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Modelling and simulation of desalination process using artificial neural network: a review

Rajesh Mahadeva[a], Gaurav Manik[b,*], Om Prakash Verma[c], Shishir Sinha[d]

[a]*Department of Polymer and Process Engineering, Indian Institute of Technology, Roorkee, Saharanpur Campus, Saharanpur, Uttar Pradesh, 247001, India, Tel. +91 9909030497; email: rajeshmahadeva.dps2017@iitr.ac.in*
[b]*Department of Polymer and Process Engineering, Indian Institute of Technology, Roorkee, Saharanpur Campus, Saharanpur, Uttar Pradesh, 247001, India, Tel. +91 132 2714340; Fax: +91 132 2714311; email: manikfpt@iitr.ac.in*
[c]*Department of Instrumentation and Control Engineering, Dr. B. R. Ambedkar National Institute of Technology, Jalandhar, Punjab, 144011, India, Tel. +91 7579279839; email: vermaop@nitj.ac.in*
[d]*Department of Chemical Engineering, Indian Institute of Technology Roorkee, Roorkee, Uttarakhand, 247667, India, Tel. +91 1332 285648; email: shishir@iitr.ac.in*

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ABSTRACT

Water is the natural, yet very essential, resource for survival of humans, animals and plants. However, only 3% pure water (present in lakes, rivers, as groundwater and frozen water) is available globally and 97% being saline is not suitable for drinking and agriculture purposes. Surprisingly, only 1% of this pure water is within reach of humans for existence. Hence, it is quite imperative to improve the water quality as well as its availability. Desalination, a process for converting the saline water into fresh water, may help in achieving this objective by providing water suitable for consumption by humans and animals, for agriculture and industrial applications. In this paper, we review various desalination techniques namely: reverse osmosis, vapor compression distillation, electrodialysis, multi-stage flash, etc., and their hybrids being increasingly used for treating seawater. Modelling and simulation of such processes is vital for improving water quality and quantity as well as understanding, analysis and reporting of the physical, chemical and biological results for appropriate process measurement and control. Artificial neural network (ANN) involves representing such processes with models inspired by the architecture of a biological neural network of human brain. An exhaustive review of ANN-based models, improvised recently to more effectively simulate process behavior for optimizing operating conditions, has been presented.

Keywords: Desalination; Modelling and simulation; Artificial neural network; Optimization

1. Introduction

Water is one of the most important constituents on the earth, needed for various household, agricultural, industrial and recreational activities for humans and life processes of animals and plants. It is, hence, important that water needed for drinking should be of sufficiently high quality so as to avoid many diseases such as polio, typhoid, diarrhea, cholera, dysentery, etc., that crop up due to consumption of contaminated drinking water. The gravity of the problem can be assessed from a recent report by World Health Organization which indicates only 71% of the global population (5.2 billion) uses pure drinking water while remaining lack even basic drinking water services

* Corresponding author.

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(Fig. 1) [1,2]. A similar data to highlight the seriousness of this issue has been reported by United Nations International Children's Emergency Fund on accessibility, availability and quality of drinking water services worldwide from ~2000 data sets on basic drinking water services (300 censuses, 312 administrative or sectorial sources, and 1,363 household surveys) (Table 1) [3]. It shows that only 106 out of 225 countries across the world have utilized improved quality drinking water services.

Freshwater forms a very small percentage (~3%) of the total water available on earth while the remaining (97%) is saltwater. Freshwater is available as frozen water (77%), groundwater (22%) and in lakes and rivers (1%) on the earth. Unfortunately, only 1% of this available pure water is within reach of humans and animals [4]. In every 20 years, consumption rate doubles, while limited and unreliable water remains a major problem for the quality of life. The demand of pure drinking water is increasing at a huge pace due to rapid industrialization, irrigation and population growth. Therefore, a holistic approach that employs techniques of rainwater harvesting, water reuse, water purification, brackish water desalination and seawater desalination is needed for improving the water quality, availability as well as its accessibility.

The water quality index is expressed in terms of its chemical composition with the permissible values ranging widely across different parts of the world. Moreover, different permissible values are applicable for drinking as well as crop irrigation purposes. The excessive limit is the maximum value that is unacceptable for humans and animals consumption [5–7]. Table 2 lists various such parameters of source and permeate water from a reverse osmosis (RO) system. Total dissolved solids (TDS) represent the total concentration of dissolved elements in water. A TDS < 300 mg/L is excellent,

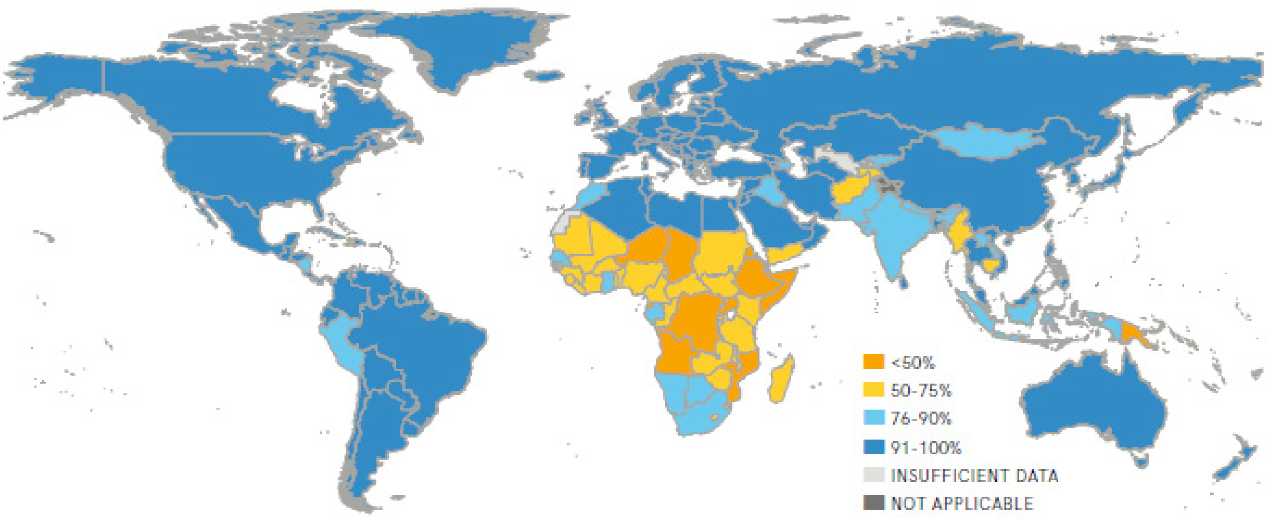

Fig. 1. Illustration of fraction of population using basic drinking water services across the globe (Source: UNICEF and World Health Organization [2]).

Table 1
Data on basic drinking water services from a number of countries, areas, and territories worldwide

Region	Number of countries, areas, and territories	Household surveys and censuses	Drinking water services			
			Accessibility	Availability	Quality	Total
Caucasus and Central Asia	8	8	–	7	4	7
Developed countries	55	49	1	27	43	52
Eastern Asia	6	4	–	4	4	5
Latin America and Caribbean	46	32	1	40	19	44
Northern Africa	6	5	1	5	–	5
Oceania	20	12	1	16	11	18
Sub-Saharan Africa	51	49	2	34	13	36
Southern Asia	9	9	2	6	4	7
South-eastern Asia	11	10	–	7	5	9
Western Asia	13	9	–	10	3	11
World	**225**	**187**	**8**	**156**	**106**	**194**

Source: WHO and UNICEF [3].

Table 2
Chemical composition of seawater and permeate from membranes

Chemical composition of water	Seawater to feed pumps		Feed pumps to membranes		Permeate from membranes	
	ppm ions	ppm $CaCO_3$	ppm ions	ppm $CaCO_3$	ppm ions	ppm $CaCO_3$
Flow, m^3/h	950.00	–	950.00	–	380.00	–
Free CO_2, ppm	–	13.70	–	13.70	–	13.70
Temperature °C	30	–	30	–	30	–
Cations						
Calcium (++)	529.00	1,322.50	541.18	1,352.95	0.95	2.36
Magnesium (++)	1,531.00	6,295.23	1,566.25	6,440.16	2.78	11.43
Sodium	14,239.00	30,958.39	14,566.80	31,671.10	104.28	226.69
Potassium	544.00	695.72	556.52	711.74	4.55	5.82
Total cations (+)	16,843.00	39,271.84	17,230.75	40,175.94	112.54	246.30
Anions						
Chloride (–)	24,975.00	35,218.72	25,549.97	36,029.51	163.57	230.87
Bromides (–)	0.00	0.00	0.00	0.00	0.00	0.00
Sulphate (–)	3754.48	3,908.48	3,840.92	3,998.46	2.51	2.61
Phosphate (–)	0.00	0.00	0.00	0.00	0.00	0.00
Fluorides	0.00	0.00	0.00	0.00	0.00	0.00
Nitrates	6.20	5.00	6.34	5.12	6.02	4.86
Carbonate	0.11	0.18	0.11	0.18	0.00	0.00
Bicarbonate	141.68	116.09	144.94	118.77	1.45	1.19
Total anions (–)	28,877.47	39,248.47	29,542.28	40,152.03	173.56	239.32
M (T) alkalinity	–	116.27	–	118.95	–	1.19
P alkalinity	–	0.09	–	0.09	–	0.00
Carbonate hardness	–	116.27	–	118.95	–	1.19
Non-carbonate hardness	–	7,501.48	–	7,674.15	–	12.61
Total hardness	–	7,617.73	–	7,793.10	–	13.80
pH	–	7.20	–	7.21	–	7.21
TDS, mg/L	45,720.47	–	46,773.03	–	286.09	–

Source: Migliorini and Luzzo [7].

300–600 mg/L is good and >1,200 mg/L is undesirable for humans. The pH value of the drinking water shows its acidity or alkalinity and is a measure of hydrogen atoms present in water. A neutral pH of 7.0 is considered more suitable for pure drinking water.

Such seawater desalination plants based on RO have been modelled earlier. For example, Migliorini and Luzzo [7] presented an original model of such systems based on the classical carbonate system that allows complete seawater analysis and performance index of RO membranes. It enables easy understanding and analysis of plant information such as product chemical composition and permeate index of RO membranes. The basic selection and necessary conditions for the installation of such desalination plants are its simplicity, availability, ease of handling, assurance of pure water production, suitability of locations and minimum cost with higher efficiency.

2. Desalination

Desalination technology focuses on the removal of salts from water. In nature, desalination occurs as water evaporating from lakes, oceans and land surfaces leaves salts behind and forms clouds that produce rain on earth. This technology serves many purposes in the world, for example, in domestic as drinking water, irrigation and industrial processes. The applications of desalination technologies have increased in many arid and water scorched areas (Middle East, Arabian Gulf, North Africa, etc.) of the world. The origin of such technologies dates back to 1790 when Thomas Jefferson received permission from U.S. government to employ distillation method to convert saltwater to pure water. Later in 1852, a British patent was granted for desalination [8]. In 1928, desalination process was first established in Curacao in the Netherlands, and subsequently in 1938, a high capacity desalination plant was built in Saudi Arabia. Desalination plants played an important role during World War II for serving military needs in remote places. After World War II, the desalination process and related research received increasing attention in various countries especially in the United States. For example, in 1952, U.S. government passed the Saline Water Act (PL 448), which created an office of saline water to deal with issues related to quality of saline water. Later in the early 1960s, Kuwait established advanced desalination plants. In 1977, U.S. spent around $144 million for research and development in this area. In due course, many countries accelerated research and development in this field of desalination of seawater, brackish water and others. As a result of this increased focus, majority of desalination plants were established in Saudi Arabia, Kuwait, United Arab Emirates and United States. In United States as against other mentioned countries, most of these plants were primarily based on RO and vapor compression techniques.

Fig. 2 illustrates a simple process block diagram of an RO desalination unit. In such a plant, raw seawater is first stored in a storage tank using a low-pressure pump. This is followed by its pre-treatment involving separation and purification using a membrane module. Essential chemical additives are added as post-treatment and the treated fresh water is stored for consumption of humans or animals and irrigations purposes while the concentrated brine is rejected to the sea [9–12].

Shahzad et al. [13] investigated that more than 18,000 desalination plants in 150 countries producing around 38 billion m^3 fresh water per year. The worldwide analysis of desalinated water from seawater, brackish and waste water in different regions across the world shows that the share of seawater for treatment is lacking compared with its availability. Currently, 59% seawater, 23% brackish water, 7% rivers, 5% wastewater and 6% other sources are used for desalination.

Nowadays, advanced desalination technologies have been developed for autonomous desalination plants. It converts desert lands into sustainable areas and with improved quality of human life. Fig. 3 shows the growth in desalination units and capacities (m^3/d) from years 1966 to 2016 forecast globally [14]. It is interesting to note that the capacity has seen an enormous growth of ~1,000 folds during this period, which highlights a growing attention to this approach of water treatment and utilization.

To bring focus and limelight to desalination technologies, a large number of international organizations have got established globally namely: International Desalination Association, Australian Desalination Association, American Desalination Association, European Desalination Society, Indian Desalination Association and Middle East Desalinisation Research Centre, etc. These organizations are putting enormous efforts to bring effective utilization of available advanced technology in the area.

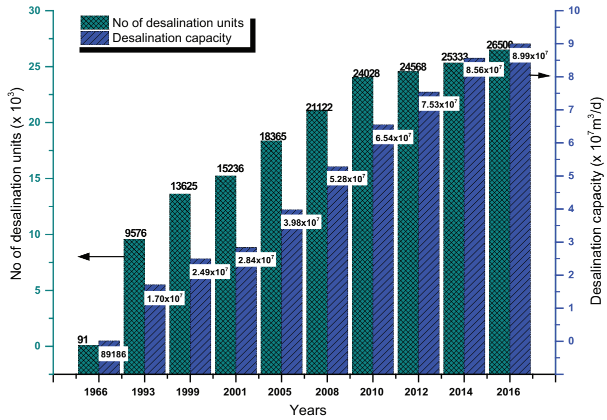

Fig. 3. Literature statistics of desalination units and their capacity (m^3/d) across the world (Source: Balaban [14]).

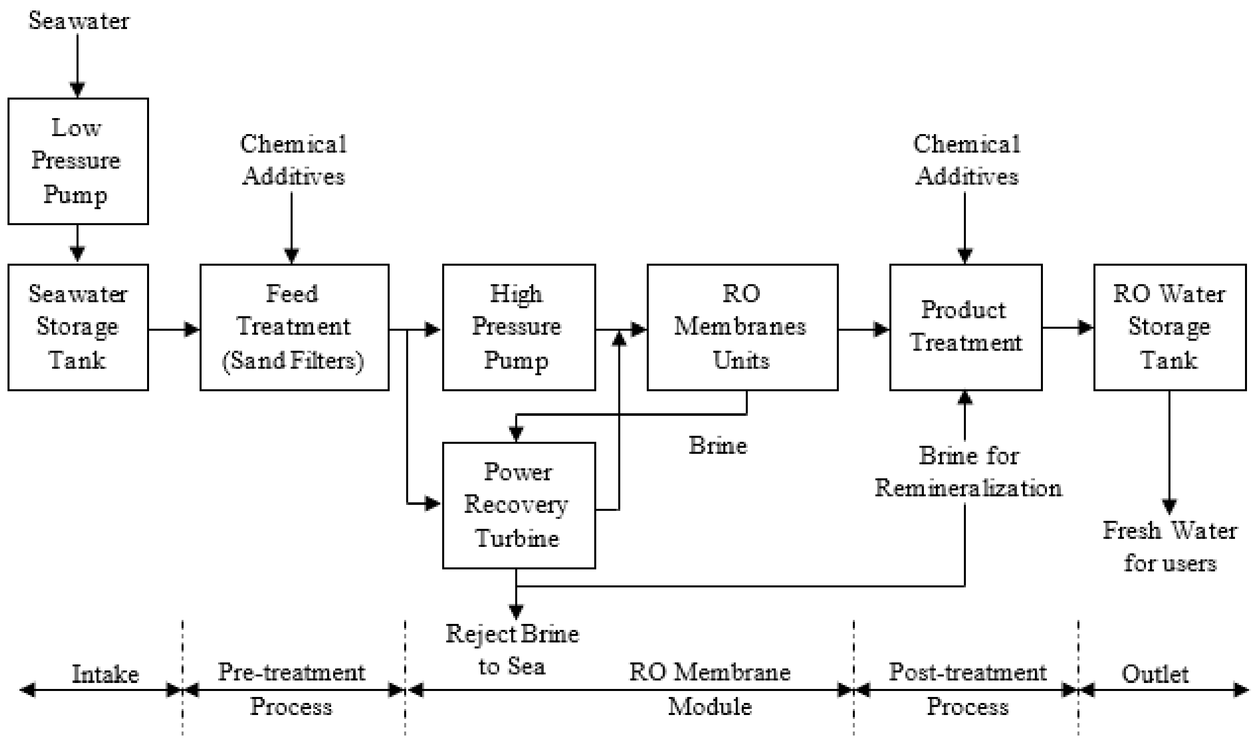

Fig. 2. Generalized reverse osmosis (RO) desalination plant.

2.1. Desalination with renewable energy

Till date, desalination processes have been able to drive only 0.02% of total desalination capacity using renewable energy. Renewable sources are suitable for seawater desalination plants due to many reasons: (a) energy availability: the use of renewable energy in the seawater desalination is accelerating especially in remote areas where electrical energy (conventional energy) is not easily available, (b) plant location: renewable sources of energy are quite sustainable for coastal and remote plant locations, (c) high availability and self-sufficiency of renewable energy (especially, solar energy) and (d) easy maintenance and operations of renewable energy systems for desalination plants [15].

Nowadays, many renewable energy resources have become interesting alternative energy source for desalination plants. Solar energy is the most promising, highly available and an economic source of energy for seawater desalination [16]. Wind energy is another promising alternative primarily employed for coastal and remote areas. Other renewable energies (geothermal, ocean, biomass, etc.) are also used for seawater desalination processes and plants. Fig. 4 illustrates the schematics of the scope of mentioned prime renewable energy sources and their suitability for desalination processes of various types.

2.2. Desalination technologies

Based on the type of separation process involved, the desalination technologies have been classified into three types: evaporation–condensation, filtration and crystallization technology [15]. Evaporation–condensation is further divided into thermal and mechanical processes. A review of numerous desalination technologies employed for desalination plants to understand their economics and sustainability has been attempted earlier by Ghaffour et al. [17]. RO, multi-effect distillation (MED) and multi-stage flash (MSF) are the most implemented technologies for the production of drinking water. Around 62% RO, 14% MED, 10% MSF, 5% electrodialysis (ED), 5% VC and 4% other technologies are used around the world [15]. A summary of various available technologies in the area has been presented through a schematic in Fig. 5. The western and developed countries prefer RO while the Middle East and Gulf countries prefer MSF and MED technologies.

RO is the most efficient technology that offers advantages of low power consumption and ease of adaptation to local conditions. However, it requires comprehensive pre-treatment, suffers from membrane fouling issues and requires a large number of chemicals to prevent fouling. Comodi et al. [18] have shown that RO-based plant produces a high permeate freshwater with reduced electrical consumption. The application of RO in the desalination of various water resources to produce pure water involves technologies such as seawater RO (SWRO), brackish water RO, low-pressure RO, RO electro deionization and RO demineralizer (RO-DM) [19]. A new desalination technology, namely, the draw solution-assisted RO has been proposed to produce fresh water with minimum energy consumption and economic perfections [20]. Further, it has been mathematically modelled to understand its cost-effectiveness and process sensitivity. Imbrogno et al. [21] investigated the critical aspects of RO desalination plants. The harmful algal blooms in the marine environments and their effects on SWRO plants have been described earlier by Villacorte et al. [22].

MED is most suitable for renewable energy usage and can be operated between 0% and 100% capacity. Ge et al. [23] analyzed and designed a seawater MED plant with thermal power generating unit producing 10,000 ton/d of freshwater. Sen et al. [24] described the design and fabrication, performance analysis and heat transfer aspects of an MED unit for rural microenterprises.

MSF can easily manage salty water up to 70,000 mg/L but cannot operate at below 60% capacity. MSF and MED technologies require more amount of thermal energy, 10–15 kWh/m^3. Global optimization solutions of MSF seawater desalination

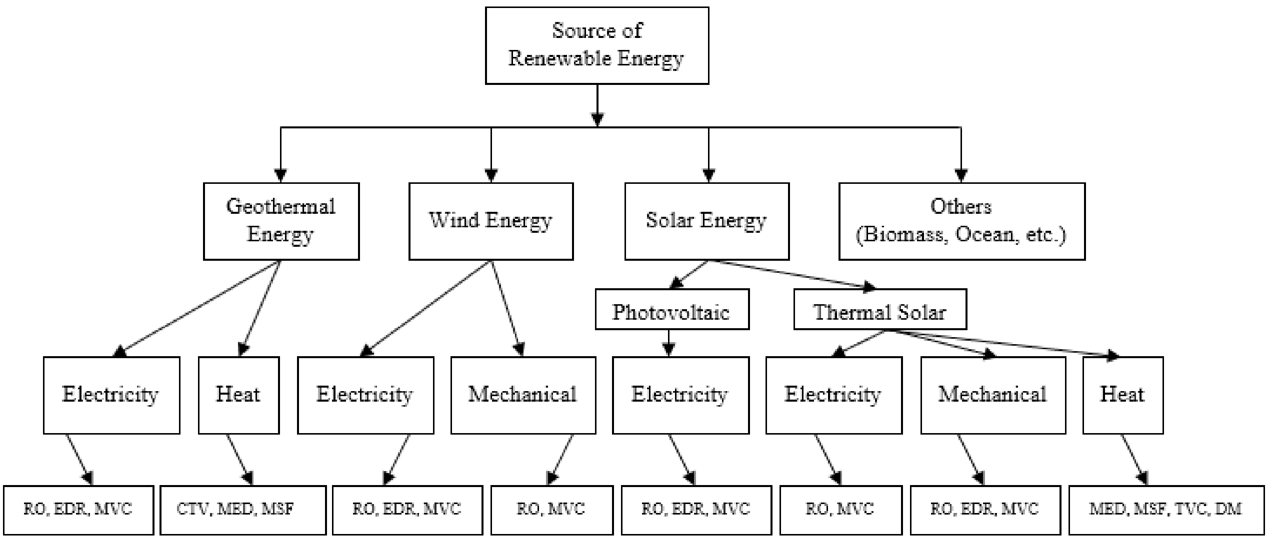

Fig. 4. Desalination technologies supported with variety of renewable energy sources.

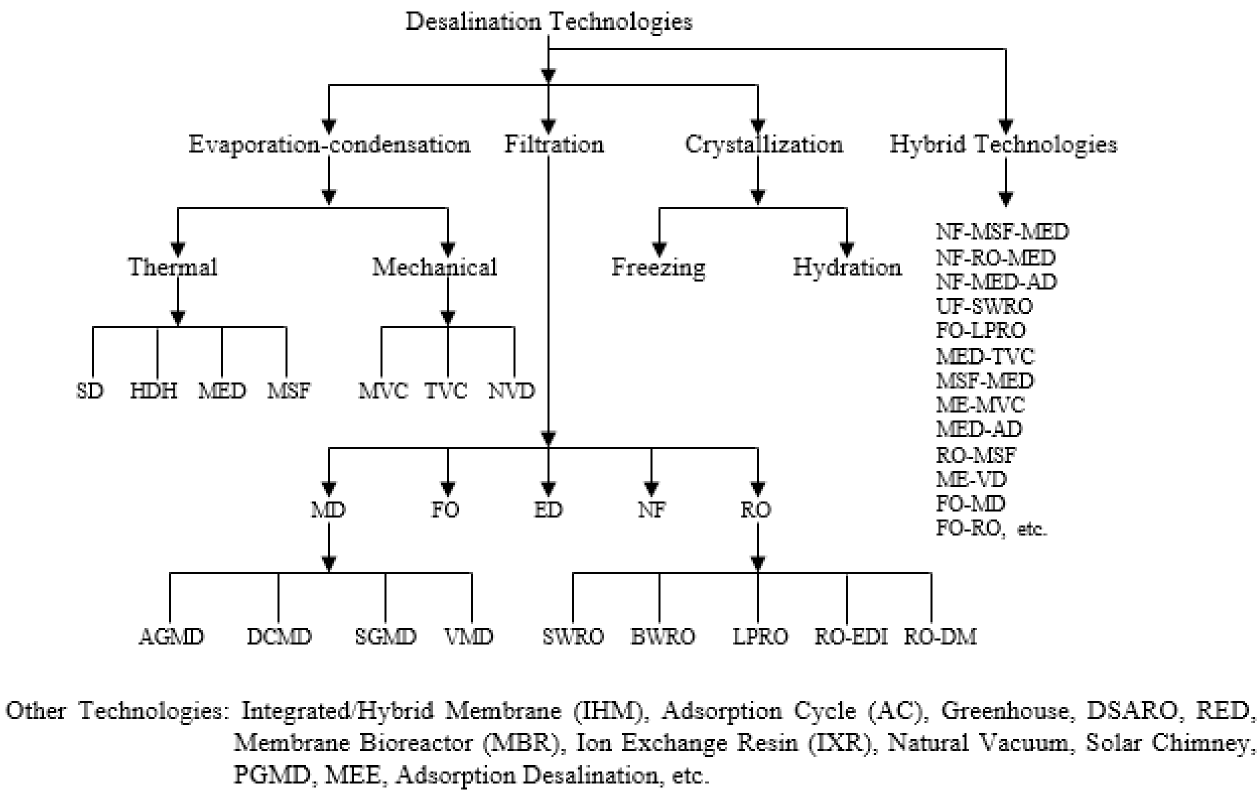

Fig. 5. Summary of desalination technologies used globally in various desalination plants.

using different techniques such as MSF-once through (MSF-OT), MSF-simple mixture (MSF-M) and MSF-brine recycle (MSF-BR) have been proposed by Bandi et al. [25].

ED has a longer life of up to 15 years and a highest recovery rate of 94%, but its installation cost is more than that of RO. Solar still distillation is the simplest, low cost, low maintenance, low energy and environmentally friendly technology, suitable for remote areas with small-scale desalination plants. Membrane distillation (MD) technology has different configurations effective since 1960s. MD, a thermally driven technology with moderate operating temperatures, is divided into four types: air gap MD (AGMD), vacuum MD (VMD), direct contact MD and sweep gas MD (SGMD) [26]. A permeate gap membrane distillation technology is also designed for optimized internal heat recovery [27]. Kim et al. [28] described the forward osmosis (FO) membrane characteristics such as water permeability, solute permeability and structural parameter. It is the fastest growing technology that attracts researchers due to its fundamental and technical advantages. Mei and Tang [29] investigated the recent developments, critical operating conditions and future perspective of reverse electrodialysis based on membrane components. Goh et al. [30] presented some novel methods in membranes, materials and their processes with an ecological perspective and improved efficiency. Al-Mutaz and Wazeer [31] observed that total equivalent energy consumption of a multi-effect evaporation system is approximately 4.5–12.5 kWh/m^3 while the optimal ratio of product pure water and total input seawater flow should be 0.1–0.25 for minimum capital investment.

Hybrid technologies have been developed in parallel with low energy consumption, better efficiency and high product output. For example, Multi-effect desalination with thermal vapor compression (MED-TVC) improves system efficiency by reducing the energy consumption with a high gain output ratio (GOR). An accurate and efficient model for such a system has been previously developed and presented by Al-Mutaz and Wazeer [32]. Likewise, Zhang et al. [33] presented the economic evaluation of multi-effect vacuum membrane distillation (ME-VMD) process which increases the water recovery and GOR but decreases the distillate flux. The authors observed that maximum GOR recorded was 12.1 at an inlet temperature of 90°C. Khalid et al. [34] presented MED-TVC for large-scale desalination plants which showed high performance ratio and low specific flow rate. The advantage of this plant proposed was that the plant capital cost would not be affected by placing the TVC at the optimum location while the performance ratio increases. Very recently, Jamil and Zubair [35] presented a model based on multi-effect desalination with mechanical vapor compression (MED-MVC) technology that uses three different feed flow arrangements: forward feed, parallel feed and parallel cross feed. A detailed analysis of desalination plants in terms of energy consumption, heat transfer area, exergy destruction and product overall cost was presented. It was concluded that forward osmosis with membrane distillation had excellent thermal stability, high solubility and water flux with low viscosity seawater as well as brackish water desalination plants [36].

Some other emerging and advanced technologies are under development albeit with little demonstrated use.

The novelty lies in reducing energy consumption, minimizing cost, decreasing environmental impact and minimizing use of chemicals with high productivity [37]. Despite these developments in recent years to solve issues of water shortage, scope of such technologies remains limited due to many problems, such as noise pollution, land occupation, environmental issues (especially marine environment) and limitations due to cost, higher temperature of seawater, use of high amount of chemicals and others. Ensuring a proper action to solve these problems would require appropriate selection and implementation of desalination technologies.

3. Artificial neural network approach

William James published the first work about the brain activity patterns in 1890s which laid the foundation of inventions in the field of neural network. Later, McCulloch and Pitts [38] investigated the fundamentals of mathematical modelling of biological neurons in the 1940's and Donald Hebb provided the first mathematical theory based on neurons in 1949 [39]. The words "artificial neural networks" originated first in the book "Principle of Neurodynamics" by Frank Rosenblatt during 1957–58 [40]. The new era of artificial neural network (ANN) initiated with the work of Hopfield in 1982, wherein he demonstrated advantages of ANN in solving many problems such as "Travelling salesman problem" in constant time over the conventional methods [41]. Over the past era, ANN has become more popular in many fields of problem-solving due to its flexibility and capacity to solve highly complex and complicated problems possessing highly non-linear relationships.

ANN is a new information processing and computing system which is inspired by the biological analogy of human brain. It is a simplified mathematical model with an ability to learn from examples and produce meaningful solutions. A model has basically three layers such as input layer, hidden layer and an output layer. The input layer accepts the weighted inputs from single or multiple sources and transmits its output to hidden layer through links to produce an appropriate output. Each link is assigned some weight for estimation of network strength [42]. The general ANN model with mentioned three layers has been represented in Fig. 6.

The mathematical Eq. (1) represents the output (y_k) with three layers of ANN involve input signals x_i ($i = 1, 2, 3, \ldots, n$); individual neuron k; weights w_{ik}; and activation function ϕ.

$$y_k = \varphi\left(x_{0k} + \sum_i w_{ik}.x_i\right) \tag{1}$$

Many ANN architectures have abilities to solve different models of data such as simple neuron with a single scalar

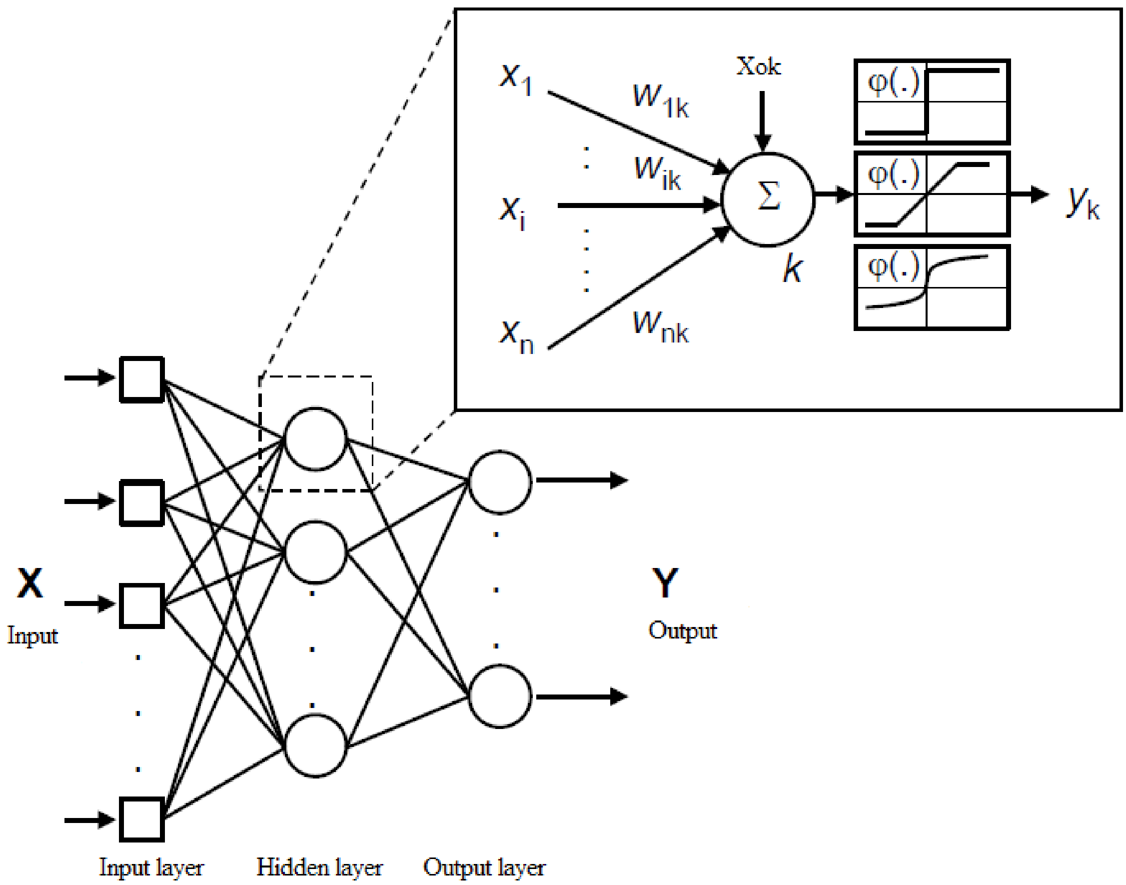

Fig. 6. A general artificial neural network (ANN) model with three layers (Source: Bürger and Kolditz [42]).

input (neuron with and without bias), a neuron with vector input and layers of neurons (perceptron and multilayer network). A multilayer network has several layers and each layer has weight matrix and bias vector. In general, ANN learns using supervised, unsupervised and reinforcement learning by adjusting the weight parameters. There are many methods used for training of neural networks, such as back-propagation (BP), also known as multi-layer perceptron (MLP), radial basis function (RBF) networks, generalized regression neural networks, Hopfield networks, feed forward neural network, self-organizing neural network, learning vector quantization, recurrent neural networks (RNNs), modular neural network and physical neural networks, etc.

General applications of ANN are in areas of: automatic recognition of targets, automobile engine diagnosis, economic prediction of the stock market, economic load dispatching, defence applications in processing sensor data to classify targets, design optimization of electromagnetic devices, dynamic security assessment, geophysical surveying, medical diagnosis, robotics and speech recognition [43].

4. Modelling and simulation of desalination processes using ANN

The era of the 1980s was the revival era of ANN both for theory as well as practical applications of different areas. The potential applications of the ANN in desalination plants enumerated by El-Hawary [43] are mentioned below:

- Alarm processing and fault detection: abnormal valve operating conditions, abnormal pump operating conditions, electric utility failure, equipment failure, failure of low-pressure steam supply, failure of seawater supply, failure of medium pressure steam supply and water contamination (distillate, a condensate of brine heater), etc.
- Control system applications: brine level in the last stage, circulating brine temperature, circulating brine flow, condensate level in brine heater, distilled water level in the last stage, heating steam temperature, make-up seawater flow (circulating brine concentration ratio control) and sea water temperature, etc.
- Operational optimization*:* minimizing operating costs, cost of electric energy for pumping which depends on flow rate, cost of pre-treating of seawater (chemicals cost) which depends on the make-up flow, labor cost, maintenance cost, steam cost which depends on the quantity of steam and its pressure, minimizing energy consumption, minimizing energy losses and maximizing town-water output, etc.
- Load forecasting: dispatch, maintenance scheduling, unit commitment, etc.
- Potential for security assessment: static and dynamic security assessment, etc.

4.1. ANN applied to reverse osmosis desalination technology

Among the various desalination technologies, RO is the most widely used technology with 62% of plants using this technology globally. Jafar and Zilouchian [44] proposed a model based on adaptive receptive fields and ANN. It was observed to be much faster than the three-layer perceptron trained algorithms. Murthy and Vora [45] presented an experimental RO model to represent a process that attempts to separate the sodium chloride water system. The training data includes feed rates from 300 to 1,500 mL/min, a pressure range from 20 to 100 atm and concentration range from 1,000 to 30,000 ppm with error of within ±1% range. Abbas and Al-Bastaki [46] used feed forward neural network model to predict the performance with the use of FilmTec SW30 membrane. Libotean et al. [47] used back-propagation and support vector regression algorithms for neural network modelling. The results reflected improved permeate flux with good accuracy. Lee et al. [48] developed a model of seawater RO desalination plant consisting of five input parameters such as feed temperature, feed TDS, feed flow rate, feed flow time and feed trans-membrane pressure, with two output parameters namely TDS and flow rate of permeate.

Khayet et al. [49] developed an ANN-based response surface methodology (RSM) predictive model for RO desalination plants. It consists of four input variables, that is, feed temperature, feed flow rate, operating hydrostatic pressure and sodium chloride concentration in feed solution with permeate flux as response. The model helped predict maximum performance index. Barello et al. [50,51] developed a time-dependent neural network RO desalination plant under fouling conditions. It was observed that water permeability constant values at low pressure were within a wide range. Aish et al. [52] presented an ANN multilayer perceptron and RBF model for RO desalination plant in the Gaza Strip. It predicted the TDS and permeate flow rate of the water. Salami et al. [53] proposed an ANN model to simulate RO membranes. This model was trained with feed forward back-propagation algorithm which is highly reliable to provide an accurate RO model. Cabrera et al. [54] proposed a small-scale seawater RO desalination plant modelled using ANN for managing the operation of the island of Gran Canaria (Spain). Ruiz-Garcia and Feo-García [55] modelled seawater RO desalination for drinking water supply in coastal areas and simulated operating and maintenance cost of 12 SWRO desalination plants placed in Fuerteventura (Canary Islands) using ANN.

4.2. ANN applied to multi-stage flash

The MSF desalination technology is also a widely used technology with ~10% deployment across the world. Abdulbary et al. [56] presented the preliminary study on modelling and simulation of large-stage desalination plant using ANN. Selvaraj et al. [57] modelled and simulated the multivariable identification MSF desalination plants using ANN with a single hidden layer and an error-back-propagation algorithm used for neural network weight. The obtained correlation coefficients were greater than 0.99. Woldai et al. [58] presented an adaptive control strategy based on ANN for a MSF (18-stage) plant in the United Arab Emirates. Tarifa et al. [59] investigated the fault diagnostic system for MSF-based desalination. The system determines whether the process state is normal or not and shows a variable index between 0 and 1. The results were obtained after a careful selection of the system and training modules. Tanvir and Mujtaba [60] presented an optimal design and operation of MSF desalination process. The authors suggested several neural network correlations for predicting temperature elevation (TE) very closely. Aminian [61] developed a neural network model based on RBF for estimating TE during MSF process. The mean squared error was found to be improved than the thermodynamics and MLP-based neural networks. Tayyebi and Alishiri [62] proposed a more accurate and robust nonlinear inverse control strategy based on neural networks for controlling complex and nonlinear MSF desalination process.

4.3. ANN applied to other desalination technologies

Niemi et al. [63] developed a method for the simulation of membrane processes using ANN which helps estimate the permeate flux and rejection over the entire range of the process variables. The process variables were temperature, pressure, superficial flow velocity and solute concentration. It demonstrated ease of use and enabled faster computation with better accuracy. Dornier et al. [64] developed a dynamic neural network model for raw cane sugar syrup feed stream concentration. Delgrange et al. [65] presented a neural network ultrafiltration model to predict the evolution of the hydraulic resistance arising due to fouling and its impact on water quality parameters. Delgrange-Vincent et al. [66] developed a model to predict the productivity of an ultrafiltration (UF) plant to produce drinking water operated with sequential backwashes. The model considers both reversible and irreversible fouling and models system behavior with minimum number of parameters. It employs two interconnected RNNs and satisfactorily predicts the filtration performances. Bowen et al. [67] developed an ANN model for a nanofiltration membrane to predict its rejection capability of single salts (NaCI, Na_2SO_4, $MgCl_2$ and $MgSO_4$) and their mixtures. Shetty and Chellam [68], and Shetty et al. [69] developed a robust ANN model for nanofiltration with minimal training and efficiently predicted membrane fouling of surface and groundwater. It demonstrated capability of capturing changes in feed water quality, flux and recovery and more accurately overcomes the difficulties and issues associated with modelling of such systems.

Al-Zoubi et al. [70] attempted modelling of experimental data of three nanofiltration membranes (NF90, NF270 and N30F) with different salt solutions (KCl, Na_2SO_4 and $MgSO_4$) for seawater desalination. The NF90 and NF270 showed high rejection of KCl and Na_2SO_4 salts, while N30F gave lower rejection values. Gao et al. [71] developed a heat pump type seawater desalination plant using ANN. Yangali-Quintanilla et al. [72] developed an ANN model for rejection of neutral organic compounds by NF and RO. The model was based on quantitative structure–activity relationship equation and predicted good correlations (0.97) with standard deviation of error of ~5%. Khayet and Cojocaru [73] developed an experimental model based on ANN to describe the performance of AGMD process for different working conditions. It comprised of input variables such as air gap thickness, feed flow rate, condensation temperature, feed inlet temperature, with the output variables as the permeate flux and salt rejection factor. The model provided good correlation coefficient of ~0.992 with residual error less than 1%. Esfahani et al. [74] proposed a systematic approach for MED-TVC desalination system and used preheated feed water temperature, temperature difference and motive steam mass flow rate as input variables. The effect of input variables was investigated using RSM and partial least squares technique. Sargolzaei et al. [75] employs the back-propagation artificial neural network (BPANN), RBF and adaptive neuro-fuzzy inference system (ANFIS) to predict starch removal from wastewater. The model considered four input variables: feed flow, feed temperature, pH and concentration of permeate. The BPANN model employs four hidden layers for permeation and better performance for the system.

Salehi and Razavi [76] presented an ANN model to predict permeate flux and hydraulic resistance with high correlation coefficients (0.96 and 0.98, respectively) for nanofiltration of waste brine. Khayet and Cojocaru [77] developed a SGMD using ANN for desalination process. The authors performed 53 different experimental tests based on feed-forward neural network model and found salt rejection factors to be more than 99.4%. Porrazzo et al. [78] developed an optimized feed-forward neural network membrane distillation system which was tested with and without the control system. This system was allowed to set the feed flow rate at an optimal value even when the external operating conditions were not normal. Soleimani et al. [79] investigated commercial poly(acrylonitrile) based UF membranes for suitability for treatment of oily wastewaters. The experimental information such as trans-membrane pressure, cross-flow velocity, feed temperature and pH, were used as input to simulate permeate flux and fouling resistance. An excellent match between the experimental data and predicted values was observed. Anupam et al. [80] developed a three-layered feed-forward ANN model to predict the adsorption capacity and efficiency for the removal of chromium (VI) from wastewater using activated carbon. Salehi and Razavi [81] investigated a nanofiltration process using ANN and ANFIS to predict the permeate fluxes and sodium chloride rejection in waste brine. Both models were trained using 30% of available experimental data. ANN with one hidden layer and eight neurons were used as training method. Pardeshi et al. [82] developed a Taguchi-neural approach to predict optimum conditions for FO groundwater desalination.

Cao et al. [83] developed a vacuum membrane distillation (VMD) desalination model using ANN after considering different operating parameters such as feed inlet temperature, vacuum pressure, flow rate and salt concentration of feed. The overall agreement between the ANN and experimental data, expressed in terms of correlation co-efficient, was impressively found to be more than 0.994. This model obtained maximum permeate flux and acceptable coefficient of variation. Shirazian and Alibabaei [84] developed an AGMD system using ANN and particle swarm optimization. It includes input variables such as feed flow rate, cold feed inlet temperature and hot feed inlet temperature with output variables such as distillate flux, cold feed outlet temperature and GOR. Cabrera et al. [85] simulated and modelled wind-powered SWRO plant installed on the Gran Canaria (Spain) using three machine learning techniques, ANN, SVM and Random forests to predict the performance of desalination plant. It includes performance variables such as feed flow rate, pressure, permeate flow rate and permeate conductivity. A short summary of research contributions around desalination technologies using ANN by researchers has been presented in Table 3.

Table 3
Summary of research contributions pertinent to advanced desalination concepts using ANN approach

Authors		Year	Artificial neural network applications
Abdulbary et al.	[56]	1993	Preliminary work, modelling of MSF desalination plant
Selvaraj et al.	[57]	1995	Identification of MSF desalination plant
Niemi et al.	[63]	1995	Simulation of membrane separation
Dornier et al.	[64]	1995	Dynamic modelling of crossflow microfiltration
Woldai et al.	[58]	1997	Adaptive control of MSF desalination plant
Al-Shayji and Liu	[86]	1997	Modeling of large-scale commercial water desalination plants
Delgrange et al.	[87]	1998	Prediction of UF transmembrane pressure
Delgrange et al.	[65]	1998	Modelling of UF fouling
Delgrange-Vincent et al.	[66]	2000	Fouling and backwash efficiency in UF for drinking water
Bowen et al.	[67]	2000	Predicting salt rejections at NF membranes
Jafar and Zilouchian	[44]	2001	Modelling of RO desalination plant
Tarifa et al.	[59]	2002	Fault diagnosis for an MSF
Al-Shayji and Liu	[88]	2002	Modelling of large-scale desalination plant
Cabassud et al.	[89]	2002	Modelling of UF plant
Shetty and Chellam	[68]	2003	Predicting membrane fouling using NF
Shetty et al.	[69]	2003	Predicting contaminant removal drinking water NF
Murthy and Vora	[45]	2004	Prediction of RO performance
Abbas and Al-Bastaki	[46]	2005	Modelling of an RO water desalination unit
Zhao et al.	[90]	2005	Predicting RO/NF water quality
Tanvir and Mujtaba	[60]	2006	MSF desalination process
Al-Zoubi et al.	[70]	2007	Modelling of sulfate and potassium salts by NF
Gao et al.	[71]	2007	Heat pump type seawater desalination plant
Darwish et al.	[91]	2007	Modelling of NF membranes
Libotean et al.	[92]	2008	Organic compounds passage through RO membranes
Libotean et al.	[47]	2009	Modelling the performance of RO membrane desalting
Lee et al.	[48]	2009	Optimizing operation of SWRO desalination plant
Yangli-Quintanilla et al.	[72]	2009	QSAR for rejection of neutral organic compounds by NF and RO
Ali Aminian	[61]	2010	Prediction of temperature elevation for seawater in MSF
Khayet et al.	[49]	2011	Methodology of desalination plant by RO
Khayet et al.	[73]	2012	Modelling and optimization of desalination by AGMD
Esfahani et al.	[74]	2012	Modelling of MED-TVC desalination system
Sargolzaei et al.	[75]	2012	Membrane permeate flux and rejection factor prediction
Salehi et al.	[76]	2012	Modelling of nanofiltration process
Khayet et al.	[77]	2013	Modelling of SGMD system
Porrazzo et al.	[78]	2013	Solar-powered membrane distillation unit
Soleimani et al.	[79]	2013	Modelling of membrane separation
Barello et al.	[50]	2014	Modelling of RO desalination process
Tayyebi et al.	[62]	2014	Modelling of MSF desalination plant
Barello et al.	[51]	2015	Modelling of RO desalination process in batch mode
Aish et al.	[52]	2015	Modelling of RO desalination plant in the Gaza Strip
Salami et al.	[53]	2016	Mathematical modelling to simulate osmosis membrane
Anupam et al.	[80]	2016	Modelling for removal of chromium (VI) from wastewater
Salehi et al.	[81]	2016	Modelling of waste brine nanofiltration process
Pardeshi et al.	[82]	2016	FO using Taguchi-Neural approach
Cao et al.	[83]	2016	Modelling and simulation of VMD desalination process
Cabrera et al.	[54]	2017	Simple seawater reverse osmosis plant
Ruiz-Garcia and Feo-García	[55]	2017	Seawater reverse osmosis desalination plants
Shirazian and Alibabaei	[84]	2017	Modelling of AGMD systems
Abujazar et al.	[93]	2018	Modelling of inclined stepped solar still system
Roehl et al.	[94]	2018	Modelling of a three-stage RO system
Cabrera et al.	[85]	2018	Modelling of SWRO using ANN, SVM and Random forests

Fig. 7 illustrates quantitatively the progress in research contributions globally from 1993 to 2018 and focussed on the modelling and simulation of desalination processes using ANN. The analysis of recent trends shows that the research contributions using ANN have increased significantly in the last 5 years highlighting increased contribution of ideas and interest in this field.

The modelling strategy of desalination process using ANN involves identification of basic input and output parameters for modelling and evaluating the performance of the plants (Fig. 8). The input parameters may include temperature, TDS, flow rate, trans-membrane pressure, NaCl concentration and pH of feed; motive steam flow rate, while the output parameters may involve permeate flow rate, permeate and distillate flux, cold feed outlet temperature and GOR. The selection of parameters depends upon

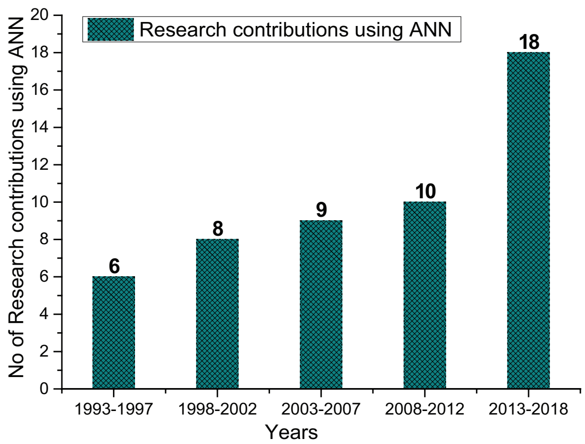

Fig. 7. Number of research papers related to ANN applications in desalination from 1993 to 2018.

the requirements of the desalination plants. Li et al. [95,96] presented the modelling strategy of ANN, through training and testing. The authors have explored the power of prediction of machine learning algorithms for optimizing solar water heater performance [95] and also review the interesting application of ANN in catalysis. The training process also called as learning process, consists of dataset preparation and involves judicious choice of variables. For a good training and data fitting process, dataset should be large and data range be wide. Testing process involves validation of the so formed training model.

Rather than ANN, some other machine learning algorithms are also used in desalination field. The performance of any such algorithm depends upon the quality as well as quantity of data [97]. ANN has some inherent limitations and challenges in a particular task or process. To overcome these, deep neural networks (DNNs) are sometimes used. DNN is a recent machine learning algorithm that includes multiple levels of representation and abstraction to appropriately represent the dataset of any process or plant. ANN is not limited to feed form algorithmic but the kernel-based ANN is also widely used in desalination processes. For instance, Cabrera et al. [85] presented the kernel-based ANN to resolve linear regression problems using support vector machines (SVM) in order to appropriately model a wind powered SWRO plant. It is a set of related supervised learning method used for classification and regression. The advantage of SVM over ANN is that the former provides a global and unique solution while the latter may suffer from multiple local minima. Every machine learning algorithm (including ANN) have merits and demerits and are used depending upon the performance of the plants. The advantages of ANN include its adaptability to easily train and operate in any operating conditions; minimal effect of noisy or incomplete data; provides great flexibility; training time of this approach may be long, but once trained,

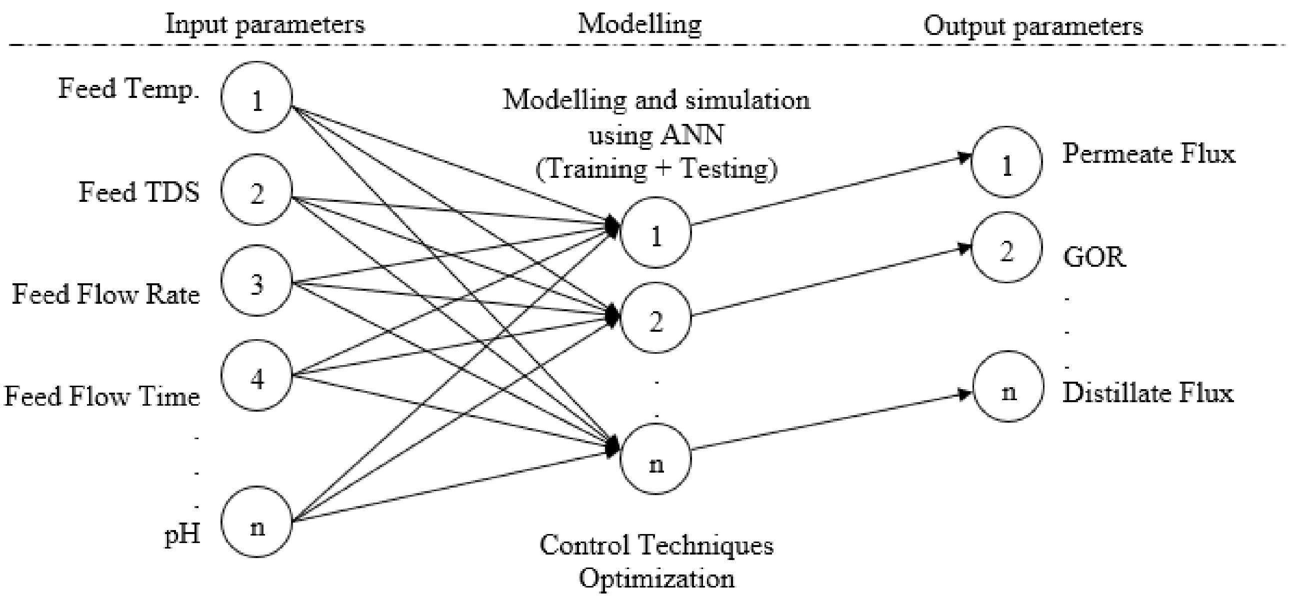

Fig. 8. Modelling strategy of desalination process using ANN.

takes less time to calculate results; potential to be used online in a control system; etc. Some of its limitations include: takes long training time and efforts which increases with the complexity of the problem; reliability depends on the accuracy of training data set used; performance depends upon the proper selection of input and output variables; need of large amount of training data set, etc. These limitations require making appropriate changes in ANN methodologies and implementation to model such desalination systems effectively.

5. Conclusions

This review summarizes the necessity of quality water for survival of human, animals and plants. The analysis of different prospective of water: chemical composition of seawater, water quality index and basic drinking water services across the globe has been detailed. The recent trends and significant developments in the area of desalination plants from 1966 to 2016 have been presented. The use of automation and control has saved time, money, energy and provided high drinking water capacity. The current scenario of desalination has been highlighted with focus on advances in control system, information technology, system diagnosis, measurement and instrumentation system, modelling, simulation and use of artificial intelligence. Many renewable energy resources such as solar energy, wind energy, geothermal energy, etc., being used in different remote and desert areas to assist such desalination plants, have been reviewed. Among various desalination technologies used globally, RO is the most efficient and low power consuming technology with about 62% fractional usage of all available technologies. Recently, advanced and hybrid technologies (MED-TVC, ME-VMD) have been developed with low energy consumption, better efficiency and high product output. A review of recent trends and development of desalination technology using ANN by various researchers from 1993 to 2018 shows the different prospective and increasing importance and interest in this area. While every technology has its own merits and demerits, the review indicates that RO is the most widely used desalination technology across the world and its modelling and simulation using ANN is a challenging area in this field. The literature study presented here reflects that ANN is an important and appropriate tool to assist desalination plant operations, by enabling efficient decision making.

Symbols

AC — Adsorption cycle
AD — Adsorption desalination
AGMD — Air gap membrane distillation
ANFIS — Adaptive neuro-fuzzy inference system
ANN — Artificial neural network
BPANN — Back-propagation artificial neural network
DM — Demineralization
ED — Electrodialysis
EDR — Electrodialysis reversal
FO — Forward osmosis
HDH — Humidification-dehumidification
IHM — Integrated/hybrid membrane
IXR — Ion exchange resin
GOR — Gain output ratio
MBR — Membrane bioreactor
MD — Membrane distillation
MED — Multi-effect distillation
MLP — Multi-layer perceptron
MSE — Mean squared error
MSF — Multi-stage flash
MSF-OT — MSF-once through
MSF-M — MSF-simple mixture
MSF-BR — MSF-brine recycle
MVC — Mechanical vapour compression
NF — Nanofiltration
NVD — Natural vacuum desalination
LBQ — Learning vector quantization
ppm — parts per million
RED — Reverse electrodialysis
RO — Reverse osmosis
RO-DM — Reverse osmosis demineralizer
RNN — Recurrent neural networks
RSM — Response surface methodology
SGMD — Sweep gas membrane distillation
SWRO — Seawater reverse osmosis
TDS — Total dissolved solids
TE — Temperature elevation
TVC — Thermal vapour compression
UAE — United Arabs Emirates
US — United States
VMD — Vacuum membrane distillation

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