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**Can machine language and artificial intelligence revolutionize process automation for water treatment and desalination?**

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# Abstract

Artificial intelligence (AI) is a powerful tool that is commonly applied in engineering multi-disciplines owing to its functionality to resolve real-world problems where deterministic solutions are arduous to achieve. Revolution in water treatment and desalination process automation has been emerging recently. Several challenges are present in the water sector related to data structuring and smart water services through which AI would have great potential once those issues are addressed. The distinctive tools of AI, mainly; artificial neural networks (ANNs), as a regression model, and genetic algorithm (GA), as one of the global optimization techniques, have been immensely applied in desalination and water treatment for multi-purpose applications. Modelling desalination and water treatment processes and optimizing the operating condition are few among the many applications. In the current review, paramount applications of AI tools in desalination and water treatment have been thoroughly reviewed. In addition, benchmarking ANNs with the conventional modelling approaches were highlighted, along with the shortcomings and challenges expected to associate with these common tools in some complex nature practical application. It was concluded that the use of AI tools will undoubtedly pave the way in the water sector towards better operation, process automation, and water resources management in an increasingly volatile environment.

Keywords**: Artificial intelligence, desalination, machine learning, artificial neural network, genetic algorithms, process automation.**

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#  Introduction

Potable water resources represent one of the most precious commodities for sustaining human life on earth [1]. Even though water counts for about three-quarters of the total Earth’s area; around 99% of available water is salty, brackish or frozen, whilst only about 1% is fresh. Along with that, the steadily growing world population, industrialization and climate changes are placing more pressure on the deficiencies of these resources that are projected to grow in the upcoming decades. In this regard, tremendous advancements in seawater desalination and water treatment technologies have emerged over the past half-century. Diverse water treatment/desalination processes have demonstrated great eligibility to bestow viable solutions to the aforesaid issues. Among these technologies, distillation and membrane separation are the two major seawater desalination technologies. Multi-stage flash (MSF) distillation, multi-effect evaporation (MEE) distillation, vapour compression (VC) and reverse osmosis (RO) are convenient to meet the massive demand for freshwater [2,3]. However, the overstrain costs of these techniques raise the demand for process identification, control, and optimization. The complexity in the nature of desalination system, in terms of parameters affecting the cost of building a plant and parameters affecting the performance instability, requires the use of innovative methods in controlling and optimizing the current desalination systems [4–8].

Day by day, the current trend of process automation and big data exchange, or what renowned by Industry 4.0, is becoming an increasingly relevant and extremely important in various industrial applications for multimode reasons. Industry 4.0 could bestow significant potentials to overcome process challenges and boost design processes. Yet, leading to long-term sustainability and profitability. This can be achieved through implementing the four design principals of Industry 4.0, which consists the interconnection, information transparency, technical assistance and decentralized decisions [9].

The development of modelling methods for supporting systems in desalination and wastewater treatment has been improved drastically in the last few decades. Advances in computers speed along with the significant reduction in their cost have favoured the application of model predictive controllers for processes of commercial interests [10]. Smart or intelligent control systems have been significantly spreading around due to their enormous features. These include self-tuning, self-diagnosis, expert systems, life management, equipment health monitoring, modelling, and simulation, hence, showing an increasing trend towards more efficient desalination plants necessitates more sophisticated automation technologies [11]. Artificial intelligence (AI) was introduced in the field of computer science in the mid-1950s. Thereafter, it has generated a significant number of powerful and practical tools in the field of engineering to overcome tricky problems as well as to address complex problems of the real-world applications though which classical or conventional methods and approaches are ineffective or infeasible. Practically, it can be defined as the ability of a computer-powered machine to take a set of information, analyze, decide, and autonomously take actions [12]. Data processing, analyzing and tackling operational issues may cause a delay in response time even with highly qualified plant personnel, leading to a reduction in throughput, raising costs and deteriorate effluent quality. That does not necessarily mean that workforce is no longer required, as they always could serve as first-line guards to combat complex natural and dynamic system disruptions and to bestow better decision-making tools and flexibility to resolve these complexities. The other misconception about AI has reckoned that operators/engineers may lose the entire control of their system and there would be no way to correct any deviation. In fact, utilizing AI would not affect their ability to manually control the system and, by contrast, brings to their hands immediate and accurate response features of a computer in a timely manner [12,13]. In this regard, AI tools could be pivotal for the Industry 4.0 through providing better quality control for plants, increasing the plant productivity, minimizing human errors, optimizing operation and production costs, and improve overall process efficiency via concentrating human efforts on non-repetitive tasks [14].

AI has been applied in numerous disciplines of engineering, including desalination and water treatment applications, and can be pivotal for optimizing the inevitable variability of process conditions [15]. Some of the AI tools comprises knowledge-based systems, fuzzy logic, particle swarm optimization (PSO), Monte Carlo simulation (MCS), genetic algorithms (GA), and artificial neural networks (ANNs), and so forth [16–18]. A considerable amount of research work for predicting and optimizing water treatment and desalination industry has been conducted using ANNs and GA. ANNs are the AI tools normally devoted for predicting the removal of pollutants in many treatment processes owing to their abilities of self-adapting and self-learning [19]. Other applications of ANNs and GA include dynamic simulation of the fouling process in membranes [20], flux decline [21,22], water production ratio [23], energy consumption [24], and so forth. A combination of more than one tool was also reported [25]. Research on AI for the prediction and optimization of desalination processes has been intensified in recent years. The number of scientific publications wherein keywords including “artificial intelligence” and “desalination” were discussed has continued to increase worldwide. According to the search results obtained from the Google Scholar database using these keywords, an increasing trend of research on AI for the prediction, automation, control, and improvement of desalination performance was observed. These search results are illustrated in Fig. 1.

Fig. 1. The annual number of scientific publications on modelling of desalination technologies using AI, as obtained from the Google Scholar database.

As aforesaid, the realistic predictive horizons of the AI approach in multifaceted applications represented a hot research area in various technology disciplines including chemical engineering. This short review presents an endeavour dedicated to present the cutting-edge research on up to date advances in desalination and water treatment plants automation and to shed the light on how AI can be introduced to desalination field aiming to redefine the water treatment and desalination technologies. Initially, AI has been benchmarked with conventional approaches. Hereinafter, the recent advances and application of different AI tools, namely; the ANNs and the GA were covered. These applications range from modelling contaminant removal and cost optimization of various desalination and wastewater plants to membrane properties and performance. In addition, the current challenges and adapted solutions have been highlighted as well.

#  Reliability of artificial intelligence (AI) vs conventional modelling approaches

Interestingly, AI tools have proven their capacity as alternative approaches to information processing over the past few decades [26]. Applications of AI modelling disclosed that they can handle various problems with any degree of complexity and difficulty [27]. This is the primary trait of AI tools when benchmarked with classical approaches. By contrast, and for the latter case, several assumptions should be taken into account to simplify the system under consideration [28]. For instance, for the optimization and prediction of certain pollutant removal in treatment processes; the definition of a dependent variable for each combination of independent variables should be determined; more specifically varying one variable at a time whilst keeping other variables as constants [29]. These assumptions may unexpectedly comprise certain deviations between theoretical models and experimental observations due to insufficient knowledge regarding the system complexity and hamper the model accuracy indeed [30]. Eventually, these methods obviously require a broad range of expensive and time-consuming tests to be conducted whereas the impact of the interactions among the independent variables cannot be revealed [31–33]. Another trait of AI tools indicates that they don’t require deep knowledge about the phenomena or the process under study. ANNs have been considered as a black box model, which means it can model any process with little knowledge required. More precisely, neither numerical or governing equations nor detailed assumptions describing the fundamental engineering phenomena is required. From given input variables and obtained outputs; ANNs can learn the complex transport processes of a system, making it a powerful tool for universal data approximation [30]. On the other hand, ANNs require a long training process, especially for deep networks which are the most accurate architectures for most technical problems. For the training process, and to achieve the best performance, different design models with different design elements have to be tested, such as the number of layers, the number of nodes in each layer, and the activation function which introduces non-linearity into the output, in addition to the model architecture. This may take a long time, especially if the computation is performed on a central processing unit (CPU) instead of a specialized graphics processing unit (GPU) or a field programmable gate array (FPGA) [34,35].

Nevertheless, and as will be explained later in this review, GA is copying the logic of natural evolutionary to estimate all possible solutions for engineering or science problems. In contrast to GA, most classical techniques perform a deterministic procedure in order to approach an optimal solution. These algorithms usually begin with a random guess solution, then a search direction is obtained based on a predetermined transition rule. Later, a unidirectional search is carried out to determine the optimum solution. Such a classical optimization technique is not efficient in water desalination application and wastewater treatment since the dependency of the optimal solution is based on the selected initial solution. In addition, it gives local maximum and minimum whereas designers are seeking for global maximum and minimum. whilst GA can generate a Pareto set that shows the global optimum point and predicts all possible solutions [33].

#  Artificial neural networks (ANNs) for desalination and water treatment applications

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## Background

Noticeably, ANNs have brought about the attention in many science disciplines as one of the major AI tools. ANN model is comparatively simple owing to its nonparametric technique that can capture the nonlinearity of any system characteristics. Unlike conventional prediction models; precise ANN predictions were achievable even without using an industrial or laboratory plant as inputs [26]. An ANN is a computational model derived from biological neural networks in the human brain which is able to learn (after training it) to solve different technical problems. The basic processing unit of the ANN model is the neuron (Fig. 2). It receives input from an external source or from other neurons (x1, x2, x3,.. etc), performs some computations, and generates an output (Y).

Fig. 2. The basic unit of the artificial neuron (node) [36].

The inputs of a neuron are associated with weights (w) which are calculated in the training process. One additional input is associated with the neuron is called bias (b). The bias has a weight of 1 and it provides every node with a trainable constant value. The neuron applies a function $f$ (called activation function) to the weighted sum of its inputs as shown in Fig. 2. The activation function introduces non-linearity into the output of a neuron as most real-world data are non-linear. The commonly used activation functions are step, linear, sigmoid, and tanh functions.

Fig. 3. The general structure of the artificial neural network (ANN) [37].

Combining the neurons in a group and arranging them in parallel layers that are fully interconnected by weighted connections, forms the ANNs (Fig. 3). ANNs receive inputs through the input layer whilst emitting their outputs through the output layer [28,38]. One hidden layer lies between the input and output layers. Several ANN parameters can be determined. These include the number of hidden layers, the number of neurons in each hidden layer and the training algorithm in each hidden layer and the activation function. An iterative solution was chosen so as to select parameters that generate optimal results [28]. In each stage known as “an epoch”; the network receives the training data set whilst the corresponding output is determined. Then, the error between the desired output and the network output is obtained through which the network weights are calculated as per the specified learning algorithm. Also, the validation data set in each stage “epoch” is fed into the network where the validation error is determined. This process of training continues until the validation error matches the initial desired and predefined value. The predictive capability of the network is examined with the test data which were not used during the training phase [36,39].

## Modelling of ions and pollutant removal

Salt rejection is caused by charge, steric, dielectric and transport effects, which leads to the complexity of modelling the salt rejection mechanisms. Different approaches were devoted for modelling the salt separation mechanism of membranes. For instance, Spiegler-Kedem model, which suffers from being limited to a binary salt system, is derived based on the physical description and full understanding of the nanofiltration (NF) membrane process, which is complex from the mathematical perspective as they require detailed knowledge about the membrane and solution properties. Unlike that, AI prediction models, like ANNs, do not require much understanding of the system being modelled and are capable of modelling highly nonlinear and complex systems. [40]. Bowen et al. have applied ANNs to predict the rejections of single salts (MgC12, Na2SO4, NaCl, and MgSO4), as well as a mixture of these salts at the surface of NF membrane. The influence of different process parameters such as mixture composition, salt concentration and pH was studied. They were found to exhibit complex non-linear dependencies on these parameters. The flexibility of the ANNs allowed using only single optimized ANN, which has the ability to switch between the input neurons for all predictions. The results showed a general agreement between experimental data and ANN predictions for both mixtures and single salts. The advantage of ANN approach over the physics-based model is that the ANN can be used simply and readily to predict the salt rejection for higher salinity solutions without considering the theory of non-ideal solutions [28]. ANNs have been also harnessed to investigate the influence of four parameters (flow rate, feed concentration, reaction temperature, and applied voltage) on the separation removal of NaCl solution by electrodialysis (ED). Two prediction methods, back propagation (BP) neural networks, and improved BP algorithms (adaptive learning rate method and flexible BP algorithm), were compared in this study. Using ANNs, it was found that improved BP algorithms showed better prediction results due to increasing ratios of learning rates and weights properly. At higher temperatures and voltages conditions; improved BP algorithms, due to their generalization ability for high values, were predicted to manifest greater separation performances [40].

Along with the steady evolution in ANNs applications, they have been employed frequently for the prediction of pollutant removal including nutrient removal, heavy metal removal, persistent organic pollutant removal, and others. The majority of conducted research have disclosed good modelling and optimization capabilities. Singh et al. [41] presented the potential of ANNs, gene expression programming (GP) and support vector machine (SVR) modelling approaches to forecasting the presence of trihalomethanes (THMs) in chlorinated waters. Five parameters such as dissolved organic carbon, pH, temperature, contact time and bromide concentration were utilized as the input variables. The results revealed the nonlinear correlation between disinfection operating conditions and the formation of THM, was captured by all the three predictive models and manifested an excellent predictive and generalization capabilities [41]. In another research for wastewater applications, intelligent systems based on back propagation neural network (BPNN), adaptative neuro-fuzzy inference systems (ANFIS) and radial basis function (RBF) were used to predict the removal of starch from starchy wastewater employing hydrophilic polyethersulfone microfiltration (MF) membrane. This comparison research focused on the evaluation of membrane performance using optimal operating conditions which impacted the removal of COD and water flux. Optimum BPNN performance was obtained with four hidden layers for water permeation and pollutant rejection factor prediction for BPNN. ANFIS and RBF simulations were used for comparison with the results obtained from BPNN. The results manifested a decent agreement between models predicted and experimental data under all tested operating conditions. Nonetheless, the results obtained from the ANFIS prediction were better compared to RBF and BPNN reporting 99% [26]. Another effort was made to simulate the adsorption process of ranitidine hydrochloride (RH) from simulated pharmaceutical aqueous solution employing response surface methodology (RSM) and ANNs [42]. The adsorption process of RH was well predicted by constructing a three-layer ANNs with 10 neurons in the hidden layer. In the utilized ANN model, it was found that the linear transfer function with resilient BP to be the best fitted hidden layer algorithm. The validation of both models (ANNs and RSM) using residual fluctuations was investigated via validating the experimental results. It was also analysed statistically by three statistical estimators which showed that ANNs could achieve better prediction when compared to RSM, see Table 1.

Table 1: Comparative statistical analysis of ANN and RSM [42].

## Modelling of membrane properties and performance

Another application of ANNs is to predict the performance and properties of various membrane processes under various circumstances. Such multifaceted applications of ANNs approach can be advantageous when employed in support of plant design and prior to conducting expensive large-scale experiments [30,39,43,44]. It is well known that the flux drop in membrane processes, whether caused by reversible/irreversible deposition on the surface of the membrane and/or internal pores blockage, is the main stumbling block in industrial operations which also indicates deterioration of the entire process performance. Therefore, accurate modelling of flux decline is essential for further optimization, simulation, and process scale-up. The applicability of semi-empirical and ANN modelling methods for the prediction of cross-flow MF membrane characteristics has been scrutinized by Ghandehari et al. [44]. Flux decline trends and potential retentions against bovine serum albumin (BSA) were predicted with the aid of ANNs under variable operating circumstances, namely; cross-flow velocity, transmembrane pressure (TMP), feed solution pH and concentration. Subsequently, both feed-forward ANNs and classical pore blocking was employed to predict the experimental flux data. The influence of network structure and learning algorithm on the performance of ANNs was investigated. The adopted network structure for the permeate flux consisted of an input layer with 5 neurons and 2 hidden layers with 6 and 8 neurons (Fig. 4), whilst for the membrane rejection, a similar network with 5 neurons in the input layer and 6 neurons in both hidden layers was considered. Both networks manifested excellent agreement (R2 = 0.996 and R2 = 0.994) with experimental data for flux and membrane retention; respectively. Based on classic mechanisms of fouling; results concluded that semi-empirical models could only predict flux for a specified operating time. Whereas, based on the training algorithm and selected network structure; ANN models were capable in predicting membrane filtration systems with the desired accuracy at the entire filtration time and for all operating conditions. Worth mentioning, both ANNs and the classical fouling mechanism (intermediate blocking mechanism) gave a relatively similar result at low feed concentration whilst at higher concentration, the superiority of ANNs was evident. Similarly, the ANN approach has been employed by Chen and Kim [25] to investigate the impact of solution properties and operating parameters on the long-term flux decline in a crossflow membrane filtration of a colloidal suspension. In this study, different training algorithms were used including the radial basis function neural network (RBFNN) to study the effect of TMP, particle size, solution pH, ionic strength, and elapsed filtration time when used as inputs to predict the long-term permeate flux decline. Simulation results from the RBF neural network were accurately predicted and were in good agreement with actual ones. It has been concluded that increasing the ionic strength and the TMP could accelerate the rate of flux decline, whilst pH didn’t have a remarkable impact. Comparing the obtained results, the RBFNN have eventually produced better predictability than those obtained from the multiple regression (MR) method and even to those obtained from the multi-layer feed-forward BP neural network [30].

 Another ANN model has been successfully established for modelling turbulence promoter-assisted crossflow microfiltration (CFMF) of particulate suspensions [45]. The inflow velocity, pressure across membranes and the feed concentrations were taken as primary inputs whilst the flux improvement efficiency (FIE) by turbulence promoter was obtained as an output. According to the results of the study, it was found that TMP had the highest impact on the FIE. MF operation conditions could be optimized to reveal a high FIE depending upon the feed concentration, which could be used as a guide for turbulence promoter applications. Moreover, another study dealing with the performance of RO desalination plant has been forecasted through predicting the changes in total dissolved solids (TDS) and permeate water flux over a one-week period. Feed water parameters including pressure, conductivity, and pH were used to train and construct the multilayer perceptron (MLP) and RBF neural networks. The results showed that both neural networks were able to predict the TDS level in the permeate water product. However, the prediction results from ANN using the same feed water quality parameters revealed better accuracy when compared to conventional methods [46]. In another work, response surface methodology (RSM) and ANNs were proposed and compared in terms of their predictive abilities to optimize the RO desalination process over a wide range of feed salinity [47]. For RO membrane desalting performance (permeate flux and salt passage); a neural network-based modelling approach with BP and support vector regression (SVR) algorithms were investigated as a tool for developing data-driven models for predicting the performance of RO plant and its potential use for operational diagnostics. Sequential and marching forecasting models were constructed. In the sequential model, the time-variation within each forecasting time-interval was considered as input information, whereas target values were predicted at fixed future times from past plant information in the marching forecasting model. The prediction of the performance of the RO plant using both models reported a good level of accuracy for short-term memory time-intervals in the range of 8–24 h for permeate flux and salt passage for forecasting times up to 24 h [43]. Another research for modelling sweep gas membrane distillation (SGMD) process using ANN methodology was proposed by Khayet and Cojocaru [36]. A feed-forward ANN was sophisticated by means of BP training method for the prediction of the performance index and based on a set of 53 different experimental SGMD investigations. SGMD was used for the desalination of an aqueous solution of sodium chloride (NaCl) through which the interaction influences of different input variables on the performance index have been scrutinized. Under optimal operational conditions, an optimal performance index of 1.493×10−3 kg/m2.s was experimentally achieved [36].

ANN approach has been also proposed for modelling the water permeability constant (Kw), one of the substantial parameters that influence optimal operation and design of RO processes [48]. The developed ANN model structure, with 1 hidden layer and 4 neurons in the hidden layer, was able of predicting the dynamic Kw. The results were very close to those predicted by existing correlations in literature. Compared to the existing correlation, the developed ANN model can predict Kw at a wide range of operating pressure and any feed salinity [48]. Operational conditions, such as feed concentration, flow rate, feed temperature, and operating pressure, have been introduced as input variables whilst performance index was considered as a response. Both ANN and RSM predictive models were developed based on experimental investigations. Two empirical polynomial RSM models which were valid at different ranges of feed salt concentrations were carried out. In contrary, the predicted ANN model which was valid over the entire range of feed salt concentration has demonstrated significant ability to overcome the constraints of the RSM quadratic polynomial model. In another investigation on the prediction of flux decline in wastewater related application; the performance of different approaches to modelling namely ANNs, the pore-blocking, and the genetic programming (GP) were compared [22]. A feed-forward backpropagation network utilizing Levenberg–Marquardt and Bayesian Regulation training methods were developed based on the experimental results. Controlling parameters of permeate flux, crossflow velocity, temperature, TMP, pH, and filtration time were used as network inputs. The internal and architecture parameters of the network have a significant impact on the prediction performance of the ANNs. A trial-and-error approach was used to regulate hidden layers and neurons. The individual program proposed by GP included a population of 700 individuals (500 generations) with a depth of 10. The tested models were compared according to the relative error obtained from the experimental results. It was reported that ANNs performed better than the GP and pore-blocking models [22].

Fig 4: Suggested feed forward ANNs for prediction of permeate flux [44].

For fouling prediction in the ultrafiltration (UF) membrane, one should take into account the phenomena occurring in both short-term and long-term operation. Fouling involved during filtration of water affects the performance of UF membranes causing particle deposition on the membrane surface. Fouling could be caused by the adsorption of organic matter on the membrane surface and into the pores of the membrane. This type of fouling can’t be removed by backwash and thus called irreversible fouling [49]. In a research conducted by Delgrange-Vincent et al. [39], ANN approach was proposed for modelling fouling phenomena in a UF membrane through predicting the evolution of resistance (i.e., the resistance of membrane, the resistance of reversible and irreversible fouling) and the TMP at different operating parameters. To account for the effect of two types of fouling; two interconnected recurrent ANNs systems were developed; the first one was developed for modelling the resistance at the end of the filtration cycle through which the inputs to this model were the filtration operating parameters and the water quality parameters. whilst the second ANN model was developed to predict the resistance at the beginning of the next cycle (after the backwash) to determine the efficiency of the backwash process. The inputs to this model were the water quality parameters, the resistance at the end of the filtration process, and the backwash operating parameters. The developed ANN models were able to identify the important parameters affecting the fouling which were the permeate flow rate, turbidity, filtration time, dissolved oxygen, UV, pH, backwash pressure, and chlorine concentration. The data used for the training and validation were pilot plant data. These models proved to be able to predict the performance of the UF membrane in both long-term and short-term with a satisfactory accuracy for different types of water quality and different operational conditions [39]. ANN model consisting of one input layer, two hidden layers, and one output layer for a steady-state contaminant elimination during NF of surface and groundwater, was derived and validated by Shetty el at. [50]. The investigation was performed under a set of operating conditions such as flux, feed water recovery, contaminant recovery, and feed water quality parameters including TDS concentration, pH, contaminant concentration, and where possible the diffusion coefficients were utilized as inputs for modelling the ratio of permeate/ feed concentration of the target contaminant. Additionally, source waters were chosen from seven different locations and two commercial thin-film composite membranes were considered in the study. The conducted deterministic and pseudo-stochastic simulations manifested that the ANN approach closely predicted the permeate concentration of each contaminant. Using ANNs to predict the contaminant removal on municipal water is much simpler than solving the highly non-linear Nernst–Planck equation to determine solute removal from multi-component solutions at high recovery. In addition, ANNs can predict the transport of water treatment contaminants that are heterogeneous and difficult to characterize such as natural organic matter and disinfection by-product precursors that have obscure physicochemical properties.

## Modelling of desalination efficiency and cost

AI models like ANNs have demonstrated their capability to endow more reliability for predicting the efficiency of different desalination technologies among classical models [36,51–53]. Brine discharge presents a great challenge in the desalination industry. Brine is characterized by high temperature and high salinity level. In thermal desalination processes such as MSF and MED; controlling the top brine temperature (TBT) is important [54]. Economically, higher TBT increases water production with respect to the amount of the steam utilized in the process. Notwithstanding the above, due to scaling, TBT cannot be increased beyond a certain limit. In addition, the levels in the stages need to be controlled or constrained. The too high level might result in flooding whilst too low level might result in corrosion problems of the stages. ANNs have been used to enable identifying the MSF process in term of specifying the effect of steam and recycle flowrates on the TBT, the distillate flow rate generated from the last stage, and the level of brine pool in the last stage. An error-back-propagation learning rule with a momentum algorithm was employed to adjust the network weights. Multiple inputs-single outputs and multiple inputs-multiple output networks were modelled and showcased very close predicted outputs (greater than 0.99) to the actual ones been used for the purpose of identification. It was found that the blowdown flows affect the level of the brine pool in the last stage significantly, however, the level of the brine pool is affected slightly by the changes in steam or by the recycle flow rates. In conclusion, the ANNs can serve as an excellent alternative for predicting nonlinear systems such as MSF desalination plants where no need for the specification of a structure for process identification [10]. For Seawater temperature elevation (TE) prediction purposes in the MSF desalination process, several neural networks (NN) based correlations were developed by Tanvir and Mujtaba [55]. It is found that the NN based correlations are capable to very closely predict the experimental TE. Also, for a given architecture, any correlation can be updated with additional data from other sources or a new correlation can be developed for the new source data. Similarly, RBF neural network model was developed for estimating TE in MSF desalination processes. The constructed ANN model use as input variables the boiling point temperature (BPT) and salinity. The developed RBF neural network was found to be precise in predicting TE from the input variables and performed better than the empirical correlations, thermodynamic models and MLP neural network [56].

For the purpose of monitoring the performance of MSF distillation process, another work has been conducted for developing a fault diagnostic system using ANNs [57]. The developed system processes the plant data (obtained from different detectors) to define whether the plant is operating normally or not. In the latter case, the developed system tries to identify the cause of the fault. The diagnostic system has an ANN for each potential fault. Based on an exact selection of the diagnostic system outputs and the employed method of training; a proper value for the output of each ANN can be calculated instead of adjusting it at 0 or 1 only. A decision tool based on fuzzy neural networks (FNNs) methodology has been developed by Hernandez et al. [58]. The tool adopted in their work was implemented using Matlab software. It was based on ANFIS, which is a neural fuzzy Sugeno-type model, an application that combines fuzzy logic with neural networks. The model intended to provide the analysis of instant and seasonal profile of brine discharge from desalination plants. This was basically to assist in taking management measures to increase the dilution of brine prior to discharge whilst reducing the impact on receiving medium. The study concluded that over 70% of the salinity increment in the affected area was attributed just to three significant variables; brine discharge, seasonal variations, and climatic conditions. Research findings demonstrated that neural-fuzzy model predictions are fulfilled for the follow-up and management of brine discharge [58]. The findings reported in recent studies on ANNs for desalination and water treatment are summarized in Table 2.

Table 2. Research findings reported in recent studies on ANNs for desalination and water treatment.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Technology** | **Pollutant or pollutant source** | **Output variable** | **Input variables** | **Method** | **Ref.** |
| NF | NaCI, Na2SO4, MgC12, MgSO4 and a mixture of these salts  | Salt rejection | Salt concentration, mixture composition, pH  | Single optimized ANNs | [28] |
| ED | NaCl | Salt rejection | Salt concentration, flow rate, reaction temperature, applied voltage | BP ANNs, and adaptive learning rate method  | [40] |
| Chlorination | THMs | Formation of THMs in chlorinated waters | Dissolved organic carbon, water pH, temperature, contact time, bromide concentration | ANNs, GEP and SVM | [41] |
| MF | Starch | COD removal, permeate flux | Feed flow rate, feed temperature, pH, permeate concentration  | BPNN, ANFIS, and RBF  | [26] |
| Adsorption | RH  | RH adsorption | Adsorbent dose, solution pH, and agitation  | RSM and BPANN | [42] |
| MF | BSA  | Flux decline trends, BSA retentions | TMP, cross-flow velocity, feed solution pH, concentration | Feed-forward ANNs and classical pore blocking model | [44] |
| UF  | Silica | Long-term permeate flux decline | TMP, ionic strength, solution pH, particle size, elapsed filtration time | RBFNN | [25] |
| RO |  Seawater or brackish water | TDS, permeate flow rate  | Feed water pressure, pH, conductivity |  MLP and RBF neural networks | [46] |
| RO | Brackish water  | Permeate flux, salt passage | Feed flow rate, feed conductivity, overall pressure drop, pressure drop across the stage, feed pH | BP and SVR algorithms  | [43] |
| SGMD | NaCl  | Performance index, defined as the product of distillate flux and salt retention factor | Feed inlet temperature, feedflow rate or feed circulation velocity, air circulation velocity  | Feed-forward ANNs  | [36] |

#  Applications of genetic algorithms (GA) in desalination and water treatment

1.

## Background

GA is the most noticeable example of the evolutionary computation which is a machine language in computer science [59]. The main function of GA is to obtain the optimum solution of the engineering problems by applying the idea of evolution that inspired form Darwin theory. Several biological terminologies used in the GA such as chromosome which represents one of the possible solutions of a certain problem. Selection, crossover, and mutation are the main principles genetic operators were applied to the population of the chromosome to generate the new offspring for an optimization problem to find all possible candidate of solutions which will be evaluated by a fitness value that shows how well the performance of the selected solution. The iteration will keep running till have the least fitness value which is the best candidate for a problem [60]. GA is functional to extract mathematical models as well. GP which is an extension and follows the similar approach of GA that used to find the optimum mathematical model rather than individual value. The only difference that GP provides a mathematical model (evolves function tree) whilst GA has one value of a certain parameter. It’s unlike an ANN, GP is an inductive data-driven machine learning that provides a good relationship between input and output variables [61]. It has many applications and can be used as an optimization tool when combined with another machine language as a hybrid system to obtain the optimum model of a certain system [62]. An illustration of a GA procedure is given in Fig. 5.

Fig. 5. Solution procedure of the Genetic Algorithm approach [63].

## Modelling of ions and pollutant removal

GA has been commonly used to solve and investigate many issues related to water desalination, wastewater and membrane applications. Mainly, it has been applied to salt and contamination removal problems and to enhance the properties and performance of desalination technologies. Not only for post and pre-treatment of membrane and desalination technologies, but GA was also spectacularly applicable for wastewater as well. GA approach has been proposed to generate optimum salt removal by Dawood et al. [64]. When it’s applied to the flocculation in wastewater treatment to study novel flocculent dosage and wastewater pH, the optimization approach of GA was performed, and the estimated result was slightly better than these determined by RSM, which has been adequately fitted experimental data to quadratic polynomial models. GA optimization predicts were 96.6% and 83.5% for the removal efficiency, whilst RSM estimates were 83.5% and 96.4% for COD removal and turbidity; respectively. A research was conducted to perform multi-objective optimization (MOO) for MSF with brine recirculation (MSF-BR) and hybrid MSF–RO desalination systems employing GA technique [65]. Simultaneously, four objectives; maximum grain ratio, maximum distillate production, minimum exergy destruction, and minimum product cost were considered in the study. The desalination systems were optimized for single, double and triple simultaneous objectives. The performance of both systems being optimized has been enhanced as indicated in the work. However, optimized results were mightily relying on desired objectives and process synthesis and cannot be generalized. For heavy metals modelling, copper (Cu) removal function from synthetic wastewater was initially derived using ANNs and RSM to evaluate the performance of an electrocoagulation system. Cu concentration, voltage, pH, and treatment time were the parameters investigated as operating conditions for collecting data and building models. Results indicated that the ANN model was capable to capture the nonlinear correlations of the experimental data in a better way when compared to the RSM model with a combined R2 of 0.982 for Cu removal efficiency and energy consumption. Following that, MOO for minimizing the energy consumption whilst maximizing the Cu removal efficiency was conducted using GA over the ANN model. The optimization process resulted in the development of nondominated optimal points which indicated the optimal operating conditions of such process [66]. In other recent work, Al-Obaidi et al. [67] have proposed GA for the optimization of the RO-based wastewater treatment system for the removal of chlorophenol. A one-dimensional distributed model using spiral-wound RO system was developed to: (1) simulate the transport phenomena of water and solute through the membrane, and (2) describe the variation of operating parameters along the x-axis of the membrane. According to literature, the stability of the proposed model was then evaluated using real experimental data obtained from a pilot scale RO plant for the removal of chlorophenol. The model was then optimized with a GA platform comprising two objective functions of (1) minimizing the operating pressure, and (2) maximizing the removal of chlorophenol. Results manifested that the removal of chlorophenol could be optimized up to 26.6% for the set of five inlet feed concentrations [67].

## Modelling of membrane properties and performance

GA and GP are commonly used in water treatment and desalination technologies as a robust approach for developing mathematical models to tackle the engineering problem and improve technical performance and unit properties [68]. Thus, the performance of these technologies could be enhanced and improved. A study conducted by Suh et al. [61] have employed the GP approach for developing a mathematical model to predict the degree of membrane damage, that was considered as a challenge and hard to be predicted by membrane integrity tests [61]. The experiment was conducted through utilizing different size (0.5 μm to 0.7 μm) fluorescent nanoparticle to be filtered by a membrane in order to estimate the degree of breaching area on the damaged membrane. Such that, the data were collected and introduced to the GP for the calculation and determination of the correlation between inputs (permeate flux and TMP, concentration of fluorescent nanoparticle, and the mass of permeate particles) and output (area of the membrane breach). All possible correlations were determined by GP and the optimum one was chosen based on the mean absolute error (like fitness value in the GA) and variation of input parameters. This investigation by GP indicated that the mass of permeated particles and its concentration were the most influencing parameters on the membrane breach area. Another study done by Lee et al. [69] applied GP for membrane characteristic evaluation in a pilot-scale potable water production system. The mathematical prediction model of the membrane fouling pattern was derived by investigating the influence of feed water quality (temperature, turbidity, and algae pH), flow rate and filtration time. The data were collected for different operating conditions and different water quality to construct the GP model, noting that the inputs and output parameters were normalized first. The obtained result was close to the experimental results in revealing the membrane resistance as shown in Fig. 6. Results demonstrated that the GP model was an efficient tool since it is easier now to determine the best membrane cleaning intervals as well as the optimal operating conditions of a membrane system [69].

Fig. 6. Correlation of predicted data by genetic programming (GP) model vs. experimental results [69].

In another investigation, a novel methodology was applied for determining an optimized control method for feed water temperature in seawater RO desalination with the aid of GP to determine functional forms through training data [70]. The operation data were collected from the Fujairah SWRO plant over four years to generate two functional models for the flow rate of the desired product and salt passage. More than 90% accuracy between experimental and predicted results has been obtained from both models in terms of the average error rate. At different feed water temperature and feed TDS, other parameters were simulated by using two functional models such as the permeate flow rate, net desire pressure, ratio recovery and permeate TDS. When the optimized temperature control method applied to Fujairah SWRO plant at identical operating conditions, results manifested a significant increase in permeate flow rate up to 900 m3/d under 600 mg/L in permeate TDS. Nevertheless, the combination of two computational intelligence machine languages is commonly used in desalination technologies to end up with preferable results. For example, ANNs and GA were combined as a hybrid system for building an accurate model for estimating the evaporation rate of saline water [62]. The combined predictive model could be categorized into supportive combinations; ANNs or GA used as the main solver to tackle the problem whilst other supports it. The other category is collaborative combinations; both GA and ANNs performed together to find the solution to a problem. For this study, GA devoted for optimizing the collected data and parameters constructed by ANNs. The results implied a conclusion that the hybrid system (GA and ANN) has provided better results in comparison with the performance of single machine language (ANNs) and the classical model. Table 3 supports the conclusion and shows the results of the evaporation rate of saline water experiments.

Table 3. Results of the Neural Network, Genetic Algorithm, and Classical model [62].

## Modelling of desalination efficiency and cost

Along with the aforementioned applications, GA has been devoted for optimization purposes in desalination applications as well, especially for economic improvement with enhancing the production rate. MOO is one of the most sought-after tools for each desalination plant. A systematic approach to optimization has been proposed by Esfahani et al. for multi-effect distillation thermal vapour compression (MED-TVC) desalination system [71]. The study presented a new model based on the ANN approach which has been later optimized by GA. The hybrid machine language was utilized to reduce total annual cost, increase permeate flow rate and gain output ratio. Different operating conditions were introduced to the ANNs as input variables such as preheated feedwater flowrate, motive steam flow rate, and temperature differences in order to collect data and derive a non-linear equation that describes the relationship between inputs and outputs, such that the collected data was trained by GA to achieve the comprehensive optimum. GA was performed, and the Pareto optimal solution was generated to choose the optimum operating conditions that offer the optimum solution. The number of effects which are 6 has helped to save 14% in cost and reduce the utilizing steam in the process by 50% for production of 1 m3 of water. In another study, an optimum plant configuration methodology, which gives the optimum sizing of each unit in the plant and the number of modules to minimize the total cost, was proposed [2]. The power supply system with photovoltaic and wind generator energy sources of a desalination plant was implemented and optimized using GA. The combination of all possibilities of RO unit, PV modules, battery charger, wing generator, and DC/AC inverter types was extracted from GA and the optimum combination was selected based on the minimum total cost, Fig. 7 explains the optimization methodology. Corresponding optimal sizing results have confirmed that the total cost of the desalination system was quite influenced by the characteristics of the different devices comprising the system which impact the degree of exploitation of the available wind and solar energy potentials [2].

Fig. 7. The proposed optimization methodology [2].

For obtaining the optimal integrating design of site utility steam network with MED-RO desalination unit, total site analysis, and exergoeconomic optimization was carried out by Manesh et al. using GA [1]. The objective of this enhancement was to minimize total cost and increase the gain output ratio of the hybrid system. Pareto set was determined by GA to find out global optimum for the MOO problem. The result demonstrated the benefits of GA since the desalinated water production increased up to 126,300 m3/d with a cost of $0.81/m3 whilst the gain output ratio was 9.1. In another work, Shakib et al. [72] modelled a cogeneration plant which comprised a gas turbine (GT) with and without an air preheater (APH), a multi-effect evaporation thermal vapour compression (ME-TVC) desalination, and a heat recovery steam generator (HRSG). The dual-purpose system designated to produce 40 MW of power and 14,000 m3/d of desalinated water for an industrial plant. Following the simulation process, a thermoeconomic analysis was performed and, then, a multi-objective genetic algorithm (MOGA) was applied to accomplish the best design at optimal conditions. Ultimately, it was concluded that the system combined with APH and applying optimization principle, the exergy efficiency could be scaled up by 19%, and the reduction in total cost of the product was by the same percentage [72].

Table 4. Summary of genetic algorithm (GA) applications in desalination.

|  |  |  |
| --- | --- | --- |
| **Application ions and pollutant removal** | **Application in membrane properties and performance** | **Application in desalination efficiency and cost** |
| Copper removal | Prediction of breaching area of the damaged membrane | MOO of MED-TVC system (hybrid system) |
| Optimization of flocculation parameter (COD, turbidity) | Prediction of fouling rate of a membrane | MOO for the system configuration of the cogeneration plant. |
| Estimating the interaction level for the liquid-liquid system containing salt | Optimization of feed water temperature in SWRO Fujairah plant | MOO for the system configuration of coupling utility site with MED-RO |
|  | Estimation the evaporation rate of saline water (Hybrid system) | MOO MSF-RO desalination |

The optimization of MED desalination systems both thermodynamically and thermoeconomically with thermo-vapour compressor was studied using a hybrid meta-heuristic optimization tool based on a combination of GA and simulated annealing [73]. Comprehensive energy and exergy thermodynamic and economic modelling based on the total revenue requirement method (TRR) were carried out. The approach was employed to either minimize the cost of the desalinated water and/or maximize the exergy efficiency of the system. The proposed MED system having 6 decision variables was taken into account for optimization. Three scenarios of optimization were considered: (1) thermoeconomic single-objective, (2) thermodynamic single-objective, and 3) multi-objective optimizations. Both thermoeconomic and thermodynamic objectives were considered, simultaneously in MOO whilst the results were obtained and compared accordingly. In another work [74], the cost optimization for designing integrated water and power plant was investigated. The study focused on the design of an integrated GT and MSF desalination plant. The proposed design was considered using exergetic, reliability, economic and environmental aspects, and a MOGA for modelling purposes. The study showed that optimizing the performance has led to minimizing the objective whilst maximizing the system efficiency. The results of the study declared that the cost and environmental cost impact were reduced by 13.4% and 53.4%; respectively. This shows that improvements in all aspects can be achieved using the optimization process. Apart from that, sensitivity analysis revealed the relationship between pollution damage; fuel cost, and objective functions [74]. Ansari et al. [75] presented a comprehensive methodology for the optimization of a thermo-vapour compressor (MED-TVC) desalination plant coupled with a 1000 MW pressurized water reactor (PWR) nuclear power plant. Similarly, comprehensive energy and exergy thermodynamic and economic modelling based on the TRR method were carried out. The proposed hybrid plant having10 decision variables for the nuclear power plant and 6 decision variables for the (MED-TVC) desalination plant were optimized by the MOO approach. Three scenarios of optimization were considered: (1) thermoeconomic single-objective, (2) thermodynamic single-objective, and (3) multi-objective optimizations using GA. the results were obtained and compared accordingly. It was found that the MOO is a generalized optimization approach that enhances both economic and thermodynamic features of the dual nuclear-desalination system [75]. GA approach has been also proposed for cost optimization in wastewater treatment applications. Gopal & Satyanarayana attempted to explore the pervaporation process economics by employing the AI approach [76]. During their study, non-dominated sorting genetic algorithm-II (NSGA-II) has been proposed for the cost analysis for the removal of volatile organic compounds (VOCs) from water by pervaporation. The work proposed a MOO problem and represents an extension of the study, done by Suggala and Bhattacharya [77] on the removal of VOC using single stage pervaporation without recycling. It attempted to find the associated costs such as the capital cost, pumping cost, and other related costs. The trade-off costs such as the pumping cost were considered using the model. The study using the NSGA-II shows that the primary costs of removal of VOC are significantly dependent on the pumping cost, capital cost, and vacuum and condensation.

#  Current shortcomings and adaptations of artificial intelligence (AI) tools in desalination and wastewater treatment applications

The optimization of seawater desalination and wastewater treatment processes is a highly desirable trait for the sustainable operational performance of plants. This would be achieved by adopting an appropriate AI tool to yield an optimum process from the beginning to end up with the best configuration and integrated system. However, the extremely complex nature of engineering optimization problems under certain circumstances may not provide satisfactory performance with respect to nonlinearity and uncertainty in the real world of desalination and wastewater processes [78]. One of the challenges and limitation for machine language is the system deviates from the expected result when some changes happened. For instance, GP has been employed to develop the model for estimating membrane deterioration in the membrane integrity test. It was found that a different phenomenon was observed in the membrane integrity test for the large membrane breach [61]. Similarly, process prediction by ANNs encounters imperfect performance under certain circumstances. ANNs exhibit poor reproducibility since bias and weight between neurons are presented randomly and easily fall into a local optimal solution [19]. Chen and Kim [30] claimed that RBFNN confers a better alternative to BPNN since RBFNN bestows faster training procedure, easier initialization, and more stable performance [30] even thought BPNN is well known as one of the common networks utilized for information extraction and classification [79,80]. This conclusion was drawn due to several serious shortcomings associated with BPNN modelling such as the susceptibility to converging to a local minimum, slow convergence during its training step and inability to detect over-fitting [81]. In another work, to allow GA cope with multimodal problems and not be constrained in a local solution; Al-Obaidi et al. [82] have suggested species conserving GA (SCGA) approach for simulation and optimization of a multistage RO processes with permeate reprocessing and recycling for the removal of N-nitrosodimethylamine from an industrial effluent [82]. SCGA is generally able to determine multiple solutions of the optimization problem at the end of each iteration, as opposed to a single solution. This approach bestows a wide opportunity to obtain an appropriate optimized solution for any input data of operation. In a more precise word, the SCGA will guide the optimizer to choose the best optimal from a bunch of optimal solutions which would satisfy certain process requirements. For predicting membrane fouling and performance purposes, a statistical and mathematical hybrid model has been explored by Hwang et al. [83]. Proposing a hybrid model has been suggested to yield the advantages of both statistical and mathematical models instead of applying them individually. Practically, mathematical models are capable to predict microscopic phenomena whilst statistical models are helpful in predicting complex and non-linear behaviour models. The performance of hollow fibre membranes has been studied using the Hagen-Poiseulle equation and filtration models modified with the critical flux concept whilst statistical models such as the ANNs were employed to correlate operating conditions with respect to membrane fouling. The study data were collected from a pilot plant using hollow fibre MF membranes. Different methods for hybridizing the two models were compared. The results showed that hybrid models generated accurate results which would be an initial step towards intelligent membrane systems. The combination of two AI tools was also presented to end up with a more preferable prediction for optimal operating parameters [62]. Badrnezhad and Mirza [84] proposed a hybrid process modelling and optimization based on computational intelligence paradigms where the combination of artificial neural network ANNs and GA meets the challenge of specified-objective. The authors indicated that proposed hybrid (ANN–GA) approach has provided a very effective and gainful tool to help engineers to choose optimum operational parameters involved in the wastewater treatment process for enhancing the membrane performance. Its major advantage is that it allows process modelling and optimization solely on the basis of process input-output data [84]. Another research paper investigated the application of a hybrid model comprising the theories of fuzzy logic with ANNs and thus can make optimal use of easy interpretability of fuzzy logic along with superior learning ability and adaptive capability of ANNs in order to avoid existing shortages of both models [85]. Fuzzy neural networks (FNNs) predictive control scheme have been proposed for studying the coagulation process of wastewater treatment in a paper mill industry. The adaptive FNNs to predict the nonlinear relationships between chemical dosages and the corresponding rate of pollutants removal in order to adapt the system to a variety of operational conditions and achieve higher flexible learning ability. Results disclosed reasonable forecasting and control performance have been acquired through the optimized system. In this regard, several ANN hybrid prediction systems reported in the literature for other applications have not been experienced in desalination yet. Adaptive sliding mode control with neural network based hybrid models [86] and Sequentially Trained Bootstrap Aggregated Neural Networks [87] are some examples among them.

#  Conclusion remarks and future recommendations

The implementation of AI approaches proposed yet in literature can offer new research frontiers into the utilization of a comprehensive management plan for the construction and operation of various desalination and wastewater treatment plants aiming to promote water insecurity solutions. AI has transformative potentials to endow new insights and provide support decision in various water industry sectors. This includes efficiency and cost optimization purposes and bringing about a change in process performance issues. This paper focused on the state of the art applications, of two commonly utilized tools of AI approach, namely; ANNs and GA, for a wide range of water treatment and desalination technologies, covering optimization of ions and pollutant removal, performance and membrane properties as well as cost and efficiency. The review intended to showcase the benefits of AI in extracting nonlinear equations for the different operating conditions of the desalination process and the relationship among them, unlike the classical approach. The brief comparison between classical and AI approaches was also highlighted that demonstrate artificial intelligence has acted as an efficient tool in engineering and water desalination applications. Moreover, shortcomings arose from various modelling scenarios have been discussed along with proposed predicting models. It has been indicated that hybridization of ANNs and GA with other classical modelling approaches and/or AI tools can manifest a greater potential to be utilized for generating optimal operational, especially under complex operational circumstances.

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# Nomenclatures

|  |  |
| --- | --- |
| AI | Artificial intelligence |
| ANN | Artificial neural networks |
| BPT | Boiling point temperature |
| TE | Temperature elevation |
| GA | Genetic algorithm |
| MEE | Multi-effect evaporation distillation  |
| MSF | Multi-stage flash distillation |
| VC | Vapour compression |
| RO | Reverse osmosis |
| PSO | Particle swarm optimization |
| MCS | Monte Carlo simulation |
| NaCl | Sodium chloride |
| Na2SO4 | Sodium sulphate  |
| MgC12 | Magnesium chloride  |
| MgSO4 | Magnesium sulphate  |
| ED | Electrodialysis |
| BP | Back propagation |
| THMs | Trihalomethanes |
| COD | Chemical oxygen demand |
| BPNN | Back propagation neural network |
| ANFIS | Adaptative Neuro-Fuzzy Inference Systems |
| RBF | Radial basis function |
| MF | Microfiltration |
| RH | Ranitidine hydrochloride |
| RSM | Response surface methodology |
| BSA | Bovine serum albumin |
| TMP | Transmembrane pressure |
| MR | Multiple regression |
| CFMF | Crossflow microfiltration |
| FIE | Flux Improvement Efficiency |
| TDS | Total dissolved solids |
| MP | Multilayer perceptron |
| SVR | Support vector regression |
| SGMD | Sweeping gas membrane distillation |
| Kw | Water permeability constant |
| GP | The genetic programming |
| UF | Ultrafiltration |
| TBT | Top brine temperature |
| FNNs | Fuzzy neural networks |
| MOO | Multi-objective optimization |
| MSF-BR | Multi-stage flash distillation with brine recirculation |
| SWRO | Seawater reverse osmosis |
| MED-TVC | Multi-effect distillation thermal vapour compression |
| GT | Gas turbine |
| APH | Air preheater |
| HRSG | Heat recovery steam generator |
| METVC | Multi-effect evaporation thermal vapour compression  |
| MW | Mega Watt |
| MOGA | Multi-objective genetic algorithm |
| NSGA-II | Non-dominated sorting genetic algorithm-II  |
| VOCs | Volatile organic compounds  |
| SCGA | Species conserving genetic algorithms |

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