Estimation Global Solar Radiation and Modeling Photovoltaic Module Based on Artificial Neural Networks

Lalia Miloudi, Dalila Acheli
Faculty of hydrocarbons and chemistry, University M'hamed Bougara Boumerdès
Avenue de l'Indépendance 35000 Boumerdès, Algeria
* Email Correspondence author: lmiloudi@umbb.dz

ABSTRACT

Artificial neural networks are used for the performance estimation the global solar radiation and modeling curves (I-V) of PV module. The structures tested are MLP and RBF, The obtained coefficients of correlation R were very satisfactory. What shows the efficiency of the ANNs to predict the behavior of the photovoltaic systems.

NOMENCLATURE

I_o Extraterrestrial radiation on horizontal surface

I_T Global solar radiation on tilted surface

I_s Solar constant

Symbols Greeks

β Inclination photovoltaic module (dgr)

δ Declination (dgr)

ρ Ground albedo

ω Angle horaire (dgr)

Abbreviations

ANN artificial neurons networks
GSR Global solar radiation
MLP multi-layer perceptron
PV Photovoltaic
RBF Radial basis function

1-INTRODUCTION

The artificial intelligence finds more and more a broad application in the field of scientific research and engineering. The artificial neural networks (ANNs), the genetic algorithms, for the identification of the complex processes industrial and nonlinear system, for modeling and control, for the supervision and diagnoses and for prediction. In particular in the field of meteorology to consider the solar radiation in all the places of world. A brief review in its engineering applications follows below. In the first Zervas and al [1] carried out prediction model of total solar radiance distribution one horizontal surfaces based one neural-network and has been applied to the meteorological database. The model performed can predict the daily global solar radiation distribution as a function of weather conditions and each calendar day. The authors varied their investigations, indeed the extraction of power of PV systems depend on many parameters such as the weather conditions, the geographical situation, the materials of manufacture of photovoltaic module, the electronic devices of tracking solar trajectory. The stabilization of PV field's depends also on the management of the batteries of storage and the stored energy. From where the large variety and diversity of the investigations of the researchers to maximize the output of PV systems.
N.D. Kaushika [2]and all reported comparative study of estimates ANNs model with data base meteorology the results showed good compatibility. The global solar radiation on tilted planes has been investigated using isotropic and anisotropic sky conditions. The results seem to be favoring an isotropic model during the year-round cycle. AMellit and all [3]conducted an overview of the artificial intelligence techniques for sizing PV systems: stand-alone PVs, grid-connected PV systems, PV-wind hybrid systems etc. Published literature presented in this paper show the potential of artificial intelligence as a design tool for the optimal sizing of PV systems. Amit Kumar Yadav and al[4] presented the update status of research and applications of various methods for determining solar panel tilt angle using different optimization techniques. The study shows that for maximum energy gain, the optimum tilt angle for solar systems must be determined accurately for each location. The review will be useful for designers and researchers to select suitable methodology for determining optimal tilt angle for solar systems at any site. H. Sarimveis and al [5]performed the optimum tilt angle and orientation for solar photovoltaic arrays in order to maximize incident solar irradiance exposed on the arrays, the method is extended by introducing a

second objective, minimization of variance of the produced power. Previous studies such as that Murat Kacira and al [6] carried out the performance of a PV panel is affected by its orientation and its tilt angles. A mathematical model was used to estimate the total solar radiation on the tilted PV surface, and to determine optimum tilt by searching the values of angles for which the total radiation on the PV surface was maximum for the period studied. The study also investigated the effect of two-axis solar tracking on energy gain compared to a fixed PV panel. The authors analyzed and deducted that the application of the ANNs is a promising alternative to solve numerous problems mathematical of control and command.

2-Artificial Neural Networks

According the literature review, artificial neural network patterned after the human nervous system, consists of interconnected neurons or nodes that implement a simple nonlinear function of the inputs[7]. The neural network approach offers several advantages, compared with the command by internal or inverse model. This simplicity and speed greatly facilitates the development and maintenance of complex process systems. The networks operate very quickly and can be easily implemented in software. Artificial neural networks can approximate functions with arbitrarily high degrees of nonlinearity with a good choice of the numbers of nodes and layers[8]. Where an ensemble of input/output pairs is used to empirically derive statistical relationships between the ensembles. In the case of linear regression, second order statistical moments (covariance) are used to compute a linear fit that minimizes the sum-squared error between the fit and the data. Mathematical structure of a neural networks is chosen to afford several desirable properties, including scalability and differentiability. The mathematical techniques utilized, such as mean-square error minimization, but an experimental approach is often necessary. Heuristic methodology and techniques of network learning are needed, since often no theory is available for selection of the appropriate neural system for a specific application[9].

2.1 Feedforward or Multi-layer Perceptron (MLP) Neural Networks

The first artificial neural networks used is the multi-layer perceptron (MLP). This type of network is in the general family of the networks with forwards propagation, that in normal mode of use: information is propagated in a single direction, entries towards the exits without any feedback. The multi-layer perceptron is one of the neural networks more used to solve problems of approximation, of classification and prediction. MLP is known for its ability to approximate any function. Its are usually constitute of two or three layers neurons completely connected the mathematical model is expressed as follows[10]:

$$y = g\left(\sum_{i=1}^{m} v_j f\left(\sum_{i=1}^{n} w_{ij} x_i + b_i \right) + c \right) \qquad (1)$$

Where y is the output of the network, X=[$x_{1,..}x_i$] is the data inputs vector, (w_{ij},v_j) and (b_i,c) are the weights and the biases respective of every hidden layer. The functions g and f can be a simple threshold function, sigmoid, hyperbolic tangent or other.

2.2 Radial Basis Function Topology

The basic structure of the RBF is shown in Fig.1, it consists of three layers namely input, hidden and output layers. The activation function is Gaussian as presented in equation (3). Each node j has a center value c_j, where c_j is a vector whose dimension is equal to the number of input to the node. For each new input vector **X,** the Euclidean norm (2) of the difference between the input vector and the node center is calculated as follows [11]:

$$\upsilon_j(x) = \|c_j - x\| = \sqrt{\sum_{i=1}^{N} (x_i - c_{j,i})^2} \qquad (2)$$

The output of the network is given by:

$$\hat{y} = \sum_{i=1}^{L} w_m \, exp\left(-\frac{\upsilon^2}{\sigma^2} \right) \qquad (3)$$

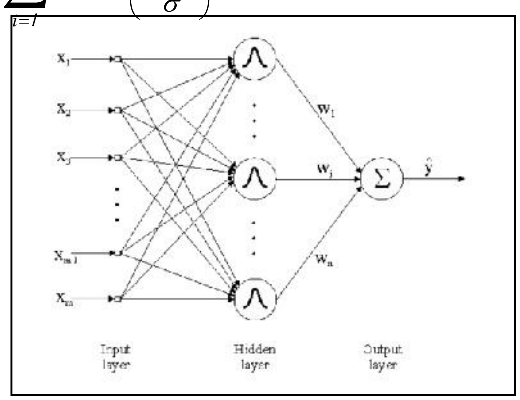


Figure1
Typical structure of an RBF neural network

2.3 Statistical coefficient performance

The most popular statistical parameters indicators to evaluate the performances of the models of the estimation the ANNs are the mean bias error MBE, the root mean square error RMSE, and the coefficient of determination R^2. Where $Y_{i,est}$ and $Y_{i,mes}$ are respectively, the ith estimated values and ith measured values of variables. Numerous works compared and presented their results by these coefficients [12] [13] [14]:

2.3.1. The mean bias error

$$MBE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{i,est} - Y_{i,mes}\right) \quad (4)$$

2.3.2. The root mean square error

$$RMSE = \left[\frac{1}{N}\sum_{i=1}^{N}\left(Y_{i,est} - Y_{i,mes}\right)^2\right]^{\frac{1}{2}}$$

(5)

2.3.3Coefficient of determination

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_{i,mes} - Y_{i,est})^2}{\sum_{i=1}^{N}(Y_{i,mes})^2} \quad (6)$$

3-Solar Radiation

3.1 Mathematical model of solar radiation

Many works was developed very detailed and very explanatory to determine the mathematical models of the solar irradiation by a clear sky or cloudy sky on a tilted level which one selected some[2],[4],[6].In general the total intensity of the solar irradiation on a tilted level is given by:

$$I_T = I_{bT} + I_{dT} + I_{rT} \quad (7)$$

The daily total sunning is obtained by integrating eq. (1) from the hours of sunrise to sunset:

$$H_T = 3600\left[\int_{h_{rT}}^{h_{sT}} I_{bT}\,dt + \int_{h_r}^{h_s}(I_{dT} + I_{rT})\,dt\right] \quad (8)$$

If an isotropic sky model is used it can be expressed by :

$$I_T = I_b R_b + I_d R_d + I R_r \quad (9)$$

Where:

$$R_b = \frac{\cos\theta}{\cos\theta_Z}\ ;\ R_d = \frac{(1-\cos\beta)}{2}\ ;\ R_r = \rho\left(\frac{1-\cos\beta}{2}\right) \text{ and}$$

$I_b = I_{bn}\cos\theta_z$.

For evaluation the various angles representing in the calculations several works were suggested such as [15].The solar incidence angle(θ) is the angle between the normal of the panel and the sun's rays, the general formula is:

$$\begin{aligned}\theta = \cos^{-1}\{&\sin(L)\sin(\delta)\cos(\beta) - \cos(L)\sin(\delta)\sin(\beta)\cos(a)\\ &+\cos(L)\cos(\delta)\cos(\omega)\cos(\beta) + \sin(L)\cos(\delta)\sin(\beta)\cos(a)\\ &+\cos(\delta)\sin(\omega)\sin(\beta)\sin(a)\}\end{aligned} \quad (10)$$

The azimuth solar angle (a) can be calculated by:

$$a = \sin^{-1}\left(\frac{\cos(\delta)\sin(\omega)}{\cos(h)}\right) \quad (11)$$

Murat Kacira and all detailed in[6]. For two axis tracking system θ=0 and the tilt angle of the two axis tracking panel was determined by:

$$\beta = 90 - h \quad (12)$$

3.2 Data Base

There are many sites which give the researchers the data in real time daily or monthly solar irradiation. As it is the case for our study [web sites], that allowed us to build the data base to develop our calculations and to exploit the various values of the components of the solar irradiation. The grip of measure the total solar irradiation is given to each 15 minutes for Boumerdès one of the cities of the south to the Mediterranean sea in Algeria localized at 36°46' 3 " N, 3°42' 10 " E. After arrangement of the data base is evaluated the average monthly variation of the total solar irradiation with clear sky in (W/m^2) for year 2012. Counting 696 values for the 12 months of the year, as represented in Fig.2 It should be noted that the solar irradiation is weak for December until April, then a considerable rise for May until November.

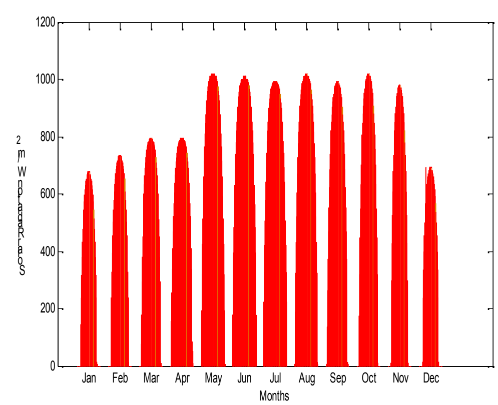


Figure 2
The monthly variation of solar radiation

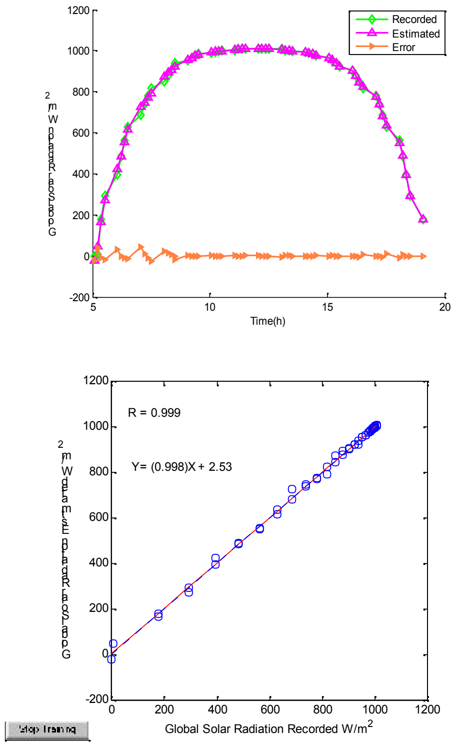
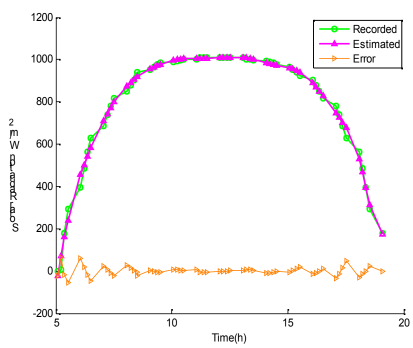


Figure 3
Comparison between recorded GSR in sunny period and estimated by MLP-model. Regression analysis between the network response and the corresponding targets



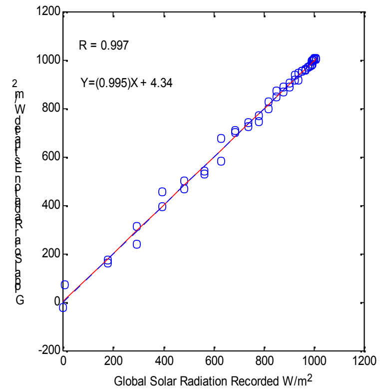


Figure 4
Comparison between recorded GSR in sunny period and estimated by RBF-model. Regression analysis between the network response and the corresponding targets

4-Photovoltaic Module Representing

Any PV module exposed to the solar rays becomes generating of current and thus being able to extract an electrical power. The figure 5 presents the equivalent diagram of a PV cell under illumination. It corresponds to a generator of current in parallel on a diode. The serial resistance depends on the impedance of material, the resistance of shunt corresponds to a resistance of the junction. For an ideal cell, serial resistance s tends towards zero, the resistance of shunt tends towards the infinite, q is the electron charge and K the Boltzmann constant [16]

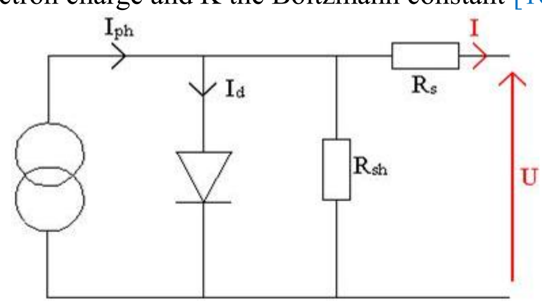


Figure 5
Equivalent circuit of the PV generator

The characteristic current-tension is put in the form:

$$I(U) = I_{ph} - I_d(U) \qquad (11)$$

The complete equation of the PV cell taking into account resistances is written:

$$I = I_{ph} - \beta(T)S\left[\exp\left(\frac{q(U + R_S I)}{KT}\right) - 1\right] - \frac{U + R_S I}{R_{sh}} \qquad (12)$$

The temperature is a considerable factor on the characteristic I = F (V) of a PV cell as the figure 3 indicates it. The increase in the temperature of a PV cell modifies its performances, Icc (the short circuit current) increase slightly and Vco (the tension of open circuit) decreases what generates a reduction in the optimum capacity. The figure represents the influence of the temperature on the characteristic voltage obtained by simulation the equation (12). The best operating temperature of the PV cells varies around 25° Celsius.

The location of the maximum power point always changes dynamically depending on solar radiance and temperature. As shows on Fig.6 I–V curves under increasing radiance at the constant temperature, and Fig.7 shows the I–V curves at the same radiance value but with a higher temperature are observable voltage shifts where the controller is required to track the new maximum power point.

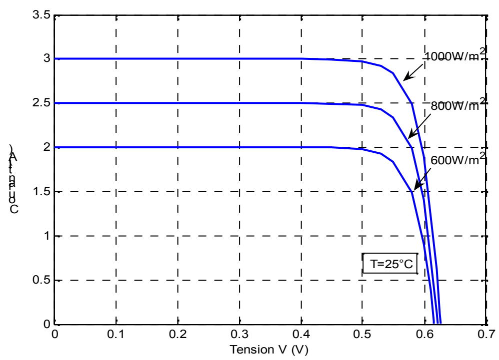


Figure 6

Calculated I–V at constant temperature (25C) varying solar radiation

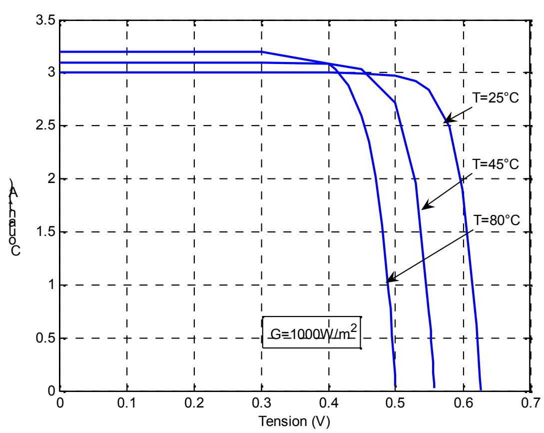


Figure 7

Calculated I–V at constant solar radiation (1000W/m^2) varying temperature

Curve I-V is observed and it is deduced of any PV module is a function of this form:

Curve(V-I) = f(T$_c$,G) (13)

According DaCosta [17] the characteristic I-V is written as:

$$I(G_c,T_c) = I_{sc}\left\{1 - exp\left[\frac{(v_{oc}-v)}{\tau}\right]\right\} \tag{14}$$

$$I_{cc2}(G_2,T_2) = I_{cc1}(G_1,T_1)\frac{G_2}{G_1} + \alpha(T_2 - T_1) \tag{15}$$

$$V_{co2}(G_2,T_2) = V_{co1}(G_1,T_1) + A\,ln\left(\frac{G_2}{G_1}\right) + \beta(T_2 - T_1) \tag{16}$$

The PV module under consideration for simulation is the PWX 500 polycrystalline marketed by international PHOTOWAT subsidiary of Matrix Solar Technology, whose parameters given are as follows: at standard test conditions V_{co}=21.6 V, I_{cc}=3.05 A, I_{max}= 2.80 A and V_{max}=17V.

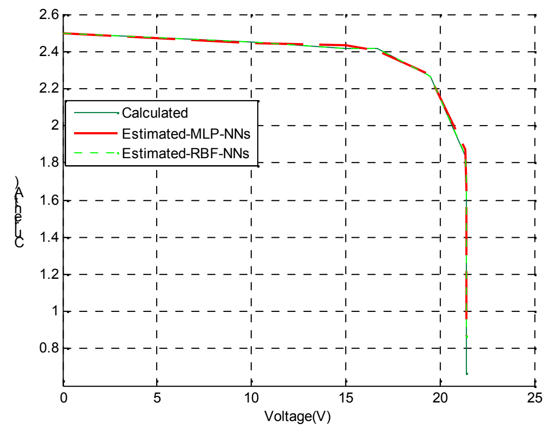


Figure 8

Different I–V curves used in train process and I–V curves generated by the MLP and the RBF –ANNs

Table 1

Statistical coefficients performance

Model	R^2	MSE (%)	Best linear fit
MLP	0.9726	0.99	Y= (0.9719)X + 0.0542
RBF	0.9738	0.95	Y= (0.9641)X + 0.0684

RESULTS AND DISCUSSION

The correlation coefficients obtained between the predicted and training data set is 0.997 and 0.998 for global solar radiation respectively, by MLP-ANNs and RBF-ANNs. The correlation coefficients for prediction curves I-V of PV module equal to 0.9726 and 0.9738 as show in Table1.

The advantages of the proposed approach include the simplicity in the implementation, when the characteristics of the system components are not known, as well as the potential to improve the capability of the ANNs to predict the performance of the PV solar system.

CONCLUSIONS

ANNs learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data, its operate like a "black box" model. An advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters.

KEYWORDS

Artificial neural network (ANNs), multiple-layer perceptron (MLP), radial basic function(RBF), global solar radiation, photovoltaic module, characteristic current-tension.

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Web sites

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http://eosweb.larc.nasa.gov/sse/(NASA)
http://portail.cder.dz/spip.php?rubrique47 (Réseau CHEMS)