Artificial neural network estimation of 5-min solar global radiation values using air temperature, relative humidity and wind speed in the region of Blida (Algeria)

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***Abstract — S*olar energy estimation procedures are very important in the renewable energy field for development of mathematical models, optimization, and advanced control of processes. Solar radiation data provide information on how much of the sun's energy strikes a surface at a location on earth during a particular time period. These data are needed for effective research into solar-energy utilization. Due to the cost and difficulty in measurement, these data are not readily available. Therefore, there is the need to develop alternative ways for generating these data. In this study, an artificial neural network (ANN) was used for the estimation of daily global solar radiation (5-min R-G) on tilted surface using data measured from the meteorological station located inside the University of Blida. Six input parameters were used to train the network. These parameters were elevation, longitude, latitude, air temperature, relative humidity, and wind speed. The optimized network obtained with lowest deviation during the training was one with 6 neurons in the input layer; neurons in the hidden were obtained by trial and error, and one neuron in the output layer. The results show that the ANN can be accurately trained and that the chosen architecture can estimate the 5-min R-G with acceptable accuracy: mean absolute error (MAE) less than 20% for both training and validation step. The low deviations found with the proposed method indicate that it can estimate R-G with better accuracy than other methods available in the literature.**

Keywords-component*; *direct artificial neural network*; *solar radiation*; *air temperature*; *wind speed*; *humidity.

I. INTRODUCTION

Energy is essential for the economic and social development and improved quality of life in Algeria and principally in Blida because it is an industrial city. It is located in the center of Algeria characterized by its very hot climate in summer and cold weather in winter. Therefore, the energy resources are of vital importance both economically and environmentally. Solar energy is being seriously considered for satisfying a significant part of energy demand in this region [1-17].

Solar energy estimation procedures are very important in the renewable energy field for development of mathematical models, optimization, and advanced control of process. Solar radiation data provide information on how much of the sun's energy strikes a surface at a location on earth during a particular time period. These data are needed for effective research into solar energy utilization. Due to the cost and difficulty in measurement, these data are not readily available. Therefore, there is the need to develop alternative ways to generate these data. Many models have been developed to predict the solar radiation such as Angstrom and Hottel. Comparative studies of artificial neural networks (ANNs) and the traditional regression approaches in modeling global solar radiation (RG) have been shown that ANN methodology offers a promising alternative to the traditional approach. The relationship between radiation and meteorological data is highly non-linear, and consequently an ANN can be a suitable alternative to model the underlying radiation properties.

Neural networks (NNs) are the nature-based computing techniques which have been applied widely in tasks such as control, prediction, optimization, system identification, signal processing and pattern recognition, etc. A three-layer feedforward artificial neural network can approximate any nonlinear continuous function to an arbitrary accuracy [18-19]. The use of NNs to solve real problems always includes selecting the appropriate network models and network

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topology, as well as the efficient training algorithms [20]. Meanwhile, the design of NNs can be considered as a complex optimization problem in multidimensional space where each point represents a potential NN with different network structures and link weights. Because of their global searching capability, evolutionary algorithms (EAs), such as genetic algorithm [21-22], genetic programming [23], evolutionary programming and evolution strategy [20, 24], have been employed widely in evolving NNs. The learning power of NNs and the adaptive capabilities of EAs are fully utilized in evolving NNs.

In this paper an ANN has been trained to predict the global solar radiation on horizontal surface at the University of Blida, which can help students to design solar prototypes.

II. REVIEW OF THE APPLICATION OF THE ANN IN MODELING SOLAR RADIATION

In Figure 1 and 2, the number of papers published in different journals from 1978 to 1993 is compared with the number published from 1994 to 1997, from 1998 to 2001, from 2002 to 2005, from 2006 to 2009 and from 2010 to 2013. While in the early years about 35 articles were published each year, this number increases by 6–7 each year, so that in 2012 more than 10 times as many articles appeared as in 1994.

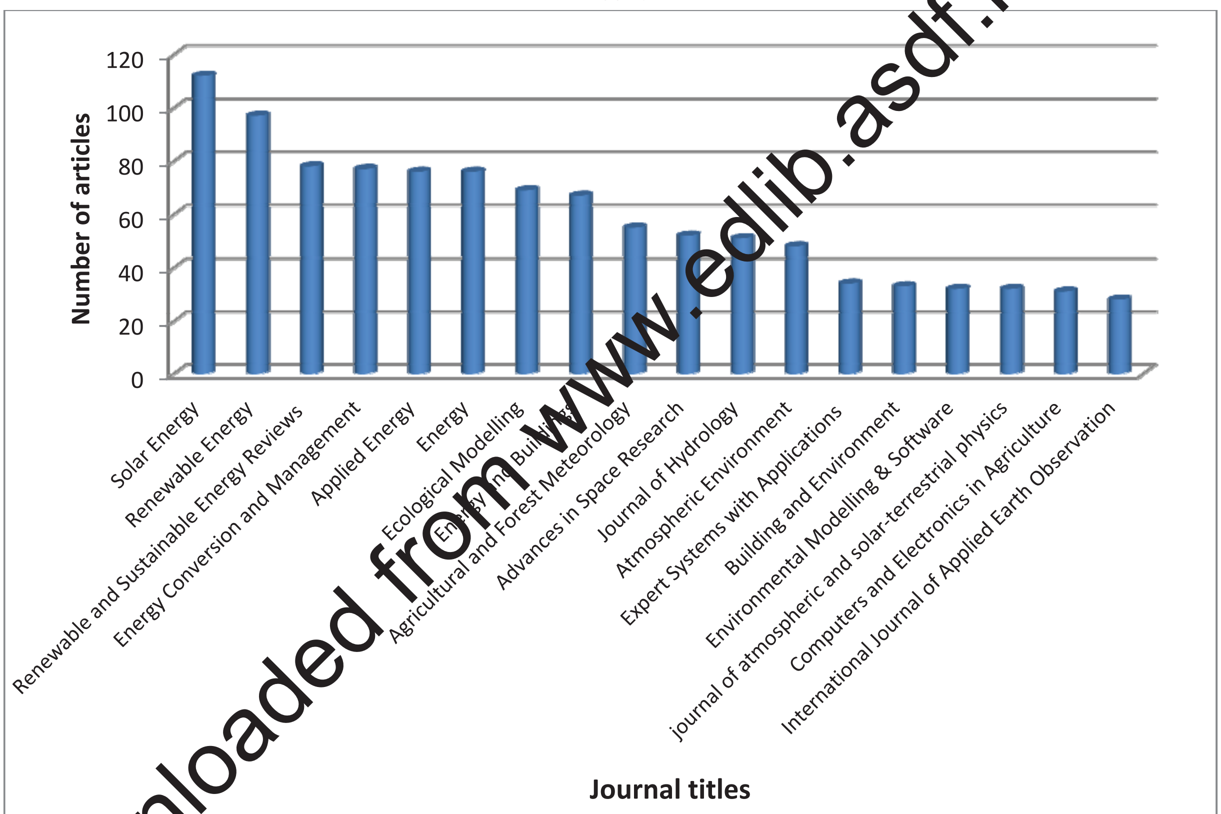

Figure 1. Bibliographic information

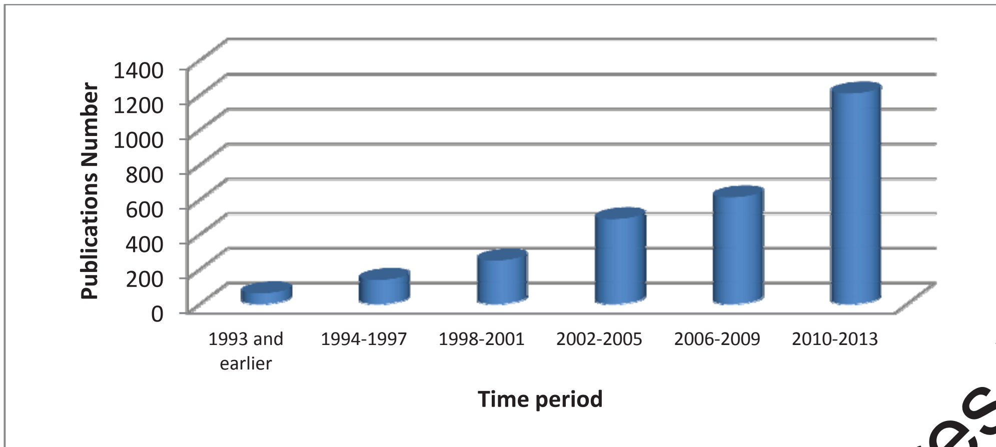

Figure 2. Number of articles vs period of time

III. TOPOGRAPHY AND ENERGY DATA OF ALGERIA

Algeria's geographic location has several advantages for extensive use of most of the renewable energy sources (RES) (wind, geothermal, biomass, solar, etc.). Algeria is situated in the center of North Africa between the 35° and 38° of latitude north and 8° and 12° longitude east, has an area of 2,381,741 km2 and a population of 32.5 millions of inhabitants. The Sahara occupies the 80% of the area. It lies, in the north, on the coast of the Mediterranean Sea. The length of the coastline is 2400 km. In the west Algeria borders with Morocco, Mauritania and occidental Sahara, in the southwest with Mali, in the east with Tunisia and Libya, and in the southeast with Niger. The climate is transitional between maritime (north) and semi-arid to arid (middle and south). The mean annual precipitation varies from 400 mm (in the north) to 150 mm (in the south). The average annual temperature is about 12 °C [25].

IV. NEURAL NETWORK MODELLING

A. Basic concept of Neural Network

Artificial neurons are arranged, as illustrated in Figure 3, in layers wherein the input layer receives inputs (u_i) from the real world and each succeeding layer receives weighted outputs ($w_{ij} \cdot u_i$) from the preceding layer as its input resulting therefore a feedforward ANN, in which each input is fed forward to its succeeding layer where it is treated. The outputs of the last layer constitute the outputs to the real world. In such a feedforward ANN a neuron in a hidden or an output layer has two tasks:

- It sums the weighted inputs from several connections plus a bias value and then applies a transfer function to the sum as given by (for neuron j of the hidden layer):

$$z_j = f_h\left(\sum_{i=1}^{n} w_{ji}^{I} u_i + b_{hj}\right) \quad (1)$$

- It propagates the resulting value through outgoing connections to the neurons of the succeeding layer where it undergoes the same process as given by (for instance outputs z_j of the hidden layer fed to neuron k of the output layer gives the output v_k):

$$v_k = f_O\left(\sum_{j=1}^{m} w_{kj}^{h} z_j + b_{ok}\right) \quad (2)$$

Combining equations 1 and 2 one obtains the relation between the output v_k and the inputs u_i of the NN.

$$v_k = f_O\left(\sum_{j=1}^{m} w_{kj}^{h} f_h\left(\sum_{i=1}^{n} w_{ji}^{I} u_i + b_{hj}\right) + b_{ok}\right) \quad (3)$$

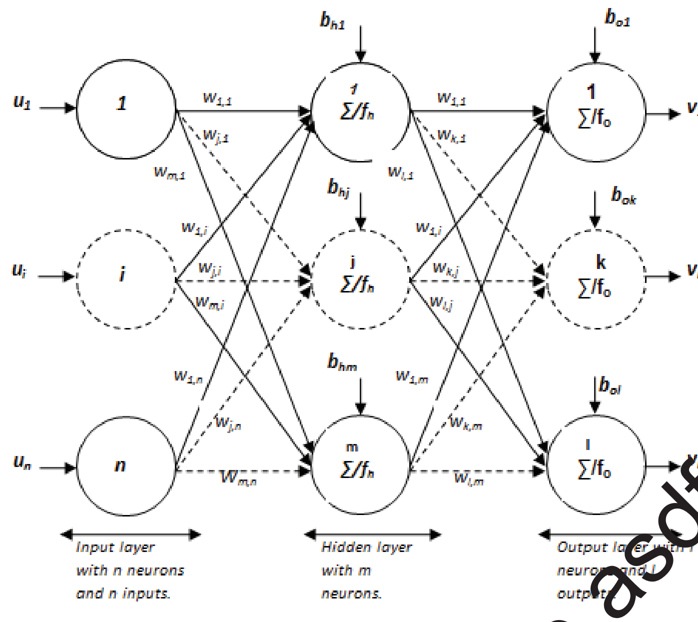

Figure 3. Three-layer feedforward neural network.

The output is computed by means of a transfer function, also called activation function. It is desirable that the activation function has a sort of step behavior. Furthermore, because continuity and derivability at all points are required features of the current optimization algorithms, typical activation functions which fulfil these requirements are: hyperbolic tangent sigmoid transfer function, logarithmic sigmoid transfer function and pure linear transfer function.

V. DATABASE DESCRIPTION

A data set of 14745 points of one year (2011) was used to develop the ANN method. All data base was taken from the meteorological station of Blida University recorded using Davis Vantage Pro2 Weather station. The meteorological data are: air temperature (TA (°C)), relative humidity RH (%), and wind speed Ws (ms-1). Figure 4 shows the geographical location of the meteorological station.

Figure 4. Geographical location at the University of Blida of the meteorological station involved in this study.

Table 1 shows the basic information for weather station and the data ranges of the properties of interest. As seen in table 1, 5-min RG cover wide ranges going from 2 to 10.78 (kWh.m-²), relative humidity from 17 to 92 (%), air temperature from 6.8 to 42.3 (°C) and wind speed from 0.4 to 2.2 (m.s^{-1}).

TABLE 1. SOLAR RADIATION DATABASE AND BASIC INFORMATION FOR WEATHER STATION

Altitude (m)	Longitude	Latitude (°N)	T_A (°C)	RH (%)	W_s (m/s)	5-min RG (kWh/m²)	Period (yr)	No. Data
0120	02.47E	36.27	6.8 - 42.3	17 - 92	0.4 - 2.2	0 - 10.78	2011	14745

The weather station is successfully installed at Electronic Department (ED), Blida University. The main purpose of weather station installations is to improve the study in assessment of wind and solar energy especially for students to study, design and develop prototypes that work with renewable energy. Figure 5 shows a Davis Vantage Pro2 weather station data center in ED.

Figure 5. Davis Vantage Pro2 weather station center

VI. ANN ELABORATION METHODOLOGY

Figure 6 presents a block diagram of the program developed and written in MATLAB 2013. The development of the neural network model implies the following stages: collecting the experimental data, making up the training and testing data sets, developing the neural network topology, training and, finally, establishing the performance of the neural network model by comparing the network prediction to unseen (validation) data.

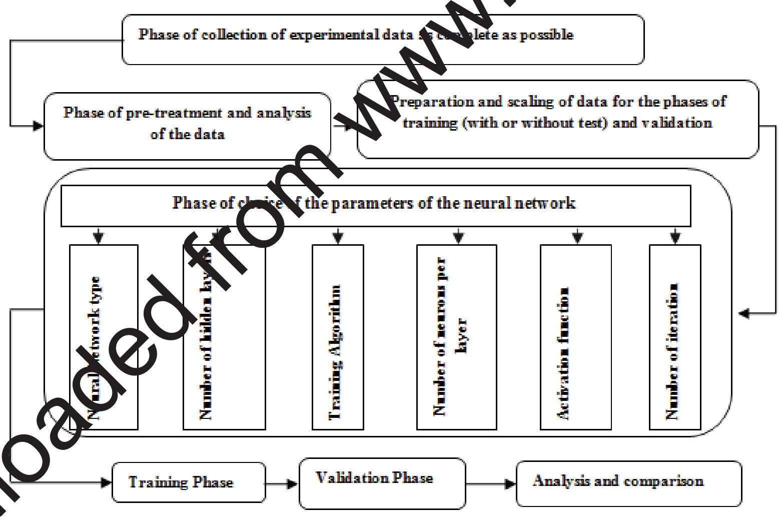

Figure 6. Flow diagram for training of ANN

TABLE 2. STRUCTURE OF THE OPTIMIZED ARTIFICIAL NEURAL NETWORKS MODEL.

Type of network	Training Algorithm	Input layer	First and second hidden layer		Output layer	
		No. of neurons	No. of neurons	Activation function	No. of neurones	Activation function
FFBP NN	BRBP using Levenberg-Marquardt optimisation.	3	20	Tangent sigmoid	1	Linear

We used the back-propagation algorithm for training several multi-layer feed-forward neural networks to estimate the values of global solar radiation. The best network consists of 3 inputs, 20 neurons in first hidden layer, 20 neurons in second hidden layer and one neuron in the output layer. The air temperature, relative humidity and wind speed values have been used as inputs to the network. The output is the value of the global solar radiation. The training process continues until the error function approaches a prespecified minimum value. After the training is completed, the developed model is used for testing, where 4915 is used. These results indicate the viability of this method for global solar radiation modeling.

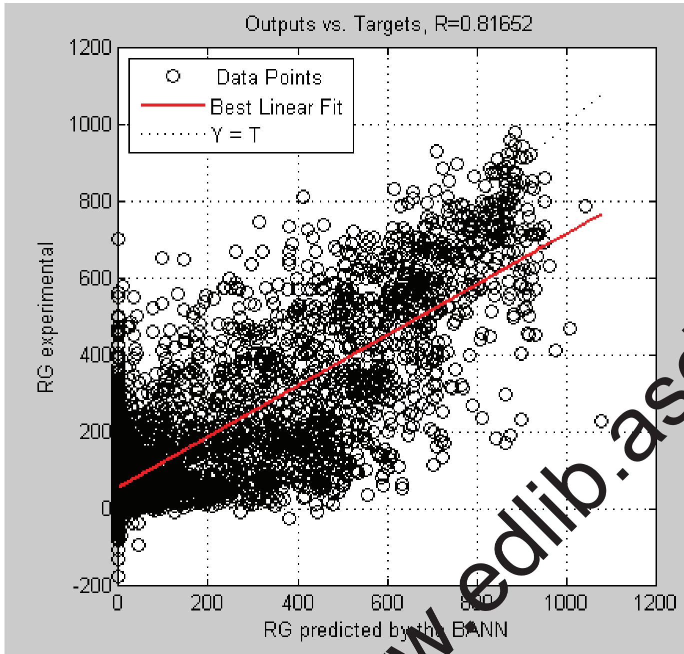

Figure 7. Validation agreement plot of the most predictive model of the GSR

GSR estimates from the ANN compared with the actual data using simple error analysis and linear analysis with the following parameters: coefficient of correlation (R) and mean absolute error (MAE). The coefficient of correlation equal to 0.81652.

VII. Conclusion

Global solar radiation (GSR) data are desirable for many areas of research and applications in various engineering fields. However, GSR is not as readily available as air temperature data. Various equations have been developed to compute the solar irradiation data measured on horizontal surface. These equations constitute the conventional approach. In this article, an alternative approach, generalized regression type of neural network, is used to predict the solar irradiation on horizontal surfaces, using the minimum number of variables involved in the physical process.

Artificial neural networks have been successfully used in recent years for optimization, prediction and modeling in energy systems as alternative to conventional modeling approaches.

Artificial neural networks (ANNs) are effective tools to model nonlinear systems and require fewer inputs. The objective of this study was to test an artificial neural network (ANN) for estimating the global solar radiation (GSR) as a function of air temperature, relative humidity and wind speed data in a in the south-western region of Algeria. The measured data of 2011 were used for training and testing the neural networks data. The testing data were not used in training the neural networks.

Obtained results show that neural networks are well capable of estimating GSR from temperature and relative humidity. This can be used for estimating GSR for locations where only temperature and humidity data are available.

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