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A Comprehensive Review of AI Algorithms for Performance Prediction, Optimization, and Process Control in Desalination Systems

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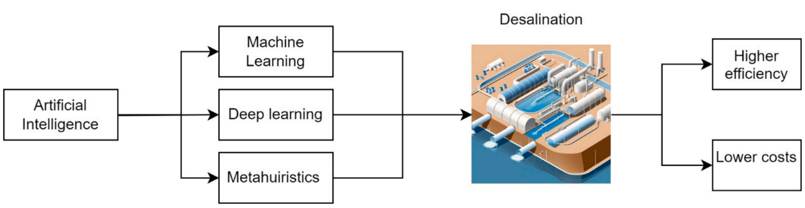
GRAPHICAL ABSTRACT



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ABSTRACT

Water scarcity is a global issue which is predicted to worsen in the upcoming decades. To deal with this challenge, various desalination technologies have been deployed to produce freshwater from saline water. Artificial Intelligence (AI) algorithms have emerged recently as a tool for optimizing desalination processes and forecasting their performance. This comprehensive review examines the various AI algorithms employed in desalination literature. In addition, it reviews their various applications which include performance prediction models. These models make use of historical data to forecast system performance under differing circumstances. In order to improve efficiency, AI algorithms are also used in desalination modelling to optimize system parameters and aid in process control. The history of AI utilization in desalination in addition to its application in standalone desalination systems, hybrid desalination systems, renewable energy desalination, and poly/multi-generation systems was discussed thoroughly. In addition, a future outlook for the topic and gaps in the current literature have been identified and presented. In general, it was observed that AI algorithms have had a significant impact on desalination literature. This is especially true for process modelling where the impact is expected to expand. The reasons for this expansion are largely associated with the advantages offered by AI algorithms when compared with mathematical modelling such as their low computational requirements.

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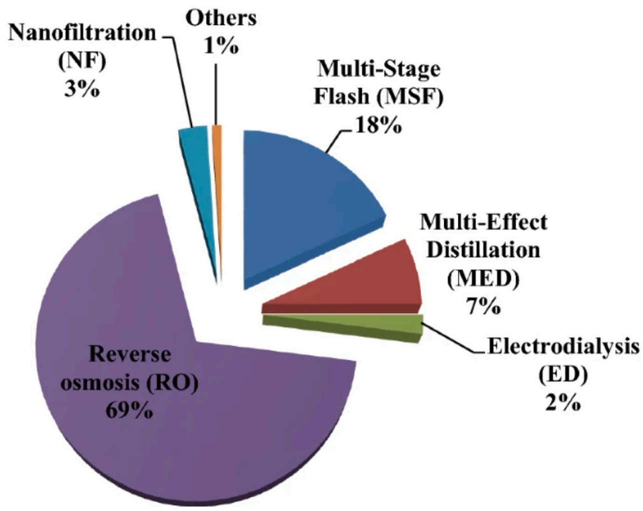

Fig. 1. Breakdown of global desalination capacity by technology [28].

1. Introduction

Global water consumption has risen over the past few decades mainly due to population and economic growth in addition to shifting socio-economic and water consumption patterns [1]. According to global estimates, around 4 billion people live in regions that suffer from water scarcity at least one month of the year while approximately half a billion people live in regions suffering from severe water scarcity all year round [2]. One of the main solutions for water scarcity is the separation of salt from water in a process named desalination [3]. Desalination allows for the utilization of around 97 % of the water on earth which is considered too saline for direct human consumption [4–6]. Current desalination methods are energy intensive and require large costs; therefore, research to improve current methods and discover new ones is ongoing [7].

Mathematical modelling is utilized in desalination literature to better understand systems, predict their performance, and optimize their parameters. It involves the development of mathematical equations that link input and output variables subsequently solving them to predict system performance under varying conditions [8]. Similarly, mathematical optimization finds optimum parameters which result in the best performance using system governing equations. Mathematical modelling and optimization are commonly coupled with experimentation either to validate results or to find optimum design parameters [9]. The challenge posed by mathematical modelling and optimization is that they require intricate knowledge of the investigated system and its governing equations which can be challenging with complex and nonlinear processes such as desalination [10]. The other limitation of mathematical modelling and optimization is their high computational requirements which increase as the model complexity increases. For example, during the operation of membrane desalination processes, ions of the rejected species which does not pass through the membrane accumulate on its boundary establishing a concentration gradient [11]. The phenomenon is named concentration polarization (CP) and has a negative impact on process performance [12,13]. Modelling phenomenon such as CP or membrane fouling hinders model performance because they introduce nonlinearity; therefore, most models in the literature either ignore the effect of such phenomenon all together or rely on linearized models thereby reducing model accuracy [14,15].

Artificial intelligence (AI) algorithms serve a similar function to mathematical modelling and optimization in desalination research; however, with major differences in their process of arriving at results. First introduced in the middle of last century, AI has seen much recent attention due to its potential applications in many fields aided by its flexibility and robust operation [16]. AI is a field of computer science that mimics human intelligence in functions such as learning and reasoning [17]. An important subset of AI algorithms named machine learning (ML) allows for the mapping of input to output variables relying solely on historical data instead of system governing equations thereby offering fast computations when compared with conventional methods [18]. Similarly, another subset of AI algorithms named metaheuristics (MH) can be used for optimization using historical data only [19]. These advantages make AI very useful in the study of complex and nonlinear systems, such as desalination, which are difficult to model mathematically without significant assumptions [20–22]. Their robustness also allows them to provide real-time predictions potentially aiding in autonomous and efficient process control for desalination systems [14, 23,24]. In the context of desalination, data for AI models are usually obtained through experimentation or first principles modelling. Subsequently, they are generalized or optimized using AI algorithms such as artificial neural networks (ANN) which have become a recent trend in desalination research due to their pattern recognition capabilities.

This review aims to investigate how AI algorithms are utilized in the performance prediction, optimization, and control of desalination systems. This involves identifying which AI algorithms have been deployed and how often, which ones have future potential due to their unique advantages, and which desalination systems are most investigated using AI algorithms. Another aim is to identify potential hybridization strategies either between different AI algorithms or between AI algorithms and conventional modelling and optimization techniques. This is important because hybridization may allow researchers to leverage the advantages of different methodologies arriving at accurate, fast, and robust models. Lastly, the review aims to identify the challenges associated with AI utilization in desalination and areas of potential future research.

Although specific algorithms such ANNs are the dominant in desalination literature, other algorithms such as decision trees (DT) and random forests (RF) are increasingly observed. These algorithms could potentially offer improved performance, and a discussion of their implementation is lacking in other reviews. Moreover, some reviews focus on specific types of desalination systems when reviewing the influence of AI. For example, He et al. [25] investigated the use of AI in renewable energy desalination systems while Reza et al. [26] reviewed the use of multi-level perceptron (MLP) in desalination and water treatment. Finally, Al Aani et al. [7] analyzed the use of ANN and GA in desalination performance prediction and optimization. This review is innovative in its holistic view of utilization of any AI algorithm in all desalination systems aiming to assess the performance of different algorithms and their potential applications in the field. In addition, the focus on the input and output parameters of the discussed models and the sensitivity analysis undertaken assists future research by providing insight into the most influential parameters to consider for various desalination technologies. Finally, investigating the use of AI algorithms in modelling of polygeneration systems which include desalination is unique to this review. Polygeneration systems are increasingly investigated as an alternative to standalone desalination offering better synergy with renewable energy sources.

2. Desalination overview

2.1. Working principles of desalination

Desalination technologies are generally classified into thermal and membrane technologies. Thermal technologies principally change the phase of saline water to achieve separation as is the case with multi-stage flash distillation (MSF) and multi effect distillation (MED). Meanwhile, membrane desalination technologies employ semi permeable membranes to achieve salt separation as in reverse osmosis (RO) and electrodialysis (ED). Currently, membrane technologies account for about 70 % of global desalination capacity while thermal technologies

Table 1
Energy consumption and costs of various desalination technologies with seawater as feed.

Desalination technology	Energy consumption (kWh/m^3)	Reference	Specific water production cost ($\$/m^3$)	Reference
MSF	15.8 to 23.5	[29]	0.8 –1.5	[32]
MED	14.2 to 21.6		0.7 –1.2	
RO	4 to 6		0.5 –1.2	
ED	2.64 to 5.5		1.532	[33]
AD	1.5	[34]	0.3	[35]
MD	0.6 to 1.8	[36]	0.489 –4.7 (solar powered)	[37]
FO	2.4 to 3.3	[38]	-	
CDI	0.01 to 0.1	[39]	0.11 –1.41	[40,41]

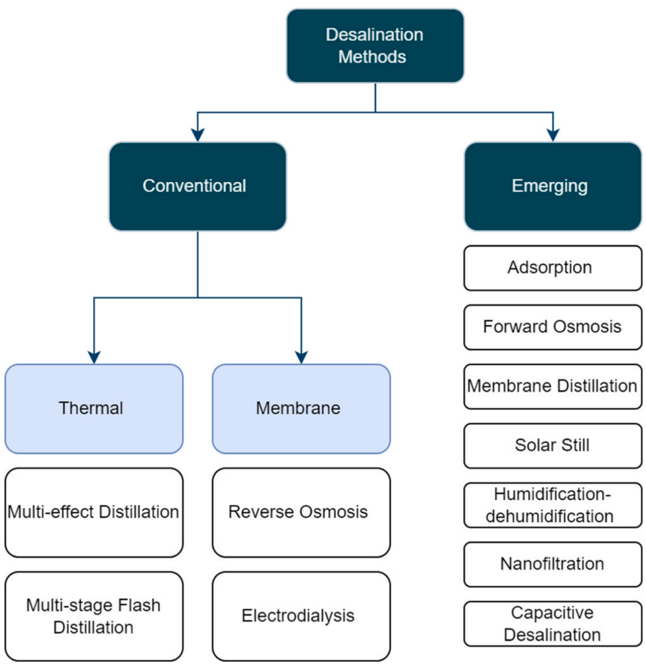

Fig. 2. Classification of desalination technologies into conventional vs. emerging and membrane vs. thermal.

constitute another 25 % as presented in Fig. 1 [27].

2.2. Performance indicators of desalination technologies

An integral part of modelling any desalination system is identifying the main performance indicators used to assess it. This identification also aids attaining a numerical timeline of performance improvement in the field since most investigations report their results using those indicators. For thermodynamic performance, it is important to note that there is no singularly accepted thermodynamic indicator which allows for accurate comparisons between different desalination technologies. The most common approach is energetic efficiency or energy consumption in $\frac{kW-h}{m^3}$ which is useful in comparisons between desalination technologies which utilize the same form of energy [29]. However, it is limited by its failure to capture the difference in quality of energy forms consumed by desalination processes. Moreover, it does not account for the efficiency gains of hybrid processes such as coupling thermal desalination with combined-cycle power plants which is a commonly utilized configuration. On the other hand, exergy analysis is a more encompassing thermodynamic performance indicator for desalination systems but is less commonly reported in the literature. In general, exergy analysis studies have demonstrated excellent performance of RO desalination systems in comparison with MED, MSF, ED, and CDI which all have comparable results [30].

Another axiom of assessing desalination performance is financial costs which are usually reported as specific costs per unit volume of water produced. They vary significantly depending on a multitude of factors aside from the technology utilized including feed water properties, energy costs, plant size, and labor costs among other site-specific factors [31,32]. This explains the wide range of values in the cost estimates presented in Table 1 which presents a comparison of the thermodynamic performance and financial costs for various desalination technologies.

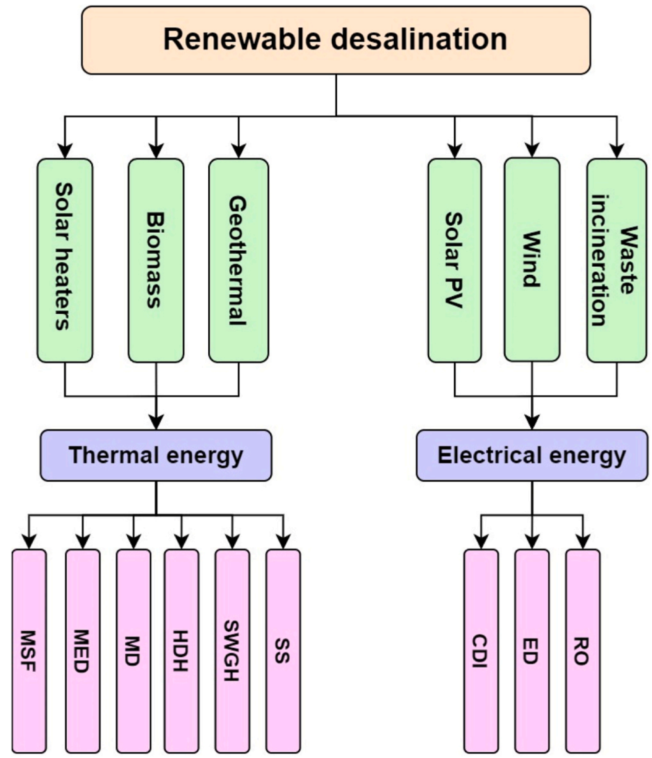

Fig. 3. Potential renewable energy integration with the various desalination technologies.

2.3. Conventional and emerging desalination technologies

There exists a general breakdown of desalination technologies which is often used in literature since it aids in identifying the level of technology maturity. The four most utilized desalination technologies MSF, MED, RO, and ED are often referred to as conventional desalination technologies since they constitute the majority of current desalination plants [42,43]. Even though conventional technologies are well established, they suffer from high costs and energy requirements which incentives research and development of alternative technologies commonly named emerging technologies. Fig. 2 presents the classification of the main desalination technologies into conventional and emerging. Examples of emerging technologies include adsorption desalination (AD), membrane distillation (MD), forward osmosis (FO), humidification-dehumidification (HDH), solar stills (SS), nanofiltration (NF), and capacitive deionization (CDI). In theory, each of them offers an inherent advantage over conventional technologies in some aspect. However, they frequently suffer from technical limitations such as low water production rates that render them infeasible for large scale applications [44]. For example, AD has low energy consumption when compared with conventional technologies and therefore it is estimated to have significantly reduced costs as shown in Table 1. Despite the potential, AD is absent from the market currently due to limitations such

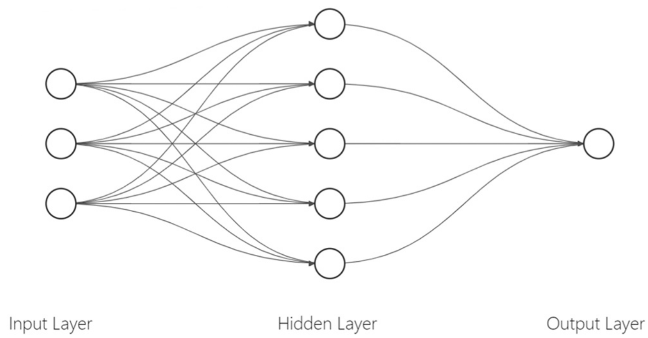

Fig. 4. Schematic diagram representing the typical structure of an artificial neural network.

as low productivity and cyclic instead of continuous operation [35].

2.4. Important fields of research in desalination

Desalination literature involves several subfields which utilize AI for various purposes. First, modelling of conventional systems in various scenarios and applications is very prevalent. Mostly, this involves predicting the performance of RO desalination based on a unique set of feed conditions or other input parameters. Second, a lot of research is focused on the feasibility of different potential configurations of emerging technologies. By improving the technical and financial profile of those technologies, they could potentially offer advantageous alternatives. Another important field of research in desalination is membrane design where advanced membranes that achieve higher salt rejection, water flux, minimize fouling among other improvements are investigated [45–47].

Aside from research into membranes and emerging technologies, the integration of renewable energy sources into desalination is the subject of extensive analysis and is reported to significantly reduce energy costs. As presented in Fig. 3, this integration can take one of two distinct paths depending on the energy form produced by the renewable sources. First, renewables which produce heat can be used to power thermal desalination directly; for example, direct utilization of solar energy in SS. Alternatively, renewable sources may be used indirectly to produce electricity powering membrane desalination methods such as photovoltaic (PV) powered RO [48,49]. A significant number of the latest studies on emerging desalination technologies, desalination membrane design, hybrid desalination systems, poly/multi generation systems, and renewable energy desalination involved the use of AI algorithms. A large number of AI algorithms exist for various applications, and some are more favored in desalination modelling. The next section introduces the main algorithms utilized in desalination and their working principles.

Finally, hybridization of different desalination technologies has been a topic of extensive research in desalination literature. Results of different analysis of such systems report improved efficiency and energy consumption for the overall process which takes advantage of the unique strengths offered by the different technologies it combines [50]. A similar concept is also applied in poly/multi-generation systems. They produce not only water but multiple energy vectors such as electricity, heating, and cooling in addition to other products such as hydrogen within one system [51,52]. Such systems have been reported to offer economic and environmental advantages over standalone processes due to synergies that may be exploited between the different subsystems included [53].

3. Artificial intelligence algorithms

To grasp the reasons behind the extensive deployment of AI algorithms in modelling desalination systems, their working principles and unique advantages must be understood. AI is an umbrella term which encompasses all algorithms that learn processes in a manner mimicking human learning. They usually utilize a learning set generalizing from it to provide responses to new situations [54]. There are multiple approaches to classify the various AI algorithms; however, for the purpose of this work they will be divided into MH and ML.

First, ML is a subset of AI which assists in correlating and finding patterns in raw data. Based on the primary working principle and type of data required, ML algorithms can be divided into three groups. Supervised learning uses labeled data to find correlations between model inputs and outputs giving it the ability to predict the output of new input data [55]. On the other hand, an unsupervised learning algorithm is fed unlabeled for classification based on their features [56]. Lastly, reinforcement learning (RL) algorithms are the third branch of ML that involve the use of reward and penalty functions to learn by trial and error with no requirement for an initial set of data [57]. In desalination modelling, supervised learning is almost exclusively utilized because of their ability to generalize experimental datasets with high accuracy and reduced computational requirements [58].

Distinct from ML algorithms, MHs are a class of AI algorithms aimed at solving difficult search or optimization problems [59]. They search for the set of inputs which lead to best possible performance results. As opposed to the deterministic nature of mathematical optimization, MH algorithms provide a prediction of the optimum result; therefore, they have minimal computational requirements in comparison [60]. In addition to being thought of as "black-box" techniques that don't require knowledge of the dynamics of the system, the simplicity of MH algorithms incentivizes their utilization by researchers [61,62]. The incentive is especially present for optimizing complex desalination systems where optimization is mostly done as part of a larger modelling or experimental analyses thereby lower accuracies are tolerable.

Desalination research makes extensive use of both ML and MH techniques for regression and optimization. The AI techniques that are most relevant to the desalination literature are introduced in this section and their working principles are summarized. ML algorithms that were found to be of importance in desaliantion include ANNs, DTs, and support vector machines (SVMs). Moreover, MH algorithms including evolutionary algorithms (EA) and swarm intelligence (SI) were featured prominently. It is important to note that algorithms such as multiple linear regression (MLR), stepwise linear regression (SLR), Bayesian optimisation algorithm (BOA), k-nearest neighbourhood (KNN), Gaussian process regression (GPR), deterministic policy gradient (DDPG), and soft actor critic (SAC) which were employed in some studies are not covered in this section due to their comparitvely low utilization in the literature.

3.1. Regression and classification algorithms

3.1.1. Artificial neural network algorithms

ANN's solve classification and regression problems numerically by mimicking the biology of the human brain [63–65]. Neurons in an ANN are divided into input, output, and hidden layers as presented in Fig. 4. Input layer neurons represent the input data whereas the output layer neurons represent the predicted outputs with a hidden layer in between. In an ANN, interconnections between the layers are assigned weights and allow the network to communicate data across layers. Each neuron is assigned the summation of weighted inputs from all neurons in the previous layer. A bias is also added to the weighted sum of inputs to aid in data fitting. The summation is then applied to a nonlinear or squashing activation function which determines whether a neuron should be activated. Whether a neuron is activated or not decides if it produces an output at all. The output of activated neurons is communicated further down the network until the output layer whose neurons represent predicted outputs [66–69]. Networks structured in a manner like ANNs with multiple hidden layers are called MLP networks and are commonly utilized as well. Similarly, deep learning (DL) algorithms are a class of ANN's with multiple hidden layers possibly in the thousands.

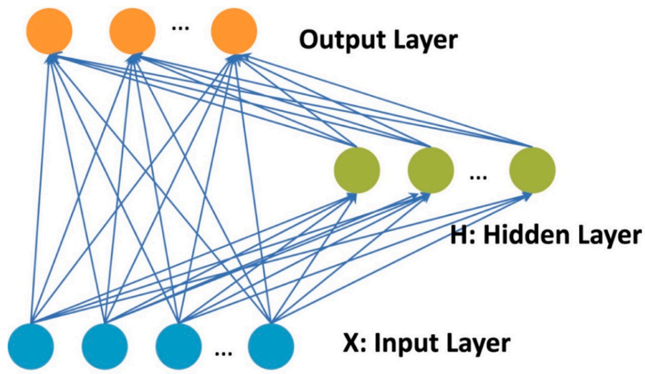

Fig. 5. Schematic diagram of typical RVFL network structure [72].

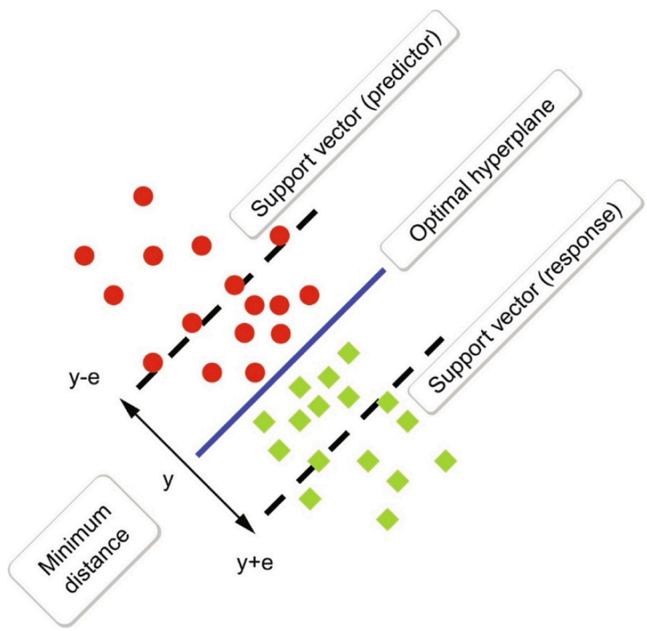

Fig. 6. Diagram presenting the separating hyperplane, support vectors, and margin within an SVM classification problem space [79].

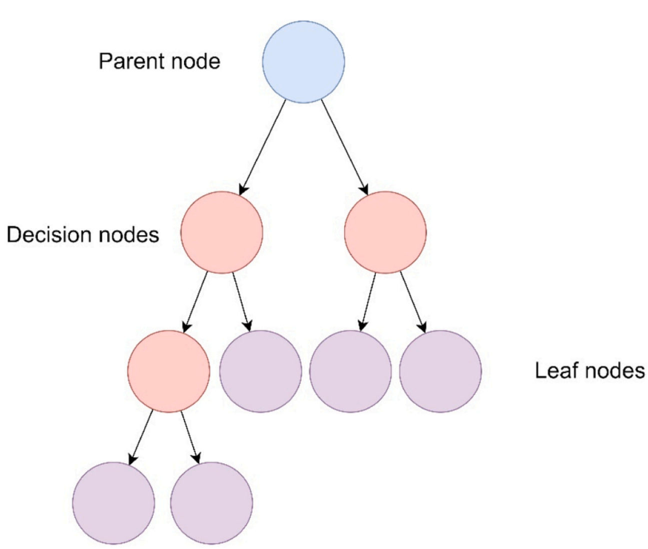

Fig. 7. Schematic diagram of typical DT structure.

These algorithms were developed to have enhanced abilities in handling unstructured data such image, video, speech, and natural language processing. Most common examples of DL algorithms include deep neural networks (DNNs), convolutional neural networks (CNNs), recurring neural networks (RNNs), self-organizing maps (SOMs), and long short-term memory (LSTM) algorithms with each having its advantages in certain applications [70].

Another type of neural networks is random vector functional link (RVFL) which offers a much faster learning process. RVFL includes both direct connections between the input and output layers in addition to the regular input-hidden-output layer connections as presented in Fig. 5. Furthermore, only the weights of the output layer connections are varied and evaluated for fitness using the least squared method with input layer parameters being kept constant throughout in RVFL [71].

ANNs including MLPs and RVFLs are most prevalent in desalination performance prediction studies. Their training datasets usually include inputs such as feed salinity among other design variables and feed condition aiming to predict the performance at varying conditions. Their excellent generalization capability is one of their main advantages. This ability is aided by the widescale availability of training algorithms and strategies for ANN's which further improves their performance especially in the context of desalination.

3.1.2. Support vector machine algorithms

Aside from ANNs, SVMs are another class of supervised learning ML algorithms used for both data regression and classification problems [73]. For classification problems, the objective of an SVM model is finding a hyperplane that linearly separates the data into their different classes based on their distinctive features as presented in Fig. 6. The training set of an SVM in classification applications is used by the algorithm to find the hyperplane that maximizes its margin. The margin describes the distance between the hyperplane and the support vector points on either side [74,75]. Kernel functions are often used when linear separation is insufficient, and nonlinearity must be introduced [76]. Examples of commonly used functions include radial basis function (RBF), polynomial, and quadratic kernels [77]. In the case of support vector regression, the same process is followed by finding a hyperplane with the minimum error; however, the definition of error in regression differs from classification algorithms [78]. Serving a function similar to ANNs in desalination modelling studies, significant attention has been paid recently to SVM regression.

3.1.3. Decision trees and random forests

Another class of AI algorithms encountered in desalination literature are DTs. They are a well-established supervised ML algorithms that are applied in classification and regression problems using a sequence of rules or conditions and can be visualized in a tree-like structures [80–82]. For classification problems, DT algorithms are fed data points that are grouped in different classes based on a set of features that influence their classification. The training data are recursively split or partitioned based on their features using conditional statements or rule checks. Child notes are either successive decision nodes or pure class partitions called leaf nodes as presented in Fig. 7. Partitioning steps or nodes continue to grow until the members of all partitions are of a single class or until a stopping criterion for the purity of partitions is met [83–86]. The features of a new input data point are tested at each node by the conditional statements established during the learning process eventually placing it in one of the partitions.

An extension of the DT algorithm is the RF or random decision forest algorithm which involves the training of multiple DT's for both regression and classification problems [87]. This involves the breaking down of a large DT training data set into random subsets in a process called bootstrapping. Each subset includes some of the features of the original data set but not all. Subsequently, smaller DTs are trained for each subset and predictions for new data points are based on the aggregate results of those trees [88–90]. RF algorithms provide predictions with

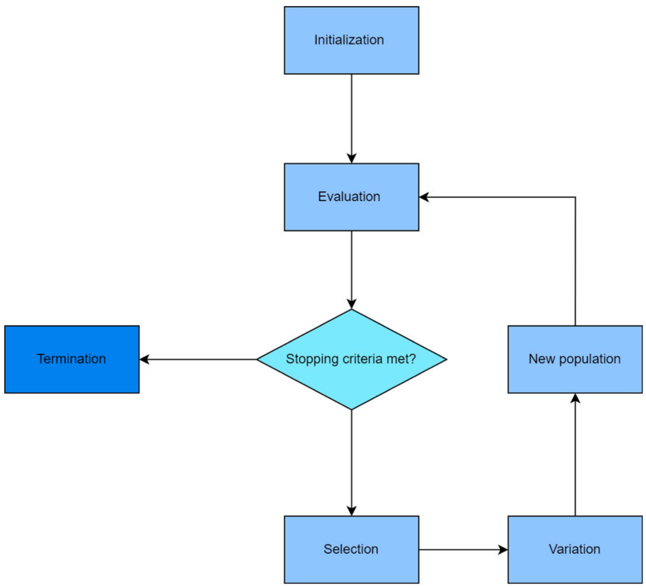

Fig. 8. Decision flow chart of an evolutionary algorithm.

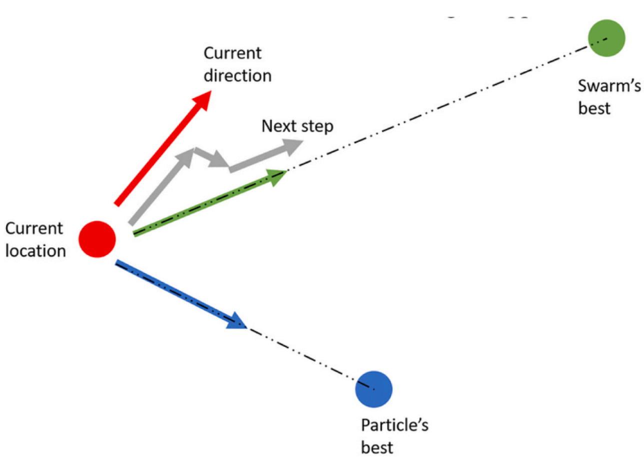

Fig. 9. Schematic diagram presenting the different factors influencing the movement of an individual within the search space of a PSO [98].

higher accuracy and have better generalization capability since DT's tend to overfit data. In addition, RF's can be used to rank the features based on their influence on the final prediction. However, these advantages come at the cost of computational requirements which are significantly higher when compared to DT's [91]. Other AI algorithms such as gradient boosting trees (GBT), adaptive boosting (AdaBoost), and extreme gradient boosting (XGBoost) deploy a similar concept of using multiple decision trees to model the training data with minor differences from their parent algorithm. XGBoost for example assigns weights to each tree varying their contribution to the final result; in addition, errors from each tree are accounted for in building a new one [92]. DTs and their various offshoot algorithms have been applied is a significant number of desalination systems to assess their generalization ability when compared with ANN's.

3.2. *Optimization algorithms*

3.2.1. *Evolutionary algorithms*

Inspired by evolutionary theory, EAs are an integral class of MH optimization algorithms that predict the optimal solutions for a wide range of optimization problems. Similar to biological theory, the solutions evolve over iterations with the aim of finding the best estimates of the optimum solution. Moreover, concepts from evolutionary theory are employed to describe optimization problems. For example, the overall problem, objective function, solution search space, and any single possible solution are denoted by the environment, fitness, species or population, and individual. When optimizing a desalination system for example, the objective function usually involves minimizing or maximizing performance indicators such as energy consumption or salt rejection. Input variables include various design variables which have been identified as having an impact on the performance such as feed flowrate. It follows then that the search space is the range of possible values for input variables decided by the model designer based on realistic limitations. Any possible set of input variables that falls within the search space is a single solution or individual. Fig. 8 presents the decision flow diagram of a typical EA including its key operations.

Key defining processes within any EA include selection and variation. Variation involves generating evolved offspring from the current population while selection involves the generational replacement strategy which governs which individuals remain in the population and which ones are discarded [93]. Genetic algorithms (GAs) are one of the most common EAs; however, other algorithms with differing selection and or variation strategies are also commonly employed. Examples include differential algorithm (DA), genetic programming (GP), evolutionary programming (EP), strength pareto evolutionary algorithm (SPEA), pareto envelope-based selection algorithm (PESA), gene expression programming (GEP) and estimation of distribution algorithm (EDA).

3.2.2. *Swarm intelligence algorithms*

Similar to EAs, SI algorithms are a class of nature-based population optimization algorithms inspired by the behavior of animal flocks such as birds [94]. They rely on the behavior of a population where the individuals communicate information with each other which gives rise to a collective intelligence that is not necessarily available to the individuals [95]. For example, particle swarm optimization (PSO), the most popular SI algorithm, simulates the movement of a single particle (bird) within a flock (swarm) and the flock's ability to move in sync while changing both speed and direction [96]. Each bird moves within the search space based on its current momentum, historical knowledge of its best previous position, and the historical knowledge of the positions occupied by other individuals in the swarm as presented in Fig. 9 [97]. Any new position with the search space is assessed for optimality by the objective or fitness function. The main idea behind their utilization to investigate desalination systems is the same as with EAs; however, the difference lies in their method for reaching an approximate solution within the search space.

Other common examples of SI algorithms encountered in desalination literature include grey wolf optimizer (GWO), golden jackal optimizer (GJO), ant colony optimizer (ACO), grasshopper optimization algorithm (GOA), dove swarm optimization (DSO), artificial bee colony (ABC), thermal exchange algorithm (TEA), salp swarm intelligence (SSI), dragonfly algorithm (DA), water cycle algorithm (WCA), sine cosine algorithm (SCA), manta ray foraging optimizer (MRFO), heap based optimizer (HBO), Runge Kutta optimizer (RUN), artificial ecosystem-based optimization (AEO), Harris hawks optimizer (HHO), and humpback whale optimizer (HWO). All of the aforementioned regression and optimization algorithms are deployed in desalination literature for various applications. The next section presents and discusses those applications in a comprehensive manner.

4. Applications of Artificial Intelligence in Desalination

AI algorithms in desalination are mainly used in the service of two objectives. First, they are employed to serve as a substitute for mathematical modelling. Complete substitution is not necessarily always the case with some studies opting to utilize AI algorithms for only a

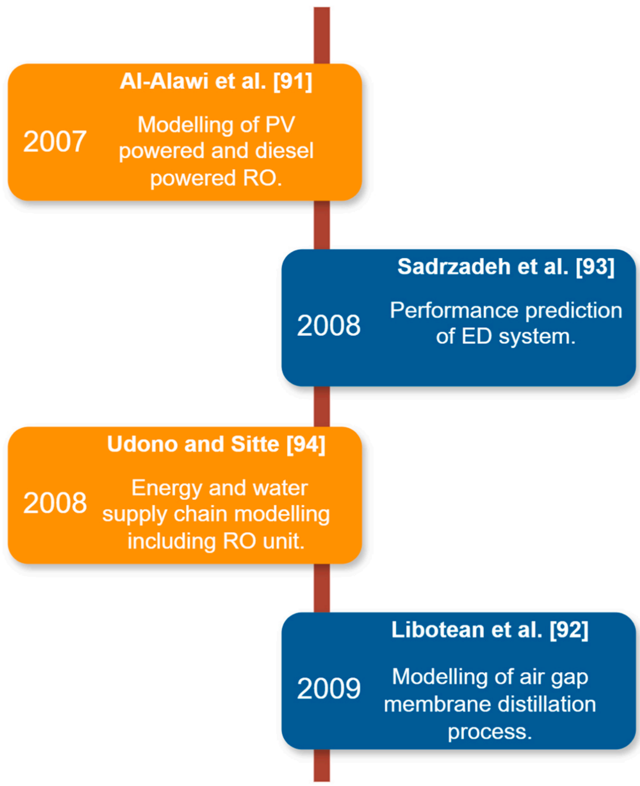

Fig. 10. Historical timeline of AI utilization in desalination literature.

subsection of an overall system coupled with conventional modelling for other subsections. Performance prediction models were the most prevalent in this case. They generalize previously obtained data for varying operational, design, and environmental parameters. Data used in training AI algorithms is either obtained experimentally, from first principles models, or both. Subsequently, the trained algorithm is used to predict the performance of the system for a set of input parameters different from the ones in the training set thereby generalizing the obtained results.

Another common application of AI algorithms in desalination is the optimization of system parameters based on single or multiple objectives. MH algorithms are widely utilized for this purpose and are coupled in some cases with regression algorithms. By employing an MH algorithm to search for possible solutions from the search space and using an ML regression algorithm to predict the objective function values of those solutions, the strengths of both ML and MH algorithms are combined. The use of MH algorithms to adjust the parameters of an ML algorithm is another example of this coupling. The aim in this case is to improve the prediction capability of the regression algorithm, not to optimize the investigated system. Desalination studies which utilize AI algorithms for performance prediction, optimization, or any other application are classified based on the type of investigated desalination system and discussed in this section.

4.1. History of artificial intelligence use in desalination literature

First, it is important to analyze the emergence of AI use in desalination studies because it gives an idea how fast the field is evolving. Fig. 10 presents a summary of the first desalination studies to utilize AI. In 2007, Al-Alawi et al. [99] presented the first study utilizing an AI algorithm to investigate a desalination system. A RO system was coupled with PV for solar energy, diesel generator producing power, and an energy storage system and was modelled using an ANN. In the two years which followed, Libotean et al. [100], Sadrzadeh et al. [101], and Udono and Sitte [102] all utilized ANNs to model various desalination systems.

Table 2
Summary of literature research papers investigating RO desalination systems utilizing AI algorithms.

Reference	AI algorithm	Main remarks and findings
Bonny et al. [23]	ANN-DDPG	Use of DL-RL hybrid algorithm to optimally control desalination process. Algorithm finds the trans membrane pressure in RO operation that satisfies desired flux and salt rejection.Input parameters include the maximum height of water in the tank, salt concentration of feed flow, temperature of feed flow, recovery ratio, and salt rejection ratio. The average reward for RL algorithm was found to be very high, showing that the performance of the proposed control agent is very high.
Libotean et al. [100]	ANN SVM SOM	Use of classification ML algorithm to classify different operational data into distinct classes.Prediction of RO plant performance and its time variability using ML regression.The model outputs were salt passage and permeate flux. Model inputs included feed flow rate, feed conductivity, feed pH, overall pressure drop, temperature, permeate flux from previous time steps, and selected time interval.
Khayet et al. [106]	ANN Monte Carlo stochastic method	Performance prediction of RO process using ML regression algorithm and subsequent optimization using Monte Carlo stochastic algorithm.Input variables include feed concentration, feed temperature, feed flowrate, and operating pressure.A performance index which accounts for salt rejection factor and permeate flux was the only output. Salt concentration was found to be the most significant input parameter followed by feed temperature. Comparison of algorithm results with RSM results showed that ANN requires more data; however, provides more optimal conditions and performance.
Brooke et al. [112]	ANN	Performance prediction of low salinity RO plant using ML regression algorithm. Input parameters included feed conc., applied pressure, and feed temp.A performance index which considers both permeate flux and salt rejection efficiency was the sole output.[3:10:1] ANN structure was utilized.Feed conc. found to be the most significant input parameter followed by temp. and pressure.
Alghamdi [24]	DNN DSO PSO SSI SVM	Utilizing AI to improve PID control of RO plant.Probability based-MH algorithm is used to find optimum PID parameters. Deep ANN is used to predict process performance based on new control parameters.Input parameters included seawater conductivity and pH, feed pressure, time, feed flow rate, feed temperature, and feed conductivity while permeate flowrate was the predicted output.For given input data, DSO is used to find optimal controller parameters. Permeate properties are extracted before implementing the optimal control strategy in the RO phase. Extracted attributes are fed to DL algorithm predicting performance.Performance of DSO and DNN was compared with similar algorithms and found to be the best.
Wang et al. [107]	ANN	Brackish water desalination through RO was modelled using mathematical

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Table 2 (*continued*)

Reference	AI algorithm	Main remarks and findings
		modelling and ANN.15 experimental sets were obtained with input parameters including feed salinity, flowrate, and concentration to desalination ratio with salt rejection, membrane flux, and energy consumption as outputs.GA was used to optimize ANN parameters and optimum network structure was 3 −10 −4. Dataset was divided into 70 % training, 15 % validation, and 15 % testing.
Chandru and Dhinagaran[103]	ANN	Performance prediction of effluent water treatment plant using either RO or MED. Salt rejection was the sole performance indicator with feed pH, conductivity, total dissolved solids, and chemical oxygen demand as model inputs.Both models demonstrated high generalization ability with R values of 0.90651 and 0.92382 for the RO and MED systems respectively.
Alardhi et al. [108]	ANN	Utilizing ANN and mathematical modelling to model and optimize RO wastewater desalination.Key parameters were identified as flowrate, feed conductivity, feed pressure, and solution temperature. Output water conductivity representing the salt removal was chosen as the main performance indicator. Optimum ANN structure included two hidden layers, 20 first layer nodes, 30 s layer nodes, and 11 hidden layer nodes. MSE was below 0.0003 and R^2 was above 0.99 which demonstrates the excellent performance of ANN in RO performance prediction.
Masuodi et al. [109]	ANN	Three different ML algorithms were utilized to predict the removal ability of RO and NF.Input parameters were molecular weight and compound size for the pollutants to be removed.ANN demonstrated the best data fitting capability followed by RF and XGBoost respectively.
Mahadeva et al. [113]	ANN	Use of ML regression for RO performance prediction.Analyzed and compared between different choices within an ANN structure including number of hidden layers, hidden layer nodes, activation functions, training function, dataset splits, and error performance functions. Input parameters included the condenser/evaporator inlet temperatures, feed flow rate, and feed water salt concentration while permeate flux was the desired output.The optimum number of hidden layer nodes was found to be 20. Also found that (80 - 10 - 10) was the best data split for training, validation, and testing.
Taloba[104]	MLP	Use of ML regression algorithm for RO performance prediction.The results are then used to find optimum operating conditions.Optimization was achieved by testing different strategies for chemical dosing during pretreatment using the trained algorithm to find the strategy with minimum costs.
Aish et al.[105]	MLP RBF	Performance prediction using ML regression algorithms.Inputs included feed pressure and temperature in addition to salt concentration.Outputs were the permeate flowrate and total dissolved solids.MLP demonstrated slightly higher prediction accuracy when compared to RBF.Strong negative correlations observed between total dissolved solids and feed pressure.

First, Libotean et al. [100] investigated the performance of an air gap MD by obtaining the permeate flux and salt rejection. Variables such as air gap thickness, feed temperature, and flowrate among others were considered as model inputs. Meanwhile, Sadrzadeh et al. [101] predicted the separation percent of a lab scale ED system using MLP and mathematical modelling by considering feed concentration, temperature, operating voltage, and flowrate as inputs. The performance of the ANN exceeded the mathematical model with correlation coefficients of 0.99 and 0.97 respectively. Despite the ANNs advantage in dealing with the nonlinearity of the system, the model performed more efficiently at higher flowrates and lower voltages.

Lastly, Udono and Sitte [102] simulated the supply and demand cycles of energy and water using a mathematical model coupled with multiple ANNs predicting outputs for smaller subsystems. Supply for a region with limited water resources and frequent droughts was met using waste incineration powered RO and dam water. Detailed RO system modelling was not part of the scope for the study which focused more on the fluctuating demand/supply cycle. The hybrid model was used to test the viability of wind energy as an energy source for the desalination process and it was found to be inferior to waste incineration. When analyzing those early studies, there is not much difference in their application of ANNs from subsequent studies as can be seen from the remainder of this section. However, the scale at which they are relied upon has expanded exponentially. This demonstrates the excellent performance of AI algorithms in desalination modelling.

4.2. *Standalone desalination systems*

4.2.1. *conventional desalination systems*

Out of the three conventional desalination technologies MSF, MED, and RO; only the latter was found to have studies analyzing its performance using AI algorithms. This can be attributed to the high interest in RO when compared with other conventional desalination technologies. However, one exception was a study by Chandru and Dhinagaran [103] which modelled both MED and RO systems using ANNs. Table 2 provides a summary of all of those studies and demonstrates that performance prediction was the most prevalent utilization of AI in RO modelling studies. Furthermore, feed conditions such as concentration (salinity) and temperature were most considered for inputs while the permeate flux and flowrate were the output parameters accounted for the most. To this end, some studies such as Taloba [104] utilized a single algorithm while others such as Aish et al. [105] utilized multiple algorithms and compared their respective performances while Khayet et al. [106] utilized a Monte Carlo stochastic algorithm to optimize the overall process. Utilization of AI for performance prediction in this application can be very useful due to its fast responses and generalization capabilities.

Wang et al. [107] modelled an RO brackish water system using experimental datasets. Salt rejection, flux, and energy consumption were predicted using both a mathematical model and an ANN relying on inputs such as feed salinity flowrate. GA was used to optimize the neural network parameters leading to a 3–10-4 structure. Results indicated ANN's superior prediction abilities. Finally, a hybrid optimization process was implemented to find optimum feed conditions. Mathematical optimization was coupled with the trained ANN which provided estimates for performance at different input values. Chandru and Dhinagaran [103] considered feed conditions such as salinity, pH, conductivity, total dissolved solids (TDS), and chemical oxygen demand as model inputs predicting the salt rejection of a RO system utilizing an ANN. Further, a MED neural network was trained to predict steam

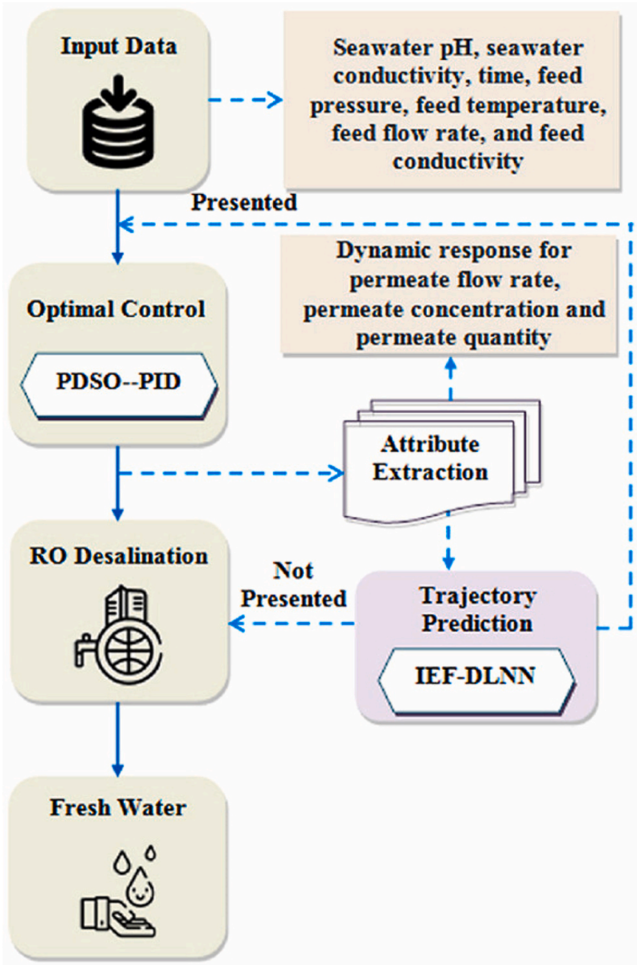

Fig. 11. Flow chart of the hybrid control model utilized for RO desalination presented by [24].

output by considering pH, TDS, and flowrate. The prediction capability of the two networks was high and subsequent optimization was carried out to find optimum conditions. Similarly, Alardhi et al. [108] also modelled and optimized a RO system using mathematical modelling and ANN. Different ANN structures were tested to find the optimum network parameters and the results demonstrated their high prediction accuracy. Uniquely, Masuodi et al. [109] utilized an ANN, RF, and XGBoost to assess the removal rates of RO and NF processes based on molecular weight and compound size. While all three algorithms demonstrated high prediction capability, ANN proved superior followed by RF and XGBoost respectively.

Uniquely, Bonny et al. [23] and Alghamdi [24] made use of various standalone and hybrid ML-DL algorithms in addition to MH optimizers to find optimum RO desalination process control procedures. The results obtained by Bonny et al. [23] proved the viability of using AI to improve control. Meanwhile, Alghamdi [24] compared between different AI algorithms to find the optimum results and found that the performance of DSO and DNN was the best. As presented in Fig. 11, the analysis utilized an MH algorithm to optimize its parameters of a PID controller. In addition, a trained DL neural network provided predictions for the desalination performance under the influence of the PID output.

Unlike performance prediction investigations, use of AI algorithms in desalination process control could potentially find wide implementation in the industry. For example, Synauta is a 2018 startup which offers software packages for RO plants, the first being the energy saver claimed to lead to 18 % energy savings. It uses ML assisted optimization to find new control set points based on historic plant data. Similarly, a chemical

Table 3
Summary of research papers which utilized various AI algorithms to study emerging desalination systems.

Reference	desalination technology	AI algorithm	Main remarks and findings
Ullah et al.[122].	MCDI	RF CNN-LSTM	Performance prediction using both a hybrid DL and tree-based regression algorithms. Input variables included current, voltage, influent pH, and influent salt concentration.Effluent pH and effluent salt concentration were the predicted outputs.Tree-based models had comparable prediction results to the DL algorithm.In the case of pH and concentration prediction, the RF model demonstrated the highest prediction accuracy.The use of binary features significantly increases the generalization ability of the RF model. The tree-based model also showed advantages in the use of lesser computer resources. It required almost 100 times less time than the DL model.
Salari et al.[117].	CDI	ANN MLP	Performance prediction of emerging desalination technology using ML.Single pass configuration CDI was proposed.Input variables included voltage applied to the cell, fluid flow rate, and initial salt concentration.Output variables were concentration of exit water or salt removal percentage.Initial salt concentration had the greatest effect on performance followed by the voltage applied to the cell. Meanwhile, feed flowrate had the least effect on performance.
Son et al.[120].	MCDI	CNN-LTSM	Performance prediction of emerging desalination technology using hybrid DL regression algorithm. Constant current and constant voltage operational modes were modelled.The pH of MCDI effluent was the lone output variable. Input variables were current, voltage, influent conductivity, influent pH, and effluent conductivity.Data split: 64 % training, 16 %

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Table 3 (*continued*)

Reference	desalination technology	AI algorithm	**Main remarks and findings**
			validation, and 20 % testing.A hybrid CNN-LTSM algorithm was compared to standalone LTSM and found to provide more accurate results.The voltage of the MCDI process was the factor which affected performance the most.
Sadrzadeh et al. [101].	ED	MLP	Performance prediction using ML.Model inputs included cell voltage, feed flow rate, temperature, and concentration. Effluent pH was the predicted output.ANN successfully correlated the nonlinear behavior of SP versus temperature, voltage, concentration, and flow rate.
Cao et al.[123].	Vacuum MD (VMD)	ANN	Prediction model for emerging desalination technology and configuration using ML. Model inputs included feed inlet temperature, vacuum pressure, feed flow rate and feed salt concentration.The permeate flux was the predicted output.Data split: 70 % training, 15 % testing, and 15 % validation.Comparison of different ANN structures to find optimum number of layers and neurons was undertaken. The optimum ANN structure was feed forward with 4 input layers, 3 hidden layers, and 1 output layer.Vacuum pressure was the input with most significant impact.
Khayet and Cojocaru[124].	Sweeping gas MD (SGMD)	ANN	Performance prediction of emerging desalination technology using ML regression algorithm.Model inputs included feed inlet temperature, air circulation velocity, and liquid circulation velocity.Performance index accounted for the distillate flux and salt rejection factor.Inlet feed temp. was found to be the most significant input parameter followed by sweeping air flowrate and liquid circulation velocity.
Khayet and Cojocaru[125].	Air gap MD (AGMD)	ANN Monte Carlo stochastic method	Performance prediction of emerging desalination technology using ML regression algorithm.Subsequent optimization of design parameters using Monte Carlo stochastic algorithm.Data split: 75 % training, 17 % validation, and 8 % testing.Comparison of different ANN structures to find optimum number of layers and neurons. Input variables included air gap thickness, cooling inlet temperature, feed flow rate, and feed inlet temperature.Predicted performance index accounted for permeate flux and the salt rejection factor. Optimum ANN: feed forward (4:10:1). Model inputs were found to explain more than 99 % of the variability in response.
Yang[126].	AGMD	ANN MLR GA	Performance prediction of emerging desalination technology using ML regression algorithms.Subsequent optimization using MH. Data split: 75 % training and 25 % validation. Output parameters were permeate flux and gain output ratio.Input parameters included hot temperature, coolant temperature, feed flow rate, and feed concentration.RBF trained ANN gave the best prediction results when compared with MLR and back propagation trained ANN.Results analysis showed that increasing the hot temp. and decreasing the feed conc. had a positive impact on both performance indicators.
Saffarimiandoab et al.[118].	CDI	RF ANN	ML regression algorithms are utilized to determine the most influential design parameters of CDI.A comparison between the effect of electrode features and operational features was done. Operational features were found to have a high influence on the desalination capacity but weak influence on time by when desalination stops. Electrodes micropore volume has positive effect on desalination capacity but negative one on ions transport

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Table 3 (*continued*)

Reference	desalination technology	AI algorithm	**Main remarks and findings**
			speed.Electrodes with lower oxygen content and higher nitrogen content are ideal as they lead to shorter desalination time and higher desalination capacity, respectively.
Zhu et al.[121].	MCDI	RF MLP	ML regression algorithms were used for: 1. prediction of cycle time which is considered as a long-term performance indicator (RF and ANN). 2. change in water production prediction based on operational variables thereby finding optimum cleaning strategies (RF). 3. optimization of control parameters to maintain specific performance levels (RF). ANN and RF prediction models demonstrated superior prediction accuracy for the cycle time.Results showed that optimizing control parameters instead of using fixed values improves performance anywhere from 2 % to 10 %.
Almahfoodh et al. [127].	MD	ANN	DL regression is used to predict performance of emerging desalination tech.Hollow fiber membrane MD was assessed, and temperature polarization was predicted.Input parameters: feed and permeate inlet temperatures, module length and area, and feed and permeate flow rates.Output variable was permeate flux. Results showed that the flux increases with the feed flow rate and decreases with shell diameter due to the temperature polarization effect.The flux production was observed to reduce along the length of MD module.
Yang et al.[128].	VMD	ANN	ML regression algorithm was used to predict performance of emerging desalination technology.Input parameters included feed inlet temperature, feed flow rate and membrane length. Output parameters included permeate flux and specific heat consumption.Data split: 70 % training, 10 % validation, and 20 % testing.Optimum ANN structure was found to be (3:7:1). Despite small data sample, high prediction capability was demonstrated for both outputs.Flux tended to increase with feed inlet temp. and feed flow rate. However, it decreased with length. Specific heat consumption increased with increasing length and decreased with increasing feed inlet temp. and feed flow rate.
Jawad et al.[129].	FO	ANN MLR	ML regression algorithms used to predict performance of emerging desalination tech.Input parameters: membrane type, membrane orientation, draw solution type, molarity of feed solution and draw solution, crossflow velocity of the feed and draw solutions, and their temperatures. Permeate flux was the predicted performance variable.Data split: 70 % training, 15 % validation, and 15 % for prediction.ANN was found to give better predictions than MLR.
Park et al.[119]	CDI	RF	ML regression algorithm was used for performance prediction of emerging desalination technology.Input parameters were specific surface area and capacitance of electrode, salinity, applied voltage, and flow rate.The predicted performance variable was salt absorption capacity.Data split: 70 % training and 30 % validation.Results showed that specific capacitance is the most significant input.
Ahmed et al. [130].	HDH	ANN	Performance prediction of HDH using regression ML to assess three different configurations: zero, single, and double extractions of humid air to the humidifier. Performance indicators included gain output

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Table 3 (*continued*)

Reference	desalination technology	AI algorithm	**Main remarks and findings**
			ratio, water-to-air mass flow rate ratio, recovery ratio, seawater and air temperatures, energy effectiveness, critical enthalpy pinch, and humidifier/ dehumidifier size.Input parameters were minimum and maximum seawater temperatures, enthalpy pinch, and extractions count.The zero, single, and double extractions neural network models had minimum accuracy of 98.3 %, 96.4 %, and 98.9 %, respectively.
Li et al.[131].	AD	GA	Performance prediction using ensemble-based ML regression to assess the impact of a finned-tube bed with branched fins in adsorption production (exact algorithm not mentioned). Relationship between fin configuration parameters and system overall output found and optimization of those parameters using GA is performed.When the optimal fin design is used, a 20.4 % increase in water production was reported.
Faegh et al.[132].	HDH	RBF-ANN MLP adaptive neuro fuzzy inference system (ANFIS)	Three ML regression algorithms were used for performance prediction of heat pump assisted HDH.Input parameters: saturation temperature of the evaporator and evaporative condenser, spraying saline water temperature, refrigerant and air mass flow rates, and dry/wet-bulb temperatures of ambient air.Target variables: gain output ratio in addition to evaporator and evaporative condenser heat rejection rates.MLP provided the best predictions.
Shrimali et al. [133].	Atmospheric water extraction (AWE)	GPR	Assessment of the feasibility of emerging desalination technology by using ML regression algorithm to predict performance.VC refrigeration-based AWE was utilized. Experimental results of performance were obtained for varying temperatures and humidity levels.A 70/30 data split was used for model training/ validation.

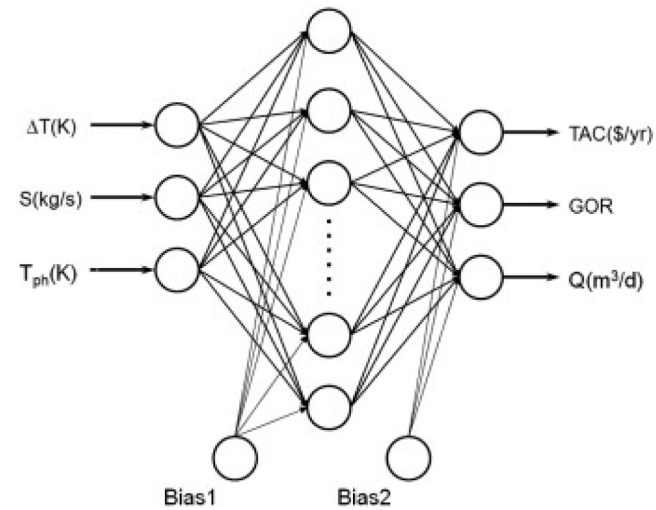

Fig. 12. Structure of MLP utilized to predict the performance of an MED-TVC system [137].

saver application gives predictions for the optimum membrane cleaning dates leading to a 15 % operational cost reduction as per the company's official website [110]. Applications of AI in process control have been reported in other industries, notably the world's first autonomous industrial facility by YKOGAWA/ENEOS. The AI controlled industrial facility utilizes an autonomous control system first implemented in April 2022 for a butadiene production plant with reported 40 % reductions in steam usage [111]. It is difficult to predict whether similar success can be replicated in desalination control; however, it is an interesting area of research with potential for wide scale impact on the desalination industry.

4.2.2. Emerging desalination systems

For emerging desalination technologies, Table 3 presents a breakdown of studies that utilized AI algorithms mostly for performance prediction of various CDI and MD configurations indicating the high levels of interest in those technologies. Salt removal capacity or effluent salinity and permeate flux were the most common performance indicators in CDI and MD respectively. This directly correlates with the principal limitations of both technologies since those variables are widely recognized as some of the main obstacles towards their large-scale adoption [114,115]. Utilization of AI for performance prediction of emerging technologies performance is likely to continue due to the continued research efforts into developing improved configurations. In addition, the complexity of emerging technologies such as CDI makes them difficult to model and therefore increases the attractiveness of AI utilization in generalizing experimental results [116].

Conventional CDI performance prediction studies were performed by Salari et al. [117], Saffarimiandoab et al. [118], and Park et al. [119] while Son et al. [120], Zhu et al. [121], and Ullah et al. [122] evaluated membrane CDI (MCDI). The latter study generalized results for an MCDI system with both constant voltage and constant current operational modes. Furthermore, binary features were added to an RF model to enhance its ability to distinguish between the different modes of operation. A hybrid CNN-LTSM was also utilized, and its performance was compared to the RF algorithm. Results indicated that the use of binary features significantly enhanced the model's ability to generalize. Moreover, the RF model proved to be much faster and have less computational requirements when compared with the DL algorithm without a compromise in generalization ability. Notably, Zhu et al. [121] extended their analysis past predicting system performance to finding optimum control strategies that lead to a predefined level of performance.

Table 4
Summary of literature papers investigating membrane design utilizing AI algorithms.

Reference	AI algorithms	Remarks and main findings
Yao et al. [146].	ANN SVM RF	Three ML regression algorithms were used to predict the performance of an RO plant with MOF nanomaterial membranes.Membrane design factors such as pore size and diameter in addition to operational parameters such as salt concentration and process pressure were considered as input parameters. Meanwhile, water flux and salt rejection were chosen as performance indicators. Experimental data collected from the literature with 80 % being used for training and validation and the rest for evaluation and prediction.The most influential parameters on performance were found to be the thickness of the selective layer and the MOF pore diameter.ANN provided more accurate predictions when compared with SVM and RF models.
Meng et al. [149].	ANN PSO	Structural data of a proposed porous 2D graphene-like membrane material were predicted using CALYPSO.The molecular dynamics model was used to obtain performance indicators (mechanical and thermodynamic properties) corresponding to the structural data obtained.The results of the molecular dynamics model were generalized using an ANN.
Yeo et al. [147].	GBT	Structural data of a proposed thin film nano composites (TFN) membrane were predicted using an ML regression algorithm.Using the predicted structural data, another ML regression algorithm was used to predict the performance. The algorithm was trained using experimental data.Water permeability and salt rejection were chosen as the performance indicators based on the loading, pore size, shape of nanoparticle, and properties of the composite membranes.Porous nanoparticles were found to have better performance than non-porous ones.Loading, size, and hydrophilicity were determined to be the parameters with the most influence on performance.
Li et al.[148].	PSO	Structural data of a proposed novel graphene-like stimulus-responsive material membrane material was predicted using CALYPSO.A molecular dynamics model was used to obtain performance indicators (mechanical and thermodynamic properties) corresponding to the structural data obtained.Results showed promising molecular diffusion rates, mechanical properties, and electronic structure, with satisfactory water flux and salt ions rejection for the proposed membrane material.
Fan et al. [152].	PSO	Structural data of a proposed 2D graphene-like nanomaterial membrane were obtained using CLAYPSO.A molecular dynamics model was used to obtain performance indicators (mechanical and thermodynamic properties) corresponding to the structural data obtained.The results of the molecular dynamics model were generalized using an ML and the results were assessed.The ML included 49 different features as inputs related to chemistry, pore/membrane structure, partial charges, and mechanical properties.Water flux and salt rejection were chosen as performance indicators.Predicted properties/performance indicate that the novel material has promise in desalination applications.

4.3. Hybrid desalination systems

Hybrid desalination systems are an area of growing interest as a potential solution to many of the challenges facing desalination methods. Exploiting the synergies between different desalination methods could lead to reduced costs, increased efficiency, reduced energy consumption, and higher yield [134]. For example, RO produces highly saline brine which poses an environmental risk when released back into the sea. Hybridizing RO with a another desalination method has been reported to reduce the brine rejection factor of an RO process helping improve its environmental profile [135]. Some of the proposed systems rely completely on conventional desalination technologies such as hybrid RO-MED or RO-MSF configurations [136]. In contrast with emerging technologies, such configurations have the potential for a short path towards market implementation because the technologies are already well established.

In terms of modelling hybrid systems, all the aforementioned complexity associated with conventional mathematical modelling and optimization is increased because multiple desalination processes must be modelled. This factor should incentivize the utilization of AI algorithms in modelling hybrid desalination systems; however, the number of such studies is very limited. One of those studies was performed by Esfahani [137] which presented an MLP regression model for the performance prediction of an MED-TVC system. As presented in Fig. 12, relevant operational and design input parameters were included such as feed water temperature and number of effects. The annual costs, output ratio, and effluent rate were predicted as performance indicators. Subsequently, the outputs of the ANN were optimized utilizing a multi objective GA algorithm. The results demonstrated that pareto optimum number of MED-TVC effects that achieved the maximum gain output ratio while maintaining the lowest costs was 6.

Moreover, the performance of NF-RO hybrid desalination system via its permeate flow rate and recovery was assessed by Abba et al. [138] utilizing an emotional ANN (EANN). EANN is an improved version of an ANN which includes artificial hormones that modulate the output of neurons within the network. In this study, EANN demonstrated higher prediction accuracy when compared to conventional ANN.

Unique in its analysis of a liquid desiccant regeneration system, Naik et al. [139] evaluated the performance of a membrane liquid desiccant regenerator (MLDR) system powered by solar heat using both a first principes thermal and ML models. Liquid desiccant cooling systems are being investigated as an alternative for vapor compression. Desiccant materials are contacted with humid air to absorb moisture during a dehumidification step and a subsequent desiccant regeneration step removes moisture from the desiccant. Naik et al. [139] proposed a KNN algorithm that was trained using data from the literature to for performance prediction. Water was used as the working fluid for the regenerator absorbing moisture from the desiccant thereby achieving both desiccant regeneration and water desalination. Results indicated that desiccant temperature greatly influences overall system performance; moreover, the vapor flux and energy exchange were 2.3 $\frac{Lpm}{m^2}$ and 12 kW at the optimal operating conditions. Based on the results of these studies, reliance on AI regression and optimization algorithms in hybrid desalination investigations is expected to increase. A potential reason for the lack of AI utilization currently could be the limited availability of experimental datasets. The small number of experimental studies of hybrid systems can be noticed when looking at a review of hybrid desalination systems such as the one presented by Al-Obaidi et al. [136].

4.4. Membrane design and other subsystems

Membranes in desalination are a subject of continuous research aiming to improve parameters such as water permeability and salt rejection or minimizing negative phenomena such as fouling leading to cost reductions [140,141]. Membrane fouling in desalination plants operating technologies such as RO and NF has been reported to contribute 24 % of overall plant operational costs which highlights the significance of such research [142]. The aforementioned properties are interlinked in many cases, for example, there exists a tradeoff between permeability and salt rejection in many cases [143]. Methodologies such as molecular dynamics simulation and density functional theory are

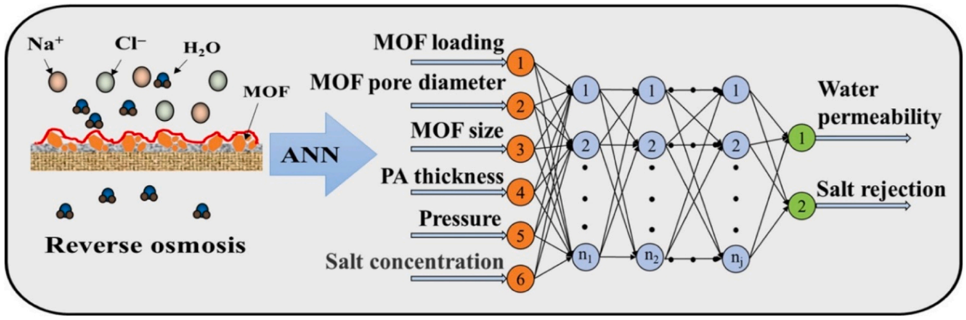

Fig. 13. Input variables and performance indicators for an ANN predicting the performance of an RO system utilizing MOF membranes as presented by Yao et al. [146].

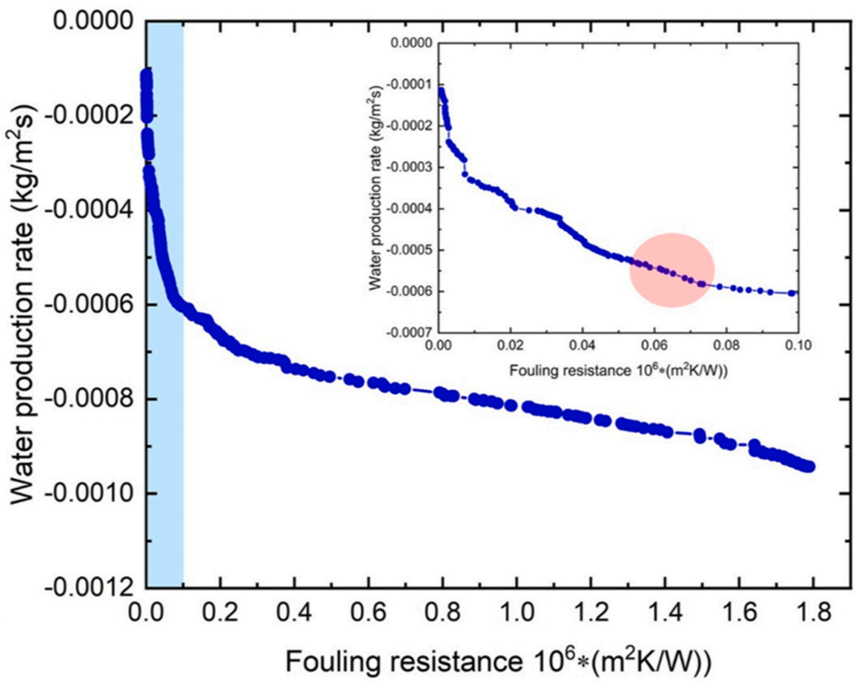

Fig. 14. Pareto front for two objective optimization using GA of falling film evaporator [150].

used to predict the performance of different membrane materials and structures. However, theoretical methods are challenging in some instances; for example, the results of molecular dynamics simulations include very large data volumes which makes them difficult to interpret [144]. This leads to researchers incorporating the MH based CALYPSO program or AI algorithms in membrane design studies in multiple ways. Table 4 provides a summary of all those studies and the way they utilize AI. CALYPSO, which uses PSO, is an open source program based on ML that predicts stable crystal structures at differing chemical compositions and external conditions [145].

The first methodology for AI incorporation in membrane studies involved the generalization of results from previous studies using ML algorithms such as the analysis by Yao et al. [146] and Yeo et al. [147] for example. The performance of RO plants with metal organic framework (MOF) nanomaterial membranes was predicted using ANN, SVM, and RF regression models in Yao et al. [146], with ANN proving to be superior. Performance indicators included water permeability and salt rejection; meanwhile, inputs for the three algorithms included MOF size, MOF loading, and feed water salt concentration among others as presented in Fig. 13. The analysis showed that the pore diameter and selective layer thickness were the parameters with the highest impact on performance. On the other hand, a GBT algorithm was used by Yeo et al. [147] to forecast structural data and performance indicators for thin-film nano composites (TFN) membranes.

The second methodology was utilized for example by Li et al. [148] and Meng et al. [149] which involves the deployment of CALYPSO to screen for stable membrane structures that were later modelled using molecular dynamics simulations. Meng et al. [149] extended the analysis to generalize the results of the model and forecast structural data for porous 2D graphene-like membrane materials using an ANN.

Analysis of desalination subsystems other membranes using AI algorithms were performed by Shahane et al. [150] and Ridwan et al. [151]. Shahane et al. [150] predicted the performance of a falling film evaporator for use in thermal desalination with the aim of reducing scale formation. To this end, a computational fluid dynamics (CFD) model was proposed, and its results were generalized using a DL algorithm which was subsequently linked to a GA algorithm to find optimum design and operational parameters. Pareto frontiers of competing objectives such as water production rate and fouling resistance were presented as shown in Fig. 14.

In the investigation by Ridwan et al. [151], chemical dosing during reverse osmosis (RO) pretreatment was optimized using ANN, DT, and RF algorithms with ANN proving to be the best predictor. Notably, the application of AI algorithms resulted in significant cost savings due to a

Table 5
Summary of research papers involving the use of AI algorithms in investigating solar powered thermal desalination.

Reference	Desalination technology	AI tools	Model description and findings
Salem et al.[161].	MD	CNN	Use of DL classification algorithm to predict performance of solar powered MD system.Operational parameters such as ambient and inlet water temperatures were considered in the prediction of the system performance.Using an explainer algorithm which assesses the contribution of the inputs on the prediction.Results of the explainer algorithm are looped back to improve DL performance in subsequent runs.DL model had an accuracy of 82.6 %.
Elaziz et al.[162].	SS	RVFL RVFL-SCA RVFL-MRFO RVFL-HBO	Prediction of the performance ultrasonic wave atomizer coupled SS using MH coupled ML regression algorithms. Performance was indicated by the basin water temperature and freshwater yield.Inputs of the models were ambient temperature, solar intensity, atomizer number, off and on times and water depth.70 % of the experimental data obtained was used for training and the rest for testing.RVFL-HBO provided the most accurate predictions when compared with other algorithms assessed.
Elsheikh et al.[163].	SS	RVFL RVFL-RUN RVFL-PSO	Performance prediction of SS based distillation tower using ML algorithm.Standalone RVFL was assessed in addition to being coupled with two different MH optimizers.RVFL-RUN was found to have the highest prediction accuracy.
Essa et al.[164].	SWGH	RVFL RVFL-AEO	Energy consumption of emerging renewable desalination technology predicted using ML regression algorithm.ML algorithm coupled with MH optimizer to tune its parameters.Hybrid algorithm had better prediction capability when compared with standalone RVFL.
Essa et al.[165]	SS	ANN ANN-HHO SVM	SS configurations were assessed using three different ML regression algorithms.Solar irradiance, ambient temperature, time, wind speed, and vapor velocity were chosen as input parameters to predict productivity.ANN-HHO was found to be the superior algorithm due to superiority of MH optimizer in tuning ANN weights.
Salem et al.[154].	SS-HDH	MLP DT Adam optimizer-MLP	Hybrid renewable energy desalination system proposed, and its performance was predicted using three different ML algorithms.Input variables included solar radiation intensity, ambient temperature, relative humidity, wind speed, humidifier feed water flow rate, air flow rate, flow rate of water circulate in solar water heater. Performance indicators water productivity of HDH unit, water productivity of SS, and water temperature inlet to the solar water heater were predicted.The hybrid Adam optimizer-MLP was found to give the highest accuracy.
Mashaly et al.[166].	SS	MLP ANN	Performance of SS with different feed water types was assessed using ML regression algorithm.Seawater, groundwater, and agricultural drainage water were the three feedwater types assessed.System operational parameters such as temperature of feed water in addition to weather conditions such relative humidity was used to predict performance.Performance indicators included distillate water productivity, recovery ratio and thermal efficiency.70 % of experimental data was used for training, 20 % for testing, and 10 % for validation.Feed temperature was found to be most significant in predicting the distillate water productivity and thermal efficiency.Ultraviolet index was the largest contributor in recovery ratio prediction.
Mashaly and Alazba [167].	SS	ANN MLR	prediction of SS performance with agricultural drainage water as feed using two ML regression algorithms. Thermal efficiency was chosen as the performance indicator.Relative humidity, wind speed, solar radiation, total dissolved solids of feed water, and feed temperature were chosen as input parameters.70 %, 20 %, and 10 % data split for training, testing, and validation was adapted.ANN showed higher accuracy in predicting thermal efficiency when compared with MLR.
Abujazar et al.[168].	SS	ANN MLR	SS performance prediction using two different ML algorithm while taking uncertainty into account.Instead of conventional feed forward ANN, cascaded forward ANN was utilized.Inputs were solar radiation, ambient temperature, month number, day number, number of hours per day, wind speed, humidity, cloud cover, vapor temperature, water temperature, basin temperature and the difference between the inner and outer surface of glass temperature while productivity was the predicted output.ANN algorithm showed better performance than MLR and linear regression.
Zarei et al.[169].	SWGH	SVR	Performance prediction of SS using ML regression to assess the effect of design parameters.Inputs included greenhouse dimensions, height of the first evaporator, and roof transparency. The output was freshwater production.Data split of 70 % training and 30 % testing was employed.Excellent prediction capability of proposed algorithm demonstrated.
Yu et al.[170].	SS	ANN	The use of polymeric solid wastes to synthesize an interfacial solar evaporator for freshwater production was assessed.Experimental results from one location are generalized for different environmental parameters to predict the performance of the proposed system globally using ML.Model inputs included temperature and solar flux. Water production rate was predicted as the only output.85 % of the data was used for training, 5 % for validation, and the remaining 10 % for additional testing.Acceptable salinity of permeation was achieved by the proposed system.Water production rates in different regions varied between 3.32 and 5.31 kg/m^2.
Moustafa et al. [171].	SS	ANN ANN-HWO ANN-PSO	Performance of proposed tubular SS configuration was assessed based on the systems predicted yield and energy/exergy efficiencies.Regular SS configuration was also modelled, and results were compared.The effect of an electric heater on the tubular SS was also assessed.HWO coupled, PSO coupled, and standalone ANN algorithms were all used, and their prediction capabilities compared.Data split of 80 % for training and the rest for testing. Standalone ANN gave the least accurate predictions while ANN-HWO gave the most accurate.The addition of an electric heater to tubular SS proved to have positive effects on its overall performance.
Liu et al.[172].	SWGH	MLP- GA MLP-PSO MLP-ES MLP-PBIL MLP-ACO MLP-BBO	Investigation of coupling ML algorithm with different MH optimizers for improved parameter tuning.Six models were tested to simulate the system including MLP hyper-tuned by GA, PSO, evolution strategy (ES), Population-Based Incremental learning (PBIL), ACO, and biogeography-based optimization (BBO).Most optimum results found with ES and GA.GA and BBO demonstrated the lowest prediction error for water generation and power consumption.
Ghandourah et al. [173].	SS	ANN ANN-GJO ANN-GA ANN-PSO	Assessment of two different materials for possible use in the basin and absorber plate of an SS is performed using ML regression.The two materials assessed were aluminum and polycarbonate.Performance was predicted via the heat transfer coefficient, energy efficiency, exergy efficiency, and distillate output.Inputs for the algorithms were incident solar irradiance, ambient temperature, water temperature, and absorber plate temperature.Aluminum showed better thermal performance when compared with polycarbonate.ANN-GJO gave the most accurate predictions closely followed by the other two hybrid algorithms while standalone ANN gave the least accurate predictions.
Behnam et al.[174].	MD	MLP LSTM	Assessment of solar powered direct contact MD by generalizing experimental system performance results. Different time dependent operational and environmental parameters such as solar intensity and mass flow rate were used as inputs to the ML algorithms.Performance was measured by the flux, efficiency, and gain output ratio.

(continued on next page)

Table 5 (*continued*)

Reference	Desalination technology	AI tools	Model description and findings
			Data split of 80 % training and the rest for testing was employed.Mass flow rates had insignificant effects on the overall performance of the system.Temperatures at different points in the system and solar intensity had a significant impact on performance.MLP model outperformed the LSTM model in terms of prediction accuracy.
Maddah et al.[175].	SS	SLR	Novel insulating material for SS was studied using experimentation.Experiment results were generalized using ML to obtain performance results for other insulating materials based on their properties.Using the algorithm, operational parameters such as water-glass temperature were correlated to the systems outputs.Lowering the feed rate was found to positively impact evaporation rates.High water glass temperature had a very significant positive impact on performance regardless of flow rate.
Elsheikh et al.[153].	SS	ANN SVM ANFIS	Three different performance prediction ML algorithms were used to generalize experimental data for both conventional SS and a modified configuration.The modified configuration utilized low-cost heat localization bi-layered structure.Freshwater productivity, energy efficiency, and exergy efficiency were considered as performance indicators.The modified SS configuration achieved higher maximum water yield, exergy efficiency, and overall energy efficiency.The cost of freshwater per liter obtained by the modified solar still was found to be 0.015 $/l
Sohani et al.[176].	SS	ANN	Performance prediction of enhanced solar still designANN regression algorithm coupled with four different training algorithms (feed forward, backpropagation, and radial basis function).Input parameters included ambient temperature, wind speed, radiation levels, depth of basin water.Outputs were water temperature in the basin and distillate production.Feed forward and radial basis function ANN's were best at water temperature and distillate production predictions.
An et al.[177].	HDH	RF-BOA ANN-BOA SVM-BOA linear SVM-BOA	Four ML regression algorithms utilized to generalize performance results found experimentally (performance prediction).Solar radiation, meteorological conditions, carrier air flow rate, and temperatures of air and water paths were chosen as inputs.Outputs included productivity, cost, and gain output ratio.80 % of data was utilized for training and the rest for testing.ANN-BOA and RF-BOA models revealed the best prediction ability.

decreased consumption of chemicals. This highlights the potential role of AI in enhancing desalination process efficiency by optimizing process control as discussed previously.

4.5. Renewable energy desalination systems

Powering energy intensive desalination processes with renewable energy desalination is an attractive option limited mainly by the high cost of such configurations [3]. Research in this topic in general and into thermal renewable desalination specifically has been extensive with AI algorithms being deployed in various thermal desalination studies as summarized in Table 5. These studies used a variety of DL and ML algorithms such as CNN, LSTM, RVFL, ANN, MLP, SVR, and RF. Desalination technologies such as SWGH, HDH, MD, and SS, which all rely on direct solar energy, were investigated.

Performance prediction of SS using ML algorithms was most widely observed renewable thermal desalination system analysis. Various SS configurations have been proposed and investigated with the aim of maximizing the utilization of solar energy through their design. An example of such investigation was presented by Elsheikh et al. [153] where ML regression algorithms were used to predict the performance of a novel SS configuration presented. The proposed bilayer design used a low thermal conductivity material for the bottom layer in addition to a top absorbing layer made of a photo thermal material as presented in Fig. 15. The choice for photo thermal material was made due to their high sunlight absorptivity coupled with their high conversion efficiency. ANN, ANFIS, and SVM algorithms were trained to predict the freshwater productivity, energy efficiency, and exergy efficiency of the proposed system and a conventional SS configuration for comparison. Solar radiation and ambient temperature were the two input parameters

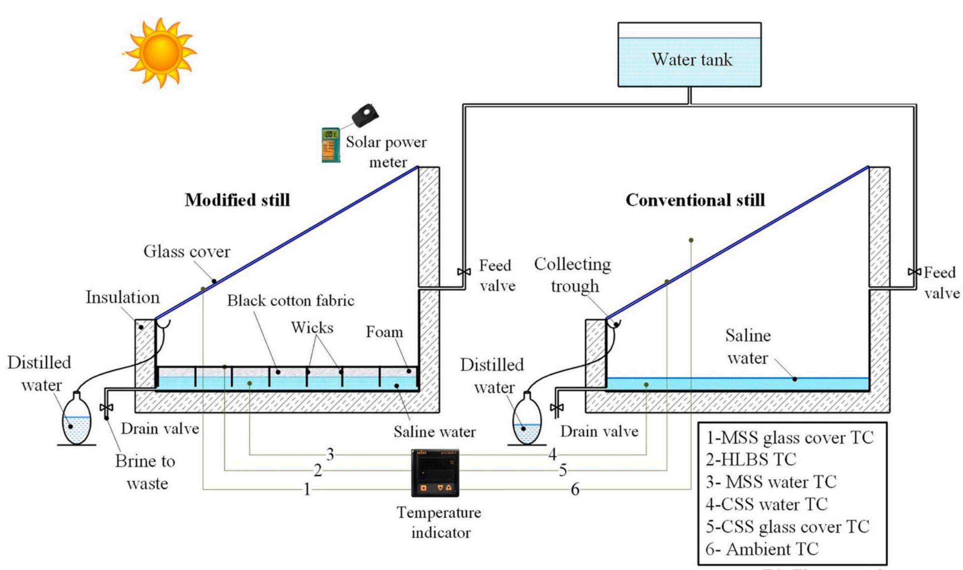

Fig. 15. Schematic diagram of experimental units for both modified and conventional SS configurations investigated by Elsheikh et al. [153].

Table 6
Summary of research papers which employed AI algorithms to investigate renewable RO processes.

reference	energy source	AI tools	main remarks and findings
Udono and Sitte[102].	Waste incineration	ANN	Simulation of overall system using both ML models and system equations.Power for RO units produced by municipal solid waste incineration.ML is utilized for subsystems which are difficult to model with equations.
Cabrera et al.[156].	Wind	MLP SVM RF	Performance prediction of RO plant under varying operational conditions caused by inconsistency in energy source.Impact of battery-based energy storage system was assessed.Each of the four ML algorithms created was trained to correlate certain input parameters to desired outputs which are subsequently used as inputs in another algorithm.Time dependent inputs included power supplied by the wind turbine (WT) in addition to feedwater conductivity and temperature.Time dependent outputs included operating pressure, recovery rate, permeate flow rates, and permeate conductivity.RF had the best performance followed by SVM and ANN respectively.
Ruiz-García et al. [157].	Solar	MLP	PV powered RO desalination plant with energy recovery system was analyzed using ML algorithms.Conductivity and feed conditions including pressure, temperature, and flowrate were chosen as inputs to algorithm.Target variables were the conductivity and flowrate of permeate.The proposed algorithm showed higher accuracy in predicting flowrate than conductivity.
Chitgar et al.[158].	Geothermal	ANN-GA	Optimization of three different renewable energy desalination systems each with a different organic Rankine cycle configuration for RO plant.Different working fluids were also considered and compared.ML algorithm coupled with MH optimizer to reduce computational time of optimizer.
Soleimanzade et al. [159].	Solar	CNN-SAC	Investigation of a hybrid RO-PRO desalination plant powered by PV.DL-RL hybrid algorithm developed for the energy management strategy for overall system.Transmembrane pressure and RO feed flow rate are two decision variables associated with the RO plant through which the agent can control the permeate flow rate, rejection percentage, and power consumption of the desalination unit.Hybridization of CNN with other RL algorithms investigated and CNN-SAC demonstrated the best performance.
Carta and Cabrera [155].	Wind	GA RF	Optimization of sizing parameters of proposed system which makes use of water storage as a replacement for energy storage. The system also included an uninterrupted power system (UPS) which ensures constant supply to control systems.The optimum size of all subsystems is found including size of water storage and number of WTs etc.Input data regarding wind, turbine, RO units, demand, costs of storage, batteries, life expectancy and discount rates are required.Future wind speed is predicted using a trained RF algorithm while the optimization is carried out using GA.
Aldaghi et al.[160].	Solar	MLP SVM GPR DT	Ground water desalination system powered by PV is investigated using four different ML algorithms.Produced energy, carbon emissions, initial and maintenance costs are the chosen performance indicators.Estimated 1400 tons of emissions savings over 25 years due to system implementation.GPR demonstrated highest prediction accuracy.

considered. Experiments involving the design and operation of a conventional SS in addition to the proposed one were carried out to obtain the data used to train algorithms for both configurations. The novel design demonstrated better performance in all the three metrics considered and its production cost per liter of water was estimated to be 0.015$.

With the exception of Salem et al. [154] which investigated a hybrid SS-HDH process, all other investigations were of standalone operations with a strong emphasis on operational parameter optimization to increase system efficiency and save costs. Furthermore, the performance metrics most considered were freshwater yield, energy consumption, efficiency, and productivity. The consistent consideration of these specific parameters by multiple studies points to the fact that they are the prime limitations of current SS configurations. No investigations of systems using conventional thermal desalination systems such MSF and MED powered with solar energy were found. This is mainly due to their high heating requirements that are difficult to meet using solar energy.

The conversion of renewable energy to electrical power that is required for membrane desalination allows for the use of various renewables as opposed to solar being the only option as is the case with thermal technologies. All the research studies utilizing AI algorithms in renewable membrane desalination investigated RO systems. AI algorithms were utilized for performance prediction or optimization applications in off-grid or micro-grid systems as presented in Table 6. Grid connected systems would not require such investigations as the grid connection would eliminate the power source fluctuations problem which is usually the main point of focus in such studies.

An example of an optimization problem in the manner described was presented by Carta and Cabrera [155] where a GA algorithm was used to find the optimum system sizing for a wind powered RO system. A water storage system was proposed to provide the flexibility needed as shown in Fig. 16 which presents the various processes taking place within the system. Due to the fluctuations in the power source, it served as a cheaper alternative to energy storage. In addition, a constant power source was included to provide energy to vital systems within the process such as equipment control modules. A trained ML algorithm was utilized to predict future wind speed and communicate the results to the optimizer as an input parameter. Other input parameters included operational data regarding the turbines in addition to other factors such as future demand projections and costs of proposed storage systems among others. Meanwhile, Cabrera et al. [156] estimated the performance of a similar RO plant under various wind energy conditions, taking into account the effects of an energy storage system based on batteries.

Ruiz-García et al. [157] focused on conductivity and feed parameters when analyzing a PV-powered RO desalination plant with an energy recovery system. Also, Chitgar et al. [158] optimized numerous geothermal-powered renewable energy desalination systems, taking into account different system designs and working fluids. Soleimanzade et al. [159] looked at a hybrid RO-pressure retarded osmosis (PRO) desalination system that used solar energy and a DL-RL hybrid energy management algorithm. Finally, Aldaghi [160] investigated a groundwater desalination system powered by PV assessing energy output, carbon emissions, and costs.

4.6. Poly-generation systems

Due to the complexity of modelling multiples subsystems within poly-generation systems, AI algorithms have been widely utilized for performance prediction and optimization in this regard. In such investigations, first principles analyses including thermodynamic, economic, environmental, and exergy factors are usually performed. These analyses allow for sensitivity analysis and parametric studies in addition to providing a data set of the overall system performance at different input parameters. ML algorithms are subsequently utilized to generalize those results and correlate design and operational parameters to overall system performance. An example of such investigation was performed by Ghazaie et al. [178] which assessed the economic viability of coupling of an MED unit and a nuclear plant producing freshwater and power as presented in Fig. 17. A sensitivity analysis was performed to find the parameters that most influence overall costs. A comprehensive data set was obtained and used to train the utilized GEP algorithm which

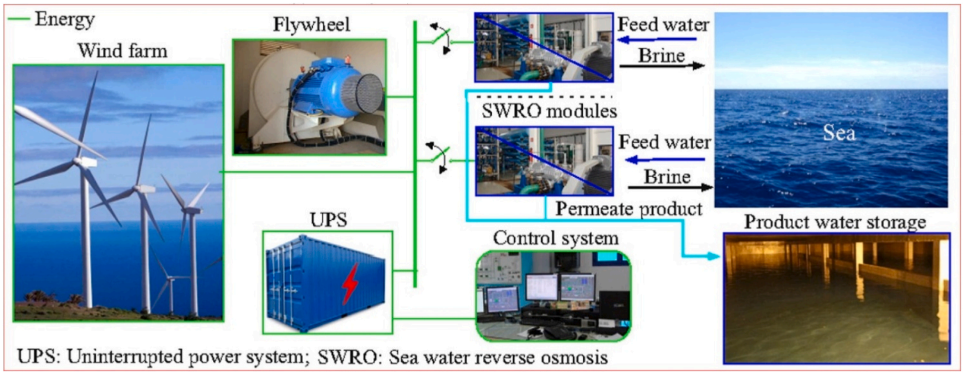

Fig. 16. Schematic diagram of process flow diagram for wind powered RO system investigated by Carta and Cabrera [155].

correlated the relevant input parameters with the costs. The results were compared with values reported in the literature and high prediction accuracy was demonstrated by the algorithms employed.

Besides performance prediction, optimization of poly-generation systems using MH optimizers has also been observed in the literature. MH algorithms are usually coupled with ML algorithms as they are utilized to compute the value of the objective function reducing computational requirements. It is important to note that not all studies investigate the overall system using AI algorithms with some opting instead to predict the performance of only specific complex subsystems. The same process is followed for obtaining data sets that are subsequently generalized using ML algorithms for those specified subsystems; however, other subsystems within the overall process are simulated using the first principles models. An example of such investigation was performed by Rabeti et al. [179] based on a poly-generation system relying solar and biomass energy. The proposed system produced a heat load, hydrogen, oxygen, carbon dioxide, methanol, power, and water as presented in Fig. 18. Utilizing trained ANNs that were linked to the simulator, the performance of the MED unit chosen to desalinate water in addition to the carbon dioxide capture and methanol synthesis systems were generalized and predicted. On the other hand, the first principles models of other subsystems such as RO units, Kalina cycle, pressure steam cycle, organic RC, microbial fuel cell, and Brayton gas cycle were directly used by the simulator. Subsequently, the simulator was linked to four different SI algorithms to optimize the overall system based on multiple objectives such as maximizing energy and exergy efficiencies. Table 7 presents a summary of the literature papers which modelled using AI single energy sourced poly-generation systems

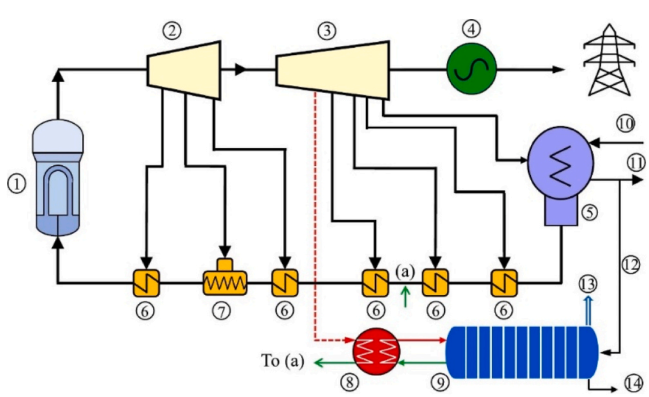

Fig. 17. Schematic diagram of MED and nuclear poly-generation system proposed by [178]. Numbers represent: 1. Steam generator of nuclear plant, 2 and 3. High- and low-pressure turbines, 4. Generator, 5. Condenser for nuclear plant, 6. Preheater, 7. Deaerator, 8. Heat exchanger, 9. MED unit, 10 and 11. seawater feed to nuclear plant condenser and its outlet, 12. Feed to MED system from condenser outlet, 13. Product water, and 14. Brine.

involving desalination while Table 8 does the same for multiple energy sourced poly-generation systems.

5. Challenges of artificial intelligence utilization desalination and areas of future potential

Despite the immense advantages of AI algorithms and their proven record in desalination studies, multiple challenges have been identified. First, AI algorithm utilization is dependent on the availability of extensive experimental datasets. Small datasets and may lead to overfitting which negatively affect model performance. If experimental datasets are not available, first principles models must be used to come up with data. However, first principles modelling requires intricate knowledge of system governing equations which negates a significant advantage of AI modelling. Moreover, AI models lack some of the features of mathematical modelling which come with intimate knowledge of the system in question. For example, mathematical models can be used to conduct sensitivity analysis which provides deep insight into the influence of each input parameter on system performance. Sensitivity analysis can obviously provide immense benefit in many applications such the design of lab scale units. Lastly, AI algorithms provide approximate solutions instead of deterministic ones which limit their use in accuracy sensitive applications. Despite these challenges, multiple gaps in the literature where AI could excel have been identified such as:

- Use of hybrid AI algorithms may have significant future potential since it can leverage the advantages of multiple algorithms. Coupling ML with MH algorithms has shown improvements in prediction accuracy for example. Another example is the hybridization of two DL algorithms such as CNN-LTSM. Other combinations may be explored with the aim of improving performance and discovering new applications aside from regression and optimization.
- Utilization of DL algorithms and comparison of their performance with ML algorithms. Despite their higher computational requirements, they may provide increased accuracy in some applications.
- Hybrid desalination systems should be a good candidate for AI modelling and optimization due to their potential as an energy efficient and practical solution to the challenges faced by desalination systems. Moreover, the complexity of hybrid desalination systems should incentivize AI utilization. However, experimental analysis and datasets are needed before such implementation is observed. Otherwise, AI algorithms can only be used to generalize results of mathematical models in which case one of the main advantages of AI in terms of not requiring intricate system knowledge is nullified.
- Utilization of AI algorithms in studies that investigate and optimize the overall water and energy supply chains for long periods as part of strategic planning long term planning. ML or DL algorithms can be used in predicting future values of specific input parameters such as

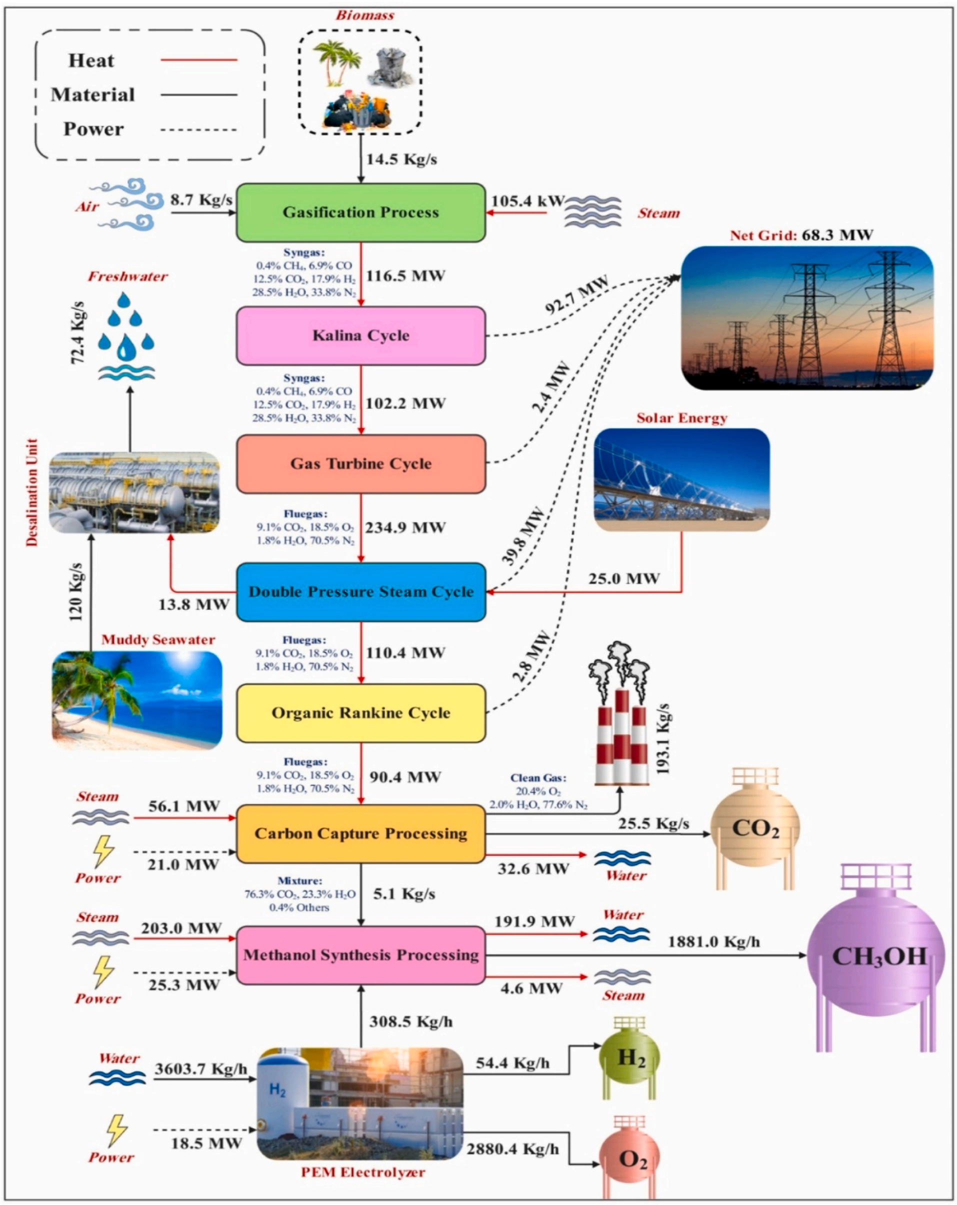

Fig. 18. Schematic diagram of mass balance for biomass powered poly-generation system presented by [179].

Table 7
Summary of single energy sourced poly-generation system modelling using AI in the literature.

Reference	Subsystems	Energy source	AI algorithms	Products	Optimization
Musharavati et al. [180].	MED-TVCGasifierCompressorHeat exchangerGas turbineCombustion chamber	Biomass	GWO ANN	Freshwater Power	Yes
Haghghi et al.[181]	HDHTranscritical CO2 RCAbsorption refrigeratorElectrolyzer	Geothermal	ANN GWO	Freshwater Power Cooling Hydrogen	Yes
Zhang et al.[182].	HDHGasifierMolten carbonate fuel cellElectrolyzer	Biomass	ANN GWO	Irrigation water Power Fertilizers	Yes
Ghazaie et al.[178].	MEDNuclear plant	Nuclear	GEP	Freshwater Power	No
Hai et al.[183].	MEDFlame assisted fuel cell	Not specified	ANN GWO	Freshwater Power	Yes
Javaherian et al. [184].	ROGas turbineSupercritical-CO2Recompression Brayton cycleOrganic RCAbsorption refrigeration system	Fossil fuels	ANN GA GWO	Freshwater Power	Yes

weather conditions. Also, MH optimizers may be utilized for long-term system design optimization. This type of analysis may aid in developing long term solutions in prediction and strategy regarding future challenges in the water sector. AI can provide huge value is such applications because deterministic modelling of large-scale systems is computationally demanding.

- Utilization of AI algorithms to enhance current desalination plants control systems using historical plant data with the aim of

Table 8
Summary of multiple energy sourced poly-generation system modelling using AI in the literature.

Reference	Subsystems	Energy sources	AI tools	products	Optimization
Lu et al.[185].	MSFGasifierRCSolar collectorsElectrolyzer	Biomass Solar	ANN GA	Freshwater Power Hydrogen Ammonia	Yes
Al-Alawi et al. [99].	ROPVDiesel generatorEnergy storage	Solar Fossil fuels	ANN	Freshwater Power	No
Manesh et al. [186].	MEDCombined cycle plantSolar collectors	Solar Fossil fuels	ANN GA	Freshwater Power	Yes
Wang et al. [187].	ROPVWind turbinesDiesel generatorsEnergy storage	Wind Solar Fossil fuels	ANN	Freshwater Power	No
Alirahmi et al. [188].	MED-TVCGas turbineRCOrganic RCSolar collectorGasifierPEM electrolyzer	Biomass Solar	ANN GA PSO PESA SPEA	Freshwater Power Hydrogen Heating load Hot water	Yes
Shakibi et al. [189].	ROWind turbinesSolar collectorThermoelectric generatorRCAbsorption chillerPEM electrolyzer	Wind Solar	ANN GWO	Freshwater Cooling load Hydrogen	Yes
Rabeti et al. [179].	MEDROKalina cycleBrayton gas cycleDouble-pressure steam cycleOrganic RCMicrobial fuel cellCarbon dioxide capture systemMethanol synthesis system	Solar Biomass	ANN TEO SSI WCA DA	Freshwater Power Heat load Hydrogen Oxygen Carbon dioxide Methanol	Yes
Pombo et al. [190].	ROMSFNuclear plantPVWind farm	Nuclear Solar Wind	CNN-LTSM RF	Freshwater Power	No
Hai et al.[191].	MEDGasifierGas and steam turbinesCompressed air energy storageGround source heat pumpAdsorption chiller	Biomass Geothermal	GPR GA	Freshwater Power Cooling load Heating load	Yes
Shakibi et al. [192].	TVC-MEDGas turbine cycleSolar collectorSteam RCOrganic RCThermoelectric generator	Solar Fossil fuels	SVR GWO GOA	Freshwater Power	Yes
Rabeti et al. [193]	MEDROKalina cycleGas turbine cycleDouble-pressure steam cycleOrganic RCPEM electrolyzerGasifier	Solar Biomass	ANN GA	Freshwater Power Heating load Hydrogen	Yes
Khani et al. [194].	HDHGas and steam turbineOrganic RCCO2 captureSolar collector	Solar Fossil fuels	ANN GA GP	Freshwater Power Carbon dioxide	Yes

minimizing operational costs. Multiple DL, ML, and MH algorithms may be coupled for such applications. Not only can such algorithms lead to improved system control and performance, but they may also lead to increased automation within desalination plants.

6. Conclusion

In conclusion, this review has analyzed the various applications of AI algorithms in different desalination systems, assessed their performance, identified their potential, and highlighted the challenges faced by them. AI algorithms have been successfully implemented in desalination studies to replace or augment conventional modelling and optimization approaches. ANNs were the most dominant algorithms; however, others such as DT, RF, and SVM among others were observed though to a significantly lesser extent. Whenever comparative analyses were carried out, ANNs consistently demonstrated regression and generalization capabilities exceeding mathematical modelling and other ML algorithms which explains their favorability. Furthermore, a small number of studies opted for the use of DL algorithms and their lack of utilization can be explained by their computational requirement. Aside from regression, optimization was carried out in many studies using MH algorithms with GA being the most prominent of them. Optimization was either carried out to optimize the investigated system or to optimize the parameters of the ML algorithms to increase their accuracy.

In terms of the system types, many investigations of standalone desalination were observed. This included a significant number of studies which predicted the performance of RO in addition to emerging technologies such as CDI, MD, SS, and HDH. Furthermore, both desalination membranes, their properties, and performance were augmented by AI regression algorithms. Furthermore, a significant number of studies investigated poly-generation systems which produced fresh water and electrical power in addition to other chemicals and energy vectors. AI algorithms showed high flexibility to be implemented in many different applications while providing good generalization and optimization abilities. Since they do not require intricate knowledge of system dynamics and governing equations, AI algorithms offered significantly reduced computational time and complexity for correlating control variables to performance indicators of desalination systems. These studies show that AI-driven analysis and optimization has the potential to improve system performance, save costs, and lessen environmental impacts in desalination processes. Lastly, gaps in a number of subtopics within desalination are considered to offer future potential for research. These include the optimization of desalination control, long-term water supply chain modelling and optimization, hybrid desalination performance prediction, and utilization of DL algorithms among others.

CRediT authorship contribution statement

Hadil Abukhalifeh: Writing – review & editing, Supervision. **Hadi Jaber:** Writing – review & editing. **Mahmoud Ibnouf:** Writing – original draft. **Mohammad Alkhedher:** Writing – review & editing, Supervision. **mohamad ramadan:** Writing – review & editing, Supervision. **Mohammed Ghazal:** Writing – review & editing.

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.

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Data availability

No data was used for the research described in the article.

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