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Radial basis function neural networks model to estimate global solar radiation in semi-arid area

Abdelaziz RABEHI*, Mawloud GUERMOUI, Djelloul DJAFER, and Mohamed ZAIANI

Research Unit Applied Renewable Energy, URAER, Renewable Energy Development Centre, CDER, 47133, Ghardaïa, Algeria
E-mails: Rab_ehi@hotmail.fr, rabhi_abdelaziz@uraer.dz
Corresponding author, phone: 00(213)029 87 01 26; fax: 00(213)029 87 01 46

Abstract

For many developing countries, solar radiation measurements are only available for selected stations due to the cost of the measurement equipment and techniques involved. In this study, a simple model based on Radial Basis Function neural networks is proposed to estimate the Daily Global Solar Radiation using a limited meteorological data measured at Ghardaïa station. The study covered three years from 2012 (1st January) to 2014 (28th October). The obtained results show that the Radial Basis Function neural network model predicts the Daily Global Solar Radiation of clear and perturbed days with a good accuracy. The difference between the measured and the predicted values show a Root Mean Square Error of 0.014.

Keywords

Global solar radiation; Prediction; Neural network; Regression; Radial Basis Function (RBF)

Introduction

The Sun is the driving force for all atmospheric processes. Solar radiation intensity is the expression of that input of energy upon the planet Earth. Therefore, the ability to understand and quantify its value and distribution accurately is important in the initial

understanding and modeling of any other thermodynamic or dynamic process in the Earth-ocean-atmosphere system. Unfortunately, too little is known about the spatial and temporal distribution of incoming solar radiation. A more complete and precise description of that distribution will prove usefulness to many fields of study that rely on atmospheric energy input, such as agricultural, architectural and engineering planning [1].

To assess the availability of solar radiation at different locations, measurements of global radiation, diffuse radiation, beam radiation, Sun shine hours, bright Sun shine hours, maximum and minimum temperature, humidity, pressure, visibility, wind speed and its direction, gust speed, water precipitation and air mass are very important parameters for designers of solar energy systems. For these reasons, several papers previously published on different types of clear sky models, analysis, and validation for various measurement locations. Each paper has its own benefit for looking at differing complexities, models for each component of irradiance and accuracy for a given location or geographic region.

Gueymard analyzed eleven clear sky irradiance models for predicting beam, diffuse and global radiation on a horizontal surface [2].

Bird and Hulstrom analyzed six atmospheric clear sky models for direct, diffuse sky, diffuse sky/ground and Global Horizontal Irradiance [3]. Badescu looked at five very simple clear sky models for GHI for two cities in Romania [4]. Younes and Muneer evaluated four clear sky models for six locations in UK, Spain and India [5]. Gueymard and Wilcox did a very detailed study on 18 broadband radioactive clear sky models that predict direct, diffuse and global irradiances under clear skies from atmospheric data [6].

In the present work, we propose a simple model based on Radial Basis Function (RBF) neural networks to estimate Global Solar Radiation (GSR) using a limited meteorological data measured at Ghardaïa station.

Material and method

RBF neural networks

Radial-Basis Function Networks (RBFN) can be used for a wide range of applications, primarily because they can approximate any function and their training faster compared to Multi-Layer Perceptors (MLP). This fast learning speed comes from the fact that RBFN have just two layers (see Figure 3) of parameters (centers, widths and weights). The RBFN is based

on the idea of approximating a function F(x) through a linear combination of radial basis functions Ψ [7-10].

$$\hat{F}(x) = \sum_{j=1}^{P} \lambda_j \Psi_j(\|x - c_j\|) \quad (1)$$

where P, λ_j, and c_j are the number, the weight and the center (prototype) of the radial functions, respectively

A typical choice for the radial basis function is the Gaussian kernel:

$$\Psi_j(\|x - c_j\|) = exp\left(-\frac{1}{2}\left(\frac{\|x-c_j\|}{\sigma_j}\right)^2\right) \quad (2)$$

where σ_j is the width parameter of the jth hidden unit (basis function) of the hidden layer

For a given RBFN architecture based on the Gaussian kernel (i.e., for a fixed value of P), the training algorithm consists in finding the parameters λ_j, c_j and σ_j such that $\hat{F}(x)$ its the desired function F(x) as best as possible. Since F(x) is unknown, the goodness of fit is measured empirically by means of the available training samples. Briefly, the training of the hidden layer, which is equivalent to the computation of the kernel parameters (c_j and σ_j), is performed by applying the k-means clustering algorithm (with k = P) to the available training samples.

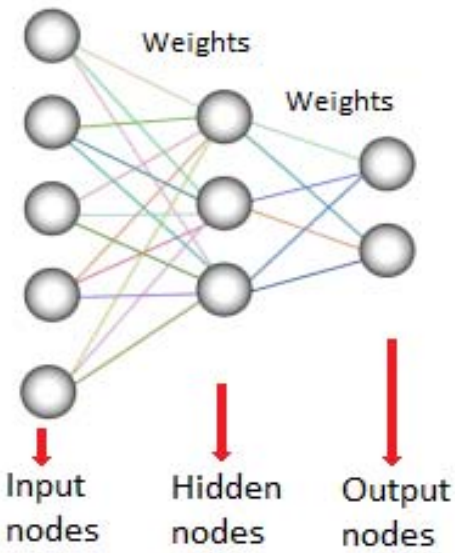

Figure 1. *Architecture of a radial basis function neural network (RBFN)*

In this work, for the sake of simplicity, we will assume that all kernel functions have the same width ($\sigma_j = \sigma$) [11, 12]. The training of the output layer (i.e., the estimation of the λ_j parameter) is accomplished by formulating the estimation problem as a linear system of

equations solved according to the pseudo-inverse technique.

Site location and solar radiation data

The data used to perform the present study have been recorded at the Applied research Unit for Renewable Energies (URAER) situated in the south of Algeria far from Ghardaïa city of about 18 km. The latitude, longitude and altitude above the sea level of the URAER are respectively +32.37°, +3.77° and 450 m above (see the top of Figure 2) [13,14]. They are recorded every 5 minute and consist in data of temperature, direct, diffuse, and global solar irradiance. The radiometric station used to measure the three components of irradiance (direct, diffuse and global) is show on Figure 2 [15]. The daily variation of GSR during the years 2012-2014, is shown on Figure 3.

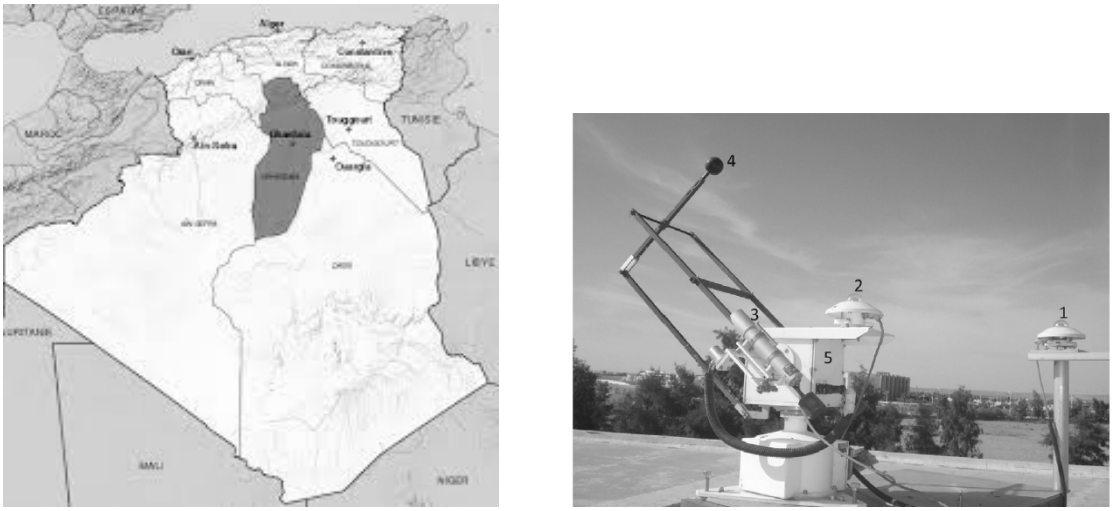

Figure 2. *Location of Ghardaïa city (left). Instrumentation station (right) for measuring the global, the direct and the diffuse solar radiation: (1) Pyranometer for measuring the global solar irradiance. (2) Pyranometer for measuring the diffuse irradiance component. (3) Peryheliometer for measuring the direct irradiance component. (4) The ball used to permanently hide the pyranometer (2). (5) The 2-axis solar tracker [15].*

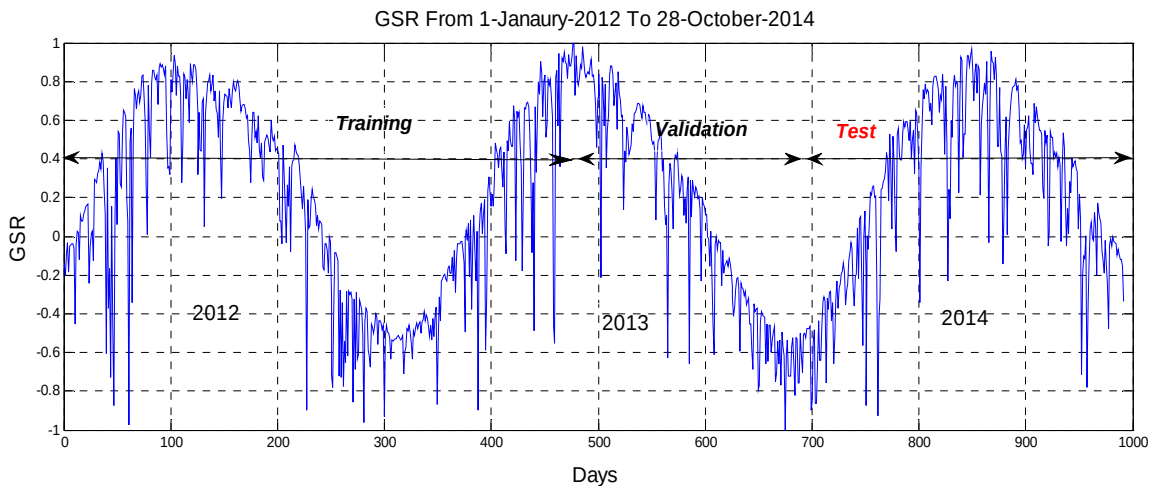

Figure 3*. Daily global solar radiation at Ghardaïa city*

Results and discussion

In order to obtain the optimal model for prediction of the global solar irradiance, firstly we normalize the data to [-1,1], Then divides the data into two sets named as learning and test sets (see Figure 3). The learning set is divided in its turn to two sets: (i) training set which is used to train the model and (ii) validation set which is used to validate the performance of the model. The Learning data is divided according to the following percentages: 75% for the training set and 25% for validation set. Finally, the test set (data of 2014) is used to verify the performance of the obtained model.

The RBF prediction algorithm is shown on Figure 4.

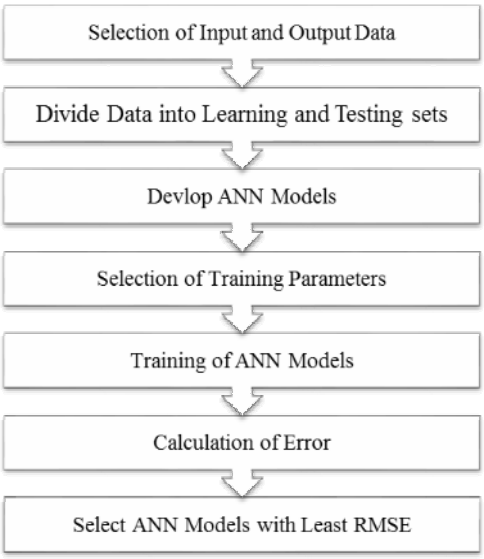

***Figure 4**. The RBF prediction algorithm*

To perform this work, four parameters were used as input to the RBF neural network which are: (1) the day of the year, (2) the maximum temperature, (3) the mean temperature (4) the sunshine duration in hour and one output which is the Daily Global Solar Radiation (DGSR). The list of the training parameters is shown in Table.1.

Table 1. The training parameters of the proposed RBF model

Nbr of Training and Validation Samples	700
Nbr of Testing Samples	271
Nbr of Inputs	4
Nbr of Outputs	1
Coarse Search of the width σ_j	[0.1:0.1:1]
Nbr of Neurons in hidden Layer	[1:25]

After several tests, the RBF model with three neurons in the hidden layer and an optimal width of the Gaussian equal to 2 can model the DGSR with high accuracy and the error is

about 0.014. Figure 5 shows the error of the trained process and it is minimal value.

The data from 2014 was used for testing the performance of the model. The estimated DGSR values were compared with the measured data as shown on Figure 6. The root mean square error (RMSE) between the estimated and the calculated values of the DGSR is found to be 0.014.

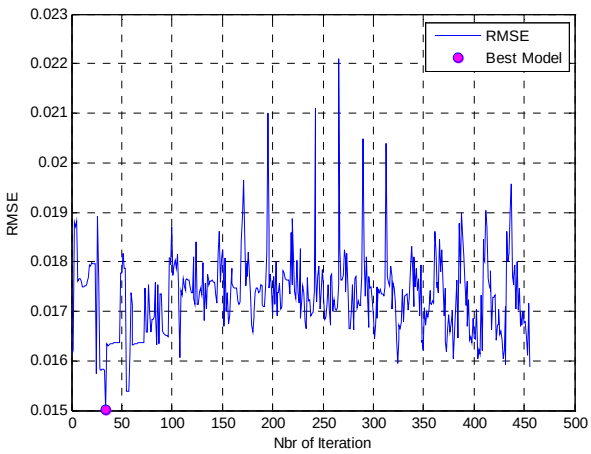

Figure 5. *The ERROR of the training process as a function of the number of iterations*

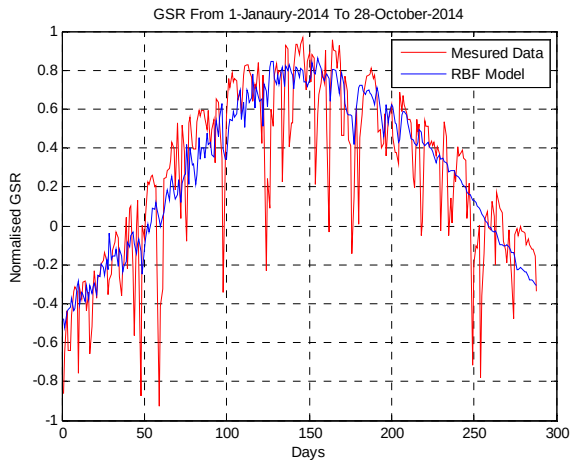

Figure 6. *The predicted DGSR (red) superposed to the measured DFSR (blue)*

From the obtained results, the selected model can predict the DGSR with good accuracy. The Root Mean Square Error (RMSE) between the measured and the predicted values is equal to 0.014. This small difference can be explained the fact by using perturbed and clear day.

According to Figure 6, the prediction of DGSR of the perturbed day is difficult to obtain by the model. This phenomenon can be seen by the presence of outliers. In order to estimate the DGSR of the perturbed day by the model, more meteorological data rather than the temperature are needed such as relative humidity, wind speed, pressure and turbidity parameters (Linke factor, angstrom coefficient and exponent coefficient) [16] that characterize the state of the atmosphere. The use of all these parameters together will certainly ameliorate the performance of the model.

In this paper a simple RBF neural network model have presented for the prediction the DGSR using both clear and perturbed days and the available meteorological data at the semi-arid area of Ghardaïa.

The obtained results shows that model predict the DGSR with good accuracy. The Root Mean Square Error (RMSE) between the measured and the predicted values is equal to

0.014.This small difference can be explained the fact by using perturbed and clear day together. In addition, the prediction of the DGSR of the perturbed day is difficult to obtain by the model due to the few parameters available. In order to estimate the DGSR of the perturbed day by the model, more meteorological data rather than the temperature are needed such as relative humidity, wind speed, pressure and turbidity parameters (Linked factor, angstrom coefficient and exponent coefficient). In future work will be used all these parameters as soon as we acquire the instruments that record them to model the GSR and to study the importance of each parameter in the model.

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References

1. Pandey C. K., Katiya A. K., *Solar Radiation: Models and Measurement Techniques*, Journal of Energy, 2013, 2013, Article ID 305207.
2. Gueymard C. A., *Critical analysis and performance assessment of clear sky solar irradiance models using theoretical and measured data*, Solar Energy, 1993, 51(2), p. 121-138.
3. Bird R. E., Hulstrom R. L., *A Simplified Clear Sky Model for Direct and Diffuse Insolation*, SERI/TR, 1981, p. 642-761.
4. Badescu V., *Verification of some very simple clear and cloudy sky models to evaluate global solar irradiance*, Solar Energy, 1997, 61, p. 251-264.
5. Younes S., Muneer T., *Clear-sky classification procedures and models using a world-wide data-base*, Applied Energy, 2007, 84(6), p. 623-645.
6. Gueymard C. A., Wilcox S. M., *Assessment of spatial and temporal variability in the US solar resource from radiometric measurements and predictions from models using ground-based or satellite data*, Solar Energy, 2011, 85(5), p. 1068-1084.
7. Benoudji N., Cools E., Meurens M., Verleysen M., *Chemometric calibration of infrared spectrometers: selection and validation of variables by non-linear models*, Chemometrics

and Intelligent LaboratorySystems, 2004, 70(1), p. 47-53.

8. Park J., Sandberg I., *Approximation and radial-basis-function networks*, Neural computation, 1993, 5(2), p. 305-316.
9. Howlett R. J., Jain L. C., *Physica -Verlag Heidelberg Printed in Germany*, 1st edition, 2001.
10. Zhao Z., Wu X., Lu C., Glotin H., Gao J., *Optimizing widths with PSO for center selection of Gaussian radial basis function networks*, Science China Information Sciences, 2014, 57(5), p.1-17.
11. Orr M., Introduction to Radial Basis Function Networks, *Technical Reports*, (1996). Online: http://www.anc.ed.ac.uk/mjo/papers/intro.ps
12. Ng W. W. Y., Yeung D. S., Firth M., Tsang E. C., Wang X. Z., *Feature selection using localized generalization error for supervised classification problems using RBFNN*, Pattern Recognition, 2008, 41(12), p. 3706-3719.
13. Gairaa K. , *Characterization and evaluation of solar radiation in Ghardaïa site University of Annaba*, Annaba, Algeria, 2012.
14. Gairaa K., Benkaciali S., *Analysis of solar radiation measurements at Ghardaïa area, South Algeria*, Energy Procedia, 2011, 6, p. 122-129.
15. Djafer D., Irbah A., *Estimation of atmospheric turbidity over Ghardaïa city*, Atmospheric Research, 2013, 128, p. 76-84.
16. Liu X., Mei X., Li Y., Wang Q., Jensen J. R., Zhang Y., Porter J. R., *Evaluation of temperature-based global solar radiation models in China*, Agricultural and Forest Meteorology, 2009, 149(9), p. 1433-1446.