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REVIEW ARTICLE

A review of recent developments in the application of machine learning in solar thermal collector modelling

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Abstract

Over the past few decades, the popularity of solar thermal collectors has increased dramatically because of many significant advantages like being a free, natural, environmentally friendly and permanent energy source. Today, developing and optimising different solar thermal energy systems are more important than before. Thus, there are various methods for investigating the performance of these systems, such as experimental, numerical and mathematical methods. One of the cutting-edge methods is artificial intelligence, which can predict key and effective parameters in solar collector efficiency. This review identified recent machine learning modelling, including multilayer perceptron artificial neural network (MLP-ANN), group method of data handling (GMDH), radial basis function (RBF), artificial neuro-fuzzy inference system (ANFIS), support vector machine (SVM) and studies regarding different types of solar thermal collectors, namely non-concentration and concentration. Furthermore, it investigated the effect of various essential factors on the accuracy, potential issues and challenges facing the application of artificial intelligence in these systems. Finally, it will also be recommended opportunities for future research.

Keywords Solar thermal collectors · Machine learning · Artificial neural network · Solar energy

Nomenclature

ABC	Artificial bee colony
AC	Ant colony
ACO	Ant colony optimisation
ANFIS	Artificial neuro-fuzzy inference system
ANN	Artificial neural network
b_k	Bias
BFOA	Bacterial foraging optimization algorithm
BP	Back propagation
BPNN	Backpropagation neural network
c_j	Centre point
CFD	Computational fluid dynamics
CNN	Convolutional neural network
CTR	Central tower receiver
CQDs	Carbon quantum dots
DASC	Direct absorption solar collector
E	Error
EG	Entropy generation
EHP	Electrolytic hydrogen production
ET	Evacuated tube
ETHP	Tube heat pipe
EO	Equilibrium optimizer
f	Activation function
FA	Firefly algorithm
GA	Genetic algorithm
GWO	Grey wolf optimisation
GMDH	Group method of data handling
GSHP-PVT	Ground source heat pump systems with solar photovoltaic thermal collectors
GEP	Gene expression programming
h	Hour
HVAC	Heating, ventilation and air conditioning
HWST	Hot water storage tanks
ISAC	Innovative solar air collector
LSE	Least squares estimation
LCOE	Levelised cost of energy
LSSVM	Least squares support vector machine
LM	Levenberg–Marquardt
L	Litre

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MBE	Mean bias error
MLP-ANN	Multilayer perceptron artificial neural network
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MARS	Multivariate adaptive regression spline
m	Mass
METSC	Modified evacuated tube solar collector
MO	Mayfly-based optimisation
MT	Model tree
MLR	Multi-linear regression
ηt	Thermal efficiency
NN	Neural network
NPV	Net present value
ODR	Orthogonal distance regression
PSO	Particle swarm optimization
PCM	Phase change material
PTC	Parabolic trough collector
PTSC	Parabolic trough solar collector
PTR	Parabolic trough receiver
PTSTPP	Parabolic trough solar thermal power plant
PVTC	Photovoltaic/thermal collector
RGO	Reduced graphene oxide
RVFL	Random vector functional link
RBF	Radial basis function
RMSE	Root mean square error
R^2	Coefficient of determination
r	Radial distance
RO	Reverse osmosis
SCG	Scaled conjugate gradient
SAHs	Solar air heaters
SPDC	Solar parabolic dish collector
SVM	Support vector machine
VAF	Variance accounted for
WWF	World Wide Fund for Nature
y_k	Predicted output

Introduction

Rising energy prices, declining access and security, the growing dependence of industry and technology on fossil fuels and increasing environmental concerns in the twenty-first century continue to change the world's energy landscape (Aydoğan and Vardar 2020; Ghiasi et al. 2020; Mujtaba et al. 2020). More than ever, the need for new and renewable energy sources is felt (Usman et al. 2020; Zhu et al. 2020). Considering the environmental (Naves et al. 2019), safety and economic (Aman et al. 2015) characteristics of the different renewable energy sources, namely wind energy, solar energy, geothermal, hydro and biomass (Khan et al. 2018; Kumar et al. 2019), as reported by REN21, only 11% of consumed energy in 2018 was supplied from renewable resources. Figure 1 indicates the proportion of different types of energy consumption this year (Murdock et al. 2021). Considering the importance of renewable energy, the World Wide Fund for Nature (WWF) reported that more than half of electricity consumption, half of building heat and 15% of required industrial heat would be from sustainable resources by 2050 (Singer et al. 2017).

One of the most commonly available and vast sources of renewable energy throughout the globe is solar energy. The received solar energy amount by the atmosphere of the earth, the earth and oceans is about 3,850,000 Exa-Joule per year, which is approximate 173 Petawatts, 30% reflected to outer space and 70% absorbed. According to this valuation, the amount of energy absorbed by the earth in 1 h is sufficient to answer the power demand of the whole globe for 1 year (Khan et al. 2019). Various solar technologies convert the different types of solar energy into usable energy for work to harness this energy. Of these, the use of photothermal is of particular importance because of its potential use in thermal systems (Suresh and Saini 2020), power generation (Lai et al. 2017) and chemical technology (Mustafa et al. 2020). In solar systems based on thermal, collectors play a vital role in converting photothermal energy.

Various methods for evaluating and analysing different thermal solar collectors' performance have been considered, generally referred to as experimental methods and theoretical modelling (Raj and Subudhi 2018). In any scientific field, practical and laboratory techniques will undoubtedly yield reliable and repeatable results if used with careful tools and proper studies. Because experimental methods require outstanding facilities and equipment, which can be costly and time-consuming, modelling methods and algorithms can replace practical approaches (Liu et al. 2017; Yılmaz and Mwesigye 2018). These methods include a variety of modelling by numerical methods and artificial intelligence.

Machine learning is one of the most exciting among the various potential modelling methods. It can be considered a powerful tool for solving challenging puzzles on multiple issues. Generally, it is a subset of artificial intelligence and includes techniques that enable computers to independently find and make sense of data and provide artificial intelligence applications. Due to the high processing speed, extensive capacity and ease of use, many researchers favour artificial intelligence over classical models for predicting and modelling thermal system performance (Ghritlahre and Prasad 2018a). One of the significant obstacles to this modelling method is collecting data needed for training, testing and validation of the model. If there is no access to data, particularly experimental or measured data, in each system, it

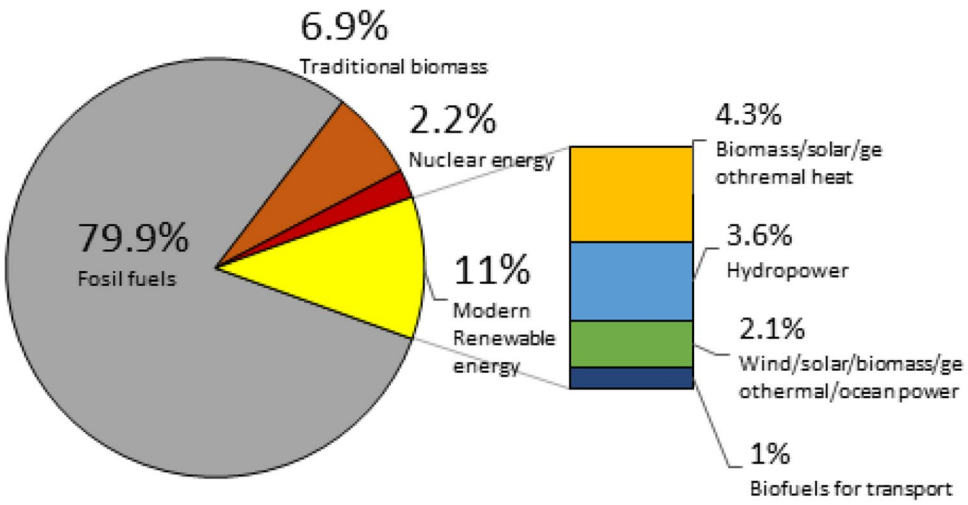


Fig. 1 The share of world energy supply sources in 2018 (Murdock et al. 2021)

is impossible to use this method to predict the results, which are considered output (Riahi et al. 2021).

The artificial neural network (ANN) is an essential machine learning tool that predicts any phenomenon. The algorithms in the artificial neural network training process play a vital role in the accuracy and validity of the model (Si et al. 2022). Various techniques have been successfully used as a learning algorithm for the training process in machine learning modelling. Generally, it can be divided into two categories: (1) mathematical methods such as Backpropagation (Kartal and Özveren 2022; Taghinezhad and Sheidaei 2022; Ti et al. 2021) and Levenberg–Marquardt (Deo and Şahin 2017; Ozonoh et al. 2020; Soltani et al. 2022), and (2) metaheuristics algorithms, such as genetic algorithm (GA) (Debnath and Mourshed 2018; He et al. 2022; Kermadi and Berkouk 2017; Zhang et al. 2020), ant colony optimisation (ACO) algorithm (Babes et al. 2022; Gupta and Raza 2022; Noushabadi et al. 2021; Pradeep et al. 2022), artificial bee colony (ABC) algorithm (Atia 2020; Roy 2021; Yildiz and Açikgöz 2021), firefly algorithm (FA) (Ehteram et al. 2022; Kommula and Kota 2022; Lahiri et al. 2022), particle swarm optimisation (PSO) algorithm (Kardani et al. 2022; Li et al. 2022; Mu et al. 2022; Oboh et al. 2022; Sahraei and Çodur 2022), grey wolf optimisation (GWO) algorithm (Li et al. 2021; Nazari et al. 2022; Tütüncü et al. 2021; Uzlu 2021) and bacterial foraging optimization algorithm (BFOA) (Dhaliwal and Pattnaik 2017; Punitha et al. 2020; Roy et al. 2018).

In recent years, many researchers have reviewed the application of machine learning modelling to predict different parameters in solar energy systems, such as solar radiation prediction (Álvarez-Alvarado et al. 2021; Malik et al. 2022), solar air heaters (Ghritlahre et al. 2021; Ghritlahre and Verma 2021b), photovoltaic systems (Garud et al. 2021; Pathak et al. 2022) and solar drier (Prakash et al. 2016). In 2019, Elsheikh et al. (2019) summarised and reviewed the ANN application in the modelling and optimising of different solar energy systems, namely solar thermal collectors, solar air heaters, photovoltaic/thermal (PV/T) systems, solar cookers, greenhouses, solar dryers and solar stills. In another research, Ghritlahre and Prasad (2018a) published a review article regarding applying the ANN method for predicting solar collector performance. They summarised reports on the role of the ANN method in predicting solar energy systems until 2018. However, according to the authors' knowledge and research, there are no recent published review articles on applying the machine learning method in thermal solar collectors. Thus, this paper will present the machine learning method application, including multilayer perceptron artificial neural network (MLP-ANN), group method of data handling (GMDH), radial basis function (RBF), support vector machine (SVM) and artificial neuro-fuzzy inference system (ANFIS), in solar thermal collectors, such as flat plate collectors, PV/T collectors, parabolic trough collectors, compound parabolic collectors, parabolic dish and solar tower by the summarised of literature available.

The structure of this review is as follows:

- Explanation and definition of types of machine learning methods and investigation of vital essential parameters in these methods.
- Introducing different types of solar thermal collectors, including non-concentrating and concentrating collectors.
- Investigation of the application of machine learning and metaheuristic algorithms in the prediction of effective parameters in solar energy systems.
- Explanation and investigation of current challenges and limitations in this modelling method.
- Finally, conclusions and suggestions for future research will be presented.

Machine learning

Multilayer perceptron artificial neural network

Multilayer perceptron (MLP) is an example of a feed-forward neural network which is well-known as an approximator that can estimate any continuous functions (Colak et al. 2020; Žnidarec et al. 2019) and implement any nonlinear input−output mapping (Guha 2021). This method has three layers: the input layer, the output layer and one or more hidden layers. Every layer contains multiple neurons whose connection is named edge in various layers. The structure of MLP is fully connected, which means every neuron is connected to all neurons in the previous and subsequent layers (Isha et al. 2020). At the beginning of the process, the network is fed by raw signals given to the input layer to start learning. As a result, the output of each perceptron becomes the input of the next hidden layer (Hejase et al. 2013; Li et al. 2019a).

The concept of MLPs is inspired by the human brain function, which allows the network to learn by finding the relationships between the input and output value (Pang et al. 2020). Every perceptron in the hidden layers consists of a nonlinear activation function f (e.g. *logistic function*, *hyperbolic tangent function*) (Gajic et al. 2016) which is considered a fraction for the input layers and produces the subsequent hidden layers. As a result, the main aim of the MLP method is to combine neurons which carry a specific weight to make more complex features and obtain the target output. Many tasks are performed using MLPs, such as pattern recognition, data classification and performance prediction (Hontoria et al. 2006). It is worth mentioning that the number of layers and nodes, known as hyperparameters, is arbitrary and should be optimised according to the network's performance. The formulation for neuron k is defined as follows:

$$y_k = f(u_k + b_k) \tag{1}$$

$$u_k = \sum_{i=1}^{n} w_{ki} x_i \tag{2}$$

where the network is given n features as input $x = (x_1, x_2, \ldots, x_n)$, $w = (w_{k1}, w_{k2}, w_{k3}, \ldots, w_{kn})$ are the neuron connection weights, u_k is the linear output obtained by the linear combination of weighted inputs, b_k is considered the bias term, f is the activation function and y_k is the predicted output shown in Fig. 2.

In this algorithm, the data goes in the forward direction, known as the forward propagation. The outputs are determined and compared to the original outputs to calculate the error. The next step is to reduce the error and increase the accuracy by adjusting the weights and biases of the neurons. The most used and popular supervised training

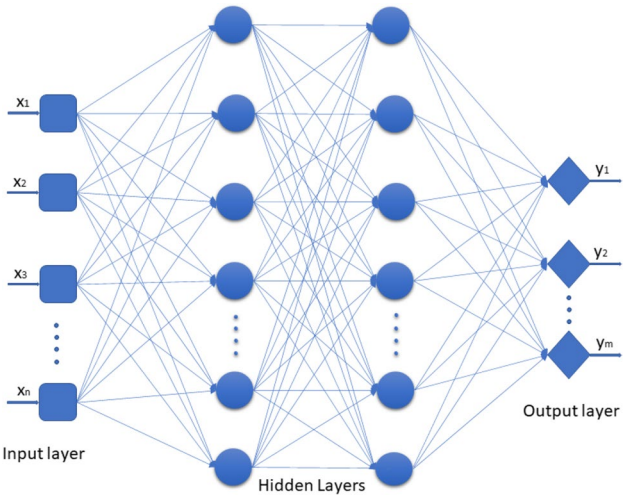


Fig. 2 A structure of MLP

algorithm to minimise the error function is the backpropagation algorithm, whose task is to update the model during multiple epochs (Khoshroo et al. 2018). Two effective methods to develop this algorithm are radiant descent and momentum gradient descent optimisation algorithms used to optimise the network (Ojha and Nicosia 2022).

During the training phase, the weights and biases are adjusted according to the error propagation (Tariq et al. 2022). The error is propagated in the opposite direction (from the output to the input). This procedure is repeated until the training set is trained successfully and the error function is acceptable and minimised as much as possible.

Group method of data handling

GMDH neural network is a well-known technique based on heuristic self-organisation utilised mainly for prediction, automatic optimisation, pattern recognition, complicated system modelling, data mining and etc. GMDH algorithms are classified into polynomials, harmonic, multiplicative and fuzzy according to the type of activation function. However, the second-order polynomial is the most used and popular activation function; other partial descriptions have been utilised to increase the accuracy of the surveys. In GMDH, there are multiple inputs and a single output y that is simply defined as:

$$y = a_0 + \sum_{i=1}^{m} a_i f(x) \tag{3}$$

The primary purpose of this technique is to create a feed-forward network using a conducted mapping function f, which is inspired by the form of the Kolmogorov-Gabor polynomial series shown in the following equation:

$$\hat{y} = a_0 + \sum_{i=1}^{m} a_i x_i + \sum_{i=1}^{m} \sum_{j=1}^{m} a_{ij} x_i x_j + \sum_{i=1}^{m} \sum_{j=1}^{m} \sum_{k=1}^{m} a_{ijk} x_i x_j x_k + \ldots \quad (4)$$

where $X = (x_1, x_2, x_3, \ldots, x_m)$ is the vector of inputs, and $a = (a_1, a_2, a_3, \ldots, a_m)$ is the vector of weights. The nonlinear activation function is a second-degree transfer function defined as a Volterra series analysed by Eq. 5 (Elbaz et al. 2021; Mohseni-Gharyehsafa et al. 2021).

$$G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i^2 + a_4 x_j^2 + a_5 x_i x_j \quad (5)$$

The weights or coefficients of the neural network should be calculated using the regression technique to solve the problem to minimise the variance between the actual and predicted output. In this algorithm, the number of nodes in each layer greatly depends on the number of input variables. For instance, if the number of inputs is considered p, considering all possibilities of pairwise combinations of input parameters, the neuron number in the first hidden layer is equal to $h = \binom{p}{2} = \frac{p-(p-2)}{2}$. The schematic of the GMDH algorithm is shown in Fig. 3, which indicates some selected and unselected neurons in which coefficients are determined. According to Fig. 3, the number of active neurons is equal to p, which becomes the input of the next layer, and the number of passive neurons is equal to $h - p$, which are not involved in the next layer (Dag and Yozgatligil 2016).

To evaluate the accuracy of predicted output and optimise the coefficients, the least squares method is applied, which should be minimised to find the optimum model, as indicated below (E stands for error):

$$E = \frac{\sum_{i=1}^{M} (y_i - G_i)^2}{M} \quad (6)$$

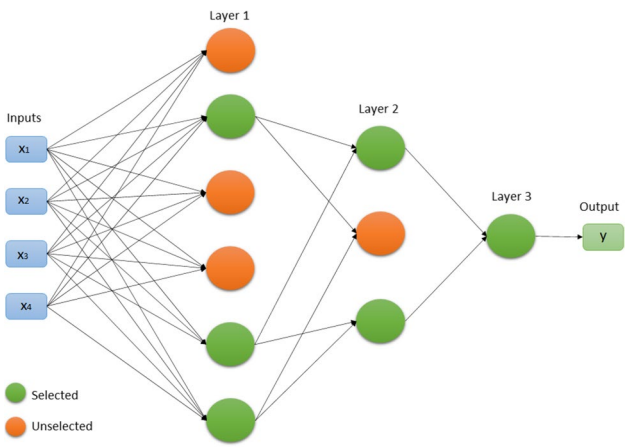


Fig. 3 Multilayer GMDH algorithm

where y_i is the actual value, G_i is the predicted output and M is the number of observations. Due to the ability of GMDH algorithms to reduce computation time and increase accuracy, for the training process, less time is needed compared to deep learning methods, and sophisticated hardware is not required (Hosseini et al. 2021).

Radial basis function

The RBF neural network is a feed-forward neural network approach with a single hidden layer used in classification and regression algorithms. The method has three different layers, including the input and the output layers, connected by a middle layer named the intermediate layer. Several nodes are involved in the input layer, which receives many raw variables and transmits the information to the intermediate layer. In the RBF network, the hidden layer is of a higher dimension than the input layer (Rezaei et al. 2021). In this method, the centre point $c_j = (c_1, c_2, \ldots, c_n)$ of the hidden nodes plays a key role, as the radial distance r between the input vector $X_i = (x_1, x_2, \ldots, x_n)$, and the centres should be calculated to produce the basis function $G(r)$, which results in mapping the input vector into the higher dimension. The most commonly used activation function of the radial basis is the Gaussian kernel owing to its versatility. The formulation of the radial distance r and the basis function $G(r)$ are illustrated in Eq. 7 and Eq. 8.

$$r = \|X_i - c_i\| = \sqrt{(x_1 - c_1)^2 + (x_2 - c_2)^2 + \cdots + (x_n - c_n)^2} \quad (7)$$

$$G(r) = exp\left(-\frac{r^2}{2\sigma_j^2}\right) \quad j = 1, 2, 3, \ldots, k \quad (8)$$

where σ_j stands for the expansion constant known as the width of the basis function, and k is the number of hidden nodes. The RBF neural network output y_i is given by calculating the linear sum of the radial basis function, as shown in Eq. 9:

$$y_i = \sum_{j=1}^{k} w_j G(r) = \sum_{j=1}^{k} w_j G\left(\|X_i - c_i\|\right) \quad (9)$$

In the RBF method, it is necessary to determine some parameters that significantly impact the performance of RBF, including the number of input and hidden neurons, the number of output layers and all neurons' weights. It has been proved that the number of neurons in the hidden layer directly relates to the model accuracy, but after finding the optimum number of neurons, adding more neurons only makes the computational structure of the network more powerful and complex. In addition, during the training, some critical criteria should be updated to build the final model, such as the

centre points and the weights in the hidden nodes, the basis function and the connection weights between the hidden layer and the output (Abdullah and Allwright 2012; Bharath Kurukuru et al. 2020; Zhang et al. 2022a). The structure of an RBF neural network is illustrated in Fig. 4.

In the testing procedure, there are some evaluation criteria commonly used to anticipate the accuracy of the model, such as mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE), which indicate the performance of the prediction; the formulas are shown as follows:

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \tag{10}$$

$$MAPE = \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \tag{11}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{12}$$

where n stands for the prediction horizon, $\hat{y}_i$ is the forecasted value and y_i is the target output (Deng et al. 2022).

Artificial neuro-fuzzy inference system

An adaptive fuzzy-neural inference system combines an ANN with a fuzzy system to have the advantages of both. A hybrid of fuzzy inference systems and ANN can create a powerful prediction technique named an adaptive fuzzy-neural inference system. This system can establish and infer nonlinear communication between inputs and outputs (Jang 1993). The ANFIS model often consists of a five-layer network structure using a Takagi–Sugeno fuzzy system, shown in Fig. 5 (Takagi and Sugeno 1985).

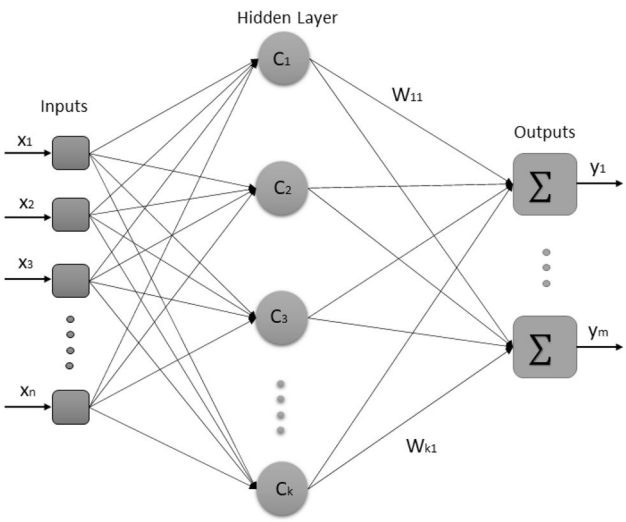


Fig. 4 Structure diagram of RBF neural network

Adaptive and multilayer networks include nodes and directional (forward) communication links. In this network, all or some of the nodes are adaptive; in other words, their output depends on parameters that are adjusted based on learning algorithms to reduce modelling error. Each node executes a distinctive part of the signal it receives in an adaptive network, known as a node function, and it depends on the node's parameters (Jang 1992).

The basic law used in the adaptive network's training is the law of gradient reduction. Using gradient reduction is not favourable because of the slowness and local minima tendency to change the parameters of the network. However, hybrid methods, which result from combining gradient reduction and other such methods, result in an accelerated speed of learning least squares estimation (LSE). The set of parameters of an adaptive network includes the parameters of all network nodes that should be adjusted based on the data and the learning method based on gradient reduction. The flowchart of ANFIS modelling is shown in Fig. 6.

Support vector machine

SVM algorithm is a state-of-the-art and supervised machine learning approach superior to other statistical algorithms due to its simple structure, fewer parameters, good practicability and strong ability to generalise problems with high accuracy. This algorithm is widely utilised to solve category and regression issues (Li et al. 2019b). The primary theory of SVM regression is to select a training set of data to estimate a relationship between the independent and dependent variables to reach the minimised error of the predicted value compared to the target output (Liu et al. 2020). Since classification problems can contain two (binary) or more classes, SVM is used for multi-class classifications to create a discriminant hyperplane that separates the training values to accurately anticipate the memberships of the class using the new higher-dimensional space. The SVM model is illustrated in Fig. 7.

Therefore, SVM is known as a large margin classifier. The model uses proper penalty parameters, and kernel function applied to cope with linearly non-separable data to map the input data to the higher-dimensional feature space. The method is based on the data point separation in hyperspace through the capability of parallel hyperplanes, by which partitions are created for classification (Jufri et al. 2019; Lin et al. 2020). Kernel functions greatly impact the predictive performance of this algorithm. Some commonly used kernel functions include linear kernel function, polynomial kernel function, multilayer perceptron kernel function and radial basis function (RBF). The SVM approach is appropriate for small samples and high-dimensional and nonlinear problem

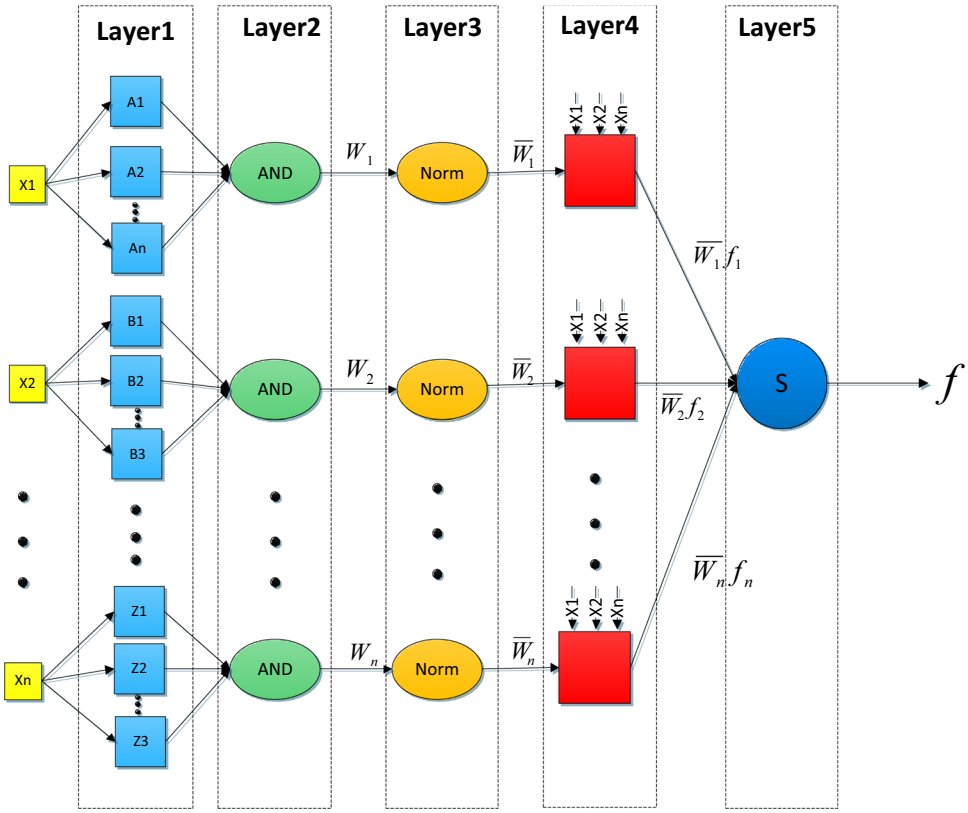


Fig. 5 The schematic of an ANFIS modelling structure

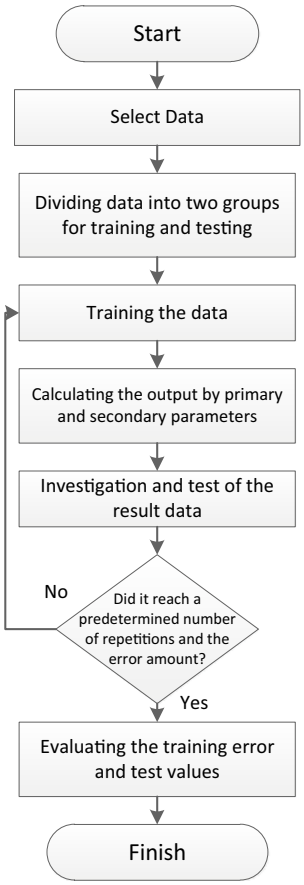


Fig. 6 The flowchart of ANFIS modelling

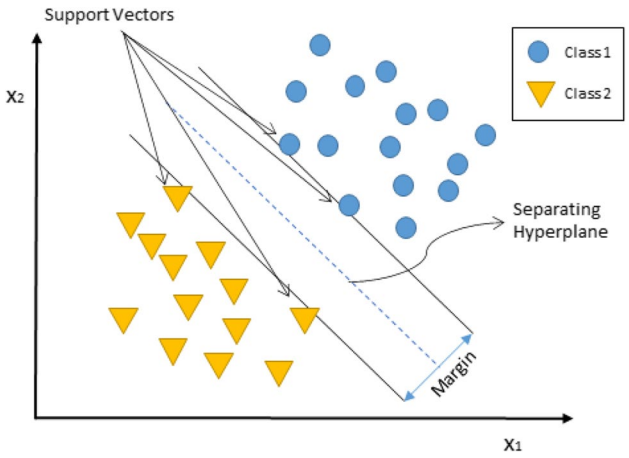


Fig. 7 A schematic diagram of support vector machine

predictions and can potentially overcome the weak points of traditional NN (Pan et al. 2020; Yuan et al. 2019).

Machine learning application in solar collectors

In recent years, because of the high capability of artificial intelligence techniques in relating input data to output data, these methods have been widely used in

modelling solar energy systems. Each of these techniques, modelled on the human nervous system and brain, adjusts and corrects its parameters and ultimately achieves a logical relationship between the inputs and outputs of the problem. This method is not limited to a particular branch of science and is used in almost all disciplines and scientific fields, which is one of their unique features. According to the optimisation methods used in these systems, the results are usually the best answers and cause high accuracy in predicting the data. In this section of the article, recent studies which have used these techniques to model and estimate the performance of solar thermal systems will be reviewed.

Solar thermal systems include low-temperature (Sharma and Chauhan 2022) and high-temperature (Hachicha et al. 2019) thermal collectors. These systems usually use solar sources for final heat consumption. These systems are functionally divided into two general categories: concentrating (Rubbi et al. 2021) and non-concentrating (Gao et al. 2022). Figure 8 shows different types of solar collectors according to this category.

Thermal systems have a storage section to allow solar thermal energy for night use. Most solar heating systems are for commercial water heating (Lim and Sobhansarbandi 2022), swimming pools (Li et al. 2020) or water for use in different buildings such as villas, apartments and hotels (Manokar and Karthick 2021), and a large part of the demand for HVAC systems (Yoon et al. 2021) and supply energy to heat absorption pump circuits and absorption chiller systems (Camara and Sulin 2022).

Non-concentrating collectors

Flat plate collectors

Flat plate solar collectors produce heat by absorbing solar radiation and transferring the thermal energy to the working fluid. Heated fluid is used for various domestic and industrial purposes. These collectors have a fixed surface to collect incoming radiation and are usually fixed during the day. The collectors' efficiency is defined based on how much thermal energy on the surface of the absorber is transferred to the fluid. Minimising the output heat loss and maximising the absorption of solar radiation can improve the collector's efficiency (Vengadesan and Senthil 2022a).

Among the types of flat plate collectors, because of the volumetric solar collector, one of the flat plate solar collectors, solar radiation is absorbed by the working fluid directly. Thus, thermal losses are lower than conventional flat plate solar collectors. Therefore, the efficiency of this type of solar collector increased dramatically compared to other collectors (Vakili et al. 2016). Other collectors absorb the sun's radiation on the surface, leading to an increase in the temperature of the surface and, as a result, an increase in heat loss to the outside environment through the surface (Vengadesan and Senthil 2022b).

Ghritlahre and Prasad (2018b) used an artificial neural network (ANN) model with two different algorithms, which were scaled conjugate gradient (SCG) and Levenberg–Marquardt (LM) learning algorithms, for training data to forecast a solar air heater efficiency. They used 50 sets of

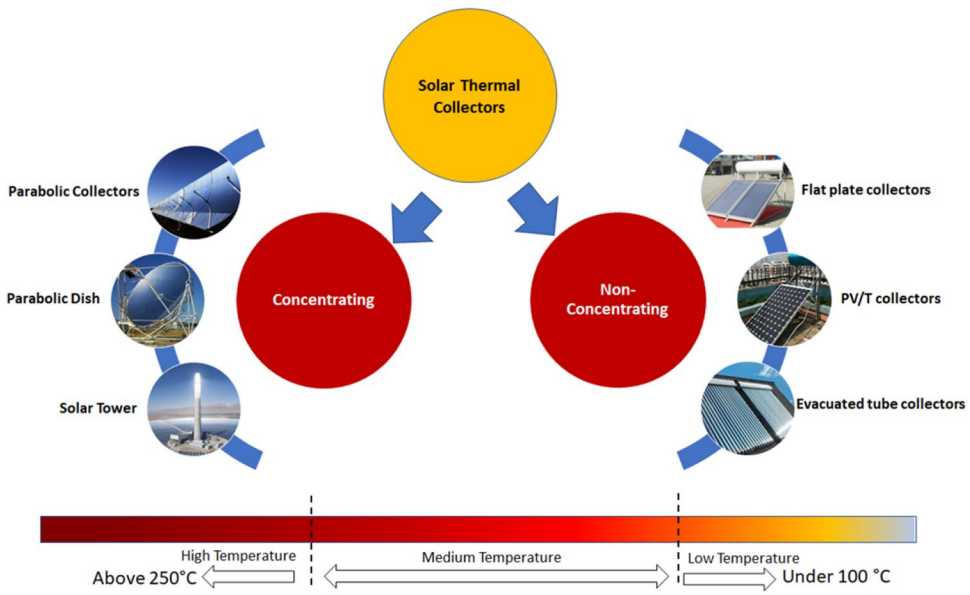


Fig. 8 The classification of solar thermal collectors

experimental data with various absorber plates in that study. Their investigation showed that the model with LM learning algorithms with six neurons and scaled conjugate gradient with seven neurons could be considered the best model based on statistical indexes. They compared the experimental and prediction results and investigated the model's accuracy with the coefficient of determination (R^2) index. Their results indicated that the R^2 for the MLP ANN model with LM learning algorithms was about 0.99882, which is near one shown in Fig. 9. This amount showed that the accuracy and validation of the model are acceptable.

Using the computational intelligence technique, Diez et al. (2019) forecasted the outlet temperature of a flat plate solar collector with three different working fluid flows, namely 1, 1.6 and 2 L per minute. According to their results, it can be mentioned that the accuracy of their model, which was an artificial neural network, was in agreement with experimental results with statistical indexes, which were about RMSE = 0.1781 °C and R^2 = 0.9991 for working fluid with 2 L/min.

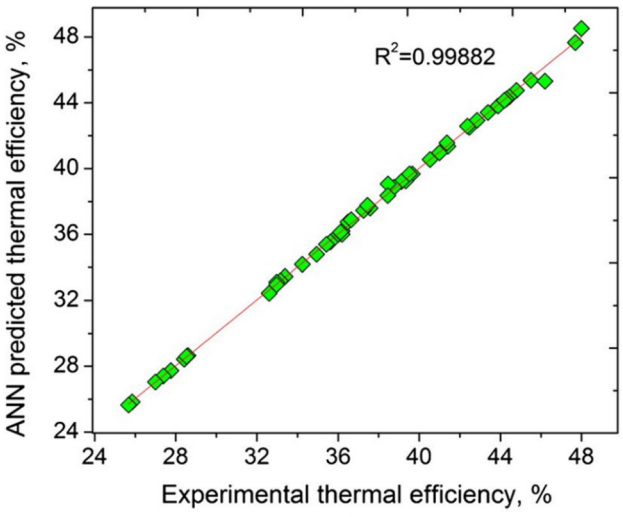


Fig. 9 The results of experimental data compared to the ANN data (Ghritlahre and Prasad 2018b)

Sadeghzadeh et al. (2019) provided three different algorithms for modelling the flat plate solar collector's efficiency. These algorithms were MLP-ANN, RBF-ANN and Elamn BP-ANN. In that study, they used TiO_2 as a nanoparticle in deionised water as a working fluid at three different volumetric flow rates (36, 72 and 108 L m^{-2} h^{-1}) in the solar collector. Their result indicated that the modelling results of MLP-ANN could predict better other models, while other models could also forecast output data with acceptable errors. According to their result shown in Fig. 10, the maximum and minimum errors were about − 3.8% and 0%, respectively.

Delfani et al. (2019) assessed the application of an artificial neural network to forecast a DASC's efficiency based on nanofluid in different flow rates as a working fluid in this type of solar collector. They used the depth and length of the collector, flow rates, nanofluid concentration and the declined temperature difference as input data for forecasting the Nusselt number and performance of the direct absorption solar collector. The best collector's performance was accused when they used a collector length of 300 mm and nanofluid concentration of 1000 ppm by achieving an MAPE of 1.470% for efficiency and an MAPE of 2.576% for the Nusselt number, shown in Fig. 11.

Shafieian et al. (2020) assessed various modelling methods, namely ANN, TRN, ANFIS and other Fuzzy methods, to predict the outlet temperature of heat pipe solar collectors, which is shown in Fig. 12, under different climatic and operation systems. Their results indicated that the artificial neural network model was the best in comparison with other models, followed by the ANFIS and TRN methods. The fuzzy method was not suggested because its accuracy was not in good agreement with laboratory data.

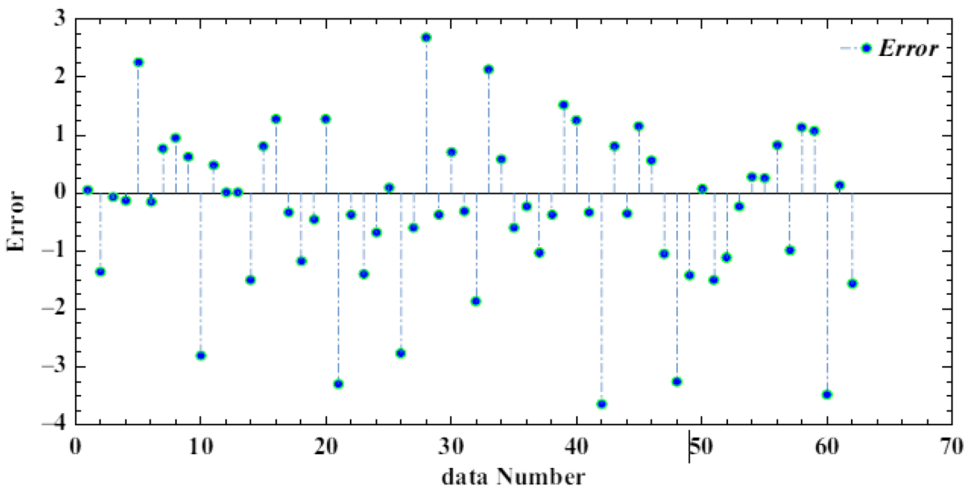


Fig. 10 The percentage error of ANN modelling (Sadeghzadeh et al. 2019)

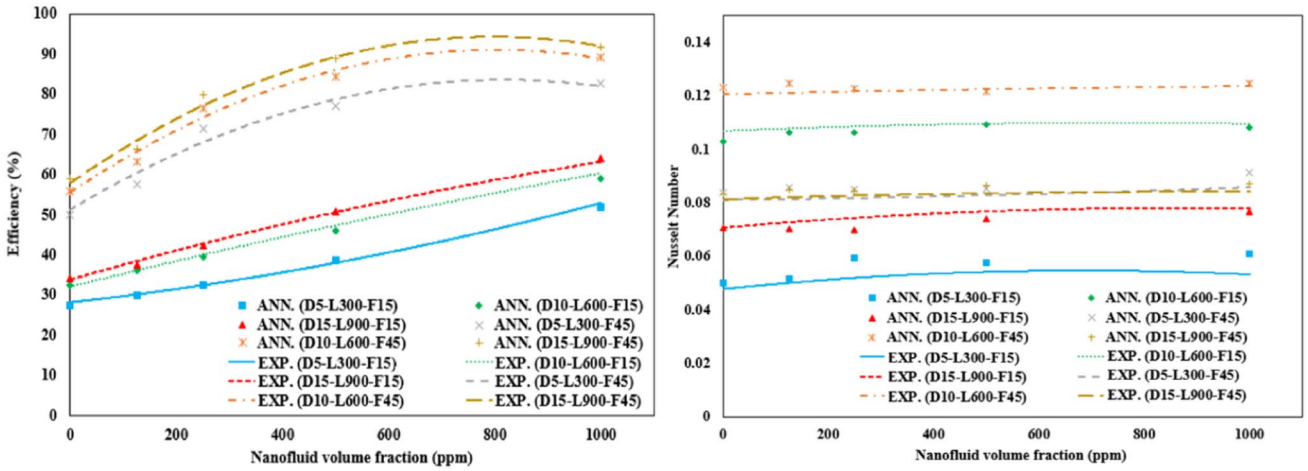


Fig. 11 The comparison of MLP-ANN modelling and experimental data for efficiency and Nusselt number (Delfani et al. 2019)

Shafiey Dehaj et al. (2020) applied a backpropagation artificial neural network to forecast the working fluid outlet temperature in a flat plate solar collector under semi-arid weather conditions. They assessed different models with various input data, namely solar radiation, inlet temperature, flow rate, wind speed and ambient temperature. Their results indicated that the model with four input data, bar wind speed, could predict more accurate than five parameters, including wind speed.

Abu-Hamdeh et al. (2021a) employed a mixture of titanium dioxide and silicon dioxide to make a composite dispersed in water to create a nanofluid utilised in flat plate solar collector. ANN algorithms and fuzzy models were applied to enhance the thermal conductivity and efficiency of TiO_2/SiO_2 nanofluid. The results proved that the combined materials have higher potential and capability in energy systems than a single material.

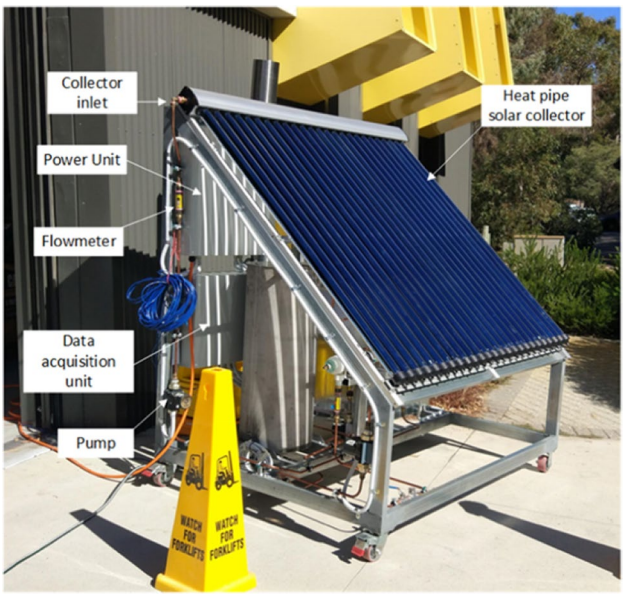


Fig. 12 The experimental setup (Shafieian et al. 2020)

Two different ANN algorithms, including Levenberg–Marquardt (LM) and orthogonal distance regression (ODR), and other fuzzy models were applied by Abu-Hamdeh et al. (2021b) to compare the results to predict the heat transfer, viscosity and prediction trend. Their results indicated that nanofluid could obtain the efficiency enhancement of thermal and energy systems. Also, the fuzzy model gave the best forecast model compared to LM/ODR method.

Kabiri et al. (2021) introduced three theories for repowering: In the first theory, the low-pressure feedwater heaters were replaced by parallel collectors, while in the second and last theories, low-pressure feedwater heaters were replaced by parallel solar collectors combined with desalination units, in turn. They also employed a hybrid ANN-GA to optimise the multi-generation complex power, heat and freshwater cycles. The first theory showed that the *R*-ratio is 1.21, and the efficiency of cogeneration changes from 35 to 45% in most months. In the other theories, nevertheless, cogeneration efficiency was 50%. The study indicated that using solar energy and adding desalination units can enhance the efficiency of cogeneration during a year.

Using two types of solar collectors with smooth and roughened surfaces, Ghritlahre and Verma (2021a) employed different methods, namely multi-linear regression (MLR) models, artificial neural network (ANN) and group method of data handling (GMDH), to predict the exergy efficiency of solar air heaters (SAHs). However, the performance of GMDH, ANN and MLR techniques was accurate and precise, with correlation coefficient (*R*) of 0.98977, 0.99981 and 0.97693; in turn, ANN gave the highest accuracy. As

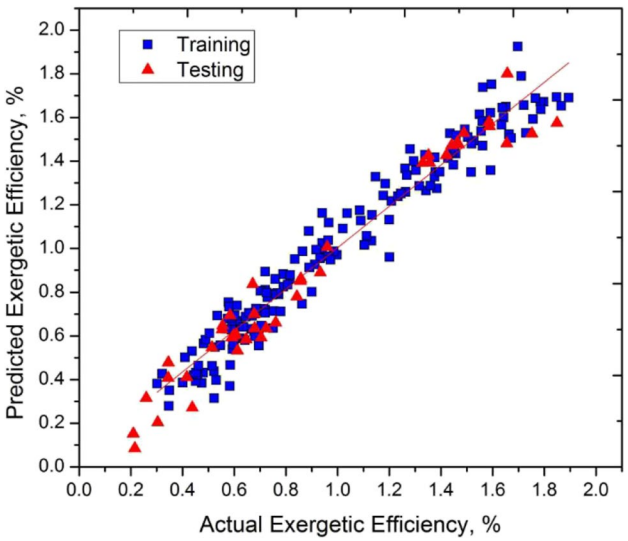


Fig. 13 The comparison between actual and predicted data of a solar air heater (Ghritlahre and Verma 2021a)

shown in Fig. 13, there was a good match between actual and predicted data in this study because all of the data were near the central line in the graph. It could also be mentioned that the results regarding testing are better than training.

Hu et al. (2021) presented a new data-driven technique to forecast the system off-design performance, allowing the lifetime design of the hybrid geothermal-solar power system to consider its real-time operation. The ANN algorithm was combined with a multi-objective optimisation technique to predict the hybrid system's hourly performance. The results showed that this ANN-based approach could potentially decrease time computing and improve net present value (NPV) and lifetime electricity generation (Etot) by 14% and 17%, respectively. In addition, as the price of solar collectors fell to 75 $\$\cdot m^{-2}$, this hybrid system indicated improved turbine/pump efficiency during operation and potential thermo-economic benefits in comparison with the stand-alone geothermal power plants.

Mehla et al. (2021) proposed an ANN-based model of an innovative solar air collector (ISAC) system to anticipate the ISAC performance using phase change material (PCM) (acetamide). According to the experimental results, the outlet air temperature of ISAC was predicted using the back-propagation neural network (BPNN), which was a useable and reliable tool.

Vakili et al. (2021) developed an artificial neural network (ANN) adaptive neuro-fuzzy inference system (ANFIS) model to anticipate the performance of a low-temperature direct absorption solar collector (DASC) improved with nanofluids (Fig. 14). This work considered input inlet temperature, ambient temperature, solar radiation rate, nanofluid weight percentage and mass flow rate. According to the results, the ANN method gave a very accurate model to predict the collector's efficiency. The accuracy evaluation criteria were proved by calculating the coefficient of determination (R^2), the mean absolute percentage error (MAPE), the root-mean-square error (RSME) and mean bias error (MBE), which were obtained 0.999, 0.031, 0.008 and 7e-4 in turn. As shown in Fig. 15, the point regarding the sub-clustering method was near the zero-line, so this method, compared to other methods used in this study, is more accurate.

Mirzaei and Mohiabadi (2018) applied an artificial neural network (ANN) model to determine the flat plate solar collector performance and compare three different working fluids (Al_2O_3/water nanofluid and CuO, and pure water). It was proved that ANN is a reasonable tool to predict the flat plate collector performance at all three working fluids. The results also revealed that ANN could be considerably time-saving and cheaper than conventional testing methods. According to Fig. 16, the model for predicted solar collector efficiency with Al_2O_3 nanofluid as a working fluid is more accurate than CuO nanofluid. However, generally model had good accuracy as an expected tool.

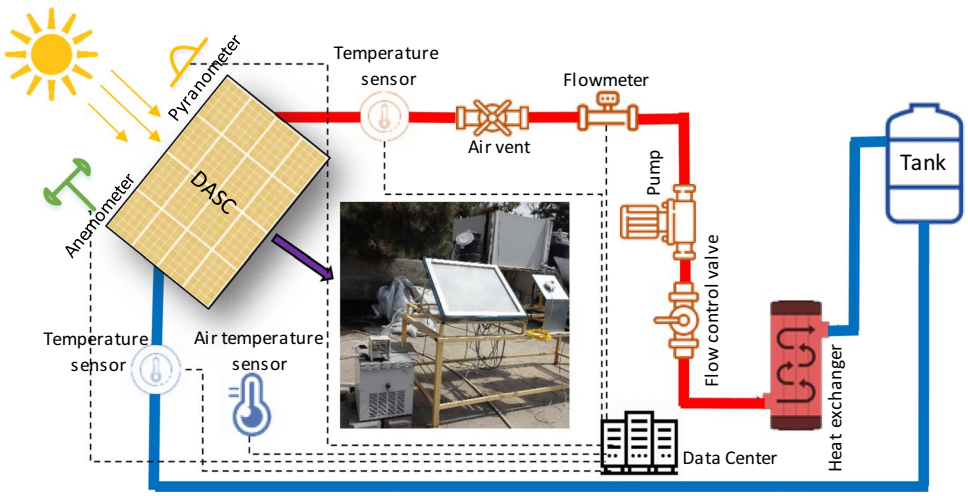


Fig. 14 Schematic of experimental setup (Vakili et al. 2021)

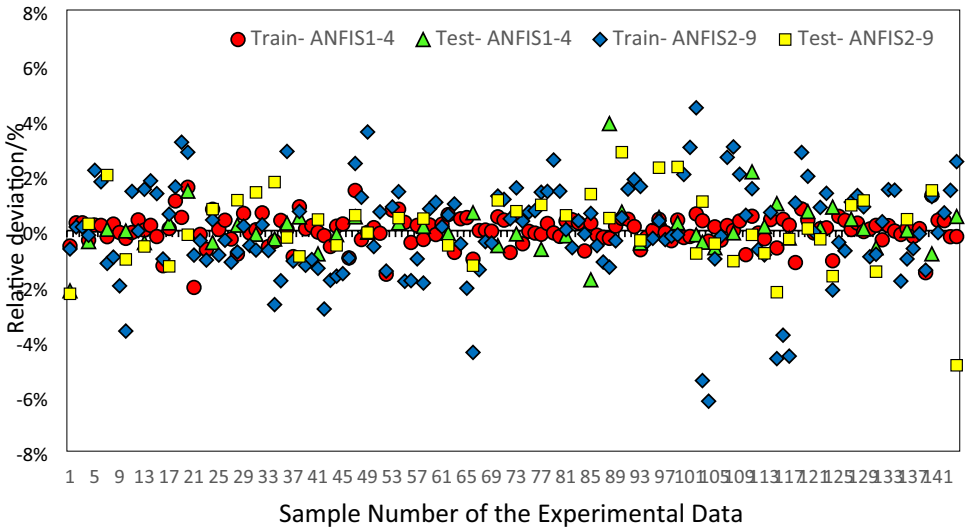


Fig. 15 Investigation of relative deviation (%) of testing and training data in a direct absorption solar collector (Vakili et al. 2021)

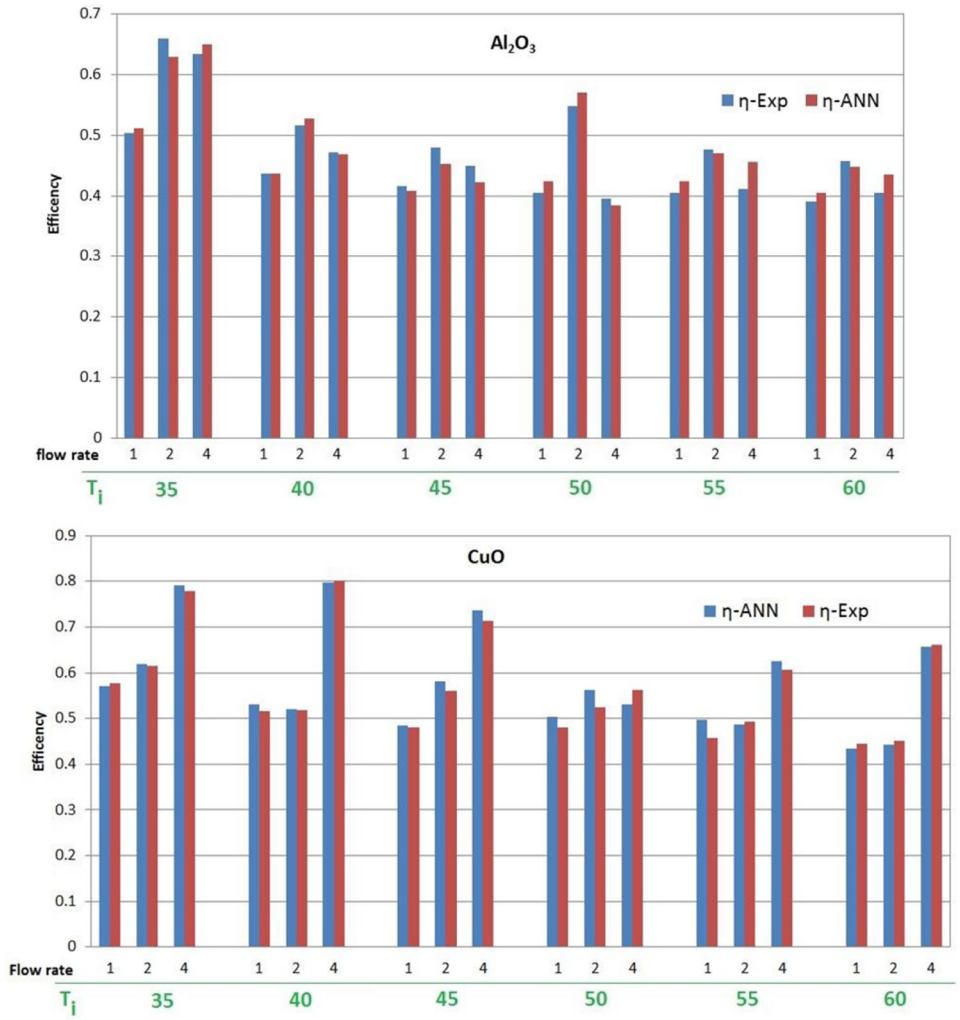


Fig. 16 The comparison between experimental and predicted data for a flat plate solar collector working with nanofluids (Mirzaei & Mohiabadi 2018)

Victor et al. (2022) used a hybrid black widow particle swarm optimisation and deep neural network to increase the efficiency of a solar still combined with a linear and helical tube solar collector. They considered different parameters to model the system's effectiveness, including glass temperature, average evaporation temperature, inlet and outlet temperature, water temperature, air temperature, yield, solar intensity and wind speed. Moreover, they proved their results by statistical indexes, such as RMSE, MAE, MRE and ECR. Their modelling results showed that this approach could predict the efficiency of this system compared to experimental data.

Zhang et al. (2022b) applied different learning algorithms, including orthogonal distance regression (ODR), Levenberg–Marquardt (LM) and the fuzzy system of recursive least squares, in an artificial neural network for predicting the thermal conductivity and viscosity of nanofluid in a flat plate solar collector. They used nanofluid (reduced graphene oxide (rGO)/water) as the working fluid in this collector. Their result indicated that this nanofluid could dramatically increase the efficiency of that system, and an artificial neural network could accurately predict the thermal conductivity and viscosity compared to experimental results.

Du et al. (2022) used the back propagation (BP) and convolutional neural network (CNN) models in an artificial neural network to improve and provide a model with more accuracy and validation for predicting solar collectors' performance. The solar radiation intensity, ambient temperature, wind speed, fluid flow rate and fluid inlet temperature were considered input data for the training and testing of the model. The model could predict the performance of solar collectors in sunny conditions with R^2, RMSE and MAE of 0.9693, 0.0039 and 0.0030, respectively. Furthermore, the ANN collector prediction model accuracy could increase by data clustering.

Hybrid photovoltaic/thermal collectors

The technology of hybrid photovoltaic thermal collectors is well-known in the solar collector industry. Photovoltaic cells are semiconductor materials that directly convert short-wavelength rays emitted from the sun into electricity. The temperature of the photovoltaic modules absorbed by the solar radiation that has not been converted into electricity increases and reduces its electrical efficiency. One of the ways to reduce the temperature of the photovoltaic module is to use the heat behind the module to heat water/air or other fluids (Hossain et al. 2022). The use of PV/T collectors has advantages such as the simultaneous use of thermal and electrical units, increasing the electrical efficiency of the photovoltaic module and the overall efficiency of the device, optimal use of the available space, increasing the filling factor and not requiring an external electrical source for fluid circulation (Anandaraj et al. 2022). Furthermore, it increases the lifespan of the photovoltaic module, creates a uniform architecture on the roof of the building and shortens the investment return time (Tiwari et al. 2022).

Xia et al. (2018) introduced a new model for optimising combined ground source heat pump systems with solar photovoltaic thermal collectors (GSHP-PVT). They applied an artificial neural network (ANN) model with a genetic algorithm (GA) for the performance prediction of the system. This model predicted the system's performance based on the critical design parameters, which are considered for minimising the GSHP-PVT system life cycle cost. Their results indicated that the artificial neural network model

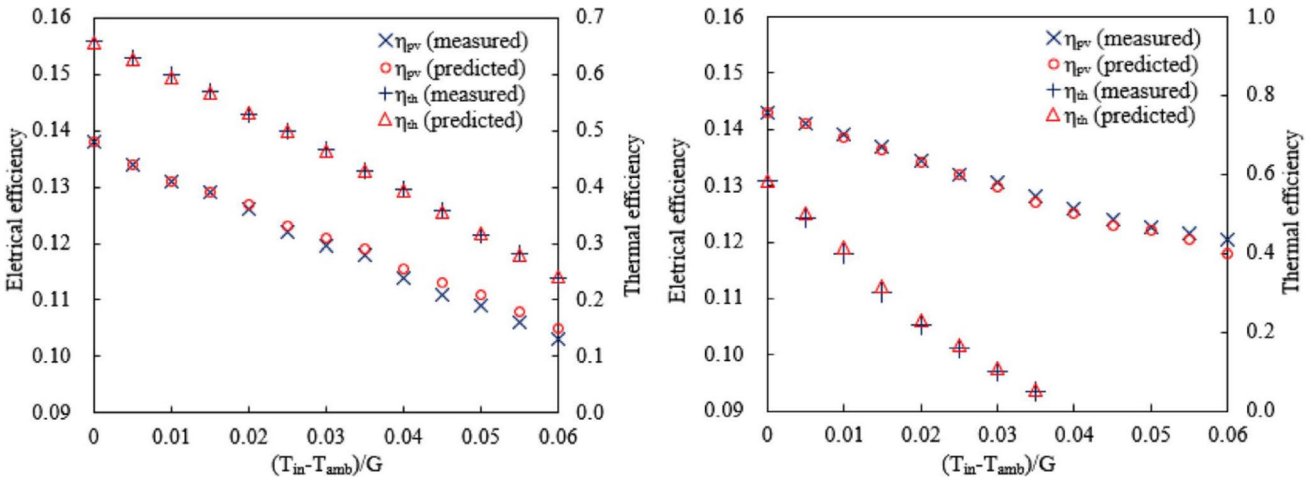


Fig. 17 The comparison between the experimental data of electrical and thermal efficiency with modelling data (Xia et al. 2018)

could provide an acceptable forecast of the operational cost of the GSHP-PVT system. As shown in Fig. 17, this model has good accuracy for modelling the efficiency of hybrid solar collectors. It could be mentioned that the prediction of thermal efficiency is more accurate than electrical efficiency, although both were acceptable results.

Chamkha and Selimefendigil (2018) predicted photovoltaic thermal (PV/T) performance based on SiO_2/H_2O nanofluid using a radial basis function artificial neural network. Their results showed that the ANN data had a good match with computational fluid dynamics modelling data. However, ANN modelling applied in this study was cheaper and faster than CFD.

Dimri et al. (2019b) analysed a photovoltaic thermal collector combined with a thermoelectric cooler by two different models, thermal and artificial neural network (ANN) models. They used three other PV modules: opaque, semi-transparent and aluminium base. They claimed that the ANN model did not need several parameters and complicated computations, while the thermal model needed those. Their results showed that the aluminium base PVT-TEC water collector could gain more electrical and thermal energies than other PV modules. Moreover, the ANN predicted data agreed with the thermal method's modelled data.

Al-Waeli et al. (2019) investigated the efficiency of four different PV/T systems shown in Fig. 18, namely conventional PV, PVT based on water, nanofluid and nanofluid/nano-PCM, under the same situations by an MLP-ANN system. Their result demonstrated that nanofluid/nano-PCM could enhance electrical and thermal efficiency by 13.32% and 72%, respectively. Also, they used different statistical indexes such as the mean absolute error (MAE), mean square error (MSE), correlation (R) and coefficient of determination (R^2) to investigate the accuracy and validation of their model. According to Fig. 19, their ANN model could predict the efficiency of

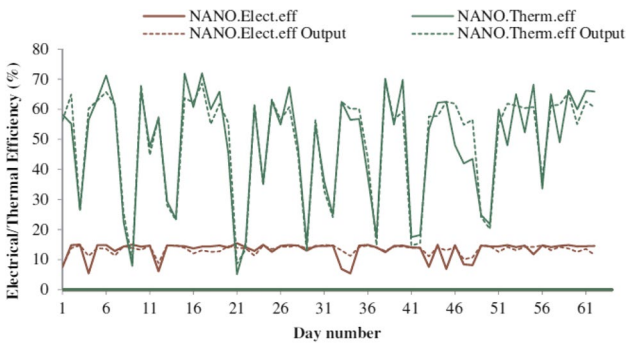


Fig. 19 The investigation of ANN modelling results for electrical/thermal efficiency prediction (Al-Waeli et al. 2019)

PVT with MSE of 0.0229 and 0.0282 in the training and cross-validation phase, respectively.

Dimri et al. (2019a) used a feed-forward artificial neural network with three layers to model a glass-Tedlar photovoltaic thermal (PVT) air collector applied to a cooler system. The input data for the artificial neural network was considered global solar radiation, diffuse solar radiation and ambient temperature. They studied collectors' monthly and annual outputs installed in New Delhi, India. Their results showed that the model's accuracy and validation were acceptable compared to experimental data collected during a year.

Ahmadi et al. (2020) applied machine learning methods, namely ANN, LSSVM and ANFIS, to predict the heat efficiency of a photovoltaic thermal (PV/T) solar collector. They considered five key parameters, such as inlet temperature, flow rate and solar radiation, as input data in machine learning models for the training process. Their investigation and comparison of modelling data with experimental data showed that the LSSVM model had a good agreement with other methods. However, exploratory analysis and laboratory measurements were usually costly and time-consuming.

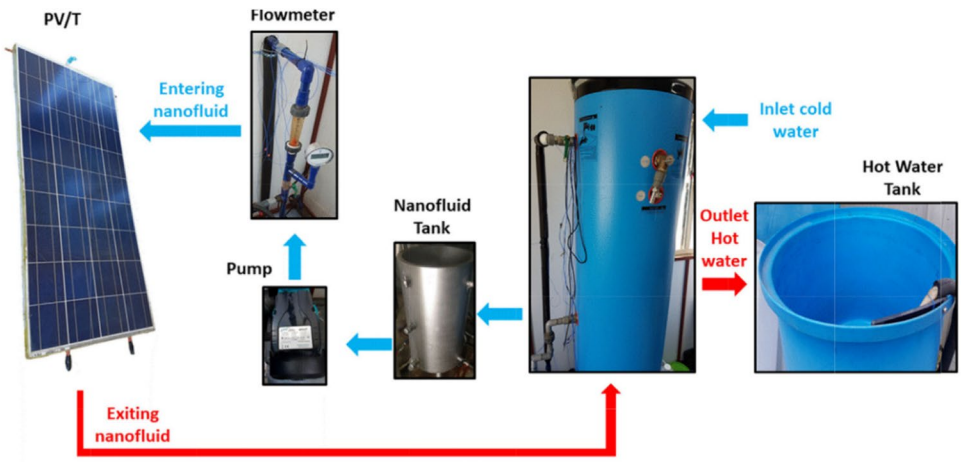


Fig. 18 The experimental setup of PVT (Al-Waeli et al. 2019)

Beniwal et al. (2020) used three different ANN methods to optimum cost, temperature and thermal efficiency of a semitransparent PV/T air collector. They could develop the Markov model, which combined with an artificial neural network to go up the semitransparent PV/T air collector availability by 100%. Moreover, their result showed that this model could be an effective method for use in different solar systems under other conditions. Finally, they claimed that the performance of a semitransparent PV/T air collector was better than a semitransparent PV system.

Tyagi et al. (2021) employed an artificial neural network technique named the firefly algorithm to optimise and compare the photovoltaic parameters of the two nanostructured solar cells. One of the structures was developed by amalgamating zinc oxide and carbon quantum dots, and another incorporated graphene oxide into zinc oxide. The trigeneration systems were based on photovoltaic thermal collectors, photovoltaic modules and heat pumps. The results showed a compression between two hybrid solar cells that adding CQDs to ZnO led to a significant rise in ISC, VOC and FF values. It is noticed that the results given by experiments and ANN were considerably matched. In addition, the obtained values for parameters of both solar cells proved that hybrid cells made of CQDs could be a better candidate. The research claimed that this algorithm could be utilised on any model of the hybrid solar cell, resulting in advancement in the solar cell field and efficiency enhancement.

Abd Elaziz et al. (2021) used a novel optimised artificial method to anticipate the photovoltaic/thermal collector (PVTC) performance combined with an incorporated electrolytic hydrogen production (EHP) system. This work also employed a new metaheuristic algorithm, the mayfly-based optimisation (MO), implemented with random vector functional link (RVFL) network to make the prediction forecast more precise. The experiments were done under two different cooling fluids: water and air. The results showed that the experiments and the prediction model were perfectly fitted and revealed the vital role of MO in estimating the best RVFL parameter factors that maximise the prediction forecast performance.

Wang et al. (2021) proposed an optimal optimum model plan of a hybrid system based on nondominated sorting genetic algorithm II to minimise the environmental effects of the hybrid system, including acidification, global warming, respiratory effect and acidification and global warming. The main aim is to present a life cycle, assessment-based robust multi-objective optimisation model of a hybrid solar-assisted CCHP system driven by the complementarities of photovoltaic/thermal collectors and gas turbines. The research compared partially with fully covered photovoltaic/thermal collectors, which found that the partially covered collectors lower the effects of respiratory and acidification by 28.4% and 6.7%, in turn.

Nikbakht Naserabad et al. (2021) used the genetic algorithm using one-hundred samples for training a black-box model as the algorithm's fitness function for tri-objective optimisation to obtain the optimum size of a building energy supplier system that generates electricity, cooling and heating loads. The best size of system components was estimated to increase energy efficiency and minimise the CO_2 index and the total cost, and CO_2 index. The novelty of this work was the combined combination of optimisation and ANN, which led to an accurate and fast optimisation process, as shown in Fig. 20. Tri-objective optimisation indicated the best point optimal point of Pareto Frontier had given the CO_2 index, the total cost rate, the exergy efficiency, 425.15 g/kWh, 5.78 $/ and 64.23%, respectively.

Cao et al. (2022) simulated and optimised photovoltaic/thermal (PV/T) electrical performance based on nano-coolants using machine learning and an evolutionary algorithm. They applied three machine learning methods: artificial neural networks, least squares support vector regression and adaptive neuro-fuzzy inference systems. They used 200 experimental datasets for modelling, and then their results showed that adaptive neuro-fuzzy inference systems (ANFIS) were the best method for modelling compared to other models. Modelling data were compared to experimental data, and their accuracy was assessed with the absolute average relative deviation and mean squared error statistical indexes, 13.6% and 2.548, respectively.

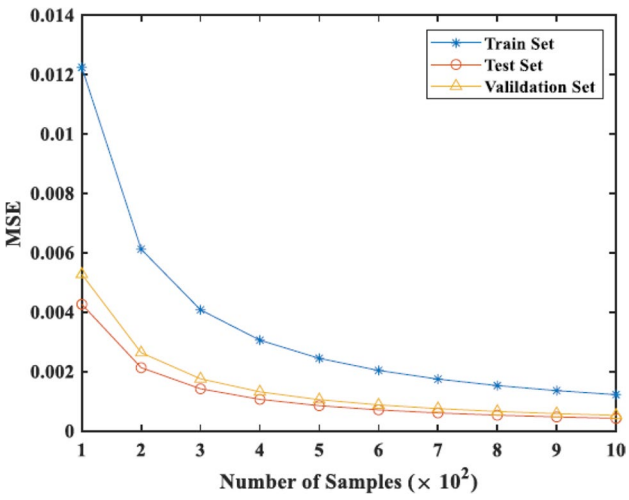


Fig. 20 Investigation of sample number effect on the MSE in three stages, namely training, validation and test (Nikbakht Naserabad et al. 2021)

Evacuated tube collectors

Like a two-tube heat exchanger, an evacuated tube collector comprises two overlapping metal and glass tubes. In this collector, the metal tube is mainly made of copper, called the absorber tube (Sharma et al. 2022). The fluid flows inside the absorber tube, and a glass tube is placed outside, preventing displacement losses between the environment and the absorber tube. To minimise displacement losses, the space between two pipes is emptied of air. The heat pipe is a copper pipe closed on both sides, and the flow of the working fluid (usually water or a solution of water and ethylene glycol) is carried out due to displacement (convection)(Sharma et al. 2021).

Tolon et al. (2019) investigate experimentally and numerically a tube heat pipe (ETHP) solar energy system, shown in Fig. 21, based on water as a working fluid. According to their experimental results, the tube heat pipe solar energy's exergy efficiency was 32.94%. Then, they predicted energy efficiency and optimisation of various processes, namely pressure, temperature and ambient temperature affecting exergy efficiency, by the artificial neural networks modelling method. Their modelling results showed that the effects of radiation (I), mass (m) and the environmental temperature (Tair) were 0.04237, 0.07473 and 0.02935, respectively, on the system's exergy.

Sadeghi et al. (2020a) investigated the energy and exergy of an evacuated tube solar collector based on nanofluid (Cu_2O/water) at three different mass flow rates, namely 10, 30 and 50 L/h, by artificial neural network method. In that study, they used two machine learning methods, the multilayer perceptron (MLP) and radial basis function (RBF), to forecast the solar collector efficiency. According to the experimental and modelling comparison data, their results showed that the MLP method was more accurate than another method. Sadeghi et al. (2020b), in another study, investigated the heat characteristics, including energy efficiency and inlet–outlet working fluid, of an evacuated tube solar collector by three different artificial intelligence modelling methods, including multivariate adaptive regression spline (MARS), model tree (MT) and gene-expression programming (GEP). Their investigation showed that the multivariate adaptive regression spline method could predict more accurate output data than other methods regarding forecasting the collector's efficiency. Moreover, their result indicated that going up the flow rate and concentration of nanofluid could improve the efficiency of that collector. As shown in Fig. 22, the MARS methods have better performance than other methods mentioned in the graph. Furthermore, the accuracy of all training models is more accurate than testing because points regarding training were near the cross-line.



Fig. 21 The evacuated tube heat pipe collector (Tolon et al. 2019)

Sadeghi et al. (2021) experimented with the modified evacuated tube solar collector (METSC) with a bypass pipe using copper oxide/distilled water (Cu_2O/DW) nanofluid. They also anticipated the METSC's performance of METSC through using ANN techniques called MLP and RBF. The input variables were different diameters of the bypass pipe, the various volumetric concentrations of the nanofluid, various diameters of the bypass pipe and different storage tank volumes. The temperature difference of fluid in a 1-h period and the METSC energetic efficiency were considered the output. The results revealed that the daily energy efficiency of METSC is up to 4% by the Cu_2O/DW nanofluid. The tank volume alteration had a significant impact on the METSC performance.

Moreover, both MLP and RBF methods were useable and reliable for anticipating the METSC thermal characteristics, and their mean relative percentage error was obtained at 0.576 and 0.907, respectively. According to their results in Fig. 23, in the testing stage, which is the most critical stage of modelling, the predicted data are a good match with experimental data. Thus, this type of modelling can be used for other key parameters in solar systems.

Du et al. (2021) applied several multiple artificial neural network (ANN) techniques to predict the thermal performance of an all-glass straight thermal performance by using an evacuated tube solar collector. The performance of ANN methods was compared to the multiple linear regression and support vector regression model. As shown in Fig. 24, the best prediction accuracy belonged to radial basis function (RBF) neural network method followed by the back propagation (BP) model.

Sanaye and Sarrafi (2021) employed artificial neural network (ANN) to determine the electricity usage of the chiller and RO (reverse osmosis) system at various operation points. The chiller and RO system electricity consumption during each operating point meet heating demand. The hybrid system consisted of hot water storage tanks (HWST), gas water heaters, micro-CHP units, evacuated tube (ET) collectors, micro-CHP units, gas water heaters and hot water storage tanks (HWST) to supply heating demand. The research found that the innovative

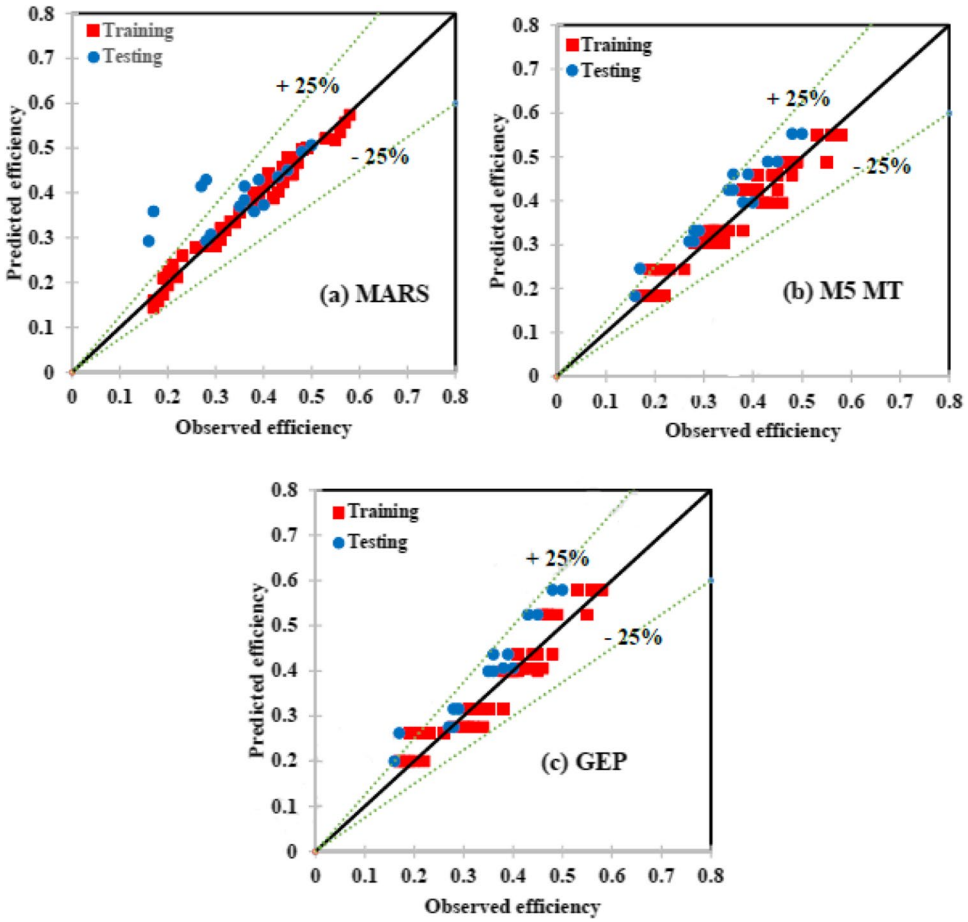


Fig. 22 Investigation of different AI models' performance for prediction of a solar collector efficiency. **a** MARS. **b** M5 MT. **c** GEP (Sadeghi et al. 2020b)

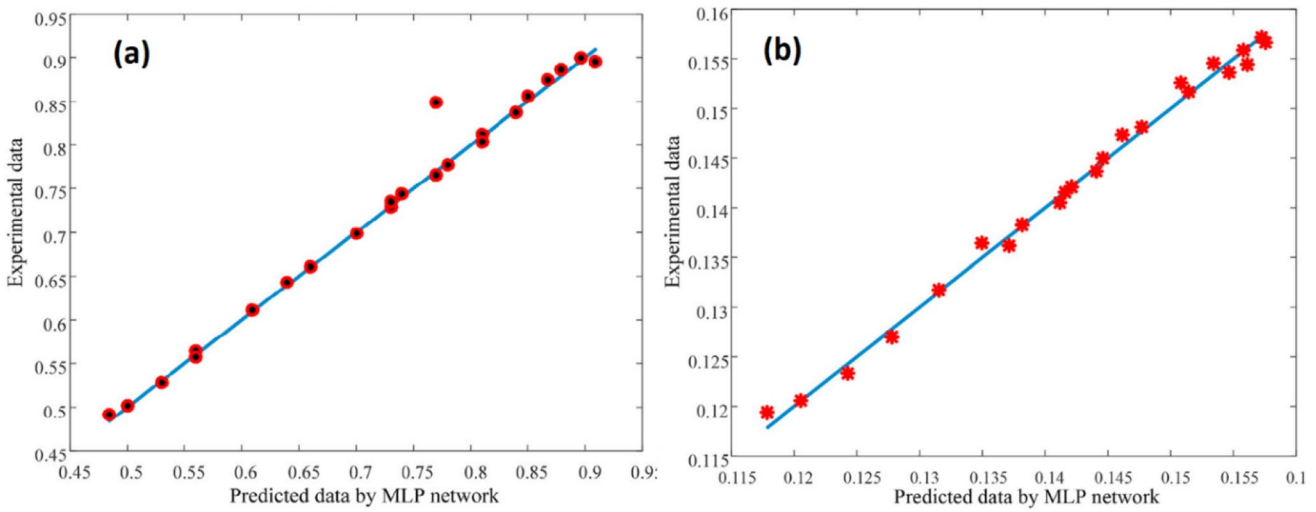


Fig. 23 The regression graph for modelling the maximum fluid temperature (**a**) and energy efficiency (**b**) of a solar collector in the testing stage (Sadeghi et al. 2021)

creative combined ANN and PSO optimising methods reduced the run computing time by almost 10%. Moreover, RO electricity consumption was decreased by utilising excess extra heat in preheating RO feedwater. For more investigation, Table 1 shows a summary of data about applying different ANN models in various solar collectors.

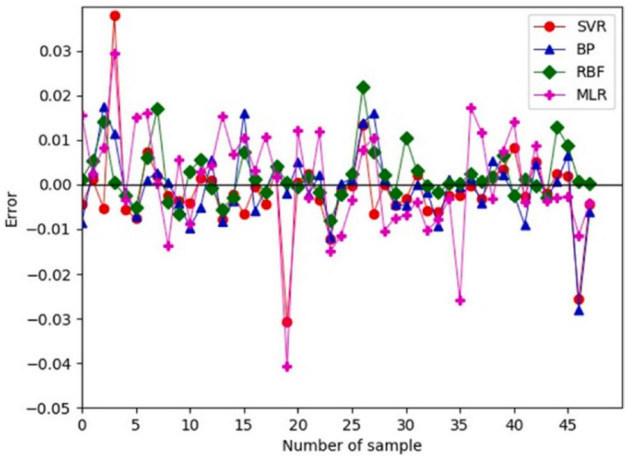


Fig. 24 The comparison of different modelling methods' performance (Du et al. 2021)

Concentrating collectors

Parabolic trough collectors

The parabolic trough is the most widely used concentrating solar collector, especially since high temperatures are needed. The temperature range for the PTC is in the wide range, 30–400 °C (Zaaoumi et al. 2021a). Aluminium, steel sheets or any reflective mirrors are commonly used as a light-reflecting surface in these collectors, which are highly polished to reflect solar radiation effectively. The capability of producing superheated steam for power generation makes these collectors applicable to solar power plants. The working fluid used in this type of collector is water vapour, industrial oils, molten salt and such base fluids, in which due to the low thermal conductivity of these types of fluids, the collector's efficiency is low. Much research has been carried out to improve the heat transfer rate between the absorbent, the working fluid and the heat transfer coefficients (Rashidi et al. 2020).

Over the past few decades, many changes have been made to solar thermal power plants based on parabolic trough collectors to develop these products in different terms, especially in the electricity sector (Naveenkumar et al. 2021). Artificial intelligence has become a popular and useful modelling method to model the system and predict the performance of PTC in order to increase the temperature of heat transfer fluids, capacity factor, stability and efficiency.

Ebrahimi-Moghadam et al. (2018) applied ANN and quadratic algorithm to minimise entropy generation of Al_2O_3-60:40% EG/W nanofluid flow in parabolic trough solar collector. Their model could determine optimised different data, such as Reynolds number and nanoparticle concentration. Moreover, their investigation indicated that the entropy generation rate declined by dropping volume fraction, going up particle diameter and rising average flow temperature. Furthermore, their results showed that increasing volume fraction could rise frictional and reduce thermal entropy generation. As shown in Fig. 25, ANN modelling in the test stage could predict accurately, and almost points were near the central line in the graph.

Jamali et al. (2019) predicted the performance of a solar space heating system equipped with a parabolic through collector by a hybrid artificial neural network model with a PSO-GA optimisation algorithm. Their results indicated that the multilayer perception algorithm could predict a system's efficiency more accurately than the PSO-GA algorithm (Fig. 26). The maximum error belonged to sample two, and sample eight had the lowest error in all modelling methods, namely PSOGA-ANN (hybrid particle swarm optimization/genetic algorithm and artificial neural network), PSO-ANN (hybrid particle swarm optimization and artificial neural network) and GA-ANN (hybrid genetic algorithm and artificial neural network). Furthermore, they used different statistical indexed such as mean absolute percentage error (MAPE), variance accounted for (VAF), the coefficient of determination (R^2) and root mean square error (RMSE) for the investigation of accuracy and validation of the model.

Heng et al. (2019) provided an accurate and fast model to predict the exit temperature of a parabolic trough collector. They applied an artificial neural network method, hybridised with the superposition principle. They used ANN to forecast the exit temperature rise caused by a single heat flux pulse, whereas they applied superposition to forecast from multiple heat flux pulses. They claimed their model is fast because it can model the 1-year exit fluid temperature data in less than 6 h. Moreover, they mentioned that these data could be applied to plan the initial system, analyse heat balance and design the parabolic trough collector under weather conditions worldwide.

May Tzuc et al. (2020) used a novel computational methodology, a multivariate artificial neural network, to make decisions for the design of a parabolic trough collector in the industrial sector. Their study's scope was analysing economic, operational and environmental factors for designing the solar collector. Their results showed that the energy contribution of this thermal system could cover approximately 40–80% of the required energy in the industries. Moreover, as shown in Fig. 27, they claimed that this model could use in different sectors.

Okonkwo et al. (2020) applied hybrid GA/ANN (genetic algorithm and artificial neural network) to minimise entropy generation in a parabolic trough collector based on nanofluid (SiO_2/H_2O). They employed a genetic algorithm to optimise the entropy generation rate while using an artificial neural network to forecast key parameters' role, volumetric concentration, mass flow rate and inlet temperatures on the entropy generation rate. They claimed that their model had

Table 1 The summary of information about the accuracy of different models in non-concentrating collectors

Type of solar collectors	Input parameters	Output parameter	Model	Results	Reference
Flat plate collectors	Mass flow rate of air, relative roughness height, atmospheric temp., mean fluid temperature, absorber plate temp., solar intensity	Thermal efficiency	-ANN-SCG -ANN-LM	-R^2 = 0.82485 -R^2 = 0.99882	Ghritlahre and Prasad (2018b)
	Solar irradiance, ambient temperature, inlet temperature and working fluid flow	Outlet temperature	ANN	RMSE = 0.1781 R^2 = 0.9991	Diez et al. (2019)
	Inlet temperature, volumetric flow rate, nanofluid concentrations	Thermal efficiency	-MLP-ANN -RBF-ANN -Elamn BP-ANN	R^2 = 0.960	Sadeghzadeh et al. (2019)
	Depth and length of the collector, flow rates, nanofluid concentration and the declined temperature difference	-Thermal efficiency -Nusselt number	ANN	-MAPE = 1.470% -MAPE = 2.576%	Delfani et al. (2019)
	Solar radiation, inlet temperature, flow rate, wind speed and ambient temperature	Working fluid outlet temperature	BP-ANN	MBE = −0.554 RMSE = 5.22	Shafiey Dehaj et al. (2020)
	Ambient temperature, wind speed, relative humidity, fluid inlet temperature, fluid mean temperature, mass flow rate, plate temperature, wind direction, solar intensity and solar elevation	The exergy efficiency	-MLR -ANN -GMDH	-R = 0.98977 -R = 0.99981 -R = 0.97693	Ghritlahre and Verma (2021a)
	Inlet temperature, ambient temperature, solar radiation rate, nanofluid weight percentage and mass flow rate	Thermal efficiency	ANFIS	R^2 = 0.999 MAPE = 0.031 RSME = 0.008 MAPE = 7e-4	Vakili et al. (2021)
	The solar radiation intensity, ambient temperature, wind speed, fluid flow rate and fluid inlet temperature	Thermal efficiency	ANN	R^2 = 0.9693 RMSE = 0.0039 MAE = 0.0030	Du et al. (2022)
Hybrid photovoltaic/thermal (PV/T) collectors	Solar irradiation and ambient temperature	PV/T current (A), PV/ T voltage (V), PV/T electrical efficiency (%) and PV/T thermal efficiency (%)	MLP-ANN	MSE = 0.0229	Al-Waeli et al. (2019)
	The global solar radiation, diffuse solar radiation and ambient temperature	Thermal energy gain, electrical energy gain, overall thermal energy gain and overall exergy gain	ANN	R^2 = 0.9997 MSE = 0.86×10^{-1}	Dimri et al. (2019a)
	Inlet temperature, flow rate, heat, solar radiation and sun heat	Thermal efficiency	ANN LSSVM ANFIS	R^2 = 0.94 MSE = 0.037	Ahmadi et al. (2020)
	nanofluid flow rate, radiation intensity, type and size of nanoparticles and their concentration in water	Electrical efficiency	ANFIS LS-SVR ANN	AARD = 13.6% MSE = 2.548 R2 = 0.9534	Cao et al. (2022)
Evacuated tube collectors	Tank volume, nanofluid concentration and flow rate	Thermal efficiency	ANN-MLP ANN-RBF	MAE = 0.0203 MRE = 1.9497 RMSE = 0.0249	Sadeghi et al. (2020a, b)
	Diameters of the bypass pipe, the various volumetric concentrations of the nanofluid, various diameters of the bypass pipe and different storage tank volumes	Energy efficiency	ANN-MLP ANN-RBF	MRE = 0.576 MRE = 0.907	Sadeghi et al. (2021)

a good agreement with experimental data through statistical indexes: a mean square error of 0.02288 for training and 0.0282 for testing, and an R^2 value of 0.9999.

Bagheri et al. (2020) investigated and modelled the efficiency of a cylindrical parabolic collector and solar panels applied as a desalination system by an artificial neural network (Fig. 28). Their result indicated that the ANN model could predict their output compared to experimental and mathematical data. Thus, they showed that increasing the system's performance depended on the solar unit's efficiency. Therefore, declining the solar panel's temperature during hot hours of the day can rise the system's performance.

According to Fig. 29, the number of neurons affects modelling accuracy. It could be mentioned that the model accuracy increases moderately when using more neurons, although the calculating time increases slightly.

Al-Rashed et al. (2021) numerically used the Eulerian-Eulerian two-phase methods to investigate and estimate the performance of a parabolic trough collector (PTC), which was applied using solid insulation and non-circular absorber tube and solid insulation. They estimated and investigated the impacts of some vital criteria on the performance metrics, such as nanoparticles' diameter and insulation angle, the volume of nanoparticles, the Reynolds number, nanoparticle volume concentration, nanoparticle diameter and insulation angle. In this work, the artificial neural network technique was applied to predict an efficient model for collector efficiency. The results showed that the optimum number of neurons was 8, which creates a model to predict collectors' efficiency with high accuracy. The maximum deviation and the *R*-square were obtained at less than 0.2% and 0.9998, respectively.

Ajbar et al. (2021a) presented some models using four multiple linear regression (MLR) and six artificial neural network models (ANN). Four multiple linear regression (MLR) models were used to find the essential factors for the outlet temperature of a parabolic trough solar collector (PTSC) outlet temperature by predicting and optimising the input. According to the ANN-1 model, the PTSC outlet temperature was influenced by the inlet temperature being the most significant parameter affecting the PTSC outlet temperature. However, ANN-1 and ANNi were potentially able to decrease computing time and increase the accuracy compared to MLR-SOE (multiple linear regression with second-order equation) for modelling and optimising the PTSC outlet temperature. The MLR-SOE method was more straightforward, cheaper and affordable than the ANN method.

Zaaoumi et al. (2021b) applied three alternative models to determine the hourly electric production of a parabolic trough solar thermal power plant (PTSTPP)

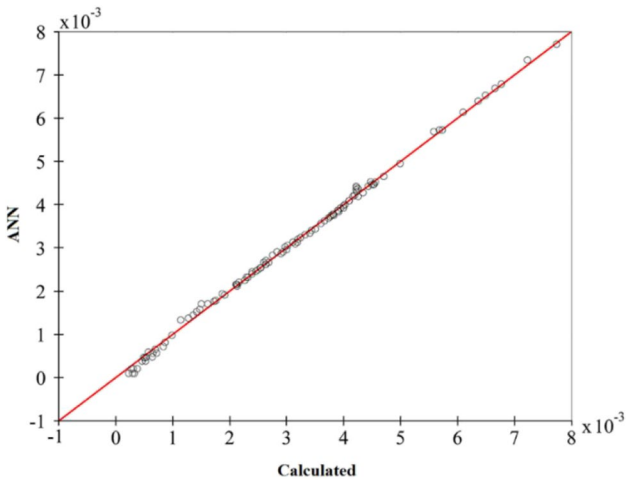


Fig. 25 Comparison between calculated data with ANN modelling data (Ebrahimi-Moghadam et al. 2018)

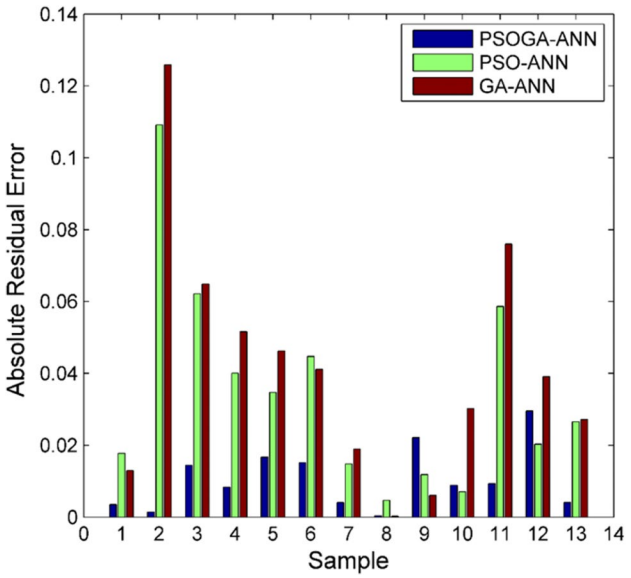


Fig. 26 The investigation of absolute residual error of different models (Jamali et al. 2019)

situated in Eastern Morocco by conducting three different models. The first model (AM I) calculated heat losses for parabolic trough collectors (PTCs). In contrast, the second analytical model (AM II) used the thermal efficiency of PTCs used in the second analytical model (AM II), and an artificial neural network (ANN) model was used. The third model was based on an artificial neural network (ANN) model. The results showed that the ANN model performance performed of the ANN model was much significantly better than that of the analytical models. In addition, the developed ANN model is suitable for determining energy production for PTSTPP.

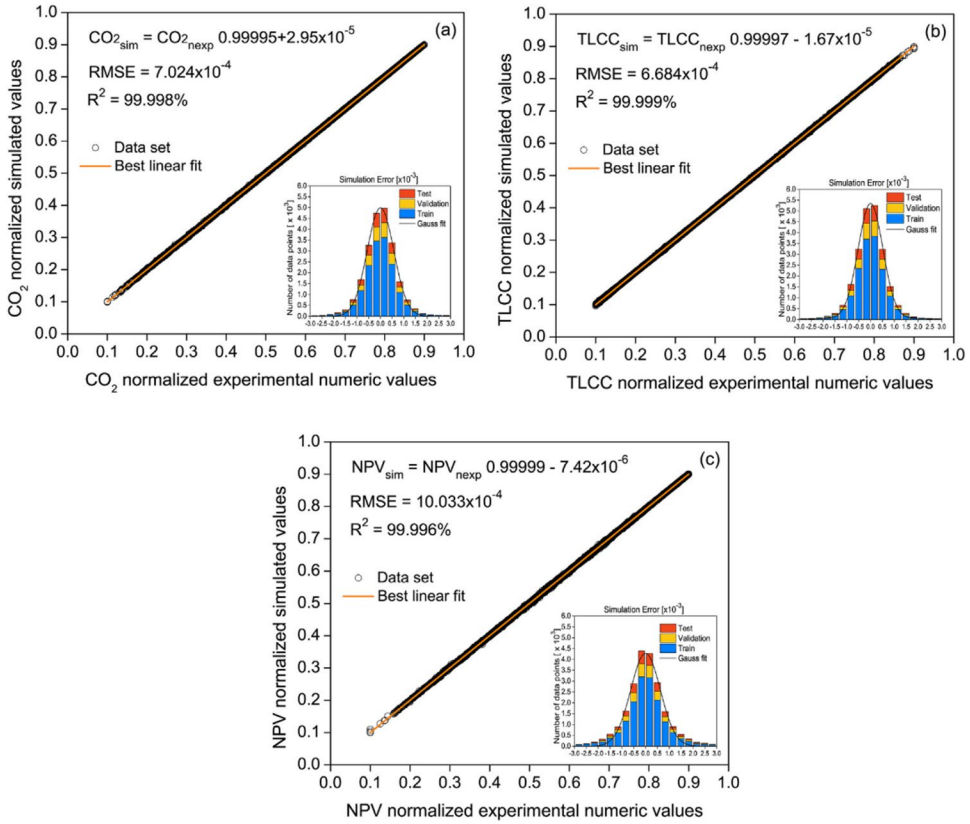


Fig. 27 The investigation of the artificial neural network model approach for prediction. Mitigated carbon (**a**), total life cycle (**b**) and net present value (**c**) (May Tzuc et al. 2020)

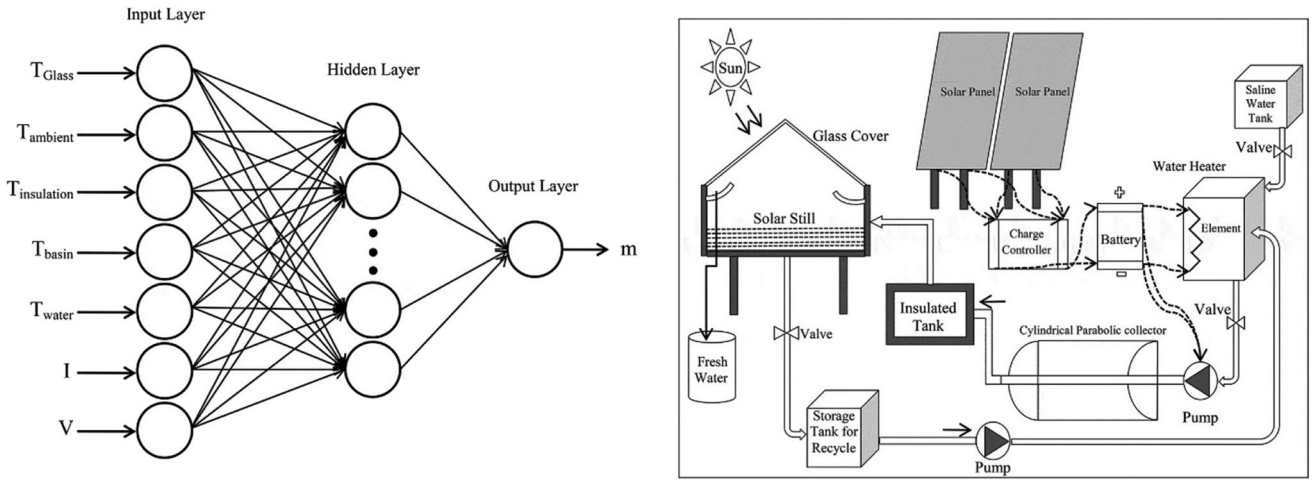


Fig. 28 A schematic of the solar collector system and artificial neural network (Bagheri et al. 2020)

Ajbar et al. (2021b) presented a mod named ANNim to conduct two ANN models to anticipate the PTC thermal efficiency (ηt). Also, they introduced a new technique capable of enhancing the efficiency of PTC thermal by estimating multiple several optimum input variable values. The Levenberg–Marquardt training algorithm employed a linear function (PURELIN) in the output layer and two nonlinear activation functions (TANSIG and LOGSIG) in the hidden layer. The results revealed that satisfactory results were obtained by both ANN models within which the root mean square error and the coefficient of determination were equal to 0.0193 and a determination coefficient of 0.9511 in turn and a root mean square error of 0.0193 (Fig. 30). The artificial neural network (ANN) models were inverted to achieve the multivariable objective function, which was able to

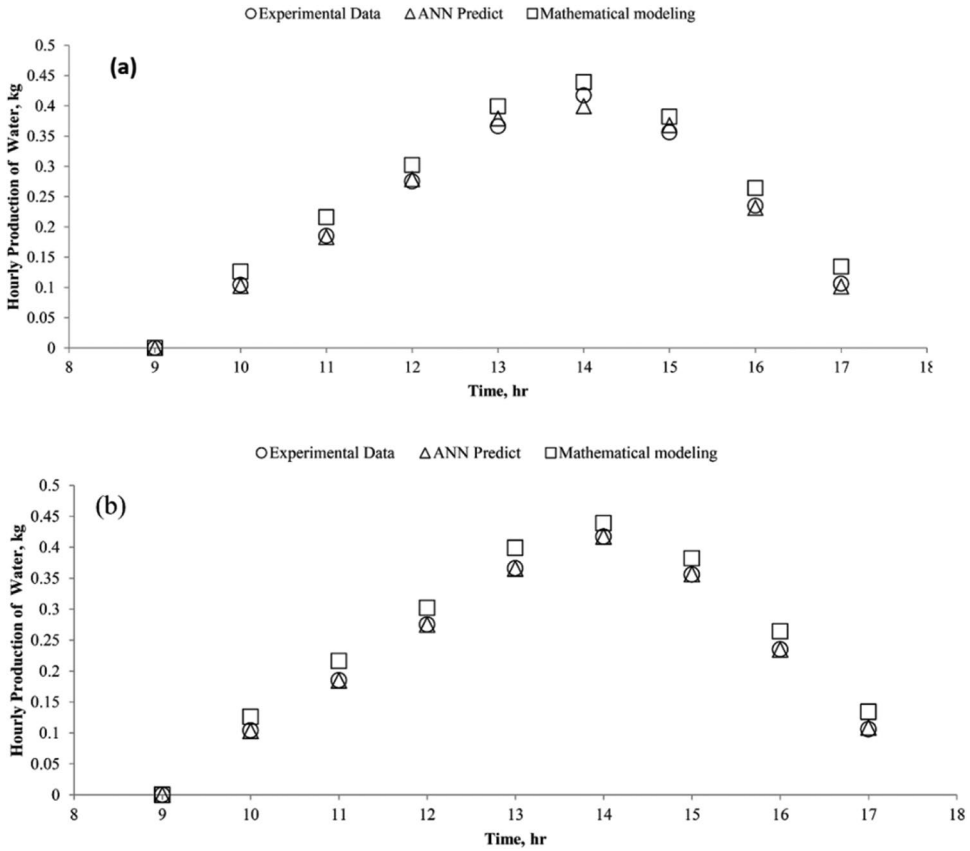


Fig. 29 A comparison between the results of experimental, ANN and mathematical investigations in different numbers of neurons. **a** 4 neurons. **b** 7 neurons (Bagheri et al. 2020)

be solved using particle-swarm-optimisation (PSO) and genetic algorithms (GA) and particle-swarm-optimisation (PSO). Results showed that the PTC performance of the PTC can be enhanced using the ANNim method by optimising from one, two and three variables at the same time simultaneously.

Hamdani et al. (2021) employed the artificial neural networks (ANN) to minimise the levelised cost of energy (LCOE) from a parabolic trough collector for a 1-MWe power plant. Considering design parameters, such as solar multiple, direct average irradiation, cycle, absorber and mirror efficiency, which directly impact LCOE, the effects were estimated by ANN. The results indicated that the ANN was a useful and reliable best model to anticipate the LCOE using the optimum topology of 5–7-1 neurons. The optimal plant design point was obtained at 1.94, 20.88%, 0.8673 and 0.8537 for the solar multiple, the cycle efficiency, the mirror efficiency and the absorber efficiency, respectively. According to Fig. 31, in general, with increasing the number of neurons, the RMSE index declines significantly until to hidden layers with five neurons. As mentioned in the previous section, the calculating time also rises when the number of neurons increases. Thus, one of the critical parameters which should be considered in modelling is the number of neurons in different hidden layers.

Liu et al. (2021) enhanced the PTC thermo-mechanical performance using a ribbed absorber tube with a parabolic trough receiver (PTR). In addition, multi-objective optimisation was applied to estimate the optimal parameter combinations using 3D numerical simulation and the genetic algorithm (GA). The results indicated that the ribbed absorber tube could effectively disturb the fluid near the boundary and induce longitudinal vortex flow, which dramatically enhances heat transfer between fluid and absorber tube, improving PTC performance. The heat transfer and flow resistance improved by 57–225% and 222–630%, respectively. The heat loss was decreased by up to 79.3%, which resulted in 2.3% and 2.2% enhancement in the heat collecting efficiency and overall efficiency.

Parrales et al. (2022) investigated experimentally and theoretically a parabolic trough solar collector system, shown in Fig. 32 schematically. They considered seven key parameters, namely the inlet temperature of the fluid, month, day, hour, ambient temperature, glass surface temperature and reflective surface temperature, as input data. The Levenberg–Marquardt algorithm was used for training the model with 19 neurons in the hidden layer. Their result showed that this model has good accuracy with R^2 0.9894, RMSE 0.6829 and MAPE 0.0405%.

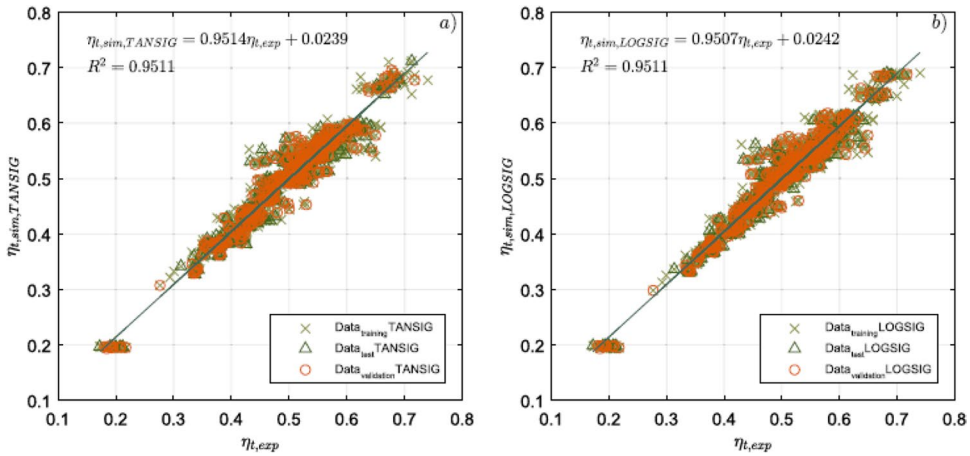


Fig. 30 A comparison between the results of ANN modelling in different functions. **a** TNASIG function. **b** LOGSIG function (Ajbar et al. 2021a)

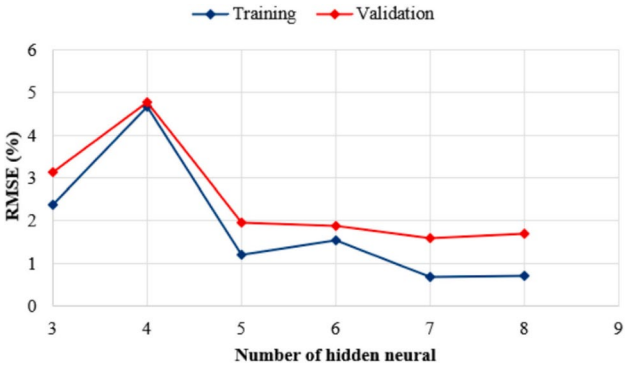


Fig. 31 A comparison between the results of RMSE index for training and validation process in different numbers of neurons (el Hamdani et al. 2021)

Parabolic dish

A parabolic dish collector is a reflective device with a circular, parabolic shape which concentrates the solar radiation to one point. The high concentration ratio and employing two-axis tracking systems make parabolic dish concentrators (PDCs) achieve a high-temperature range of up to 1200 °C (Sahu et al. 2022). The collector consists of a receiver that plays a key role in a PDC. The less heat loss of the receiver, the higher temperature ranges achieve. There are different types of receivers, such as an external, cavity and flat. However, according to the literature, the highest energy conversion efficiency and the lowest heat loss belong to the cavity receivers as compared to non-cavity receivers, owing to their different geometries and shapes. Based on the geometrical shape of the cavity, the most commonly employed types of cavity receivers in PDCs are classified as cylindrical, conical, hemispherical and cubical (Kopalakrishnaswami and Natarajan 2021). Due to good thermal conductivity properties, aluminium and copper are mainly employed as the receiver material (Kumar et al. 2022).

Loni et al. (2018) predicted a dish concentrator's thermal performance and the cavity heat gain, shown in Fig. 33, utilising a hemispherical cavity receiver based on nanofluid (multi wall carbon nano tube/oil) as a working fluid by GMDH. While thermal efficiency and the cavity heat gain were output variables for modelling, solar irradiation, ambient and outlet temperature were considered input data. Their modelling results showed that the network could model data by R^2 index, 0.9567 and 0.9709 for thermal efficiency and the cavity heat gain, respectively. Since this index was near one, the model can be considered an accurate model for predicting thermal efficiency and other parameters regarding this type of solar collector. Furthermore, in Fig. 34, they compared the experimental result with modelling data. As shown, the modelling output has a good match with experimental results. Thus, this method can be used for modelling other parameters in solar parabolic dishes.

Somehsaraei et al. (2019) monitored and optimised the operation of a parabolic dish solar concentrator hybrid with a micro gas turbine by an artificial neural network combined genetic algorithm. Their model had good agreement with actual data and had high accuracy for monitoring applications.

Khosravi et al. (2019) investigated the impact factors on designing a solar dish located in Natal-Brazil by artificial intelligence modelling methods, namely GMDH, ANFIS and MLP-ANN (Fig. 35). They use metaheuristic algorithms, such as particle swarm optimisation (PSO) and genetic algorithm (GA), for optimising the training process in artificial neural network modelling. They considered dish diameter, day hours, solar radiation, geometric concentration factor and working gas-specific constant as input parameters, while power generation,

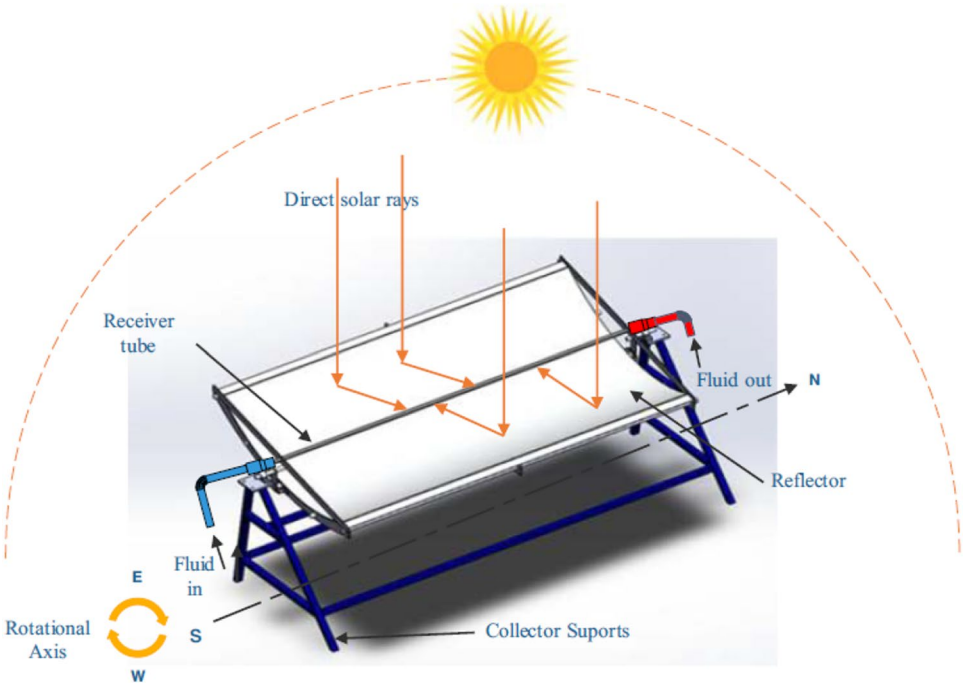


Fig. 32 A schematic of a parabolic trough solar collector (Parrales et al. 2022)



Fig. 33 The experimental setup of a dish concentrator (Loni et al. 2018)

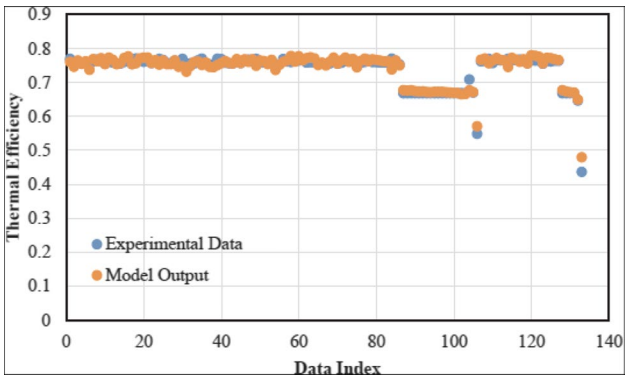


Fig. 34 The experimental setup of a dish concentrator (Loni et al. 2018)

global efficiency, the heat used, hot Stirling chamber temperature and engine speed were output and target data. According to their result, shown in Fig. 36, the hybrid particle swarm optimization and artificial neural network model was more accurate compared to other methods used in this study.

Zayed et al. (2021) developed a method model to anticipate the thermal performance parameters of SPDC with a cylindrical cavity receiver using based on the adaptive neuro-fuzzy inference system (ANFIS) integrated with an equilibrium optimiser (EO) which is applied as a new metaheuristic method to increase the ANFIS prediction forecast accuracy. In this work, three different predictions and optimisation methods were compared, such as ANFIS-EO, ANFIS and the conventional artificial neural network, to find the optimum values of ANFIS parameters for solar parabolic dish collector (SPDC) operation. The achievements showed that the best prediction accuracy was the ANFIS-EO technique, a powerful optimiser to anticipate the SPDC energetic performance.

Basem et al. (2022) investigated the exergy and energy of a combined parabolic solar dish with a diameter of 3 incorporated with a steam power plant. They used an artificial neural network to show the influential function of helpful energy in the parabolic solar dish. Their results showed that the model had a high accuracy with R^2 of 91.3%.

Solar tower

The solar tower is a structure that converts the energy of sunlight into electricity and is one of the clean energies since the operation of a solar power tower plant has no

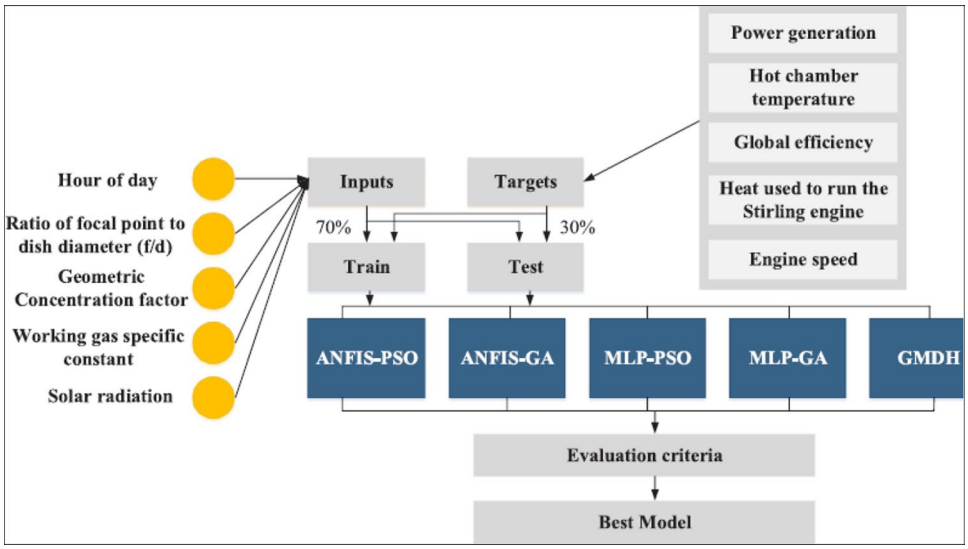


Fig. 35 A schematic of the artificial intelligence process diagram (Ali Khosravi et al. 2019)

detrimental impacts on the environment (Chen et al. 2022). The structure is classified into two different categories. The first type, the solar tower, which is based on a reflective state and heating the air inside the tower, consists of a rotating tower with a specific high located near a reflector area surrounded by thousands of mirrors called heliostats applied with a specific angle and a particular and limited distance from the tower. Each mirror is independent in tracking and reflecting the sunlight towards the tower. The second type uses liquid sodium and nitrate-based molten salts as the heat absorption and heat transfer fluid inside the tower receiver. The energy production cycle starts as the fluid heats up (Alexopoulos and Hoffschmidt 2017).

Fadaei et al. (2018) used a multilayer neural network to model and forecast the performance of a solar chimney, which is shown in Fig. 37. They used eight inputs and four outputs for modelling and training the network. In comparison with the experimental results, their modelling result had good accuracy. Their results showed a correlation between the predicted ANN data and the experimental data was above 99%. Furthermore, the average of the relative errors was under 3%.

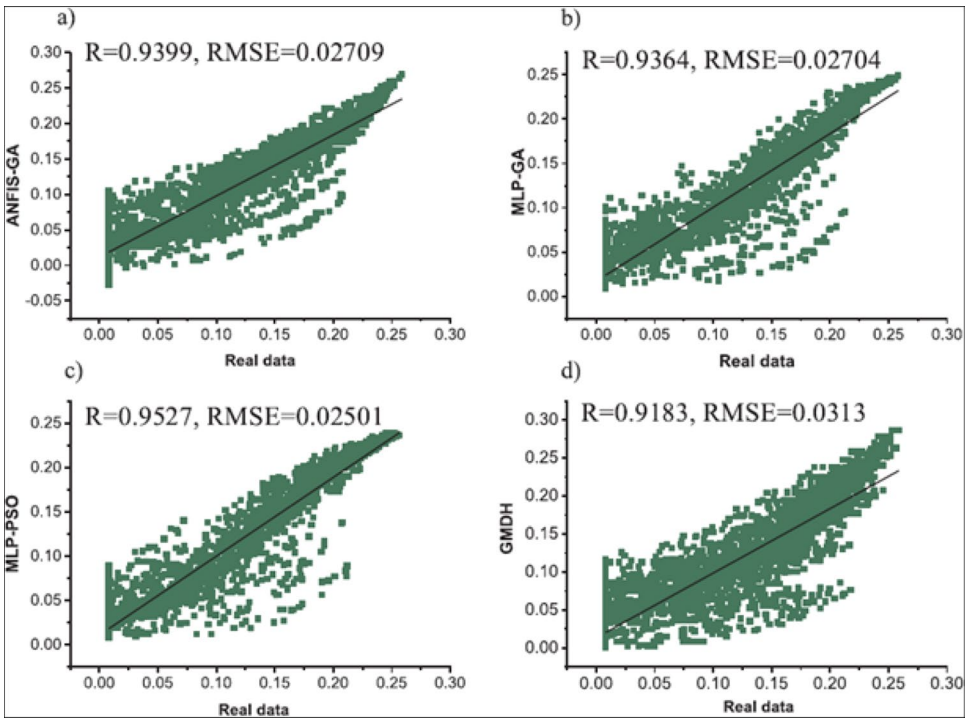


Fig. 36 The regression graphs for forecasting the global efficiency for different modelling methods. **a** ANFIS-GA. **b** MLP-GA. **c** MLP-PSO. **d** GMDH. **e** ANFIS-PSO (Ali Khosravi et al. 2019)

López et al. (2018) used vital parameters, such as sun position, mirror-to-receiver slant range and tower height, as input data in an ANN to forecast the corresponding DNI attenuation. Their results showed that modelling data had good agreement with accurate data, which can be applied to forecasting actual energy simulation codes in solar tower plant design.

Moukhtar et al. (2018) simulated a central tower receiver (CTR) by an artificial neural network. They used 888 datasets and three different algorithms, Levenberg–Marquardt (LM), quasi-Newton and scaled conjugate gradient, to train their model, which was the multilayer perceptron neural network. According to statistical indexes, the Levenberg–Marquardt algorithm with the root means square error, coefficient of variance and coefficient of determination of 0.0037, 0.0011 and 0.9999, respectively, showed that it was more accurate than other algorithms (Fig. 38).

Khosravi et al. (2020) modelled the design parameters of the solar power tower, namely the solar multiple, design direct normal irradiance and thermal storage hours by a hybrid adaptive neuro-fuzzy inference system and genetic algorithm. Since the learning process is vitally important in the machine learning method, they used the genetic algorithm for optimising the learning process. In that model, latitude, longitude, design point direct normal irradiance (DNI) and solar multiple (SM) are considered input data, whereas the cost, production and energy capacity are output data. Their result showed that the model could predict accurate data with a correlation coefficient of nearly one.

Ballestrín et al. (2020) applied an artificial neural network to model extinction as a significant variable in solar power tower plants. That study aimed to predict the essential parameter in the design and operation condition of that solar energy power plant. They considered two parameters, including aerosol particles and water vapour, travelling by solar radiation as the leading causes of the extinction. Thus, they could model this phenomenon well by ANN, and their result showed that the ANN modelling could be used in this application.

Wang et al. (2020) modelled the solar tower's thermal power by an artificial neural network under the meteorological conditions of Zhangbei (Fig. 39). Figure 40 shows that modelling data annually had good agreement with experimental data with the root mean square error and mean absolute error of 5.061 MWt and 2.871 MWt, respectively.

Benammar and Tee (2021) applied an artificial neural network to forecast the criticality index of solar tower power plants. They investigated and compared the actual data with modelling data and claimed that the provided model was acceptable for predicting index values. They used modelling data to maintain the solar tower power plants and suggested new recommendations for optimising process maintenance.

Generally, the result investigations showed that the employment of different learning algorithms for optimal ANN models could be used successfully for forecasting CSP system performance, such as parabolic troughs, linear Fresnel, parabolic dish and solar tower CSP power plants (Zayed et al. 2022).

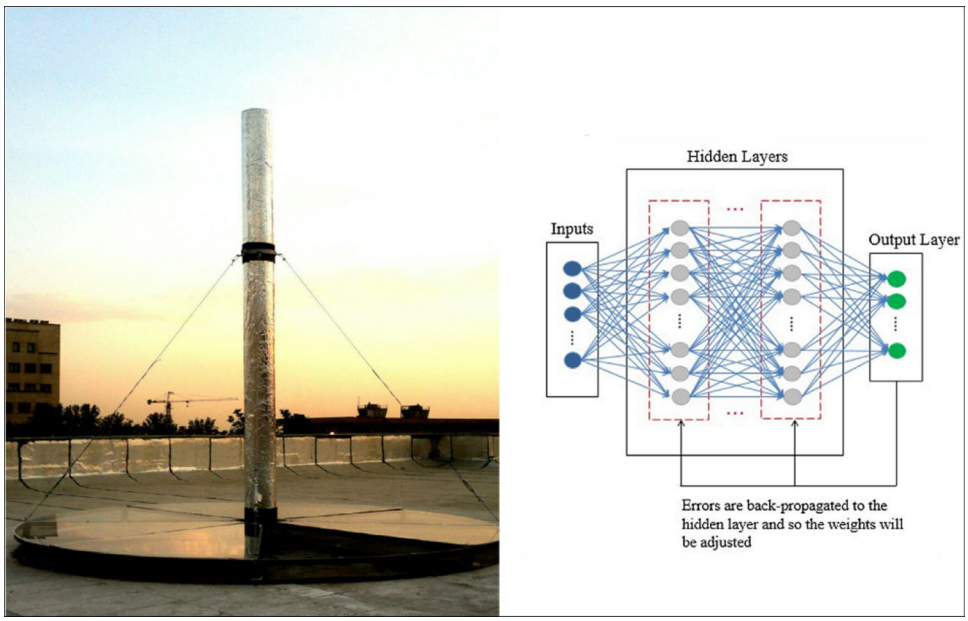


Fig. 37 The experimental setup and ANN structure (Fadaei et al. 2018)

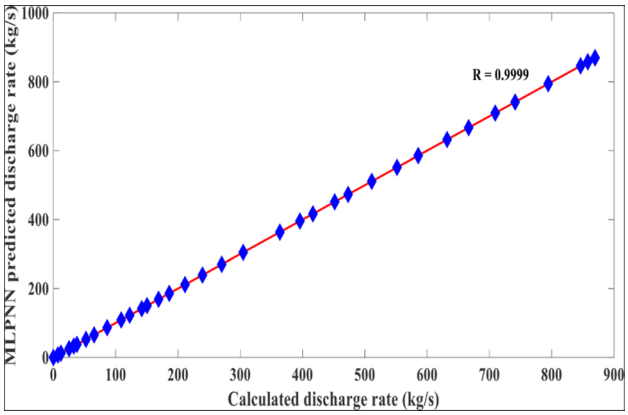


Fig. 38 The comparison between calculated discharge rate and MLPNN data (Moukhtar et al. 2018)

Current challenges and limitations

Several serious problems are related to machine learning methods for predicting different effective parameters in solar collectors. However, artificial intelligence can positively affect on cost and speed of the modelling process. Based on the studies carried out by other researchers, the main difficulties with the application of artificial intelligence in solar thermal collectors are related to the following issues:

- One of the significant limitations of machine learning is data collecting for the training, testing and validation process. Since gathering data for testing solar collector needs special weather conditions according to standard, this limitation can be considered a modelling problem.
- A considerable number of experimental or actual data are needed for modelling. This can be spent a large amount of budget for gathering data during a test.
- Due to the fact that the training data required play a key role in the model accuracy, optimising and selecting them are vitally important.
- Overtraining is another major limitation of machine learning modelling in an artificial neural network. Because the number of data usually is less than needed, this happens to model solar collectors more than other phenomena.
- No significant number of data sets is usually correctly applied in the training process because of uncertainties in the experimental data.
- Neural network models do not answer to extrapolation above the training data.
- A trial-and-error process selects the number of hidden layers and neurons. Thus, this process is time-consuming and may not be a suitable method.

Conclusion and future recommendations

Energy plays a vital role in human beings' life. Our energy consumption has been mainly dependent on non-renewable fuels for many years. Exploiting such primary sources has detrimental impacts on the environment and human well-being. To move away from fossil fuels, crude oil, natural gas and other exhaustible resources, we are to utilise free, sustainable, non-polluting energies, i.e. solar energy, used to generate sustainable electricity and thermal energy. Solar collectors are the most critical equipment for absorbing and transferring solar energy. So, the

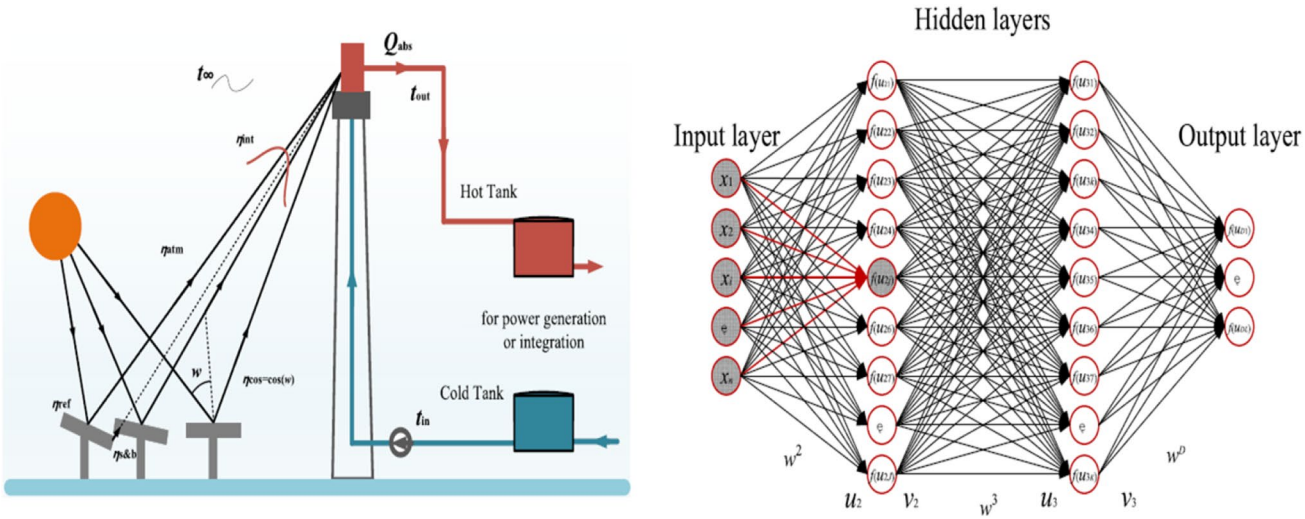


Fig. 39 A schematic of solar tower setup and ANN structure (Jianxing Wang et al. 2020)

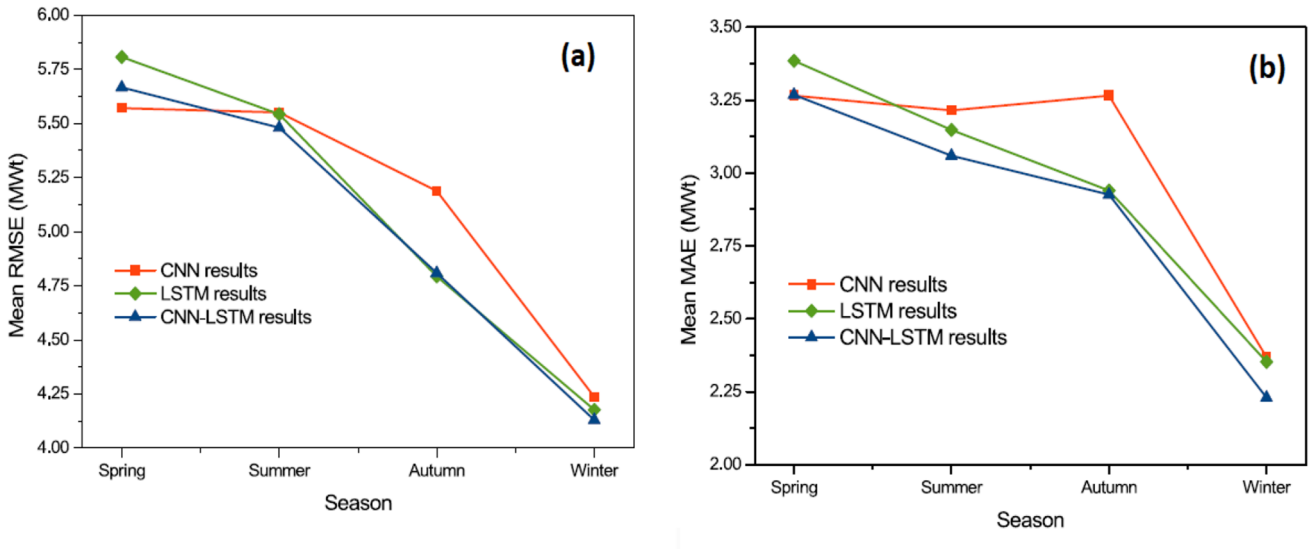


Fig. 40 The investigation of the results of statistical indexes in different seasons. **a** RMSE. **b** MAE (Jianxing Wang et al. 2020)

present review aims to summarise the recent advancements and research on the application of artificial intelligence in different types of solar thermal collectors, namely non-concentrating and concentrating, such as flat plate solar collectors, PV/T collectors, parabolic dishes, evacuated tube collectors, parabolic collectors and solar towers. The thermal, energy and exergy performances and heat transfer characteristics and design parameters were anticipated successfully by different machine learning methods, such as MLP-ANN, GMDH, RBF, ANFIS and SVM. According to the researchers' investigation, it can be mentioned that artificial intelligence can be considered an accurate, fast and low-cost method compared to other modelling methods such as computational fluid dynamics (CFD) and mathematical. Based on the investigations of new research, which authors have done, and according to the challenges mentioned before, the scope for future studies can be identified as follows:

- Investigate the role of the hidden layer number and neurons on the model accuracy and provide a new stable formula for calculating those.
- Comparative study of the accuracy and validation of machine learning method with another modelling method, such as CFD.
- The combination of population-based metaheuristic algorithms, such as genetic algorithm, particle swarm optimization algorithm, imperialist competitive algorithm, bee colony algorithm, firefly algorithm, artificial immune system algorithm, ant colony optimization algorithm and harmony search algorithm, with an artificial neural network for optimising the training process.
- The combination of single-solution metaheuristic algorithms, such as tabu search, simulated annealing, GRASP search, guided local search, variable neighbourhood search and iterated local search, with an artificial neural network for optimising the training process.

Author contribution M. Vakili: original draft preparation, writing, reviewing and editing.
S.A. Salehi: writing, reviewing and editing.

Data availability The data supporting this study's findings are available from the corresponding author upon reasonable request.

Declarations

Ethical approval Not applicable.

Consent to participate Not applicable.

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