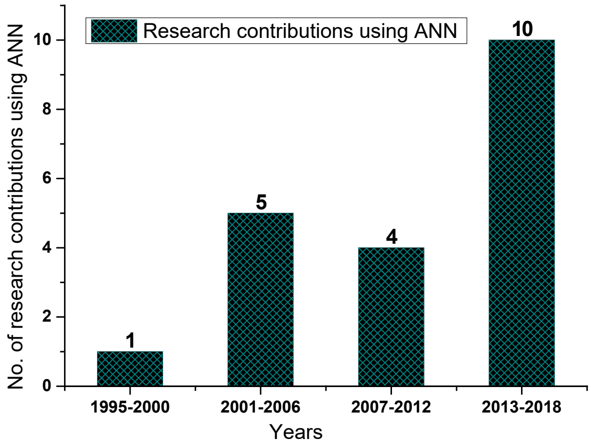

Fig. 7. Research contribution of researchers using ANN from 1995 to 2018 (based on Table A1 in the appendix).

4. Future aspects of ANN in modelling and simulation of RO desalination plants

Various research and engineering possibilities in the area of modelling and simulation of RO desalination plants using ANN have been discussed in the literature survey. We notice and express a few important and relatively unexplored prospectives as follows:

Firstly, with growing requirement of freshwater for humans, animals, and plants, the attention in using renewable energy (solar, wind, etc.) for desalination in the desert/remote areas has increased but needs more extensive attention and efforts. Shahzad et al. [33] proposed a state of art review based on renewable energy and future aspects in this regards. It helps to save energy as well as protect the environment to achieve sustainable goals. Verma et al. [34] presented a comprehensive review of source of renewable energy and its optimization in MSE using dynamic modelling and simulation.

The second possibility is the use of process optimization. Many researchers in their previous articles (1995–2018) have used BP algorithm, L-M method, RBF neural network, MLP, SVM, etc. The models may be simulated extensively with other optimization techniques as well such as particle swarm optimization (PSO), deep neural network (DNN) or a combination of above to explore further improved results. The structure of the neural network may also be modified with different possibilities such as hidden layers and nodes variations to meet the required goals.

Another possibility is the use of more number of input/output variables for deep learning. Most of the researchers till date have analyzed only the RO modules input/output variables in the modelling. In addition to the RO modules, pre-processing and post-processing also play an essential role in the desalination process. We can, therefore, involve all input/output variables including those in pre- and post-processing for the improvement of overall performance.

Other relatively unexplored area is the use of maintenance and control strategy. Alatiqi et al. [35] presented a newly developed strategy for process control and instrumentation in desalination plants. They included various controllers such as proportional integral derivative (PID) and fuzzy-logic based systems to improvise the process control. Cabrera et al. [31] well defined the use of control strategy in their research, managing the operation using ANNs for a small scale SWRO desalination plant located at Gran Canaria, Spain.

Another less explored area in RO is impact of membrane fouling. Modelling and simulation of membrane fouling is also an important parameter for operating RO desalination plants efficiently. Roehl et al. [36] presented a membrane fouling mechanism using ANN for a large scale RO desalination plant. They have developed two models, theoretical as well as ANN, to simplify and define the fouling process. Both models were tested under steady-state conditions at pilot and laboratory scales with interesting results.

Another area of future interest could involve the use of the right number (in %) of data used for training, testing and validating. Moradi et al. [23] have randomly divided experimental datasets into 3 parts, 70% applied for training, 15% for validation and the remaining 15% for testing. Some other researchers have used a different weightage of such datasets for different plants.

Another area of future research could involve hybridizing efficient technologies. The choice of water treatment equipment depends upon the quality and quantity requirements of water. Many researchers have used single technology (RO, MSF, MED etc.) for water treatment. The modelling and simulation of hybrid technologies (RO-MSF, RO-MED, etc.) to explore improved operating parameters and outputs could also provide remarkable results in this field. Salehi et al. [37] proposed modelling of waste brine NF process through the neuro-fuzzy system and ANN. This model predicted proficiently the sodium chloride rejection of waste brine and permeate flux.

Further, many conventional mathematical models such as solution diffusion, Kimura-Sourirajan analysis, finely porous model, surface force pore flow model, etc. have nicely predicted the performance of the desalination process. We can use conventional mathematical concepts with efficient solution algorithms for solving the models of desalination plants.

Desalination plant cost, which includes the cost of installation, maintenance, labor, instruments as well as training, is one of the key parameters that needs serious analysis. Ruiz-Garcia et al. [38] implemented an ANN-based model after considering operating and maintenance cost as weighing parameters in SWRO plant located in Fuerteventura (Canary Islands). It involved the specific cost of the cartridge filter, chemicals, membrane replacements, staff and maintenance and was verified with the good estimation.

Use of efficient simulation tools may enable accurate prediction of plant performance. For example, MATLAB neural network toolbox is the most versatile toolbox for the machine learning community and is used in solving many research problems. Some researchers have also used ASPEN PLUS (Process simulation software), SAS Enterprise Miner (data mining software), NeuroShell Simulator, ANOVA, ROSA software, Monte Carlo simulation method, etc. for the simulation of desalination plants. We can implant a plant optimization strategy by using another toolbox available in MATLAB such as global optimization toolbox, statistics, and machine learning toolbox. In addition to aforementioned software, other software such as Smooth Particle Hydrodynamics (SPH), Laboratory Virtual Instrument Engineering Workbench (LabVIEW), etc., may be employed in real time environments for better visualization, optimization of the process, control and maintenance of desalination plants. The success of SPH in hydraulics as explained earlier by Violeau et al. [39] stated in their vision paper that challenging applications are required to consolidate SPH codes for engineering purposes. The modelling of membrane fouling and optimization, considering particle deposition and its effect on the membrane's performance, is a suitable application for SPH numerical approach, which can cope with multiple fluid-structure interaction phenomena. Complex geometries are no issue because SPH is a meshless method. SPH can easily deal with multiphase flows, efficiently handle multiple species, the three phases gas, liquid, solid, and transitions between these (liquefaction, vaporization, and vice versa). Still concerning solids: elastic and plastic deformation (including fracture) can also be simulated through SPH as demonstrated earlier by Zisis [40]. Initially developed in the field of astrophysics and applied to fluid dynamics in engineering during the last two decades, SPH has recently been adapted and effectively used for the description of hydraulic transients in pipe flow by Hou et al. [41] and Korzilius et al. [42]. Additionally, NI software LabVIEW is a powerful graphical versatile software for measurement and control and offers more flexibility to programmers to simply view and adjust data or control inputs.

In section 4, we have thus presented the possible future aspects in terms of different unexplored or less explored possibilities in modelling and simulation of RO desalination plants.

5. Conclusion

Modeling and simulation have been proposed to predict the performance of membrane-based desalination systems such as SWRO, BWRO, LPRO, RO-EDI, RO-DM, RO-MSF, RO-FO, NF-RO-MED, UF-SWRO, RO renewable energy, etc. The literature survey suggested that it can be combined with deterministic models that comprise hybrid models (neuro-fuzzy and the like). An artificial neural network model, the computing model inspired by the human brain, and its variants, that have been developed and can optimize the operation of membrane-based desalination system, effective decision making, better design, etc. are expected by analyzing the complex experimental and real-time data. Based on the reviewed literature of the ANN-based modelling and simulation approaches applied to RO desalination processes, ANN has an improved capability to predict linear, nonlinear, complicated complex systems with high accuracy and with better control. Its prediction ability has attracted several researchers to work in this field and to solve diverse engineering problems. ANN behave like a MIMO system with the capability to handle many independent input-output variables. An exhaustive future perspective of ANN in RO desalination plants involving specific applications related to renewable energy, process optimization, improved maintenance and control, predicting and eliminating membrane fouling, cost analysis, etc., forms a strong basis to attract and motivate the researchers to work in this field in future.

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Table A1
Literature survey and analysis of different parameters of RO desalination plants using ANN by various researchers

Reference	Process/Algorithms	Input Variables	Output Variables	Simulation Tools	Remarks
Niemi et al., 1995 [14]	Feed-Forward Neural Network (L-M method)	1. Pressure 2. Concentration of solute 3. Temperature 4. Flow velocity	1. Permeate flux 2. Rejection	Matlab NN Toolbox	1. Simulation of separation of ethanol-water and acetic acid water system. 2. Results compared with conventional method.
Jafar et al., 2001 [15]	Adaptive RBFN	1. Pressure 2. pH 3. Temperature 4. Feed water salinity	1. Permeate flux 2. System recovery 3. TDS	Matlab NN Toolbox	1. Better performances than back-propagation (based on Least Mean Square algorithms). 2. Requires more computational burden.
Al-Shayji et al., 2002 [16]	Feed-Forward Neural Network (BP algorithm)	1. Seawater flowrate 2. Makeup flowrate 3. Seawater recycle flow 4. Seawater inlet temperature 5. Seawater outlet temperature 6. Blowdown flowrate 7. Brine inlet temperature 8. Stage 24 brine temperature 9. Brine heater inlet temperature 10. Stage 1 brine level 11. Brine heater shell temperature 12. Brine heater shell pressure 13. Steam temperature 14. Condensate temperature 15. Condensate flow rate 16. Recirculating brine flow rate	1. Top brine temperature 2. Distillate produced 3. Steam flow rate	ASPEN PLUS (Process simulation software)	1. Modelling of large-scale MSF and RO desalination plants 2. It can handle noisy data with more effectively.
Murthy et al., 2004 [11]	Feed-Forward Neural Network (L-M method)	1. Pressure 2. Concentration 3. Flow rate	1. Permeate flux 2. Rejection	Matlab NN Toolbox	1. Separation of sodium chloride. 2. Predicted the system variables within the error range of ±1%.
Abbas et al., 2005 [17]	Feed-Forward Neural Network (L-M method)	1. Feed pressure 2. Temperature 3. Salt concentration	1. Permeate rate	Matlab NN Toolbox	1. Modelling of brackish and seawater RO plants. 2. It uses a FilmTech SW30 membrane.
Zhao et al., 2005 [18]	MLP and NRBF.	1. Feed TDS	1. Permeate TDS	SAS Enterprise Miner (Data mining software)	1. Used modified solution diffusion model (SDM) and two ANN model for development. 2. Predicted more accurately permeate TDS than existing models.
Al-Alawi et al., 2007 [19]	BP algorithm	1. Time 2. Power from battery 3. Power from inverter 4. Power from PV panels	1. Diesel power 2. On/Off	NeuroShell Simulator	1. Developed for the optimum operation of an integrated hybrid renewable energy-based water and power supply system (IRWPSS). 2. It can predict the power usage and generator status at any time with high accuracy.
Lee et al., 2009 [20]	BP algorithm	1. Feed temperature 2. Feed TDS 3. TMP 4. Feed flow rate 5. Time	1. Permeate TDS 2. Flow rate	Matlab NN Toolbox	1. Results shows that variation of the feed water temperature and TMP was found significant affect on permeate TDS and flow rate. 2. It has used one year operation data from Fujairah SWRO plant (U.A.E.)

(*Continued*)

Table A1 (*Continued*)

Libotean et al., 2009 [21]	BP and SVR algorithms	1. STM time-interval	1. Permeate flux 2. Salt rejection	Matlab NN Toolbox	1. An ASP and two types of forecasting models (sequential and matching) have been developed for real time RO performances. 2. Good predictive accuracy for STM time intervals in the range 8-24 h.
Khayet et al., 2011 [22]	RSM and BP algorithms. Monte Carlo method.	1. Feed concentration 2. Feed temperature 3. Feed flow rate 4. Feed pressure	1. Permeate flux 2. Salt rejection	Matlab NN Toolbox, ANOVA	1. Sodium chloride aqueous solutions were employed as model solutions. 2. It applying polyamide thin film composite membrane.
Moradi et al., 2013 [23]	BP algorithm and MD-SF-PF model	1. Average longitude concentration 2. Operational condition 3. Parameters of MD-SF-PF model	1. Separation factor 2. Pure solvent flux 3. Total flux	Matlab NN Toolbox	1. Modelling for RO membrane performances. 2. Achieved less than 0.0007 MSE and 0.99 correlation coefficient.
Garg et al., 2014 [24]	RSM (CCD) and ANN (BP algorithm)	1. Feed temperature 2. Feed pressure 3. Feed concentration 4. pH	1. Water recovery 2. TDS rejection 3. SEC	Matlab NN Toolbox, ANOVA	1. Optimal water recovery (19.18%), TDS rejection (89.21%), and SEC (17.60 KWh/m3). 2. It observed minimum uses of energy consumption of the plant.
Barello et al., 2014 [25]	BP algorithm	1. Operating pressure 2. Feed salinity	1. Permeability constant	Matlab NN Toolbox	1. ANN model based on correlation to predict Kw under fouling conditions. 2. It is able to predict Kw values for any two membrane types, any operating pressure and any feed salinity within a wide range.
Aish et al., 2015 [26]	MLP, RBF and MLR	1. Feed temperature 2. pH 3. Conductivity 4. Pressure	1. Permeate flowrate 2. Predicting TDS	Matlab NN Toolbox	1. Modelling of a five large and small scale brackish water plants in Gaza strip. 2. MLP predictive results slightly better than RBF.
Salgado-Reyna et al., 2015 [27]	BP algorithm	1. pH 2. Antiscaling agent concentration 3. Inlet SiO_2 concentration 4. Inlet TDS concentration	1. Permeate water flow rate 2. Outlet SiO_2 concentration 3. Outlet TDS concentration	Matlab NN Toolbox	1. It showed 96.1% acceptable removal TDS and maximum effluent recovery close to 72%. 2. The experimental and predicted data were well collated and determination coefficient between 0.97 and 0.99 achieved.
Madaeni et al., 2015 [28]	BP algorithm, GA	1. Time 2. Transmembrane pressure 3. Conductivity 4. Flow rate	1.Permeate flow 2. Permeate conductivity 3. RMSE	Matlab NN Toolbox	1. Modelling, optimization and control of RO water treatment. 2. GA was used to find optimum paths of TMP, feed flow rate and control strategies.
Salami et al., 2016 [29]	BP algorithm	1. Feed data generated by ROSA software	1. TDS 2. Temperature 3. Flow rate 4. Recovery percentage	Matlab NN Toolbox, ROSA software	1. Simulate 8 types of SWRO membranes. 2. Feed data was generated by ROSA software.
Iranmanesh et al., 2016 [30]	RBFNN	1. Model parameters 2. Membrane properties 3. Operational conditions	1. Separation factor 2. Pure solvent 3. Total flux	Matlab NN Toolbox	1. Modelling of MD-SF-PF model. 2. Predicted and experimental results are correctly to each other.
Cabrera et al., 2017 [31]	MLP	1. Power 2. Temperature 3. Conductivity	1. Pressure 2. Flow rate	Matlab NN Toolbox	1. Use wind energy in SWRO desalination plant. 2. Model were able to manage varying available electrical power.
Cabrera et al., 2018 [32]	ANN, SVM and RF	1. Constant pressure and flow rate with wind-battery microgrid. 2. Variable pressure and flow rate without energy storage.	1. Pressure 2. Feed flow rate 3. Permeate flow rate 4. permeate conductivity	Matlab NN Toolbox	1. SVM and RF are significantly better predictions than ANN. 2. Variable pressure and flow rate operates more continuously than the constant pressure and flow rate.