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RESEARCH ARTICLE - SPECIAL ISSUE

Novel hybrid computational intelligence approaches for predicting daily solar radiation

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Abstract
Accurate estimation of solar radiation is crucial for harnessing this abundant natural resource effectively. Measuring solar radiation directly requires ground station networks, which are either unavailable or very limited in many regions of the world, including Vietnam, particularly in remote areas due to resource constraints. Therefore, this study was carried out with the objective to develop hybrid artificial intelligence (AI) models to predict solar radiations correctly using other meteorological data such as wind speed, relative humidity, maximum and minimum temperature and rainfall which can be measured at site easily. In this study, we have proposed three novel hybrid AI models, namely ANFIS-GA, ANFIS-BBO and ANFIS-SA, which combine the adaptive neuro-fuzzy inference system (ANFIS) technique with genetic algorithm (GA), biogeography base optimization (BBO) and simulated annealing (SA), respectively, for predicting daily solar radiation in Hoa Binh province, Vietnam. The performance of these hybrid models was evaluated using statistical indicators, including correlation coefficient (R), root-mean-squared error (RMSE) and mean absolute error (MAE). The results demonstrate that all three optimized models outperform the single ANFIS model. Among them, the ANFIS-BBO model exhibits the highest predictive capability (RMSE = 3.141 MJ/m^2, MAE = 2.439 MJ/m^2, R = 0.874). Sensitivity analysis reveals that maximum temperature is the most influential factor for predicting daily solar radiation. The findings of this study have significant implications for predicting solar radiation using AI methods, particularly ANFIS-BBO, with minimal meteorological data in remote locations not only in Vietnam but also globally.

Keywords Solar radiation · Artificial intelligence · Meteorological variables · ANFIS

Introduction

Solar radiation prediction is an important factor as its impact on living matter and feasible applications for many productive purposes such as renewable energy (Lee and Cheng 2016; Mohanty et al. 2016), direct or indirect conversion of sunlight into electricity (Saberian et al. 2014; Okoye and Solyalı 2017; Lalwani et al. 2011) and heating systems for water (Kalogirou et al. 1999) or air (Karim and Hawlader 2004). Solar radiation on Earth's surface plays a vital role in many fields, including meteorology [8,9], irrigation (Gao et al. 2013; Twersky and Fischbach 1978; Hernandez-Ramirez et al. 2014), solar energy (Yeh and Lin 1996; Bilal et al. 2012; Cruz-Peragon et al. 2012; Bataineh and Dalalah 2012; Lv et al. 2018) and drought monitoring (Zhang et al. 2019). The solar energy exhibits a vastly lower environmental impact, in terms of pollution, compared to other types of energy such as fossil fuels (Chen et al. 2015; Handayani et al. 2019). Recently, increasing numbers of solar farms have been installed all over the world to harvest this type of renewable energy (Park et al. 2015; Shiva Kumar and Sudhakar 2015; Yang et al. 2017). Therefore, precise estimation of solar radiation is one of the primary requirements for sustainable development, for every country around the globe (Bishoge et al. 2018).

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Daily solar radiation on the surface of Earth depends on spatial and temporal factors (Nomiyama et al. 2011; Voyant et al. 2012) such as local weather, local landscape, season, time of day and geographic location. Measuring solar radiation and related factors requires ground station networks, which are unavailable or very limited in many regions of the world, particularly in developing countries including Vietnam (Rao 1983; Polo et al. 2015b; Xue 2017). Traditional prediction models tried to analyze the correlation between long-term measurement of solar radiation and several parameters, namely sunshine duration, wind speed, air temperature, precipitation, cloud conditions and relative humidity (Taşdemiroğlu and Sever 1991; Gouda et al. 2019; Khorasanizadeh and Mohammadi 2013; Mghouchi et al. 2016; Mohammadi et al. 2015; Mousavi et al. 2017; Paoli et al. 2010) and geographical parameters (latitude, longitude and altitude) (Jain 1986; Lewis 1992; Türk Toğrul and Onat 1999; Chegaar and Chibani 2001; Chen et al. 2004). Various empirical equations for estimating solar radiation were proposed by researchers, namely Angström (1924), Angström–Prescott (PRESCOTT 1940), Bahel et al. (1987), Bristow and Campbell (1984), Allen (1997), Hargreaves et al. (1985) and Jin et al. (2005).

In recent decades, artificial intelligence (AI) techniques have been widely utilized for the prediction of solar radiation (Voyant et al. 2017), which are considered as more advanced approaches than traditional techniques in analyzing nonlinear relationship between input variables and target variables (Yadav and Chandel 2014). Many researchers (Paoli et al. 2010; Zeng and Qiao 2013; Voyant et al. 2013; Güçlü et al. 2014; Belaid and Mellit 2016; Bou-Rabee et al. 2017) applied and compared artificial neural networks (ANN) with conventional models for forecasting daily solar radiation and stated that ANN model had better performance than the conventional models. Other most common AI techniques used for predicting solar radiation include support vector machine (SVM), regression tree (RT) and random forest (RF) (Voyant et al. 2017). Ağbulut et al. (2021) applied and compared various AI models, namely kernel and nearest-neighbor (k-NN), ANN, SVM and deep learning (DL) for the prediction of daily global solar radiation of four provinces of Turkey (Nevşehir, Tokat, Kırklareli and Karaman). Cornejo-Bueno et al. (2019) applied and compared different AI models, namely SVM, ANN, extreme learning machine (ELM) and Gaussian process (GPR) for the prediction of global solar radiation based on geostationary satellite data in the Toledo, Spain. Similarly, linear regression and GPR models were applied to predict the daily solar radiation using the weather data (wind speed, temperature, pressure and humidity parameters) obtained from the meteorological department in Zonguldak province in Turkey (Hacioğlu 2017). Various AI models, namely SVM, gradient boosted regression (GBR) and RF, were applied and compared for prediction of solar radiation obtained from seven weather stations located in Spain (Gala et al. 2016). In general, the AI models, especially hybrid AI models, are quite effective and accurate for solar radiation prediction (Gala et al. 2016).

In the present study, the main aim is to develop novel hybrid AI models, namely ANFIS-SA, ANFIS-BBO and ANFIS-GA which are the combination of adaptive neuro-fuzzy inference system (ANFIS) and various optimization methods including simulated annealing (SA), biogeography base optimization (BBO) and genetic algorithm (GA), respectively, to predict solar radiations correctly using meteorological data such as relative humidity, wind speed, maximum and minimum temperature, sunshine duration and precipitation which can be easily measured. We have selected Hoa Binh province, Vietnam, as a study area, where the facility to directly measure solar radiation is very limited in comparison to measurement of other meteorological parameters (Nguyen and Pryor 1996, 1997; Polo et al. 2015a, b). Validation of these hybrid models was carried out using statistical methods, namely root-mean-squared error (RMSE), correlation coefficient (R) and mean absolute error (MAE). MATLAB software was used for the model's development.

Description of methods used

Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS was first introduced in the 1990s (Jang 1993). It is considered a universal estimator with the ability to approximate nonlinear functions (Jang 1997; Abraham 2005). In this method, the fuzzy inference system corresponds to IF–THEN rules (Takagi and Sugeno 1983, 1993). Type-2 ANFIS architecture is illustrated in Fig. 1. Structurally, it is a feed-forward multilayer neural network consisting of five layers with one target (f) and two inputs (x, y). Circles and rectangles, respectively, denote fixed nodes and adaptive node functions. Description of the five layers is given in literatures (Mashaly and Alazba 2018; Bui et al. 2018; Dao et al. 2019a, b).

ANFIS is well known as one of the effective AI models (Mukerji Aditya et al. 2009). However, it has a limitation in finding the optimal hyper-parameters for training the model (Bui et al. 2016). Therefore, optimization techniques including GA, SA or BBO are good tools in solving this limitation and improving the performance of ANFIS (Tien Bui et al. 2016; Pham and Prakash 2017; Jaafari et al. 2019).

Genetic algorithm (GA)

GA was first introduced by John Holland (Goldberg and Holland 1988; Holland 1992) and influenced by biological evolution in nature as described by Darwin's law (McCall 2005). It has been successfully utilized by researchers in

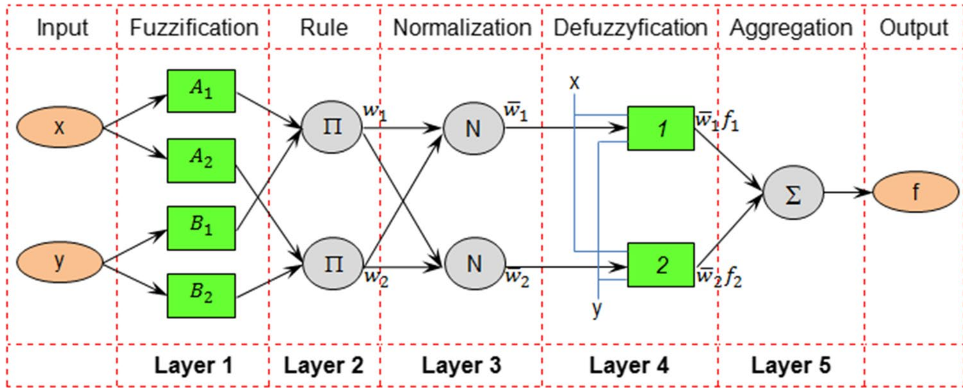

Fig. 1 Five-layer ANFIS architecture

a range of fields for optimizing complex problems (Cheng et al. 2017; Sohail 2017; Bui et al. 2018; Hong et al. 2018; Le et al. 2019). GA is considered to be a population, where each individual is called a chromosome, composed of different problem variables that function as genes in the algorithm (Melanie 1999). GA procedure is created by randomly developing a chromosome population and then producing the next generation through several steps, such as (1) the size and initial population are randomly generated by defining upper and lower bounds, and each chromosome is defined as a binary string, (2) the best chromosomes (i.e. the best solutions) are chosen by computing the fitness function of each one, (3) combining a pair of chromosomes (parents) to produce a new chromosome (offspring or child) with the best genetic characteristics, (4) inserting new characteristics into the offspring population by randomly changing some of the genes inside the chromosomes, and (5) when the generation process is terminated, the chromosome with the highest fitness value is decoded to get the optimal results. Recently, GA was adopted as an effective optimization algorithm for solving multi-dimension space problems (Cheng et al. 2017; Bui et al. 2018; Hong et al. 2018). The technique has been widely implemented in various hybrid optimization investigations; for instance, GA combined with response surface methodology has been examined by Winiczenko et al. (2016) and Unni et al. (2019) as an optimization of ANN.

Simulated annealing (SA)

SA is a powerful optimization technique based on the similarity between the annealing algorithm and search algorithm used in metallurgy (Metropolis et al. 1953). It simulates the cooling process by steadily decreasing the temperature of the system until it reaches a stable state to avoid damage due to freezing when cooling too quickly, or the time-consuming nature of the cooling if too slow. Search algorithms focus on promising solutions without ignoring better solutions.

In order to eliminate crystalline imperfections, solid metal is heated and then cooled slowly in the annealing process; thus, the free energy of the solid is optimized as a minimum (Laarhoven and Aarts 1987; Vidal 1993; Pham and Karaboga 2000; Salamon et al. 2002; Pétrowski and Taillard 2005). Consequently, in simulated annealing, temperature is parametrized in order to control the heating and cooling process. Initial heating is indispensable to prevent a local minimum. The principle of SA is illustrated in Fig. 2.

SA algorithm normally consists of successive jumps in the problem solving process, but can be divided into three basic steps as follows (Laarhoven and Aarts 1987; Vidal 1993): (1) assign a solution with current temperature, (2) change the temperature by the specified rate to create a new solution, and (3) evaluate the system improvement.

Biogeography base optimization (BBO)

BBO, introduced by Simon et al. (Simon 2008), is an algorithm based on the science of biogeography, which studies the distribution of living organisms (plants and animals) in both time and space. Its purpose is to explain behaviors of the shifting populations of species in various habitats (Christy and Raj 2014). In the BBO algorithm, a habitat H, which is an N-value integer vector, is first initialized based on the values of SIV. In order to reach the global minimum error, each individual in the population needs to be evaluated before optimizing the population using migration and mutation. Indeed, the flowchart of the BBO algorithm is presented in Fig. 3, consisting of five main steps (Simon 2008, 2013), such as (1) generation of initial population based on given population size, (2) evaluation of the objective function and sorting of solutions, (3) the immigration and emigration rates of each candidate

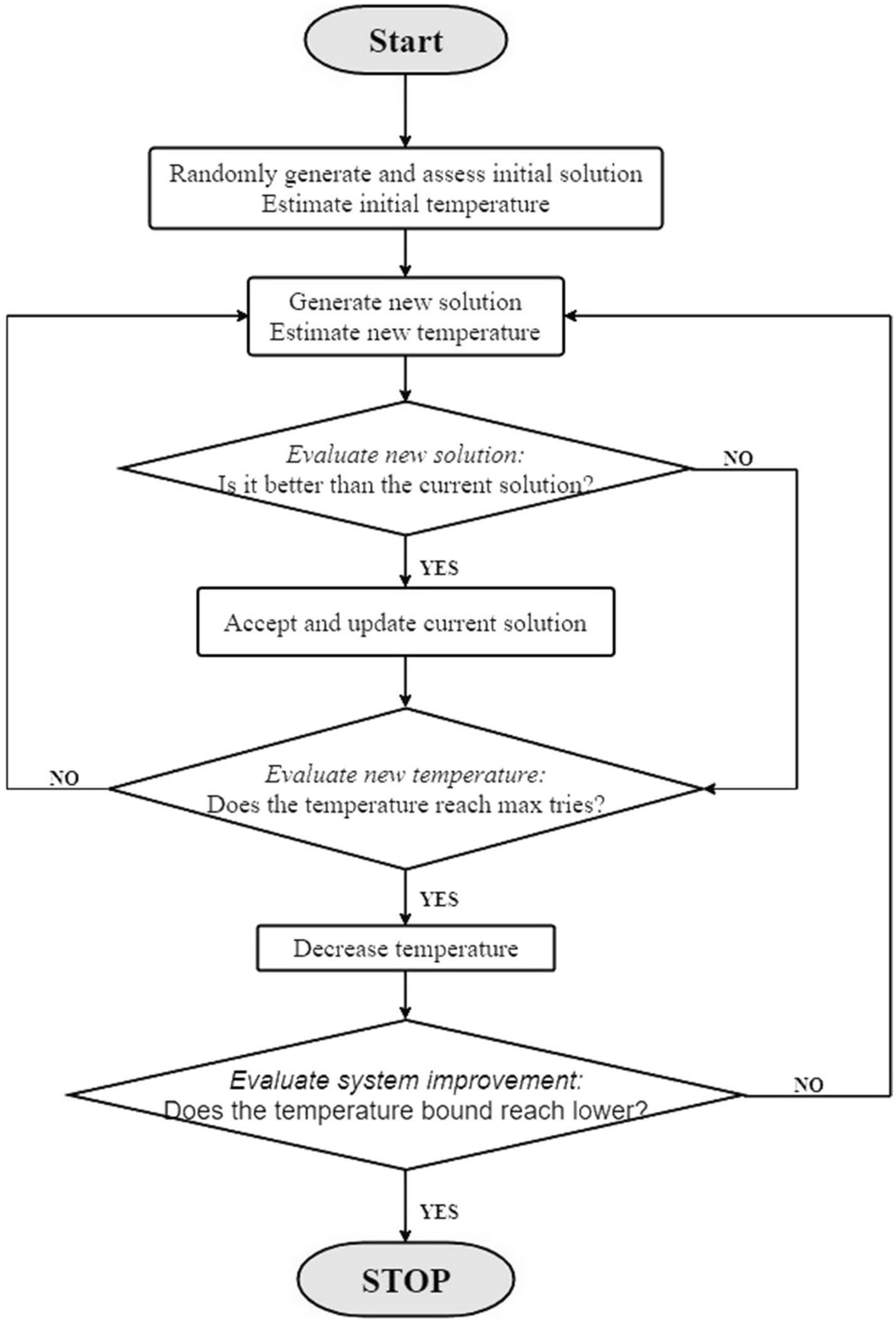

Fig. 2 Simulated annealing process

solution are computed, (4) the mutation rate of each candidate solution is computed based on the immigration and emigration rates, and (5) the objective function is evaluated until the stop criteria are satisfied.

Validation criteria to assess models' performance

In this study, three most common validation metrics: MAE, R and RMSE, were used to assess the effectiveness of the proposed AI models (Devore 2015; Ly et al. 2019; Pham et al. 2019). MAE measures the average magnitude of the differences between target values and the modeled predictions, without considering their direction or weights. RMSE is the square root of the median of squared differences between target values and predictions (Nguyen et al. 2022a, b; Rehamnia et al. 2023). MAE and RMSE can only be used to compare the models if their errors are measured in the same units. Both methods are negatively oriented and indifferent to the direction of error. However, RMSE is more useful than MAE in the case of particularly undesirable errors, because it gives greater weight to larger errors. R is the proportion of variance of the dependent

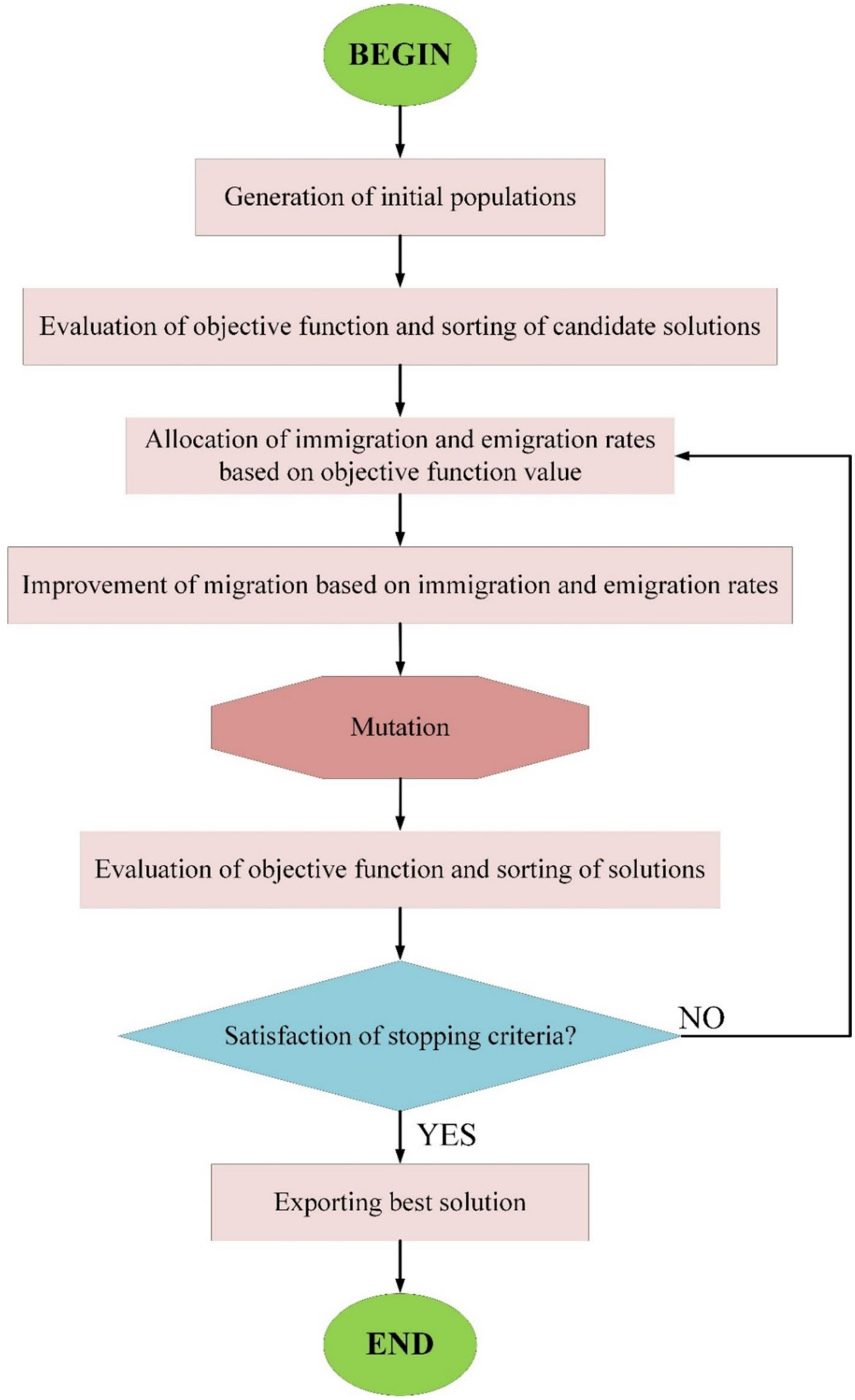

Fig. 3 Algorithm of the BBO method

variable explained by the regression model, calculated from the sum of squares terms. In general, lower RMSE and MAE show better performance of the models. *R* values range between 1 and − 1. *R* value "0" indicates very little correlation, − 1: negative correlation, whereas + 1: positive correlation. In addition, other metrics, namely standard deviation of relative error (StD_{Error}) and mean relative error ($Mean_{Error}$), were also used to validate and compare the models.

Data collection and preparation for modeling

In this study, we collected daily meteorological data over a period of 10 years, from January 01, 2004, to December 31, 2013. The data included solar radiation, relative humidity, wind speed and temperature and were obtained from the National Centers for Environmental Prediction (NCEP) (https://globalweather.tamu.edu). Rainfall data were obtained from a rain gauge in Cao Phong district, Hoa Binh province, Vietnam (20.763° N, 105.312° E). The daily weather data from this site were calculated and determined using the Climate Forecast System Reanalysis (CFSR) (Fuka et al. 2014). In the model study, we considered input variables such as relative humidity, wind speed, temperature (maximum and minimum) and rainfall. The output variable was solar radiation. Figure 4 presents histograms of these variables' data. We observed that the histograms of all variables are highly asymmetric, indicating that a Gaussian distribution would not adequately represent the probability density of these variables. Particularly, in terms of rainfall, a high concentration of days with no rain at all was observed. Table 1 shows minimum, median, maximum values, coefficient of variation and quantiles such as Q10, Q25, Q75 and Q90 of variables used. The non-Gaussian form of the probability density distribution of the variable can be quantified by statistical analysis of the data (Table 1). The daily maximum temperature varied from 6.97 to 42.91 °C, with a median value of 27.82 °C and coefficient of variation (Cv) of 24.99%. Minimum temperature ranges from −0.94 to 27.94 °C, with a median value of 19.18 °C and coefficient of variation of 28.96%. Wind speed varies from 2.26 to 13.47 km/h, with a median value of 4.71 km/h and coefficient of variation of 25.41%. Relative humidity varies from 0.21 to 0.99, with a median value of 0.85 and coefficient of variation of 13.94%. The rainfall varies from 0 mm (no rainfall) to 94.12 mm, with a median value of 2.93 mm and coefficient of variation of 136.42%. The solar radiation varied from 1.03 to 30.38 MJ/m^2, with a median value of 16.40 MJ/m^2 and coefficient of variation of 42.16%.

In this study, the input data were prepared to train and validate AI models. Data were first randomly split into two sets: 70% for training and 30% for validating, as suggested

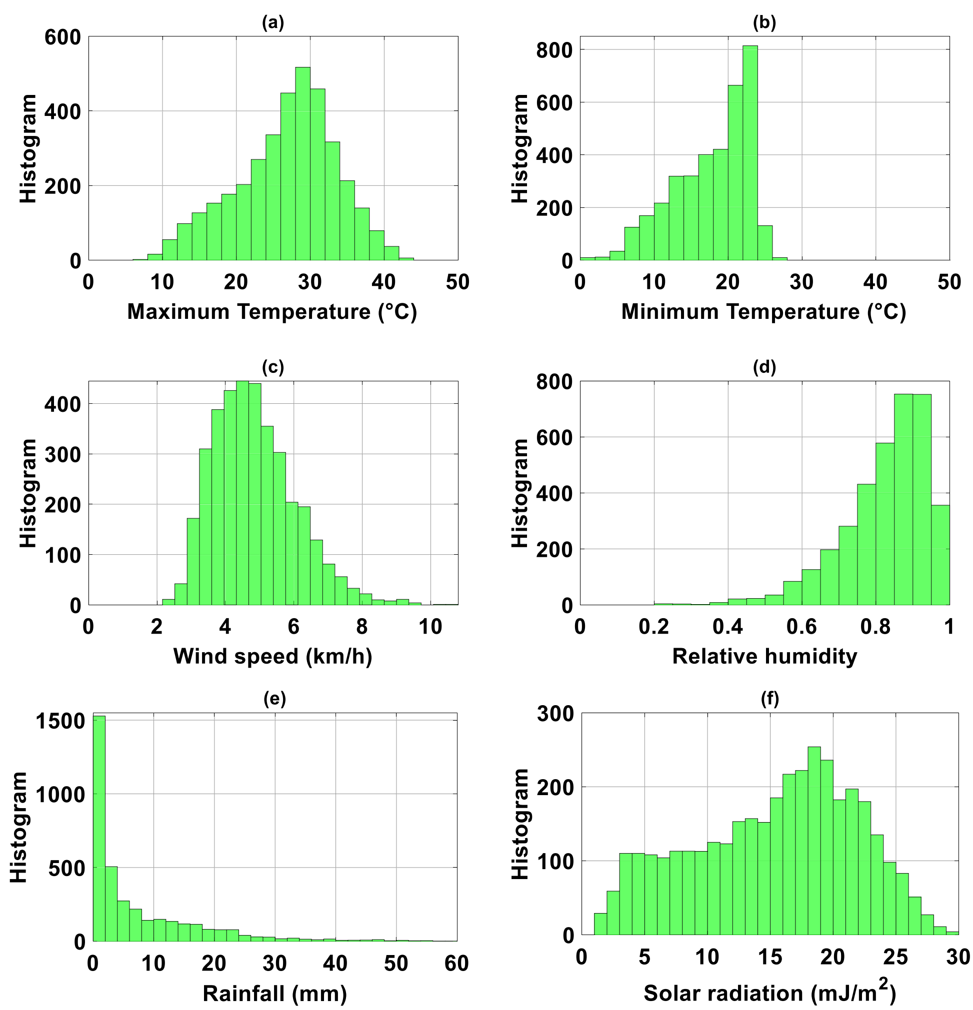

Fig. 4 Histograms of data used in this study: **a** max. temperature (resolution of 2 °C), **b** min. temperature (resolution of 2 °C), **c** wind speed (resolution of 0.4 km/h), **d** relative humidity (resolution of 0.05), **e** rainfall (resolution of 2 mm) and **f** solar radiation (resolution of 1 MJ/m^2)

Table 1 Statistical analysis of meteorological data used in this study

Statistical estimation	Max. temperature (°C)	Min. temperature (°C)	Wind speed (km/h)	Relative humidity	Rainfall (mm)	Solar radiation (MJ/m$^{2)}$
Min	6.97	−0.94	2.26	0.21	0.00	1.03
Q10	16.84	10.13	3.44	0.67	0.07	5.57
Q25	22.66	14.11	3.95	0.77	0.76	10.38
Median	27.82	19.18	4.71	0.85	2.93	16.40
Q75	31.46	22.09	5.57	0.91	10.83	20.32
Q90	34.90	23.37	6.48	0.95	20.58	23.29
Max	42.91	27.94	13.47	0.99	94.12	30.38
Cv	24.99	28.96	25.41	13.94	136.42	42.16

by several researchers (Leema et al. 2016). For the model study, we have utilized a common method called Min–Max scaling to standardize the data. This process involves rescaling the values of variables to a new range [−1, 1] while preserving the relationships between the data points (Cao et al. 2016), which might help in improving the predictive capability of the machine learning (ML) models. Normalization parameters such as min. and max. values of inputs are given in Table 2. Finally, these normalization parameters were used to scale the data in the testing part in order to prevent initial statistical correlation before training. A reverse formula was also obtained in order to convert the normalized data back to the original.

Methodological flowchart

Methodology for predicting daily solar radiation can be divided into the following four main steps (Fig. 5), such as: (1) dataset preparation: the data were randomly divided into two sets: the 70% of data were utilized for building (training) the models, while the another 30% of data were utilized for validating the models. A normalization procedure was then applied to scale the training and testing data into the [−1; 1] range. (2) Building models: four prediction models including single ANFIS and three hybrid models: ANFIS-SA, ANFIS-BBO and ANFIS-GA, were built using the training dataset. ANFIS was optimized by SA, GA and BBO using population sizes of 25, 25 and 50, respectively. These values were the best as identified by trial-and-error method. Optimal iterations were obtained as 1000, 1000 and 2663 for SA, GA and BBO, respectively. (3) Evaluation of models: Four prediction models were evaluated utilizing the testing dataset. In this step, statistical indicators such as MAE, RMSE and R, as well as other techniques (error analysis and linear fit), were used to quantify the effectiveness of the trained models. A comparison of enhancement in the performance achieved by the proposed AI models was then presented, and (4) sensitivity analysis: the sensitivity of input variables such as precipitation, relative humidity, wind speed and minimum and maximum temperature on the prediction of solar radiation by the models was investigated.

Results and discussion

Evaluation of the performance of the models

Performance of the four AI models (ANFIS, hybrid ANFIS-SA, ANFIS-BBO and ANFIS-GA) in predicting daily solar radiation was evaluated by regression analysis (Fig. 6) and cumulative density function analysis (Fig. 7). Figure 6b, d, f, h shows the output of ANFIS, ANFIS-SA, ANFIS-GA and ANFIS-BBO associated with the training and testing datasets. The relative errors between predicted and actual solar radiation for both training and testing datasets were plotted in histograms (Fig. 8). Results of prediction capability of models are presented in Table 3.

Analysis of the models' study results shows that for the training (learning) dataset, ANFIS-BBO model gave relatively smallest value of RMSE (3.099) in comparison to ANFIS (4.448), ANFIS-SA (3.406) and ANFIS-GA (3.128). Similar results were obtained for MAE, R and also of StD_{Error}.

Table 2 Normalization parameters obtained after scaling the training data

Training data	Max. temperature (°C)	Min. temperature (°C)	Wind speed (km/h)	Relative humidity	Rainfall (mm)	Solar radiation (MJ/m^2)
Min	6.97	−0.94	0.63	0.21	0.00	1.12
Max	42.91	27.59	3.74	0.98	80.32	30.38

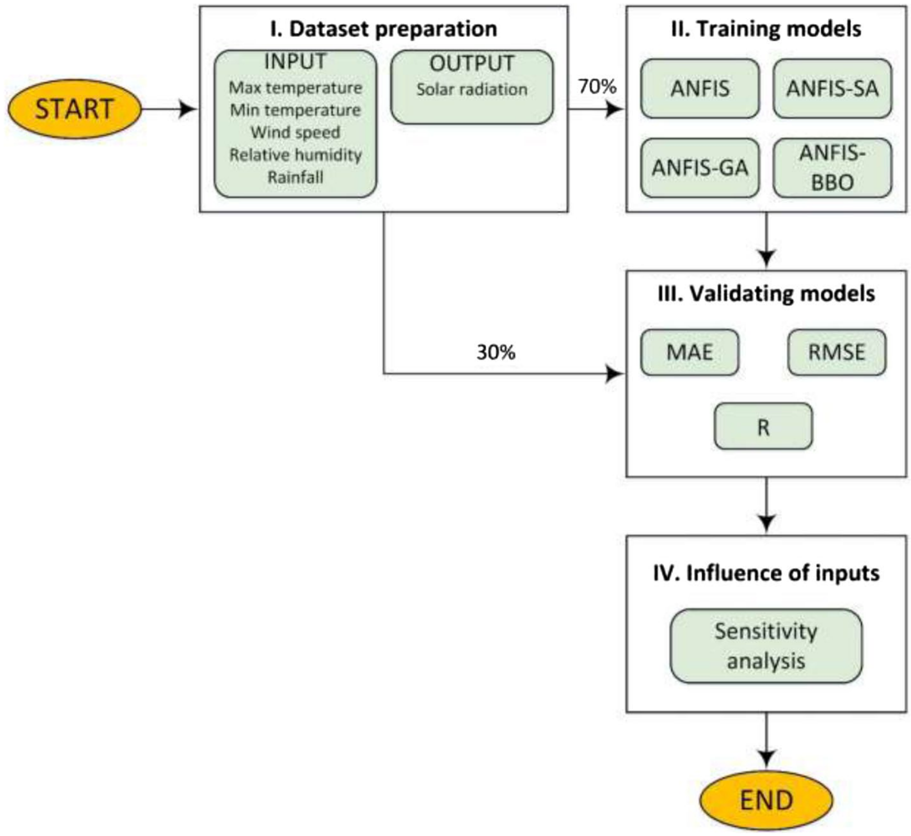

Fig. 5 Methodology of prediction of solar radiation

$\text{Mean}_{\text{Error}}$ produced by ANFIS-SA was the lowest (−0.009), as compared to −0.482, 0.281 and −0.066 produced by ANFIS (alone), hybrid ANFIS-GA and ANFIS-BBO, respectively. Furthermore, ANFIS-GA yielded the smallest deviation in slope value in comparison with the diagonal line (slope angle = 21.759, 34.077, 38.020 and 37.424° for ANFIS, hybrid ANFIS-SA, ANFIS-GA and ANFIS-BBO, respectively), and the slope angle of ANFIS-BBO was only about 0.6° less.

For the testing part, the ANN-BBO model exhibited the best performance according to five statistical criteria: MAE, RMSE, R, $\text{Mean}_{\text{Error}}$ and $\text{StD}_{\text{Error.}}$ The statistical analysis values of ANFIS, hybrid ANFIS-SA, ANFIS-GA and ANFIS-BBO models are: RMSE = 4.432, 3.457, 3.188, 3.141; MAE = 3.684, 2.767, 2.458, 2.439; R = 0.775, 0.846, 0.873, 0.874; $\text{mean}_{\text{Error}}$ = −0.303, 0.121, 0.436, 0.063; $\text{StD}_{\text{Error}}$ = 4.424, 3.456, 3.160 and 3.142, respectively. However, the slope of the linear regression for the ANFIS-BBO model does not show the smallest change while comparing diagonal line as shown in Fig. 6 and Table 3. The slopes (m) of ANFIS, hybrid ANFIS-SA, ANFIS-GA and ANFIS-BBO models are: 0.395, 0.677, 0.791 and 0.774, respectively. Overall statistical analysis results suggest that ANFIS-BBO offered the best prediction capability and thus can be considered as most efficient model for daily solar radiation prediction.

Performance enhancement of ANFIS model by using optimization techniques

Performance of the ANFIS model was enhanced by using SA, GA and BBO optimization techniques. An increase of performance index denoted by I is as below:

$$I = \frac{\left|V^{hybrid} - V^{ANFIS}\right|}{V^{ANFIS}} \times 100, \tag{1}$$

where V^{hybrid} and V^{ANFIS} were the considered criteria (RMSE, MAE, R and $\text{Error}_{\text{StD}}$ in this study) obtained using hybrid and ANFIS models, respectively. Table 4 indicates the values of index I regarding RMSE, MAE, R and $\text{StD}_{\text{Error}}$. In addition, Fig. 9 and Table 4 show the evaluation of index I in increasing order. Performance of the hybrid models ANFIS-SA, ANFIS-GA and ANFIS-BBO for the training dataset is 23.429, 29.673 and 30.311%, respectively, for RMSE; 25.459, 33.964 and 34.487%, respectively, for MAE; 9.61, 12.776 and 12.943%, respectively, for R; and 22.976, 29.543 and 29.915%, respectively, for $\text{StD}_{\text{Error}}$. It

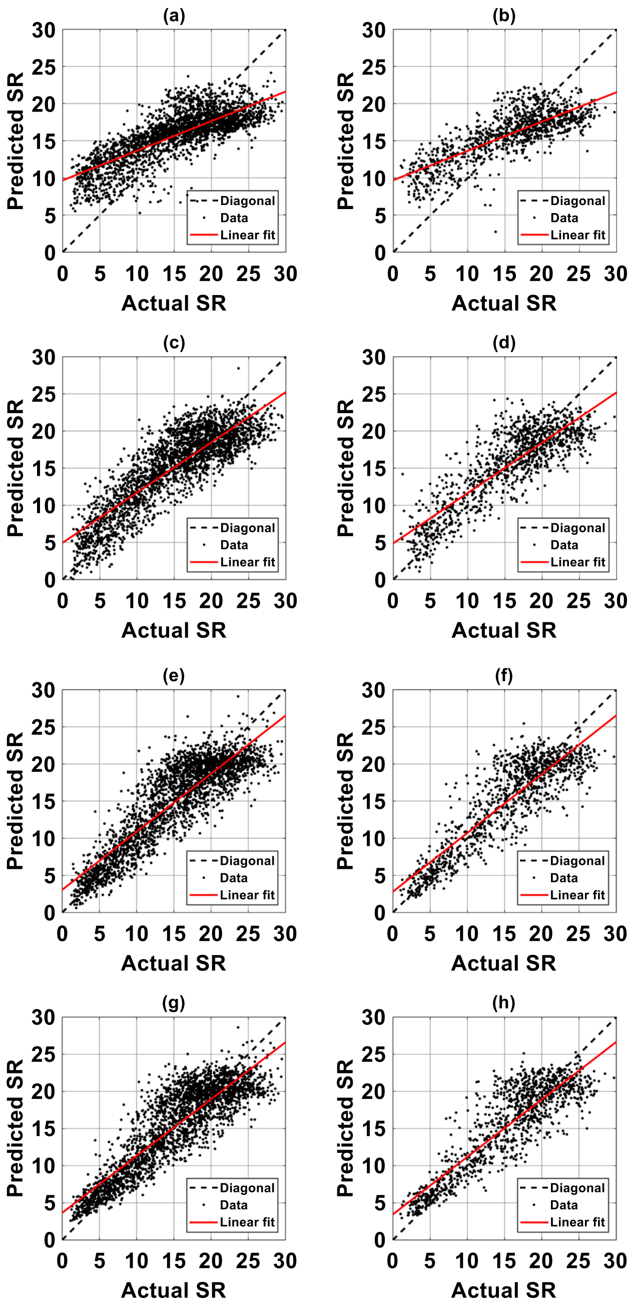

Fig. 6 Regression analysis graphs between predicted and measured values of solar radiation SR (MJ/m^2) during training process: **a** ANFIS, **c** ANFIS-SA, **e** ANFIS-GA, **g** ANFIS-BBO; and testing process: **b** ANFIS, **d** ANFIS-SA, **f** ANFIS-GA, **h** ANFIS-BBO

shows that the values of I are relatively higher in all cases for BBO optimization. Similar results of performance index I for hybrid models (ANFIS-SA, GA and BBO) were obtained for the testing dataset: 22.012, 28.069 and 29.136%, respectively, for RMSE; 24.876, 33.283 and 33.788%, respectively, for MAE; 9.127, 12.604 and 12.730%, respectively, for R; and 21.878, 28.579 and 28.985%, respectively, for StD_{Error}. Therefore, it can be concluded that BBO is the best technique for improving the prediction capability of ANFIS model.

Sensitivity analysis of input parameters

This task was performed to evaluate the significance of input parameters over output variables in daily solar radiation prediction. This analysis was done for all the AI models used in this study. For a given input variable, eleven levels of values were calculated as quantiles from zero to one with a step of 0.1, respectively, denoted by Min., Q10, Q20, Q30, Q40, Q50, Q60, Q70, Q80, Q90 and Max. The values of these levels for all input variables are presented in Table 5.

In this sensitivity analysis, each input varied from its lowest (Min.) to highest (Max.) level of values, while all others remained at their Q50 values. To quantify the influence of input variables, a parameter called level of sensitivity of the considered input is introduced and calculated as below:

$$LS_p^q = \frac{\left| Y_p^q - Y_{\text{median}}^{\text{all}} \right|}{Y_{\text{median}}^{\text{all}}} \times 100. \quad (2)$$

$Y_{\text{median}}^{\text{all}}$ was output solar radiation when all other inputs were at Q50. Y_p^q is the solar radiation response of AI models when applying the qth input at its pth level, and LS_p^q is the corresponding level of sensitivity of input q ($q = 1{:}5$, $p = 1{:}11$). Figure 10 and Table 6 present the levels of sensitivity of all input variables, calculated by using ANFIS, hybrid ANFIS-SA, ANFIS-GA and ANFIS-BBO models, respectively.

Sensitivity analysis results show that the maximum temperature was the most sensitive input, having a significant impact on the prediction of solar radiation using all four AI models. Indeed, as indicated in Table 6, the prediction result shows deviation value: 58.96, 165.47, 187.08 and 163.72% using ANFIS, hybrid ANFIS-SA, ANFIS-GA and ANFIS-BBO, respectively, when varying the max. temperature from its median to min. value. In the opposite direction, with an increase of the max. temperature from its median to max. value, we observed deviation value: 56.90, 49.23, 79.72 and 69.48% using ANFIS, hybrid ANFIS-SA, ANFIS-GA and ANFIS-BBO, respectively. Based on the sensitivity analysis study, it is observed that a reduction of max. temperature from its median to min. value generated higher deviations in prediction results than from its median to max. value. This fact was confirmed with the histogram plotting of max. temperature (Fig. 4a). An asymmetric distribution was observed, with great standard deviation to the left of the peak than the right. Such

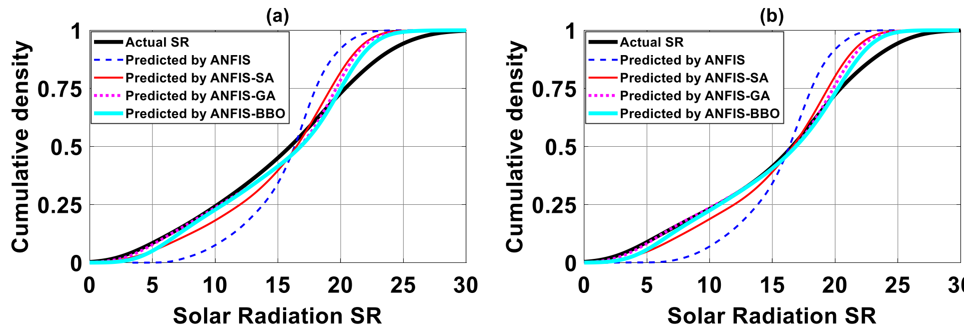

Fig. 7 Cumulative density functions of actual values of solar radiation and those predicted using ANFIS, ANFIS-SA, ANFIS-GA and ANFIS-BBO for the training data (**a**) and for the testing data (**b**)

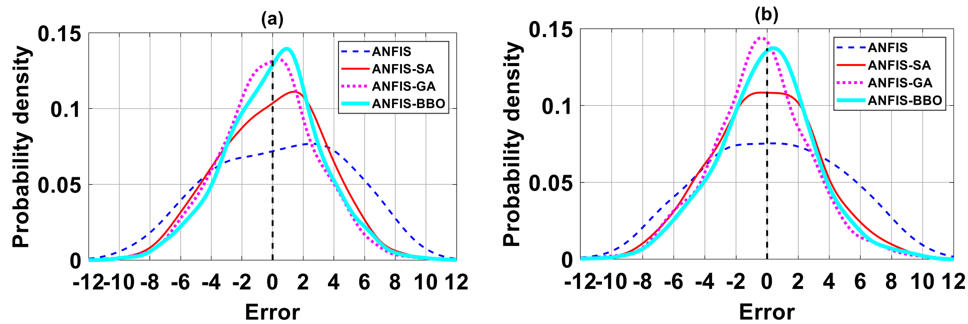

Fig. 8 Probability density functions of prediction errors using ANFIS, ANFIS-SA, ANFIS-GA and ANFIS-BBO for the training data (**a**) and for the testing data (**b**)

Table 3 Prediction capability of the models

Dataset	Model	RMSE (MJ/m^2)	MAE (MJ/m^2)	*R*	Mean$_{Error}$ (MJ/m^2)	StD$_{Error}$ (MJ/m^2)	Slope(m)	Slope angle (°)	Intercept *n*
Training	ANFIS	4.448	3.729	0.778	−0.482	4.422	0.399	21.759	9.666
	ANFIS-SA	3.406	2.780	0.853	−0.009	3.406	0.676	34.077	4.954
	ANFIS-GA	3.128	2.462	0.877	0.281	3.116	0.782	38.020	3.054
	ANFIS-BBO	3.099	2.443	0.878	−0.066	3.099	0.765	37.424	3.655
Testing	ANFIS	4.432	3.684	0.775	−0.303	4.424	0.395	21.530	9.702
	ANFIS-SA	3.457	2.767	0.846	0.121	3.456	0.677	34.110	4.888
	ANFIS-GA	3.188	2.458	0.873	0.436	3.160	0.791	38.345	2.808
	ANFIS-BBO	3.141	2.439	0.874	0.063	3.142	0.774	37.726	3.451

Table 4 Increase of performance index I (in %) using optimization techniques

Dataset	Criterion	ANFIS-SA	ANFIS-GA	ANFIS-BBO
Training	RMSE	23.429	29.673	30.311
	MAE	25.459	33.964	34.487
	R	9.681	12.776	12.943
	Error$_{StD}$	22.976	29.543	29.915
Testing	RMSE	22.012	28.069	29.136
	MAE	24.876	33.283	33.788
	R	9.127	12.604	12.730
	Error$_{StD}$	21.878	28.579	28.985

observation demonstrated the relevance of the AI models developed in this study—especially ANFIS-BBO—in analyzing significant statistical information of inputs. In addition, the sensitivity analysis results for max. temperature input are close to the results from three hybrid AI models, namely ANFIS-SA, ANFIS-GA and ANFIS-BBO (Fig. 10b, c, d). However, the same sensitivity level was not correctly determined when using ANFIS (Fig. 10a). It can be deduced that the ANFIS model, without combination with other models, was not able to provide good sensitivity analysis results of input variables; this conclusion is supported by other AI models. The minimum temperature was the second most important sensitivity factor (Fig. 10b, c, d and Table 6). However, the levels of sensitivity of this

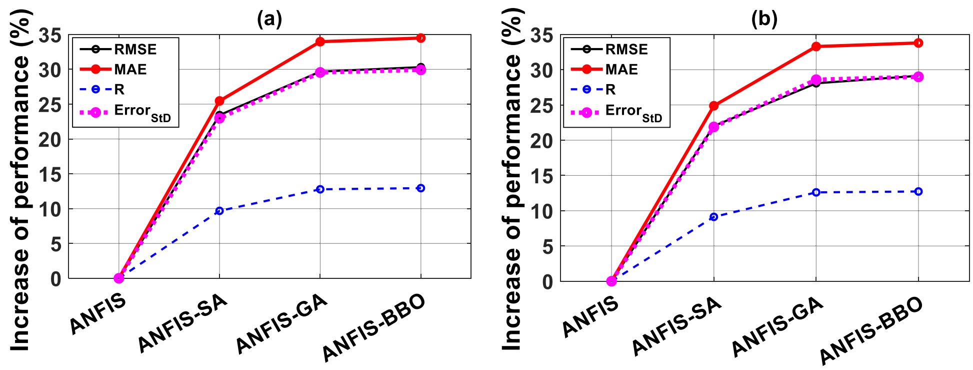

Fig. 9 Increase of performance versus ANFIS alone using SA, GA and BBO techniques for the training data (**a**) and for the testing data (**b**)

Table 5 Values of 11 levels of input variables in the normalized space (normalization parameters given in Table 2)

Input parameters	Min	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90	Max
Max. temperature	−1.00	−0.45	−0.22	−0.05	0.07	0.16	0.23	0.32	0.41	0.55	1.00
Min. temperature	−1.00	−0.22	−0.01	0.14	0.27	0.41	0.51	0.58	0.64	0.70	1.00
Wind speed	−1.00	−0.79	−0.73	−0.67	−0.62	−0.56	−0.51	−0.45	−0.37	−0.25	1.00
Relative humidity	−1.00	0.20	0.39	0.50	0.58	0.66	0.73	0.79	0.84	0.91	1.00
Rainfall	−1.00	−1.00	−0.99	−0.97	−0.95	−0.93	−0.87	−0.79	−0.67	−0.49	1.00

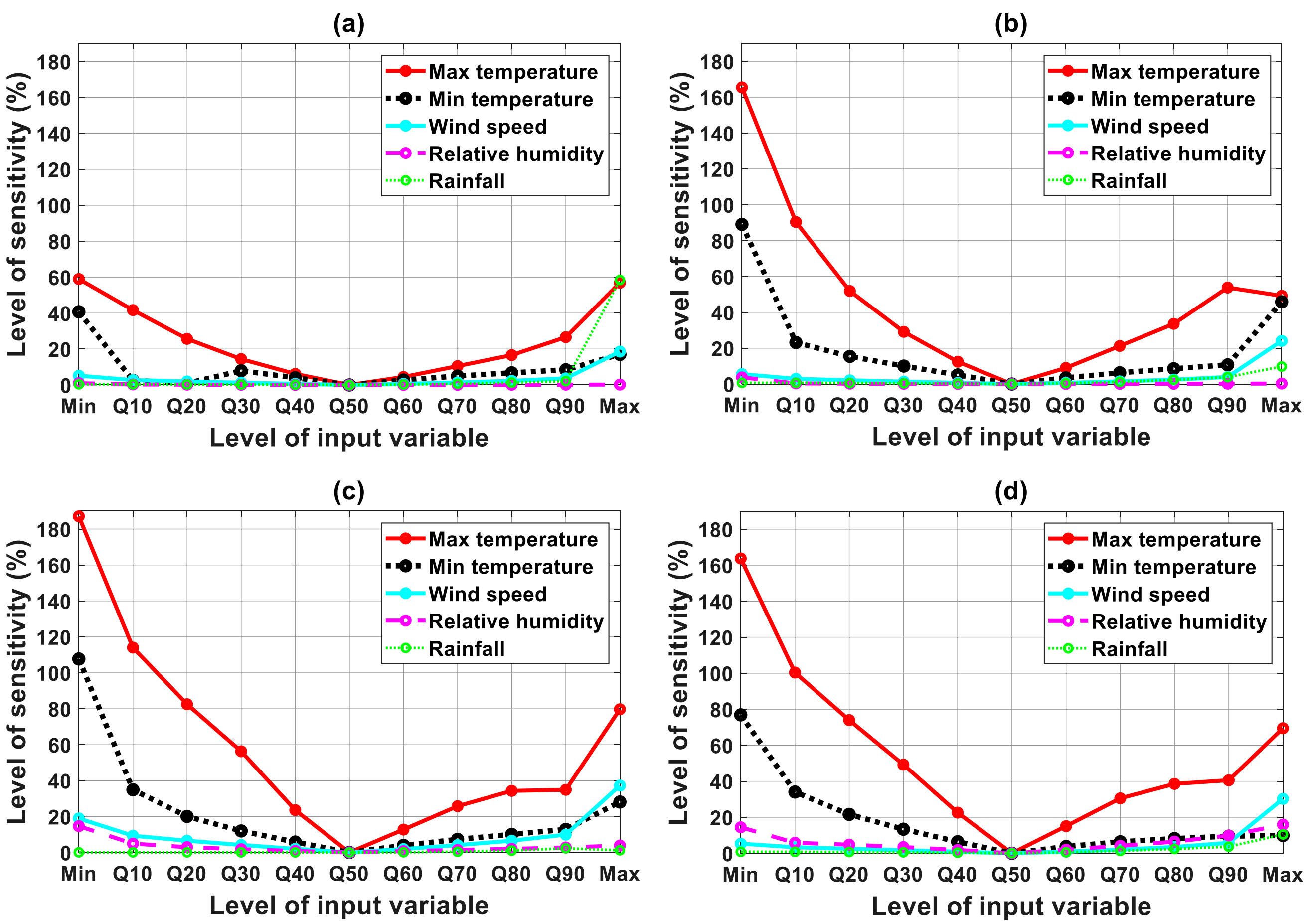

Fig. 10 Determination of sensitivity levels of input parameters using **a** ANFIS, **b** ANFIS-SA, **c** ANFIS-GA and **d** ANFIS-BBO

Table 6 Values of sensitivity levels (in %) calculated by using four AI models at different levels of input variables. Note that at Q50, all values of levels of sensitivity are zero by definition

Model	Input	Min	Q10	Q20	Q30	Q40	Q60	Q70	Q80	Q90	Max
ANFIS	Max. temperature	58.96	41.66	25.66	14.41	6.16	4.45	10.51	16.61	26.61	56.90
	Min. temperature	40.72	2.53	0.89	7.91	4.02	2.72	4.97	6.75	8.46	17.01
	Wind speed	5.17	2.72	1.97	1.29	0.64	0.63	1.39	2.30	3.69	18.56
	Relative humidity	1.00	0.28	0.16	0.10	0.05	0.04	0.07	0.11	0.15	0.20
	Rainfall	0.37	0.36	0.31	0.24	0.15	0.26	0.68	1.30	2.17	58.40
ANFIS-SA	Max. temperature	165.47	90.36	51.89	29.14	12.46	9.00	21.25	33.60	53.82	49.23
	Min. temperature	89.04	23.18	15.43	10.03	5.09	3.45	6.30	8.56	10.73	45.85
	Wind speed	5.54	2.92	2.11	1.38	0.68	0.68	1.49	2.47	3.95	24.10
	Relative humidity	3.72	0.36	0.21	0.13	0.06	0.05	0.10	0.14	0.19	0.26
	Rainfall	0.67	0.65	0.56	0.43	0.26	0.47	1.21	2.33	3.89	9.79
ANFIS-GA	Max. temperature	187.08	114.05	82.54	56.33	23.58	12.76	25.78	34.31	34.91	79.72
	Min. temperature	107.71	34.92	20.08	11.99	5.82	3.94	7.30	10.08	12.85	28.11
	Wind speed	18.96	9.31	6.56	4.19	2.02	1.91	4.10	6.54	9.91	37.26
	Relative humidity	14.68	4.92	2.97	1.81	0.84	0.72	1.40	2.01	2.77	3.87
	Rainfall	0.07	0.07	0.07	0.06	0.04	0.11	0.39	1.04	2.33	1.22
ANFIS-BBO	Max. temperature	163.72	100.40	73.98	49.23	22.59	15.08	30.53	38.54	40.57	69.48
	Min. temperature	76.88	34.05	21.61	13.38	6.41	3.75	6.39	8.15	9.51	9.89
	Wind speed	5.32	3.32	2.50	1.69	0.86	0.90	2.04	3.47	5.77	30.24
	Relative humidity	14.46	5.83	4.79	3.46	1.84	1.95	4.15	6.44	9.85	15.92
	Rainfall	0.83	0.80	0.68	0.52	0.32	0.54	1.33	2.39	3.66	10.47

input were much smaller than those of the max. temperature (about three times smaller). All other meteorological variables showed less sensitivity—negligible in comparison to temperature (Fig. 10; Table 6).

Conclusions

Solar radiation is an abundant natural source of energy in many parts of the world. Facilities of direct solar radiation measurement are available in many regions, especially in developing countries. In this study, we have developed and evaluated the performance of novel hybrid AI models (ANFIS-SA, ANFIS-GA and ANFIS-BBO) for correctly predicting daily solar radiation in Hoa Binh province, Vietnam, using easily measurable parameters: wind speed, relative humidity and maximum and minimum temperature and rainfall. These models combine the ANFIS technique with GA, BBO and SA to improve predictive capability. The results demonstrate that all three optimized models outperform the single ANFIS model, with the ANFIS-BBO model (RMSE = 3.141 MJ/m^2, MAE = 2.439 MJ/m^2 and $R = 0.874$) exhibiting the highest predictive capability. Sensitivity analysis reveals that maximum temperature is the most influential factor for predicting daily solar radiation.

The findings of this study have significant implications for predicting solar radiation using AI methods in remote locations not only in Vietnam but also globally. These developed hybrid AI models can be used for correctly predicting solar radiation with meteorological data even in remote places. However, as solar radiation depends on local spatial and temporal factors, more studies at different places are needed to confirm the best capability of solar radiation prediction of these developed ANFIS hybrid models.

In the context of future research, it would be valuable to expand upon this work by including model comparisons with other existing machine learning (ML) models. This would provide further insights into the effectiveness of these ANFIS-based models and their potential for wider application in predicting solar radiation.

Author contribution BTP and H-BL contributed to conceptualization, methodology, project administration and funding acquisition; BTP, K-TTB and H-BL performed data curation; All authors performed writing—original draft preparation. BTP and H-BL performed visualization and investigation. BTP performed supervision. BTP and H-BL contributed to software and validation. BTP, IP and H-BL performed writing—reviewing and editing.

Availability of data and materials The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest to report regarding the present study.

Ethical approval Not applicable.

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