Neural network for prediction solar radiation in Relizane region (Algeria) - Analysis study

Abdennasser Dahmani[1,2*], Yamina Ammi[2], Salah Hanini[2]

[1*]Department of Mechanical Engineering, Faculty of Science and Technology, University of Relizane, ALGERIA
[2]Laboratory of Biomaterials and Transport Phenomena (LBMPT), University of Medea, ALGERIA

[*]Corresponding author: Email: dahmani.abdennasser@univ-relizane.dz

Abstract – *Global solar radiation prediction is the most necessary part of the project and performance of solar energy applications. The objective of the present work is to predict global solar radiation (GSR) received on the horizontal surface using an artificial neural network (ANN). For the city (Relizane) in the western region of Algeria. The neural network-optimal model was trained and tested using 80 %, and 20 % of the whole data, respectively. The best results were obtained with the structure 10-25-1 (10 inputs, 25 hidden, and 1 output neurons) presented an excellent agreement between the calculated and the experimental data during the test stage with a correlation coefficient of R = 0.9879, root means squared error of RMSE = 47.7192 (Wh/m^2), mean absolute error MAE = 27.7397 (Wh/m^2), and mean squared error MSE = 2.2771e+03(Wh/m^2), considering a three-layer Feed forward neural network with Regularization Bayesienne (trainbr) training algorithm, a hyperbolic tangent sigmoid and linear transfer function at the hidden and the output layer, respectively. The results demonstrate proper ANN's predictions with a root mean square error (RMSE) of less than 0.50 (Wh/m^2) and a coefficient of correlation (R) higher than 0.98, which can be considered very acceptable. This model can be used for designing solar energy systems in the hottest regions.*

***Keywords**: Prediction, Global Solar Radiation, Artificial Neural Networks.*

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I. Introduction

Solar radiation statistics are needed by architects, engineers, and Scientists in the structure of research on photovoltaic or thermal solar radiation. The time step of facts relies upon the use that is supposed. If week-to-week average values permit us to comprehend an initial Sizing or design solar systems, everyday values, and better but, hourly Values are required if we are to carry out a greater accurate and unique Sizing. It is miles the same aspect if we want to represent the behaviour of the solar machine whilst a time-lag happens among production and Intake and that a strength storage way or an electrical Electricity buffer is in the device [1].

Algeria has a massive benefit regarding sun strength capacity due to its geographic position. The sunshine period at the complete Algerian country-wide territory exceeds 3.000 hours every year and might even attain 3.900 h on excessive plateaus and Sahara [2, 3], The solar radiation is one of the most sustainable energies most vital, it could be transformed into heat or electric powered power, and is used for plenty sun programs, which includes sun construction, sun consumption, heat pumps, air conditioning, agriculture, and studies of atmospheric physics [4].

Unfortunately, for lots of regions in this country, solar radiation measurements aren't effortlessly to be had due to the problem to afford the measurement equipment (pyranometers/ solarimeters) and the strategies involved (value, preservation, calibration requirement). Despite the existence of some of the meteorological stations at many locations in Algeria, now and again the measurements are not available continuously because of recording deficiencies due to heavy power cuts specifically in summers, or the number of recording variables is constrained. Therefore, it's far alternatively essential to difficult techniques to estimate as it should be the sun radiation based on greater readily available meteorological data, we use proven techniques to evaluate the solar radiation components, as the empirical modelling and intelligent techniques(artificial neural networks) [5].

nonlinear autoregressive recurrent neural networks with exogenous inputs (NARX) to be able to expect the hourly worldwide sun irradiation at 24-h forecast in New Zealand. An assessment among the NARX strategies with the artificial neural network (ANN) primarily based Multi-layer Perceptron (MLP) method, autoregressive shifting average (ARMA), and a reference persistence technique have proven appropriate results [6], successfully confirmed the ability of MLPs to generate very short-term inclined irradiation estimations (5 min) in Algiers (Algeria). The input data used: global horizontal irradiation, extraterrestrial irradiation, zenith angle, and azimuth declination. The study showed that the exclusion of azimuth as well, develops the accuracy of the model [7], Applied ANN techniques to predict components of solar radiation in New Delhi (India) [8], developed a variety of model ANNs for global solar radiation forecasting in Tamilnadu (India). The ANN models had better results than the other approaches in this study [9]. Used the comparison between the artificial neural network (ANN) Bayesian neural network (BNN), and empirical model for estimating the daily global solar irradiation with input data, air temperature, sunshine duration, relative humidity, and extraterrestrial irradiation. It was been deducted that the BNN model performs better than ANN approaches and empirical models [10]. Utilized the radial basis function (RBF) in order to predict daily global solar radiation with the air temperature, sunshine duration, and relative humidity as input data collected in Al-Madinah city in Saudi Arabia. It was found that the RBF approach uses the sunshine duration and air temperature as input parameters [11], and has focused on the prediction of the monthly average daily GSR over Italy via multi-location ANN by using other independent meteorological parameters, including the geographical coordinates [12], Developed a nonlinear model based on ANN and simulated annealing (SA) to predict the daily solar radiation on the horizontal surface [13].

This paper endeavors to propose an optimisation methodology for reaching a better multi-layer perceptron (MLP) network; based on almost all aspects of ANN modeling such as the division of the total databases (training, validation, testing), the activation function in the hidden layers, the training algorithms, pre-and post-processing, number of neurons in the hidden layers. In this work, an ANN approach model is used with aim of predicting the hourly values of global solar radiation based on ten climatological and meteorological parameters for 68 months in the region of Relizane–Algeria.

II. Material and method

II.1. Artificial neural network

Neural network technology possesses the advantages of self-learning, adaptability, fault acceptance, and distributed storage, allowing to implementation of a variety of nonlinear mappings in various fields neural network does not need a mathematical equation for the nonlinear connection between the inputs and outputs. It only learns some rules through its training, and the result closest to the expected output value can be obtained when the input value is given [14].

Artificial neural network models have been successfully used in many fields. The algorithm is the core of the ANN to achieve its functions. The processes to establish the ANN methods. The basic configuration of an ANN consists of many interconnected computing processors, named neurons or nodes, grouped into input, hidden, and output layers. Each node in an ANN takes values from its inputs, multiplies them by the corresponding weights, and sums up all the results plus a constant bias value. The summation then passes a transfer function and produces the output of the node [15].

Figure 1 presents a three-layer feed-forward neural network (FFNN) for global solar radiation (GSR).

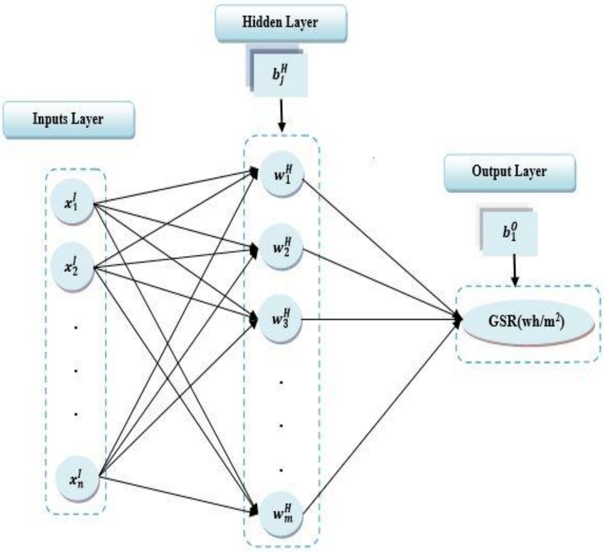


Figure 1. Three-layer feed-forward neural network for global solar radiation (GSR)

II.2. Modeling procedure

In this work, a procedure based on the design and optimisation of the architecture of the neural network is advanced as described in Figure 2.

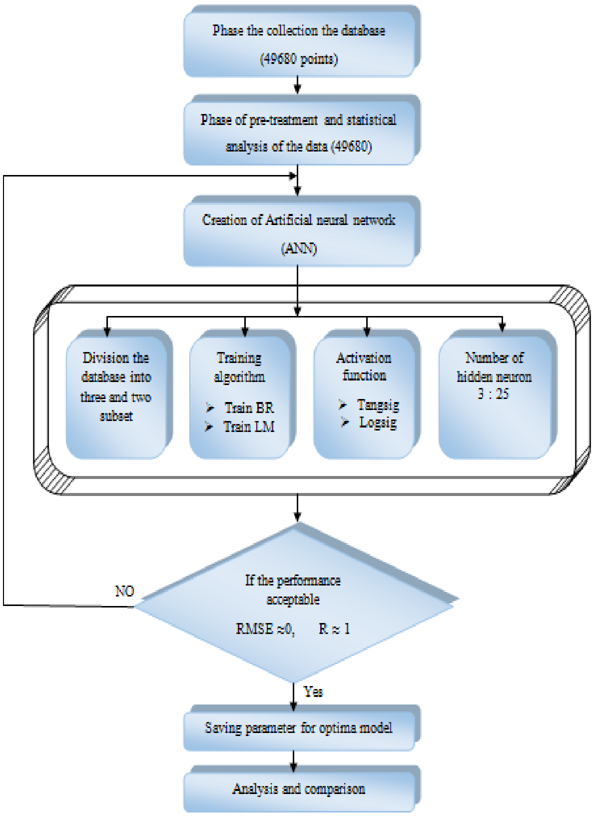


Figure 2. The procedure of the design and optimization of the architecture of ANN

II.3. Database collection and pretreatment

The database was provided for Relizane [16, 17], it is situated in the western region of Algeria, with a latitude: of 35.73°, longitude: of +0.55°, and altitude of 0 m above the mean sea level (Figure 3). The 68 months of database (1 January 2016 to 31 August 2021) were applied for forecasting hourly global solar radiation using neural networks (NN) for the ten parameter configurations.

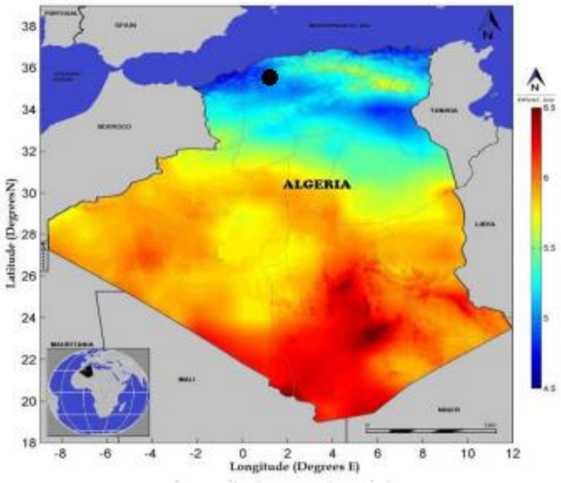


Figure 3. The Location of Relizane, Algeria [18]

Figure 4. shows the global solar radiation (GSR "Wh/m^2", 0.000 ≤GSR≤1041.5670) as a function temperature (T"K" 274.2100 ≤T ≤317.2100) for the total database (49680 points). Global solar radiation increases with increasing temperature at some points. There are null values of global solar radiation when the temperature is high, because, it is the night hours of the summer.

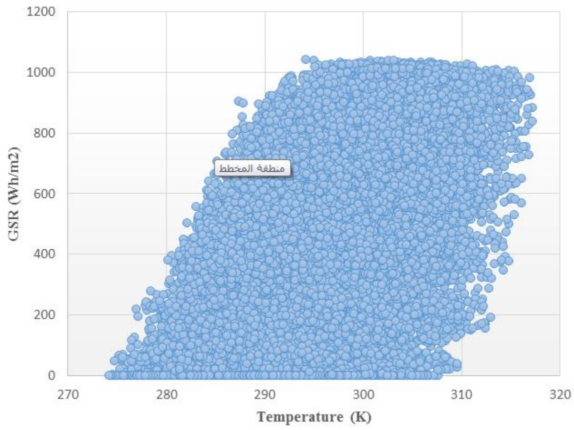


Figure 4. Global solar radiation (GSR "Wh/m^2") is a function of temperature (K)

The statistical analysis of the inputs and output data was done in terms of the minimum "min", the average "mean", the maximum "max", and the standard deviation "STD" which are mentioned in Table 1.

Table 1. Statistical analysis of inputs and output

		Min	Mean	Max	Std
Inputs	Time(h)	0.0000	11.5000	23.0000	6.9222
	Day	1.0000	15.7314	31.0000	8.8011
	Month	1.0000	6.2869	12.0000	3.3957
	Year	2016.0000	2018.3521	2021.0000	1.6430
	Temperature (k)	274.2100	292.3606	317.2100	8.2585
	Relative Humidity (%)	8.4600	57.8022	115.7000	21.6250
	Pressure (mbar)	960.7300	980.6193	998.9500	5.3782
	Wind speed(m/s)	0.0200	3.9565	15.9600	2.2281
	Wind direction(°)	0.0000	198.0728	359.9900	102.5724
	Rainfall (kg/m²)	0.0000	0.0427	8.7194	0.2387
Outp	Global solar radiation (Wh/m²)	0.0000	227.2048	1041.5670	305.4021

II.4. Modeling with neural network

The total databases (49680 points) were divided into three subsets according to the learning algorithm Levenberg-Marquard "LM" (training database, validation database, and testing database) and into two subsets according to the learning algorithm Regularization Bayesienne "trainbr"(training database and testing database) to test the predicting ability of the proposed models.

The number of neurons in the hidden layer varied from 3 to 25 neurons. The tangent hyperbolic (tanh), and the log sigmoid (logsig), transfer functions were used in the hidden layer. The pure-linear (purelin) was used in the output layer. The neural network was trained using two training algorithms Levenberg-Marquard (LM) and Regularization Bayesienne (trainbr).

The optimisation stage of neural network architecture for solar radiation estimation was performed using MATLAB 2020b software which goes through several steps such as algorithms, the distribution of the database, one of the hidden layers, the number of neurons in the hidden layer, the transfer functions for the hidden and the output layer respectively.

III. Results and analysis

Table 2 shows the error values (root mean squared error "RMSE" and coefficient of correlation "R") obtained for the global solar radiation under the influence of the division of the database for ANNs model with division 1 (39744 points for training (80%), 4968 for validation phase (10%), and 4968 for testing phase (10%)), division 2 (34776 points for training (70%), 7452 for validation phase (15%) and 7452 for testing phase (15%)), and division 3 (29808 points for training (60%),9936 for validation phase (20%), and 9936 for testing phase (20%)) for the learning algorithm Levenberg-Marquard "LM".

Table 2 demonstrates that division 2 with the learning algorithm Levenberg-Marquard "train-LM" has lower RMSE than divisions 1 and 3 (RMSE = 49.9423 and R = 0.9866 for the testing phase). Therefore, it is clear that division 2 with the learning algorithm Levenberg-Marquard "LM" with tansig represents the best result for modeling the global solar radiation using the ANN model.

Table 2. Effect of dividing the database with the learning algorithm Levenberg-Marquard "train-LM"

	Database	%	Train-LM RMSE (Wh/m²)	Train-LM R
Division 1	**Training phase :** 39744 data points	80%	49.8901	0.9865
	Validation phase : 4968 data points	10%	48.0259	0.9878
	Testing phase : 4968 data points	10%	50.9649	0.9862
	Total phase : 49680 data points	___	49.8158	0.9866
Division 2	**Training phase :** 34776 data points	70%	48.7469	0.9871
	Validation phase : 7452 data points	15%	51.3991	0.9859
	Testing phase :7452 data points	15%	**49.9423**	**0.9866**
	Total phase : 49680 data points	___	49.3335	0.9869
Division 3	**Training phase :** 29808 data points	60%	49.8128	0.9866
	Validation phase : 9936 data points	20%	52.8543	0.9848
	Testing phase :9936 data points	20%	51.4737	0.9858
	Total phase : 49680 data points	___	50.7682	0.9861

Table 3 shows the error values (root mean squared error "RMSE" and coefficient of correlation "R") obtained for the global solar radiation under the influence of the activation function (Log sigmoid "Logsig", Hyperbolic tangent sigmoid "Tansig") in the hidden layer. The ANN model with learning algorithms Regularization Bayesienne (trainbr) and with Hyperbolic tangent sigmoid "Tansig" gives lower errors than the other models (RMSE = 47.7192 and R = 0.9872 for the testing phase). We conclude the superiority of the ANN model with learning algorithms Regularization Bayesienne (trainbr) and with hyperbolic tangent sigmoid "Tansig" for modeling the global solar radiation.

Table 3. Effect of activation function in the hidden layer and the learning algorithms

		Log sigmoid "Logsig"		Hyperbolic tangent sigmoid "Tansig"	
		Train-BR	Train-LM	Train-BR	Train-LM
R	Training phase	0.9870	0.9874	0.9872	0.9871
	Validation phase	___	0.9864	___	0.9859
	Testing phase	0.9876	0.9869	**0.9879**	0.9866
	Total phase	0.9872	0.9872	0.9873	0.9869
RMSE (Wh/m²)	Training phase	48.9533	48.4635	48.6154	48.7468
	Validation phase	___	49.7874	___	51.3991
	Testing phase	48.1620	49.2661	**47.7192**	49.9423
	Total phase	48.7960	48.7851	48.4375	49.3335

Hence, the structure of the ANNs for the modeling of global solar radiation is mentioned in figure 5. Its more detailed architecture is illustrated in table 4. The weight matrices and bias vectors of the optimized ANN models are Applied,

w_I : the input-hidden layer connection weight matrix (25 rows x 10 columns);

w_h : the hidden-output layer connection weight matrix (25 rows x 1 column);

b_h : the hidden neurons bias column vector (25 rows);

b_o : the output neurons bias column vector (1 row).

The optimized ANN models shown are in Figure 5. Assimilation of the global solar radiation can be depicted by a mathematical model incorporating all inputs x_i, it is given by the following equations:

The instance outputs Z_j of the hidden layer:

$$Z_j = f_H\left[\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right] = \frac{\exp\left(\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right) - \exp\left(-\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right)}{\exp\left(\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right) + \exp\left(-\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right)}$$

j=1, 2, …, 25

The output "global solar radiation"

$$GSR = f_0\left[\sum_{j=1}^{25} w_{1j}^H Z_j + b_1^o\right] = \sum_{j=1}^{25} w_{1j}^H Z_j + b_1^o$$

The combination of Eqs. (1) and (2) lead to the following mathematical formula which describes global solar radiation by taking into account all inputs.

$$GSR = \sum_{j=1}^{25} w_{1j}^H \frac{\exp\left(\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right) - \exp\left(-\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right)}{\exp\left(\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right) + \exp\left(-\sum_{i=1}^{10} w_{ji}^I x_i + b_j^H\right)} + b_1^o$$

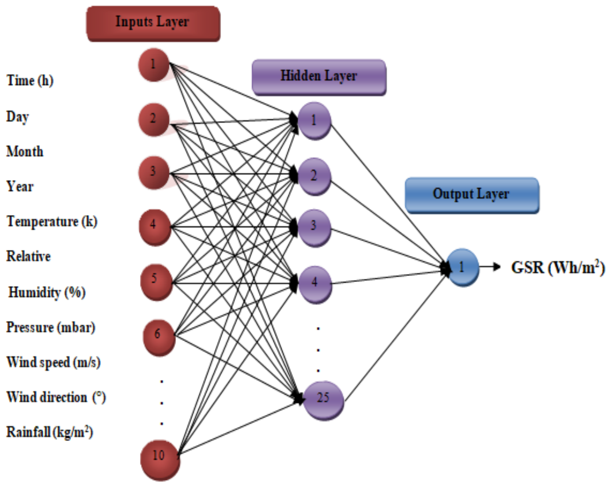
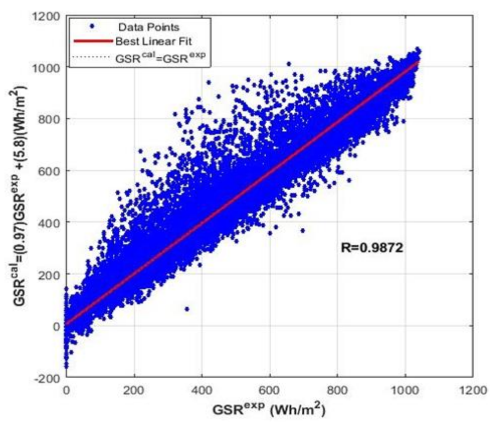


Figure 5. Three-layer feed-forward neural network for modeling the global solar radiation

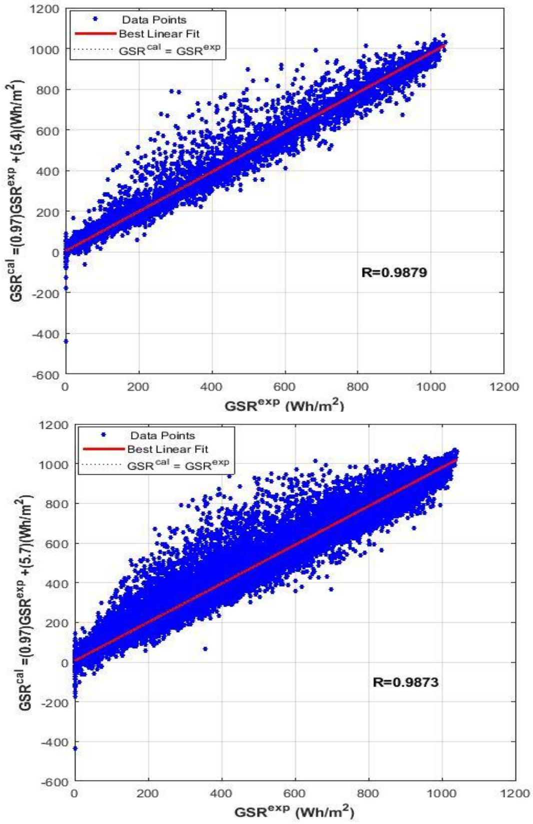
Table 4. Structure of the optimized ANN model

Training Algorithm	Input layer	Hidden layer		Output layer	
	Neurons number	Neurons number	Activation function	Neurons number	Activation function
Regularization Bayesienne (trainbr)	10	25	Sigmoid (tansig)	1	Linear (purelin)

The parameters and the plot of the linear regression are, straightforwardly obtained using the MATLAB function "postreg" (Figures 6a, b, and c). The comparison between experimental and calculated values of global solar radiation obtained by the ANN model optimal shows that there is excellent agreement between them with agreed vectors approaching the ideal [a(the slope), β(y-intercept), (correlation coefficient)] = [0.9745, 5.7842, 0.9872] for the training phase, [a, β, R] = [0.9727, 5.3708, 0.9879] for the testing phase, and [a, β, R] = [0.9741, 5.7027,0.9873] for the total phase.



(a)



Figures 6. Comparison between experimental and calculated values for the whole dataset, (a) training, (b) testing, and (c) all

The errors of the ANN model optimal for the training phase, testing phase, and total phase are: the correlation coefficient (R), the mean absolute error (MAE), the model predictive error (MPE), the root mean squared error (RMSE), the standard error of prediction (SEP), residual predictive deviation (RPD), range error ratio (RER), the mean square error (MSE), the mean relative squared error (MRSE), the accuracy factor (A_f), and bias factor (B_f) are given by following equations. The errors were calculated to confirm the prediction capacity of global solar radiation. Equations of those parameters are given below [19]:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\left(y_{i,exp} - y_{i,cal}\right)\right| \tag{4}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{i,exp} - Y_{i,cal}\right)^2}{n}} \tag{5}$$

$$\mathrm{SEP}(\%) = \frac{\mathrm{RMSE}}{Y_e} \times 100 \tag{6}$$

$$\mathrm{RPD} = \frac{\mathrm{SD}}{\mathrm{RMSE}} \tag{7}$$

$$\mathrm{RER} = \frac{\mathrm{Max} - \mathrm{Min}}{\mathrm{RMSE}} \tag{8}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_{i,exp} - y_{i,cal}\right)^2 \tag{9}$$

$$\mathrm{MRSE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_{i,exp} - y_{i,cal}}{y_{i,exp}}\right)^2 \tag{10}$$

$$A_f = 10^{\left(\sum_{i=1}^{n}\left|\log\frac{y_{i,cal}}{y_{i,exp}}\right|/n\right)} \tag{11}$$

$$B_f = 10^{\left(\sum_{i=1}^{n}\frac{\log\frac{y_{i,cal}}{y_{i,exp}}}{n}\right)} \tag{12}$$

Where n is the total number of data points, $Y_{i,exp}$ is the experimental value, $Y_{i,cal}$ represents the calculated value from the neural network "NN" model, and Y_e is the mean value of experimental data. STD is the standard deviation of experimental data, Min is the minimum of experimental data, and Max is the maximum of experimental data.

The statistical parameters of the ANN model optimal for the phases concerning the training, testing, and total are shown in Table 5. The correlation coefficient (R) for the training phase is 0.9872, which indicates the ideal agreement. The testing phase correlation coefficient represents a comparison between the experimental data and predicted results in order to show the interpolating ability of the ANN model optimal. For the testing phase, the correlation coefficient is 0.9879, which demonstrates the good agreement between the experimental global solar radiation and the predicted global solar radiation.

On the other hand, we adopted the five-level interpretations of Residual Predictive Deviation "RPD" and Range Error Ratio "RER" provided by Viscarra Rossel: excellent predictions (RPD and RER > 2.5); good (RPD and RER of 2.0 to 2.5); approximate quantitative predictions (RPD and RER of 1.8 to 2.0); possibility to distinguish high and low values (RPD and RER of 1.4 to 1.8); and unsuccessful (RPD and RER< 1.40) [20].

The RPD and RER of the neural networks model optimal are higher than 2.5 (RPD = 6.3051 (wh/m^2) and RER= 21.5033 (wh/m^2) for ANN) for the total phase. Moreover, the values of R,MAE,SEP, RER,RPD, MSE, MRSE, REA, A_f, B_f (for the training phases, for the testing phase, and the total phase) in addition to the RMSE imply that the ANN model has more predictive power in this work. They allow the representation of the nonlinear relationship the global solar radiation.

Table 5. Statistical Evaluation of the Models Performance

	Training phase	Testing phase	Total phase
R	0.9872	0.9879	0.9873
MAE (wh/m²)	27.8925	27.7397	27.8619
RMSE (wh/m²)	48.6154	47.7192	48.4375
SEP(%)	21.4145	20.9351	21.3188
RER(wh/m²)	21.4246	21.7716	21.5033
RPD(wh/m²)	6.2714	6.4435	6.3051
MSE(wh/m²)	2.3635e+03	2.2771e+03	2.3462e+03
MRSE(wh/m²)	2.6865e-04	3.5958e-04	2.8597e-04
REA (wh/m²)	0.0164	0.0190	0.0169
A_f(wh/m²)	1.0001	1.0081	1.0017
B_f(wh/m²)	1.0001	1.0081	1.0017

The statistical parameters of the ANNs model for the phases concerning the training, testing, and total are shown in Table 2. The correlation coefficient (R) for the training phase is 0.9872, which indicates the ideal agreement. The testing phase correlation coefficient represents a comparison between the experimental data and predicted results in order to show the interpolating ability of the ANNs model.

For the testing phase, the correlation coefficient is 0.9879, which demonstrates the good agreement between the experimental global solar radiation and the predicted global solar radiation.

The contribution of the input variables (Time(h), Day, Month, Year, Temperature (k), Relative Humidity (%), Pressure (mbar), Wind speed (m/s), Wind direction (°), Rainfall(kg/m^2)) on the output was determined by a sensitivity analysis using the "Weight" method and thus for the neural network optimal.

This method was proposed initially by [21]. and repeated by [22].provides a quantification of the relative importance (*RI*) of the inputs on the output of the neural network [23]. It is based on the partitioning of connection weights to [19]

- Connection weights of input – hidden;
- Connection weights of hidden - output.

The process of the "Weight" method is composed of four steps, which are depicted in Figure 7.

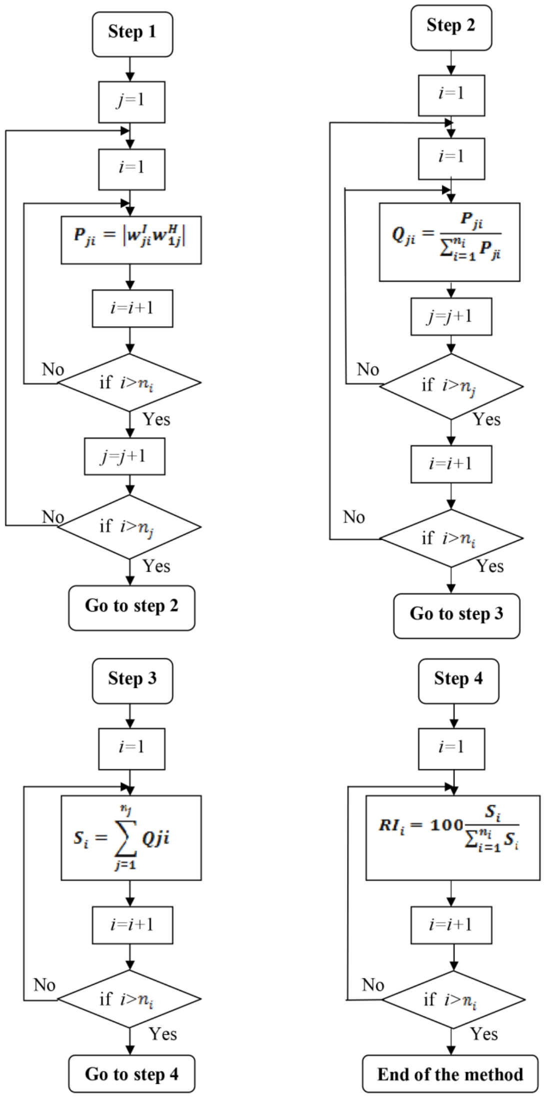


Figure 7. Flowchart of the "weight" method [19]

The contribution results are shown in Figure 8. The most important variables that may influence global solar radiation are Day, Rainfall (kg/m^2) Time (h), Year, Relative Humidity (%), Pressure (mbar), and Wind direction (°), the input relevant variables cited above have a significant contribution (RI > 2 %). This sensitivity analysis by the weight method successfully identified the true importance of almost all the variables used for the modeling of global solar radiation, and therefore, proves the correctness of the choice of variables that were used in this study.

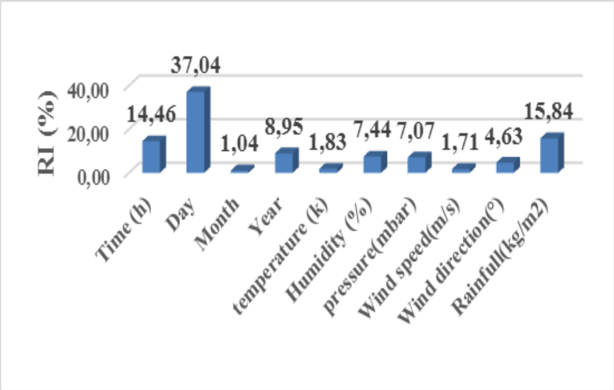


Figure 8. Relative importance (*RI*) Histograms

Comparison with different models

For the significance of the problem encountered during global solar radiation, models have been developed to study the performance of these processes. Among these models, we meet the neural networks optimal. However, there is a major number of works cited in the literature relating to work on modeling global solar radiation during the years 1998-2021.

Table 6 lists the only notable examples of studies predicting global solar radiation by the neural network model published over the years. Table 6. shows that our model is the only model that brings the prediction of global solar radiation in Relizane, Algeria.

In our model, we used ten input variables (Time (h), Day, Month, Year, Temperature (k), Relative Humidity (%), Pressure (mbar), Wind speed (m/s), Wind direction (°), Rainfall (kg/m^2)). Then other authors used the same or different input variables: [24] added the mean vapor and mean sunshine hours as our input variables; [25] used the inputs extra the latitude, longitude, and altitude; [26] were working with other inputs like the declination, the elevation of the sun, the azimuth, the angle incidence, and the air mass; and append the extraterrestrial solar irradiation and sunshine duration and other parameters [27].

In our current study, we used feed-forward neural networks (FFNN) with two training algorithms (Regularization Bayesienne (trainbr) and Levenberg-Marquard (LM)) and two activation functions (Sigmoid logistic and Tangent sigmoid)in the hidden layer for prediction hourly global solar radiation. Each literature cited in Table 6. Used the same organization (artificial neural networks, algorithm learning, and activation function), just [4] used Quasi-Newton Back Propagation (BFGS) as a training algorithm, and [18]: utilized an Elman Neural Network (ENN) as artificial neural networks type.

The comparison between our artificial neural network optimal model (ANN-optimal) and the literature models for predicting solar radiation in terms of the root mean squared error (RMSE), and the correlation coefficient (R), which were calculated using the data.

Our study presented the good performance of ANN-developed models. ANN models show a higher correlation coefficient (R=0.9879 and RMSE = 47.7192 (Wh/m^2) for the testing phase of our ANN optimal model), the correlation coefficients are generally considered to be excellent ($0.90 \leq R \leq 1.00$) for each ANN model compared to the ANN models reported in the literature Table 6 confirms the strength and accuracy of ANN models for the prediction of hourly global solar radiation.

Table 6. Results of our model versus various similar models

Models	Input variables	ANN Type Algorithm Learning Activation Function in Hidden Layer	Prediction error
Al-Alawi and Al-Hinai. [24]	-Month -Mean relative humidity -Mean temperature -Mean pressure -Mean vapour - pressure -Mean wind speed -Mean sunshine hours	-Feedforward Neural Network (FFNN)	-R = 0.93 à 0.95
Benghanem and Mellit [11]	-Air temperature -relative humidity -sunshine duration -day of the year	-FeedForward Neural Network (FFNN) - Levenberg-Marquard(LM)	-R =0. 9765 -RMSE = 0.04425%
Rezrazi et al. [27]	-Air temperature -Relative humidity -Number of days -Local time	-FeedForward Neural Network (FFNN) - Levenberg-Marquard (LM) and Regularization Bayesienne (trainbr). -Sigmoid logistique	-R = 0.9929 -RMSE = 14.06%
Siham et al. [4]	-Day -Time -Relative humidity -Temperature -Speed of wind -Wind direction -Atmospheric pressure	-FeedForward Neural Network (FFNN) -Quasi-Newton Back Propagation (BFGS) -Tangent hyperbolic	-R = 0.997 -RMSE = 4.82 %
Kurniawan and Shintaku. [25]	-Latitude -Longitude -Altitude -Number of months -Average, minimum, and maximum temperature -Sunshine duration - Precipitation -Wind speed -Relative humidity	-Feedforward Neural Network (FFNN) - Levenberg-Marquard(LM)	-R= 0.999
Amiri et al. [26]	-The declination -The elevation of the sun -The azimuth -The angle incidence -The air mass -The temperature - Relative humidity	- FeedForward Neural Network (FFNN) -Sigmoid logistic and Tangent hyprbolique	-R=0.995 -RMSE = 6.37%
Benatiallah et al. [18]	- Average temperature-Wind speed -Relative humidity - Atmospheric pressure -Extraterrestrial solar irradiation -Sunshine duration.	- FeedForward Neural Network (FFNN) and Elman Neural Network (ENN) - Levenberg-Marquard(LM) -Tangent sigmoid	-RMSE=0.703(KWh/m^2/day) -R = 0.9332
Present work	-Day -Month -Year -Time -Temperature -Relative humidity -Pressure -Wind speed -Wind direction -Rainfall	-FeedForward Neural Network (FFNN) - Levenberg-Marquard(LM) and Regularization Bayesienne (trainbr) -Sigmoid logistic and Tangent sigmoid	-R=0.9869 and R=0.9879 -RMSE= 49.2661(Wh/m^2) and RMSE=47.7192(Wh/m^2)

IV. Conclusion

In this study, the artificial neural network optimal model (ANN-optimal) was developed for modeling the 49680points of global solar radiation.

The best results were obtained with the structure 10-25-1 (10 inputs, 25 hidden, and 1 output neurons) presented an excellent agreement between the calculated and the experimental data during the test stage with a correlation coefficient (R) of 0.9879, root means squared error(RMSE)of 47.7192 (Wh/m^2), mean absolute error (MAE) of 27.7397 (Wh/m^2), and mean squared error 2.2771e+03(Wh/m^2), considering a three-layer feedforward neural network with Regularization Bayesienne (trainbr) training algorithm, a hyperbolic tangent sigmoid and linear transfer function at the hidden and the output layer, respectively.

The sensitivity analysis by weight method identified that the most important variables that influence the global solar radiation are: Day, Rainfall (kg/m^2), Time (h), Year, Relative Humidity (%), Pressure (mbar), and Wind direction (°).These input relevant variables have a significant contribution (relative importance RI >2 %).Our ANN-optimal model can be used for designing global solar radiation systems in the hottest regions.

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Declaration

- The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.
- The authors declare that this article has not been published before and is not in the process of being published in any other journal.
- The authors confirmed that the paper was free of plagiarism.

References

[1] G. Notton, C. Paoli, S. Vasileva, ML. Nivet, JL. Canaletti, C. Cristofari, "Estimation of hourly global solar irradiation on tilted planes from horizontal one using artificial neural networks," Energy, vol. 39, 2012, pp. 166-179. https://doi.org/10.1016/j.energy.2012.01.038

[2] A B Stambouli, Z Khiat, S Flazi, Y Kitamura, "A review on the renewable energy development in Algeria: Current perspective, energy scenario and sustainability issues," Renewable and sustainable energy reviews, vol. 16, no. 7, 2012, pp. 4445-4460. https://doi.org/10.1016/j.rser.2012.04.031

[3] Algerian Ministry of Energy and Mines. Renewable energy and energy efficiency program. Available from :< http://www.men-algeria.org>, [accessed on 2021]

[4] CM Siham, H Salah, L Maamar, K Latifa, "Artificial neural networks based prediction of hourly horizontal solar radiation data: case study," International Journal of Applied Decision Sciences, vol. 10, 2017, pp. 156-174. http://doi.org/10.1504/IJADS.2017.084312

[5] M Laidi, S Hanini, A Rezrazi, MR Yaiche, AA El Hadj, F Chellali, "Supervised artificial neural network-based method for conversion of solar radiation data: case study: Algeria," Theoretical and Applied Climatology, vol. 128, 2017, pp. 439–451. https://doi.org/10.1007/s00704-015-1720-7

[6] A Ahmad, TN Anderson, TT Lie, "Hourly global solar irradiation forecasting for New Zealand," Solar Energy, vol. 122, 2015, pp. 1398-1408. https://doi.org/10.1016/j.solener.2015.10.055

[7] K Dahmani, R Dizene, G Notton, C Paoli, C Voyant, ML Nivet, "Estimation of 5-min time-step data of tilted solar global irradiation using ANN (Artificial Neural Network) model," , vol. 70, 2014, pp. 374-381. https://doi:10.1016/ j.energy.2014.04.011

[8] ND Kaushika, RK Tomar, SC Kaushik, "Artificial neural network model based on interrelationship of direct, diffuse and global solar radiations," Solar Energy, vol. 103, 2014, pp. 327-342. https://doi.org/10.1016/j.solener.2014.02.015

[9] R Kumar, RK Aggarwal, JD Sharma, "Comparison of regression and artificial neural network models for estimation of global solar radiations," Renewable and Sustainable Energy Reviews, vol. 52, 2015, pp. 1294-1299. https://doi.org/10.1016/j.rser.2015.08.021

[10] R Yacef, A Mellit, S Belaid, Z Şen, "New combined models for estimating daily global solar radiation from measured air temperature in semi-arid climates: Application in Ghardaïa, Algeria," Energy Conversion and Management, vol. 79, 2014, pp. 606-615. https://doi.org/10.1016/j.enconman.2013.12.057

[11] M Benghanem, A Mellit, “Radial Basis Function Network-based prediction of global solar radiation data: Application for sizing of a stand-alone photovoltaic system at Al-Madinah, Saudi Arabia,” Energy, vol. 35, 2010, pp. 3751-3762. https://doi.org/10.1016/j.energy.2010.05.024

[12] EF Alsina, M Bortolini, M Gamberi, A Regattieri , “Artificial neural network optimisation for monthly average daily global solar radiation prediction,” Energy Conversion and Management, vol. 12, no. 15, 2016, pp. 320-329. https://doi.org/10.1016/j.enconman.2016.04.101

[13] SM Mousavi, E S Mostafavi, , P Jiao, “Next generation prediction model for daily solar radiation on horizontal surface using a hybrid neural network and simulated annealing method,” Energy conversion and management, vol. 153, 2017, pp. 671-682. https://doi.org/10.1016/j.enconman.2017.09.040

[14] Y Chen, L Shen, R Li, X Xu, H Hong, H Lin, J Chen, “Quantification of interfacial energies associated with membrane fouling in a membrane bioreactor by using BP and GRNN artificial neural networks,” Journal of colloid and interface science, vol. 565 2020, pp. 1-10. https://doi.org/10.1016/j.jcis.2020.01.003

[15] X Xue, “Prediction of daily diffuse solar radiation using artificial neural networks,” International journal of hydrogen energy, vol. 42, no. 47, 2017, pp. 28214-2822. https://doi.org/10.1016/j.ijhydene.2017.09.150

[16] SODA data. http://www.soda-pro.com/web-services#meteodata [accessed on 2021].

[17] Infoclimat. http://www.infoclimat.fr [accessed on 2021].

[18] D Benatiallah, K Bouchouicha, A Benatiallah, A Harouz, B Nasri, “Artificial Neural Network Based Solar Radiation Estimation of Algeria Southwest Cities,” In International Conference in Artificial Intelligence in Renewable Energetic Systems, 2020, pp. 573-583. https://doi.org/10.1007/978-3-030-63846-7_54

[19] Y Ammi, L Khaouane, S Hanini, “Prediction of the rejection of Organic compounds (neutral and ionic) by nanofiltration and reverse osmosis membranes using neural networks,” Korean Journal of Chemical Engineering, vol 32, no. 11, 2015, pp. 2300-2310. https://doi.org/10.1007/s11814-015-0086-y

[20] Y Ammi, L Khaouane, S Hanini, “A Comparison of" Neural Networks and Multiple Linear Regressions" Models to Describe the Rejection of Micropollutants by Membranes,” Kemija u Industriji, vol. 69, 2020, pp. 111-127. https://doi.org/10.15255/KUI.2019.024

[21] GD Garson, “Interpreting Neural Network Connection Weights,” Artificial Intelligence Expert, vol. 6, 1991, pp. 47–51. https://dl.acm.org/doi/10.5555/129449.129452

[22] A Goh, “Back-propagation neural networks for modeling complex systems,” Artificial Intelligence in Engineering, vol. 9, no. 3, 1995, pp. 143-151. https://doi.org/10.1016/0954-1810(94)00011-S

[23] M Gevrey, I Dimopoulos, S Lek, “Review and comparison of methods to study the contribution of variables in artificial neural network models,” Ecological Modelling, vol. 160, no 3, 2003, pp. 249-264. https://doi.org/10.1016/S0304-3800(02)00257-0

[24] SM Al-Alawi, HA Al-Hinai, “An ANN-based approach for predicting global radiation in locations with no direct measurement instrumentation,” Renewable Energy, vol. 14, 1998, pp. 199-204. https://doi.org/10.1016/S0960-1481(98)00068-8

[25] A Kurniawan, E Shintaku, “ A neural network-based rapid maximum power point tracking method for photovoltaic systems in partial shading conditions,” Machine Learning and Computing, vol. 56, no. 3, 2020, pp. 157-167. http://doi.org/10.3103/s0003701x20030068

[26]. B Amiri, R Dizène, K Dahmani, “ Most relevant input parameters selection for 10-min global solar irradiation estimation on arbitrary inclined plane using neural networks,” International Journal of Sustainable Energy, vol. 39, no.8, 2020, pp. 779-803. https://doi.org/10.1080/14786451.2020.1758104

[27] A Rezrazi, S Hanini, M Laidi, “ An optimisation methodology of artificial neural network models for predicting solar radiation: a case study,” Theoretical and applied climatology, vol. 123, 2016, pp. 769-783. http://doi.org/ 10.1007/s00704-015-1398-x