Computers, Materials & Continua

Tech Science Press

DOI: 10.32604/cmc.2024.051002

ARTICLE

Solar Radiation Estimation Based on a New Combined Approach of Artificial Neural Networks (ANN) and Genetic Algorithms (GA) in South Algeria

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Received: 25 February 2024 Accepted: 12 April 2024 Published: 20 June 2024

ABSTRACT

When designing solar systems and assessing the effectiveness of their many uses, estimating sun irradiance is a crucial first step. This study examined three approaches (ANN, GA-ANN, and ANFIS) for estimating daily global solar radiation (GSR) in the south of Algeria: Adrar, Ouargla, and Bechar. The proposed hybrid GA-ANN model, based on genetic algorithm-based optimization, was developed to improve the ANN model. The GA-ANN and ANFIS models performed better than the standalone ANN-based model, with GA-ANN being better suited for forecasting in all sites, and it performed the best with the best values in the testing phase of Coefficient of Determination (R = 0.9005), Mean Absolute Percentage Error (MAPE = 8.40%), and Relative Root Mean Square Error (rRMSE = 12.56%). Nevertheless, the ANFIS model outperformed the GA-ANN model in forecasting daily GSR, with the best values of indicators when testing the model being R = 0.9374, MAPE = 7.78%, and rRMSE = 10.54%. Generally, we may conclude that the initial ANN stand-alone model performance when forecasting solar radiation has been improved, and the results obtained after injecting the genetic algorithm into the ANN to optimize its weights were satisfactory. The model can be used to forecast daily GSR in dry climates and other climates and may also be helpful in selecting solar energy system installations and sizes.

KEYWORDS

Solar energy systems; genetic algorithm; neural networks; hybrid; adaptive neuro fuzzy inference system; solar radiation

Nomenclature

GSR	Global solar radiation
GA	Genetic algorithm
ANN	Artificial neural networks
ANFIS	Adaptive neuro fuzzy inference system

1 Introduction

Previous research has demonstrated that green energy sources, particularly solar and wind, may serve as effective substitutes for conventional sources of energy in order to meet worldwide demand without harming the environment [1]. Accurate knowledge regarding global solar radiation (GSR) statistics can be critical for optimizing solar power system development and selection. However, because of the high expense and difficulty of measuring solar radiation, this information is not easily accessible in numerous countries [2]. Machine learning models (ML), on the other hand, can handle complex nonlinear issues. ML offers a wide range of possible uses and is highly sought after by experts around the world [3]. Because of the stochastic nature of weather conditions, solar energy generated by sunlight is not schedulable [4]. Evaluating the fundamental elements of solar radiation is a critical metric for solar power implementation [5]. As a result, solar radiation prediction is crucial for solar energy systems that are meant to generate energy on a large scale and/or are grid-connected in order to balance energy demand and supply. Modern research has determined that many solar systems may operate in an off-on mode during clear or cloudy weather. As a result, it is critical to anticipate sun radiation at various time intervals [4].

Artificial neural networks (ANNs) produce favorable outcomes with limited parameters; therefore, they are frequently used for solar radiation predictions. Using meteorological data from the province of Isparta [6], reference [7] explored the forecasting of solar radiation using Random Forest, Artificial Neural Network, k-Nearest Neighbor, and Deep Learning techniques. The usage of dummy variables, according to the results, increases performance for ANN and DL methods while decreasing it for RF and k-NN methods. When it comes to forecasting solar radiation, ANN and DL perform best. While in [8], an artificial neural network (ANN) approach for precise forecasting of direct normal irradiance (DNI), which is important for solar energy systems, is presented. Two artificial neural network (ANN) models were created, one that used instantaneous predictions and the other that used a period of better DNI forecasts before the anticipated time. When the models were assessed for Evora, Portugal, they produced encouraging findings. They showed good agreement across a number of locations and time steps in southern Portugal, as well as improvements in coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) over initial forecasts. Also, reference [9] developed a neural model for estimating hourly GSR for the Adrar region. Investigating nine models, they experimented with various input data combinations, each with a different level of precision, and found that 15 neurons within the hidden layer using the logistic sigmoid function may be more useful for assessing GSR intensities. In Greece [10], solar radiation was estimated using empirical equations, multi-linear regression (MLR), and ANN methods. Daily meteorological readings were employed. ANN models produce consistent results with MLR methods that make use of identical input variables. Reference [11] offered a new strategy using a multi-task hybrid evolutionary ANN, and the best appropriate topology is determined using an evolutionary algorithm. The study concluded that results obtained using sigmoidal units were superior. In reference [12], a 5-year period of solar radiation and meteorological data from Kocaeli province are used to develop an artificial neural network model. The model makes use of neural networks' capability to examine relationships and data structures in order to handle the complexity of solar radiation. Findings demonstrate the accuracy of solar radiation forecast and emphasize its importance for energy-related enterprises and climate research.

A model that incorporates ANN and fuzzy inference is called the adaptive neuro-fuzzy inference system (ANFIS). To reduce the search space, the method splits a representation related to prior knowledge into subgroups. then the fuzzy parameters are adjusted using the backpropagation process. The end product is an adaptive ANN that has a linear relationship and functions exactly like a first-order Takagi-Sugeno inference system [13]. For situations with a single input parameter, where sunshine duration (n) is found to be a significant input, reference [14] presented an ANFIS model for estimating daily diffuse sun radiation. For comparing the performance of the ANFIS, ANN, and Iqbal models, use the assessment statistical indicators (R^2) and (RMSE). The findings revealed that the suggested ANFIS could determine the daily Hd with accuracy in China. Reference [15] in Saudi Arabia developed a reliable model for predicting the global horizontal irradiance for the next day. They used ANFIS to adjust the membership function parameters in the developed model. The results of the simulation demonstrated that, in comparison to starting from scratch, the subtractive clustering technique offered ANFIS a suitable starting solution and improved its performance. The final model, constructed using the subtractive clustering approach and refined by ANFIS, exhibited significant improvement over the initial model. Reference [16] developed fifteen ANFIS-based models based on deferent combinations of parameters along with membership functions (T_{avg}) and (RH), hour angle (HA), along with the Gaussian membership function to estimate GSR models in four sites in Algeria.

GAs are widely employed in optimization problem solving, in both machine learning and research [17]. The paper [18] presented innovative hybrid approaches for optimizing deep learning predictions by combining GAs and deep neural networks. GA is used to determine the optimal number of sizes of windows and units as compared to other forms of neural networks. While reference [19] established in research a model for GA optimization of wavelet neural networks (GAO-WNN), simulation findings show that the approach can accurately estimate daily sun radiation. This investigation [20] uses GA and PSO to increase both the accuracy and generalizability of the back propagation neural network (BPNN) approach for anticipating daily Hd. The founding suggests the BPNN be enhanced using the PSO method to offer the capacity to accurately estimate daily Hd.

To the best of our knowledge, the use of optimizing algorithms such as GA to build hybrid models and comparing the use of fuzzy logic and genetic algorithms on the same multi-layer feed-forward neural network model in terms of enhancing prediction model accuracy have not yet been fairly included. Little is known about which method to inject into the model to get the best performance when trying to develop a hybrid model in arid areas. So far, it is not clear whether injecting optimization algorithms is better or whether the use of fuzzy logic is the best choice. The primary aim of our study is to systematically simulate daily GSR using our developed hybrid GA-ANN model, a combined machine learning approach, for forecasting global solar radiation. Subsequently, we evaluate its performance against two other approaches: A standalone ANN and an ANN-based method named ANFIS, using meteorological data from three chosen research regions (Adrar, Ourgla, and Bechar) in the Algerian desert.

2 Material and Models

2.1 Study Areas and Data Collection

The subject of the study region is located in Algeria's desert (Fig. 1); the locations that are under investigation are listed in Table 1. The climate in the southern region of Algeria is hot in the summer and cold in the winter. It additionally features significant solar energy potential [21].

The southern part of Algeria has the maximum insolation time at 3900 h [22]. On a flat surface, the average amount of solar power is 5 kWh/m^2 for the large part, or approximately 2263 kWh/m^2/year in the south of this country [23].

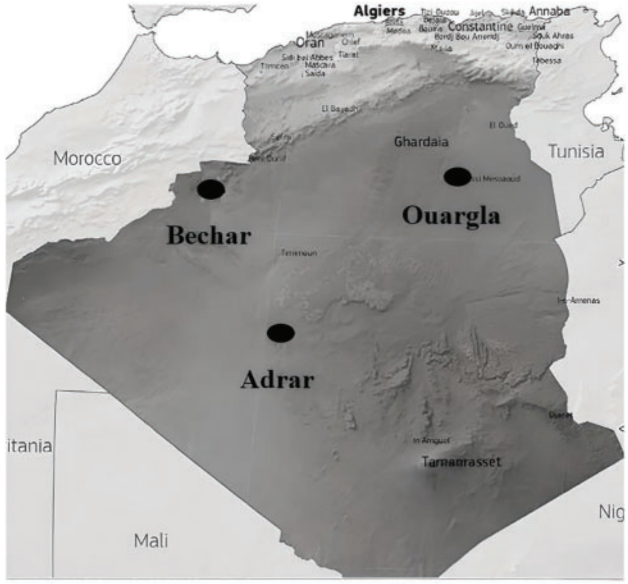

Figure 1: Algeria's solar potential

Table 1: Location's coordinates

Provinces	Latitude (°)	Longitude (°)	Altitude (m)
Adrar	26.489	−1.358	286
Ouargla	30.998	6.766	178
Bechar	31.386	−2.012	785

We build up a vast database that may be used for testing and training our model. Our research utilized daily data over 3 years (2019–2021) obtained from the Simple Ocean Data Assimilation Database (SODA) [24] with N = 1096 observations for each of the variables (see Table 2), and 20% of the data was used for testing and the rest was set to the training stage. In order to accurately estimate solar radiation levels at a certain location and time, these six inputs together provide essential information on atmospheric characteristics, solar geometry, and environmental conditions.

Table 2: The parameters used

Parameters	Abbreviation	Unit	Type
Day of the year	D	/	Numerical
Average temperature	T_{avg}	°C	
Relative humidity	RH	%	
Declination	DE	Degree (°)	
Hour angle	HA	Degree (°)	
Extraterrestrial solar irradiation	H_0	Wh/m^2	

2.2 Data Preprocessing

By correctly understanding the previous pattern, this technique could significantly reduce the issue of inadequate training as well as computation costs. As a result, preprocessing the inputs significantly improves the anticipating model's efficiency. A variety of strategies can be used to preprocess the data that was provided to the forecasting approaches. In our paper, the normalizing [25] approach was chosen to be applied.

The approach selects a subset of inputs out of a larger set. In consequence, regression inaccuracy could potentially be decreased by limiting the data to an interval of zero to one, increasing precision, and maintaining the relationship between the data sets' correlation.

$$I_{\mathrm{norm}} = \frac{I_{\mathrm{now}} - I_{\mathrm{min}}}{I_{\mathrm{max}} - I_{\mathrm{min}}} \tag{1}$$

I_{norm} and I_{now} are normalized and original data, respectively. I_{norm} lies between 0 and 1 based on the minimum I_{min} and maximum I_{max} values of the input data. In the present case, we are extracting the anticipated actual solar irradiation and analyzing the model.

2.3 ANN Model

The neural activity of our brains is simulated by the ANN model [26]. Before applying a non-linear activation function to construct an output signal uj for n hidden layers, each unit (i.e., neuron) within the structure calculates a weighted by W_{ij} summation corresponding to its p input signal yi. (Eq. (2)).

$$uj = \sum\nolimits_{i=0}^{n} W_{ij}\, yi \tag{2}$$

Eq. (2) incorporates bias terms W_{ij}, into the neural network model, which are necessary to improve the model's ability to successfully capture complex data relationships.

The multi-layer feed-forward neural network (MLF), which has three layers (i, j, and k), which employs (BP) algorithm, is the most widely used ANN method for predicting solar radiation. The ability of this approach to represent issues which may not be separated by linearity makes it effective. Each of the layers is linked together by weights W_{ij} and W_{jk}.

The transformation in which each neuron adds a bias term to the sum before nonlinearity converts it into an output is known as the node activation function. Commonly used functions are the tangent-sigmoid transfer function (Eq. (3)) in the hidden layer and the linear function (Eq. (4)) in the output layer [27].

$$f(w) = \frac{2}{1 + e^{-2w}} - 1 \tag{3}$$

$$f(x) = x \tag{4}$$

With w being the input weighted sum and x being the output layer input.

In our approach, we design an ANN to anticipate daily GSR. The characteristics are illustrated in Fig. 2 and Table 3.

For our MLP architecture, we used only one neuron (see Fig. 2) in the output layer to represent the anticipated daily GSR. For every one of the three areas we chose. For all models, we used a script code that was generated by the software MATLAB.

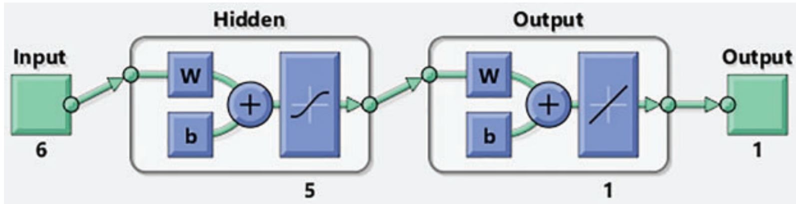

Figure 2: The designed ANN characteristics

Table 3: Features of the model and training details

Aspect	Description
Network architecture	With a "tansig" activation function for the hidden layer, this feedforward neural network has five hidden layers, each with five neurons.
Data preprocessing	The mapminmax function is used to apply min-max normalization to the input (P) and target (T) data.
Training parameters	'Levenberg-Marquardt Backpropagation' is the training algorithm, with a maximum of 1000 epochs and a goal error of 0.000001.
Training process	80% of the provided data was used for training, and the remaining 20% was used for testing.
Monitoring training	A training record (tr), which tracks both training and testing errors, is used to track the progress of the training process.

2.4 ANFIS Model

ANFIS integrates fuzzy and ANN algorithms; it involves fuzzy variables being handled by nodes in various feed-forward network layers. This is comparable to distributed variable fuzzy inference systems (FIS) [28].

The ANFIS is essentially built of five layers (see Fig. 3):

1st Fuzzification Layer:

- For adaptive nodes, make use of fuzzy C-means clustering.
- Based on input values, membership grades for linguistic labels are generated.
- Uses particular formulas to define the parameters of the premise.
- Membership functions guarantee that outputs fall between 0 and 1.

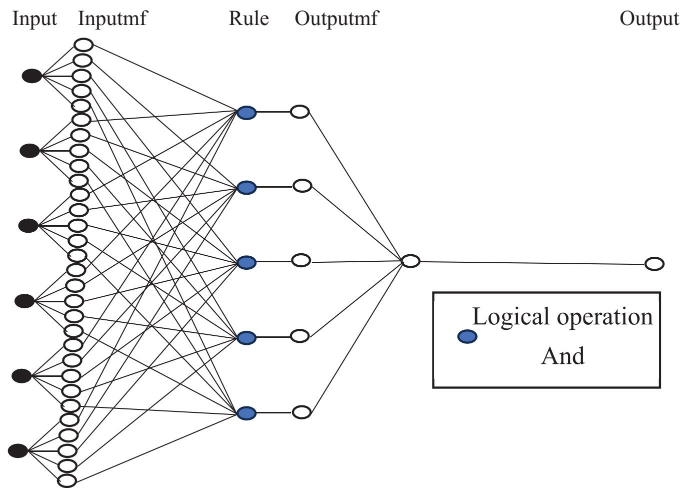

Figure 3: ANFIS model used in our stud

2nd Rule Activation Layer:

- Nodes multiply membership grades to determine the rule firing strength.
- Determines rule products for every pair of linguistic labels.

3rd Normalization Layer:

- Nodes normalize firing strengths that come from the layer before.

4th Consequent Layer:

- The normalized firing strength is squared by each node and combined with the resulting parameters.

5th Output Layer:

- The weighted products from the previous layer are aggregated by a single node to get the overall output [29].

We employed the following input and output Membership Functions Types, respectively:

Gaussian

$$\mu_{\mathrm{Ai}}(\mathrm{x}) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{5}$$

Linear

$$\mu_{\mathrm{Ai}\ (\mathrm{x})=a.x+b} \tag{6}$$

{a.b.c.d} are MFs parameter sets where the maximum and minimum values are 1 and 0 [13].

2.5 Genetic Algorithm

These selection-based heuristic combinatorial methods of search are known as GAs. The major goal is to replicate the fundamental concepts of natural genetics in order to mimic the biological evolution processes of chromosomes, also known for their string structures. The GA procedure consists of:

• Determining which chromosomal sequencing should be utilized for testing or to represent a solution.

• Select a fitness function that will be utilized for testing GA solutions and determining if these results are suitable for use as solutions for the next generation.

The primary distinctions between GAs and conventional methods of optimization are [30]:

- GAs encode parameter sets rather than the parameters themselves.
- A population of GAs is used to seek the local optimum, rather than a single point.
- GAs rely on objective function information rather than derivatives or other adjutant knowledge.
- GAs use probability-based evolution rules rather than deterministic rules.

The purpose of this hybrid model is to train the ANN using some data and then train it further using a GA to optimize its performance. This approach is summarized in Fig. 4.

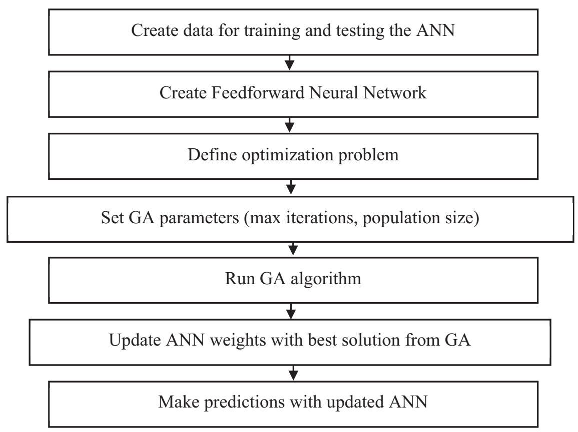

Figure 4: GA-ANN approach steps

This model can be given in three main steps:

1. Create the data that will be set to train and test the developed ANN.
2. Then a hybrid training ANN-GA function is employed when training ANN using a hybrid approach that combines backpropagation with a GA. The function then sets the biases and weights of the developed model.
3. An apdated ANN is then used to make predictions on the input data.

– The hybrid training ANN-GA function is a function that trains an ANN model using a GA optimization technique. The function takes in two inputs: The ANN model and the data to be used for training. The function first defines the optimization problem to be solved by setting the cost function.
– The optimization problem in this case is to find the set of weights and biases that minimize the root mean squared error (RMSE).
– The cost function is defined using another function that takes in the ANN weights and data to return the cost of the ANN model. The problem is then defined by setting the number of variables, the variable range, and the maximum and minimum values for each variable. Next, the GA parameters (the size of the population and the most iterations possible) are defined at the beginning. These parameters are used to set up the GA algorithm. The GA algorithm is

then run using the defined problem and parameters. ANN-GA model parameters are given in Table 4.

– Finally, the best solution found by this algorithm is employed to update the ANN weights, leading to an updated ANN, which is then used to make predictions on the input data.

Table 4: ANN-GA parameters

Number of hidden layers	Max iterations	Population size	Selection method	Crossover percentage	Mutation percentage
5	100	1000	Roulette wheel	0.6	0.4

3 Statistical Evaluation Indices

Metrics frequently seen in evaluation scores were used to evaluate the effectiveness of the methodologies being investigated [31]. These indices are displayed in Table 5.

Table 5: Some assessment indicators

Indice	Ideal	Equation
RMSE	Zero	$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(G_{pre.i} - G_{Act.i}\right)^2}{N}}$ (7)
MAPE	Zero	$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left\lvert\frac{G_{pre.i} - G_{Act.i}}{X_{Act.i}}\right\rvert$ (8)
R	One	$R = \frac{\sum_{i=1}^{N}\left(G_{pre.i} - \overline{G}_{pre}\right)\left(G_{pre.i} - \overline{G}_{Act}\right)}{\sqrt{\sum_{i=1}^{N}\left(G_{pre.i} - \overline{G}_{pre}\right)^2} \times \sqrt{\sum_{i=1}^{N}\left(G_{pre.i} - \overline{G}_{Act}\right)^2}}$ (9)

Where G_{Act} and G_{pre} stand for actual and predicted values, respectively, and N represents the total number of observations.

4 Findings and Discussions

Daily GSR was anticipated by the developed ANN, ANFIS, and GA-ANN models across three Algerian localities. Table 6 shows some statistical indicators of the performance of each model. According to the results, it is clear that the offered combined GA-ANN technique performed efficiently and provided satisfactory precision.

The ANN, ANFIS, and GA-ANN models are designed in order to predict daily GSR. It is obviously visible, as seen in Table 6 and Fig. 5, that the coupled approaches, such as the investigated GA-ANN and ANFIS, outperformed the stand-alone ANN model.

That is shown in the scatter plots (see Fig. 5) of the models that predict daily GSR; it displays the predicted data as a set of dots scattered near the straight line (red), the optimum fit, illustrating the correlation among the values that were predicted and those that were observed in all three cities that were chosen for the study.

Table 6: Results of the model's overall performance

City	Adrar			Ouargla			Bechar		
Model	ANN	ANFIS	GA-ANN	ANN	ANFIS	GA-ANN	ANN	ANFIS	GA-ANN
R	0.8909	0.9206	0.9008	0.8865	0.9304	0.9076	0.8839	0.9017	0.8877
rRMSE%	10.33	9.05	10.05	13.11	10.76	12.32	13.88	13.07	13.85
MAPE%	7.11	5.87	6.80	9.05	7.27	8.43	10.09	9.24	10.01

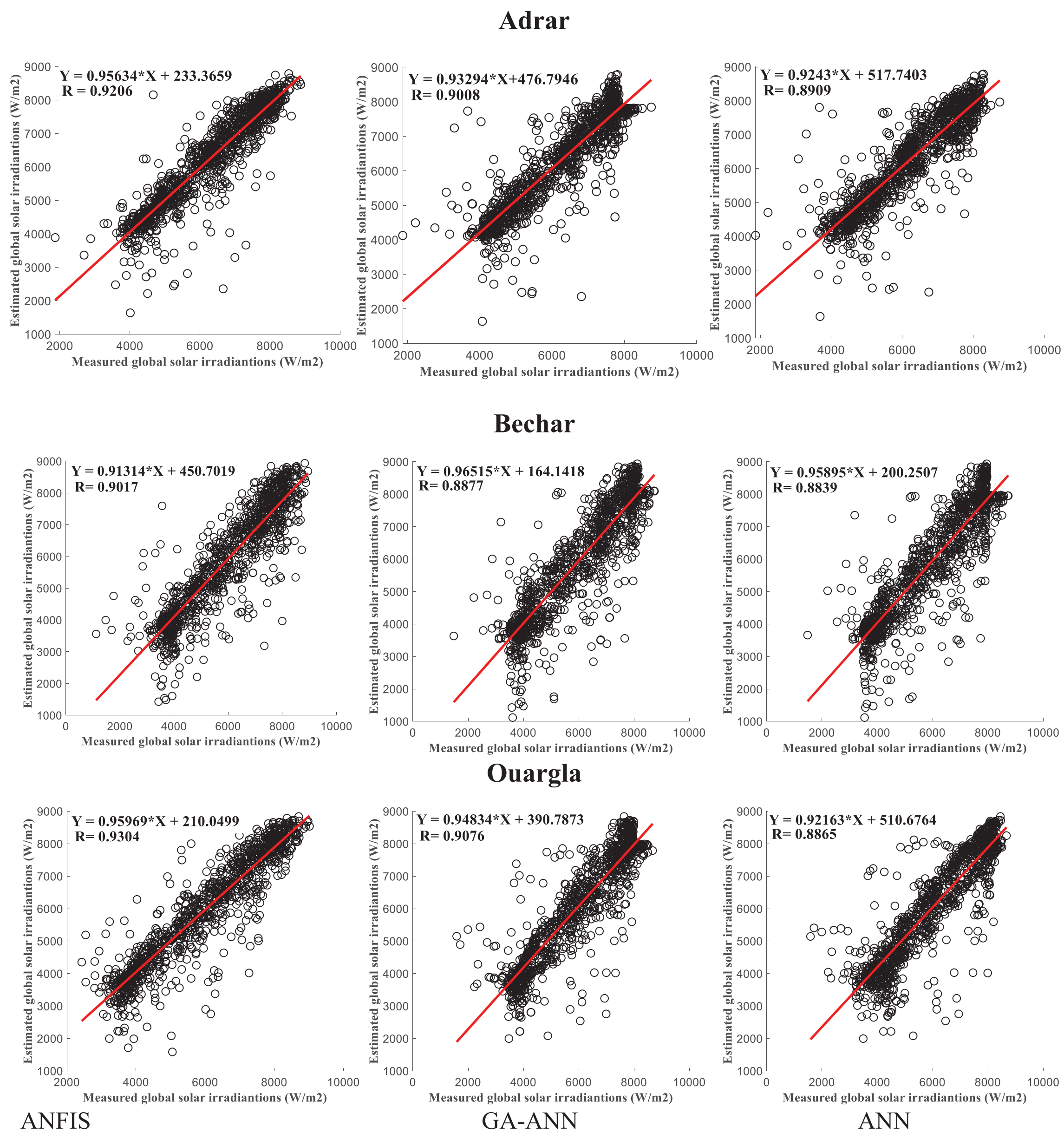

Figure 5: Scatter plot of the suggested models

Based on statistical assessment measures, ANFIS is the most precise and accurate model when the results from the three approaches are compared. Following ANFIS, GA-ANN demonstrates relatively strong performance, while the stand-alone ANN model appears less accurate. This underscores the success of employing GA to optimize the stand-alone ANN, thereby enhancing its performance. Nevertheless, the other hybrid model (ANFIS) was able to perform even better in all locations.

We have now established that the two hybrid ANN-based approaches outperformed the stand-alone ANN model. To thoroughly investigate the effectiveness of the hybrid ANFIS and GA-ANN approaches. We can see in Fig. 6, showing the error plot, that the ANFIS model shows a more consistent error pattern with lower deviations from zero in all three cities. This is consistent with the lower values of MAE, MSE, and RMSE, as well as the higher values of Nash-Sutcliffe Efficiency (NSE). ANFIS surpasses the other hybrid GA-ANN approach in terms of prediction performance, showing that ANFIS is more accurate at estimating daily (GSR). The superior performance of ANFIS, along with its adaptability to complex patterns and reduced need for manual adjustments, positions it as the preferred choice for accurate and reliable GSR forecasts in this context. This may result from model refinement in representing the relationship between independent and dependent variables, potentially incorporating influential variables. Consequently, the ANFIS model demonstrates the best stability and robustness in the model's predictions.

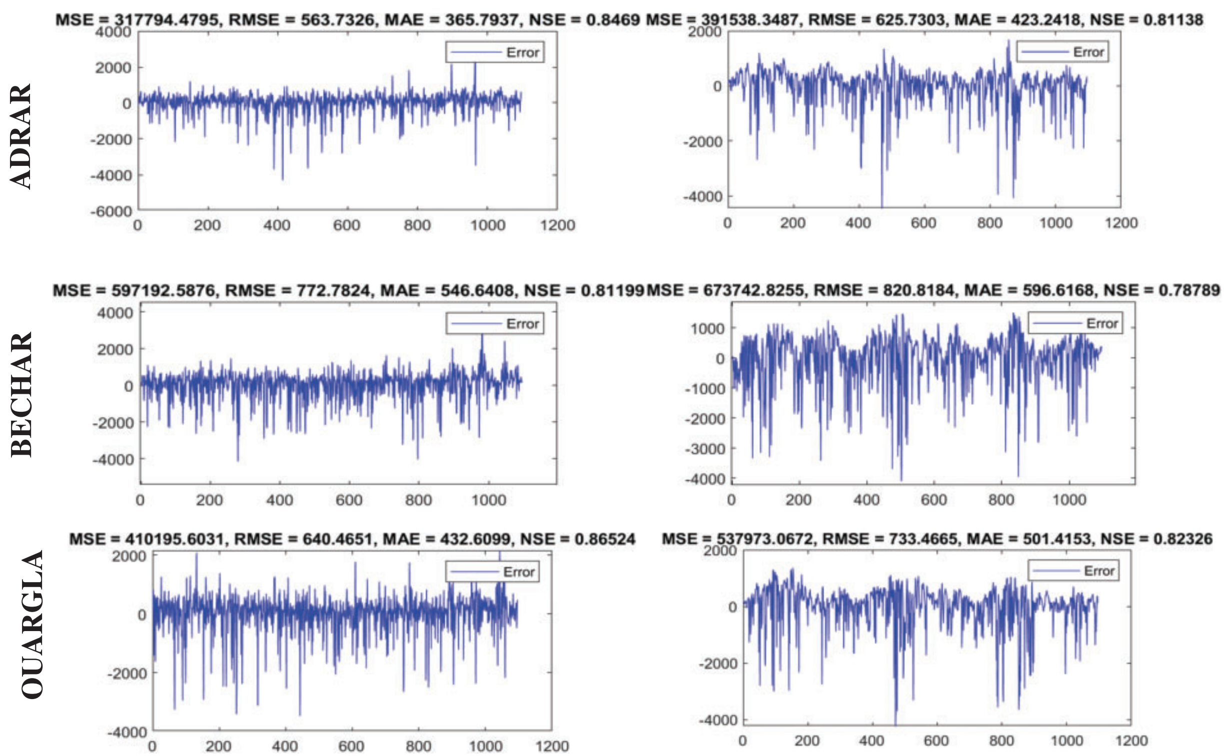

Figure 6: Error plot of the predicted GSR for ANFIS (left) and GA-ANN (right) models

The ANFIS model performs better than the GAANN model when it comes to daily solar radiation prediction. ANFIS has a stronger linear relationship and higher precision, especially for lower radiation values, as seen by Fig. 7's higher slope and lower intercept in its regression line. In contrast, GA-ANN has a higher intercept and a somewhat lower slope, indicating less accurate predictions, particularly for lower values. Because of its superior accuracy and higher predictive capabilities, especially for lower radiation levels, ANFIS is generally a better choice for predicting daily solar radiation.

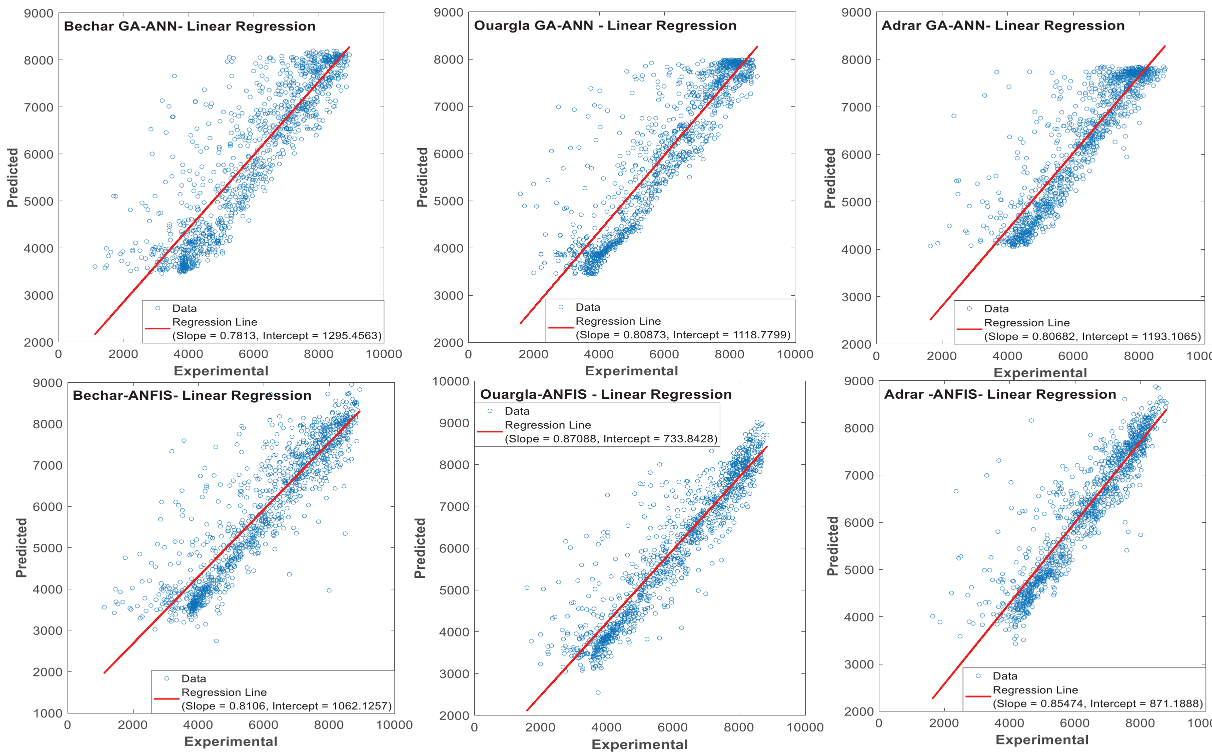

Figure 7: The GA-ANN and ANFIS models' linear slope and intercept tests

We can certainly establish that in this research, the hybrid ANFIS model resulted in the most accurate performance when anticipating the daily GSR according to the overall results. Therefore, we performed a deeper investigation to see how the two hybrid ANN-based (ANFIS and GA-ANN) models performed in the testing and training phases. Table 7 displays the statistical indicators of performance for both models in all considered sites. With the higher R values and the lowest rRMSE and MAPE values, we can see that ANFIS performed the best in both phases.

Table 7: Statistical indicators result for the testing and training phases

		Training			Testing		
City	Model	R	rRMSE%	MAPE%	R	rRMSE%	MAPE%
ADRAR	ANFIS	**0.9224**	**8.99**	**5.75**	**0.9196**	**9.28**	**6.34**
	GA-ANN	0.8971	10.21	6.86	0.9017	9.35	6.51
OUARGLA	ANFIS	**0.9298**	**10.81**	**7.14**	**0.9374**	**10.54**	**7.78**
	GA-ANN	0.9095	12.26	8.43	0.9005	12.56	8.40
BECHAR	ANFIS	**0.9056**	**12.67**	**8.88**	**0.8987**	**14.63**	**10.74**
	GA-ANN	0.8894	13.61	9.92	0.8811	14.98	10.79

Despite the fact that fuzzy logic provides a mathematical foundation for handling imprecision and uncertainty, it is usually used in control systems and decision-making processes, and it is not an optimization algorithm like GAs, which find the best solution in fields like machine learning. Upon comparing the models developed in this work, it is clear that combining fuzzy logic with ANNs gave better results than the approach where ANN was combined with GA.

For forecasting solar radiation using the same input set, ANFIS emerges as a suitable approach. Its adaptability to rule-based and data-driven patterns, combined with improved interpretability via fuzzy logic, make it a favorable competitor. ANFIS effectively integrates language rules with data-driven learning and demonstrates abilities in dealing with the difficulties of nonlinear data relationships. Notably, it reduces the need for considerable manual tuning, making it ideal for scenarios involving both rule-based and complex data patterns. Although employing the same inputs, the hybrid GA-ANN model optimizes the weights of the artificial neural network (ANN) using genetic algorithms (GA). While it provides flexibility and customization in terms of ANN architecture and hyperparameters, its performance is primarily dependent on the evolutionary algorithm's capacity to optimize weight. This model has the ability to excel in activities that need a high level of customization and optimization, particularly in complicated domains.

In our scenario, this model succeeds in outperforming the standalone ANN model by optimizing its weights. Consequently, it may be concluded that the application of optimization algorithms such as GA might not be the best option when developing a hybrid ANN model. It is undeniable that optimization algorithms do enhance the stand-alone model's performance.

Table 8 shows various types of models used to forecast GSR. ANNs and other machine learning approaches can be compared to the proposed GA-ANN method.

Table 8: The presented models performance compared across various studies

Reference	Model	Time step	Location	R
[32]	ANN	daily	France	0.7800
[33]	ANN	daily	Iran	0.8940
[34]	ANFIS	daily	Nigeria	0.8540
[20]	PSO-BPNN	daily	Beijing, China	0.9530
[35]	FFA-ANN	daily	ELoued city, Algeria	0.9321
The presented study	ANFIS	daily	Ouargla city, Algeria	0.9304
The presented study	GA-ANN	Daily	Ouargla city, Algeria	0.9076

The calculated assessment indice (R) is used to assess the predictability of the stated and current methodologies. When compared to other methodologies, the suggested investigation's outcomes show comparable effectiveness in terms of predictability and forecasting proficiency.

5 Conclusions

In a study spanning three cities in southern Algeria (Adrar, Ouargla, and Bechar), the efficacy of three techniques (ANN, GA-ANN, and ANFIS) at forecasting daily global solar radiation (GSR) over a 3-year period (2019–2021) using six input variables has been assessed. Our hybrid GA-ANN model, which aims to improve the ANN technique by optimizing ANN weights, outperforms the standalone ANN according to the statistical metrics (rRMSE, R, and MAPE). Nevertheless, in comparison to the other approaches, the GA-ANN model required more computing time. Conversely, ANFIS demonstrated the effectiveness of fuzzy logic in conjunction with ANNs by outperforming GA-ANN in forcasting daily GSR across all locations. Furthermore, the usage of the GA is yet to be investigated for optimizing other aspects of the ANN model, such as the hidden layers number, and even using other optimizing algorithms before establishing that fuzzy logic is superior for constructing hybrid models. In conclusion, whenever data is available, the model that was developed may be used to anticipate daily GSR in regions that are dry as well as other locations with similar conditions. It may also be useful while deciding on the installation of solar power installations.

Acknowledgement: The authors are grateful to the laboratory of Sustainable Development and Computer Science (LSDCS) for supporting this research, and to the Directorate-General for Scientific Research and Technological Development (DGRSDT).

Funding Statement: The authors received no specific funding for this study.

Author Contributions: Study conception and design: Djeldjli Halima, Ghasri Mehdi, Benatiallah Djelloul; data collection: Benatiallah Djelloul, Benabdelkrim Bouchra; analysis and interpretation of results: Djeldjli Halima, Benatiallah Djelloul; draft manuscript preparation: Djeldjli Halima, Tanougast Camel, Benatiallah Ali. All authors reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author, Djeldjli Halima, upon reasonable request.

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

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