Energy and AI 7 (2022) 100123

Contents lists available at ScienceDirect

Energy and AI

journal homepage: www.sciencedirect.com/journal/energy-and-ai

Artificial intelligence application in a renewable energy-driven desalination system: A critical review

Qian He, Hongfei Zheng, Xinglong Ma, Lu Wang, Hui Kong *, Ziye Zhu

School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China

ARTICLE INFO

Keywords:
Artificial intelligence
Desalination
Renewable energy
Algorithms

ABSTRACT

Artificial intelligence, an emerging technology, widely exists in the field of engineering science and technology. Due to its high efficiency and precision, artificial intelligence is increasingly used in the optimal control of water treatment and seawater desalination. Generally, the design of a desalination system includes four processes: site selection, energy prediction, desalination technology selection and systematic parameter optimization. To a large extent, these choices depend on the experience and relevant criteria of researchers and experts. However, facing the scientific and technological progress and growing expectations, it is impossible to solve such complex nonlinear problems by simple experience and mathematical models, but artificial intelligence is good at this. In this paper, we synthetically analyzed and summarized the application of artificial intelligence in the field of seawater desalination with renewable energy. Artificial intelligence application in desalination is mainly divided into four aspects: expert decision-making, optimization, prediction and control by sequence. The features of artificial intelligence employed in the design of desalination systems not only realize the maximum of efficiency and minimum of cost, but release the human resources. After analyzing the four processes of desalination, it is found that artificial neural network and genetic algorithm are more widespread and mature than other algorithms in dealing with multi-objective nonlinear problems. This paper overviewed the application of artificial intelligence technologies in decision-making, optimization, prediction and control throughout the four processes of desalination designs. Finally, the application and future development prospect of artificial intelligence in the field of seawater desalination are summarized.

1. Introduction

According to the report "The Global Risks Report 2018" by the World Economic Forum [1], the water crisis has been seen as the fourth global risk in terms of impact on society. Desalination is an intelligent and promising technology to solve the crisis of freshwater resources. Therefore, more and more institutions and programs turn their focus on seawater desalination to obtain freshwater for agricultural irrigation and domestic water, etc. Traditional desalination technologies consume a lot of fossil energy, which can bring about the environmental pollution and energy exhaustion. The high-level energy consumption and greenhouse gas emissions somehow restricted the development of seawater desalination. People tend to find a sustainable way to drive this process, such as solar energy, wind energy, ocean thermal energy and geothermal energy, even including radiative cooling technology [2], which is a passive refrigeration mode without extra energy consumption. Therefore, seawater desalination based on renewable energy (RE) becomes a priority for solving the freshwater problem.

Generally, the desalination process involves many aspects, such as site selection, size optimization, the operation parameter selection and many other complex nonlinear problems with multi-degree of freedom, especially with RE systems. In most cases, the selection of parameters relies on the experience of engineers and researchers. Moreover, the overall design of the large-scale desalination plants which involves a number of design requirements and design variables has become a complex integrated design problem. Besides, with the influence of uncertain factors such as different loads and energy input, there is no single fixed feasible scheme that is always effective or keeps the system optimized. It is hard to meet the multi-objective requirements of efficiency and cost simultaneously only by the experience and knowledge of engineers and researchers. These factors somehow hinder the development of large-scale seawater desalination. More and more organizations and researchers long to seek a kind of engineering technology means that not

* Corresponding author.
E-mail address: konghui@bit.edu.cn (H. Kong).

https://doi.org/10.1016/j.egyai.2021.100123
Received 14 July 2021; Received in revised form 19 September 2021; Accepted 16 October 2021
Available online 18 October 2021

Nomenclature

Abbreviation

AI	artificial intelligence
ANN	artificial neural network
AHP	analytical hierarchal process
ANFIS	adaptive neuro-fuzzy inference systems
AGMD	air gap membrane distillation
BP	back propagation
CI	computational intelligence
DSS	decision support system
ED	electrodislysis
ES	expert system
FL	fuzzy logic systems
GA	genetic algorithm
GRG	generalized reduced gradient method
GOR	gained output ratio
HDH	humidification-dehumidification
HRESs	hybrid renewable energy systems
LM-BP	Levenberg-Marquardt back propagation
MCDM	multi-criteria decision making
MSF	multi-stage flash
MED	multi-effect distillation
ML	machine learning
MPPT	maximum power point tracking algorithms
MLP	multilayer perceptron hybridized
ORC-RO	organic rankine cycle-reverse osmosis
PSO	particle swarm optimization algorithm
QP	the successive quadratic programming
RE	renewable energy
RO	reverse osmosis
RBF	radial basis function
RSM	response surface methodology
SSP	solar distiller productivity
SGMD	gas membrane distillation process
SAA	simulated annealing algorithms
SWP	stepwise regression
SOS	symbiotic organisms search
SVR	support vector regression algorithms
TDS	total dissolved solids
VC	vapor compression

only can realize all aspects of optimal control, but liberate manpower and realize efficient and complex computing.

Therefore, in the information age, with the development of network techniques, a growing number of countries have launched programs to take the lead in the industrial field. They integrate machine learning and other artificial intelligence (AI) techniques into energy system design processes, such as the "DIFFERENTIATE" program launched by the U.S. Department of Energy's (DOE's) [3], the "three-year action plan" for promoting the development of a new generation of AI industry (2018–2020) by the China Ministry of industry and information technology. AI is known for its explanation ability, flexibility and semiotic reasoning in the field of engineering application. The use of AI technology will not affect the operator's control of the system or manual control capability. On the contrary, the instant and accurate response of computer machines will provide better performance on quality control and production efficiency. In this aspect, by focusing on non-repetitive tasks to improve overall process efficiency and minimizing human error. Especially, in multi-variables and nonlinear problems, AI technologies have huge advantages in smart decision-making and weighing. As a new engineering technology, AI technologies can also play an important role in the field of seawater desalination, which could release human resources to carry out these complex calculations, optimization design and control under disturbance.

The history of AI used in seawater desalination can be traced back to the 1990s [4]. On the employment of computational intelligence (CI) systems, numerous studies have been undertaken in the field of seawater desalination. The application of CI in desalination processes is mainly involved in three aspects: prediction (load forecasting), control (alarm processing and fault detection) and overall evaluation (operational optimization, security assessment and economic assessment) [5]. As a branch of the AI system, CI is only an experienced computer thinking program with independent thinking ability to assist human beings to deal with various problems. Based on intelligent computing, a number of experts constantly improved the mathematical basis of intelligent algorithms to realize the processing like a human. Hu et al [6] designed an optimized aperiodic superlattice to minimize coherent phonon heat conduction by alternately coupling coherent phonon transport calculation and machine learning. Chao Chen et al. [7] outlined the combination of sustainable clean energy with desalination technologies. By comparing the potential coupling methods of solar desalination, the related research was useful in comprehending the freshwater crisis in China. Hu et al. [8] proposed to achieve high performance of thermophotovoltaic systems by using machine learning algorithm. EI-Arwash et al. [9] proposed an initialization method with particle swarm optimization (PSO)-based genetic algorithm (GA). It was time-saving and efficient in solving the desalination compensation circuit allocation and size. It also proved that this hybrid algorithm used to solve high-dimensional variable problems has more advantages than the traditional way. Abid et al. [10] used GA to optimize the multi-effect desalination (MED) system with energy recovery. Considering the maximization and minimization of multiple objective functions, the cost of water production was reduced by 8.25%. However, the use of AI technologies has not formed a complete architecture and framework in the design process of desalination. The algorithms tend to have different performance in optimizing and predicting, which would bring out the deviation of ideal operation. There should be a framework for the application of AI to the local and overall desalination system, and combine the ideas of using intelligent algorithms.

This review aims to untangle the application of AI in the process of seawater desalination with renewable energy sources and introduce the development direction of AI in seawater desalination in the future. The first part combines the relation of AI and seawater desalination. Some suggestions are provided on how to use AI technologies to optimize the desalination process more reasonably. The second part presents the AI used in the typical desalination system and the overall idea of technical relevance. The third part of the paper introduces the use of AI in four aspects, including decision-making, parameters prediction and optimization, also the control with AI technology. The fourth part compares the different algorithms and concludes their merits and demerits. The last part not only discusses the development status of this research, but also summarizes the development trend of seawater desalination.

2. Brief description of RE-desalination systems

Generally, the common desalination technologies in the world are mainly divided into physical and chemical methods [11], as shown in Fig. 1. During the process of seawater desalination system established, in order to ensure the optimal efficiency of the system, the system involves various aspects. As shown in Fig. 1, thermal solar desalination includes many modes, such as adsorption distillation, low temperature multi-effect, air humidification and dehumidification, compression distillation and refrigeration method, etc. However, the heating

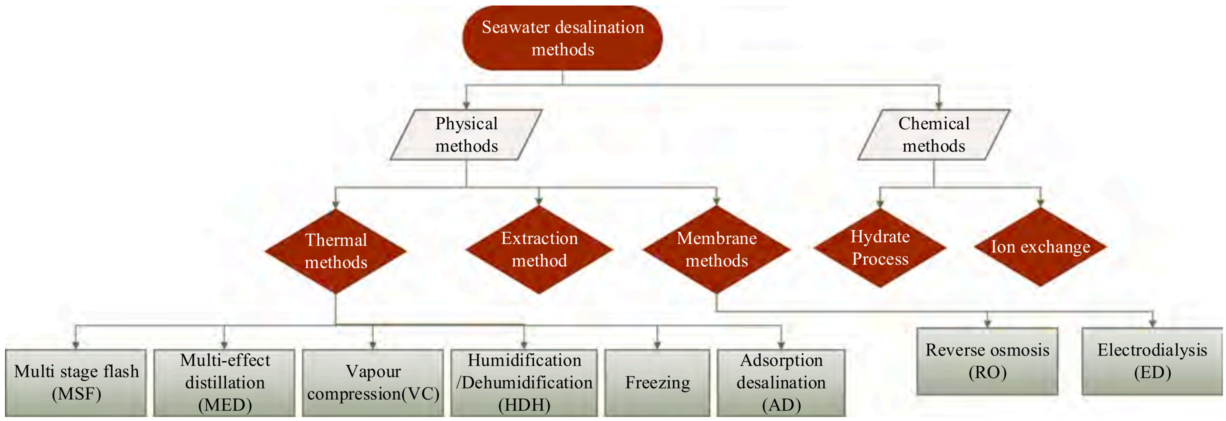

Fig 1. Schematic of desalination methods.

temperature range required by these desalination modes is different. For example, the operating temperature range of adsorption distillation is from 80℃ to 150℃, low temperature multi-effect distillation is from 40℃ to 70℃, air humidification and dehumidification is from 60℃ to 100℃, and compression distillation is from 40℃ to 60℃. Therefore, the heat source temperature provided by solar heat collection system must be considered in the choice of operation mode.

The diversity of seawater desalination technologies and the influence of various environmental and social factors make the establishment of a seawater desalination plant be complex. Generally, the application process of these seawater desalination technologies involves heat collection, heat transfer, heat storage, desalination unit, regenerative, concentrated seawater treatment and fresh water utilization, etc. At least, it can be divided into three regions, including collection region, energy storage region and desalination region, as shown in the Fig. 2. There are many parameters involved in these processes, so it is necessary to predict and optimize the parameters when setting them. AI will be able to better replace manpower for these large and complex computing tasks.

Due to the development of solar energy concentrating technology, people have developed many efficient solar energy concentrating and heat collecting systems, such as tower concentrating, parabolic trough concentrating, trough CPC concentrating, and high efficiency heat pipe vacuum tube collector. These systems can easily obtain high temperature heat energy in the range of 150℃–300℃. It can be seen from this that the operating temperature range of any single thermal desalination model mentioned above does not match well with the heat source temperature provided by the solar heat collection system. So efficient desalination system should be an integration of multiple desalination models to match the heating temperature of solar heating system. However, the integration of multiple desalination models should not be simply series, but the topological construction of many kinds of models. Therefore, in order to obtain maximum efficiency of topology system, some important parameters such as its operating temperature, the flow rate of heating water and seawater, circulating air flow rate and operating pressure need to be regulated in time, and that is where artificial intelligence can be used. In addition, because the solar energy is changed with the season and time, and the heat energy provided by the solar energy collection system is unstable, how to regulate the heating temperature and heating amount of the solar energy collection system and to achieve the optimal match with the desalination device are also where artificial intelligence can come in handy.

3. The ways of using AI in RE-desalination systems

According to the reviewed literature, it is clear that the algorithms of AI can be mainly divided into four categories: decision making [10–15], parameter optimization [16],[17], parameter prediction [18],[19] and control [20],[21], as shown in Fig. 3. The four aspects just can be applied in solar desalination field.

Firstly, because of the richness of local renewable energy source, the lack of local water resources, the price of heat source and the convenience of transportation will directly affect the economic benefits of solar seawater desalination system in the future, the decision making

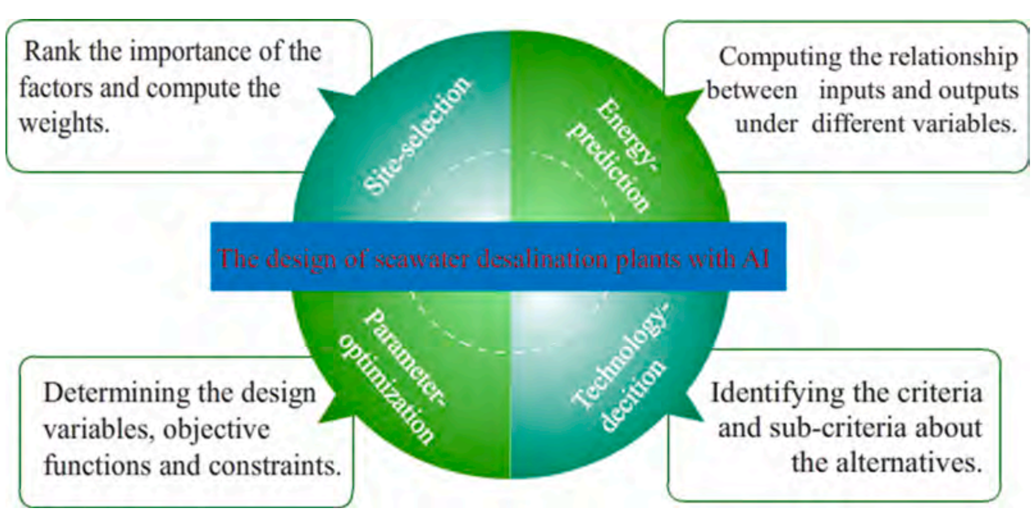

Fig 2. General process of seawater desalination.

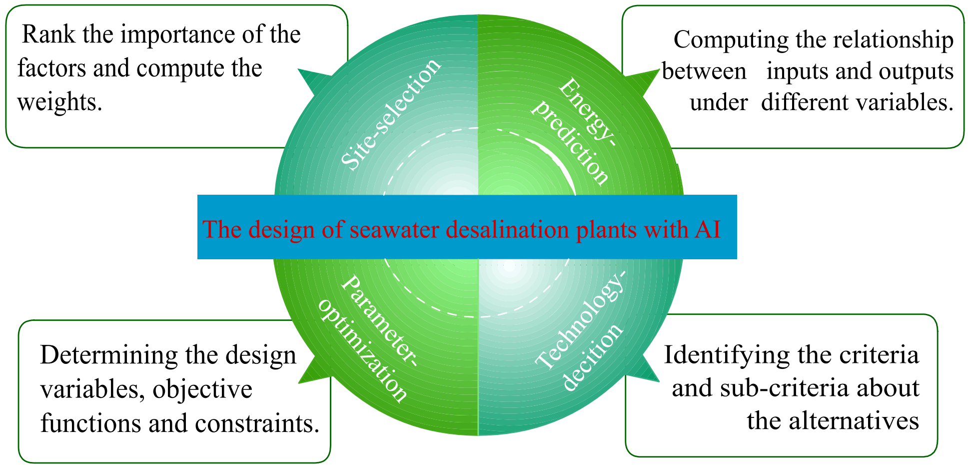

Fig 3. The design of seawater desalination plants with AI technologies.

process is facing a new challenge. AI can just provide the service for that.

Secondly, as discussed in the previous section, solar water desalination system has the characteristics of multi-parameters. Therefore, it is important to predict and optimize the operation parameters, which is reflected not only in the design stage, but also in the operation stage, including the prediction and control of energy input and production output.

Finally, there exists the heating fluctuations in solar heat collection system, and these fluctuations will have an impact on the operation parameters of desalination system. In order to obtain the highest economic benefits, the operation parameters need to be controlled, which is the application value of artificial intelligence in solar seawater desalination because AI technology has its merits to solve these multi-variable and multi-function problems.

The difference of various AI technologies lies in the different algorithms they relied upon. Based on literature materials, there are several typical algorithms generally used, as shown in Table 1. Their application aspects in RE-desalination are shown in Fig. 4.

A heuristic optimization algorithm is the preferred way to solve the operating parameter optimization problem. Many usual practices tend to select a small number of options for evaluation based on experience, knowledge and rules. This method is not real one, and it is hard to balance the local and global optimization. Therefore, new methods (Fig. 4) such as AI can be a priority to overcome the shortcomings of traditional methods to realize the desalination design. By roughly classifying the problems involved in the design process of seawater desalination, the design steps can be integrated and divided into four main directions of an intelligent algorithm. They are decision-making, optimization, prediction and control.

According to different optimization objectives and constraints, different algorithms are applied to solve the problem. These heuristic optimization algorithms mainly include genetic algorithm (GA), artificial neural network (ANN), particle swarm optimization algorithm (PSO), decision support system (DSS), back propagation (BP), etc.

Table 1
The advantages/disadvantages of commonly used algorithms of AI.

Algorithms	Advantages	Disadvantages	Application
ANN, BP	Self-learning function, associative storage function, optimal solutions at high speed	High computing cost	Applicable to optimization and prediction
GA	Large coverage, overall optimization	Low efficiency, computational complexity	Commonly used for optimization
PSO, DSS, ES	Fast convergence speed, self-renewal ability	Easily trapped local solution	More suitable for decision weight

According to different optimization contents and weights, these algorithms have their own advantages. In the literature, there is no lack of comparison on the application of various algorithms in seawater desalination, which will not be repeated here.

3.1. Decision-making by AI in RE-desalination systems

The site selection of seawater desalination plant is a strategic decision. Decision makers need to deal with a variety of standards and weight of various factors, which sometimes conflict with each other in essence. In addition to technical and operational aspects, sustainability (social, environmental and economic) needs to be considered in the site selection of seawater desalination plant. Similarly, the selection of desalination technology also has these considerations, which can be seen as the same problem with site selection. Therefore, both of the desalination plant site and technology selection are considered as a multi-criteria decision making (MCDM) problem [22]. How to make the selection among various technical elements and standards requires goal alignment. AI has become a good choice for decision-making. A multi-criteria decision support system (DSS) is put forward to rank these criteria [23]. It has been developed in many countries by considering social, environmental, economic, technical and operational aspects.

One of the most widely used DSS is based on Analytical Hierarchal Process (AHP). AHP was put forward by Saaty in 1980 and from then on, it has been developed in many applications [24]. Due to its simplicity, AHP has become the priority for managers and decision-makers by breaking down the complex problem into hierarchal structures [25]. By integrating the site selection criteria and ranking them, the DSS checks the consistency of expert decisions. Fig. 5(a) shows the factors involved in the selection process, which take the benefit into account. Generally, first step of AHP is to identify the criteria and sub-criteria of these factors, and then determine the weight of each criteria. Judgment matrix is used to explain the importance of factors quantitatively. Fig. 5(b) shows the general steps of AHP. According to the factors of location selection, the expert group can have a series of alternatives of desalination location, and then the criteria and sub-criteria are identified. Based on the two mentioned aspects, a number of optimal solutions can be obtained. If the optimal solutions are approved with the objectives function, such as minimum desalination cost, the solution will be compared pairwise. The better one will be accepted and the criteria will be ranked accordingly. Otherwise, the solution will be exerted a quantitative condition and then the new optimal solution is obtained again.

Likewise, there are many desalination technologies in the market which involve the constrains of environment, technology and financial condition, etc. This is in accord with the MCDM problem, which can also be solved by DSS. Alzu'bi et al. [26] proposed a method to upkeep

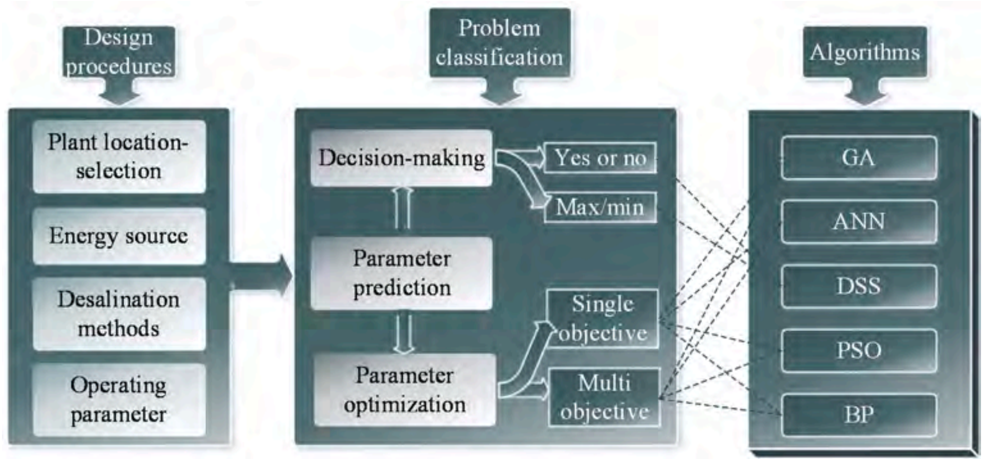

Fig 4. Application aspects of AI algorithms.

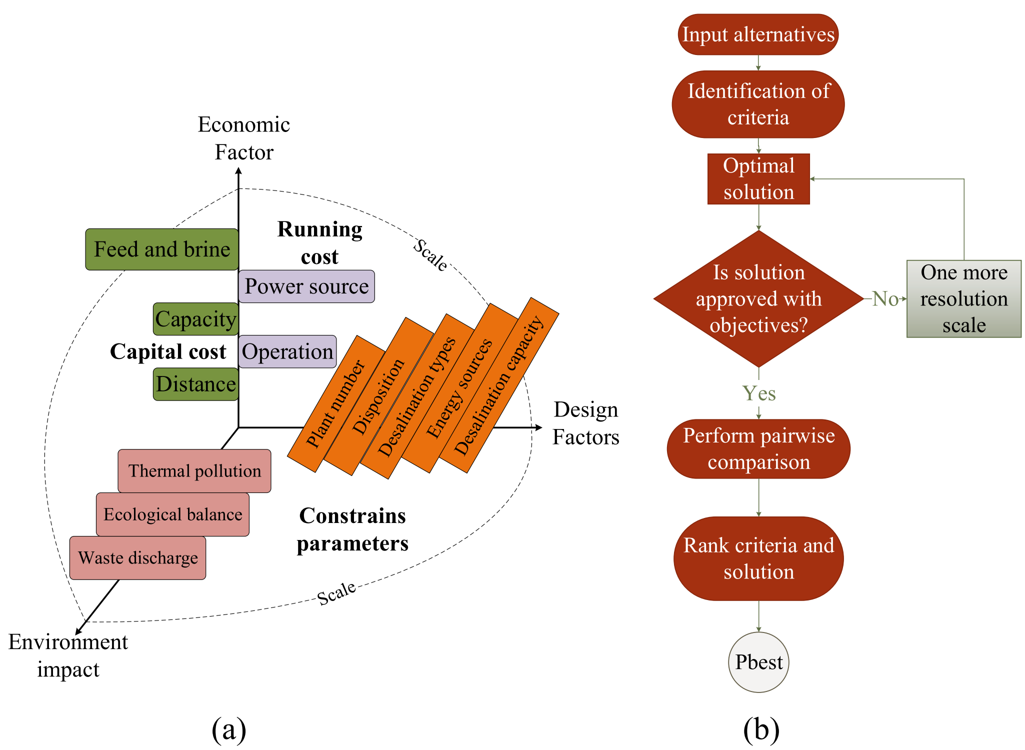

Fig 5. (a) Effecting factors for the site selection of seawater desalination. (b) The steps of decision support systems.

strategic decision-making for the best water desalination facility. This method made up for the imperfection of the decision-making system and weight the different desalination technologies. Amos Bick [27] proposed an AHP-based decision-making approach to determine the best technology for the seawater reverse osmosis plant. Hajeeh and Al-Othman [28] used a fuzzy set theory-based hierarchy model to select the desalination methods.

In MCDM problem, it is important to identify the criteria and sub-criteria about the alternatives. Generally, there are four levels in the decision hierarchy. They are overall goal, the criteria, sub-criteria and the alternative desalination technologies. By ranking the importance of the criteria, they can be categorized into three main levels and ten sub-levels in Table 2. The desalination technologies, criteria and sub-criteria structure the decision hierarchy, as shown in Fig. 6. The experts compute the weights with transfer functions to determine the desalination technologies for maximizing the overall goal. With the appearance of AI technology, the time and effort of people are released to do the above work of nonlinear multi-criteria and selection.

3.2. Parameter optimization by AI in desalination systems

Operating parameters in desalination systems refer to the parameters that can be manually adjusted in the system operation. According to the relationship between operating parameters and the desalination process, the operating parameters are divided into four categories: energy parameters (energy input), structure parameters (size), feed parameters (pressure, pH value, feed flow rate, total dissolved solids (TDS), seawater temperature) and surrounding parameters (ambient temperature, wind speed, solar radiation).

In a desalination system, the combination of different parameters can be realized by adjusting and controlling the equipment operation parameters, but the best performance cannot be obtained by simple

Table 2
The evaluation criteria, sub-criteria and definition for desalination technologies [12].

Criteria	Sub-criteria	Definition
Environmental (C1)	Brine management (SC1)	Handling and disposal of brine
	Air pollution (SC2)	Water vapor as a byproduct of the thermal desalination process
Technical (C2)	Operational (SC3)	Skill required to operate technology
	Reliability (SC4)	The ability of technology to perform steadily under stated conditions
	Expandability (SC5)	The ability of technology to accommodate additions to its capacity or capabilities
	Adaptability (SC6)	Compatibility of technology with quality of influent water
	Water recovery (SC7)	Product water relative to the input water flow
	Treated water quality (SC8)	The salinity of product water
Economical (C3)	Capital costs (SC9)	Purchase of mechanical equipment, installations and other incidental construction work
	Operating costs (SC10)	Wages and the funds spent for the energy, the products, services and maintenance.

arrangement and combination of experience. For example, it is difficult to determine the operating conditions that maximizing the water production and efficiency. The purpose of parameter optimization is to find a group or several groups of operating parameters to optimize the system performance. Therefore, parameter optimization is a very important work in the desalination system, which can directly affect the quality and the efficiency of the desalination system.

The determination of design variables, objective functions and constraints are the general steps of parameter optimization, by which the basic model of desalination system operation is established. Traditionally, doing experiments is the way to find out the relationship between the objective function and design variables. However, if the process of discovering the relationship can be transformed into an optimization problem, the optimal solution will be obtained through a mathematical model. Unfortunately, there are many variables involved in seawater desalination, also these variables are often changeful due to the weather condition change, so the traditional mathematical method cannot get the optimal design solution efficiently. Therefore, the emergence of AI, such as GA and PSO, replaces the designer to solve the optimization problem of operation parameters. In the optimization of operating parameters, the number and range of design variables decide the size of the search space, which has an impact on the system operation performance. The number of design variables determines the dimensions of the search space and the range determines the length of each dimension. How to find a position in the search space is the optimization problem, whose objective function has amount of optimal value. Generally speaking, the larger the search space, the longer the computation time. Different algorithms represent different search strategies, which can also affect the amount and time of calculation. In many conditions, a large number of variables potentially affect the targets, making the design process a tough work. However, the conventional statistical process control methods are still used by most researchers, which mainly exert a univariate statistical approach in the analysis. Oftentimes, the univariate statistics cannot succeed in catching the fundamental patterns in data processing. This happens to be the advantage of AI in solving intricate engineering problems, by using a multivariable processing method to obtain the optimal solution of the objective function.

Fig. 7 shows the number of publications until now on operating parameter optimization of desalination systems using intelligent algorithms. There are about 320 literatures on this topic. Since 2015, more than 20 literatures are published each year. As the typical algorithms of AI, GA has the most extensive application among those literatures. As a kind of evolutionary algorithm, GA is used to solve optimization problem, which has merits in optimizing the heat collection and desalination process. While it tends to converge to the local optimum, but can not reach the global optimum. ANN and PSO are also widely used in this field. They can better obtain the global optimization. Compared with PSO algorithm, the ANN has a bigger search space but a lower convergence rate. Researchers prefer to combine two or more of them for better performance of parameters optimization, such as GA-PSO, ANN-PSO. Some representative literatures are selected for review, as shown in Table 2. The constraint conditions of operation parameters in desalination design cannot be ignored, which are determined by energy source, surrounding environment and properties of feed water, etc. Due to the less of guiding significance for other studies, the constraints of operating parameters are not listed in Table 3.

3.3. Parameter prediction by AI in desalination systems

Generally, if the seawater desalination system is selected, it is necessary to evaluate the scope of the relevant parameters to achieve the optimal configuration in a certain space. The widely common prediction is energy prediction, which mainly includes the energy input of solar energy and hybrid energy, as well as the scale degree and the system efficiency. Table 4 shows that some desalination literature use AI to predict parameters of the process. It can be seen that different algorithms have unique advantages in different predicted parameters, by

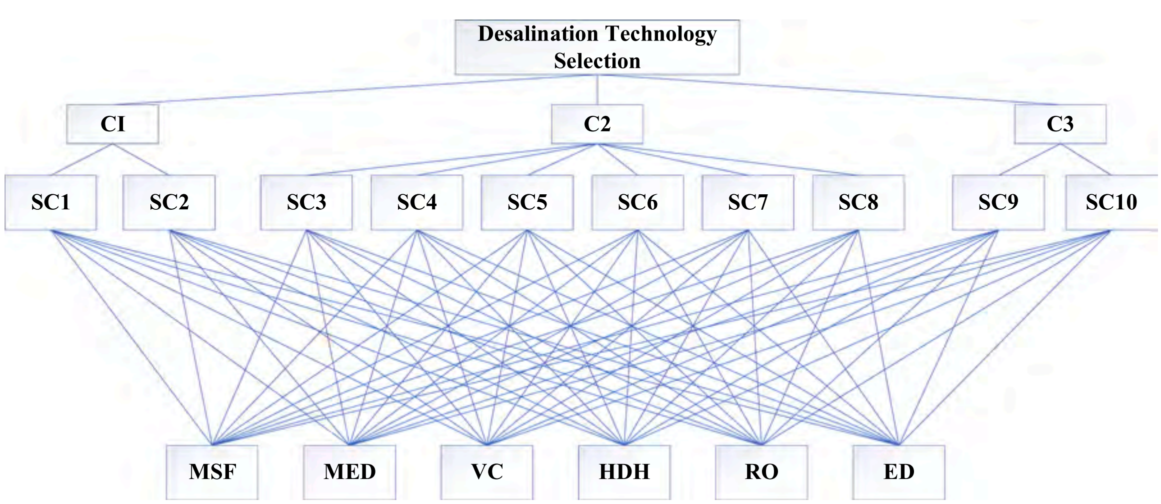

Fig 6. The decision hierarchy for desalination technology selection [12].

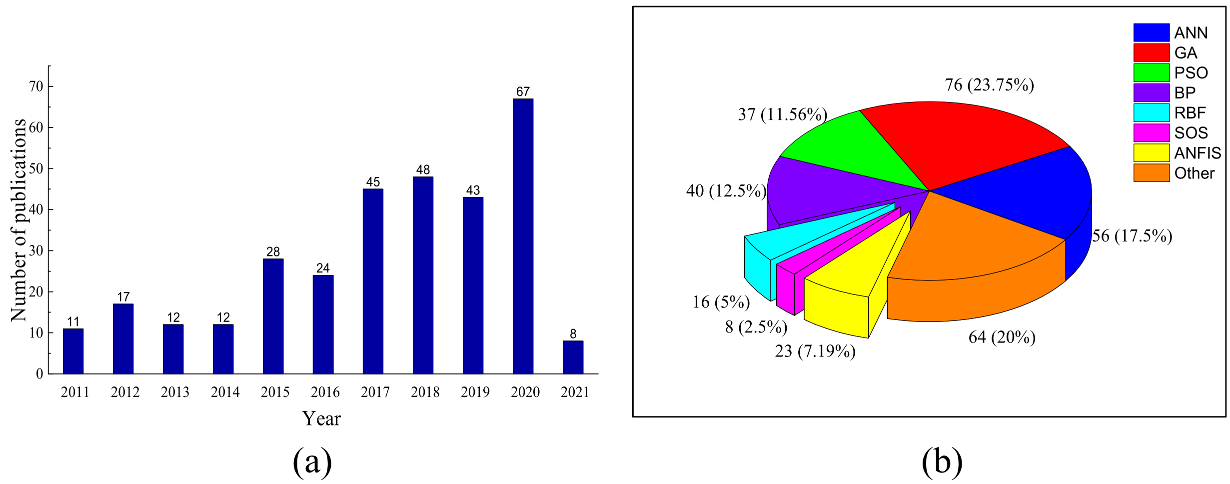

Fig 7. Statistical information of publications about operating parameter optimization; (a) Number of publications by year; (b) Number of publications on the algorithm.

which the capability and optimal allocation of the system can be clear. Combining with the objective function to establish the model, the results are very mild with the experimental data.

Mashaly and Alazba [46] used ANN to forecast the efficiency of solar still production (SSP). It is the key step in reducing capital risks involved in the desalination project. SSP, one of the most important equipment in the solar desalination process, was assumed by Mashaly as a function of relative humidity, wind speed, solar radiation, feed flow rate, temperature of feed water, and total dissolved solids (TDS) in feed water. He adopted the back-propagation artificial neural network (BP-ANN) models to predict SSP, which was used to analyzed solar still performance. By comparing the prediction results with real results, he found ANN model was more accurate than stepwise regression (SWR) model. In the AI fields, ANN is proved efficient and accurate both in modeling and predicting the performance of desalination. The prediction and optimization are two interrelated and inseparable elements, which serve each other. The controllable parameters tend to be optimized after the obtainment of the optimal solution of the objective function. And the latter is obtained by predicting the system performance parameters. Different algorithms make sense in the process of dealing with variable elements and the accuracy of the system model. However, the basic idea of these algorithms is similar, that is to simulate neurons to fragment the system by mathematical algorithms. In RO desalination, radial basis function [47] or multi-layer perceptron are common methods to predict the permeate flow, and the design variables tend to select feed parameters, such as inlet pressure, flow temperature. There is no doubt that the ANN is suitable for learning the relationship or mapping between input and output, which has the excellent compatibility between the prediction results and the experimental results. The following three sections summarized the application of AI in main commonly used renewable types of seawater desalination in detail.

3.3.1. *Predictive modeling of solar desalination by AI*

In the solar engineering field, AI techniques (e.g. artificial neural network (ANN), radial basis function (RBF) network, and adaptive neuro-fuzzy inference systems (ANFIS)) have fused machine learning for accurate prediction and modeling. Solar engineering has many nonlinear characteristics, among which the relationships between input and output cannot be obtained by a simple mathematical model. By using machine language, AI techniques generate the element mesh and discover the links among the variables. Generally speaking, ANN and ANFIS models are widely used in predicting the productivity and operational parameters of solar power plants [48]. Radial basis function (RBF) network tends to be used to model the global solar energy [49]. The solar energy is unpredictable in traditional ways due to its season relativity. Neither the solar irradiance, nor the influence of irradiance and other related factors can be accurately obtained in traditional solar desalination systems [50]. The appearance of AI techniques makes the desalination process more efficient and economical. Yaïci and Entchev [51] used ANFIS to predict the solar distiller productivity (SSP), and found that ANFIS model was an effective design tool for solar static systems. Santos et al. [52] studied the applications of ANN for predicting the performance of the solar distiller and determining the combination effect of a single input variable, such as sunlight, wind speed and temperature. Mashaly and Alazba [46], [53], [54] made a comparison between the ANN and other algorithm models.

In the literature research, it is found that the intelligent prediction and control for solar distillation has a lot of space. This is because the solar energy has a direct impact on the energy input and productivity output of the desalination system. Among these techniques, ANN is a useful mathematical model that attempts to imitate the structure and function of a biological neural network to solve complex problems, which has more advantages in estimating the daily global solar radiation [55]. The literatures of solar desalination based on ANN shows that there are three mainly used structures, Multilayer perceptron (MLP), Radial basis function network (RBF) and Recurrent neural network (RNN). The essential structure of ANN model is usually with the structure of A-B-C, which means that the developed ANN model includes an input neuron layer with different input variables X_i, a hidden neuron layer with different transfer function H_j and C output neurons [18]. In order to select the best structure of ANN, the number of neurons in the hidden layer and the best transfer function between layers must be determined by trial and error techniques. The number of neurons in the hidden layer directly affects the structure of the neural network, and its basic structure is shown in Fig. 8. The input variables, such as weed speed, feed flow rate, are located in the input layer and then reach the hidden layer through the selected transfer function. After coupling the results in the hidden layer, the objective function is obtained through the transfer function at the output terminal.

Actually, for input-output response analysis, the ANN is always a priority choice. Whatever algorithm is based on, the ANNs take each neuron as a single computing processor (Fig. 9). The input variable x_j is weighted to single computing neuron and the bias b_i also makes sense in the process. The different input variables are calculated by transfer function to output the results. Inspired from the structure and function of a biological neural network, ANN uses different transfer functions to sum up the connection between input and output and neurons by integrating the input control variables. In some times, the optimization and prediction of parameters are not separate, as they all belong to the input-output response. For example, wind speed and solar irradiance will

Table 3
A summary of parameter optimization studies.

Ref.	Year	Problem Description	Design Variables	Objects	Algorithms
El-Hawary et al. [13]	1993	Use the AI technologies to realize fault detection, control applications, operational optimization, load forecasting, and security assessment	Heating steam temperature, circulating brine temperature, circulating brine flow	The energy cost	ANN
Husain et.al. [42]	1993	Minimize energy cost	Seawater temperature, steam enthalpy and distillate demand or steam supply	Cost	GRG-QP
Fumagali et al. [40]	1994	Keep the desired distillate production	Seawater temperature, heat exchange coefficients, brine top temperature and brine recirculation flowrate	Distillate production flowrate	ES
Gao et al. [31]	2007	Optimize the performance of desalination	Dry and damp bubble temperature of the air, the inlet and outlet cooling water temperature, and the sprinkler temperature of seawater	Water production ratio	ANN
Mjalli et al. [36]	2007	Solve the large-scale MSF model	Flow rate of distillate, brine flow rate, feed flow rate	Initial guesses and starting guesses	GA/ANN
Porrazzo et al. [33]	2013	Optimize feed-forward control system	Feed flow rate	Radiation and distillate flow rate	L-M
Farhad et al. [37]	2015	Assess the ranking of potential development	Environment and the economy	Quantity and quality of water supply and demand	DSS
Shirazian et al. [32]	2017	Examine the relationships between different variables	The cold feed inlet temperature, hot feed inlet temperature, and feed-in flow rate	Gained output ratio (GOR)	PSO
Cabrera et al. [41]	2018	ANN-based control system for wind-powered prototype	Available electrical power, feed temperature and conductivity	System for wind-powered prototype	ANN
Basurto et al. [35]	2019	Optimize the range of possible solar energy and power grid combinations	Water flow of the solar thermal system and solar radiation	The energy generated within a solar thermal system	k-means clustering algorithm/SOM
Rathore et al. [29]	2019	Find optimal control parameters of the RO system	Pressure and pH value at feed stream	The performance of permeate flux and conductivity parameters	SOS
Bachar et al. [43]	2019	Optimize the power generated by PV	Temperature and irradiation	The energy produced by the photovoltaic panels.	MPPT
Khosravi et al. [38]	2019	Presents the effect of different variables on the power generation and efficiency of the system	The ratio of focal point to dish diameter, hour of day, solar radiation, geometric concentration factor and working gas specific constant	The power generation, global efficiency, heat used to run the Stirling cycle, hot Stirling chamber temperature and engine speed	ANFIS-PSO
Ibnelouad et al. [39]	2020	Use the maximum power point tracking (MPPT) method, achieve an efficient real-time tracking of this point in order to ensure optimal functioning of the system	Solar irradiation and cell temperature of the PV panel	The power generation	ANN-PSO
Yang et al. [44]	2020	Model the performance of vacuum membrane distillation process (VMD)	Permeate flux and specific heat energy consumption (SHEC) under different feed inlet temperature, feed flow rate and membrane length	Performance index	ANN
Antonio et al. [45]	2020	Propose the use of black box global stochastic optimization techniques to address the complex problem of sizing renewable sources	Energy and cost	Complex engineering simulation	RBF

affect the result of size optimization. And the forecasted data of solar irradiance also relates to sizing problems [56–59]. The published literature of AI in the photovoltaic system proves that AI technology is popular especially in remote areas. It has demonstrated that the potential of AI as a designing tool in predicting and optimizing the scale of photovoltaic systems.

3.3.2. Predictive modeling of PV/wind hybrid desalination systems by AI

Hybrid renewable energy (HRE) system-based seawater desalination is a cost effective alternative, which is superior in availability and complementarity under the requirements of the environment and energy situation [60]. However, solar and wind energy systems are facing the challenges of the intermittency and high net present cost (the net present value is the present value of current and future benefit minus the present value of current and future costs) [61]. In this context, through these standalone systems, the optimal scale has become a key factor for obtaining a reliable supply at a low cost. The optimal scale of the hybrid energy system is usually realized by the optimal configuration shown in Fig. 10. Therefore, developing algorithms for size optimization in standalone hybrid renewable energy systems (HRESs) has attracted more attention [61]. In the existing related articles, the optimal sizing methodologies can be broadly categorized as classical algorithms [14], modern techniques and software tools. In solving complex optimization problems, modern techniques which are based on single AI algorithm (such as ANN, GA and neuro-fuzzy) are more popular than classical algorithms.

Due to the restrictions of the information of energy sources, environmental conditions, technical specifications, and load profiles [60], the optimal design of HRESs is not an easy task. There have being many studies on modeling, configurations, and optimization techniques of HRESs for various locations and constraints [60],[62–64]. Among them, solar and wind hybrid systems are widely used owning to their efficient complementarity [65]. Spyrou and Anagnostopoulos et al. [66] used the stochastic optimization software based on evolutionary algorithms to

Table 4
A summary of parameters prediction studies by AI for RE desalination system.

Ref.	Year	Problem Describe	Design Variables	Objects	Algorithms
Mjalli et al. [36]	2007	Solve the large-scale MSF model	Flow rate of distillate, brine flow rate, feed flow rate	Initial guesses and starting guesses	GA/ANN
Mashaly et al. [46]	2017	Predict the solar still productivity (SSP)	The solar radiation, relative humidity, total dissolved solids (TDS) of feed	SSP	ANFIS
Alazba et al. [70]	2017	Forecast the efficiency of solar still production (SSP)	Ambient temperature, relative humidity, wind speed, solar radiation, feed flow rate, temperature of feed water	Production or the amount of distilled water	ANN
Aish et al. [71]	2015	Predict the next week values of total dissolved solids (TDS) and permeate flowrate of the product water	Water temperature, pH, conductivity and pressure	Flowrate of the product water	ANN
Khayet et al. [72]	2011	Develop predictive models for simulation and optimization of reverse osmosis (RO) desalination process	Sodium chloride concentration in feed solution, feed temperature, feed flow-rate, and operating hydrostatic pressure	The salt rejection factor times the permeate flux	ANN/RSM
Charrouf et al. [30]	2020	Study of a reverse osmosis desalination system powered by a hybrid energy source: solar–wind	Solar input and Wind input	PV power	BP
Ehteram et al. [73]	2020	predict the TDS and permeate flow rate	pH, feed pressure temperature, and conductivity	Flow rate of permeate water	MLP-PSO
Al-shayji et al. [74]	2002	Simulate and predict the operation of MSF	Steam flowrate (STF), distillate produced (DP), and TBT	The distilled water produced and top brine temperature	BP
Ibnelouad et al. [39]	2020	Use the maximum power point tracking (MPPT) method, achieve an efficient real-time tracking of this point in order to ensure optimal functioning of the system	Solar irradiation and cell temperature of the PV panel	The power generation	ANN-PSO
Fumagali et al. [40]	1994	Keep the desired distillate production	Sea water temperature, heat exchange coefficients, brine top temperature, and brine recirculation flowrate	Distillate production flowrate	ES
Cao et al. [75]	2016	predict accurately the unseen data of the VMD desalination process	The feed inlet temperature, the vacuum pressure, the feed flow rate and the feed salt concentration	Salt concentration	ANN
Abbas et al. [76]	2005	Predict the performance of a reverse osmosis (RO)	The feed pressure, temperature and salt concentration	Water permeate rate	ANN
Libotean et al. [77]	2009	Forecast models of RO plant into control strategies and process diagnostics	Normalized permeate flux and salt passage	Permeate flow and salt passage rates	BP - SVR
Barello et al. [78]	2014	Predict RO desalination processes	Membrane type, operating pressure range and feed salinity	Water permeability constant	ANN
Salman et al. [79]	2007	Predict evaporation rates	Different water and air temperatures, and different air velocities	Saline water evaporation rates	GA
Jafar et al. [80]	2002	Predict the critical desalination parameters (recovery and salt rejection)	Eight-variable vector	Permeate flow rate and permeate TDS	RBF
Aminian et al. [81]	2010	Predict the temperature elevation of seawater in multi-stage flash desalination plants	The boiling point temperature (BPT) and salinity	Temperature	RBF
AI-Shayji et al. [74]	2002	Develop predictive models	Seawater outlet temperature, seawater flow rate, distillate produced, brine inlet temperature, condensate flow rate, blowdown flow rate	Distillate produced, top brine temperature and steam flow rate variables,	BP
Sadeghzadeh et al. [82]	2019	Predict the thermal efficiency of a flat-plate solar collector	Three levels of inlet temperature, three levels of volumetric flow rate and four levels of nanofluid concentrations	Thermal performance	RBF-ANN
Rustum et al. [83]	2020	Analyze the sustainability of desalination processes	Energy costs, water costs	The economic, environmental and social factors	FL
Rao et al. [84]	1993	Predict the multistage flash desalination processes	Top brine temperature, temperature of low pressure steam, pressure of LP steam, conductivity of brine heater condensate	Performance index	ANN
Derbali et al. [85]	2017	Detect Fault	Raw data	Identification and definition of potential faults	Decision tree algorithm
Cabrera et al. [41]	2018	Predict the performance of the SWRO desalination plant	Electricity production	Pressure, feed flow rate and permeate flow rate, and conductivity	ANN

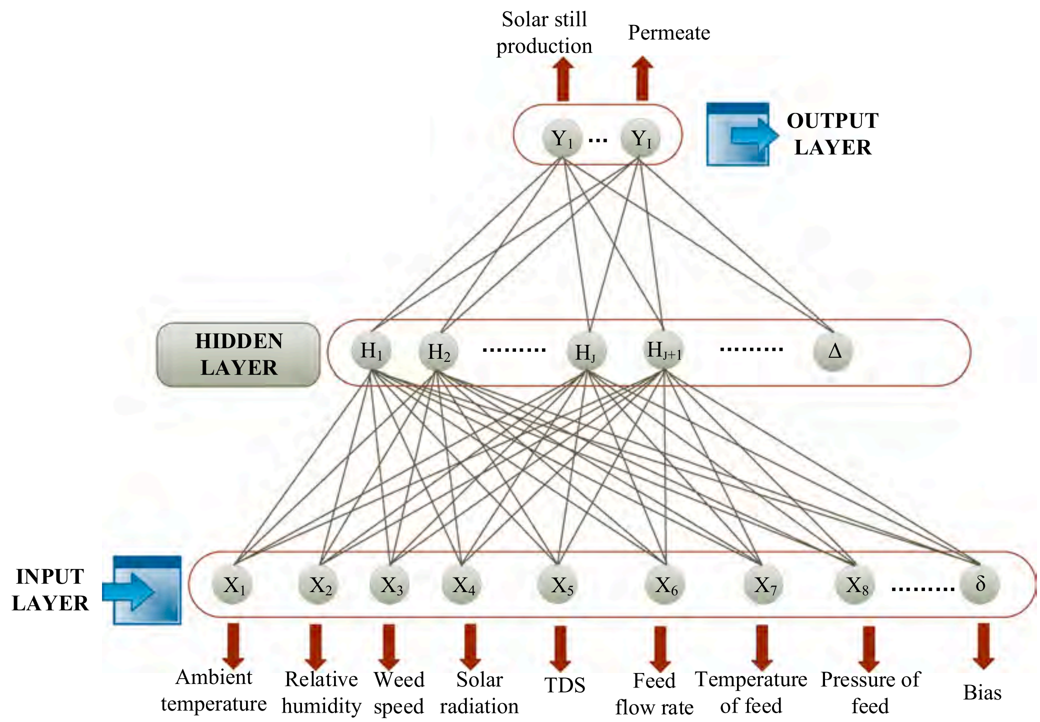

Fig 8. The schematic diagram of an artificial neural network (ANN) model [55].

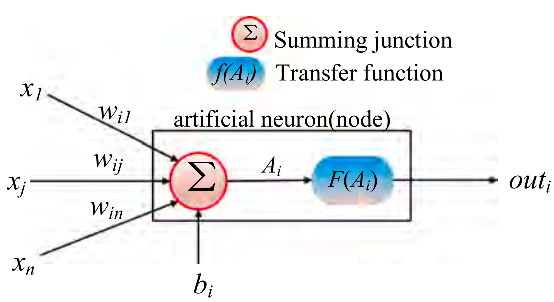

Fig 9. Operation mechanism of neural network nodes.

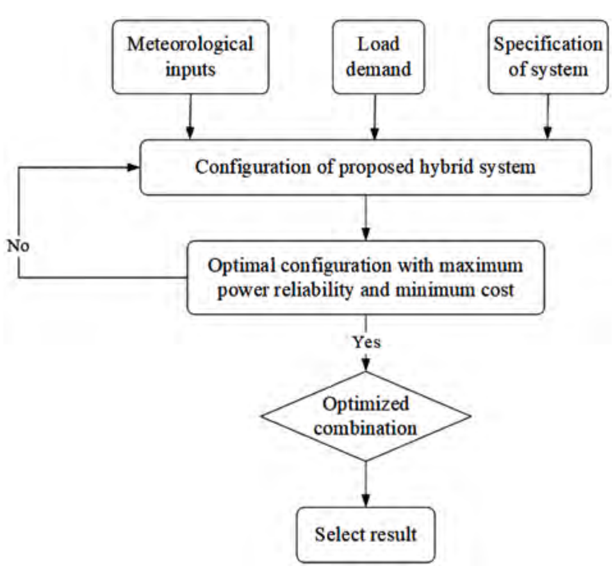

Fig 10. The scheme for the optimization of hybrid energy systems.

simulate and evaluate a stand-alone desalination system. The system was based on renewable energy and pumped water storage, which could be optimized with various objectives, such as the fresh water production cost minimization and the water demand satisfaction maximization. Koutroulis and Kolokotsa et al. [67] put forward a method to realize the size optimization of desalination systems by using PV and wind energy. In order to meet the cost minimization within 20 years, the number and type of units and their energy supply ratio need to be optimized. This method demonstrated that the operation of systems and their devices have a significant impact in total cost. By using GA, the total cost function was minimized and the size of two energy sources was also configurated reasonably. Charrouf et al. [30] used ANN to manage a small-scale RO desalination system driven by the hybrid wind–solar conversion system. Generally speaking, the results of size optimization would be affected by solar irradiance and wind speed data. When the initial and operating cost values [68] were increasing, the size optimization results tended to be float. Therefore, the accuracy of the size optimization algorithm could be improved by combining the prediction technology with the rules of prediction data and historical data. Size optimization techniques can be classified into classical techniques, modern techniques. They mainly differ in single algorithms or hybrid algorithms. The specific content of the algorithm can be found in many documents and textbooks, which will not be repeated here.

Besides, the intermittence and unpredictability of renewable energy sources leads to the hybridity of renewable energy desalination systems. Therefore, not only prediction, but optimal control is needed to obtain the smooth transfer power energy for desalination with hybrid renewable energy. Fig. 11 shows the workflow of ANN controller for the hybrid energy system. The float of the output energy will be balanced and controlled by the ANN intelligent response. It mainly relies on proportional-integral-derivative (PID) and other common controllers, which are based on different algorithms on the market. Traditionally, a combination of PID controller is incorporated to fulfill the control objectives in many applications.

3.3.3. *Prediction of other types of energy by AI*

In addition to conventional renewable energy used in desalination,

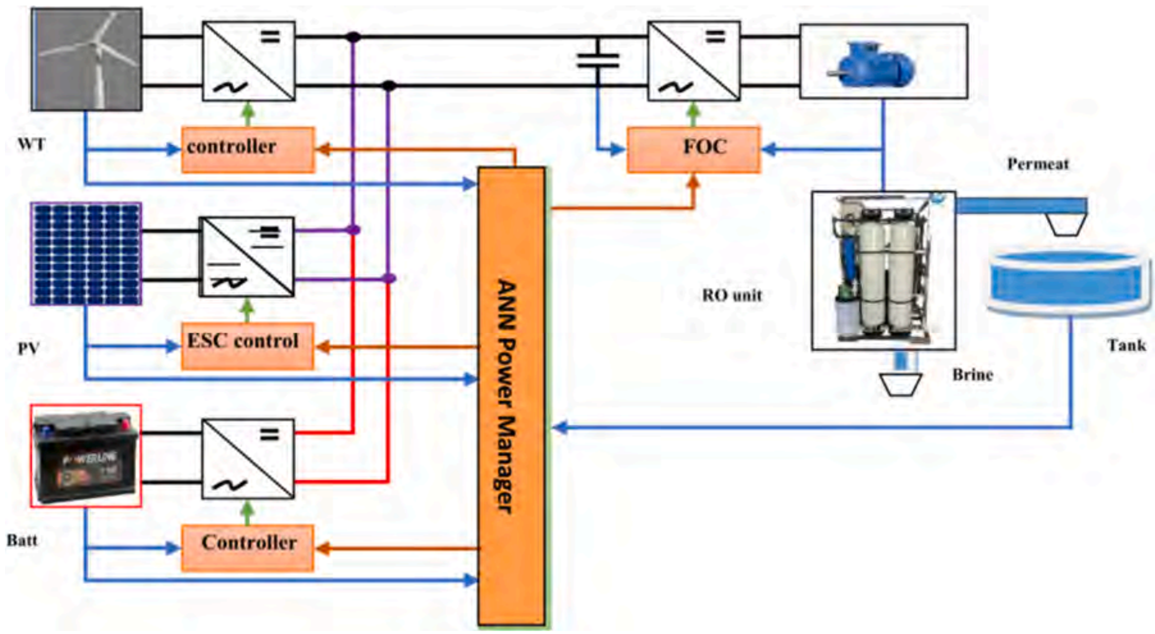

Fig 11. The sketch map of hybrid energy desalination systems [30].

the energy such as geothermal energy and waste heat from factories are also a good choice for seawater desalination. AI not only selects energy types according to the environment and objective function, but also forecasts the output of specific energy. Generally, the algorithms applied to the prediction of solar distillation rate or solar irradiance, such as ANN, can also be used to predict the input energy density of geothermal energy and waste heat, and optimize the input energy. Wu et al. [34] proposed an efficient metaheuristic technique based on tabu search to optimize the size of a RO desalination-based diesel and photovoltaic power plant. It was found that the photovoltaic/diesel/battery/RO desalination system was economically and environmentally superior to a single diesel system or single photovoltaic system in the study area. Colmenar-Santos et al. [69] proposed a clean and permanent energy source (geothermal energy) for desalination to optimize energy variability. By collocating solar energy and geothermal energy, mathematical model was used to fit the relationship between input and output variables and obtained the optimal composite energy supply system.

The use of prediction by AI in these types of energy is summarized in Fig. 12. It can be seen that the prediction in different energy types involves many parameters to be chosen. The AI technologies fit the past energy data with the consumed data in desalination to predict the suitable operational parameters.

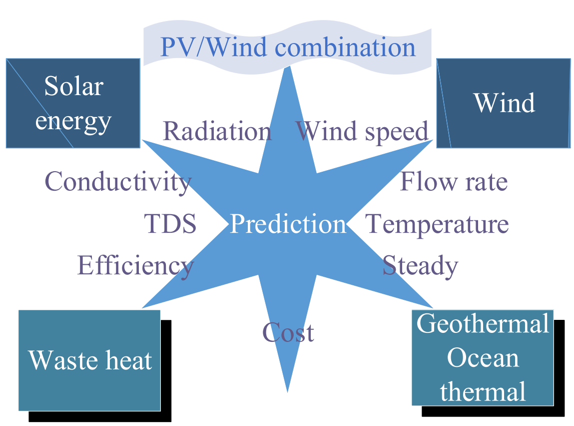

Fig 12. Prediction in desalination with different energy types.

3.4. *Automatic control by AI in desalination*

The operation stability of seawater desalination processes is of great significance for stable fresh water output. However, there are many variables involved in desalination, and the input and output tend to change with the environment. In order to obtain the maximum benefit, the operation parameters of the system need to be adjusted to make the objective function in the approximate range of the optimal solution. For example, by adjusting the feed water temperature, flow rate, and other operating parameters, the system can work in the best working condition. In the operation process, the timely response and the precise quantitative control are both needed for the best working condition. As a term, AI means the power of machine and operational management like human mind [86]. The advance of AI is reflected in the process and control optimization. At present, many research institutions have adopted AI to optimize the control of seawater desalination process. For example, the membrane fouling and concentration polarization problems of the RO technology increase the operation cost in RO system. These problems can be solved by advanced technology in process and control optimization. Abbas [87] proposed a model predictive control (MPC) method to overcome the limitation of PID controller in a reverse osmosis desalination plant. It continues to produce good control for even large changes (30%) in the gain related to feed pressure. With the development of various optimization technologies, the traditional PID controller adjustment method is being replaced by optimization-based technologies. A literature survey shows that researchers have used many intelligent optimization techniques to solve the reverse osmosis desalination problem. Zilouchian and Jafar [88] proposed a controller design for RO desalination plants based on a genetic algorithm. Gambier et al. [89] designed a controller based on multi-objective optimization for reverse osmosis desalination system. Although it was found that the algorithm is superior to the traditional method, it was still affected by the appropriate adjustment of the specific parameters of the algorithm.

In addition to the operation parameters under external influence, the instability of renewable energy is also an important reason for affecting the output of the desalination system. A special design for this renewable energy needs to be developed, especially focusing on the control system and energy buffer device. Ayala et al. [90] proposed a new predictive control strategy for distributed solar collectors. The goal of the controller is to keep the outlet or inlet temperature gradient constant.

Galvez Carrillo et al. [91] presented a nonlinear model predictive controller, which extended the dead time compensator to control the distributed solar collector field. Pickhardt [92] proposed the application of the indirect adaptive predictive controller to the solar experimental device by using the nonlinear model. Seawater desalination process is a process in which multiple input variables need to be coupled at the same time. Realizing the automatic control process of the system to achieve the best benefits is the most prominent application of AI in the field of seawater desalination engineering.

In comparison, ANN algorithm is the most used in the current AI control of RE seawater desalination system, as it has the advantages of simple algorithm, easy implementation and suitable accuracy. The utilization of ANN algorithm can generally improve the output of at least 10%. In addition, as for genetic algorithm, it has the advantages of large coverage and self-adaptation, but its efficiency is lower than other traditional optimization algorithms, and the overall optimization calculation time is too long. There are also other algorithms currently used by people, such as particle swarm optimization algorithm and BP algorithm. They are easy to implement and have fast convergence, strong nonlinear mapping ability and flexible network structure. However, they are easy to disperse and have low accuracy and long training time. In general, the use of AI technology to control the RE desalination system, is becoming a trend, for that it can not only greatly improve the efficiency of desalination system, but also make the system more simple.

4. New trends of seawater desalination with AI technology

As a regression model, ANN is widely used in prediction and optimization aspects. Meanwhile, GA as a global optimization technology, tends to be adapted into dynamic control process. The two are the most widely used AI technologies in seawater desalination and treatment. They have good performance at their strong aspects. Therefore, more and more compound algorithms are discussed and developed to obtain the optimal solution. Not only in prediction and optimization aspects, but also in decision-making process, the compound algorithms are gradually becoming a substitute for traditional algorithms.

At present, seawater desalination is an important means to solve the shortage of fresh water, whose development tends to be large-scale and large-capacity desalination equipment for improving economic benefits. However, considering that the seawater after desalination is a mostly weak acid, there are still some limiting factors in the aspect of long-distance pipeline transportation for users. So combining desalination plants with large-scale water-consuming plants becomes an idea. AI has great advantages in processing the control and optimization of the two plants. The following three aspects are the detailed summary.

(1) **Intelligent compound algorithm**

The application of AI in the field of seawater desalination is mainly by using machine language. Through constructing the intelligent algorithm model, taking the constraints into search space, the AI makes the solution of nonlinear problems closer to the experimental results, which takes place of the single algorithm. Meanwhile, AI replaces the previous decision-making method based on experience and rules. By optimizing the objectives and maximizing the interests, AI is more conducive to the realization of energy-saving, environmental protection and efficient engineering construction requirements of contemporary society. So the performance of AI mainly depends on its advanced algorithm. Now more and more algorithms are constantly updating. For example, ANN has a great advantage in regression models, GA is superior in global optimization. According to the relevant studies, it is shown that the combination of other classical modeling methods and/or AI tools can generate a greater potential for optimal operations, especially in complex operating environments. The hybrid intelligent system is increasingly popular in recent years, because of the success in solving many complex problems in the real world. By providing complementary reasoning and search methods, these computational intelligence components (such as machine learning, fuzzy logic, neural networks and genetic algorithms) generate the synergies leading the success. In the future, artificial intelligence tends to use a composite algorithm for prediction and optimization. By making full use of the advantages of various algorithms, intelligent control has been improved.

(2) **Highly integrated automation control**

AI is a powerful tool, which is usually used in engineering multidisciplinary. Its function is to solve the problem that the deterministic solution is difficult to realize in the real world. However, if the setting deviation occurs as the change of external conditions, the automatic response of the system needs a higher level of intelligent control. That is one of the developing improvements faced by the water sector. Moreover, the distribution and utilization of desalination products also need intelligent control means to maximize economic efficiency. Building a comprehensive and systematic AI desalination system, not only the device but the line of supply-desalination-transportation should be realized. It is also an important development goal of artificial intelligence in the field of seawater desalination in the future.

(3) **Intelligent configuration and control of compound plant**

To realize the multi-level utilization of energy, the more effective path is the coupling design of desalination with a power plant or chemical plant. Large-scale desalination plants can greatly reduce the cost of desalination. The stable energy output of power plants and chemical plants can simplify the operation optimization process. Besides, the desalination products can be used as the plant water supply input, which further reduces the desalination cost. AI has great advantages in dealing with such multi-parameters and multi-objective problems, which is also an effective path for further development in the future.

5. Conclusions

In this paper, the main applications of artificial intelligence in renewable energy (RE) driven seawater desalination are reviewed. This is a comprehensive and systematic summary of the desalination design, optimization prediction and control with artificial intelligence. The main conclusions are as follows:

(1) The establishment and operation of renewable energy driven desalination plants are summarized into four aspects: site selection, energy prediction, desalination technology selection, and performance optimization. These four aspects can be solved by artificial intelligence technologies, separately.
(2) By mainly modeling various manually operable variables based on the carrier, such as genetic algorithm (GA), artificial neural network (ANN), the optimal solutions are obtained. The use of artificial intelligence technologies contributes the improvement of efficiency and the productivity of freshwater can be raised by 10%.
(3) Based on the mathematical model, the controller in seawater desalination is mainly used to keep the better operation conditions. In the previous step, these conditions are determined by decision support system (DSS), optimization and prediction in the process of design. The most used function of controller is to adjust the operation variables to adapt to the change of operation conditions.
(4) ANN is good at solving the relationship between inputs and outputs, by which the prediction of parameters can both generate the ideal results involving bias and constraints. The neurons between different layers belong to a single mathematical model and its number has an impact on accuracy.

(5) The most common used intelligent algorithms in renewable energy driven desalination are ANN, and GA. The ANN is useful in the prediction process of desalination, and GA is prior in the optimization process due to their features.

In this paper, the application of artificial intelligence in renewable energy driven seawater desalination is divided into four aspects, each of which has specific application background and mode. In the future, the direction of desalination will continue to expand, but also for readers to comb a clear idea. In an increasingly turbulent environment, there is no doubt that artificial intelligence is the pathway of operation, process automation and management in the water sector.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is supported by the National Science Foundation of China (No. 51976013, No. 52006124) and the Beijing Institute of Technology Research Fund Program for Young Scholars (No. XSQD-202103005).

Contributions

The simulation and writing work of this paper are completed by Qian He. The idea behind this work is provided by Hongfei Zheng. The revision work of this paper is completed under the guidance of Hui Kong.

References

[1] Fekete BM, Revenga C, Todd M. 1. The global risks report 2018. 13th Ed., 31. Geneva: World Economic Forum; 2009. p. 50–67 [2018] http://www3. weforum. org/docs/WEF_GRR18_Report. pdf. Agricultural Economics.
[2] Xi W, Liu YD, Zhao WX, Hu R, Luo XB. Colored radiative cooling: how to balance color display and radiative cooling performance. Int J Therm Sci 2021:170.
[3] DIFFERENTIATE. Design intelligence fostering formidable energy reduction and enabling numerous totally impactful advanced technology enhancements. In: Proceedings of the Conference design intelligence fostering formidable energy reduction and enabling numerous totally impactful advanced technology enhancements. U.S. Department of Energy's; 2020 [Accessed 9 March 2020].
[4] Maude-Josée Blondin PP-M. Sanchis sáez javier. computational intelligence and optimization methods for control engineering: cham. Springer; 2019.
[5] Algobaisi DMK. Conceptual specification for improved automation and total process care in large-scale desalination plants of the future. Desalination 1994;95 (3):287–97.
[6] Hu R, Iwamoto S, Feng L, Ju S, Hu S, Ohnishi M, et al. Machine-learning-optimized aperiodic superlattice minimizes coherent phonon heat conduction. Phys Rev X 2020;10(2):2160–3308.
[7] Chao Chen YJ, Zhaoyong Ye, Yang YU, Hou L. Sustainably integrating desalination with solar power to overcome future freshwater scarcity in China. Glob Energy Interconnect 2019;2(2):98–113.
[8] Hu R, Song JL, Liu YD, Xi W, Zhao YT, Yu XJ, et al. Machine learning-optimized Tamm emitter for high-performance thermophotovoltaic system with detailed balance analysis. Nano Energy 2020;72(104687):2211–855.
[9] El-Arwash H M , Azmy A M , Rashad E M . A GA-based initialization of PSO for optimal APFS allocation in water desalination plant[J]. 2017:1378-1384.
[10] Abid A, Jamil MA, Sabah N, Farooq MU, Yaqoob H, Khan LA, et al. Exergoeconomic optimization of a forward feed multi-effect desalination system with and without energy recovery. Desalination 2021;499(2021):114808.
[11] Subramani A, Jacangelo JG. Emerging desalination technologies for water treatment: a critical review. Water Res 2015;75:164–87.
[12] Ghassemi SA, Danesh S. A hybrid fuzzy multi-criteria decision making approach for desalination process selection. Desalination 2013;313:44–50.
[13] Elhawary ME. Artificial neural networks and possible applications to desalination. Desalination. 1993;92(1–3):125–47.
[14] Chatterjee K, Joglekar M, Shah N. Average case analysis of the classical algorithm for Markov decision processes with Bachi objectives. Theor Comput Sci 2015;573: 71–89.
[15] Lattemann S. Development of an environmental impact assessment and decision support system for seawater desalination plants, fl 33487-2742. CRC Press: Taylor & Francis Group; 2010. 6000 Broken Sound Parkway NW, Suite 300 Boca Raton.
[16] Madaeni SS, Shiri M, Kurdian AR. Modeling, optimization, and control of reverse osmosis water treatment in kazeroon power plant using neural network. Chem Eng Commun 2015;202(1):6–14.
[17] Lee YG, Lee YS, Jeon JJ, Lee S, Yang DR, Kim IS, et al. Artificial neural network model for optimizing operation of a seawater reverse osmosis desalination plant. Desalination 2009;247(1–3):180–9.
[18] Mashaly AF, Alazba AA. Experimental and modeling study to estimate the productivity of inclined passive solar still using ANN methodology in arid conditions. J Water Supply ResTechnol Aqua 2018;67(4):332–46.
[19] Olatunde A, Osanaiye PAO. Effect of Training Algorithms on the performance of ANN for pattern recognition of bivariate process. Computer Applications 2013;69 (20):0975–8887.
[20] Rao GP, Algobaisi DMK, Hassan A, Kurdali A, Borsani R, Aziz M. Towards improved automation for desalination processes .2. Intelligent control. Desalination 1994;97(1–3):507–28.
[21] Silva RN, Rato LM, Lemos JM. Time scaling internal state predictive control of a solar plant. Control Eng Pract 2003;11(12):1459–67.
[22] Dweiri F, Khan SA, Almulla A. A multi-criteria decision support system to rank sustainable desalination plant location criteria. Desalination 2018;444:26–34.
[23] Ishimatsu T, Doufene A, Alawad A, de Weck O. Desalination network model driven decision support system: a case study of Saudi Arabia. Desalination 2017;423: 65–78.
[24] Subramanian N, Ramanathan R. A review of applications of analytic hierarchy process in operations management. Int J Prod Econ 2012;138(2):215–41.
[25] Gdoura K, Anane M, Jellali S. Geospatial and AHP-multicriteria analyses to locate and rank suitable sites for groundwater recharge with reclaimed water. Resour Conserv Recycl 2015;104:19–30.
[26] Alzu'bi S., Alsmirat M., Al-Ayyoub M., Jararweh Y. Alzu'Bi S , Alsmirat M , Al-Ayyoub M , et al. Artificial Intelligence Enabling Water Desalination Sustainability Optimization// 2019 7th International Renewable and Sustainable Energy Conference (IRSEC). 2019.
[27] Amos Bick GO. The use of computer aided techniques for revereosmosis desalination layout design. Desalin Water Treat 2015;31(1–3):305–10.
[28] Hajeeh M, Al-Othman A. Application of the analytical hierarchy process in the selection of desalination plants. Desalination 2005;174(1):97–108.
[29] Rathore NS, Singh VP, Phuc B. A modified controller design based on symbiotic organisms search optimization for desalination system. J Water Supply Res Technol Aqua 2019;68(5):337–45.
[30] Charrouf O, Betka A, Abdeddaim S, Ghamri A. Artificial Neural Network power manager for hybrid PV-wind desalination system. Math Comput Simul 2020;167: 443–60.
[31] Gao PH, Zhang LX, Cheng K, Zhang HF. A new approach to performance analysis of a seawater desalination system by an artificial neural network. Desalination 2007; 205(1–3):147–55.
[32] Shirazian S, Alibabaei M. Using neural networks coupled with particle swarm optimization technique for mathematical modeling of air gap membrane distillation (AGMD) systems for desalination process. Neural Comput Appl 2017;28 (8):2099–104.
[33] Porrazzo R, Cipollina A, Galluzzo M, Micale G. A neural network-based optimizing control system for a seawater-desalination solar-powered membrane distillation unit. Comput Chem Eng 2013;54:79–96.
[34] Wu BJ, Maleki A, Pourfayaz F, Rosen MA. Optimal design of stand-alone reverse osmosis desalination driven by a photovoltaic and diesel generator hybrid system. Sol Energy 2018;163:91–103.
[35] Basurto N, Arroyo A, Vega R, Quintian H, Calvo-Rolle JL, Herrero A. A hybrid intelligent system to forecast solar energy production. Comput Electr Eng 2019;78: 373–87.
[36] Farouq SM, Jabbar NA, Ettouney H, Qiblawey HAM. Advanced computational techniques for solving desalination plant models using neural and genetic based methods. Chem Prod Process Model 2007;2(3).
[37] Yazdandoost F. Desalination from an integrated water resources management perspective. Environmental and Marine Outfall Systems 2015;14:205–15.
[38] Khosravi A, Syri S, Pabon JJG, Sandoval OR, Caetano BC, Barrientos MH. Energy modeling of a solar dish/Stirling by artificial intelligence approach. Energy Convers Manag 2019;199:112921.
[39] Ibnelouad A, El Kari A, Ayad H, Mjahed M. Improved cooperative artificial neural network-particle swarm optimization approach for solar photovoltaic systems using maximum power point tracking. Int Trans Electr Energy Syst 2020;30(8): 1–14.
[40] Fumagalli B, Ghiazza E. Mathematical-modeling and expert-system integration for optimum control strategy of MSF desalination plants. Desalination 1994;97(1–3): 547–54.
[41] Cabrera P, Antonio Carta J, Gonzalez J, Melian G. Wind-driven SWRO desalination prototype with and without batteries: a performance simulation using machine learning models. Desalination 2018;435:77–96.
[42] Husain A, Algobaisi DMK, Hasan A, Kesou A, Kurdali A, Podesta S. Modeling, Simulation, Optimization And Control Of Multistage Flashing (MSF) Desalination Plants .2. Optimization and control. Desalination 1993;92(1–3):43–55.
[43] Bachar Meryem NA, Hayani S, Fahli A. Optimization of pv panel using p&o and incremental conductance algorithms for desalination mobile unit. Springer; 2019. Link.
[44] Yang C, Peng X, Zhao Y, Wang X, Fu J, Liu K, et al. Prediction model to analyze the performance of VMD desalination process. Comput Chem Eng 2020:132.
[45] Colmenar-Santos A, Palomo-Torrejon E, Mur-Perez F, Rosales-Asensio E. Thermal desalination potential with parabolic trough collectors and geothermal energy in the Spanish southeast. Appl Energy 2020;262:114433.

[46] Mashaly AF, Alazba AA. Artificial intelligence for predicting solar still production and comparison with stepwise regression under arid climate. J Water Supply Res Technol Aqua 2017;66(3):166–77.
[47] A.Braga ACC, Ludermir T, de Almeida M, Lacerda ED. Radial basis functions networks. Modelling and forecasting financial data 2020;7:160–78.
[48] Amirkhani S, Nasirivatan S, Kasaeian AB, Hajinezhad A. ANN and ANFIS models to predict the performance of solar chimney power plants. Renew Energy 2015;83: 597–607.
[49] Rizwan M, Jamil M, Kirmani S, Kothari DP. Fuzzy logic based modeling and estimation of global solar energy using meteorological parameters. Energy 2014; 70:685–91.
[50] Dumitru C D, Gligor A. Solar photovoltaic energy production forecast using neural networks. Procedia Technology 2016;22:808–15.
[51] Yaici W, Entchev E. Adaptive Neuro-Fuzzy Inference System modelling for performance prediction of solar thermal energy system. Renew Energy 2016;86: 302–15.
[52] Santos NI, Said AM, James DE, Venkatesh NH. Modeling solar still production using local weather data and artificial neural networks. Renew Energy 2012;40(1): 71–9.
[53] Mashaly AF, Alazba AA. Comparative investigation of artificial neural network learning algorithms for modeling solar still production. J Water Reuse Desalin 2015;5(4):480–93.
[54] Mashaly AF, Alazba AA. MLP and MLR models for instantaneous thermal efficiency prediction of solar still under hyper-arid environment. Comput Electron Agric 2016;122:146–55.
[55] Gairaa K, Khellaf A, Messlem Y, Chellali F. Estimation of the daily global solar radiation based on Box-Jenkins and ANN models: a combined approach. Renew Sustain Energy Rev 2016;57:238–49.
[56] Gupta RA, Kumar R, Barisal AK. BBO-based small autonomous hybrid power system optimization incorporating wind speed and solar radiation forecasting. Renew Sustain Energy Rev 2015;41:1366–75.
[57] Khatib T, Ibrahim IA, Mohamed A. A review on sizing methodologies of photovoltaic array and storage battery in a standalone photovoltaic system. Energy Convers Manag 2016;120:430–48.
[58] Louie H. Operational analysis of hybrid solar/wind microgrids using measured data. Energy Sustain Dev 2016;31:108–17.
[59] Hocaoglu FO, Gerek ON, Kurban M. The effect of model generated solar radiation data usage in hybrid (wind-PV) sizing studies. Energy Convers Manag 2009;50(12): 2956–63.
[60] Zahraee SM, Assadi MK, Saidur R. Application of artificial intelligence methods for hybrid energy system optimization. Renew Sustain Energy Rev 2016;66:617–30.
[61] Krishna KS, Kumar KS. A review on hybrid renewable energy systems. Renew Sustain Energy Rev 2015;52:907–16.
[62] Sinha S, Chandel SS. Review of recent trends in optimization techniques for solar photovoltaic-wind based hybrid energy systems. Renew Sustain Energy Rev 2015; 50:755–69.
[63] Chauhan A, Saini RP. A review on Integrated Renewable Energy System based power generation for stand-alone applications: configurations, storage options, sizing methodologies and control. Renew Sustain Energy Rev 2014;38:99–120.
[64] Siddaiah R, Saini RP. A review on planning, configurations, modeling and optimization techniques of hybrid renewable energy systems for off grid applications. Renew Sustain Energy Rev 2016;58:376–96.
[65] Fathima AH, Palanisamy K. Optimization in microgrids with hybrid energy systems-a review. Renew Sustain Energy Rev 2015;45:431–46.
[66] Spyrou ID, Anagnostopoulos JS. Design study of a stand-alone desalination system powered by renewable energy sources and a pumped storage unit. Desalination 2010;257(1–3):137–49.
[67] Koutroulis E, Kolokotsa D. Design optimization of desalination systems power-supplied by PV and W/G energy sources. Desalination 2010;258(1–3):171–81.
[68] Leong Kit Gan JKHS, Mueller MA. Hybrid wind–photovoltaic–diesel–battery system sizing tooldevelopment using empirical approach, life-cycle cost and performanceanalysis_ A case study in Scotland. Energy Conv Manag 2015;106: 479–94.
[69] Santos A C, Vera S P, Asensio E R, Sizing of Wind. Solar and storage facilities associated to a desalination plant using stochastic optimization. Proceedings of the Computational Methods in Systems and Software 2018;256(611):172–83.
[70] Mashaly AF, Alazba AA. Application of adaptive neuro-fuzzy inference system (ANFIS) for modeling solar still productivity. J Water Supply Res Technol Aqua 2017;66(6):367–80.
[71] Aish AM, Zaqoot HA, Abdeljawad SM. Artificial neural network approach for predicting reverse osmosis desalination plants performance in the Gaza Strip. Desalination 2015;367:240–7.
[72] Khayet M, Cojocaru C, Essalhi M. Artificial neural network modeling and response surface methodology of desalination by reverse osmosis. J Memb Sci 2011;368 (1–2):202–14.
[73] Ehteram M, Salih SQ, Yaseen ZM. Efficiency evaluation of reverse osmosis desalination plant using hybridized multilayer perceptron with particle swarm optimization. Environ Sci Pollut Res 2020;27(13):15278–91.
[74] Al-Shayji KA, Liu YA. Predictive modeling of large-scale commercial water desalination plants: data-based neural network and model-based process simulation. Ind Eng Chem Res 2002;41(25):6460–74.
[75] Cao W, Liu Q, Wang Y, Mujtaba IM. Modeling and simulation of VMD desalination process by ANN. Comput Chem Eng 2016;84:96–103.
[76] Abbas A, Al-Bastaki N. Modeling of an RO water desalination unit using neural networks. Chem Eng J 2005;114(1–3):139–43.
[77] Libotean D, Giralt J, Giralt F, Rallo R, Wolfe T, Cohen Y. Neural network approach for modeling the performance of reverse osmosis membrane desalting. J Memb Sci 2009;326(2):408–19.
[78] Barello M, Manca D, Patel R, Mujtaba IM. Neural network based correlation for estimating water permeability constant in RO desalination process under fouling. Desalination 2014;345:101–11.
[79] Salman A, Al-Shammiri MA. New computational intelligence model for predicting evaporation rates for saline water. Desalination 2007;214(1–3):273–86.
[80] Jafar MM, Zilouchian A. Prediction of critical desalination parameters using radial basis functions networks. J Intell Robot Syst 2002;34(2):219–30.
[81] Aminian A. Prediction of temperature elevation for seawater in multi-stage flash desalination plants using radial basis function neural network. Chem Eng J 2010; 162(2):552–6.
[82] Sadeghzadeh M, Ahmadi MH, Kahani M, Sakhaeinia H, Chaji H, Chen L. Smart modeling by using artificial intelligent techniques on thermal performance of flat-plate solar collector using nanofluid. Energy Sci Eng 2019;7(5):1649–58.
[83] Rustum R, Kurichiyanil AMJ, Forrest S, Sommariva C, Adeloye AJ, Zounemat-Kermani M, et al. Sustainability ranking of desalination plants using mamdani fuzzy logic inference systems. Sustainability 2020;12(2):1–22.
[84] Rao GP. Unity of control and identification in multistage flash desalination processes. Desalination 1993;92(1–3):103–24.
[85] Derbali M, Buhari SM, Tsaramirsis G, Stojmenovic M, Jerbi H, Abdelkrim MN, et al. Water desalination fault detection using machine learning approaches: a comparative study. IEEE Access 2017;5:23266–75.
[86] Kalogirou SA. Artificial intelligence for themodeling and control of combustion processes: a review. Prog Energy Combust Sci 2003;29:515–66.
[87] Abbas A. Model predictive control of a reverse osmosis desalination unit. Desalination 2006;194(1–3):268–80.
[88] Zilouchian A, Jafar M. Automation and process control of reverse osmosis plants using soft computing methodologies. Desalination 2001;135(1–3):51–9.
[89] Gambier A, Wellenreuther A, Badreddin E. Control system design of reverse osmosis plants by using advanced optimization techniques. Desalination Water Treat 2009;10(1–3):200–9.
[90] Ayala CO, Roca L, Luis Guzman J, Normey-Rico JE, Berenguel M, Yebra L. Local model predictive controller in a solar desalination plant collector field. Renew Energy 2011;36(11):3001–12.
[91] Galvez-Carrillo M, De Keyser R, Ionescu C. Nonlinear predictive control with dead-time compensator: application to a solar power plant. Sol Energy 2009;83(5): 743–52.
[92] Pickhardt R. Nonlinear modelling and adaptive predictive control of a solar power plant. Control Eng Pract 2000;8(8):937–47.