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Chapter

Application of Artificial Neural Network in Solar Energy

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Abstract

Accurate prediction of system performance is very important for the optimal planning of solar energy systems. The latest research of artificial neural network (ANN) technology for predicting the efficiency of solar thermal systems and the performance of photovoltaic system is reported here. Application of ANN to performance assessment of solar collectors is briefly reviewed including novel all-glass straight-through evacuated tube collectors. An overview of the most recent work of ANN for combined photovoltaic/thermal panels (PV/T) and concentrating photovoltaic collectors is also provided.

Keywords: artificial neural network, solar collector, performance prediction, thermal efficiency, photovoltaic/thermal, concentrating photovoltaics

1. Introduction

The increase of population and development of world industry requires the massive use of fossil fuel [1], resulting in environmental pollution and global warming. Renewable energy is one of the effective technical methods to alleviate this phenomenon [2]. Solar Energy is the most rapidly developing and widely used renewable energy technology. At present, there are many application forms, including solar power generation [3], seawater desalination [4], heating [5], refrigeration [6], etc. For the estimation for the efficiency of solar thermal systems, experimental study and theoretical analytic simulation codes are often utilized [7, 8]. The traditional algorithms usually employed are very complex, including the solution of complicated different equations, which usually involves large resource and takes a great quantity of time to give exact solutions [8]. Moreover, traditional analysis methods are often based on simplified assumptions, as well as simplified models and solving nonlinear partial differential equations, which reduce the prediction accuracy [9–11]. ANN is a mathematical method that mimics the behavior of human brain. It has a strong ability to learn and find nonlinear relationships between input and output in systems [12], so it has the ability to realize information processing by adjusting the connection between internal nodes [12]. Unlike complex laws and mathematical routines in traditional analysis methods, ANN can learn key information patterns in multidimensional information domain [8]. Therefore, ANN technology has obvious advantages in speed, organization ability, fault tolerance and adaptability [8]. In recent years, ANN has gained more and more applications in the solar energy field, such as solar radiation prediction [13–17], photovoltaic power generation [18–20], solar drying [21], etc.

2. Background

The solar collector converts the solar radiation energy into heat and transfers it to the heat transfer fluid [7]. Recently, the application of ANN technology in the energy-engineering systems has attracted more and more attention. ANNs have been utilized by many researchers for modeling and prediction of thermal performance of various solar collectors. Delfani et al. [22] employed ANN to determine the efficiency of direct absorption solar collector with nanofluid, and investigated the influence of collector depth and length and other important parameters on its working performance and Nusselt number. Maria et al. [23] built ANN models to evaluate the efficiency of flat plate solar collectors with silver/water nanofluid, and the results are in good agreement with the experimental data. Cuma [24] and Kalogirou et al. [25] studied various methods to predict flat plate solar collectors and solar water heater with cylindrical concentrator respectively and analyzed them comparatively. It is evident that the ANN model greatly improved the prediction accuracy.

Many ANN algorithms are employed to predict the solar heating system performance. Kumar et al. [26] investigated a roughened solar air heater, focusing on the comparison of three ANNs to evaluate its exegetic efficiency of roughened solar air heater and obviously the Radial Basis Function (RBF) model has the best performance. Abdellah et al. [27] compared the advantages and disadvantages of traditional theoretical analysis (energy balance-based) method and ANN model (data based modeling methods) in determining the performance of heat pipe solar collector. According to the results, ANN was significantly superior to other traditional theoretical methods. Kumar et al. [28] utilized ANN and multiple linear regression model to evaluate heat transfer in a solar air heater with a rough absorber and compared their performance according to a number of statistical criterias. Kumar et al. [29] further contrasted ANN models with four training functions to estimate the thermal performance of uniform flow porous bed solar air heater, and the results showed that the prediction performance of the training function was better than the other three. They also analyzed the advantages and disadvantages of three ANN algorithms for thermal performance prediction of a solar air heater with unusual physical structure [30]. Liu et al. [31] proposed an evacuated solar water heater which has high collector efficiency by developing a technology based screening method. Sadeghi et al. [32] studied the factors affecting the exergy and energy efficiency of collectors and found that the usage of copper oxide/water nanofluid in a parabolic concentrator improved the thermal efficiency. Diez et al. [33] employed various methods to evaluate the outlet temperature of working medium, and concluded after comparison that the generalized regression neural network has the best prediction effect. ANN technology with above mentioned input to estimate the characteristics of flat-plate collectors has also been presented. Comparison with conventional analytical methods indicated the superiority of ANN models [34]. Budihardjo et al. [35] modeled and analyzed heat transfer and fluid flow in single evacuated tubes. Morrison et al. [36] investigated the influence of circular heat distribution on the performance of such tubes.

3. Application of ANN in an evacuated tube solar collector

At present, the most popular evacuated tube solar collector (ETC) in the market is Dewar-tube [37, 38], because it is cheap and easy to manufacture [38]. As the fluid flow in Dewar tube is driven by buoyancy [39–41], salt usually deposit at the bottom of the tube, which worsens heat transfer. But in the all-glass straight-through evacuated tube solar collector, stronger convection promotes heat transfer, reduces heat losses and improves water quality thus eliminating the main issue of salt precipitation and weak convective heat transfer inherent in traditional Dewar-tube [37, 42]. Better performance and high efficiency [36, 43–45] decrease the cost too.

3.1 Experimental set-up

The structure of all-glass straight-through evacuated tube collector is shown in **Figure 1**. Both ends of the inner (absorption tube) and outer tube (cover glass tube) are fused together. The space between the inner and outer tubes is vacuumed with pressure <0.013 Pa to reduce convective heat loss. The selective absorption coating is coated on the outer surface of the inner tube. Hence, the working temperature of the inner tube is higher than that of the outer tube, and the temperature difference leads to thermal stress. For the safe and stable operation of the evacuated tube, the outer tube is manufactured of glass with high thermal expansion coefficient, which can withstand the thermal stress. The detailed structure of the tube is illustrated in **Table 1**.

The heat transfer fluid used in the experiment is water, which flows through the all-glass straight-through evacuated tube solar collector. The collector inlet and outlet temperatures and ambient temperature were measured by thermocouples and recorded by a data logger. The water flow rate is measured by the rotameter placed at the inlet of the tube, as illustrated in **Figure 2**.

During the experiment, water flows through the evacuated tube driven by a pump, and the flow is adjusted and stabilized by a valve connected to the flow meter. The solar radiation intensity is surveyed by a special pyrometer. The experimental site is Nanjing, China. The collected actual data include solar radiation intensity, wind speed, ambient temperature, inlet and outlet water temperature and water flow rate and. The experiment was implemented from 10 a.m. to 4 p.m. every day, and the data were recorded every 30 minutes [30].

(a) (b)

Figure 1.
(a) Overview of the all-glass straight-through evacuated tube (b) Cross-section view of the inlet of the collector tube [51].

Parameter	Value
Length, L (m)	1.8
Absorber tube diameter, D_{abs} (m)	0.047
Outer glass tube diameter, D_{gla} (m)	0.058
Thickness of glass, ΔH (m)	0.003
Thermal conductivity of absorber, k_{abs} (W/mK)	1.2
Specific heat of absorber, C_{abs} $(J/(kg \cdot K))$	980
Absorptivity of selective coating, ξ_{abs}	0.96
Transmissivity of outer glass tube, τ_{gla}	0.96

Table 1.
Parameters of an all-glass straight through evacuated tube [11].

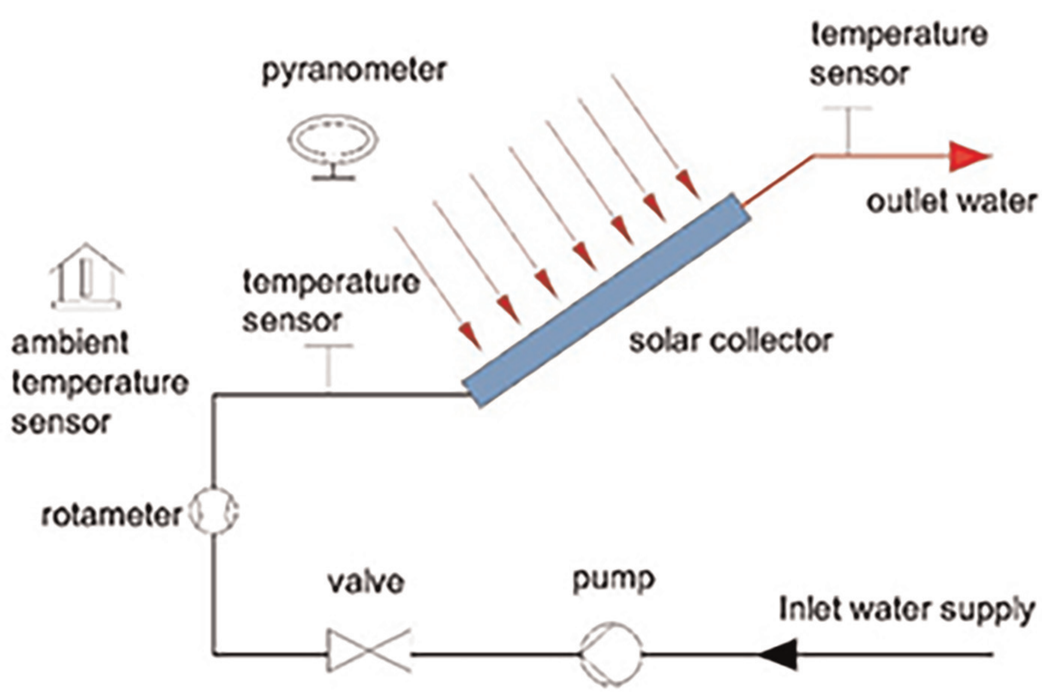

Figure 2.
Setup of the experimental system [12].

3.2 Methodology

Most of the solar energy absorbed by the evacuated tube is transferred from the tube inner wall of the tube to the working fluid flowing through the inner tube by convection heat transfer. Another part of the energy is transmitted to the inner wall of the outer glass tube through radiation and convection, and passes through the outer glass tube through heat conduction. Heat is lost to the environment by convection and to the sky by radiation from the outer surface of the outer glass tube.

Thermal efficiency is the most important criteria to evaluate the performance of evacuated tube solar collector. Here, the thermal efficiency is defined as the ratio of the heat obtained by the heat transfer fluid to the incident solar flux on the tube [30], and is written as follows [22, 46–48].

$$\eta_{th} = \frac{\dot{m}_f C_p (T_{fo} - T_{fi})}{IA_p} \quad (1)$$

where IA_p represents the solar radiation on the tube surface, T_{fi} and T_{fo} are the inlet and outlet temperature of water, respectively, $\dot{m}_f$ means the mass flow rate of heat transfer fluid, C_p is the specific heat of heat transfer fluid $(J/(kg \cdot K))$.

3.3 ANN modeling

The Multiple linear regression (MLR), Support vector regression (SVR), Back Propagation neural network (BP) and Radial basis function (RBF) are employed here for thermal efficiency prediction of the all-glass straight-through evacuated tube collector. The following variables are used as input parameters of the models: water flow rate m_f, inlet water temperature T_{fi}, wind speed w_a, ambient temperature T_a and solar radiation intensity I. The thermal efficiency of the solar collector η_{th} is the output lay. In this work, 70% of the total 158 experimental datasets are regarded as training dataset and the other 30% is test sets. In ANN models, the optimum number of neurons in hidden layer is evaluated by the equation which is recommended by Ghritlahre et al. [7]:

$$H_n = \frac{M + N}{2} + \sqrt{T_n} \# \quad (2)$$

where H_n represents the number of hidden neurons, M and N are the input and output neurons, T_n is the number of training data.

3.3.1 Data preparation

There is likely to be a large dimension and dimension units difference between the measured data, which will seriously affect the prediction performance. Data normalization is essential to eliminate the dimensional influence among the indices. Here, the normalization is expressed as:

$$Y_{norm} = \frac{Y_i - mean}{std} \quad (3)$$

where mean represents the mean of the training samples, std. means the standard deviation of the training samples. The normalized data is distributed in a reasonable range, which is beneficial for further processing and analysis.

3.3.2 Performance evaluation criteria

Several criteria can be utilized to assess the accuracy of the proposed models. Their definitions are as follows:

Coefficient of Determination:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (X_{A,i} - X_{P,i})^2}{\sum_{i=1}^{n} X_{P,i}^2} \quad (4)$$

Root Mean Squared Error:

$$\mathbf{RMSE} = \sqrt{\frac{\mathbf{1}}{\mathbf{n}}\sum_{\mathbf{i=1}}^{\mathbf{n}}(\mathbf{X_{A,i}} - \mathbf{X_{P,i}})^2} \# \tag{5}$$

Mean Absolute Error:

$$\mathbf{MAE} = \frac{\mathbf{1}}{\mathbf{n}}\sum_{\mathbf{i=1}}^{\mathbf{n}}(\mathbf{X_{A,i}} - \mathbf{X_{P,i}}) \tag{6}$$

where n represents the total number of data, $X_{A,i}$ is the actual efficiency of the collector, and $X_{P,i}$ means the predicted efficiency value.

3.4 Results and discussion

After evaluation with Eq. (2), selecting 10–16 neurons in hidden layers to verify with BP algorithm, and it is obvious that the model with 13 neurons is the best.

Table 2 illustrates the comparison of RBF, BP, MLR and SVR models in predicting the thermal efficiency of all-glass straight-through evacuated tube.

It is evident that the accuracy of RBF is superior to the other methods followed by the BP model, but obviously the SVR, BP and RBF can all successfully carry out the prediction. Dealing with nonlinear problems is not the strength of MLR algorithm [49]. For nonlinear problems, SVR finds a nonlinear mapping to map the input data to the high-dimension feature space first, so that the separation status is greatly improved. Then, to classify in such feature space, and after that return to the original space, and then get the nonlinear classification of the original input space. However, after all, SVR uses linear algorithm for nonlinear regression in high-dimensional attribute space. Comparatively speaking, the major benefit of neural network method is that it is good at solving complex nonlinear relationship among variables efficiently. Thus, the deviation between the neural network model prediction values of the evacuated tube thermal efficiency and the actual data is the minimum.

The comparison between the actual data and the prediction results of the proposed models is shown in **Figure 3**. It is evident that the results of RBF model are the closest to the actual data among the four models investigated.

3.4.1 Sensitivity analysis

Sensitivity analysis refers to finding the sensitive factors that have a significant impact on the output of the models from many uncertain factors, and analyzing and calculating their impact and relative importance on the results. In short, sensitivity

Model	MAE	RMSE	R^2
MLR	0.0095	0.0121	0.6111
SVR	0.0056	0.0092	0.8447
BP	0.0053	0.0080	0.9059
RBF	0.0043	0.0066	0.9658

Table 2.
Accuracy of the models in performance prediction [11].

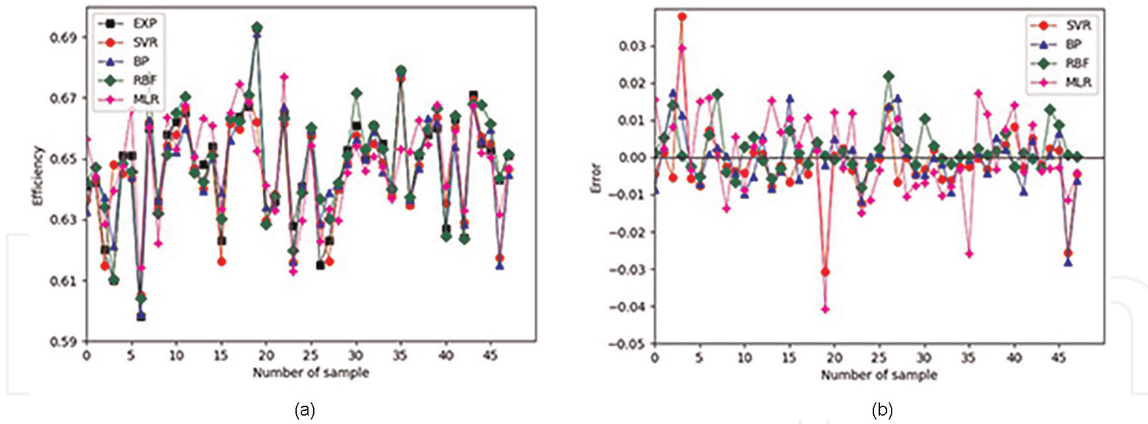

Figure 3.
(a) Comparison of experimental and MLR, SVR, BP and RBF predicted thermal efficiency. (b) Individual error with MLR, SVR, BP and RBF models [11].

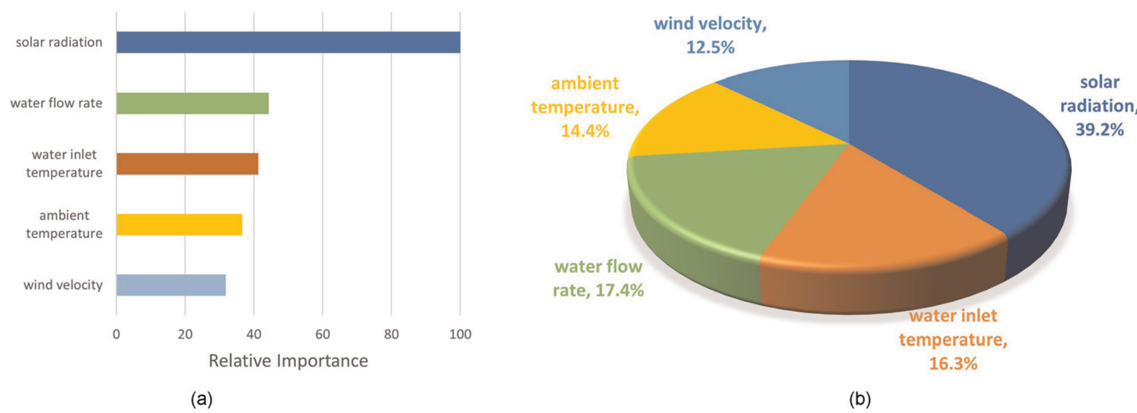

Figure 4.
(a) Relative importance of input variables based on solar radiation. (b) Relative importance (%) of the inlet variables on the thermal efficiency of the evacuated tube [11].

analysis is to see which variable changes the conclusion is sensitive to [50]. Taking the RBF model in this analysis as an example, the relative importance of every input parameter to the output result is illustrated in **Figure 4**. Clearly, the solar radiation has the largest impact on the efficiency prediction of the proposed evacuated tube, followed by collector inlet temperature and water flow rate.

The efficiency value calculated by RBF model is illustrated in **Figure 5**. With the enhancement of solar radiation and the increase of water flowrate, the convective heat transfer in the tube is promoted, and the thermal performance of the evacuated tube rises. **Figure 5(b)** shows the change of thermal efficiency of evacuated tube with water flow rate and wind speed when the solar radiation intensity is 900 $\mathbf{W/m^2}$. It is visible that the increase of wind speed promotes the heat dissipation from the surface of the outer glass tube to the environment, resulting in a rise in the heat loss of the evacuated tube and a decrease in its thermal efficiency.

3.5 Combining CFD and ANN techniques modeling

The dominant energy equations of the studied all-glass straight-through evacuated tube solar collector, as well as necessary heat and mass transfer and other related

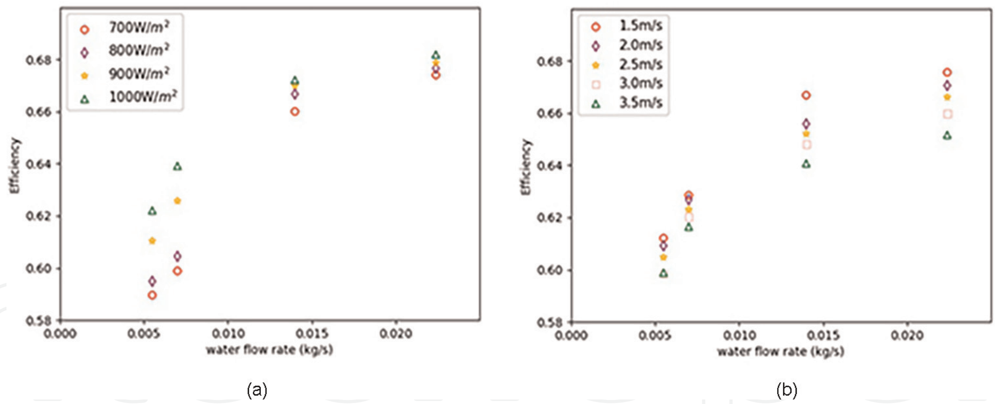

Figure 5.
(a) Efficiency vs. water flow rate (wind speed 1.5 m/s). (b) Efficiency vs. water flow rate (solar intensity 900 W/m²*) [11].*

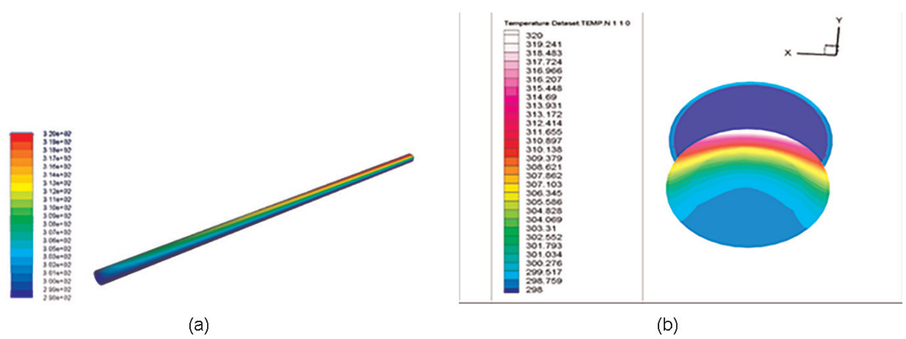

Figure 6.
(a) Temperature distribution alongside the tube. (b) Inlet and outlet temperature. Irradiance is 1000 W/m² *[51].*

conditions required for theoretical analysis have been explained in detail in [51]. The 3-D model based on these equations and conditions of the proposed evacuated tube is developed into the computational fluid dynamics (CFD) software ANSYS Fluent [47, 52, 53] to carry out the heat transfer simulation.

Figure 6 shows the temperature distribution of the evacuated tube obtained by numerical simulation of the tube model. In **Figure 6**, the inlet temperature is 298 K, the mass flow rate is 25 kg/h, and the solar radiation intensity is 1000 W/m^2.

The MLR, BP and convolutional neural network (CNN) [54, 55] models were employed to determine the thermal characteristics of all-glass straight-through evacuated tube solar collector. A total of 243 experimental data sets were employed, of which 70% were used for training and 30% were test datasets. Collector inlet water temperature, wind speed, water flow rate, ambient temperature and solar radiation intensity and the values calculated by the theoretical CFD models were used as input, the collector outlet water temperature and the thermal efficiency of the tube were regarded as output (see **Figure 7**). The output values with and without the theoretical model + CFD were compared with experimental data.

The prediction accuracies of studied models are illustrated in **Table 3**. The measurement criteria of CNN model with modeled value as one of the input parameters (CFD-CNN) is the best. Comparing the data in **Table 3**, when the modeled value of the collector outlet temperature is taken as one of the inputs, the prediction accuracies of MLR, BP and CNN models are significantly enhanced (**Figure 8**).

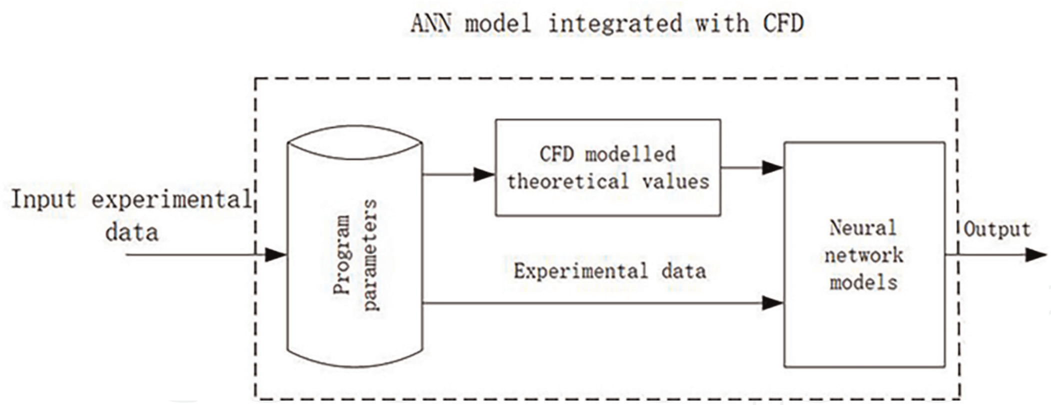

Figure 7.
Illustration of the integrated models [51].

Models	R^2		RMSE		MAE	
	Water outlet temperature	Thermal efficiency	Water outlet temperature (°C)	Thermal efficiency	Water outlet temperature (°C)	Thermal efficiency
CFD-CNN	0.9971	0.9684	0.0823	0.0044	0.0559	0.0028
CNN	0.9629	0.9548	0.3002	0.0051	0.1693	0.0036
CFD-BP	0.9937	0.9434	0.1209	0.0055	0.0910	0.0038
BP	0.9555	0.9192	0.3305	0.0067	0.2219	0.0043
CFD-MLR	0.9924	0.7443	0.0975	0.0108	0.0564	0.0086
MLR	0.7210	0.6736	0.8436	0.0112	0.6920	0.0080

Table 3.
Inaccuracies of the different models [51].

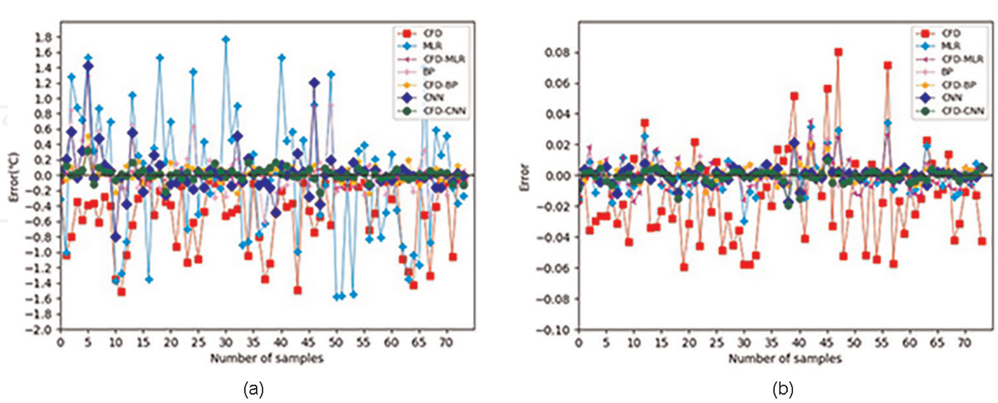

Figure 8.
Prediction error of collector (a) outlet temperature and (b) thermal efficiency by the models [51].

4. Application of ANN technique to photovoltaics

Several previous studies have reviewed the application of ANN into solar irradiance and photovoltaics (PV) power production forecasting, anomaly detection (fault diagnostic) in PV, tracking the maximum power point (MPP), etc. Here an overview of the most recent work on ANN for photovoltaic/thermal (PV/T) systems and concentrating PV(CPV) is presented.

Ammar et al. [56] investigated a PV/T based water pumping and heating system in which the PV/T panel simultaneously delivers electrical power P and thermal power Q. An ANN model was developed to determine the optimal power point (OPOP), which is defined as the crossing point of the max(P × O) curves. The focus was to calculate the optimal value of water flow with varying ambient temperature and solar radiation conditions to ensure maximum electrical power and thermal power output. The proposed neural network model regarded the solar radiation intensity and ambient temperature as the input layer and the output is the corresponding optimal water flow rate. The normal mean bias error (NMBE) was used to measure the accuracy of the ANN when the ambient temperature was 5–35°C and the solar radiation varied from 350 to 950 W/m^2, yielding a NMBE of −13.05%. The collected data was divided into cold and hot season according to the weather, for which the OPOP was computed respectively. The results show that during the hot season, with relatively stable weather conditions, the accuracy of the estimated value of the neural network model is better. The ANN algorithm provides a feasible control strategy for similar PV/T systems.

AI-Waeli et al. [57] studied a photovoltaic/thermal system using a special experimental rig for ANN analysis., Three cooling strategies were employed to verify the effectiveness of the design: PV/T with water-filled container and water as working fluid, PV/T with PCM-filled container and water as working fluid, PV/T with container filled with nanoparticles dispersed in Phase Change Material (PCM) and nanofluid as working fluid, as well as the conventional PV panel as reference. The nano-PCM and nanofluid using SiC nanoparticles yielded the best cooling effect among these methods, and the maximum efficiency reached 13.3%, while the efficiency of conventional PV was 8.1% only. Three ANN models, namely, MLP, SOFM and SVM, were used to evaluate the performance of the investigated PV/T system showing slight differences in the performance prediction.

Ahmadi et al. [58] developed ANN models such as multilayer perception (MLP), RBF, least squares support vector machine (LSSVM) and adaptive neuro-fuzzy inference system (ANFIS) to model the efficiency of a PV/T plate which contains a full circle tube as the fluid channel that is bonded to the absorber plate by special adhesives. Solar heat, solar radiation, heat, flow rate, inlet temperature were regarded as inputs, and the electrical efficiency as the output of these models. By comparing the RMSE and correlation coefficient (R^2), the LSSVM approach gave the best accuracy with R^2 = 0.9867. Using a sensitivity analysis, it was found that the inlet temperature had the greatest impact on the efficiency of the proposed PV/T system.

ANN models were also used to predict the thermal efficiency of a PV/T system that has a serpentine tube connected to the plate and using water as the cooling fluid [59]. MLP-ANN, ANFIS and LSSVM were employed to specify the thermal efficiency of the solar collector as output and inlet temperature, water flow rate and solar irradiance as input layer. The ANN model provided that best prediction performance when using the mean squared error (MSE) and determination coefficient (R^2) for the comparison. Also, here the inlet temperature proved to have the greatest impact on the thermal efficiency of the PV/T panel.

Cao et al. [60] explored six AI models, including least-squares support vector regression (LS-SVR), adaptive neuro-fuzzy inference systems (ANFIS), and four ANN methods, i.e., multi-layer perceptron (MLP), cascade feedforward (CFF), radial basis function (RBF) and generalized regression (GR) for evaluating the electrical efficiency of a PV/T system cooled by the nanofluids. Through comprehensive comparison of statistical indices such as the absolute average relative deviation (AARD), mean square error (MSE) and coefficients of determination (R^2), it was found that the ANFIS model had the best prediction accuracy for the electrical efficiency of studied PV/T system. The theoretical analysis also showed that the SiC water nanofluid was the best coolant for the PV/T system.

In [61], three ANN methods, including the radial-basis function artificial neural network (RBFANN), were employed to predict the performance of a photovoltaic thermal nanofluid (PVT/N) based collector system which is equipped with a copper sheet and tube collector and zinc-oxide (ZnO)/water nanofluid as coolant. Ten days experimental data in various weather conditions were used for training and to test of the proposed AI approach. Ambient temperature, incident solar radiation and fluid inlet temperature were regarded as input while fluid outlet temperature and electrical efficiency were set as the output layer. The ANFIS was more accurate for predicting the fluid outlet temperature, but the RBFANN was superior to the other methods to predict the electrical efficiency of the proposed PVT/N unit.

Renno et al. [62] compared the prediction performance of Random-Forest (RF), ANN and Linear Regression Model (LRM) approaches to predict the temperature of multi-junction solar cells. The studied cells constituted of InGaP/GaAs/Ge and InGaP/InGaAs/Ge under a high concentration Fresnel lens. The input variables were the local hour, global radiation, concentration factor and the environmental temperature , and the cell temperature was used as output. The RF method yielded the best performance with the lowest values of RMSE, MAE and MAPE. It was is observed that the cell temperature increased with the increasing ambient temperature, solar radiation, and concentration ratio.

In [63], the power output of a V-trough photovoltaic system was predicted with support vector machine (SVM), ANN, kernel and nearest-neighbor and deep learning (DL) methods. Through a statistical indices comparison, the support vector machine gave better performance prediction accuracy, although all the presented algorithms predicted the PV module power output satisfactorily. Also, the ANN model was not inferior to the SVM algorithm in evaluating the peak data. The prediction performance of DL and ANN were also compared with SVM. The results showed that the predicted PV power output by DL was higher than the actual data, which was likely due to the availability of data.

5. Conclusions

Application of artificial neural network for performance prediction of solar energy collectors has briefly been introduced here including comparison to traditional analysis methods.

Back propagation (BP), radial basis function (RBF), support vector regression (SVR) and multiple linear regression (MLR) were used to predict the performance of a novel all-glass straight-through evacuated tube solar collector employing experimental datasets. The RBF and BP outperformed the SVR and MLR methods, but the accuracy of the first three models mentioned above were well within acceptable limits (R^2s were 0.8447, 0.9059 and 0.9658, respectively). However, the MLR algorithm was not good in dealing with nonlinear problems. The RBF method showed the best performance with the lowest RMSE (0.0066) and the lowest MAE (0.0043) for the solar collector efficiency prediction.

A novel approach combining mathematical performance simulation (CFD) and neural networks was also investigated for determining the performance of the all-glass straight-through evacuated tube. The results show that regarding CFD modeled output as the input of ANN significantly improved the evaluation accuracy of all proposed models including MLR, BP and convolutional neural network (CNN). The CFD-CNN model is superior to the other studied models with the highest R^2 and the lowest RMSE, 0.9684 and 0.0044 (**Table 3**).

The research on applying ANN to photovoltaics was also reported with focus on the utilization of neural networks for output power prediction of photovoltaic/thermal system (PV/T) and concentrating photovoltaics (CPV). The review demonstrated the usefulness of ANN also for the PV field.

Future work of ANN in solar energy could extend to other design parameters and meteorological data as input to the neural network model. Also, using new ANN approaches such as the recurrent neural network could be relevant. Future directions of interest include the combination of some metaheuristic methods such as gray wolf optimization (GWO), genetic algorithm (GA), particle swarm optimization (PSO) and ANN to optimize ANN structure and improve ANN performance. Extensions of ANN, e.g., extreme machine learning (EML), adaptive network-based fuzzy inference system can be used to improve prediction accuracy. Based on the work presented here, it is believed that the artificial neural network will increasingly be applied in the field of solar energy.

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