Predictive Modeling for Solar Desalination Using Artificial Neural Network Techniques: A Review

Vairavel Madeshwaren[1*], Kathiresan Govindaraju[2], Pragya Pandey[3], Suresh Thangavel[4], Rajpradeesh Thangaraj[5]

[1] Department of Mechanical Engineering, Annapoorna Engineering College, Salem, TamilNadu, India

[2] Department of Mechanical Engineering, Excel Engineering College, Komarapalayam, Namakkal,Tamil Nadu, India

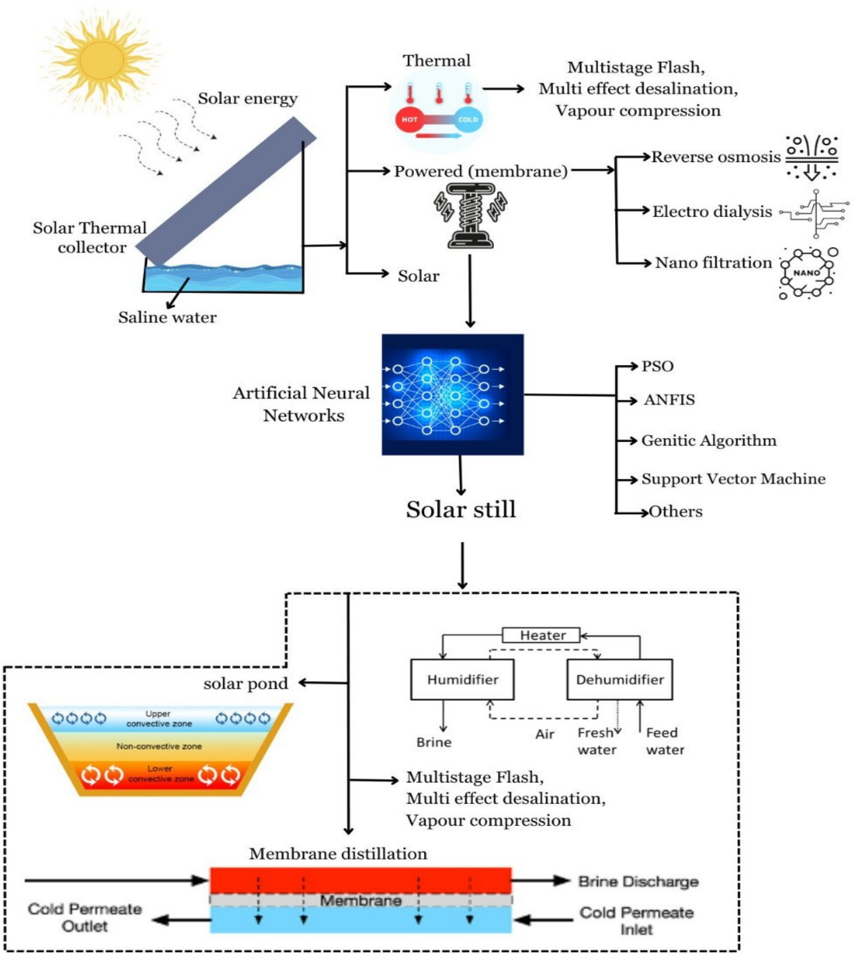
[3] Department of Mathematics, SRM IST Ramapuram, Chennai, TamilNadu, India

[4] Department of Mechanical Engineering, Kumaraguru College of Technology, Coimbatore, Tamil Nadu, India.

[5] Department of Mechanical Engineering, Kalasalingam Academy of Research and Education Krishnankoil, TamilNadu, India.

Corresponding Email: phdannauniv2020@gmail.com

GRAPHICAL ABSTRACT



ABSTRACT

Due to the limitations of fossil fuels and the environmental problems associated with their usage, renewable energy sources have been exploited for desalination through the employment of various technologies and mediums. One of the most useful renewable energy sources for solar desalination, both directly and indirectly, is solar energy. The effectiveness of solar desalination is influenced by a variety of parameters, making it challenging to forecast their performance in particular circumstances. Artificial neural networks (ANNs), PSO, ANFIS, RO, and genetic algorithms would all be suitable techniques for their modeling and output predictions in this context. In the current research, multiple data-driven approaches are used in-depth to perform modeling of solar-based desalination facilities. By utilizing these methods with the proper inputs and structures, it can be deduced that the results of the solar desalination units can be consistently and correctly projected. Additionally, several suggestions are offered for future research in the relevant areas of the study.

Keywords: Artificial neural network, solar still, ANFIS-based model, genetic algorithm, support vector machine

1. Introduction

The globe is experiencing an energy crisis, and via scientific research, researchers from all around the world are working arduously to find solutions by focusing on renewable energy sources. Energy is a crucial component needed for human life to exist on Earth and is crucial to the growth of human life. The ongoing rise in demand, the expansion of the population, and the improvement of living conditions are the causes of the energy problems. Because fossil fuels are becoming scarcer and greenhouse gas emissions are rising, it is getting harder to meet energy needs with traditional resources. Utilizing multiple natural or renewable resources is therefore necessary.

To meet one of the fundamental needs of any nation, which is the rising energy demand. The amount of energy a nation consumes determines its level of growth and advancement. The development of alternative energy sources is essential for sure and steady advancement. The best choice for it is renewable energy. There are several types of renewable energy, but the most significant source of thermal energy is solar radiation.

Modern technology is getting increasingly concerned with Thermal Energy Storage (TES). Bystoring thermal energy during times when it is abundantly available and utilizing it when and where it is needed, TES systems enhance energy management. TES is used in a variety of applications, including air conditioning, waste heat recovery, space and water heating, and more. It is therefore the most promising energy source. India is fortunate to have abundant solar radiation available virtually all year round throughout its territory. Water heating is one of the current uses for solar energy. Solar water stills are becoming more and more popular because they are relatively cheap to make and maintain. They serve as a substitute for or in addition to electric or gas geysers.

Despite being cost-effective, non-polluting, and endless, solar energy is time-dependent and has an intermittent nature. As a result, some type of TES is required, which improves solar energy utilization and is just as crucial to the development of new energy sources. Systems using Phase Change Materials (PCM) are more popular than other options for energy storage because of their consistency in latent heat storage. However, the PCM for thermal energy storage is still in the early stages of development.

Untreated water contains a variety of contaminants, such as iron, arsenic, fluoride, and more, making it unfit for human consumption. Over a billion people do not have access to clean drinking water, according to a United Nations report, and this number is expected to rise as the world's population grows compared to its water supply. Water covers about two thirds of the earth's surface. Still, the accessible water is salted and so unfit for human consumption. According to reports, 97% of the water on Earth's surface is salty. A significant amount of the 3% of water on Earth that is not salty is found in the polar regions as icebergs or as seawater. Less than 1% of this fresh water is accessible to humans, which is insufficient to cover all needs. Furthermore, 90% of urban sewage in developing nations is dumped into waterways, creating a massive amount of waste and converting the waterways into sewers or sources of contaminated water. Currently, 884 million people do not have access to clean water supplies; 1 in 8 people do not have access to safe drinking water; and every day, water-borne illnesses claim the lives of about 24,000 children under the age of five.

Some locations have far greater fluoride percentages than the 1.5 parts per million (ppm) that the World Health Organisation (WHO) recommends for drinking water. Many methods have been devised to make use of the available dirty water for the creation of safe and clean water. The majority of advanced technology rely on active mechanisms that use enormous amounts of power produced by burning fossil fuels. In the next two decades, the global demand for fossil fuels is predicted to surpass the yearly production. A lack of petrol or oil can potentially spark violence and international economic and political issues. Furthermore, burning fossil fuels creates toxic emissions that have an impact on the local, regional, and global environments. These emissions include carbon dioxide, nitrogen oxides, and aerosols.Therefore, it is challenging to produce enough drinkable water at a reasonable cost in areas where grid power has not yet been reached.Many technologies have been developed to far, primarily in underdeveloped nations, to use solar energy to create distillate; however, the efficiency of these systems are found to be rather low. To help establish an effective model for higher yield and higher-quality distillate, an attempt has been made in this work to analyse various procedures, designs, and operating factors on the performance of a solar distillation unit.

2. Artificial neural network

An area of Artificial Intelligence (AI) known as Artificial Neural Networks is a subset of computational algorithms. Biological neural systems that build an input-output mapping to learn from examples are the inspiration for ANN models. It is a straightforward mathematical method made to handle several tasks. ANN is made up of characteristics that result in ideal solutions. These qualities include mistake tolerance, parallel processing, generalization, and learning capacity. These characteristics would enable the ANN to precisely and adaptably address complicated issues.

The basic transforming units (neurons) that make up an ANN are numerous, interconnected, and layered. Input data and associated output values are required to train and test a neural network. Five components make up an artificial neuron: weights, inputs, activation function, output, and summation function. Figure 1 shows the structure of ANN.

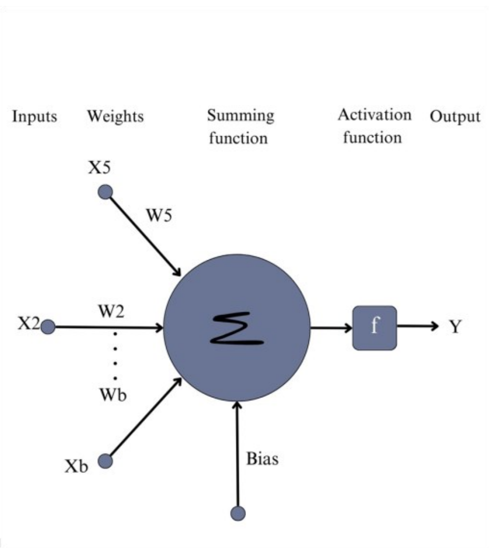


Figure 1 ANN model

W1, W2, and Wn are weights, whereas X1, X2, and Xn are input values. The appropriate weight is multiplied by each input. The output of the neuron is derived by applying the activation function to the result of the summary. Learning normally takes place during a certain training period in an artificial neural network. The network enters a production phase where it generates results on its own after training. A static network is a system that has separate learning and production phases. Dynamic networks are those that can continue to learn while they are being produced. However, the type of application and data format of a particular problem determine the best artificial neural network topology to use.

2.1. Types of ann

2.1.1. Single-layer feed-forward (SFF) neural network

When the input layer of node sources does not project into the output layer of neurons, the neural network is referred to as a (SFF) or acyclic (NN). In a one-layer network, the output layer of computer nodes is known as the single layer.

2.1.2. Multiple layers feed-forward neural network

The computation nodes in this kind of network are divided into one or more hidden layers and are referred to as hidden neurons. Hidden neurons' roles include extracting higher-order statistics and interacting beneficially between network output and external input. Neurons in the second layer of the network receive their input signal from source nodes in the input layer. The second layer's output signals are fed into the third layer, and so forth. The overall response to the pattern of activation is made up of the set of output signals from the neurons in the output layer of the neural network, which improves prediction accuracy.

2.1.3. Back Propagation (BP) Algorithm

The backpropagation (BP) learning algorithm is used in multi-layer neural network architecture to train the input and target pair patterns in a supervised way and divided into two trips over the various network layers: Backward pass and forward pass

The weights between neurons are adjusted layer by layer when input data is transmitted through the system forward during the FP (forward pass). The network's real response is then produced as a sequence of outputs. The networks' synaptic masses are fixed during the FP. An error correction rule adjusts the weights during the reverse pass.

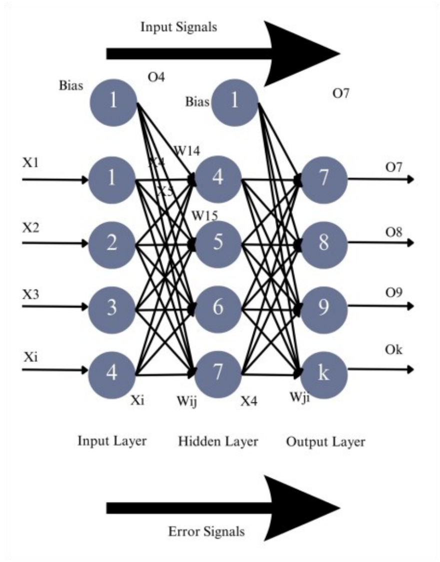


Figure 2 Feed forward back propagation model

An error signal is produced by deducting the network's actual output from its predicted response. This incorrect signal is then reverse-transmitted by the network. The prediction error is decreased across several training cycles until the network gets the required degree of accuracy. A full cycle of forward-backward passes and weight adjustments using each input-output pair in the data set is referred to as an epoch, also known as an iteration. The network consistently reaches the predetermined level of accuracy. The idea of feed forward-back propagation is demonstrated in Figure 2.

Where,

X1, X2, X3, ..., Xi are inputs

W1,4, W1,5, Wi,j, …, Wj,k are weightsO7, O8, O9, …, Ok are outputs

3. Design and development of ann model

The creation of ANN models goes through three crucial stages. Phases of Training, Testing, and Performance Evaluation sending a certain set of inputs through the network and comparing the results with a specific set of intended outputs is how training is carried out. The weights are changed to generate a set of outputs that are closer to the goal values if there is a discrepancy between the actual and target outputs. The old weight is multiplied by the error correction value to create the network masses, and the bias value is also changed. Up till the performance goal is reached, this process is repeated. The created ANN model is finalized against the testing data after the training phase is complete to meet our requirements with the least amount of error. The next sections go into great detail regarding the training and testing phase.

3.1. Training Phase

Training and neural network designs are carried out during the training phase. Thesubsequent substeps are employed:

- Acquiring the data.
- Splitting the data (for example, 80% for training and 20% for testing).
- Normalization of data from origin to destination.
- Choose the different parameters.
- NN size.
- The transfer function type that will be applied to each layer.
- The algorithm used for training.
- Identifying the best-hidden layer and hidden neurons.
- Use the training dataset to run the neural network through its learning process.
- In the event of any of the following, training is terminated:
- Achieves the performance objective.
- The maximum number of repeats (epochs) has been achieved.
- The allotted time has been exceeded.
- The performance gradient is below the established minimum value.

3.2. Testing Phase

In the testing step, the trained ANN model is assessed against testing data to determine its suitability for achieving the objective of accurate performance with little error.

4. Performance evaluation

The effectiveness of the ANN is assessed using the following parameters to calculate the statistical error between the predicted and goal: RMSE, R-value, Correlation Coefficient, and Regression Analysis - MAPE

4.1. Solar still using ann's analysis

From the aforementioned literature, it can be seen that some researchers have created mathematical models while others have carried out thorough experimental experiments to assess the effectiveness of various solar heating methods. Due to lengthy computer programming codes, the analytical approach takes a long time to produce a suitable result, especially for the solution of complex equations. To obtain results and draw useful conclusions, the experimental study also needs a significant amount of time for experimentation and analysis. Contrarily, the use of ANN delivers significant information patterns in a multi-dimensional information domain while also saving time; as a result, this technology is becoming more and more common in the scientific and engineering disciplines. In recent years, several scholars have used ANN to predict the performance of various solar stills. Without the need for intricate experiments or explicit equations, ANNs can represent complex systems. ANNs can predict the desired output of a system when sufficient experimental data is presented. Numerous research have used ANN to simulate and predict the thermal characteristics of solar energy collectors. A review of the literature on applying the ANN technique to forecast the thermal performance of various solar stills is given below:

4.*2 ANN+ Learning Algorithm*

ANN to analyze the ability of a parabolic collector solar steam generator. 396 patterns were gathered from trials on a solar steam generation setup. They built an 8-8-4 ANN model using the parameters. Three layers were employed in the hidden layer. 349 of the 396 data patterns were used for training and 47 for testing, out of which 349 were used. A learning technique was used to train the ANN model, and it correctly predicted results with a maximum range of 4.8% and an R2 value of 1.678 (Kalogirou et al.,1998).

4.3 Neural Model analysis using hidden layers

ANN was recommended and used to evaluate the effectiveness of a home solar still. To perform an ANN analysis, they gathered data. They then created a 9- 19-5 neural model with three hidden layer layers. Using the collected data to train an ANN model, two output parameters had expected values of 0.8967 and 0.8994. The actual data collected was 7.1% and 9.7%, respectively, of what was anticipated (Kalogirou et al. 1999).

ANN model with 8-28-3 neurons for thermo-siphon solar water heating system thermal performance prediction. They gathered 54 data sets for this project, of which 46 were used for training and the remaining 8 for testing. The ANN model was trained using a learning technique, and it was able to predict outcomes with maximum variations of 1MJ and 2.2oC for two output parameters (Kalogirou et al. 1999).

4.4 Performance of solar collector using ANN

The ANN approach to forecast the effectiveness of a household forced circulation solar collector still. To complete this project, they built two different ANN models using the 13-5-1 and 14-7-2 neural models. The model's training phase employed the data that had been collected. R2 was 0.9945 for the first model and 0.9825 and 0.9910 for the second model for results that were expected. For the two models, the greatest percentage variances were 1.9% and 5.5%, respectively (Kalogirou, 2000).

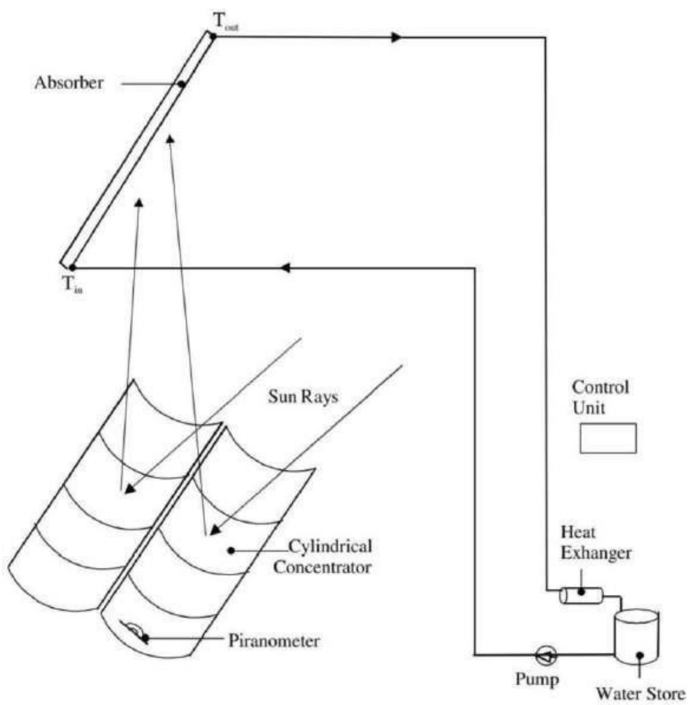
4.5 Hottel-Vhillier (H-V) model for solar still

ANN model to forecast how well a flat plate solar still would function. Three input variables—ambient temperature, air intake temperature, and solar intensity—and one output variable—air outlet temperature—were used to build the ANN model. The LM learning method was used to train the model. In the hidden and output layers, respectively, the tang and purlin transfer functions were employed. The heat network model's measured data from 17 days of data and the Hottel-Vhillier (H-V) model's generated data were both used to train the model. Finally, they believed that output temperatures from three different kinds of solar collectors would be adequate. They found that there was an average variance of 0.9 C in the outlet temperature of the solar collector (Farkas & Geczy, 2003).

4.6 Multilayer perceptron (MLP) and Radial Basis Function (RBF)

To estimate the useful heat gained and thermal efficiency, an ANN model was applied to two different types of hybrid solar stills. They built two different kinds of models, including MLP and RBF. The best MLP model for thermal efficiency and useable heat gain in tube-type collectors was found to have 9 hidden nodes. Due to the lowest MSE and in the instance of the RBF model with 8-91-2, 6 and 3 neurons in the hidden layer were found to be the optimum model for the pipe-type collector in terms of usable heat gain and thermal efficiency. Due to having the lowest MSE and an R2 value larger than 0.95, the MLP model is deemed to be marginally superior to the RBF model (Falcao et al., 2004).

An ANN model was created to forecast the performance of the solar still absorber. To do this,



they created an experimental setting (Figure. 3) and gathered data for the research. 40 data points total were gathered, of which 26 were used for testing and 6 for training. When they created an ANN model with five variables in the input layer and four parameters in the output layer, they discovered that 7 neurons in the hidden layer were the ideal number. The LM learning approach was used to train the 5-8-4 neural model, which was successful in accurately predicting outcomes with low error and high R2 values (Cetiner, 2005).

Figure. 3 Experimental setup with cylindrical collector

4.7 Solar collector analysis using SISO and MISO model

two models: multiple input, single output (MISO) and single input, single output (SISO). In contrast to the MISO model, which used thermal heat loss coefficient as both the output and the input data, the SISO model used solar radiation as both the output and the input data (Lecoeuche & Lalot, 2005). ANN tool to estimate flat plate solar collector performance characteristics (Kalogirou, 2006).

4.8 Different angles of solar still with ANN analysis

The ANN model to forecast flat plate solar collectors' thermal performance. They used an experimental setup (Figure. 4) for this work and gathered data to build an ANN model. The experimental time, date, solar radiation intensity, absorber surface temperature, tilt angle, azimuth angle, and declination angle were seven of theinput factors that were chosen. The output parameter used was the collector's thermal efficiency. In the intermediate layer, 20 neurons were chosen from two buried layers. In theneural model, the logistic sigmoid transfer function and the back-propagation learning technique were employed. The 7-20-20-1 neural model was successful in predicting the flat plate solar collector's thermal efficiency. The highest and minimum variances of the findings were discovered to be 2.558484 and

0.001969, respectively (Sozen et al., 2008).

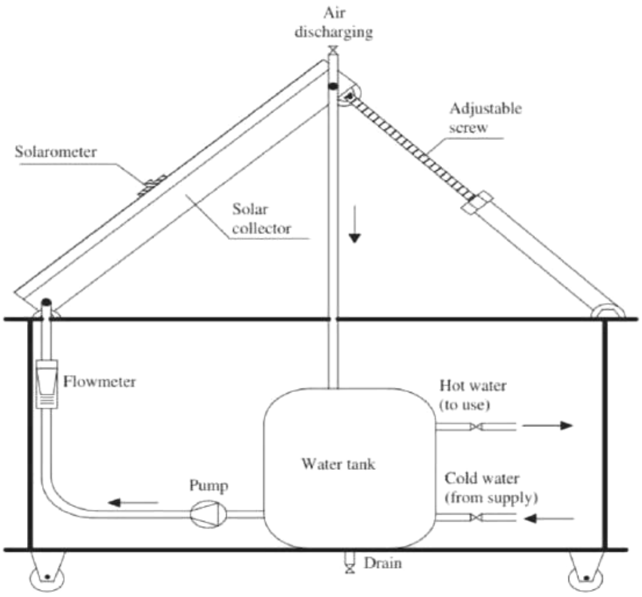


Figure. 4 Experimental setup of liquid flat plate collector

A solar still is a basic apparatus that operates using the principles of water evaporation and condensation. Essentially, it consists of a glass cover that allows for energy transfer, an absorber plate that holds saline or brackish water, and a metallic frame with a black base to support the water and cover. Blackening the base's interior surface allows it to efficiently absorb solar radiation that strikes it. In order to be purified, the brackish water is fed into the basin. At the bottom of the glass cover is a place to catch the distillate. The two main classifications of solar distillation systems, such as passive and active solar stills, can be generally categorised. Glass is utilised as a glazing material in the majority of the literature because it can transmit over 90% of incident short wave radiation. However, because it acts as an opaque material for long wave radiation, glass has a low transmittance to long wave heat radiation of wavelengths between 5 and 50 μm that is emitted by the absorber plate. There have also been reports of the usage of plastic sheets and films as glazing material. A transparent plastic cover in the shape of a hemispherical dome that has an absorptivity of 0.9 and transmissivity of 0.8 is utilised by many authors. Sometimes a very thin (few microns) dielectric substance is put on the glass cover to reduce reflectance. Utilising dielectric material has been found to reduce reflectance by up to 50%.

4.9 Direct Expansion Solar Aided Heat Pump's (DXSAHP) performance

ANN technique to forecast a direct expansion solar-aided heat pump's (DXSAHP) performance. In Calicut, India, they built their 1st experimental arrangement and gathered data under various climatic circumstances. They first created a 2-10-5 neural model with an FFBP network for investigation by the ANN technique. This research used a total of 60 data sets, of which 10 were used for testing and 50 were used for training (Mohanraj et al., 2008)

4.10 Feedforward neural network for solar still

Neural network technology to estimate the solar air's thermal efficiency. Three distinct types of absorber plates were used in the double flow SAH experiments, as illustrated in Figure. 5. Using the experimentally determined parameters, theycreated the FNN and ANN models. In the ANN model, three distinct learning algorithms, including the LM, SCG, and CGP, were utilized, however, in the FNN model, just the LM technique was applied. In the ANN and FNN models, respectively, the tang and more wavelet activation functions were applied. Due to its lowesterror and maximum R2 value among the three algorithms, the LM with 6-4-2 was determined to be the best model for ANN for a mass flow rate. The best model was LM with 6-4-2 for 0.08 kg/s. The FNN 6-5-3 model, which had the lowest error and best R2 value, was also discovered to be a better FNN model for prediction (Esen et al., 2009).

4.11 Levenberg-Marquardt (LM) algorithm

Direct growth ANN was used to forecast the energy analysis of solar desalination techniques. For this investigation, they set up a laboratory environment and collected data in Calicut, India, under various meteorological circumstances. They developed a pair of models for energy consumption and efficiency using 3-13-6 neurons. The LM learning algorithm was used to train the neural model, and it correctly predicted outcomes with lower COV and RMSE values and greater coefficients of correlation (Mohanraj et al, 2009).

Figure. 5 Type I, Type II, and Type III (absorber plates)

4.12 Stochastic Gradient Descent (SGD)

Still images and the ANN approach to predict how well the solar desalination process would work. Using the SGD method, they ran tests and gathered 60 data sets. Fifty were used for training, while ten were used for testing. ANN model built using 3-12-5 neuron FFBP network. SGD was one of three different training algorithms that were used. In Figure 6, They found that the LM algorithm for learning was the best one using statistical error analysis. They forecasted outcomes with minimum RMSE and COV values and maximum correlation coefficients of 0.9999 (Moahanraj et al., 2009).

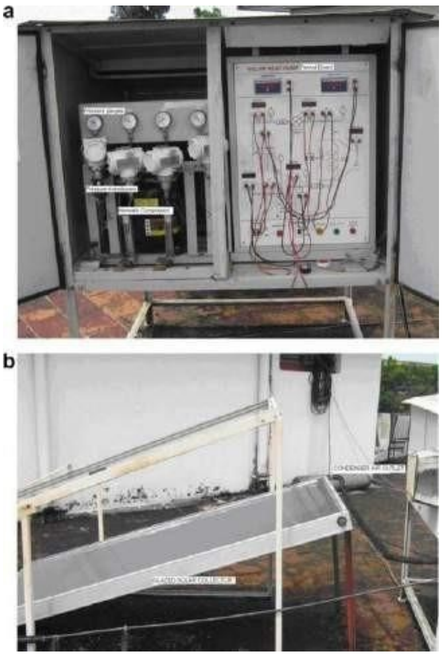


Figure. 6 Photo of the arrangement (Alizami et al., 2020) showing the solar still in (a) and the glazedabsorber in (b).

4.13 Backpropagation (BP)

To forecast the performance of solar collectors, an ANN model was created. In Beijing, they carried out experiments and gathered data. The ANN model has been created. Two variables, such as heating capacity and efficiency, were used in the output layers. The ANN structure was modeled using the BP learning approach and the logistic sigmoid transfer function, demonstrating that the model performed as predicted (Xie et al., 2009).

5. ANN methodology for temperature prediction

ANN methodology for temperature prediction of water during solar purifiers. They tested various training months over nine days. Two neurons in the input layer of the ANN model, such as solar radiation and outside air temperature, were constructed. The temperature of the water was employed in the output layer. Five alternative training methods were used to train the ANN model. They discovered that the best model for predicting food temperature was the 3-5-2 neural network with TRAINRP training techniques (Tripathy & Kumar, 2009).

Soft computing techniques to forecast solar collector performance using PCM materials (Figure. 7). ANFIS, SVM, and ANN were three different kinds of soft computing tools that were utilized. One of the important tools utilized to forecast solar collector performance was ANN. Three layers of the hidden layer were used to build an ANN network using the 5-7-1 neural model. They used the LM learning algorithm to predict outcomes, and they achieved good R2 values between 0.832 and 0.899(Varol et al., 2011).

5.1 Open-Cycle Solar Regenerator Using ANN

. To forecast the ability of an open-cycle solar regenerator, an ANN model of 2-10-1 neurons was utilized. (figure 7) They made predictions with the least amount of error and the highest correlation coefficient values (Al et al., 2011).

Figure. 7 Solar absorber experimental arrangement using PCM components (Kicsiny& Richárd, 2014).

5.2 Tansig transfer function of ANN to analyze solar still performance:

ANN tool to analyze the performance of solar still. In August and September, they carried out experiments in Turkey from 10:00 a.m. to 5:00 p.m. for 5 days. They employed flat and zigzag absorber plates, two different varieties. The experiments produced a total of 80 data sets. The ANN model was created using MLP 8-20-1 and eight factors, including the type of absorber model, the time of the tests, the exit and inlet air temperatures, the temperature of stored water, the surrounding temperature and absorber surface temperatures, and the solar intensity. The collector's efficiency was chosen as the output criterion. Algorithms for backpropagation LM learning were used to structure the ANN model. It was employed in the hidden layer of thismodel. Finally, they estimated the solar air collector's thermal efficiency and compared it to actual testing results. The neural model performed satisfactorily, as indicated by the values of SSE, MAE, MRE, R2, and RMSE were determined (Caner et al., 2011).

5.3 Neutrophil-Lymphocyte Ratio (NLR) and Multiple Linear Regression (MLR)Models

FFNN with the help of NLR and MLR to forecast the rate at which seedy grapes would dry. They performed tests using the setup (Figure. 8), which was built using two different kinds of SAC: PCM-based collector and extended surface. Data was gathered for the ANN model. The ideal ANN model for predicting outcomes was created using 3-10-1 neurons. When the FNN model's performance was compared to that of the MLR and NLR models, it was discovered that theFNN model performed better (Cakmak & Yildiz, 2011).

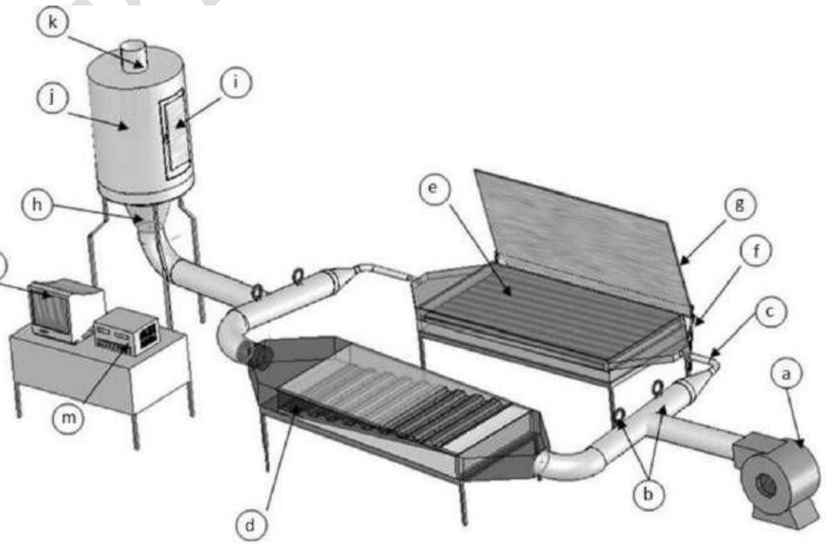


Figure.8 experimental set-up

5.4 Nonlinear Autoregressive with eXogenous input (NARx)

The ANN approach to forecasting the performance of cutting-edge solar collector modeling. They built the 5-5-1 and 5-4-1 NARX neural models, respectively, and experimented with performance-based assessments by EN 12975-2, a European Standard. The results demonstrated that the ANN model performed satisfactorily when combined with cutting-edge modeling (Fisher et al., 2012).

To analyze the ability of a hybrid Photovoltaic double-pass air heating collector, an ANN model was built. Data was obtained, and it was utilized for testing. 2000 data sets altogether were gathered from Indian states. The ANN model used FFBP methods to organize its performance prediction. 18 neurons in a hidden layer LM were selected. In the end, the results were correctly predicted by the 4-15-4 optimal model. The RMSE values for thermal, electrical, overall, and total thermal energy were found to vary from 1.10 to 2.89%, 1.12 to 2.90%, 1.23 to 3.21%, and 1.209 to 2.90%, respectively (Kamathania & Tiwari, 2012).

5.5 ANN with ANFIS

ANN and ANFIS techniques to forecast evacuated tube solar collector performance. For training and testing, they carried out experiments and gathered data. A total of 567 data patterns were gathered, of which 80% were utilized to train the NN model and 20% to test it. The mean storage tank temperature, ambient temperature, solar radiation, tilt angle, and thermal efficiency were the four input factors that made up the ANN model's structure. ANN model built using FFBP techniques. To identify the appropriate number of neurons for the buried layer, they examined models with 3 to 13 neurons. They found that the LM with 13 neurons was the best ANN model due to its low error. Finally, the neural model's prediction of the collector's thermal efficiency with a 4-12-1 accuracy was correct. Additionally, they calculated the thermal efficiency using the ANFIS approach. They claimed that because the ANN approach has lower RMSE and COV values and higher R2 values (0.811914), it is superior to the ANFIS method (Dikmen et al., 2013).

The ANN method to calculate the solar air collector's thermal efficiency. He experimented with corrugated and trapeze-shaped absorber plates, two different varieties. Experiments were carried out in Turkey in October between 9:00 and 17:00. 66 samples of data total were obtained from the studies. ANN model was built using the BP algorithm and the FF structure. The optimum ANN model was chosen using 3 to 9 neurons in the hidden layer based on a trial-and-error process. Researchers find that the ideal topology for SAC analysis is LM-3. R2 values of 1.2345 and 1.5672 for the first type and second type respectively, offer good model results (Benli, 2013).

The ANN method to forecast the solar PV/T system's ideal thermal and electricity output. They carried out trials with the PV/T setup and gathered information for the ANN model. With the use of 2-5-1 neurons, an ANN model that predicted data more accurately was created (Ammar et al. 2013).

5.6 MATLAB software for solar thermal still analysis

Flat plate solar still heat transfer analysis was predicted using an ANN model with 6-30-6 neurons. They used MATLAB software to compute 2509 data utilising an optimisation strategy for this project. The computed data were divided into three groups: validation (20%), testing (20%), and training (80%). The neural model used a hidden layer of 20 neurons and a durable back propagation learning approach (Hamdan et al., 2014).

The ANN approach to forecast how well massive solar systems will function. Over ANN modeling, experimental data were gathered over 226 days. The ANN model, which includes three additional levels and layers overall, was constructed with five neurons in the hidden layer. An ANN model was developed using experimental data and a learning algorithm, and it accurately predicted outcomes (Kalogirou et al., 2014).

5.8 Solar Still thermal energy systems (SSTES) with ANN

For estimating the performance of solar thermal still performance with thermal system, an ANN model has been implemented. From March 2011 to December 2012, they carried out trials with the STES setup and gathered data regarding the local climate in Ottawa. ANN models incorporating FFBP networks were created utilizing two distinct learning methods, such as LM and SCG. It was discovered that the 10-20-8 neural model and LM learning algorithm were the best options (Yaïci & Entchev, 2014).

To use experimental data to forecast how well a ground source heat pump system will function, ANFIA and ANN models were developed. Twelve inputs and one outcome parameter were used to set up the ANN and ANFIS models. For the ANFIA and ANN models, we used backpropagation and hybrid learning approaches, respectively. They discovered that the ANFIS performance prediction is superior to the ANN model (Esen et al., 2015).

5.10 Multiple-layer perceptron neural network (MLPNN) model.

ANN approach to forecast a PV-T evaporator's performance in a solar still. For ANN modeling, they acquired experimental data. An ANN model with 3–18–5 neurons was created. The Multiple-layer perceptron neural network model has the highest R2 and the lowest estimated variance and COV values when predicting the outcomes (Gunasekar et al., 2015).

Three different types of ANN models to forecast solar radiation, including the MLP, GRNN, and RBF models and compared the results to data predicted by the Improved Bristow-Campbell (IBC) model (Wang et al, 2016).

The ANN technique has been successfully employed for performance prediction of solar still desalination since it operates more quickly and forecasts the data with less time, according to a review of the aforementioned literature. As a result, it can be concluded that the ANN method is suitable for predicting the capability of solar desalination techniques.

Table 1 provides a selection of research papers that apply artificial neural networks to forecast solar still desalination performance.

Table 1 Artificial Neural Network technique in the solar desalination process.

Citation	Neural Model	Type of Network	Algorithms	The Work's Purpose
[Layek et al., 2099]	SISO, MISO	MLPNN	BP	approximation of solar collectors'daily performance
[Saini, 2008]	4-7-3	MLPNN	LM	estimating solar water still performance with a collector.
[Karmare & Tikekar, 2007]	ANN: 8-9-1, 9-3-1, 9-6-1 RBF:9-84-1	RBFNN, MLPNN	BP, RBF	To forecast the hybrid solar still's performance
[Jaurket et al., 2006]	3-7-1	MLPNN	TRAINLM	to evaluate the flat platesolar still's performance.

[Bhagoria et al, 2002]	13-5-1, 14-7-2	MLPNN	BP	Forced circulation solar water desalination performance estimation.
[Verma & Prasad, 2000]	7-24-2	MLPNN	BP	System for solar water desalination using thermosiphon performance analysis
[Gupta et al., 1993]	8-18-2 (3 hiddenlayers with 18 neurons)	MLPNN	BP	to forecast how well a domestic solar still will function.
[Prasad & Daini, 1988]	8-8-4 (3 hiddenlayers with 8 neurons)	MLPNN	BP	to calculate the solar still's performance.
[Kalogirou, 2000]	2-4-1	MLPNN	SCG,CGP, BFG, LM, RP	estimating the temperature of the waterduring the solar desalination procedure
[Prasad & Sahu,	5-10-10-2	MLPNN	BP	To measure the effectiveness of solar still

2017)				
[Sahu & Prasad, 2017]	2-10-4	MLPNN	LM,SCG,CGP	To determine how well direct expansion solar-driven desalination techniques perform
[Prasad& Sahu, 2016]	2-12-5	MLPNN	LM	Energy study of direct expansion solar-driven desalination techniques prediction
[Sahu & Prasad, 2016]	6-4-2, 6-5-2	WNN, ANN	ANN: LM,SCG, CGPWNN: LM	To forecast the solar still's thermal efficiency
[Behura et al., 2016]	1-9-4	MLPNN	LM	calculating a direct expansion solar still'sperformance
[Behura et al., 2016]	7-20-20-1	MLPNN	BP	To determine how well flat plate solarcollectors function thermally

[Sing & Siddhartha, 2014]	Six different model	MLPNN	BP	To forecast the flat plate solar still'sperformance metrics
[Arcaklioglu et al., 32004]	2-5-1	FINN	LM	To gauge the effectiveness of the solar PV/T system
[Pacheco et al., 2001]	8-3-1	MLPNN	LM	To calculate the thermal efficiency of two different solarstill types
[Jani et al., 2017]	4-12-1	ANFIS, FFNN	LM	To forecast how well an evacuated tube solar still will operate
[Zahraee et al., 2016]	4-15-4	MLPNN	LM	Calculate the hybrid PV/T double pass air collector's performance
[Yadav & Chandel, 2014]	5-5-1, 5-4-1	NARX	LM	comparison of neural network and cutting-edge solar stillmodeling techniques
[Karabacak&	3-10-1	FINN	LM	To calculate the rate of solar still performance inseawater.

Cetin, 2014]				
[Uma Maheswari & Meenakshi, 2018]	8-20-1	MLPNN	LM	Solar still performance analysis
[Mellit et al, 2009]	2-10-1	MLPNN	BP	estimating open-cycle solar still performance.
[Kalogirou, 2001]	5-7-1	MLPNN	LM	determine the solar collector's performance based onPCM.
[Yilmaz & Atik, 2007]	4-15-4	MLPNN	LM	To forecast a PV-T evaporator's performancefor solar-aided desalination methods
[Ertunc & Hosoz, 2006]	13-15-1	MLPNN,ANN	BP, Hybrid	To forecast the effectiveness of a ground-basedsolar desalination system
[Hosoz &	10-20-8	FFBP	LM,SCG	To gauge the effectiveness of the solar thermalenergy

Ertunc, 2006]				system
[Yigit & Ertunc, 2006]	3-5-5-5-2	MLPNN	BP	assessment of huge solar still kinds' performance
[abbassi &Bahar, 2005]	5-20-5	NARX	Rprop	To forecast the flat plate solar still's heat transferanalysis

6. Data-driven techniques in solar desalination

Heat, electrical methods, and pressure are the three basic ways utilized for desalination. The oldest method for boiling highly salinized water and collecting the steam that results is thermal distillation. Now that the steam has been collected and condensed, it may be used to make freshwater. The salt and water are separated using an electrical current in the electrical method. Pressure is the driving force behind the selective porous membrane used in the RO kind of desalination, which allows water to pass through while leaving the salt behind (Aljuyi et al, 2021). The thermal and RO kinds of desalination account for almost all of the market. Even though RO systems make up almost all of the installed capacity for desalination systems, thermal desalination has some advantages. For instance, using plant waste heat for the desalination thermal units might increase the system's overall efficiency. Studies on the utilization of data-driven techniques in SD processes have largely concentrated on thermal kinds (Soleimanzade et al., 2022) For example, (Behnam et al., 2022) used ANN to simulate the results of a humidification-dehumidification-type SD that was used to humidify the greenhouse's interior space and provide fresh water. The model's inputs were the seawater greenhouse's breadth and length, the height of the front evaporator, and the transparency of the roof. The model's output was the system's water yield. We looked at their various concealed one- and two-layer architectures. They discovered that using one hidden layer with 9 neurons produced the maximum degree of accuracy, as measured by R2, of 0.998. In addition to the model's architecture, the functions used and optimization techniques for hidden layers (Faegh et al, 2021) must also be taken into account; however, it must be remembered that a rise in the number of layers that are hidden may result in overfitting.

6.1 ANFIS-based models

One of the most crucial elements affecting how accurately data-driven methods predict the results of solar stills is the applied method and algorithm (Rezk (2022); Mashaly (2017); Nassef (2020); Olabi(2023). ANN-ANFIS-based models, multilinear regression, and random forest (RF). When compared to other methods, they discovered that employing RF produced the most accurate predictions (Mashaly et al, 2018). Another study evaluated the effectiveness of classical ANN and SVM withthe Harris Hawk optimizer in forecasting the efficiency of an active solar still. Their models took into account inputs such as time, ambient temperature, solar irradiation, wind speed, and vapor velocity (Zayed et al, 2021). They discovered that ANN performed better than models based on ANFIS and may be improved even more by applying the optimizer. R-squared values for the ANFIS and ANN-based models in their study were 0.9894 and 0.9983. Better adjusting of the parameters impacting the ability of the modeling technique can be attributed to increased accuracy of the simulations via the coupling optimizer. In a different study, the effectiveness of ANN, Multiple Regression (MR), and ANFIS was examined while predicting the efficiency of an inclined passive solar still. Relative humidity, solar radiation, TDS, and feed flow rates of brine and feed were all included as inputs in the suggested models. Another important consideration is the function that is used in the design of data-driven procedures.

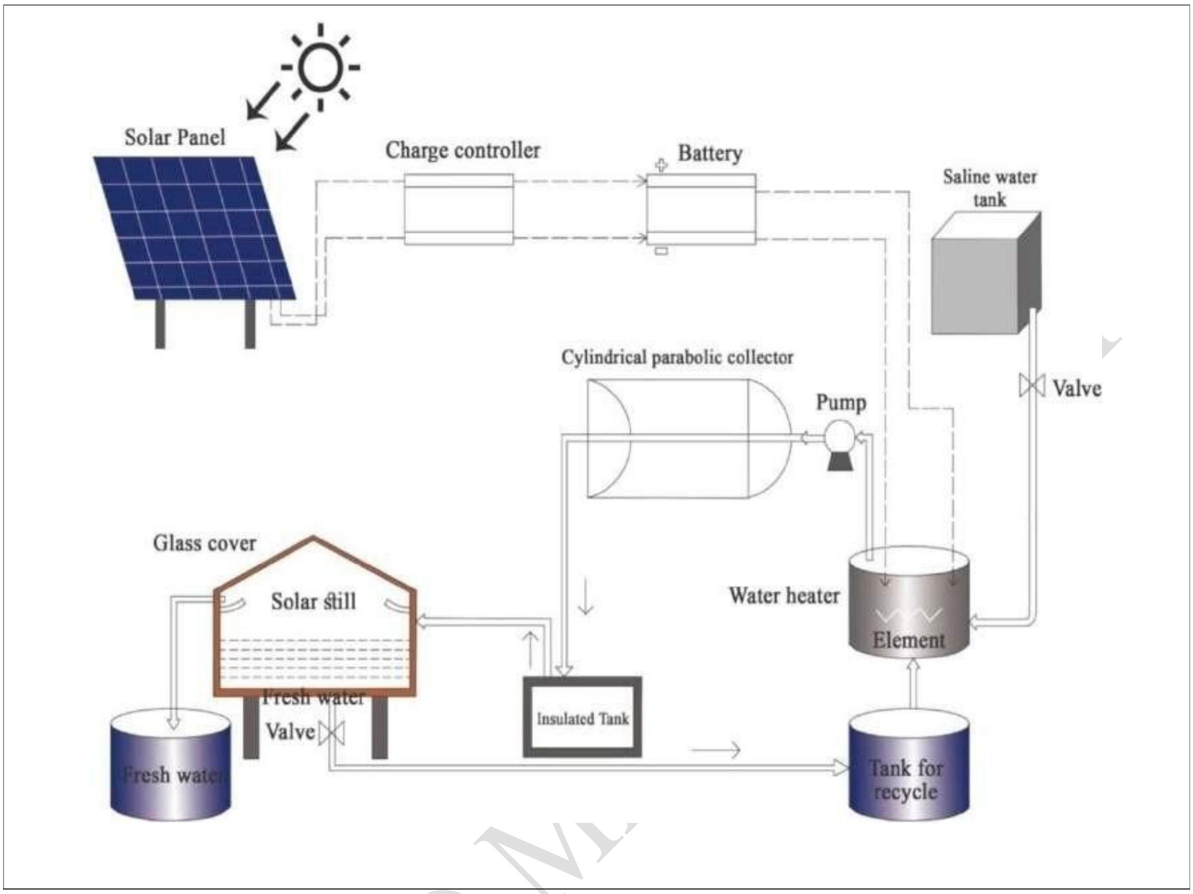


Figure 9 | A solar desalination system featuring a still, PV, and a collector.

As an illustration, (Bahiraei et al, 2021) tested various membership functions in ANFIS-based models, such as the Pi curve, trapezoid, triangle, and differential between two sigmoidal functions, to propose a model with the maximum exactness. (figure 9)Regression's correlation coefficient for training data sets employing these approaches was approximately 0.999. The most appropriate function in a network's structure for modeling can depend on the physics of the issue, which can be discovered by putting several functions to the test (Perendecie et al, 2008; Esmaili et al, 2021; Perez et al, 2010; Kharab et al, 2014).

7. Linear regression analysis model

It is crucial to take into account all of the useful components as inputs when modeling the system using data-driven techniques. To achieve greater accuracy or increase comprehensiveness, several models have included new inputs. In addition to the variables used in the bulk of the research, (Abuella et al, 2015) employed broader variables including the number of hours in a day, day, and month numbers, cloud cover, and the differential in temperature between the inner and outer surfaces of glass as an example. They used a regression, cascaded forward ANN, and linear model with various numbers of neurons in their research. They discovered that the ANN model provided a more accurate forecast of the system's production. Although this model is more thorough than the ones stated earlier, it may still be improved by taking into account additional elements like the system's specifications, such as the sizes of various sections and the material's qualities that determine how well the systems function (Ibrahim et al, 2012; Alizamir et al, 2020; Skumanich et al, 1975; Ramedani et al 2014).

SD can be combined with other elements to increase output. Forecasting the performance of these systems can be done using data-driven methods (Kicsiny & Richard, 2014). The panel was used to power the still in the tank that was used to warm the salt water before it was introduced to the solar still (Wahbah et al, 2019). Saltwater was heated further in the collector before going into the still. Figure 10 displays the system's schematic. They discovered that the maximum model accuracy was achieved while utilizing 24 neurons, with an R2 of 0.987 after testing several network designs and hidden layer neuron counts. Hybrid technology would require more inputs from the systems, making the modeling process more challenging (Ruivo et al., 2022; Bocco et al, 2012; Daut et al, 2011; Mahesh et al, 2022; Devi et al., 2011).

It is possible to model the dynamic efficiency of solar desalination systems using data-driven methodologies. A solar still with an improved design's water temperature and hourly production of water were estimated using a variety of ANNs in a study conducted by (Chiteka et al., 2020), comprising feedforward (FF), backpropagation (BP), linear SVR, Support

Vector Regression (SVR), RBF, and RF. Their models' inputs included wind speed, outside temperature, solar energy received, and basin water depth. When compared to the predicted data and the corresponding real values, FF and RBF were shown to be the most successful approaches for predicting the hourly water output and water temperature, respectively (Abubaker et al, 2021). Although they took a novel method for dynamic modeling of SD, their model's accuracy was confined and may be increased by taking into consideration additional elements like wind speed and feedtemperature.

8. Genetic algorithm

The performance of solar stills can be enhanced by using nanofluids. These solar stills can be accurately evaluated using innovative techniques. Different data-driven modeling techniques, such as ANN-GA, to simulate the capabilities of slope solar still using carbon black nanofluid at a concentration of 1.5% wt (Garud et al., 2021). The suggested model's inputs included solar radiation, ambient air temperature, vapor temperature, wind speed, glass outlet and intake temperatures, and basin temperature. To fine-tune the methods and provide the results with the best degree of accuracy, the models were combined using the Bayesian optimization technique. They discovered that while all of the suggested models could forecast the system's performance with a fair amount of accuracy, using RF produced the best results (Saadaoui eti al, 2021). The efficiency of a nanofluidic solar still combined with a thermoelectric module, for instance, was modeled using ANN in conjunction with the Imperialist Competition Method(ICM), genetic algorithm (GA), and other techniques by (Jervase et al., 2001).

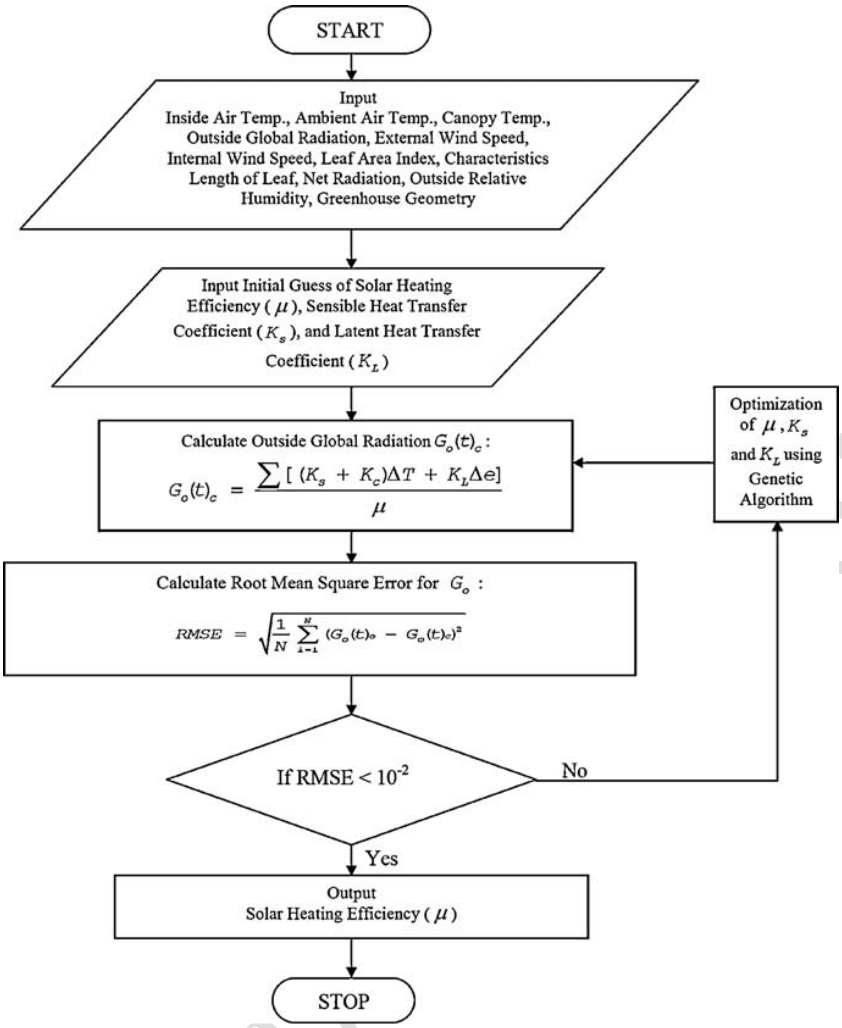


Figure 10 Genetic algorithm for solar desalinationPSO-ANFIS AND PSO-ANN

Coupling the aforementioned optimization approaches greatly enhanced the model's accuracy, with ICM having a greater impact on accuracy improvement. The modeling methodology has an impact on how accurately nanofluidic solar desalination values are projected to be. PSO-ANFIS and PSO-ANN, for instance, were employed by (Khare et al., 2013) to predict the performance of a solar still using Cu2O nanoparticles. The models' inputs were comparable to those from earlier work, and the result of the created model was system efficiency. They discovered that coupling the optimization methods increased exactness in both types of models, but that PSO-ANFIS provided the highest level of modeling accuracy. In a different study (Khanna et al., 2015), the effectiveness of MLP ANN and MLR in foretelling the instantaneous thermal effectiveness of a solar still was evaluated. In comparison to MLR, they discovered that utilizing MLP ANN produced a model with greater exactness. Due to its more sophisticated structure and ability to model complex systems more effectively, MLP ANN has a higher level of accuracy.

9. RO-ANN

The outcomes of the ANN-based model can be used to design the ideal conditions for the efficiency of desalination systems (Ghermandi et al., 2009). As an example, in a study done by (Ramanzanian et al., 2023), an ANN-based optimizing control system was used to regulate a solar-powered transmembrane distillation module. After that, a control system was put in place to maximize the system's distillate production. The suggested technology made it possible to adjust the feed flow rate to achieve continuous optimum distillate output at the ideal levels. Another example is the way (Boesch & William, 1982) uses ANN to forecast the weather and optimize a hybrid RO desalination system that is powered by solar and wind energy. The system's ideal design was created by using the network's outputs and doing optimization.

The study's conclusions can be summed up by saying that the methods used, optimization algorithms, etc., have an impact on the models' accuracy. Due to their more sophisticated structures, which allow them to more accurately mimic complex systems, intelligent approaches, like ANNs, are typically chosen in terms of accuracy. Additionally, as the parameters impacting exactness are employed at their optimum values, it is discovered that applying optimization algorithms and connecting them with intelligent approaches improves accuracy. The examined inputs have an impact on the exactness in addition to the previously specified elements. Models will be more accurate if more significant inputs are taken into account (Manolakos et al., 2008). The additional elements that might contribute to the model's discrepancies can be considered to be the data noise that is inescapable in experimental data utilized for modeling.

10. Dynamic performance of solar still using ANN

A cutting-edge technique for boosting the volume of desalinated water in solar desalination plants. Solar panels and a cylindrical parabolic collector (CPC) were employed to achieve this goal of increasing the temperature of the basin water. Investigations were also conducted into the effects of various basin solar still components on freshwater mass. Of the several elements that make up a basin, the aluminium basin has been linked to the greatest amount of water desalination. In addition, the impacts of various water depths and colours on the basin were investigated. At a 5-mm water depth, the maximum freshwater content in the black aluminium basin was 2.97 kg/day (Bagheri et al., 2021).

These days, artificial intelligence is a major technological advancement that can benefit business and research across a wide range of disciplines, including the desalination of water using solar thermal energy. Therefore, the primary goal of the research is to forecast the efficiency of water desalination, which is dependent on solar thermal energy, by using an artificial intelligence regression model. Before implementing the system, the contribution aids researchers and manufacturers in assessing the productivity of the desalination system's design in a beta setting (Salem et al., 2022).

The research team's improved design for a solar still desalination system is taken into consideration here, and ANN models are developed for it using the experimental data collected over the course of a year. One of the most widely used machine learning techniques is the development and comparison of various artificial neural network (ANN) models in order to determine which performs best in predicting the two most important system performance parameters: the hourly produced distillate and the water temperature in the basin (Sohani et al., 2021).

To improve the efficiency of solar energy-powered solar still units by utilising solar panels and cylindrical parabolic collectors. Salinized water is heated by thermal components outside the solar still unit using a 300 W solar panel. Since solar panels are cooled during the hottest parts of the day, lowering their temperature may boost the efficiency of the panels first and the solar still unit second. 2.132 kg of freshwater per day was the largest amount used in the experiment. ANNs were used to model the experiments. Neural network modelling and experimental data show a strong association, as indicated by the results of neural network simulations (Bagheri eto al., 2020).

According to the performance evaluation criteria, the ANN model outperformed the MVR and SWR models. Compared to the MVR and SWR models, the ANN model's mean coefficient of determination was around 13% and 14% more accurate, respectively. Furthermore, the MVR and SWR models' mean root mean square error values, at 6.534% and 6.589%, respectively, were nearly twice as high as the ANN model's mean values. While the findings from the SWR and MVR models were comparable, the MVR model produced superior outcomes (Mashaly & Alaza et al., 2016).

11. Minearlization process

The natural process of mineralization is how the environment stores CO2, but it takes time. One of the main causes of rock chemical weathering is the hydrolysis of CO2 in damp air or water. According to the geological record, weathering happens at a rate that can significantly lower atmospheric CO2 levels when tectonic action exposes huge rock masses to the atmosphere. Even though natural weathering may remove around 30 Gt of CO2 from the atmosphere every century, this process might potentially be accelerated and turned into an industrial process. Anthropogenic CO2 can thus react with a reactive substrate to create carbonate salts, a mineralized product that can either be disposed of or transformed into a commodity that is valued. Products that have been mineralized may be usefully used in amounts that may eventually lessen the consequences of global warming. There includes discussion of typical rock kinds and how they react with CO2 gas.

12. Thermal conductivity in solar still

The thermal conductivity of solar still using ANN and a combination of water-based Al2O3 and CuO nanofluids were assessed at different temperatures and volume concentrations. Ethylene glycol and water are combined in a base fluid mixture of 1:1 by weight. In addition, a temperature range of 15 to 50 °C was obtained, and the concentration was found to be 0.8% . In comparison to Al2O3 and CuO nanofluids, the base fluids exhibit low thermal conductivity, according to the test results that were obtained. When compared to Al2O3 nanofluids, the CuO nanofluids exhibit higher thermal conductivity at the same volume and temperature concentration. Nanoparticles suspended in any liquid provide energy to nanofluids. The parameters of base fluid heat transmission were altered by the recent addition of nanoparticles. In this experiment, the efficiency of distillation can enhance by up to 29% by combining violet dye with water. Studies were conducted on the novel nanofluid additives for solar still performance. It was calculated how much the 1000 solar still performance units would weigh overall using ANN. Based on the experiment, it was determined how introducing a carbon nanotube to the basin water affected the hoover still's yield.

13. Conclusion

Applications of data-driven methodologies for modeling solar desalination systems are given in the paper. These have been developed using a variety of inputs, such as ANN, ANFIS, PSO, RO, BP, GA, SVM, and others. The following are the key conclusions of this review article:

1. When compared to correlation, intelligent approaches can more precisely model solar desalination systems.
2. By utilizing intelligent approaches, several parameters, including output, energy, and energy efficiency, may be modeled.
3. The applied approach and algorithm as well as the taken into account inputs are some

of the factors that affect how accurate the proposed models are.

4. Using optimization techniques in conjunction with the models will increase accuracy because the hyperparameters will be set to their ideal values.

5. The type of optimization algorithm has an impact on the models' accuracy in additionto the modeling approach used.

6. Among the most crucial elements that must be employed as inputs are operating circumstances.

7. The models' outputs, which were obtained via clever techniques, can be used to improvethe systems.

8. The majority of research has used water productivity as the model's output, but it would be advantageous to take other technical factors like energy and the system's efficiency into account.

9. It would be beneficial to take into account economic and environmental elements as model outputs in addition to technical criteria.

10. It is advised to compare the amount of time and calculations needed for the training process of intelligent models using various algorithms and methodologies.

11. Models can be more accurate by using hybrid optimization algorithms, which have a better capacity to find optimal solutions.

The material for the basin has been chosen creatively, and the distinctions between the materials have been investigated. On several experiment days, heat characteristics are shown. If the right materials are employed, the temperature of the basin can be elevated, which will increase the rate of desalination and the temperature of the water. During the process, this novel approach raises the temperature of the basin water by utilising solar panels and an artificial neural network (ANN) in solar desalination facilities. There is typically good agreement between the ANN-based prediction and the experimental results when a variable number of neurons is predicted based on the ANN inputs. ANNs have been used as one of the most dependable techniques for prediction and data validation. An investigation of the total similarity of ANNs has been conducted through the use of ANN simulation.

ABBREVIATION

ANNs-Artificial neural networks

TES- Thermal Energy Storage

PCM-Phase Change Materials

AI-Artificial Intelligence

BP-Back propagation

RMSE-Root Mean Square Error,

MAPE-Mean Absolute Percentage Error

HV-Hottel-Vhillier

SISO-single input, single output

MISO-multiple input, single output

DXSAHP-direct expansion solar-aided heat pump

NLR-Neutrophil-Lymphocyte Ratio

MLR-Multiple Linear Regression

FFNN-feed-forward neural network

NARx-Nonlinear Autoregressive with exogenous input

SSTES-Solar Still thermal energy systems

MLPNN-Multiple-layer perceptron neural network

FFF-feed forward

SVR-Support Vector Regression

ICM-Imperia list Competition Method

GA-genetic algorithm

PSO-Particle Swarm Optimisation

Competing interests

The authors declare that they have no competing interests.

Authors' contribution

Author 1 supports to comparison of existing and past research literature. This helps to highlight our review manuscript from others as an enhanced one.

Author 2 assists in writing content related to Solar still using ANN analysis in our review paper. Author 3 helps and finds the performance of Solar still using ANN.

Author 4 and 5 supports and develops the studies of Soalr still thermal energy system with ANN.

Acknowledgment

I offer up our fervent prayers to the omnipotent God. I want to express my sincere gratitude to my co-workers for supporting me through all of our challenges and victories to get this task done. I want to express my gratitude for our family's love and support, as well as for their encouragement. Finally, I would like to extend our sincere gratitude to everyone who has assisted us in writing this article.

References

Kalogirou, S.A., Neocleous, C.C., Schizas, C.N. (1998), Artificial neural networks for modelling the starting-up of a solar steam-generator. *Applied Energy* **60**, 89-100.

Kalogirou, S.A., Panteliou, S., Dentsoras, A. (1999), Modeling of solar domestic water heating systems using artificial neural networks. *Solar Energy* **65 (6)**, 335 342. https://doi.org/10.1016/S0038-092X(99)00013-4

Kalogirou, S.A., Panteliou, S., Dentsoras, A. (1999), Artificial neural networks used for the performance prediction of a thermosiphon solar water heater. *Renewable Energy* **18,** 87-99. https://doi.org/10.1016/S0960-1481(98)00787-3

Kalogirou, S.A. (2000), Long-term performance prediction of forced circulation solar domestic water heating systems using artificial neural networks. *Applied Energy* **66**, p. 63-

74. https://doi.org/10.1016/S0306-2619(99)00042-2

Farkas, I., Geczy-Vıg, (2003). Neural network modelling of flat-plate solar collectors. *Computers and Electronics in Agriculture* **40**, 87-102.

Facão, J. , Varga, S., Oliveira, A.C. (2004), Evaluation of the Use of Artificial Neural Networks for the Simulation of Hybrid Solar Collectors. *International journal of green energy* **1(3),** 337-352. https://doi.org/10.1081/GE-200033649

Cetiner, C., Halici, F., Cacur, H., Taymaz, I. (2005), Generating hot water by solar energy and application of neural network. *Applied Thermal Engineering* **25,** 1337-1348. https://doi.org/10.1016/j.applthermaleng.2004.09.004

Lecoeuche, S., Lalot, S. (2005). Prediction of the daily performance of solar collectors. *International Communications in Heat and Mass Transfer* **32,** 603 611. https://doi.org/10.1016/j.icheatmasstransfer.2004.12.002

Kalogirou, S.A. (2006), Prediction of flat-plate collector performance parameters using artificial neural network. *Solar Energy* **80,** – 248 259. https://doi.org/10.1016/j.solener.2005.03.003

Sözen, A., Menlik, T., Ünvar, S. (2008), Determination of efficiency of flat plate solar collector using neural network. *Expert Systems with Applications* **35,** 1533 1539. https://doi.org/10.1016/j.eswa.2007.08.080

Mohanraj, M., Jayaraj, S., Muraleedharan, C. (2008), Modeling of a direct expansion solar assisted heat pump using artificial neural networks. *International Journal of Green Energy* **5,** 520-532. –
https://doi.org/10.1080/15435070802498499

Esen, H., Ozgen, F., Esen, M., Sengur, A. (2009), Artificial neural network and wavelet neural network approaches for modelling of a solar air heater. *Expert Systems with Applications* **36,** 11240-11248. http://dx.doi.org/10.1016/j.eswa.2009.02.073

Mohanraj, M., Jayaraj, S., Muraleedharan, C. (2009), Exergy analysis of direct expansion solar-assisted heat pumps using artificial neural networks. *Int. J. Energy Res.* **33,** 1005 1020. https://doi.org/10.1002/er.1534

Mohanraj, M., Jayaraj, S., Muraleedharan, C. (2009), Performance prediction of a direct expansion solar assisted heat pump using artificial neural networks. *Applied Energy* **86,** 1442- 1449. https://doi.org/10.1016/j.apenergy.2009.01.001

Xie, H., Liu, L., Ma, F., Fan, H. (2009), Performance prediction of solar collectors using artificial neural networks. *International Conference on Artificial Intelligence and*

Computational Intelligence, 573-576. https://doi.org/10.1109/AICI.2009.344

Tripathy, P.P., Kumar, S. (2009), Neural network approach for food temperature prediction during solar drying. *International Journal of Thermal Sciences* **48,** 1452 1459. https://doi.org/10.1016/j.ijthermalsci.2008.11.014

Varol, Y., Koca, A., Oztop, H.F., Avci, E. (2010), Forecasting of thermal energy storage performance of Phase Change Material in a solar collector using soft computing techniques. *Expert Systems with Applications* **37,** 2722-2732. https://doi.org/10.1016/j.eswa.2009.08.007

Aly, A.A., Zeidan, E.B., Hamed, A.M. (2011), Performance evaluation of open- cycle solar regenerator using artificial neural network technique. *Energy and Buildings* **43,** 454 457. https://doi.org/10.1016/j.enbuild.2010.09.032

Caner, M., Gedik, E., Keçebas, A. (2011), Investigation on thermal performancecalculation of two type solar air collectors using artificial neural network. *Expert Systems with Applications* **38,** 1668-1674. https://doi.org/10.1016/j.eswa.2010.07.090

Cakmak, Gm., Yildiz, C. (2011), The Prediction of Seedy grape drying rate using a neural network method, *Computers and Electronics in Agriculture* **75,** 132138.

Fischer, S., Frey, P., Drück, H. (2012). Comparison between state-of-the-art and neural network modelling of solar collectors. *Solar Energy* **86,** 3268-3277. https://doi.org/10.1016/j.solener.2012.09.002

Kamthania, D., Tiwari, G.N. (2012). Performance Analysis of a Hybrid Photovoltaic Thermal Double Pass Air Collector Using ANN. *Applied Solar Energy* **48(3),** 186 192. https://doi.org/10.3103/S0003701X12030073

Dikmen, E., Ayaz, M., Ezen, H.S., Kucuksille, E.U., Sahin, A.S. (2013). Estimation and optimization of thermal performance of evacuated tube solar collector system. *Heat Mass Transfer*. https://doi.org/10.1007/s00231-013-1282-0

Benli, H. (2013). Determination of thermal performance calculation of two different types solar air collectors with the use of artificial neural networks. *International Journal of Heat and Mass Transfer* **60,** 1- 7. https://doi.org/10.1016/j.ijheatmasstransfer.2012.12.042

Ammar, M.B., Chaabene, M., Chtourou, Z. (2013), Artificial Neural Network based control for PV/T panel to track optimum thermal and electrical power. *Energy Conversion and Management* **65,** 372 380. https://doi.org/10.1016/j.enconman.2012.08.003

Hamdan, M.A., Abdelhafez, E.A., Hamdan, A.M., HajKhalil, R.A. (2014), Heat Transfer Analysis of a Flat-Plate Solar Air Collector by Using an Artificial Neural Network. *J. Infrastruct. Syst.* 45-78.http://dx.doi.org/10.1061/(ASCE)IS.1943-555X.0000213

Kalogirou, S.A., Mathioulakis, E., Belessiotis, V. (2014), Artificial neural networks for the performance prediction of large solar systems. *Renewable Energy* **63,** p. 90-97. https://doi.org/10.1016/j.renene.2013.08.049

Yaïci, W., Entchev, E. (2014). Performance prediction of a solar thermal energy system using artificial neural networks. *Applied Thermal Engineering* **73,** p. 1348 1359. https://doi.org/10.1016/j.applthermaleng.2014.07.040

Esen, H., Esen, M., Ozsolak, O. (2015), Modelling and experimental performance analysis of solar-assisted ground source heat pump system. *Journal of Experimental & Theoretical Artificial Intelligence,* 1-17. https://doi.org/10.1080/0952813X.2015.1056242

Gunasekar, N., Mohanraj, M., Velmurugan, V. (2015), Artificial neural network modeling of a photovoltaic-thermal evaporator of solar assisted heat pumps. *Energy* **93,** p. 908-922. https://doi.org/10.1016/j.energy.2015.09.078

Wang, L., Kisi, O., Kermani, M.Z., Salazar, G.A., Zhu, Z., Gong, W. (2016), Solar radiation prediction using different techniques: model evaluation and comparison, *Renewable and Sustainable Energy Reviews* **61,** p. 384-397. https://doi.org/10.1016/j.rser.2016.04.024

Prasad, B.N., Saini, J.S. (1988), Effect of artificial roughness on heat transfer and friction factor in a solar air heater. *Solar energy* **6***,* 555 560. https://doi.org/10.1016/0038-092X(88)90058-8

Gupta, D., Solanki, S.C., Saini, J.S. (1993), Heat and fluid flow in rectangular solar air heater ducts having transverse rib roughness on absorber plates. *Sol. Energy* **51 (1),** 31- 37. https://doi.org/10.1016/0038-092X(93)90039-Q

Verma, S.K., Prasad, B.N. (2000), Investigation for the optimal thermo- hydraulic performance of artificially roughened solar air heaters. *Renewable Energy* **20,** p. 19 36. https://doi.org/10.1016/S0960-1481(99)00081-6

Bhagoria J.L., Saini J.S., Solanki S.C. (2002), Heat transfer coefficient and friction factor correlation for rectangular solar air heater duct having transverse wedge shaped rib roughness on absorber plate, *Renewable Energy* **25,** p. 341-369.https://doi.org/10.1016/S0960-1481(01)00057-X

Jaurker, A.R., Saini, J.S., and Gandhi, B.K..(2006), Heat transfer and friction characteristics of rectangular solar air heater duct using artificial grooved roughness, *Solar Energy.,* **80,** p. 895 907. https://doi.org/10.1016/j.solener.2005.08.006

Karmare, S.V. and Tikekar, A. N. (2007) Heat transfer and friction factor correlation for artificially roughened duct with metal grit ribs, *Int.J.Heat MassTransfer* **50,** p. 4342 51.

Saini, S.K., Saini, R.P. (2008), Development of correlations for Nusselt number and friction factor for solar air heater with roughened duct having arc-shaped wire as artificial roughness. *Solar Energy* **82,** p. 1118-3110. https://doi.org/10.1016/j.solener.2008.05.010

Layek, A., Saini, J. S., Solanki, S. C., (2009), Effect of chamfering on heat transfer and friction characteristics of solar air heater having absorber plate roughened with compound turbulators, *Renewable Energy* **34,** p. 1292 8. https://doi.org/10.1016/j.renene.2008.09.016

Singh, A.P., Siddhartha, V. (2014), Effect of artificial roughness on heat transfer and friction characteristics having multiple arc shaped roughness element on the absorber plate, *Solar Energy* **105,** p. 479-493 https://doi.org/10.1016/j.solener.2014.04.007

Behura, A.K., Prasad, B.N., Prasad., L. (2016), Heat transfer, friction factor and thermal performance of three sides artificially roughened solar air heaters. *Solar Energy* **130,** p. 46 59. https://doi.org/10.1016/j.solener.2016.02.006

Behura, A.K., Prasad, B.N., Prasad., L.(2016) Investigation for heat transfer and friction factor characteristics in three sides artificially roughened solar air heater, Ph.D. Thesis, National Institute of Technology, Jamshedpur, India. https://doi.org/10.1016/j.solener.2016.02.006

Sahu, M.K., Prasad, R. K. (2016), ENergy based performance evaluation of solar air heater with arcs haped wire roughened absorber plate, *Renewable Energy* **96**, p. 233-243. https://doi.org/10.1016/j.renene.2016.04.083

Prasad,R.K., Sahu, M.K. (2016), Investigation on Optimal Thermohydraulic Performance of a Solar Air Heater Having Arc Shaped Wire Rib Roughness on Absorber Plate, *International Journal of Thermodynamics* **19,** p. 214-224. http://dx.doi.org/10.5541/eoguijt.277772

Sahu, M.K., Prasad, R. K. (2017). Thermohydraulic performance analysis of an arc shape wire roughened solar air heater, *Renewable Energy* **108,** p. 598-614 https://doi.org/10.1016/j.renene.2017.02.075

Prasad, R.K., Sahu, M.K. (2017), Entropy generation and thermodynamic analysis of solar air heaters with artificial roughness on absorber plate, *Archives of Thermodynamics* **38** *,* p. 23-48, DOI: 10.1515/aoter-2017-0014.

Kalogirou, S.A. (2000), Applications of artificial neural-networks for energy systems. *Applied Energy* **67,** p. 17-35. https://doi.org/10.1016/S0306-2619(00)00005-2

Kalogirou, S.A. (2001), Artificial neural networks in renewable energy systemsapplications: a review. *Renewable and Sustainable Energy Reviews* **5***,* p. 373 401.

https://doi.org/10.1016/S1364-0321(01)00006-5

Mellit, A., Kalogirou, S.A., Hontoria, L., Shaari, S. (2009), Artificial intelligence techniques for sizing photovoltaic systems: a review. *Renewable and Sustainable Energy Reviews* **13,** p. 406 19. https://doi.org/10.1016/j.rser.2008.01.006 –

Uma Maheswari, C., and R. Meenakshi Reddy. 2018, "CFD Analysis of Different Types of Single Basin Solar Stills." *IOP Conference Series: Materials Science and Engineering* **330 (1)**: 012097.

Mohanraja, M., Jayaraj, S., Muraleedharan, C. (2012). Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems A review. *Renewable and Sustainable Energy Reviews* **16,** p. 1340 1358. https://doi.org/10.1016/j.rser.2011.10.015

Karabacak, K., Cetin, N. (2014), Artificial neural networks for controlling wind PV power systems: *A review. Renewable and Sustainable Energy Reviews* **29,** p. 804 827. https://doi.org/10.1016/j.rser.2013.08.070

Yadav, A.K., Chandel, S.S. (2014), Solar radiation prediction using Artificial Neural Network techniques: A review. *Renewable and Sustainable Energy Reviews* **33,** p. 772-781. https://doi.org/10.1016/j.rser.2013.08.055

Zahraee, S.M., Assadi, M.K. , Saidur, R. (2016), Application of Artificial Intelligence Methods for Hybrid Energy System Optimization. *Renewable and Sustainable Energy Reviews* **66,** p. 617 630. https://doi.org/10.1016/j.rser.2016.08.028

Jani, D.B., Mishra, M., Sahoo, P.K. (2017), Application of artificial neural network for predicting performance of solid desiccant cooling systems A review. *Renewable and Sustainable Energy Reviews* **80,** p. 352 366. https://doi.org/10.1016/j.rser.2017.05.169

Pacheco-Vega, A., Sen, M., Yang, K.T., McClain, R.L. (2001), Neural network analysis of an-tube refrigerating heat exchanger with limited experimental data. *International Journal of Heat and Mass Transfer* **44,** p. 763 70. https://doi.org/10.1016/S0017-9310(00)00139-3

Arcaklioglu, E., Erisen, A., Yilmaz, R. (2004), Artificial neural network analysis of heat pumps using refrigerant mixtures. *Energy Conversion Management* **45,** p. 1917 29. https://doi.org/10.1016/j.enconman.2003.09.028

Abbassi, A., Bahar, L. (2005), Application of neural network for the modeling and control of evaporative condenser cooling load. *Applied Thermal Engineering* **25,** p. 3176 86. https://doi.org/10.1016/j.applthermaleng.2005.04.006

Yigit, K.S., Ertunc, H.M. (2006), Prediction of the air temperature and humidity at the outlet of a cooling coil using neural networks. *International Communications in Heat and Mass*

Transfer **33,** p. 898 907. https://doi.org/10.1016/j.icheatmasstransfer.2006.04.003

Hosoz, M.H., Ertunc, M. (2006), Modeling of a cascade refrigeration system using artificial neural networks. *International Journal of Energy Research* **30,** 12- 15. https://doi.org/10.1002/er.1218

Ertunc, H.M., Hosoz, M. (2006), Artificial neural network analysis of a refrigeration system with an evaporative condenser. *Applied Thermal Engineering* **26,** 62-73. https://doi.org/10.1016/j.applthermaleng.2005.06.002

Yilmaz, S., Atik, K. (2007). Modeling of a mechanical cooling system with variable cooling capacity by using artificial neural network. *Applied Thermal Engineering* **27**, p. 2308 13. https://doi.org/10.1016/j.applthermaleng.2007.01.030

Alhuyi Nazari, Mohammad, Mohamed Salem, Ibrahim Mahariq, Khaled Younes, and Bashar B. Maqableh. (2021) "Utilization of data-driven methods in solar desalination systems: a comprehensive review." *Frontiers in Energy Research* **9**, 742615. https://doi.org/10.3389/fenrg.2021.742615

Behnam, Pooria, Meysam Faegh, and Mehdi Khiadani. (2022), "A review on state-of-the-art applications of data-driven methods in desalination systems." *Desalination* **532**, 115744. https://doi.org/10.1016/j.desal.2022.115744

Soleimanzade, Mohammad Amin, Amit Kumar, and Mohtada Sadrzadeh. (2022), "Novel data-driven energy management of a hybrid photovoltaic-reverse osmosis desalination system using deep reinforcement learning." *Applied Energy* **317**, 119184. https://doi.org/10.1016/j.apenergy.2022.119184

Faegh, Meysam, Pooria Behnam, Mohammad Behshad Shafii, and Mehdi Khiadani. (2021), "Development of artificial neural networks for performance prediction of a heat pump assisted humidification-dehumidification desalination system." *Desalination* **508,** 115052. https://doi.org/10.1016/j.desal.2021.115052

Rezk, Hegazy, Ramy H. Mohammed, Emanne Rashad, and Ahmed M. Nassef. (2022), "ANFIS-based accurate modeling of silica gel adsorption cooling cycle." *Sustainable Energy Technologies and Assessments* **50**, 101793. https://doi.org/10.1016/j.seta.2021.101793

Mashaly, Ahmed F., and A. A. Alazba. (2017), "Application of adaptive neuro-fuzzy inference system (ANFIS) for modeling solar still productivity." *Journal of Water Supply: Research and Technology—AQUA* **66(6)**, 367-380. https://doi.org/10.2166/aqua.2017.138

Nassef, Ahmed M., Shek Md Atiqure Rahman, Hegazy Rezk, and Zafar Said. (2020), "ANFIS-based modelling and optimal operating parameter determination to enhance cocoa beans drying-rate." *IEEE Access* **8**, 45964-45973.

Olabi, A. G., Hegazy Rezk, Enas Taha Sayed, Rania M. Ghoniem, and Mohammad Ali Abdelkareem. (2023), "Boosting carbon dioxide adsorption capacity applying Jellyfish optimization and ANFIS-based modelling." *Ain Shams Engineering Journal* **14(4)**, 101931. https://doi.org/10.1016/j.asej.2022.101931

Mashaly, Ahmed F., and A. A. Alazba. (2018) "ANFIS modeling and sensitivity analysis for estimating solar still productivity using measured operational and meteorological parameters." *Water Science and Technology: Water Supply* **18(4)**, 1437-1448. https://doi.org/10.2166/ws.2017.208

Zayed, Mohamed E., Jun Zhao, Wenjia Li, Ammar H. Elsheikh, and Mohamed Abd Elaziz. (2021) "A hybrid adaptive neuro-fuzzy inference system integrated with equilibrium optimizer algorithm for predicting the energetic performance of solar dish collector." *Energy* **235**, 121289. https://doi.org/10.1016/j.energy.2021.121289

Bahiraei, Mehdi, Saeed Nazari, and Habibollah Safarzadeh. (2021) "Modeling of energy efficiency for a solar still fitted with thermoelectric modules by ANFIS and PSO-enhanced neural network: A nanofluid application." *Powder Technology* **385**, 185-198. https://doi.org/10.1016/j.powtec.2021.03.001

Perendeci, Altunay, Sever Arslan, Serdar S. Çelebi, and Abdurrahman Tanyolaç. (2008) "Prediction of effluent quality of an anaerobic treatment plant under unsteady state through ANFIS modeling with on-line input variables." *Chemical Engineering Journal* **145(1)**, 78-85. https://doi.org/10.1016/j.cej.2008.03.008

Esmaili, Maryam, Sasan Aliniaeifard, Mahmoud Mashal, Keyvan Asefpour Vakilian, Parisa Ghorbanzadeh, Behzad Azadegan, Mehdi Seif, and Fardad Didaran. (2021) "Assessment of adaptive neuro-fuzzy inference system (ANFIS) to predict production and water productivity of lettuce in response to different light intensities and CO2 concentrations." *Agricultural Water Management* **258**, 107201. https://doi.org/10.1016/j.agwat.2021.107201

Köysal, Yavuz, Ali Ekber Özdemir, and Tahsin Atalay. "Experimental and modeling study on solar system using linear fresnel lens and thermoelectric module." *Journal of Solar Energy Engineering* **140(6)**: 061003. https://doi.org/10.1115/1.4039777

Pérez, José Antonio, Manuel González, and Daniel Dopico. (2010) "Adaptive neurofuzzy ANFIS modeling of laser surface treatments." *Neural Computing and Applications* **19**: 85-90.

Kharb, Ravinder Kumar, S. L. Shimi, S. Chatterji, and Md Fahim Ansari. (2014) "Modeling of solar PV module and maximum power point tracking using ANFIS." *Renewable and Sustainable Energy Reviews* **33**: 602-612. https://doi.org/10.1016/j.rser.2014.02.014

Abuella, Mohamed, and Badrul Chowdhury. (2015) "Solar power probabilistic forecasting by using multiple linear regression analysis." In *SoutheastCon*. 1-5. https://doi.org/10.1109/SECON.2015.7132869

Ibrahim, S., I. Daut, Y. M. Irwan, M. Irwanto, N. Gomesh, and Z. Farhana. (2012), "Linear regression model in estimating solar radiation in Perlis." *Energy Procedia* **18:** 1402-1412. https://doi.org/10.1016/j.egypro.2012.05.156

Alizamir, Meysam, Sungwon Kim, Ozgur Kisi, and Mohammad Zounemat-Kermani. "A comparative study of several machine learning based non-linear regression methods in estimating solar radiation: Case studies of the USA and Turkey regions. (2020), " *Energy* **197**, 117239. https://doi.org/10.1016/j.energy.2020.117239

Skumanich, A., Cr Smythe, and E. N. Frazier. (1975) "On the statistical description of inhomogeneities in the quiet solar atmosphere. I-Linear regression analysis and absolute calibration of multichannel observations of the Ca/+/emission network." *Astrophysical Journal, vol.* **200 (1)***, 747-764.* https://ui.adsabs.harvard.edu/link_gateway/1975ApJ...200..747S/doi:10.1086/153846

Ramedani, Zeynab, Mahmoud Omid, Alireza Keyhani, Benyamin Khoshnevisan, and Hadi Saboohi. (2014), "A comparative study between fuzzy linear regression and support vector regression for global solar radiation prediction in Iran." *Solar Energy* **109,** 135-143. https://doi.org/10.1016/j.solener.2014.08.023

Kicsiny, Richárd. (2014), "Multiple linear regression based model for solar collectors." *Solar Energy* **110,** 496-506.

Wahbah, Maisam, Samuel Feng, Tarek HM EL-Fouly, and Bashar Zahawi. (2019), "Root-transformed local linear regression for solar irradiance probability density estimation." *IEEE Transactions on Power Systems* **35(1)**, 652-661. https://doi.org/10.1109/TPWRS.2019.2930699

Ruivo, Celestino Rodrigues, Xabier Apaolaza-Pagoaga, Giovanni Di Nicola, and Antonio Carrillo-Andrés. (2022), "On the use of experimental measured data to derive the linear regression usually adopted for determining the performance parameters of a solar cooker." *Renewable Energy* **181,** 105-115. https://doi.org/10.1016/j.renene.2021.09.047

Bocco, Mónica, Enrique Willington, and Mónica Arias (2010), "Comparison of regression and neural networks models to estimate solar radiation." *Chilean Journal of Agricultural Research* **70(3)**, 428-435. https://doi.org/10.1016/j.rser.2015.08.021

Daut, I., M. Irwanto, Y. M. Irwan, N. Gomesh, and N. S. Ahmad. (2011), "Combination of Hargreaves method and linear regression as a new method to estimate solar radiation in Perlis, Northern Malaysia." *Solar Energy* **85(11)**, 2871-2880. https://doi.org/10.1016/j.solener.2011.08.026

Mahesh, P. Venkata, S. Meyyappan, and Rama Koteswara Rao Alla. (2022), "A new multivariate linear regression MPPT algorithm for solar PV system with boost converter." *ECTI Transactions on Electrical Engineering, Electronics, and Communications* **20(2)**, 269-281. https://doi.org/10.37936/ecti-eec.2022202.246909

Devi, L. Gomathi, and K. Eraiah Rajashekhar, (2011), "A kinetic model based on non-linear regression analysis is proposed for the degradation of phenol under UV/solar light using nitrogen doped TiO2." *Journal of Molecular Catalysis A: Chemical* **334(2)**, 65-76. https://doi.org/10.1016/j.molcata.2010.10.025

Chiteka, Kudzanayi, Rajesh Arora, and S. N. Sridhara. (2020), "A method to predict solar photovoltaic soiling using artificial neural networks and multiple linear regression models." *Energy Systems* **11(4)**, 981-1002.

Abubaker, Ahmad M., Adnan Darwish Ahmad, Binit B. Singh, Nelson K. Akafuah, and Kozo Saito, (2021) "Multi-objective linear-regression-based optimization of a hybrid solar-gas turbine combined cycle with absorption inlet-air cooling unit." *Energy Conversion and Management* **240**, 114266. https://doi.org/10.1016/j.enconman.2021.114266

Garud, Kunal Sandip, Simon Jayaraj, and Moo-Yeon Lee. (2021), "A review on modeling of solar photovoltaic systems using artificial neural networks, fuzzy logic, genetic algorithm and hybrid models." *International Journal of Energy Research* **45(1)**, 6-35. https://doi.org/10.1002/er.5608

Saadaoui, Driss, Mustapha Elyaqouti, Khalid Assalaou, and Souad Lidaighbi. (2021), "Parameters optimization of solar PV cell/module using genetic algorithm based on non-uniform mutation." *Energy Conversion and Management:* **X 12**, 100129. https://doi.org/10.1016/j.ecmx.2021.100129

Jervase, Joseph A., Hadj Bourdoucen, and Ali Al-Lawati. (2001), "Solar cell parameter extraction using genetic algorithms." *Measurement science and technology* **12(11)**, 1922. https://doi.org/10.1088/0957-0233/12/11/322

Khare, Anula, and Saroj Rangnekar. (2013), "A review of particle swarm optimization and its applications in solar photovoltaic system." *Applied Soft Computing* **13(5)**, 2997-3006. https://doi.org/10.1016/j.asoc.2012.11.033

Khanna, Vandana, B. K. Das, Dinesh Bisht, and P. K. Singh. (2015), "A three diode model for industrial solar cells and estimation of solar cell parameters using PSO algorithm." *Renewable Energy* **78**: 105-113. https://doi.org/10.1016/j.renene.2014.12.072

Ghermandi, Andrea, and Rami Messalem. (2009), "Solar-driven desalination with reverse osmosis: the state of the art." *Desalination and water treatment* **7(1-3)**, 285-296. http://dx.doi.org/10.5004/dwt.2009.723

Ramazanian, Saeed, Mehdi Aliehyaei, Mahmoud Salimi, and Mohammad Mehdi Najafizadeh. (2023), "Theoretical and experimental investigation of reverse osmosis (RO) desalination solar system using the solar panel, battery, and water turbine for high-pressure recovery of output brine." *Solar Energy* **262**, 111852. http://dx.doi.org/10.1016/j.solener.2023.111852

Boesch, William W. (1982), "World's first solar powered reverse osmosis desalination plant." *Desalination* **41(2),** 233-237. https://doi.org/10.1016/S0011-9164(00)88726-3

Manolakos, D., Essam Sh Mohamed, I. Karagiannis, and G. Papadakis. (2008), "Technical and economic comparison between PV-RO system and RO-Solar Rankine system. Case study: Thirasia island." *Desalination* **221(1-3)**, 37-46. https://doi.org/10.1016/j.desal.2007.01.066

Bagheri, A., Esfandiari, N., Honarvar, B., & Azdarpour, A. (2021). ANN Modeling and experimental study of the effect of various factors on solar desalination. *AQUA–Water Infrastructure, Ecosystems and Society*, *70*(1), 41-57.

Salem, H., Kabeel, A. E., El-Said, E. M., & Elzeki, O. M. (2022). Predictive modelling for solar power-driven hybrid desalination system using artificial neural network regression with Adam optimization. *Desalination*, *522*, 115411.

Sohani, A., Hoseinzadeh, S., Samiezadeh, S., & Verhaert, I. (2021). Machine learning prediction approach for dynamic performance modeling of an enhanced solar still desalination system. *Journal of Thermal Analysis and Calorimetry*, 1-12.

Bagheri, A., Esfandiari, N., Honarvar, B., & Azdarpour, A. (2020). First principles versus artificial neural network modelling of a solar desalination system with experimental validation. *Mathematical and Computer Modelling of Dynamical Systems*, *26*(5), 453-480.

Mashaly, A. F., & Alazba, A. A. (2016). Comparison of ANN, MVR, and SWR models for computing thermal efficiency of a solar still. *International Journal of Green Energy*, *13*(10), 1016-1025.