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Artificial Neural Networks Modeling of Relation Relaying Daily Global Solar Radiation to Astronomical and Meteorological Parameters

[1-3]Abdelghani Harrag and [1]Sabir Messalti
[1]Department of Electrical Engineering, Faculty of Technology,
Mohamed Boudiaf University, Route BBA, 28000 Msila, Algeria
[2]CCNS Laboratory, Department of Electronics, Faculty of Technology,
Ferhat Abbas University, Route Bejaia, Cite Maabouda, 19000 Setif, Algeria
[3]Department of Physics, Faculty of Sciences, Ferhat Abbas University,
El Bez Setif 1, 19000 Setif, Algeria

Abstract: Algeria naturally has a significant solar potential. This qualitative constant favors the exploitation and development of this energy resource. However, the use of this energy requires knowledge of the potential of solar radiation on horizontal and inclined planes. In fact, the objective of this study is to develop a neural model that can be used to predict the daily global solar radiation average received on a horizontal surface. Several models using different meteorological and astronomical parameters were studied in order to choose the most efficient model based on error between real and predicted irradiation. The results indicate that the model using as input variables: azimuth, zenith angle, extraterrestrial solar radiation, relative humidity, precipitation and wind speed is the most efficient among the studied models.

Key words: Forecast solar irradiation, prediction, neural network, meteorological parameters, astronomical parameters

INTRODUCTION

Our planet faces significant challenges in the 21st century because energy consumption is expected to double globally during the first half of this century. Faced with increasingly constrained oil supplies, humanity must look to other sources of energy such as solar to help us meet the growing energy demand. A useful measure of the level of a country's development is through its energy consumption and efficiency. Excessive fossil fuel energy use not only has caused severe and growing damage to the environment from greenhouse gas emissions and oil spills but also has brought political crises to countries in the form of global resource conflicts and food shortages. Solar and other forms of renewable energy offer a practical, clean and viable solution to meet our planet's growing environmental and energy challenges (Foster *et al*., 2010; Renewables, 2014; IEA, 2014).

The sun provides the earth with an enormous amount of energy. The potential of solar energy to produce heat and electricity to be supplied for our modern economies in a variety of productive activities has been widely demonstrated but not yet widely adopted around the globe due to relatively cheap fossil fuels compared to required high initial capital cost for solar energy. In addition, the solar energy source is inexhaustible and free, it is not the most convenient energy source because it is not constant during the day and not readily dispatched. In contrast, modern lifestyles demand a continuous and reliable supply of energy. However, there are ways to overcome these shortfalls (Sen, 2008).

The successful design and effective utilization of solar energy systems needs its characterization and prediction and/or to estimate the potential power plants. The availability of information on solar radiation characteristic of the location in which the systems are to be installed is of considerable interest. Unfortunately this data is either not available or difficult to harvest, the irradiance measurement-networks or meteorological stations do not always provide sufficient geographically time-site specific irradiance coverage (Sen, 2008).

Quite often, solar energy projects are not backed up by the long-term measured solar database required at the place of interest, mainly due to the capital and

Corresponding Author: Abdelghani Harrag, Department of Electrical Engineering, Faculty of Technology, Mohamed Boudiaf University, Route BBA, 28000 Msila, Algeria

maintenance costs that measuring instruments incur. Consequently, they need to be estimated from alternative information available at the site or a nearby location. This is where solar radiation modeling plays an important role (Bakirci, 2009; Besharat *et al.*, 2013; Amrouche and Le Pivert, 2014).

In this study, a neural model that can be used to predict the daily global solar radiation average received on a horizontal surface. Several models using different meteorological and astronomical parameters were studied in order to choose the most efficient model based on error between real and predicted irradiation. The results indicate that the model using as input variables: azimuth, zenith angle, extraterrestrial solar radiation, relative humidity, precipitation and wind speed is the most efficient among the studied models.

MATERIALS AND METHODS

Global solar radiation: The amount and intensity of solar radiation reaching the earth's surface depends on the geometric relationship of the earth with respect to the sun. Figure 1 shows this geometric relationship and its effects for different seasons. The position of the sun at any moment at any place on earth can be estimated by two types of calculations: first, by simple equations where the inputs are the day of the year, time, latitude and longitude and secondly by calculations through complex algorithms providing the exact position of the sun (Kashyap *et al.*, 2015).

Global solar forecasting models: The solar radiation prediction models can be categorized in three groups: empirical models (Haberlin, 2012) consisting of a few measurable meteorological parameters related to the model via the development of a set of equation; deterministic models necessitating complex geographical and meteorological parameters providing a considerable precision in their output results. The main drawback of these models resides in the amount of needed calculations and also numerous input parameters which are not available in most of the locations; artificial intelligence models (Donatelli *et al.*, 2003; Benghanem *et al.*, 2009; Mellit and Pavan, 2010; Koca *et al.*, 2011), most of them based on neural networks models, able to predict solar irradiation without mathematical model describing the relationship between the various available meteorological and astronomical parameters. This third category will be the subject of this research that can be considered as a contribution in the solar irradiation prediction using neural networks models with different meteorological and astronomical parameters.

Neural network global solar radiation forecasting: A Neural Network (NN) is an abstract computer model of the human brain. Similar to the brain, a neural network is composed of artificial neurons and interconnections. When we view such a network as a graph, neurons can be represented as nodes and interconnections as edges. Information is passed between these units along the interconnections. Data is passed through the network from layer to layer (Khatib *et al.*, 2012). The neural network global solar irradiation prediction model design procedure can be summarized by:

- Collecting a database and it's separation into three subsets (training, validation and test)
- Neural network architecture selection

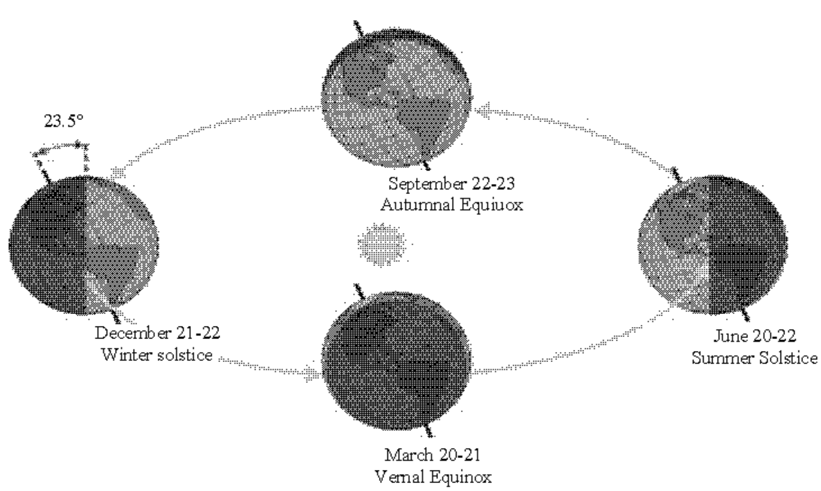

Fig. 1: Geometric relationship between sun and earth

Table 1: Model parameters

Meteorological	Astronomical
Rel. humidity	Azimuth
Precipitation	Zenith angle
Wind speed	Extraterrestrial solar radiation

Table 2: Studied models M_1-M_4

Meteorological	M_1	M_2	M_3	M_4
Azimuth	X	X	X	X
Zenithal angle	X	X	X	X
Extraterrestrial solar radiation	X	X	X	X
Relative humidity		X	X	X
Precipitation			X	X
Wind speed				X

- Neural network training
- Neuron network performance measurement

Neural netwrok architecture selection: The definition of neural network architecture is essential for an efficient system. This involves a compromise between the complexity of the network by reducing the number of hidden units and the number of neurons for each layer. For the input layer, the number of the neurons is fixed by the number of model prediction variables. Table 1 gives the possible model parameters. While Table 2 shows the parameters considered in this study.

For the output layer, the number of neurons is determined by the number of outputs to approximate, i.e., the variable we want to predict. For our application, we want to predict solar radiation, so we will use only a single neuron in the output layer.

Neural network training and tests: This step is realized using backpropagation training algorithm (Haykin, 1999). The backpropagation algorithm is a multi-layer network using a weight adjustment based on the sigmoid function, like the delta rule. The backpropagation method is a supervised learning algorithm where the target of the function is known. Once neural network training completed, it is always necessary to conduct tests to estimate the quality of generalization by presenting a different database from those used for training or cross-validation. If performance is not satisfactory, we will either change the network architecture or modify the training set.

Neural network performance measurement: To evaluate the performance estimation models, several statistical indicators were used in the literature (Rumelhart *et al.*, 1986; Wackerly *et al.*, 2008): Mean Bias Error (MBE) gives an indication of the average deviation of the predicted values from the corresponding measured values:

$$\mathrm{MBE} = \sum_{i=1}^{N}\left(H_{est}(i) - H_{mes}(i)\right)^2 \tag{1}$$

Where:

H_{est} = The estimated output
H_{mes} = The measured output
N = The number of data

Root Mean Square Error (RMSE) is a measure of the variation of the predicted values around the measured ones. Plus the value is smaller better is the model. In our case we use and compare both RMSE and MBE performance measure:

$$\mathrm{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(H_{mes}(i) - H_{est}(i)\right)\right]^{1/2} \tag{2}$$

Where:

H_{est} = The estimated output
H_{mes} = The measured output
N = The number of data

RESULTS AND DISCUSSION

The previously four defined models (M_1-M_4) were trained using both NASA (Lehmann and Casella, 1998) and NREL data for 6 year covering the period 2000-2005 (72 months). In this study, we use 52 months for training, 8 months for validation and 12 months for tests. Figure 2-8 show the different input parameters as well as the measured correspondent solar radiation output.

Table 3 and Fig. 9 show the architecture of the four ANN models studied. Table 3 show the global architecture of each model while Fig. 3 gives the considered parameters for each model. The correlations between solar irradiation and each inputvvariable of our four models are shown in Fig. 10-15. The performance measures are summarized in Table 4.

From Table 4, we can see that the RMSE or MBE errors are smaller in model M_4 compared to other models. The model M_4 using all considered parameters is the best one for predicting global solar irradiation. Figure 16 shows the validation results using the M_4 model. The results of this study confirm the ability of artificial neural networks to predict the value of solar radiation with precision. Therefore, the predicted data can be used in the absence of measures real data.

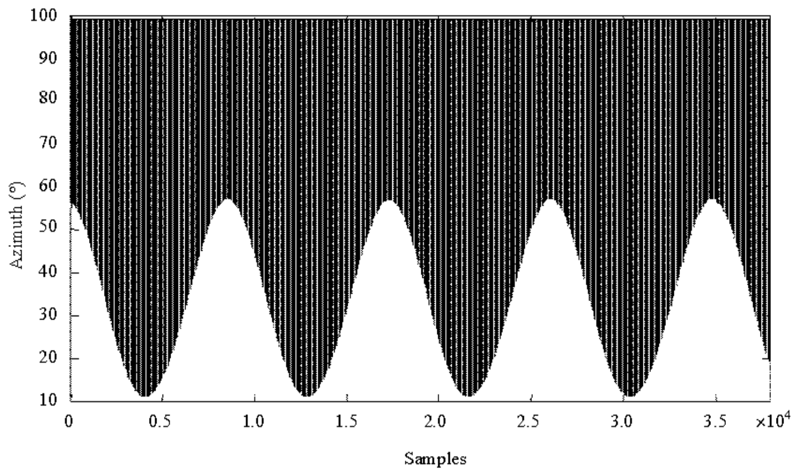

Fig. 2: Azimuth

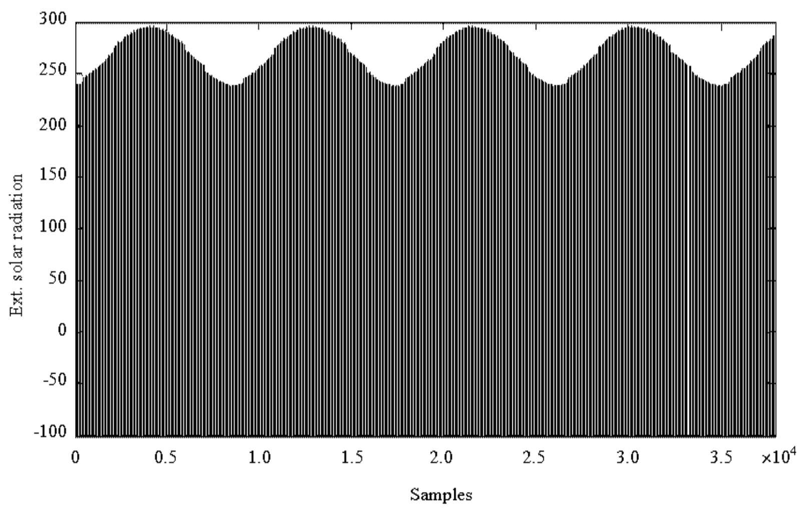

Fig. 3: Zenithal angle

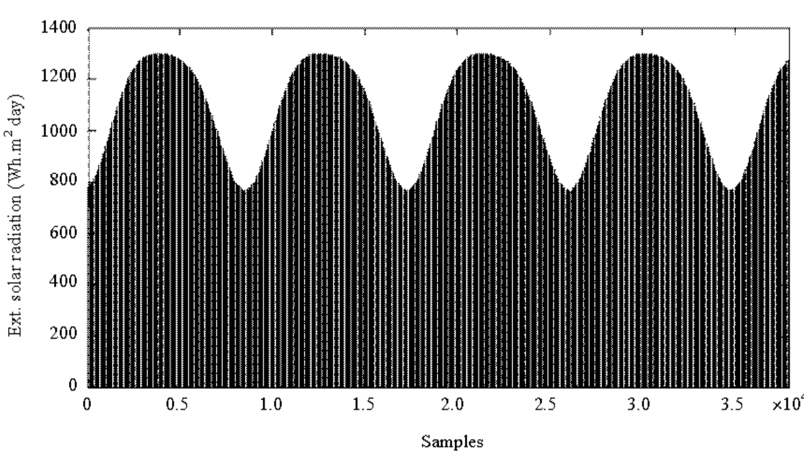

Fig. 4: Extraterrestrial solar radiation

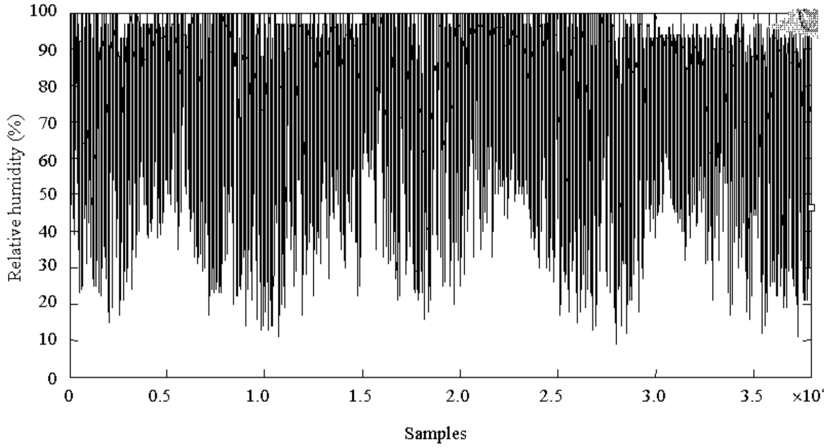

Fig. 5: Relative humidity

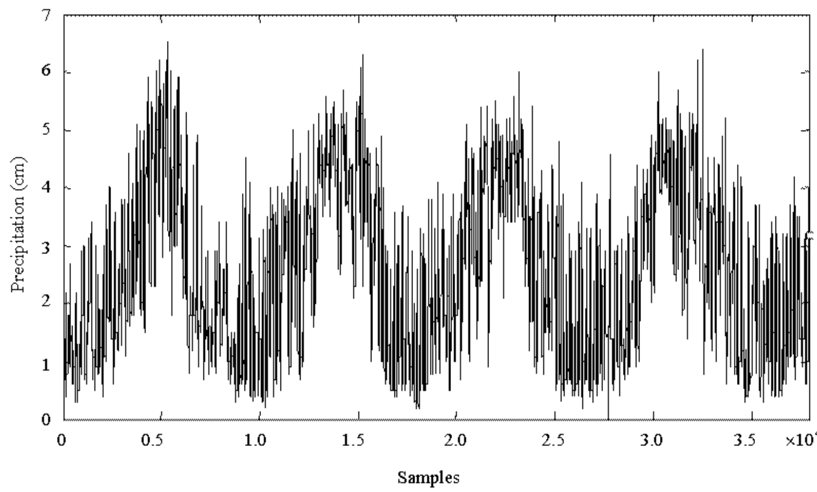

Fig. 6: Precipitationd

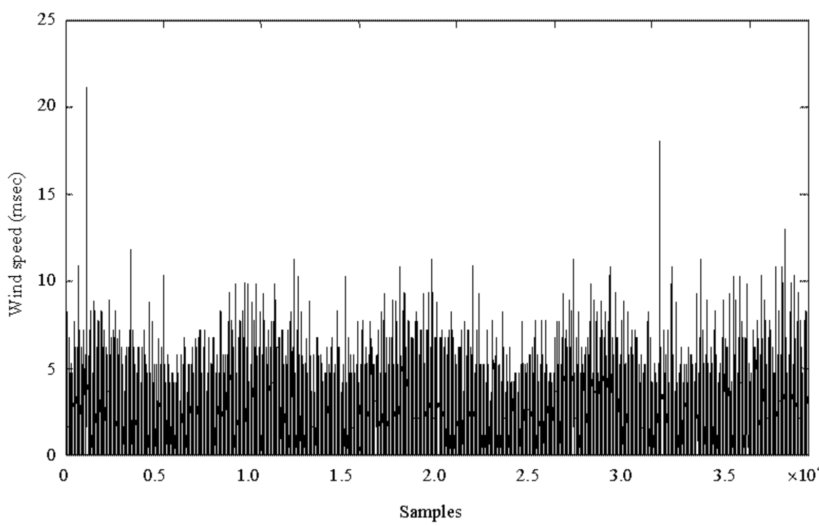

Fig. 7: Wind speed

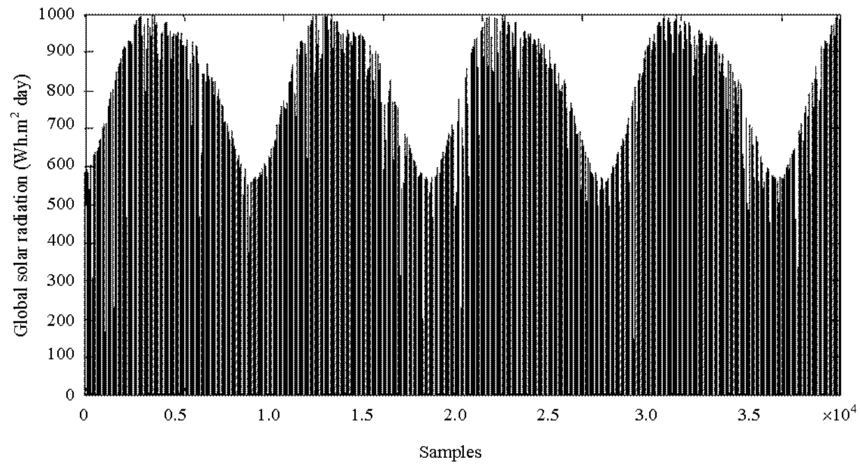

Fig. 8: Global solar radiation

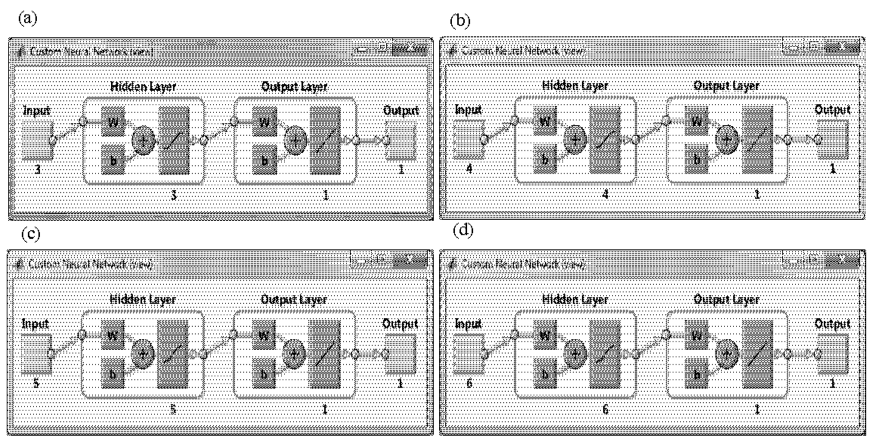

Fig. 9: Studied models: a) M1; b) M2; c) M3 and d) M4

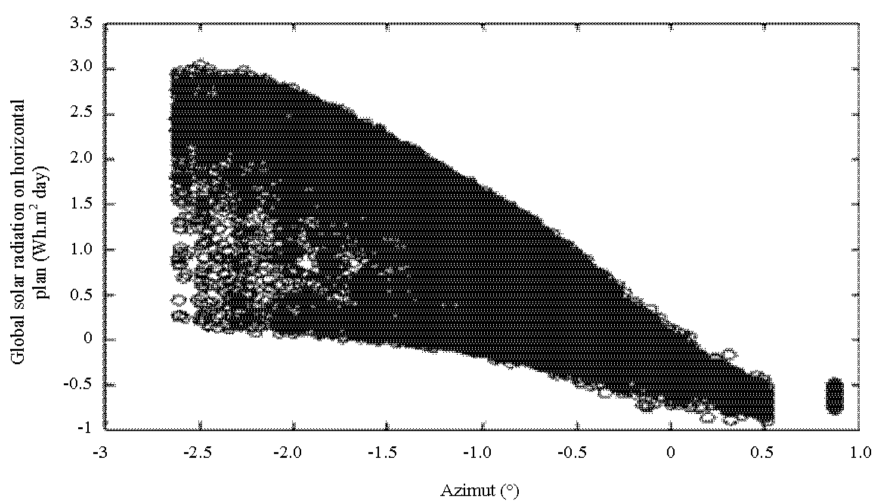

Fig. 10: Correlation between global solar radiation and azimuth

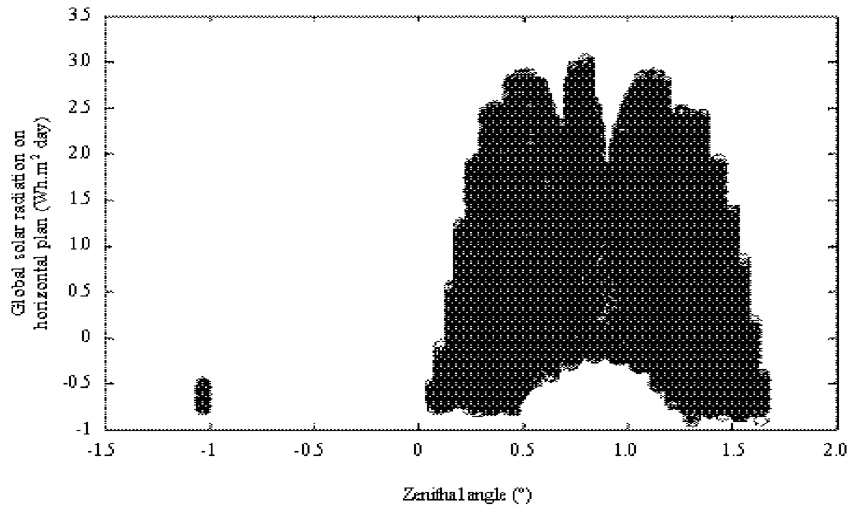

Fig. 11: Correlation between global solar radiation and zenithal angle

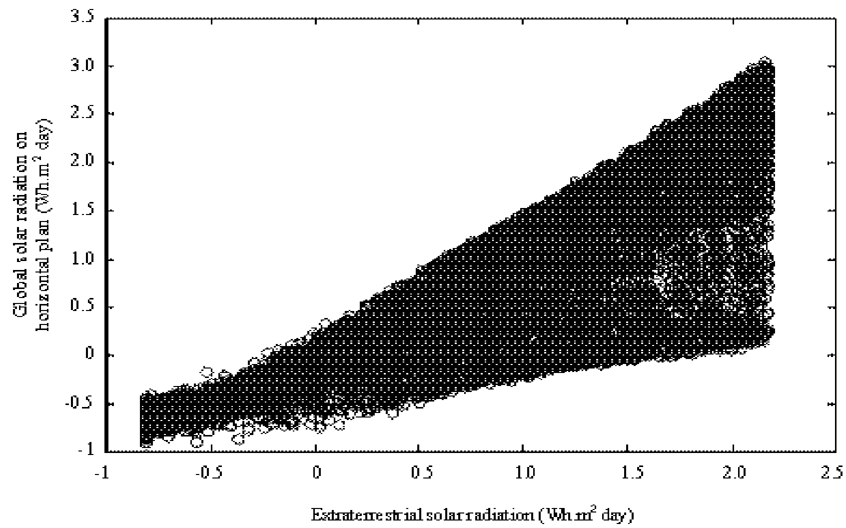

Fig. 12: Correlation between global solar radiation and extraterrestrial solar irradiation

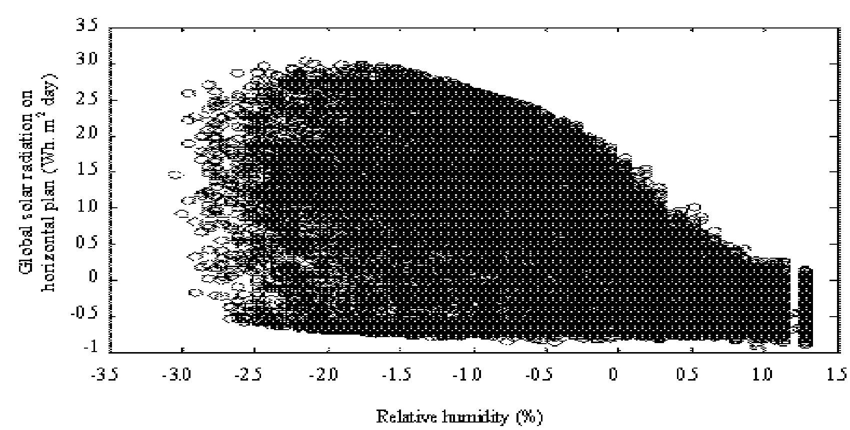

Fig. 13: Correlation between global solar radiation and relative humidity

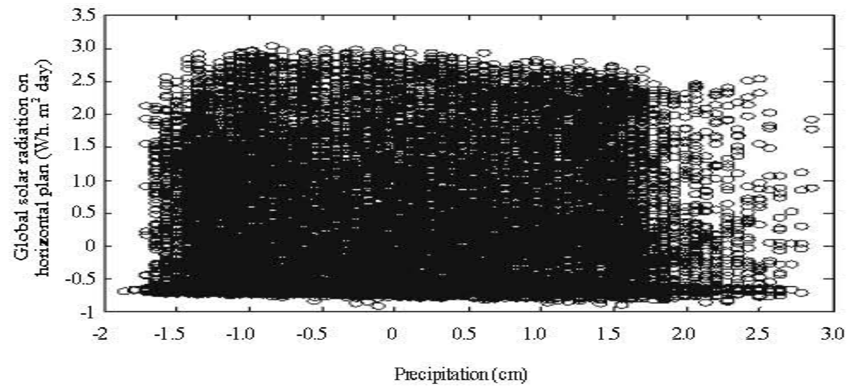

Fig. 14: Correlation between global solar radiation and precipitation

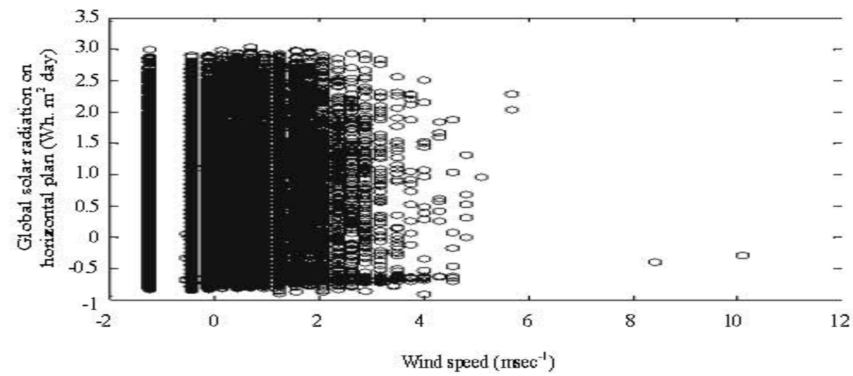

Fig. 15: Correlation between global solar radiation and wind speed

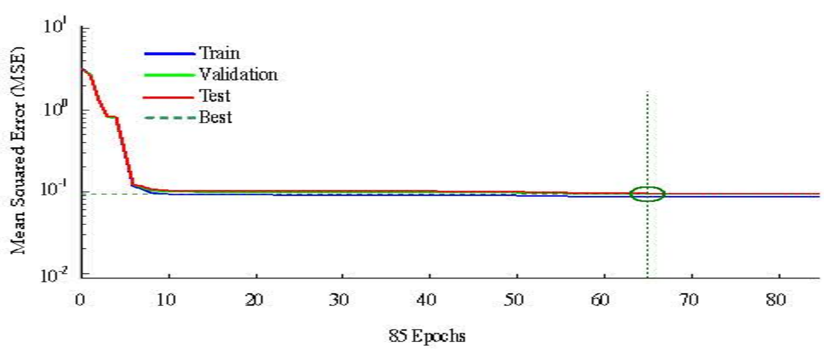

Fig. 16: Validation results using the M4 model

Table 3: The global architecture of each model

Parameters	M_1	M_2	M_3	M_4
Input				
Azimuth	X	X	X	X
Zenithal angle	X	X	X	X
Ext. solar radiation	X	X	X	X
Relative humidity		X	X	X
Precipitation			X	X
Wind speed				X
Output				
Solar radiation	X	X	X	X
Transfer function				
Hidd. layer: sigmoid	X	X	X	X
Output layer: linear	X	X	X	X

Table 4: Model performance

Model	RMSE	MBE
M_1	0.9198	0.7285
M_2	0.3005	0.1492
M_3	0.2967	0.1483
M_4	0.2927	0.1427

CONCLUSION

Solar radiation is the most important natural energy resource because it drives all environmental processes acting at the surface of the earth. The successful design and effective utilization of solar energy systems needs its characterization and prediction to estimate the potential power plants. The availability of information on solar radiation characteristic of the location in which the systems are to be installed is of considerable interest. Unfortunately this data is either not available or difficult to harvest which increases the need of researchers for prediction and forecasting using different models.

In this study, a neural model that can be used to predict the daily global solar radiation average received on a horizontal surface has been proposed. Several models using different meteorological and astronomical parameters were studied in order to choose the most efficient model based on error between real and predicted irradiation. The results indicate that the model using as input variables: azimuth, zenith angle, extraterrestrial solar radiation, relative humidity, precipitation and wind speed is the most efficient among the studied models.

REFERENCES

Amrouche, B. and X.L. Pivert, 2014. Artificial neural network based daily local forecasting for global solar radiation. Appl. Energy, 130: 333-341.

Bakirci, K., 2009. Models of solar radiation with hours of bright sunshine: A review. Renewable Sustainable Energy Rev., 13: 2580-2588.

Benghanem, M., A. Mellit and S.N. Alamri, 2009. ANN-based modelling and estimation of daily global solar radiation data: A case study. Energy Convers. Manage., 50: 1644-1655.

Besharat, F., A.A. Dehghan and A.R. Faghih, 2013. Empirical models for estimating global solar radiation: A review and case study. Renewable Sustainable Energy Rev., 241: 798-821.

Donatelli, M., G. Bellocchi and F. Fontana, 2003. RadEst 3.00: Software to estimate daily radiation data from commonly available meteorological variables. Eur. J. Agron., 18: 363-367.

Foster, R., M. Ghassemi and A. Cota, 2010. Solar Energy: Renewable Energy and the Environment. CRC Press, London, England, ISBN:0-89553-256-5, Pages: 337.

Haberlin, H., 2012. Photovoltaics System Design and Practice. John Wiley&Sons, New Jersey, USA., ISBN:9781119992851, Pages: 105.

Haykin, S., 1999. Neural Networks: A Comprehensive Foundation. 2nd Edn., Prentice Hall, New Jersey, USA., ISBN: 8120323734, pp: 443-484.

IEA., 2014. Technology roadmaps bio-energy for heat and power 2014. International Energy Agency, ?Paris, France. http:// www.iea.org/publication/

Kashyap, Y., A. Bansal and A.K. Sao, 2015. Solar radiation forecasting with multiple parameters neural networks. Renewable Sustainable Energy Rev., 49: 825-835.

Khatib, T., A. Mohamed, K. Sopian and M. Mahmoud, 2012. Solar energy prediction for Malaysia using artificial neural networks. Intl. J. Photoenergy, 2012: 1-16.

Koca, A., H.F. Oztop, Y. Varol and G.O. Koca, 2011. Estimation of solar radiation using artificial neural networks with different input parameters for Mediterranean Region of Anatolia in Turkey. Expert Syst. Appl., 38: 8756-8762.

Lehmann, E.L. and G. Casella, 1998. Theory of Point Estimation. 2nd Edn., Springer-Verlag, New York, ISBN: 0-387-98502-6.

Mellit, A. and A.M. Pavan, 2010. A 24-h forecast of solar irradiance using artificial neural network: Application for performance prediction of a grid-connected PV plant at Trieste, Italy. Solar Energy, 84: 807-821.

Renewables, 2014. Global status report. Renewables International Energy Agency, USA.

Rumelhart, D.E., G.E. Hinton and R.J. Williams, 1986. Learning representations by back-propagating errors. Nature, 323: 533-536.

Sen, Z., 2008. Solar Energy Fundamentals and Modelling Techniques. Springer-Verlag Ltd., USA.

Wackerly, D., W. Mendenhall and R.L. Scheaffer, 2008. Mathematical Statistics with Applications. Brooks-Cole Publishing, Belmont, California, USA., Page: 341.