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# Forecast of Global Solar Radiation on a Horizontal Surface by ANN for the City of Batna Algeria

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***Abstract:*** **Solar energy is one of the most enduring renewable energy sources in the world. Freely available, it can be effectively harnessed to reduce dependence on hydrocarbon-based energy. Solar radiation data plays a crucial role in the design, sizing, and efficiency of renewable energy systems. However, such data are not always accessible, particularly in remote or isolated areas. As a result, the prediction of solar radiation values often becomes the only viable method for obtaining this essential information. In fact, measured radiation data are typically limited to specific locations or regions within each country. Neural networks, a branch of artificial intelligence, are distinguished by their ability to simulate human reasoning. They have significantly advanced various fields, including complex forecasting problems. In this study, fifteen neural network models are implemented to model and predict global solar radiation on a horizontal surface. The meteorological parameters considered include sunshine duration (S), daylight hours (S0), total extraterrestrial solar radiation, temperature, and humidity. The city of Batna was selected for this research, utilizing ten years (1996–2005) of meteorological data obtained from the HelioClim1 (HC1) database. The results demonstrate that the proposed neural models are highly effective in predicting daily global solar radiation, achieving a high degree of measurement accuracy for this region.**

***Keywords:*** **Prediction, Artificial Neural Network, Solar radiation, Modeling.**

## I. INTRODUCTION

Due to its geographical location, Algeria has one of the highest solar potentials in the world, estimated at 13.9TWh per year. The country receives an annual exposure to the sun equivalent to 2500 KWh/m2. The daily solar energy potential varies from 4,66 kWh/$m^2$ in the north to 7.26 kWh/m2 in the south. High solar potentials make people's lives easier with lots of eco-friendly products and services such as LED lighting and power generation…etc.

A device called a pyranometer measures the solar radiation in greenhouses and evaluates by comparing the value of the radiation outside to estimate the losses of direct energy when passing through the roofs. The unit of measurement for radiation is watts per square meter (Wh/m2).Due to its high price, the government cannot have a pyranometer in every region, due to this inconvenience; the solar radiation data is only available at a few stations. For that and other reasons, the prediction of solar irradiation is a primordial operation in solar systems. Extraterrestrial solar radiation (above the atmosphere) G0 is the name given to solar radiation that reaches the earth's surface. Meanwhile, global solar radiation G refers to the attenuated solar radiation within the atmosphere [1].

To date, a number of predictive algorithms have been developed and are frequently used to obtain accurate data, including artificial intelligence(AI) [2,3,4], which is a set of technologies used to create machines that can mimic human intelligence(Artificial Neural Network (ANN),Fuzzy logic, Adaptive Neuro fuzzy Inference System (ANFIS), Support Vector Machines (SVM)…etc. ).


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Several works have studied the global solar irradiation of Algerian cities using neural networks, which will be cited in the following paragraphs:

In his study, Mellit et al.[5] designed and implemented an ANN based model in Filed Programming Gate Array (FPGA) hardware to predict daily global solar radiation. Mean average data of temperature, sunshine duration, and solar radiation have been used as inputs. Daily data of 9-years, of a south Algerian location, have been used to train the model and those of one year to its validation. The coefficient of correlation of the proposed model in the system of prediction (FPGA) is equal to 0.98.Another work, Mellit et al.[6]introduced an evolving polynomial ANN to predict global solar radiation. Air temperature, relative humidity, and wind speed are used as inputs of the model. Data set of meteorological time series for five years collected in Algiers (Algeria) by the National Office of Meteorology has been used in this study. The obtained result for correlation coefficient was 0.9821.

Kacem Gairaa et al [7] have developed a new combined model between Linear Autoregressive Moving Average (ARMA) and Nonlinear Artificial Neural Network (ANN) model to estimate daily global solar radiation. The major advantage of this model lies in the combination of the two advantages of the two methods. The data used are from two different sites (Bouzéreah and Ghardaia) in Algeria during the period (2012-2013). The meteorological parameters are the input. The models in term of mean absolute error (MPE) of about 18.1% and 2.7%, for the first site, of about 27.26% and 1.39% for the second site. Moreover, compared to the ARMA and ANN models a decrease in the RMSE values of about 17.1% and 3.59% compared to the ARMA and ANN models being observed .Another work of Kacem Gairaa et al [8] but in this article, they presented a model for estimating solar irradiation by employing nonlinear autoregressive (NAR) neural networks. Ghardaia city data spanning the three-year period (2012-2014) is the basis of this model. The NAR model is based on the feed-forward multilayer perception model with two inputs, which are the ratio between the global solar irradiance and the extra-terrestrial solar irradiance and the previous day series. Prediction performance is evaluated by the following statistical criteria: MPE=23.89%, RMSE=15.50% and the correlation coefficient equal to 0.91.The results obtained showed an improvement of the NAR model compared to ARMA models of the previous work in 2012.

To predict daily global solar radiation, Assas et al [9] examined five ANN models based on meteorological data sets corresponding to the site of Djelfa (Algeria). In this work, several combinations of six variables have been investigated. The results show that including relative humidity has an effective role in solar radiation prediction(RMSE of 0.1273 including humidity and0.1323 without humidity).

Hasni et al.[10] used feed-forward ANN to estimate hourly global solar radiation at Bechar city (Algeria). The ANN models used five inputs (month, day, hour, air temperature, and relative humidity). Data measured between02$^{nd}$February and 31$^{st}$ may 2011 have been used in training, while the remaining 651 hours data from June 2011 as testing data. An RMSE of 2.997 were obtained.

In the article [11], Laidi Maamar et al used an ANN to predict daily global solar radiation using data measured at the University of Blida. The best network is obtained with six inputs: altitude, longitude, latitude, air temperature, relative humidity, and wind speed. The latter contained six neurons in the input layer; six neurons in the hidden and provide a MAE which is less than 20%.

Lyes Saad Saoud et al[12] proposed the prediction of daily solar irradiation in Tamanrasset via an ANN model. The daily data obtained from the national meteorological center of Algeria in 2007, during which, 11 months were used for training and December for validation. The input parameters used are: temperature, relative humidity, and sunshine duration combined with each other. The four neural networks have two neurons in the hidden layer. To evaluate the performance of the proposed model, they use the normalized root mean squared error (nRMSE), which was found equal to 4.01% and mean absolute error (MAE) equal to 0.40.Another study of same authors [13], in which, they used the complex-valued neural networks CVNN to predict the daily solar irradiation for the great Maghreb region. Both multi-input single-output (MISO) and multi-input multi-output (MIMO) strategies are considered. The CVNN models have been validated using satellite data in the Great Maghreb, whose capitals are: Tripoli (Libya), Tunis (Tunisia), Algiers (Algeria), Rabat (Morocco), El Aiyoun (Western Sahara) and Nouakchott (Mauritania), were selected for the collection of data. The CVNN proves its abilities to predict the daily solar irradiation in both cases (MISO and MIMO strategies) for all cities and the MIMO’s one gives the best.

The main goal of the work of Rezrazi et al.[14] is to show how to reach an optimal model of ANNs for predicting of solar radiation. The measured data of the year 2007 in Ghardaïa city (Algeria) are used to validate the optimization approach. The performance evaluation and the comparison of results of ANN models with measured data are made on the basis of mean absolute percentage error (MAPE). It is found that MAPE in the ANN optimal model gives 1.17 %. In addition, this model provides a root mean square error (RMSE) of 14.06%and an MBE of 0.12. The precision of the output exceeded 97% and


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reached up 99.29 %. The obtained results show that the optimization strategy to estimate solar radiation is satisfactory when using meteorological parameters as inputs. It can successfully be generalized for any location in the world.

Miloudi et al [15] proposed two types of ANN (MLP and RBF)to estimate GSR and PV I(V) curve. In this work, around 700 solar radiation data had been recorded; every 15-min during 2012 at the Boumerdes site. The correlation coefficient obtained for MLP and RBF ANNs was 0.997 and 0.998.

In a study conducted by Guermoui et al.[16] developed an artificial neural network (ANN) model for estimation of daily global solar radiation on horizontal surface in Ghardaia city. Using five multilayer feed-forward ANN models, by combining three meteorological inputs: daily mean air temperature, relative humidity, and sunshine duration. Six hundred samples of daily data measured (2005–2008) at Ghardaïa have been used in training and one hundred for testing. The authors found out that the presence of sunshine duration and mean air temperature as inputs gave results that are more accurate. Alwen RMSE of 6.12% has been obtained for the model based on sunshine duration and mean air temperature presents the MLP model based on sunshine duration and mean air temperature output.

D. Benatiallah et al [17]have developed a model to predict the hourly global solar irradiation of the city of Adrar, Algeria using nine models of artificial neural networks. Solar geometric parameters and astronomical data as inputs of the designed models, which are collected by the Renewable Energy Research Unit based on data from SODA. This data extends over a period of six years (2013-2018). 80% of this data is used for the learning phase and 20% for the test phase. The Sigmoid activation function and the number 15 of hidden layer neurons are the parameters of the best model developed. The correlation coefficient for the measured and estimated global solar irradiation of the model is equal to 0.9825.

Asradj et al [18] have compared four linear regression models with an ANN-based model to estimate the GSR. A database of more than 26000 measurements of solar radiation and five other meteorological parameters recorded every 8-min at Bejaia site has been used. They found that the ANN model gave the best results, the RMSE was only 0.015 illustrates a scatter plot of measured (Output) and predicted (Target) using ANN model. It is noted that most of the works carried out on Algeria are very limited and for two or three cities that is all.

In this work the neural network is used to forecasting the global radiation solar, which is a popular technique due to its efficiency and good results. Because the measurement gadget of solar radiation is very expensive and not available to everyone, accessing this data is tough. To make it easier to exploit, the latter must be predicted and modeled. There is a terrible lack of research work concerning the city of Batna (Algeria).For this reason, we opted to choose it as the center of our work.

This paper is subdivided into seven sections beginning with an introduction containing general information on solar irradiation. The second section describes the Batna site and its data. A theoretical study on fuzzy logic is established in section 3.A description of the designed system is presented in section 4.The experimental study and discussion is explained in section 5 and 6. Finally, a work summary and a statement of future work are included in the last section.

## II. SITE AND DATA DESCRIPTION

Batna is a city in northeastern Algeria, located in the Aurès region ( Fig.1). It is surrounded by the following towns: Mila, Biskra, Oum-El-Baoughi, M'sila, Khenchela and Sétif. The city of Batna is considered the capital of the Aurès. The geographical coordinates of Batna are latitude: 35°33′21″ north, longitude: 6 ° 10′26″ east and altitude above sea level: 1037m. The climate of Batna is semiarid. There are two types of semi-arid climates: hot and cold semi-arid climates. Isotherms can be used to distinguish between the two types of semi-arid climates. A line connecting two spots with the same temperature is called an isotherm. Our city, Batna, is located in a cold semi-arid climate with significant temperature differences between day and night. On the other hand the annual precipitation is infrequently greater than 100 millimeters. Rainfall is infrequent and irregular, and it can go for long periods without falling.



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Fig.1 Location of Batna City Algeria.

For this study; the site of Batna is chosen; the corresponding data were obtained from the meteorological data Helio-Clim1[17].These data cover the ten-year period from 1996 to 2005.The data includes irradiation global solar G and measured sunshine duration S .Figure 2 shows global solar irradiation G for seven years 1996 to 2002.

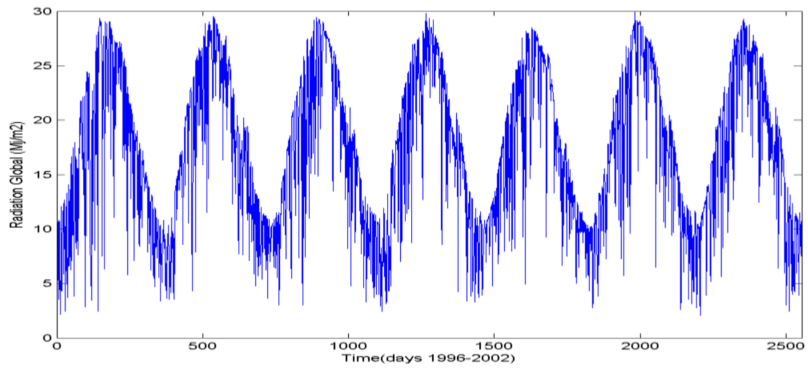


Fig.2. Global Solar Radiation Measured (Mj/m2) from 1996 to 2002

In the database, the missing data are indicated by-999 value. To rectify this lack of data, an average value of the two adjacent values is calculated. In this study, the parameters, the duration insulation $S_0$ (the time between the time of sunset and the time of sunrise) and daily mean of irradiation at the top of the atmosphere $G_0$ (extraterrestrial) in $MJ/m^2$.are used and calculated by the following formulas:

$$\delta = 23.45\left[sin\frac{360(284+n)}{365}\right] \quad (1)$$

$$w = \cos^{-1}(-\tan\lambda.\tan\delta) \quad (2)$$

$$S_0 = \frac{2}{15}w \quad (3)$$

$$G_0=\frac{24}{\pi}I_0\left(1+0.033\cos\frac{360n}{365}\right)(\cos\lambda\cos\delta\sin\omega+\frac{2\pi}{360}+\omega\sin\lambda\sin\delta) \quad (4)$$

In our work, S and $S_0$are measured in hour, G, and $G_0$ in MJ/m2.


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TABLE I

ANN CHARACTERISTICS SUMMARY OF THE LITERATURE ANALYSIS.

| Model | Authors | Site of work | Networks | Years of data | Inputs Variables | Time level | Statisticparameters |
|---|---|---|---|---|---|---|---|
| 1 | Mellit et al 2008-2010 | South Algerian | MLP | 10 years | Tm, S and G | Daily | $R^2$ |
| 2 | | Algiers | hybrid polynomial neural network combined with a genetic algorithm, | 5 years | Ta, Hum and Ws | Min, hour, and day | $R^2$ |
| 3 | KacemGairaa et al 2012-2015 | (Bouzérah and Gardaia) in Algeria | Linear Autoregressive Moving Average (ARMA) and Nonlinear Artificial Neural Network | Two years (2012 - 2013) | Time series, clear index | Daily | RMSE, nRMSE, MBE, nMBE, MPE, $R^2$ |
| 4 | | Ghardaia | non linear autoregressive (NAR) neural networks | Three years (2012-2014) | Time series, clear index | Daily | RMSE, nRMSE, MBE, nMBE, MPE |
| 5 | Assas et al 2012 | Djelfa (Algeria). | MLP | six years (2001-2005) | MeamG0, Max S0, mean Hum, mean maxi air T, mean P and Ws | Daily | RMSE, MAE, MSE. |
| 6 | Hasni et al 2012 | Bechar | Feed-forward ANN | 02 February to june 2011 | month, day, hour,air temperature and Hum | Daily | RMSE |
| 7 | LaidiMaamar et al 2014 | University of Blida | MLP | One year 2011 | Altitude, longitude, latitude, air T, Hum, and Ws | Monthly | MAE |
| 8 | Lyes Saad Saoud et al 2014-2015 | Tamanrasset | Quaternion Valued Neural Networks (QVNNs) | One year(2007) | T, Hum and S | Daily | nRMSE and MAE. |
| 9 | | The great Maghreb region | the complex-valued neural networks CVNN | 01/01/2003 to06 / 30/2005 | G, air T and Hum | Daily | MAE ,nRMSE and R2 |
| 10 | Rezrazi et al 2015 | Ghardaïa | MLP | One year 2007 | meteorological parameters | Daily | RMSE,MBE R2 |
| 11 | Asradj et al 2015 | Bejaia | MLP | One year (2010) | S, T, air Pr, Hum and R | 8 min | R2, RMSE |
| 12 | Miloudi et al 2017 | Boumerdes | MLP and RBF | One year 2012 | Real meteorological data | 15-min | $R^2$ |
| 13 | Guermoui et al 2016 | Ghardaia | MLP | Four years (2005–2008) | mean air T, Hum and S | Daily | M A BE, R MSE , RSE and $R^2$ |
| 14 | D. Benatiallahet al 2020 | Adrar, Algeria | MLP | Six years (2013-2018) | solar geometric parameters and astronomical data | Daily | $R^2$ |


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## III. ARTIFICIAL NEURAL NETWORK

The human brain contains approximately 100 billion neurons. These neurons allow you, among other things, to read, think…etc. An artificial neural network or Neural Network is a computer system inspired by the functions of the human brain to learn. An organized collection of interconnected artificial neurons that perform sophisticated operations using a learning mode that results in a form of artificial intelligence (AI).Neurologists Warren McCulloch and Walter Pitts published the first work on neural networks in the late 1950s, with a seminal article: What the frog's eye tells the frog's brain. A multi-layer perceptron neural network is composed of a number of highly interconnected units (neurons) functioning in parallel and organized in layers with a feed-forward information flow.

The architecture of the multi-layer perceptron is organized in this manner (Fig 3) the signals flow successively throughout the different layers from the input to the output layer. The intermediary layers are called hidden layers. For each layer, each elementary unit calculates a scalar product between a vector of weights and the output vector given by the previous layer. A transfer function is then performed to the result to make an input for the next layer. A general transfer function for the hidden layers is the sigmoid function:

$$f(x) = \frac{1}{1 + \exp(-x)} \qquad (5)$$

In the neuron of the output layer, other transfer function can be used; for instance, the identity function (simple linear activation) can be used for regression problems. The error back-propagation (EBP) algorithm, optimized according to a predefined criterion [9], trains the MLP neural networks. The weights of the connections are adjusted during the training process to achieve the desired input/output relation of the network.

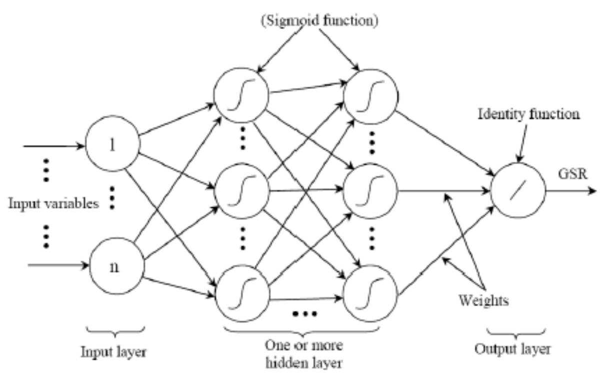


Fig .3 Building Block of a Multi-Layer Perceptron Neural Network

## IV. DESCRIPTION OF THE PROPOSED SYSTEM

In this paper, we use Artificial Neural Network ANN approach for the estimation of global solar radiation on the horizontal surface for the city of Batna.

The designed system follows the steps prescribed in the following diagram (Fig 4):


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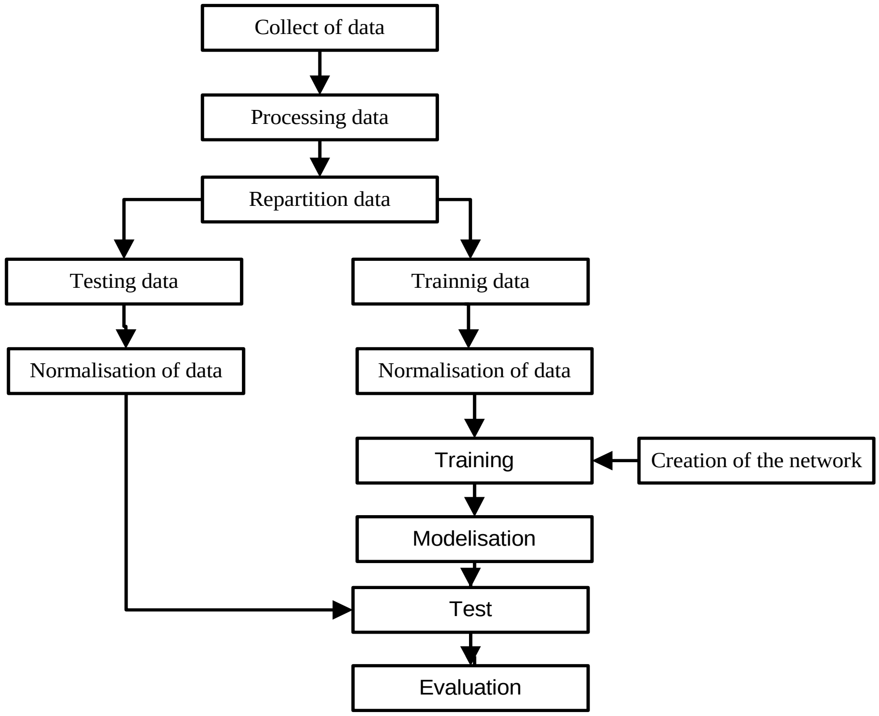


Fig . 4 Designing Artificial Neural Network Model

After data collection, three pre-processing procedures are performed for sorting, organizing the data, learning and testing the adopted models in an efficient way:

(1) **Solving the problem of missing data:** The missing data are replaced by the average of neighboring values.

(2) **Normalizing the data**: The normalization procedure before presenting the input data to the network a normalization of these data is carried out. Their values will be between one and zero.

(3) **Randomizing the data:** it is a mixture of variables of large and small amplitude.

The inputs of the designed models are: the duration insulation S0,sunshine duration S, daily mean of irradiation at the top of the atmosphere $G_0$(extraterrestrial) and the meteorological parameters: temperature, relative humidity, pressure, wind speed, wind direction and rainfall. The output is the daily global solar radiation G on a horizontal surface. While varying the number of inputs and considering the different possible combinations, 26 models were obtained. In addition, different transfer functions in the hidden layer have also been tested. We use Levenberg-Marquardt algorithm for the training of adopted models. This latter is the most used for the prediction of solar radiation. There are several activation functions for a neural system. Hyperbolic tangent sigmoid function (HTSF) and Purelin function (PF) were used as the transfer function in the hidden layer and output layer, respectively.

In this document, we have retained only the models with a correlation rate greater than 90% which are fifteen in number whose are presented in the following table (table 2). For the number of hidden layers is limited to two layers and 25 neurons for each layer. For the conception of irradiation prediction models based on ANN, it is necessary to normalize the input data in our case, meteorological data are normalized between one and zero.

TABLE II

DESCRIPTION OF MODELS ADOPTED

| Model | Inputs parameters |
|---|---|
| 1 | $S_0$,S,$G_0$, Hum |
| 2 | $S_0$,S,$G_0$, Hum and T |
| 3 | $S_0$,S,$G_0$, Hum and Pr |
| 4 | $S_0$,S,$G_0$, Hum and Ws |
| 5 | $S_0$,S,$G_0$, Hum andWd |
| 6 | $S_0$,S,$G_0$, Hum and R |


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| | |
|---|---|
| 7 | $S_0$,S,$G_0$, Hum,TandPr |
| 8 | $S_0$,S,$G_0$, Hum,T, Pr and Ws |
| 9 | $S_0$,S,$G_0$, Hum,T, Pr , Ws and Wd |
| 10 | $S_0$,S,$G_0$, Hum,T , Pr , Ws ,Wd and R |
| 11 | $S_0$,S,$G_0$and R |
| 12 | $S_0$,S,$G_0$,Rand T |
| 13 | $S_0$,S,$G_0$,Rand Pr |
| 14 | $S_0$,S,$G_0$,Rand Ws |
| 15 | $S_0$,S,$G_0$,Rand Wd |

## V. EXPRIMENTAL STUDY

Neural networks are one of the most used methods recently to solve several data estimation problems. In Algeria, we still lack models to predict the global daily solar radiation on a horizontal surface, and this work is the first attempt to generate a meteorological model to predicting the GSR for the city of Batna.

In the present work, the data for the period of 10 years are organized by dividing them into two databases: training and testing. The training one contains seven years (1996-2002) of data classified one after the other vertically however for the test database what remains (2003-2005).

For the evaluation and testing, the designed neural system, six statistical criteria (**RMSE, nRMSE, MAE, MBE and nMBE**) are used:

### *A. The root mean square error (RMSE)*

is a measure characterizing the “precision” of this estimator. It is mostly known as «squared error” (“mean” being implied); it is sometimes also called “quadratic risk” and its normalized value **(nRMSE).** Consider a variable (Y) whose measured values are ($Y_{im}$); and the estimated values by a given prediction model are ($Y_{ie}$).

$$RMSE = \left[\frac{1}{m}\sum_{1}^{m}(Y_{im} - Y_{ie})^2\right]^{\frac{1}{2}} \qquad (6)$$

$$nRMSE = \left[\frac{1}{m}\sum_{1}^{m}(Y_{im} - Y_{ie})^2 \times 100\right]^{\frac{1}{2}} \qquad (7)$$

### *B. Mean Absolute Error (MAE)*

Arithmetic mean of the absolute values of the deviations.

$$MAE = \frac{1}{m}\sum_{1}^{m}|(Y_{im} - Y_{ie})| \qquad (8)$$

### *C.The algebraic mean relative deviation (MBE)*

Which provides information on the tendency of the model to overestimate observed values (MBE>0) or to underestimate them (MBE <0) .And its normalized value (nMBE).

$$MBE = \frac{1}{m}\sum_{1}^{m}(Y_{im} - Y_{ie}) \qquad (9)$$

$$nMBE = \frac{1}{m}\sum_{1}^{m}(Y_{im} - Y_{ie}) \times 100 \qquad (10)$$

## VI. RESULTS AND DISCUSSIONS

In this section, the results as well as the discussion for learning and testing the elaborated models are presented. The following table shows the results of the training phase:

TABLE III


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PERFORMANCE EVALUATION OF NEURAL NETWORK MODELS FOR SOLAR RADIATION PREDICTION

| Model | MBE | RMSE | MAE | nRMSE | nMBE | $R^2$ |
|---|---|---|---|---|---|---|
| **1** | 0.980 | 7.702 | 14.989 | 0.064 | 0.008 | 0.913 |
| **2** | -0.186 | 5.657 | 7.287 | 0.115 | -0.004 | 0.919 |
| **3** | -0.355 | 5.697 | 7.342 | 0.116 | -0.007 | 0.920 |
| **4** | -0.028 | 5.601 | 7.276 | 0.114 | -0.001 | 0.919 |
| **5** | 0.070 | 5.609 | 7.389 | 0.114 | 0.001 | 0.912 |
| **6** | -1.261 | 5.429 | **6.648** | 0.110 | -0.026 | 0.927 |
| **7** | -0.475 | 5.539 | 7.045 | 0.112 | -0.010 | 0.924 |
| **8** | -0.132 | 5.545 | 6.968 | 0.113 | -0.003 | 0.923 |
| **9** | -0.457 | **5.332** | 6.817 | 0.108 | -0.009 | 0.930 |
| **10** | -0.173 | 6.932 | 12.801 | **0.058** | -0.002 | **0.935** |
| **11** | -0.544 | 6.271 | 8.068 | 0.127 | -0.011 | 0.905 |
| **12** | **-1.115** | 5.599 | 6.746 | 0.114 | **-0.023** | 0.925 |
| **13** | -1.007 | 5.785 | 7.206 | 0.117 | -0.020 | 0.920 |
| **14** | -0.895 | 5.585 | 7.076 | 0.113 | -0.018 | 0.918 |
| **15** | -1.062 | 5.783 | 7.237 | 0.117 | -0.022 | 0.924 |

According to the results presented in the table 3above, we can see that the best model is the sixth model where its inputs were all the meteorological parameters. The statistical criteria for this model are (MBE=-0.173,RMSE=6.932, MAE=12.801, nRMSE=0.058,nMBE=-0.002and R2=0.935).This means that each meteorological parameter has its influence on the daily global solar radiation and we deduce that there is a close relationship between the number of inputs of the network and the result obtained. Among meteorological parameters considered as inputs, there are among them that have a more apparent influence than others. The effect of the relative humidity is more dominating than the effect of others parameters. As it intervene in the first ten models where its impact appears on the result. The second and the third parameters are the temperature and the pressure; these last ones have their weights of influence because they intervene in six models.

The following graphs present the histograms of the results of the statistical indicators of learning data.

TABLE IV

2003 TESTING DATA: VALUES OF INPUT PARAMETERS FOR MODEL VALIDATION

| Model | MBE | RMSE | MAE | nRMSE | nMBE | $R^2$ |
|---|---|---|---|---|---|---|
| **1** | 1.152 | 5.656 | 4.191 | 0.347 | 0.071 | 0.717 |
| **2** | 1.115 | 5.672 | 4.219 | 0.348 | 0.068 | 0.714 |
| **3** | 1.251 | 5.681 | 4.231 | 0.348 | 0.077 | 0.718 |
| **4** | 1.010 | 5.551 | 4.102 | 0.340 | 0.062 | 0.725 |
| **5** | 0.616 | 4.621 | 3.711 | 0.283 | 0.038 | 0.808 |
| **6** | 0.786 | 5.745 | 4.205 | 0.352 | 0.048 | 0.704 |
| **7** | **-0.167** | **4.252** | **3.297** | **0.261** | **-0.010** | **0.838** |
| **8** | 1.244 | 5.631 | 4.199 | 0.345 | 0.076 | 0.722 |
| **9** | 1.064 | 5.498 | 4.083 | 0.337 | 0.065 | 0.734 |
| **10** | 0.889 | 5.609 | 4.131 | 0.344 | 0.054 | 0.721 |
| **11** | 0.309 | 5.341 | 3.872 | 0.327 | 0.019 | 0.741 |
| **12** | 0.646 | 5.590 | 4.128 | 0.343 | 0.040 | 0.723 |
| **13** | 0.672 | 5.592 | 4.069 | 0.343 | 0.041 | 0.720 |
| **14** | 0.412 | 5.456 | 3.975 | 0.335 | 0.025 | 0.734 |
| **15** | 0.459 | 5.654 | 4.052 | 0.347 | 0.028 | 0.715 |

Table IV shows the evaluation of the models designed for the test year 2003 or notice the best model is the seventh model and these results are as follows ( MBE = -0.167, RMSE = 4.252 , MAE = 3.297, RMSE = 0.261, nMBE = 0.010 and R2 = 0.838).

TABLE V

2004 TESTING DATA: VALUES OF INPUT PARAMETERS FOR MODEL VALIDATION

| Model | MBE | RMSE | MAE | nRMSE | nMBE | R2 |
|---|---|---|---|---|---|---|
| **1** | 1.171 | 5.501 | 4.258 | 0.337 | 0.072 | 0.705 |
| **2** | 1.133 | 5.508 | 4.299 | 0.337 | 0.069 | 0.703 |
| **3** | 1.270 | 5.643 | 4.359 | 0.346 | 0.078 | 0.694 |
| **4** | 1.029 | 5.461 | 4.217 | 0.334 | 0.063 | 0.706 |
| **5** | 0.635 | **4.651** | 3.772 | **0.285** | 0.039 | **0.777** |
| **6** | 0.805 | 5.543 | 4.257 | 0.339 | 0.049 | 0.698 |
| **7** | -0.148 | 4.703 | **3.632** | 0.288 | -0.009 | 0.776 |
| **8** | 1.263 | 5.585 | 4.300 | 0.342 | 0.077 | 0.698 |


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| | | | | | | |
|---|---|---|---|---|---|---|
| **9** | 1.083 | 5.561 | 4.323 | 0.341 | 0.066 | 0.699 |
| **10** | 0.907 | 5.639 | 4.340 | 0.345 | 0.056 | 0.690 |
| **11** | 0.328 | 5.349 | 4.014 | 0.328 | **0.020** | 0.713 |
| **12** | 0.664 | 5.501 | 4.236 | 0.337 | 0.041 | 0.707 |
| **13** | 0.691 | 5.541 | 4.243 | 0.339 | 0.042 | 0.699 |
| **14** | **0.430** | 5.482 | 4.177 | 0.336 | 0.026 | 0.706 |
| **15** | 0.478 | 5.605 | 4.214 | 0.343 | 0.029 | 0.694 |

The performance of the realized models is indicated by the values in table 5. The best model for the data of the test year 2004 is the fifth model where these statistical error values are respectively (MBE=-0.635,RMSE=4.651, MAE=3.772, nRMSE =0.285,nMBE=0.039and R2=0.777).

TABLE VI

2005 TESTING DATA: VALUES OF INPUT PARAMETERS FOR MODEL VALIDATION

| Model | MBE | RMSE | MAE | nRMSE | nMBE | R2 |
|---|---|---|---|---|---|---|
| **1** | 1.479 | 5.145 | 3.763 | 0.309 | 0.089 | 0.763 |
| **2** | 1.441 | 5.197 | 3.868 | 0.312 | 0.087 | 0.755 |
| **3** | 1.578 | 5.280 | 3.900 | 0.317 | 0.095 | 0.753 |
| **4** | 1.337 | 5.135 | 3.795 | 0.309 | 0.080 | 0.759 |
| **5** | 0.943 | 4.346 | 3.439 | 0.261 | 0.057 | 0.822 |
| **6** | 1.113 | 5.148 | 3.720 | 0.309 | 0.067 | 0.756 |
| **7** | 0.159 | **4.279** | 3.268 | 0.257 | **0.010** | **0.823** |
| **8** | 1.570 | 5.253 | 3.952 | 0.316 | 0.094 | 0.754 |
| **9** | 1.391 | 5.179 | 3.861 | 0.311 | 0.084 | 0.758 |
| **10** | 1.215 | 5.228 | 3.837 | 0.314 | 0.073 | 0.751 |
| **11** | **0.636** | 4.827 | **3.492** | **0.290** | 0.038 | 0.778 |
| **12** | 0.972 | 5.055 | 3.665 | 0.304 | 0.058 | 0.767 |
| **13** | 0.999 | 5.096 | 3.696 | 0.306 | 0.060 | 0.760 |
| **14** | 0.738 | 5.015 | 3.617 | 0.301 | 0.044 | 0.766 |
| **15** | 0.786 | 5.178 | 3.678 | 0.311 | 0.047 | 0.751 |

Table VI shows the results of the evaluation of the models for the year 2005 which are (MBE=-0.159,RMSE=4.279, MAE=3.268, nRMSE =0.257,nMBE=0.010and 2=0.823).

Although the models applied are the same for each test year, it can be seen that for each year the best performing model is different than for the other test years and for the learning years it comes down to the difference in the data collected.

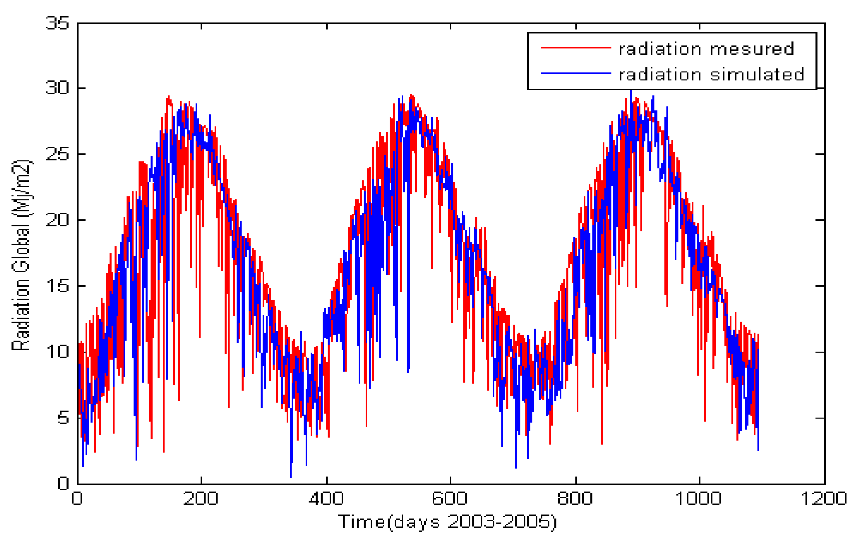


Fig.5 Irradiation Measured and Irradiation Simulated Test

Figure 9 shows the global solar irradiation measured on a horizontal surface of the three test areas (2003-2005) and the solar irradiation estimated by neural network of the tenth model. An almost perfect superposition of the two irradiations and it shows the performance of the designed model and its efficiency.


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The performance of the best model is validated by being tested with the data of the test years Figure 5 shows the estimated irradiation with the measured irradiation of the years ( 2003-2005).There is a correlation between the global solar irradiation measured on a horizontal surface and the solar irradiation estimated by the neural model, as shown in figure 10.

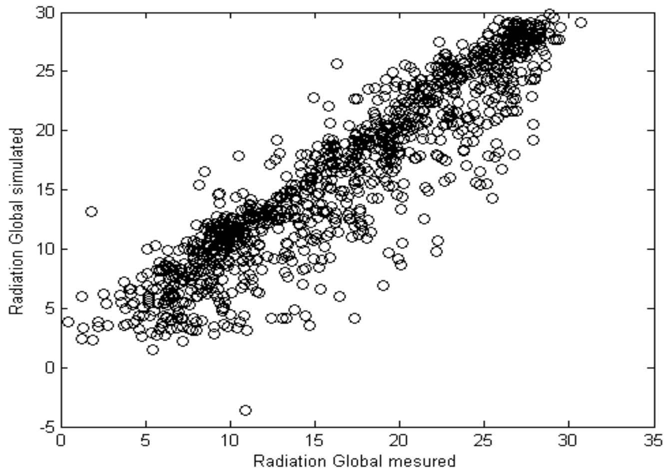


Fig.6 Correlation between daily global solar radiation and extraterrestrial daily solar radiation for Batna.

## VII. CONCLUSIONS

In this study, Artificial Neural Network (ANN) models were developed to predict the daily average global solar radiation in Batna, Algeria. Multiple ANN architectures employing the Levenberg–Marquardt (LM) training algorithm were trained and evaluated. Meteorological data spanning ten years, obtained from the HelioClim-1 database, were used for both training and testing the networks. The optimal ANN model incorporated all available meteorological parameters as inputs. Sensitivity analysis revealed that humidity and precipitation were the most influential parameters for estimating daily global solar radiation on a horizontal surface. The results demonstrate the strong predictive capability of ANN models, highlighting their dependence on both the quantity and diversity of training data. The findings confirm that ANNs can accurately forecast daily solar radiation, making them a reliable tool for renewable energy applications.

For future work, we plan to extend this research by implementing Radial Basis Function (RBF) neural networks, another powerful class of neural networks, to further enhance prediction accuracy and robustness.

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**Competing interests**

The authors declare that he has no competing interests.

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The authors are responsible for the integrity of the manuscript, including scientific ethics.

**Consent to participate**

There are no participants other than authors in this study. The authors agree to participate.

**Consent for publication**

There are no participants other than authors in this study for their consent on publication. The authors agree to publish.

**Availability of data and materials**

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

**Code availability**

The code is available and written with Matlab.

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