Revue des Energies Renouvelables Vol. 19 N°4 (2016) 617 - 631
DOI: https://doi.org/10.54966/jreen.v19i4.599

Evaluation of the global solar irradiation from the artificial neural network technique

Said Benkaciali [1,2] , Mourad Haddadi [1], Abdallah Khellaf [3],
Kacem Gairaa [2] and Mawloud Guermoui [2]

[1] Laboratoire des Dispositifs de Communication et de Conversion Photovoltaïque, LDCCP
Département d'Electronique, Ecole Nationale Polytechnique, B.P. 182, El Harrach, Algiers, Algeria
[2] Unité de Recherche Appliquée en Energies Renouvelables, URAER
Centre de Développement des Energies Renouvelables, CDER
47133, Ghardaia, Algeria
[3] Centre de Développement des Energies Renouvelables, CDER
B.P. 62, Route de l'Observatoire, 16340, Bouzaréah, Algiers, Algeria

(reçu le 10 Novembre 2016 - accepté le 25 Décembre 2016)

Abstract - *In this study, many experiments were carried out to assess the influence of the some input parameters on performance of the multilayer perceptron techniques, which is architectures one of the artificial neural network (ANN). To estimate the daily global solar irradiation (GSI) on horizontal surface, we have developed eight models by using four weather input parameters collected from a radiometric station installed at Ghardaia site (southern of Algeria), such as sunshine duration, daily mean temperature, daily relative humidity, and Solar declination. In order to select the best configuration among the chooses combinations which provides a good accuracy, three statistical formulas (or statistical indicators) have been evaluated, such as the normalized root mean square errors, (nRMSE), normalized mean bias error (nMBE, and coefficient of determination R²). We noted that the ANN model provides best performance compared to the developed empirical models. results of the nMBE, nRMSE, and R² are about 0.048%, 4.422%, and 98.00%, for ANN and 0.0772%, 5.5381%, and 97.22% for the quadratic model. Moreover, it was proved that the sunshine duration is important parameter, for predicting the GSI.*

Résumé - *Dans cette étude, de nombreuses expériences ont été menées pour évaluer l'influence de certains paramètres d'entrée sur la performance des techniques de perceptron multicouches (MLP), qui est l'une des architectures du réseau neuronal artificiel (ANN). Pour estimer l'irradiation solaire globale quotidienne (GSI) sur la surface horizontale, nous avons développé huit modèles en utilisant quatre paramètres d'entrées météorologiques collectés à partir d'une station radiométrique installée sur le site Ghardaïa, tels que la durée d'ensoleillement, la température moyenne quotidienne, quotidiennement L'humidité relative et la déclinaison solaire. Afin de sélectionner la meilleure configuration, trois formules statistiques (ou indicateurs statistiques) ont été utilisées, erreur quadratique moyenne (nRMSE), erreur moyenne (nMBE) et coefficient de détermination (R²). En outre, il a été prouvé que la durée du soleil est un paramètre important pour prédire le GSI.*

Keywords: Global solar irradiation - ANN technique - Empirical models - Statistical formulas.

1. INTRODUCTION

The solar radiation is one of the sustainable energies most important, it can be transformed into heat or electric powers, and used for various solar applications, such as solar building, solar eating, heat pumps, air conditioning, agriculture, and research of atmospheric physics.

In this case, a precise knowledge of the direct, diffuse, and global solar radiation components are required for the better exploiting solar energy. A solar radiation measurements in one site are obtained a through the radiometric stations which operate instantly and every day. Sadly, these systems cannot be available for all sites, so we use proven techniques to evaluate the solar radiation components, as the empirical modelling and intelligent techniques.

Among these methods, include the physical processes which consist to study of the interactions between solar radiation with the terrestrial atmosphere [1-4], the empirical models giving the solar radiation components as function to meteorological parameters [5-12], auto-regressive integrated moving average (ARIMA and ARMA) models [13, 14], and artificial intelligence techniques Support Vector Machine (SVM), Core Vector Machine (CVM), artificial neural networks (ANN), Genetic algorithms, hidden Markov model, etc..

Ahmad *et al.* [15] used the nonlinear autoregressive recurrent neural networks with exogenous inputs (NARX) in order to predict the hourly global solar irradiation at 24-h forecast in New Zealand. A comparison between the NARX method with the artificial neural network (ANN) based Multi-layer Perceptron (MLP) method, auto regressive moving average (ARMA) and a reference persistence approach has shown the good results, such as the root mean squared error (RMSE) equal to 0.243 MJ/m^2 compared to 0.484 MJ/m^2, 0.315 MJ/m^2 and 0.514 MJ/m^2 for the MLP, ARMA and persistence approaches respectively.

The sequences of mean monthly clearness index and total solar radiation were evaluated by Mellit *et al.* [16] by using the Adaptive Neuro-Fuzzy Inference System (ANFIS) based some on the geographical coordinate over 60 locations in Algeria. They found root mean square error (RMSE) between measured and estimated values varies between 0.0215 and 0.0235 and the mean absolute percentage error (MAPE) is less than 2.2 %. In addition they have proved the advantage of the proposed method against to artificial neural network (ANN) models.

Martin *et al.* [17] used three statistical based on time series to predicted half daily values of global solar irradiance with temporal horizon of 3 days for same sites in Spain (Murcia, Albacete, Madrid and Lerida). The Neural Networks, Autoregressive (AR) and Neuro-Fuzzy Inference System (ANFIS) methods compared between them and the Neural Networks as better models.

Wang *et al.* [18] tested three models, the Multilayer Perceptron (MLP), Generalized Regression Neural network (GRNN), Radial Basis Neural Network (RBNN), and Bristow- Campbell. Additionally, for 12 stations across in China same input variables have been selected such as the daily water vapour pressure, relative humidity, air temperature, and sunshine duration. Their results showed that the MLP and RBNN models provide better accuracy than the GRNN and BC models.

Yadav *et al.* [19] reviewed different ANN techniques to identify suitable methods for forecasting solar radiation in literature. The results indicated that the prediction accuracy was dependent on input parameter combinations, training algorithm and architecture configurations.

Mellit *et al.* [20] proposed an approach using ANN and a library Markov transition matrix (MTM) to generate a sequence of global solar radiation based on the latitude, longitude, and altitude input data and collected from 60 meteorological stations in Algeria. Results obtained indicate that the MTM model can successfully be used for the estimation of the daily solar radiation data for any locations in Algeria by using as input the altitude, the longitude, and the latitude.

Benghanem *et al.* [21] developed six ANN models for estimating the daily global solar radiation in Al-Madinah (Saoudi Arabia); based on different combination of 4 inputs variables, i.e., the temperature, relative humidity, sunshine duration, and day of year, it was found that the model using sunshine duration and air temperature as inputs, gives good accurate results since the correlation coefficient is 97.65 %. It was also noted that the model is better that empirical models.

Behrang *et al.* [22] developed two ANN models for the estimation of daily global solar radiation on horizontal surface: Multi-layer Perceptron (MLP) and radial basic function (RBF) using five inputs variables, temperature, relative humidity, sunshine hours, evaporation, and wind speed for Dezful city in Iran. It was found that the results from ANN models show very good improvements compared to the conventional models, i.e., the predicted values of the best ANN model has a mean absolute percentage error about 5.21 % versus 10.02 % for best conventional model.

Rahimikhoob [23] compared between the artificial neural network and Hargreaves-Samani (HS) approaches for the estimation global solar radiation as function of the air temperature, at Khuzestan plain in the southwest of Iran. it was found that the ANN approaches gives better estimate results than the HS model with root mean square error (RMSE) and the determination coefficient evaluated between the measured and estimated ANN are 2.534 MJ/m^2/day and 0.889, respectively.

Yacef *et al.* [24] used the comparison between the Bayesian neural network (BNN), artificial neural network (ANN) and empirical model for estimating the daily global solar irradiation with as input data, air temperature, relative humidity, sunshine duration and extraterrestrial irradiation. It was been deducted that BNN model performs better that ANN approaches and empirical models.

Benghanem *et al*. [25] used the radial basis function 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 at Saudi Arabia. It was found that the RBF approach which uses the sunshine duration and air temperature as input parameters, gives accurate results with the correlation coefficient of 98.80 %.

Lam *et al.* [26] developed the ANN models for the estimation of the daily global solar radiation using the sunshine duration as input variables collected in 40 cities in China. It was found that the coefficients of determinations are highest to 0.82.

Rehman *et al*. [27] developed three ANN architectures for the estimation of global solar radiation in Abha (Saudi Arabia) as function of air temperature and relative humidity. It was obtained that ANN methods are capable to estimate the global solar radiation from the temperature and relative humidity in the location.

Cao *et al*. [28] established new daily diffuse solar models for Northern China climates and compared them with open-access weather station data from China Meteorological Data Sharing System (CMDSS), with TRNSYS values, and also with measured data in China. It has been concluded that CMDSS and the new diffuse solar models provide good results.

In this paper we apply the Multi-layer neural network (MLP) learning methods in order to develop optimal neural networks for predicting the daily solar irradiation (GSR) on horizontal surface from twelve meteorological data collected in Ghardaia city (southern of Algeria). Additionally, two other methods have been developed and compared: Radial basis function (RBF) and empirical models.

This paper is organized as follows: This paper is organized as follows: section 2 presents a description of Ghardaia location and dataset. Section 3 provides a brief review on used empirical models. A brief introduction to Multi-layer Perceptron neural network is given in section 3. Section 4 introduces a description of the radial basis function method. Results and discussion are reported in last section.

2. LOCATION AND DATA SET

As it is mentioned previously, the used solar datasets were assembled from two different climatic sites: The CDER (Centre de Développement des Energies Renouvelables), Algiers and URAER (Unité de Recherche Appliquée pour les Energies Renouvelables), Ghardaia.

The measurements were recorded by two device stations, within the coordinates (36.8°N, 3.08°E, Altitude 345m and 32.4°, 3.8°E, Altitude 463m), respectively. Algiers, the lieu of the first experimental field is located on the Mediterranean coast, northern part of the country and is characterized by a moderate climate.

However, Ghardaïa is a desert region, located in the southern part, about 600 km from the coast and is characterized by semi-arid climate. Furthermore, both the two regions have an astonish solar potential, where the recorded yearly accumulated DSI and global solar irradiations range from 2000-2100 kWh/m^2/day, 1800-1850 kWh/m^2/day in Algiers, and 2100-2200 Wh/m^2/day, 2000-2100 kWh/m^2/day in Ghardaia.

In terms of irradiance, the maximum of direct on normal surface and global horizontal irradiances around 850 W/m^2 and 1000 W/m^2 for Algiers and Ghardaia, as shown respectively, by the figure 1.

The maximum of direct and global irradiance, received on normal and on horizontal surfaces were about 950 W/m^2 and 1100 W/m^2, respectively, as detailed in figure 2.

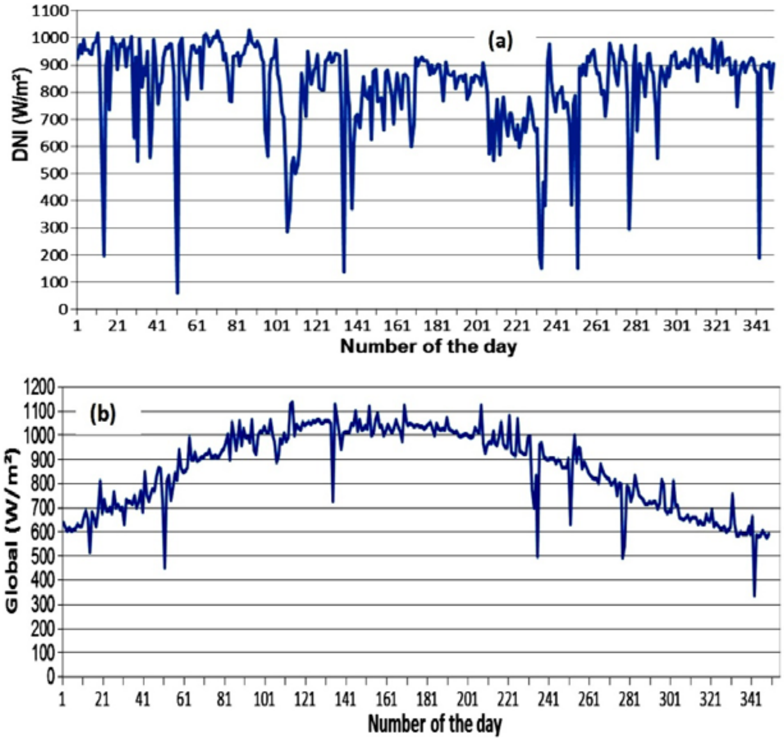


Fig. 1: Evolution of DSI and global solar irradiances on horizontal surface, at Algiers site

Moreover, for Ghardaia site, due to the high intensity of the direct normal irradiance and the high frequency of clear days, it has been observed that the DNA signal is almost stationary, as it is illustrated in the figure 1**a**. In addition, it can be seen that the rate of cloudy days is more important in Algiers than the Ghardaia, as it is confirmed by the figure 1**b** and figure 2**b**.

Regarding the daylight-hours, Ghardaia presents the more important sunshine duration with a monthly daily average varies from 5h until 14h than Algiers which received an average between 4h and 10h, as seen in the figure 3**a** and figure 3**b**, respectively.

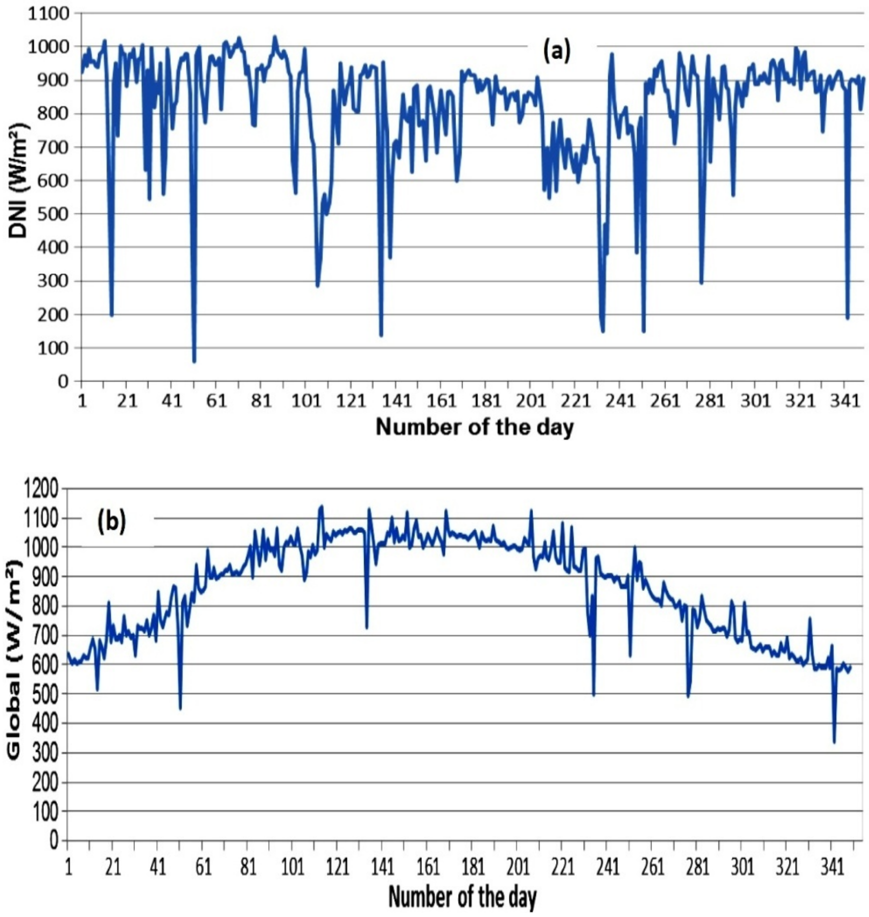
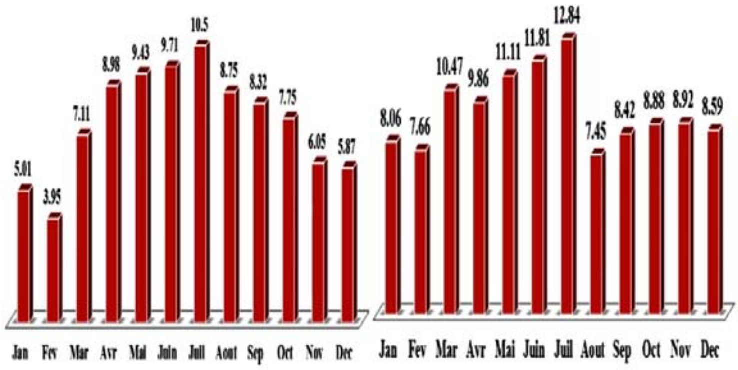


Fig. 2: Evolution of DSI and global solar
irradiances on horizontal surface, at Ghardaia site

It can be noted that the various parameters of the solar radiation and the meteorological parameters were recorded within 5 and 10 minute steps, on the two sites, respectively through outstanding instruments, during the years 2014 and 2015.

Direct solar irradiance measurements were carried out by the DR01 and Kipp-Zonen pyrheliometric sensors. The calibration is typically less than 2%, shown in **Table 1**. Additionally, the pressure, temperature and relative humidity have been measured by mean manometer and hygrometer.



-a- Bouzareah **-b- Ghardaia**

Fig. 3: Histograms of daily sunshine duration

The unavailable parameters were evaluated by empirical formulas, as the water vapor, Angström turbidity, ozone thickness, broadband atmospheric optical depth and the Linke turbidity factor, presented in the following section.

Table 1: Technical specifications for Kipp & Zonen (CHP1) and Hukseflux pyrheliometer (DR01)

Pyrhliometer	Kipp-Zonen	Hukseflux
ISO classification	First Class	First Class
Response time (95%)	5 s	18 s
Non-stability (change.year in % of full scale)	±0.5%	< 1%
Temperature dependence of sensitivity	± 0.5%	<0.1%/°C
Full opening view angle	5° ± 0.2	5°
Slope angle	1° ± 0.2	1°
Temperature range	-40°C - +80°C	-40°C - +80°C
Spectral range	200 to 4000 nm	200 to 4000 nm
Sensitivity	7.82 µV/W/m²	10 µV/W/m²
Irradiance range	0 to 4000 W/m²	0 to 2000 W/m²

3. METHODOLOGY

3.1 Empirical models

In order to estimate the daily global solar irradiation (GSI) and the DNI, on horizontal plane, we have developed seven empirical models based on six input parameters, such as the daily sunshine duration (S), length of the day (S_0), extraterrestrial irradiation (H_0), average temperature (T), average humidity (η), and solar declination (δ).

Moreover, some indexes have been employed in order to write the empirical models, like for the clearness index, $K_t = GSI / H_0$ and sunshine duration fraction, $\sigma = S / S_0$. Latter parameters characterize generally the sky clarity, i.e., more the parameters are important, more sky is clear [8-10, 29].

The first model includes a linear Angstrom-Prescot equation, which defines the clearness index in function of sunshine duration fraction, employed by [29] and developed by Angstrom [30], as shown in {Eq. (1)}.

Other empirical models can be written from the other empirical expressions based upon other variables are defined by {Eqs. (1-6)}.

$$K_t = a + b.\sigma \quad (1)$$

Other linear equations and quadratic equation are written as fellows [8, 9, and 31]:

$$K_t = a + b.\sigma + c.\sigma^2 \quad (2)$$

$$K_t = a + b.\sigma + c.T \quad (3)$$

$$K_t = a + b.\sigma + c.\eta \quad (4)$$

$$K_t = a + b.\sigma + c.\delta \quad (5)$$

$$K_t = a + b.T + c.\eta + d.\delta \quad (6)$$

$$K_t = a + b.\sigma + c.T + d.\eta + e.\delta \quad (7)$$

Where, a, b, c, d, and e are empirical constants and S_0 is the day length. The H_0 is the daily extraterrestrial irradiation on horizontal surface. S_0 and H_0 were evaluated from the equations detailed in [10].

3.2 Artificial neural network

The artificial neural networks (ANN) are the intelligent systems that have the capacity to learn, memorize and create relationships among data. ANN techniques are able to learn information patterns within multidimensional domains, such as pattern recognition, identification or prediction, control systems and classification [34].

These approaches are based on our understanding of biological nervous system through neurons, which are the basic structural unit of nervous system [35]. They receive the inputs from other sources, combine them, perform a general nonlinear operation on the result, and then output the final result [36].

Multilayer Perceptron (MLP) is one of the most widely used ANN with nonlinear approximation[32, 33].The MLP network includes three layers, namely, input, hidden, and output layers. Neurons (nodes) are the fundamental elements in each layer, and every neuron in one layer is associated and interacts with other layers.

The neurons have five basic components namely input, weights, threshold (bias), summing junction and output. A typical neuron (j) in the neural network is presented on figure 4, with an input x_i which is transmitted through a connection, and its strength is multiplied by a weigh w_{ji} to give a product $x_i w_{ji} + w_{0j}$.

The product is an argument of transfer function f which yields an output y_i for the hidden layer neurons [37], as in {Eq. (6)}. Where f is the hyperbolic tangent, defined for any variable z through {Eq. (7)}:

$$y_j = f\left(\sum_{i=1}^{N}(x_i w_{ij} + w_{0j})\right) \quad ......(8)$$

$$f(x) = \frac{2}{1 + e^{-2(x_i w_{ij} + w_{0j})}} - 1 \quad (9)$$

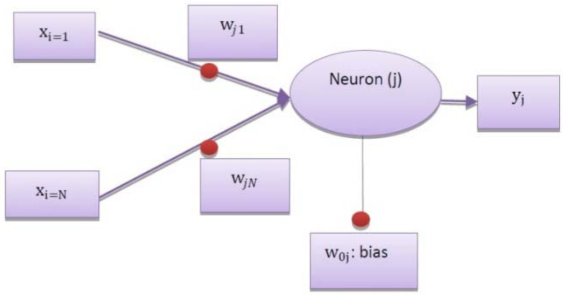


Fig. 4: Typical neuron in one hidden layer

A neural network uses a learning mode (back propagating algorithm), in which an input is presented to the network along with a desired output (supervisor type neural network), and the weights are adjusted so that the neural network attempts to produce the desired output.

The back propagating algorithm evaluates the errors between the network outputs and target to adjust the network weight. In our study, three datasets are considered in ANN applications, namely, training, validating, and testing datasets.

The training algorithm minimizes the mean square difference between the network output and the desired output. The associated error function is expressed by {Eq. (10)}. The validating dataset processes new input data with trained weights. The testing dataset is applied to check the overall performance of a trained and validated network.

$$e = \frac{1}{2} \cdot \sum_{k=1}^{k=n} (y_k - t_k)^2 \tag{10}$$

Where, e denotes the errors, n is the numbers of neurons, y_k is the network output in the k^{th} iteration (or epoch), and t_k is the target.

Levenberg –Marquardt (LM) algorithm is a popular method to solve nonlinear problems effectively due to its ability to converge from a wide range of initial input values; its efficacy is due to the computation of Jacobian matrix [39, 40].

For the principle training our neural network, LM has been used. In the other hand, in our work, we have used 654 daily GSI and we have divided them into two parts: The first part (30 %) was used for network training, the second part (20 %) for validation and (50 %) for testing.

In order to suit the consistency of the model, all source data were normalized in the range 0 and 1. Then, we returned to the estimated values of the daily GSI, i.e. to the output values un-normalized, as expressed by {Eq. (11)}.

$$GSI_{est} = \frac{GSI_{unnorm} - GSI_{min}}{GSI_{max} - GSI_{min}} \tag{11}$$

2. RESULTS AND DISCUSSION

654 days have been achieved covering the periods between 2014 and 2015 under Ghardaia site. Based on the equations relative to the solar declination (see previous section) and expression of the different regressions and ANN program, a 'Matlab' program is developed for estimating the GSI on horizontal surface,. Moreover, the

statistical tests and graphical comparisons are performed using the 'Matlab' software and Microsoft 'Excel', respectively.

2.1 Performance formulas

The performance formulas (or statistical indicators, or also Metrics) used here are the normalized mean bias error (nMBE), normalized root mean square error (nRMSE), and coefficient of determination (R^2). These indicators are usually applied in the comparison of solar radiation estimation models, as e.g., [43].

Generally, a model designed to compute the solar radiation, especially the solar GSI averred good performance, when the nMBE and nRMSE have the lowest values and to the high values of the R^2. However, the nMBE has also the advantage to provide information about the over-estimation or under-estimation average of model versus measured values.

The positive value of nMBE informs about over-estimation average, while the negative value informs about under-estimation average. Likewise, the coefficient of determination (R^2) reflects the quality of model. The model tends to a better performance when R^2 is closed to 1. These indicators are computed as:

$$\mathrm{nMBE} = \frac{1}{\overline{\mathrm{GSI}}_{mes}} \sum_1^N \frac{1}{N}\left(\mathrm{GSI}_{est} - \mathrm{GSI}_{mes}\right) \tag{12}$$

$$\mathrm{nRMSE} = \frac{1}{\overline{\mathrm{GSI}}_{mes}} \sum_1^N \frac{1}{N}\left(\mathrm{GSI}_{est} - \mathrm{GSI}_{mes}\right)^2 \tag{13}$$

$$R^2 = 1 - \frac{\sum_1^N \frac{1}{N}\left(\mathrm{GSI}_{est} - \mathrm{GSI}_{mes}\right)^2}{\sum_1^N \frac{1}{N}\left(\mathrm{GSI}_{est} - \overline{\mathrm{GSI}}_{mes}\right)^2} \tag{14}$$

GSI_{mes}, GSI_{est} are the measured and estimated global solar irradiation value, $\overline{\mathrm{GSI}}\mathrm{mes}$ the average value of the estimated GSI, and N is the number of observations.

2.2 Comparative analysis

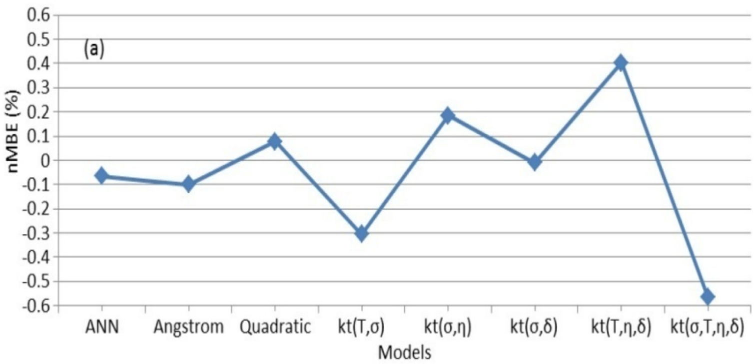
Comparative analysis between the predicted values to the measured data has been the best technique for assessing solar radiation. To this end, the predictors used herein have been applied for each model. From the program 'Matlab' and the regression method, the coefficient a, b, c, d, and e, have been assessed, as shown in presented in **Table 2**.

From the third to the seventh column, we recorded the different coefficients of adjustment for the seven empirical formulas. The 8th column contains the ANN architecture (number of neurons in input, hidden, and output layers). In this table, the accuracy values of the different methods are presented.

The nMBE, nRMSE, and R^2 results are presented in figures 5a, 5b and 5c. A good agreement with the measures appears until reaching 3 hidden neurons, and then the three indicator values are about -0.04 %, 4.428 %, and 0.9800. Accordingly, the ANN model presents a best performance compared to the regression models. In the other hand, it seems that against to the regression models, the quadratic model has the best performance. The test indicators provide about (0.0772 %, 5.5381 %, and 0.9722).Thus, it appears that among the remaining the use of the mean temperature, mean humidity and solar declination parameters does not provide any improvement. By against, the sunshine duration (σ) is an input parameter best suitable for predicting the GSI with the regression methods. In fact, for the Angström, quadratic, $K_t(\sigma,T)$, $K_t(\sigma,\eta)$, $K_t(\sigma,\delta)$, and $K_t(\sigma,T,\eta,\delta)$ models provide minimum values of the nRMSE and R^2 which are equal to 5.9348 % and 0.9681, while the $K_t(T,\eta,\delta)$ gives about (13.30%, 0.8400) which has bad performance.

Table 2: Empirical coefficients and statistical errors of seven models for evaluating the GSI

Models	a	b	c	d	e
ANN	*	*	*	*	*
Angström	0.3340	0.4300	*		
Quadratic	0.3000	0.5860	-0.1300		
$K_t(\sigma,T)$	0.3470	04300	-0.0006		
$K_t(\sigma,\eta)$	0.3380	0.4266	-0.0003		
$K_t(\sigma,\delta)$	0.3342	0.4307	-0.0000		
$K_t(T,\eta,\delta)$	1.0127	-0.0073	-0.0050	-0.0000	
$K_t(\sigma,T,\eta,\delta)$	0.4710	0.4096	-00033	-0.0013	-00006
Models	**Architecture**	**nMBE**	**nRMSE**	**R^2**	
ANN	4-03-1	**-0.0480**	**4.4220**	**0.9800**	
Angström		-0.1000	5.6431	0.9712	
Quadratic		**0.0772**	**5.5381**	**0.9722**	
$K_t(\sigma,T)$		-0.3061	5.5780	0.9718	
$K_t(\sigma,\eta)$		0.1846	5.6346	0.9713	
$K_t(\sigma,\delta)$		-0.0100	5.6427	0.9712	
$K_t(T,\eta,\delta)$		0.4032	13.304	0.8400	
$K_t(\sigma,T,\eta,\delta)$		-0.5650	5.9348	0.9681	



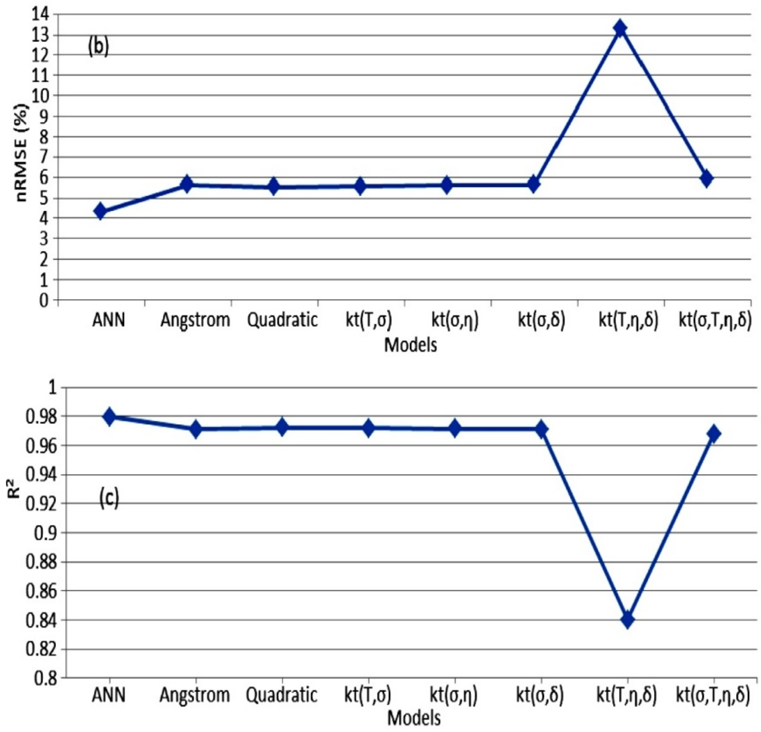


Fig. 5: Statistical results for all models: (**a**) nMBE, (**b**) nRMSE, (**c**) R^2

To illustrate the good reliability of this optimized ANN, we plotted in figure 6 the estimated data versus the experimental ones for data not used in the training phases (test phase).We see a good correspondence between estimated and measured GSI. Moreover, a greater correlation is observed in figure7, between the estimated and measured data.

According to the last figure, it is clear that the adequacy of ANN model decreases when the measured GSI is less than 3.5 kWh/m^2. Beyond this value the ANN model provides a very good compared to the measured GSI. Overall, according to the results, it is clearly observed that one of the most relevant meteorological input parameters is the sunshine duration, whether for empirical models or ANN technique used in this paper.

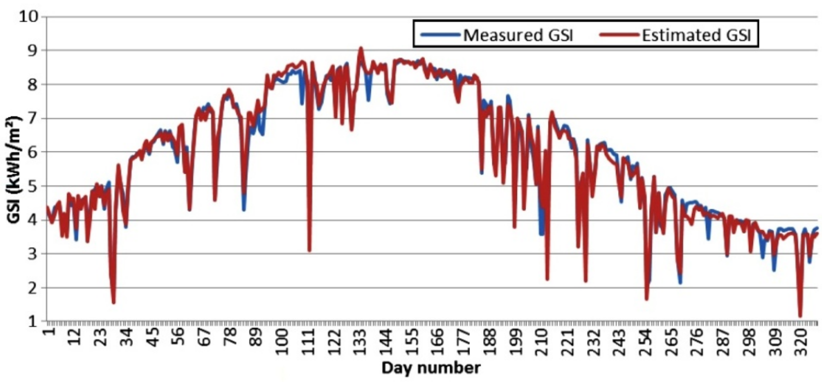


Fig. 6: Comparison between measured and estimated GSI from ANN model

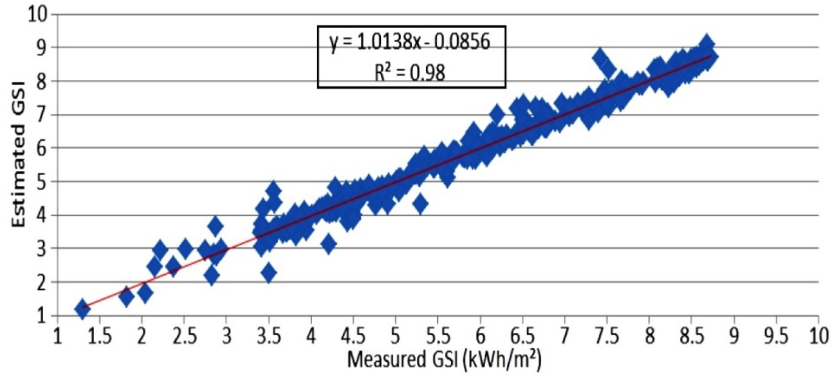


Fig. 7: Variation of estimated GSI against to the measured GSI for ANN model

3. CONCLUSION

This paper introduces two approaches for the estimation of daily global solar radiation on horizontal surface at Ghardaia site from four daily input parameters (as temperature, humidity, solar declination, and sunshine duration) implying one ANN model (with Levenberg-Marquard as learning algorithm) and seven empirical models. After the training step a comparison between the optimum ANN with the best empirical model has been made.

From statistical and by using the graphical analysis, we can to conclude that the ANN model with three hidden neurons has a best performance compared to the developed empirical models. We have also deduced that the daily sunshine duration input is more suitable to describe the daily GSI for south of Algeria, especially in Ghardaia site. We conclude that the sunshine duration has an essential influence on the model performances.

This has been proven in the case when we have eliminated the sunshine duration, implying degradation of statistical test values.

Consequently, from previous results, we have proved that the ANN approaches are well able to estimate the daily GSR at south of Algeria by using only four input parameters such as the sunshine duration, temperature, humidity and solar declination. In this regard, this technique is taken into consideration in order to use the solar projects in Algeria, by sizing various solar devices.

Future papers will consist to compare between many artificial neural network techniques to estimate the daily global solar radiation and the direct solar radiation by using other learning algorithm methods

REFERENCES

[1] R.E. Bird and C. Riodan, '*Simple Solar Spectral Model For Direct and Diffuse Irradiance on Horizontal and Titled Planes at Earth's Surface for Cloudless Atmospheres*', Journal of Climate and Applied Meteorology, Vol. 25, N°1, pp. 87 - 97, 1986.

[2] C.A. Gueymard, '*A Two-Band Model for the Calculation of Clear Sky Solar Irradiance, Illuminance and Photosynthetically Active Radiation at the Earth's Surface*', Solar Energy, Vol. 43, N°5, pp. 253 - 265, 1989.

[3] C.A. Gueymard, '*Critical Analysis and Performance Assessment of Clear Sky Solar Irradiance Models Using Theoretical and Measured Data*', Solar Energy, Vol. 51, N°2, pp. 121 - 138, 2012.

[4] V. Badescu, C. Gueymard, S. Cheval and A. Dumitrescu, '*Computing Global and Diffuse Solar Hourly Irradiation on Clear Sky. Review and Testing of 54 Models*', Renewable and Sustainable Energy Reviews, Vol. 16, pp. 1636 - 1656, 2012.

[5] J. Hassan, '*ARIMA and Regression Models for Prediction Daily and Monthly Clearness Index*', Renewable Energy Vol. 68, pp. 421 - 427, 2014.

[6] M. Nia, M. Chegaar, M.F. Benatallah and M. Aillerie, '*Contribution to the Quantification of the Radiation in Algeria*', Journal of Physics, Vol. 36, pp. 730 - 737, 2013.

[7] L.E. Akabio and S.E. Etuke, '*Empirical Correlation of Global Solar Radiation with Meteorological Data for Onne, Nigeria*', Turkish Journal of Physics, Vol. 28, pp. 205 - 212, 2004.

[8] T. Muneer, C. Gueymard and H. Kambezidis, '*Solar Radiation and Daylight Models*', Ed. Elsevier, 2004.

[9] S. Zekai, '*Solar Energy Fundamentals and Modelling Techniques*', Springer, 2008.

[10] M. Iqbal, '*An Introduction to Solar Radiation*', Second Ed, Academic Press, Canada, 1983.

[11] H.O. Menge, C. Ertekin and M.H. Sonmette, '*Evaluation of Global Solar Radiation Models for Konya, Turkey*', Energy Conversion and Management, Vol. 47, pp. 3149 - 3173, 2006.

[12] J. Almorox, '*Estimating Global Solar Radiation From Common Meteorological Data in Aranjuez, Spain*', Turk Journal physics, Vol. 35, pp. 53 - 64, (2011.

[13] Y. Dazhi, J. Panida and M.W. Wilfred, '*Hourly Solar Irradiance Time Series Forecasting Cloud Cover Index*', Solar Energy, Vol. 86, pp. 3531 - 3543, 2012.

[14] C. Paoli, C. Voyant, M. Muselli and M.L. Nivet, '*Multi-horizon Irradiation Forecasting For Mediterranean Locations Using Time Series Models*', Energy Procedia Vol. 57, pp. 1354 - 1363, 2014.

[15] A. Ahmad, T.N. Anderson and T.T. Lie, '*Hourly Global Solar Irradiation Forecasting for New Zealand*', Solar Energy, Vol. 122, pp. 1398 - 1408, 2015.

[16] A. Mellit, S.A. Kalougirou, S. Shaari, H. Salhi and Hadj Arab, '*Methodology for Predicting Sequences of Mean Monthly Clearness Index and Daily Solar Radiation Data in Remote Areas: Application for Sizing a Stand-Alone PV System*', Renewable Energy, Vol. 33, N°7, pp. 1570 - 1590, 2008.

[17] L. Martin, L.F. Zarzalejo, J. Polo, A. Navarro, R. Marchante and M. Cony, '*Prediction of Global Solar Irradiance Based on Time Series Analysis: Application To Solar Thermal Power Plants Energy Production Planning*', Solar Energy, Vol. 84, N°10, pp. 1772 - 1781, 2010.

[18] L. Wang, O. Kisi, M. Zounemat-Kermani, G.A. Salazar, Z. Zhu and W. Gong, '*Solar Radiation Prediction Using Different Techniques: Model Evaluation and Comparison*', Renewable and Sustainable Energy Reviews, Vol. 61, pp. 384 - 397, 2016.

[19] A. Yadav and S. Chandel, '*Solar Radiation Prediction Using Artificial Neural Network Techniques: A Review*', Renewable Sustainable Energy Reviews, Vol. 33, N°5, pp. 772 – 781, 2014.

[20] A. Mellit, M. Benghanem, A. Hadj Arab and A. Guessoum, '*A Simplified Model for Generating Sequences of Global Solar Radiation Data for Isolated Sites: Using Artificial Neural Network and a Library of Markov Transition Matrices Approach*', Solar Energy, Vol. 79, N°5, pp. 469 - 482, 2005.

[21] M. Benghanem, A. Mellit and S.N. Alamri, '*ANN-Based Modelling and Estimation of Daily Global Solar Radiation Data: A Case Study*', Energy Conversion and Management, Vol. 50, N°7, pp. 1644 - 1655, 2009.

[22] M.A. Behrang, E. Assareh, A. Ghanbarzadeh and A.R. Noghrehabadi, '*The Potential of Different Artificial Neural Network (ANN) Techniques in Daily Global Solar Radiation Modelling Based on Meteorological Data*', Solar Energy, Vol. 84, N°8, pp. 1468 - 1480, 2010.

[23] A. Rahimikhoob, '*Estimating Global Solar Radiation Using Artificial Neural Network and Air Temperature Data in a Semi-Arid Environment*', Renewable Energy, Vol. 35, N°9, pp. 2131 - 2135, 2010.

[24] R. Yacef, M. Benghanem and A. Mellit, '*Prediction of Daily Global Solar Irradiation Data Using Bayesian Neural Network: A Comparative Study*', Renewable Energy, Vol. 48, N°C, pp. 146 - 154, 2012.

[25] M. Benghanem and A. Mellit, '*Radial Basis Function Network-Based Prediction of Global Solar Radiation Data: Application for Sizing of a Stand-Alone Photovoltaic System Al-Madinah, Saudi Arabia*', Energy Vol. 35, N°9, pp. 3751 - 3762, 2010.

[26] J.C. Lam, K.K.W. Wang and L. Yang, '*Solar Radiation Modeling Using Anns For Different Climates in China*', Energy Conversion and Management, Vol. 49, N°5, pp. 1080 - 1090, 2008.

[27] S. Rehman and M. Mohandes, '*Artificial Neural Networks Estimation Of Global Solar Radiation Using Air Temperature and Relative Humidity*', Energy Policy, Vol. 36, pp. 571 - 576, 2008.

[28] F. Cao, H. Li, T. Yang, Y. Li, T. Zhu and L. Zhao, '*Evaluation of diffuse solar radiation models in Northern China: New Model Establishment and Radiation Sources Comparison*, Renewable Energy, Vol. 103, pp. 708 - 720. 2016.

[29] J.A. Duffie and W.A. Beckman, '*Solar Engineering of Thermal Processes*', 4nd ed. New York: John Wiley and Sons, 2013.

[30] A. Angstrom, '*Solar and Terrestrial Radiation*', Quarterly Journal of the Royal Meteorological Society, Vol. 50, N°210, pp. 121 – 125, 1924.

[31] J.A. Prescott, '*Evaporation from Water Surface in Relation to Solar Radiation*', Transactions of the Royal Society of South Australia', Vol. 64, pp. 114 – 120, 1940.

[32] 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, N°3, pp. 769 - 783, 2016.

[33] D.E. Rumelhart, G.E. Hinton and R.J. Williams, '*Learning Representations by Back-Propagating Errors*', Nature, Vol. 323, pp. 533 - 536, 1986.

[34] M. Parizeau, '*Réseaux de Neurones*', Université de Laval, Canada, 2006.

[35] R.P. Lippmann, '*An Introduction to Computing with Neural Nets*', IEEE ASSP Magazine, Vol. 4, N°2, 1987.

[36] H. Riahi-Madvar, S.A. Ayyoubzadeh and M.G.Atani, '*Developing an Expert System for Predicting Alluvial Channel Geometry Using ANN*', Expert System and Application, Vol. 38, N°1, pp. 215 - 222, 2011.

[37] Ö. Çelik, A. Teke and H.B. Yıldırım, '*The Optimization Artificial Neural Network Model with Levenberg–Marquardt Algorithm for Global Solar Radiation Estimation in Eastern Mediterranean Region of Turkey*', Journal of Cleaner Production, Vol. 116, pp. 1 - 12, 2016.

[38] G. Landeras, J.J. Lopez, O. Kisi and J. Shiri, '*Comparison of Gene Expression Programming with Neuro-Fuzzy and Neural Network Computing Techniques in Estimating Daily Incoming Solar Radiation in the Basque Country (Northern Spain)*', Energy Conversion. Management, Vol. 62, pp. 1 - 13, 2012.

[39] A. Ahmad, T.N. Anderson and T.T. Lie, '*Hourly Global Solar Irradiation Forecasting for New Zealand*', Solar Energy Vol. 122, pp. 1398 - 1408, 2015.

[40] V. Sivamadhavi and R.S. Selvaraj, '*Prediction of Monthly Mean Daily Global Solar Radiation Using Artificial Neural Network*'; Journal of Earth System Science, Vol. 121, N°6, pp. 1501 - 1510, 2012.

[41] K. Dahmani, G. Notton, R. Dizene, C. Paoli, C. Voyant, M.L. Nivet and K. Karou, '*Estimation of 5-min Solar Global Irradiation on Tilted Planes by ANN Method in Bouzareah, Algeria*', Energy Vol. 70, pp. 374 - 381, 2014.

[42] K. Bakirsi, '*Correlations for Estimation of Daily Global Solar Radiation with Hours of Bright Sunshine in Turkey*', Energy, Vol. 34, N°4, pp. 485 -501, 2009.

[43] C.A. Gueymard, '*A Review of Validation Methodologies and Statistical Performance Indicators for Modelled Solar Radiation Data: Towards a Better Bankability of Solar Projects*', Renewable and Sustainable Energy Reviews, Vol. 39, pp. 1024 - 1034, 2014.