Daily Time Series Estimation of Global Horizontal Solar Radiation from Artificial Neural Networks

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Keywords: Database, Solar Radiation, Neural Networks, Estimation.

Abstract: Obtaining a complete and efficient database is necessary for the sizing of photovoltaic systems. Despite the existence of the unit-level radiometric chain, the acquisition of data from different radiation components has problems, and thus gaps in the radiometric database. Thus, good sizing is possible only if the measurements are available continuously in space and time. The purpose of our work is to use the insolation basis for the estimation of the global daily radiation at the URER-MS research unit (Latitude 27.87 Longitude -0.272) using neuronal techniques. The efficiency of using neural networks as a global solar irradiation modeling tool.

1 INTRODUCTION

Energy assessment requires measurements and comprehensive data collection in the best conditions. Several studies have been conducted on the evaluation of solar radiation by models in order to generate artificial sequences of radiometric data.

Artificial intelligence is a term, in its broadest sense, the ability of a machine to perform functions similar to those that characterize human thought. Artificial Intelligence techniques are grouped into five branches: neural networks, fuzzy logic, genetic algorithms, expert system and hybrid systems (Mohandes, 1998), (Mubiru and Banda, 2008).

The aim of our work is to use neural models to estimate the global daily radiation at the Renewable Energy Research Unit station in the Saharan environment, in order to obtain a reliable database.

2 MODEL DESCRIPTION

2.1 Artificial Neural Network (ANN)

Is a system inspired by theories and observation of the neural structure and functioning of the human nervous system. ANN is a programmed computational nonlinear model which is widely used in the field of solar energy for design, modeling and optimization solar projects.

The Artificial Neural Network is a part of Artificial Intelligence (AI) which represents computational model that have the capability to learn from observational data. ANN model usually can be divided into three parts, named layers, the input layer which is responsible for receiving the input data, these data must be normalized before being used, the second layer is hidden layer that contains a nonlinear transfer function and the third layer produces the output (Mellit, 2005; Mellit et al 2009).

Learning an artificial neural network being reduced to an optimization problem: find the minimum of an error function, so we can build on this method of universal optimization gradient descent, which will be the gradient backpropagation rule for multilayer networks, studied after (Azadeh et al 2009).

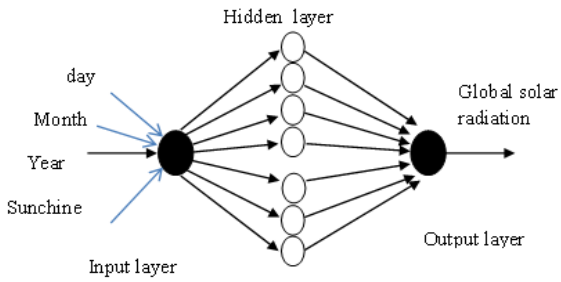

Figure 1: Neuronal network model.

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2.2 Learning Algorithm

Let p and t be the target input and output vectors used for network learning and a, is the network response. The objective is to minimize the cost function F (mean squared error between inputs and network responses) (Rahimikhoob, 2010) (CYRIL, 2011) defined as:

$$F = \frac{1}{Q}\sum_{k=1}^{Q}[t(k) - a(k)]^2 = \frac{1}{Q}\sum_{k=1}^{Q}[e(k)]^2 \qquad (1)$$

Q is the number of examples. This minimization is done according to a delta rule:

$$\Delta w = -\propto \frac{\partial f}{\partial w} \qquad (2)$$

The Least Mean Squared (LMS) algorithm estimates the kth iteration of the mean squared error e2 by calculating the derivative of the mean squared errors in relation to the network weight and bias, So:

$$\begin{cases} \dfrac{\partial e^2(k)}{\partial w_j} = 2e(k)\dfrac{\partial e(k)}{\partial w_j} & j = 1 \dots R \\ \dfrac{\partial e^2(k)}{\partial b} = 2e(k)\dfrac{\partial e(k)}{\partial b} & \end{cases} \qquad (3)$$

Or

$$\frac{\partial e(k)}{\partial w_j} = \frac{\partial[t(k)-a(k)]}{\partial w_j} = \frac{\partial[t(k)-w_p(k)+b]}{\partial w_j} = \frac{\partial t(k)}{\partial w_j} - \frac{\partial[\sum_{i=1}^{R} w_i p_i(k)+b]}{\partial w_j}$$

Simplified:

$$\begin{cases} \dfrac{\boldsymbol{\partial e(k)}}{\boldsymbol{\partial w_j}} = \boldsymbol{-p_j(k)} & j = 1 \dots R \\ \dfrac{\boldsymbol{\partial e(k)}}{b} = -1 & \end{cases} \qquad (4)$$

This means that the weights and biases of the network must change

$$\boldsymbol{2 \propto e(k)p(k)} \quad \boldsymbol{et} \quad \boldsymbol{2 \propto e(k)} \qquad (5)$$

Where α is the learning rate. For the case of several neurons, we can write:

$$\begin{cases} w(k+1) = w(k) + 2 \propto e(k)p^T(k) \\ b(k+1) = b(k) + 2 \propto e(k) \end{cases} \qquad (6)$$

Multi-layer perceptron (MLP), or layered networks, form the vast majority of networks. They are timeless (static and not dynamic networks).

3 DATABASE PRESENTATION

The data we used in our application are global insolation measurements of the Adrar site (Latitude 27.87 Longitude -0.272).

The geographical coordinates of Adrar are:
- Altitude: 278 m
- Latitude: 27 ° 52 North
- Longitude: 00 ° 17 West.

The database has been divided into two subsets, the first is used to perform the learning and the other set to do the test. The first contains four years from 2000 to 2003, and the second two-year set from June 2003 to June 2005 to test. As shown in the following figures:

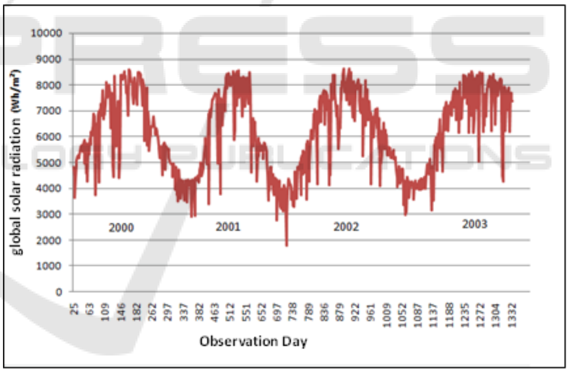

Figure 2: Daily data of global solar irradiation Horizontal 2000-2003, ADRAR area.

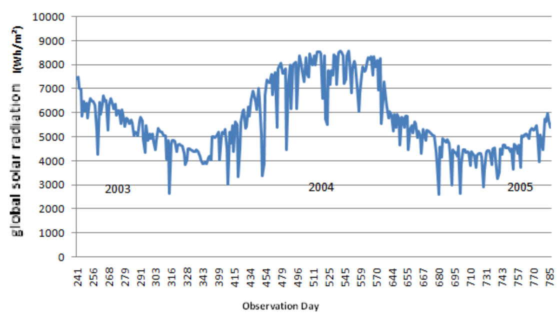

Figure 3: Daily data of global solar irradiation Horizontal 2003-2005, ADRAR. area.

4 MODEL USED

The model used to estimate global solar radiation on a horizontal plane is the modified form of the Angstrom equation. This regression equation relates the average fraction of daily radiation by the radiation in a clear sky and the average fraction of duration of sunshine (Angstrom, 924), (Prescott, 940), (Page, 1961), (Duffie and Beckman, 1991).

$$\frac{H}{H_0} = a + b\frac{S}{S_0} \quad (7)$$

H: daily global solar radiation.
H_0: extra-terrestrial solar radiation.
S: sunshine durations.
S_0: astronomical duration of the day.
a and b empirical coefficients.

$$H_0 = \frac{24}{\pi} I_{sc}\left[1 + 0.033\ cos\frac{360n}{365}\right] \left[cos\,\emptyset\, cos\,\delta\, sin\,\omega_s + \frac{\pi}{180}\omega_s\, sin\,\emptyset\, sin\,\delta\right] \quad (8)$$

Isc: The solar constant (= 1367 Wm2).
φ latitude of site, δ solar declination,
ω sunrise angle,

$$\delta = 23.45 \sin\frac{360(284+n)}{365} \quad (9)$$

$$\omega_s = \cos^{-1}(-\tan\emptyset\tan\delta) \quad (10)$$

The maximum sunshine duration S_0 can be calculated as follows:

$$S_0 = \frac{12}{15}\,\omega_s \quad (11)$$

5 SIMULATION RESULTS

For learning we used the measured data during the period 2000-2003.

The correlation coefficient for the forecast R = 0.81651.

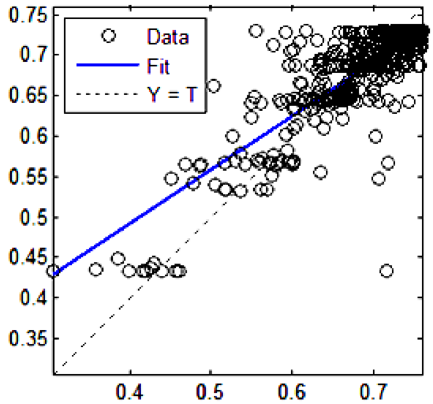

Figure 4: Learning phase (First step).

The correlation coefficient for the forecast R = 0.76259.

The mean squared error graph shows that the Lavenberg-Marquardt algorithm gives satisfactory results and the error is less than 0.7.

The correlation coefficient for the forecast R = 0.73512.

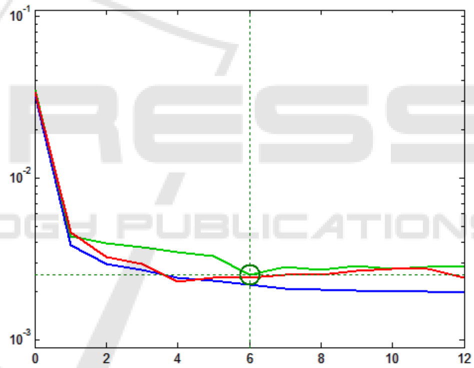

Figure 5: Quadratic Mean Error. Curves red green blue Learning, validation, test respectively.

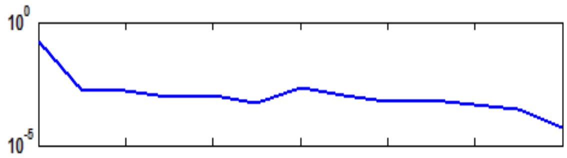

Figure 6: Gradient = 4.8735ᵉ-005 for 12 iteration.

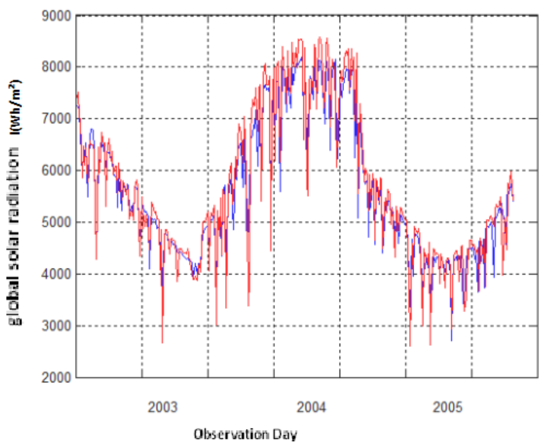

Figure 7: Global horizontal solar radiation estimated from a sunshine duration of the 2003-2005 period, in red the desired outputs, in blue the predicted outputs (simulated).

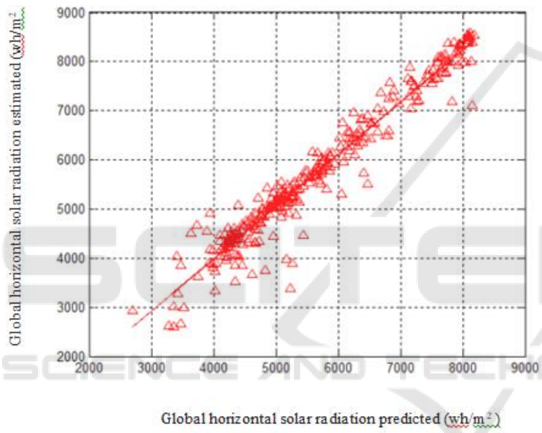

Figure 8: The correlation between the desired outputs and predicted outputs of global horizontal solar radiation.

The function represents an approximation of the correlation between predicted and desired outputs; according to the data used the coefficient is approximately 0.78 so make improvements on the model to get better results.

6 CONCLUSIONS

In our study we were interested in the neural network prediction method, in particular the multi-layer perceptron method.

For learning has used the Levenberg-Marquardt algorithm to calculate the approximation weights. For this network the inputs propagate to the output without return.

For the learning used the database 2000-2003, for the test used the data of 2003-2005, the simulation with these databases gives results of correlation coefficient equal 0.81651for learning; and 0.76259 for validation. According to the correlation graphs between the desired and predicted outputs on the one hand, and the mean square error on the other, we can use this neural model to estimate daily global solar irradiations.
Improving the model with the use of data from the Adrar URERMS research unit station remains a work of the future.

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