Prediction of the Daily Direct Solar Radiation Using Nonlinear Autoregressive Exogenous (NARX) Network Model

Zina Boussaada, Ahmed Remaci, Octavian Curea, Haritza Camblong, Najiba Mrabet Bellaaj

PREDICTION OF THE DAILY DIRECT SOLAR RADIATION USING NONLINEAR AUTOREGRESSIVE EXOGENOUS (NARX) NETWORK MODEL

Zina Boussaada, Ahmed Remaci, Octavian Curea, Haritza Camblong and Najiba Mrabet Bellaaj

CORRESPONDENCE ADDRESSES: Zina Boussaada, Ph.D. Student, Ecole Nationale d'Ingénieurs de Tunis, Université de Tunis El Manar, Tunis, Tunisia, e-mail: zina.b.88@hotmail.fr, Ahmed Remaci, Ph.D. Student, ESTIA Recherche, Bidart, France, e-mail: a.remaci@estia.fr, Octavian Curea, Ph.D., Associate Professor, ESTIA Recherche, Bidart, France, e-mail: o.curea@estia.fr, Haritza Camblong, Ph.D., Professor, Faculty of Engineering, Gipuzkoa, University of the Basque Country, San Sebastián, Spain, e-mail: aritza.camblong@ehu.eus, Najiba Mrabet Bellaaj, Ph.D., Emeritus Professor, Institut Supérieur d'Informatique, Université de Tunis El Manar, Ariana, Tunisia, e-mail: najiba_bm@yahoo.fr,

Abstract

The work presented in this paper focuses on the estimation of the direct solar radiation on a horizontal surface using Nonlinear Autoregressive Exogenous (NARX) neural network model. This study is a part of a research project which consists in supplying a sailboat with electricity using only renewable sources. Therefore the results will be used to estimate the direct solar radiation on a tilted surface and the amount of available power from Photovoltaic in the sailboat.

In this paper, the NARX neural network predicts the daily direct solar radiation using two variables: the determinist component of solar radiation and its statistical component. Due the mobility of the sailboat and the difference between the days of the year, the issue of this research is to find the best neural network to be used for the daily direct solar radiation prediction. Using several simulations, the best performance was obtained when the training phase was done periodically.

Keywords: Estimation, mathematic model, statistical model, Artificial Neural Network, cloud cover

1 INTRODUCTION

Because of environmental reasons and also the lack of fossil fuel sources in near future, using renewable energy sources e.g., Photovoltaic (PV) and wind have attracted significant attention. Amaiur Alfaro, Basque skipper has a big challenge for "Vendée Globe 2020". He would like to be the first skipper completing the race using only renewable sources as: wind turbines, PV panels, hydro generator and energy recovery system. This challenge will require the design of an advanced energy management system (EMS) which will have to consider, among other, the estimation of the available electrical energy, in order to determine when and how much energy to store. Furthermore, this EMS will require the forecasting of some variables, for instance that of the direct solar radiation.

In fact, the necessity of solar radiation prediction is related to several factors. On the one hand the solar radiation has an important influence on PV power generation; on the other hand it is greatly influenced by the mobility of the sailboat and the difference between the days of the year.

Prediction of solar radiation in particular and time series in general, has attracted important interest as a main topic of recent researches. There are several methods of prediction; they depend on the available inputs, the way of their classification and the horizon of the prediction. Among these methods, some are based on linear models such as Auto-Regressive (AR) and Auto-Regressive Moving Average (ARMA) [1]. However, because of the nonlinear behavior of the solar radiation, researchers proposed several nonlinear models such as wavelet-based methods, fuzzy models, Adaptive Neural Fuzzy Inference systems (ANFIS) and Artificial Neural Networks (ANN) [2], [3], [4]. There are also some researches which combined linear and nonlinear methods such as [5] where, authors predicted one minute ahead solar radiation using a hybrid method based on wavelet, ARMA and NARX model. In fact [5] used only the historical solar radiation as input of the predictor. So the wavelet transformation was used to decompose the historical data into the better-behaved series for prediction. Authors applied ARMA model as a linear predictor and they used NARX as a nonlinear pattern recognition tool to compensate the error of wavelet-ARMA prediction.

[2], [3] and [4] forecasted daily global solar radiation using artificial neural network. In [2], authors used correlation criteria to determine endogenous and exogenous inputs to take into account. Four endogenous time lags were taken for the clear sky modal of solar radiation. From several meteorological parameters only three were selected as exogenous inputs: relative humidity, sunshine duration and nebulosity. Based on the nature of the obtained data, authors of [3] divided data differently: predicted data and statistical data. So they combined several statistical data as: calculated cloud ratio, maximum hourly variation of the solar radiation, absolute daily variation of the solar radiation between the day (t) and the day (t-1), etc. and numerical weather prediction data which contains the one day ahead forecast of the cumulative irradiation each 3 hours. As a result a hybrid model was formed as neural network inputs. In [4], authors didn't classify inputs data, but they trained four neural networks with four combinations of input features in order to consider the effect of different meteorological parameters on prediction results. They concluded that the best performance was obtained when using the following inputs: the day of the year, the mean daily extraterrestrial solar radiation, the maximum possible sunshine hours, the mean daily maximum air temperature, the mean daily relative humidity and the wind speed.

The aim of our research is to find the best neural network for the daily direct solar radiation prediction on a horizontal surface. The developed NARX network model must take into account the change of location of the sailboat and the difference between the days of the year.

In our model it was assumed that the direct solar radiation model is composed of a determinist component which is calculated basing on the distance between the center of sun and the point of measurement; and a statistical component which depends on several meteorological parameters where, the most important is the cloud cover. Therefore the used NARX model has two inputs: a deterministic input which is the clear sky direct solar radiation and a statistical input which is the cloud cover. Using different evaluation criteria, results show that the training process must be done periodically.

The rest of the paper was organized as follows. In section 2, the clear sky direct solar radiation was defined. In section 3, the methodology of prediction was presented, by describing the NARX network model. Then, section 4 presented the used dataset and the evaluation criteria. Section 5 focused on the simulation results and discussions. Finally, section 6 concluded the paper.

2 CLEAR SKY DIRECT SOLAR RADIATION MODEL

This section focuses on the determinist component of direct solar radiation. In fact, the "Clear sky" model calculates the received solar radiation when the sky is without cloud cover [6]. Several studies modelled the solar irradiation using clear sky model, including Kasten model [7], Molineaux model [8], or also SOLIS model [9]. In this study the used model to describe the deterministic component of direct solar radiation is SOLIS model because it gives excellent results when it is compared with measures realized in Europe [10]. The proposed direct solar radiation formula is as follows:

$$G = G_0 \times \exp\left(-\frac{\tau}{\sin^b(\alpha)}\right) \quad \textbf{(1)}$$

where, b is a constant adjustment parameter, τ is the optical depth, G_0 is the solar radiation at the top of the Earth Atmosphere and α is the sun height.

G_0 is calculated as follows:

$$G_0 = \left(\frac{R_m}{R(J)}\right)^2 \times E_{sc} \times \sin(\alpha) \quad \textbf{(2)}$$

where, R_m is the mean Earth-Sun distance (Astronomical unit) and $R(J)$ is the mean distance for the J'th day. The expression $\left(\frac{R_m}{R(J)}\right)^2$ is the Earth-Sun distance correction factor: K_D, and it is calculated as:

$$\begin{aligned} K_D &= 1.000138 + 0.03341 \cdot \cos\left(\frac{2 \cdot \pi \cdot N}{365.2422} - 0.051\right) \\ &+ 0.000699 \cdot \sin\left(\frac{4 \cdot \pi \cdot N}{365.2422} + 1.474\right) \\ &+ 0.000062 \cdot \sin\left(\frac{12.37 \cdot 2 \cdot \pi \cdot N}{365.2422} + 2.2\right) \end{aligned} \quad \textbf{(3)}$$

α is defined as follows:

$$\sin(\alpha) = \sin(\delta)\cdot\sin(\varphi) + \cos(\delta)\cdot\cos(\varphi)\cdot\cos(\varpi) \quad \textbf{(4)}$$

δ is the sun's declination, ϖ is the hour angle and (φ) is the latitude in degree.

$$\delta = 0.38 + 23.26\cdot\sin\left(\frac{2\cdot\pi\cdot N}{365.24} - 1.395\right) + 0.375\cdot\sin\left(\frac{4\cdot\pi\cdot N}{365.24} - 1.47\right) \quad \textbf{(5)}$$

where, *N* is the rank of the day, beginning on 1st January 2013 (for example, *N*=32 for the 1st February 2013) .

$$\varpi = 15\times(TS - 12) \quad \textbf{(6)}$$

TS is the solar time, it is defined as:

$$TS = TCF - cc + \frac{E}{60} \pm \frac{Lon}{15} \quad \textbf{(7)}$$

TCF is the civil time, *cc* is the time difference comparing to GMT (in hour), *E* is the equation of time and *Lon* is the longitude in degree.

The term *(Lon/15)* is taken negative in the East of Greenwich and positive in the west.

The formula of *E* is:

$$E = (C + R)\times 4 \quad \textbf{(8)}$$

C is called the equation of the center and *R* is the influence of obliquity.

$$C = \frac{180}{\pi}\left[\left(2\cdot e - \frac{1}{4}\cdot e^3\right)\cdot\sin(Ma) + \frac{5}{4}\cdot e^2\cdot\sin(2\cdot Ma) + \frac{13}{12}\cdot e^3\cdot\sin(3\cdot Ma)\right] \quad \textbf{(9)}$$

$$Ma = 357.5291 + 0.98560028\times N \quad \textbf{(10)}$$

e = 0.1671, is the eccentricity of the ellipse.

$$R = \frac{180}{\pi}\left(-y^2\cdot\sin(2\cdot L) + \frac{y^4}{2}\cdot\sin(4\cdot L) - \frac{y^6}{3}\cdot\sin(6\cdot L)\right) \quad \textbf{(11)}$$

where, $y = \tan\left(\frac{\varepsilon}{2}\right)$, ε is the tilt of the Earth axis, ε=23.4372108769, and *L* is the true longitude, or ecliptic longitude of the Sun in degree. Its formula is:

$$L = 280.4665 + C + 0.98564736\times N \quad \textbf{(12)}$$

3 NARX MODEL

Considering that, on the one hand, the solar radiation is a time series, and that, on the other hand, dynamic neural networks are good predictors of time series [2], [3], [4], our research study used NARX neural network model as technique of prediction. The non linear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic neural network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time-series modeling.

In order to obtain the full performances of the NARX neural network for nonlinear time series prediction, it is interesting to use its memory ability using the past values of predicted or true time series.

As can be seen in Figure 1, there are two different architectures of NARX model, series-parallel architecture and parallel architecture given by the equations (13) and (14) respectively.

$$\hat{y}(t+1) = f\begin{pmatrix} y(t), y(t-1),\dots, y(t-n_y), x(t+1), \\ x(t), x(t-1),\dots, x(t-n_x) \end{pmatrix} \quad \textbf{(13)}$$

$$\hat{y}(t+1) = f\begin{pmatrix} \hat{y}(t), \hat{y}(t-1),\dots, \hat{y}(t-n_y), x(t+1), \\ x(t), x(t-1),\dots, x(t-n_x) \end{pmatrix} \quad \textbf{(14)}$$

where, *f(.)* is the mapping function of the neural network, $\hat{y}$ *(t+1)* is the output of the NARX at the time t for the time t+1, $\hat{y}$ *(t),* $\hat{y}$ *(t-1),…,* $\hat{y}$ *(t-*n_y*)* are the past outputs of the NARX. *y (t), y (t-1),…, y (t-*n_y*)* are the true past values of the time series. *x(t+1), x(t),…, x(t-*n_x*)* are the inputs of the NARX, n_x is the number of input delays and n_y is the number of output delays.

In the series-parallel architecture, the future value of the time series *y (t+1)* is predicted from the present and past values of *x(t)* and the true past values of the time series *y(t)*. However in the parallel architecture the prediction is performed from the present and past values of *x(t)* and the past predicted values of the time series $\hat{y}$ *(t).* Our research study considers the parallel architecture of NARX model.

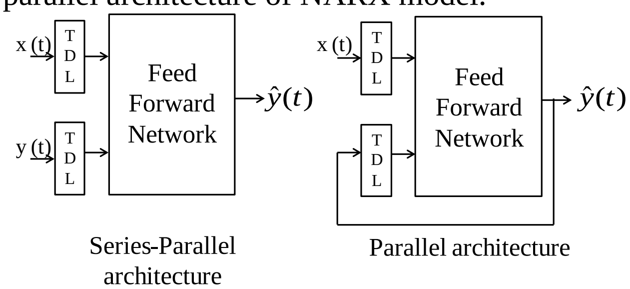

Figure 1. Architectures of NARX network

The mapping function *f (.)* is initially unknown and it is approximated during the training process of the prediction. In the NARX neural network model the internal architecture that performs this approximation is the Multi-Layer Perceptron (MLP). The MLP provides a powerful structure enable to learn any type of continuous nonlinear mapping. As seen in Figure 2, a typical MLP consists of an input, a hidden and an output layer. Other elements consist of neurons, transfer functions and weights. The direction of the information flow throughout the layers is from input to output layer. In each layer, each neuron multiplies the input vector x_j given by the previous layer by the weights vector w_{ij} to give the scalar product $x_j w_{ij}$. A transfer function f is then performed to obtain the output$y_i = \sum_{j=1}^{n} x_j \times w_{ij}$, where, i is the neuron index in the layer, and j is the input index in the neural network. The process of training consists in modifying the connection weights in an orderly way using a suitable algorithm. During the training process, an input and its desired output are introduced in the network and the weights are adjusted so that the neural network tries to produce the desired output. Another issue involved in the training phase is to find a globally optimal solution avoiding local minima. The principle is to initiate a number of random starting weights and to consider the one with the best value.

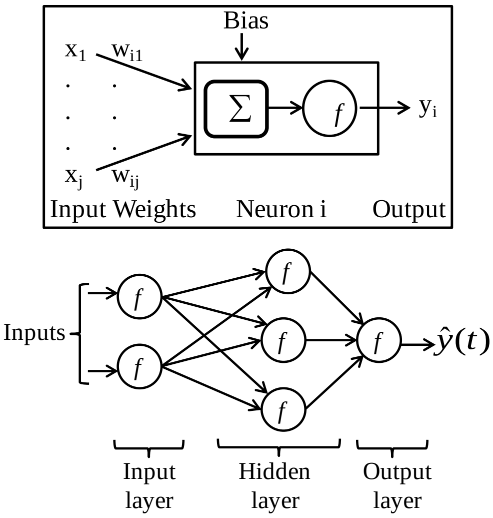

Figure 2. A MLP network (up) and details of a neuron (down)

4 DATA DESCRIPTION AND EVALUATION CRITERIA

4.1 Context and presentation of Data

The used dataset in this work consisted of:

- calculated clear sky direct solar radiation as described in section 2.
- the Cloud cover variable used as input of the neural network. It was downloaded from the website www.zygrib.org. It is the forecast of the cloud cover for a chosen number of days ahead in a defined surface. Data are spread with a step of 0.25° in Latitude and Longitude, and with a step of 3 hours time interval. Thus, to obtain the cloud cover in the location of ESTIA every 5 minutes, a 2-D interpolation according to the latitude and the longitude and a 1-D interpolation according to the time were performed.
- the global solar radiation on horizontal surface. This parameter used as target of the neural network came from the weather station of ESTIA. It is measured each 5 minutes.

4.2 Evaluation criteria

In order to evaluate simulation results, two error criteria were used: Mean Square Error MSE and Daily Energy Error (in W) EE.

$$MSE = \frac{\sum_1^N (y_i - \hat{y}_i)^2}{N} \quad \textbf{(15)}$$

$$EE = \frac{\sum_1^N (y_i - \hat{y}_i)}{N} \quad \textbf{(15)}$$

where, N is the number of pattern pairs, y_i and $\hat{y}_i$ are the measured and predicted solar radiation of the i th pattern pair respectively.

5 RESULTS AND DISCUSSIONS

Several tests have been considered to select the database structure and the neural network configuration. It should be noted that before starting simulations the dataset was divided into three parts: training, testing and validation sets. The training phase uses the training set to compute the weights and bias of the neural network and the test set to test it. After finishing this phase the validation set is used to simulate the model and evaluate its performance. All simulations are performed using normalized dataset in order to adjust it and not to saturate the neurons.

5.1 Choice of the dataset structure

The first simulations of this research study were made using a set of test and training containing several days of the year in order to represent it. The prediction was performed for different days of the year. The MSE and the EE were in the order of 0.02 and 160 respectively. Thus, to obtain best performance the idea has been to repeat the training process one time per day to forecast solar radiation for one coming day.

Table 1. Choice of the test and training size of the database

Database size	MSE	EE (W)
5 days	0.011	60.228825
10 days	0.00695	41.19645
15 days	0.009625	50.2089

As it can be seen in Table 1, the best result was obtained using a test and training set of 10 days. In this case, the MSE and the EE are 0.00695 and 41.19645 respectively.

The global solar radiation of the weather station was measured by a step of 5 minutes time interval. Therefore the interpolated cloud cover and the calculated direct solar radiation had the same time step interval. However the configured predictor is not meant to follow the rapid fluctuations of the measured solar radiation. Consequently, it is interesting to consider the average of this parameter as input of the neural network.

Moving averages of 10 and 30 minutes over intervals of one hour were performed. Prediction results were stored into Table 2.

Table 2. Choice of the time average of the database

Time average	MSE	EE (W)
10 minutes	0.00732	44.4344
30 minutes	0.00695	41.19645

From Table 2, it may be concluded that there was no a big difference between the two simulations results. Therefore for reasons of computing time optimization, the chosen interval average was 30 minutes.

5.2 Choice of the Neural Network structure

The second important step in the determination of the solar radiation predictor was to find the adequate neural network structure. Several simulations were performed in order to choose the different parameters of the NARX model. Due to the lack of the space, this part could not contain all results. Therefore some choices were presented in the Table 3, and only two parameters were presented: the choice of the neuron number in each layer and the use of weights in the different trainings.

Table 3. Parameters of the NARX model structure

Property	Choice
Number of hidden layers	1
Transfer functions in each layer	Input layer: Sigmoid Hidden layer: Sigmoid Output layer : Hyperbolic tangent
Normalization Interval of dataset	[0.05 ; 0.95]
Delay vectors	Input data: [0 1] Target: [1 2]
Training parameters	Error: MSE Learning algorithm: Levenberg-Marquardt

Table 4 presents the best results found when the number of neurons was varied in each layer of the NAX network.

Table 4. Choice of the neurons number in the different layers

Number of neurons	MSE	EE (W)
10x10x1	0.00724	59.5724
15x15x1	0.00410	30.4164
16x16x1	0.01438	73.4646
20x20x1	0.00768	45.0513
22x22x1	0.00695	41.1964

Table 4 shows that the best structure of neural network layers was obtained using 15 neurons in the input layer, 15 neurons in the hidden layer and 1 neuron in the output layer. The MSE and the EE were 0.00410 and 30.4164 W respectively.

These results were obtained using the same initial weights for all periodic trainings. In fact, the initial weights of the first training which predicted the first day were saved and used for other trainings. However, as shown in table 5, best performances were achieved when each periodic training started with weights initiated randomly by the neural network.

Table 5. Choice of registration of weights for periodic trainings

Registration of weights	MSE	EE (W)
Yes	0.00410	30.4164
No	0.00279	24.0584

The best obtained error performance was 0.00279 for MSE and 24.0584 W for EE. The Figure 3 shows an example of predicted day using the obtained NARX model.

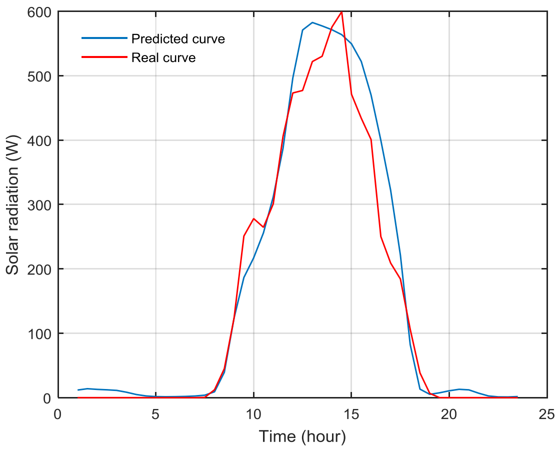

Figure 3. Predicted and 30 minutes average curves of direct solar radiation

6 CONCLUSION

This paper proposed a NARX neural network model for direct solar radiation prediction on a horizontal surface. Several simulations varying different criteria were performed and evaluated using MSE and EE errors. First, this study focused on the choice of the dataset structure including the size and the time average of the database used for the training and testing phase. The second issue of the research was the determination of the neural network structure. Different criteria were varied, in particular the neurons number of each network layer and the way to choose the initial weights. The best results (0.00279 for MSE and 24.0584 W for EE) were obtained for: a dataset of 10 days with 30 minutes time interval, and a NARX model consisting of 15 neurons on the input and hidden layers, and random initialization of weights.

REFERENCES

[1] W. Zhang, Zhao, Z. Bao, T. Han and L. Kong, “Short Term Wind Speed Forecasting for Wind Farms Using an Improved Auto regression Method,” presented at the International Conference of Information Technology, Computer Engineering and Management Sciences, 24-25 Sept. 2011.

[2] C. Voyant, M. Muselli, C. Paoli, and M. Nivet, “Optimization of an artificial neural network dedicated to the multivariate forecasting of daily global radiation,” *Energy*, vol. 36, pp. 348-359, 2011.

[3] S. Mohanty, and P.K. Patra, “Prediction of global solar radiation using nonlinear autoregressive network win exogenous inputs (narx),” presented at the 39 th National System Conference, 14-16 Dec. 2015.

[4] O. Assas, H. Bouzgou, S. Fetah, M. Salmi, and A. Boursas, “Use of the artificial neural network and meteorological data for predicting daily global solar radiation in Djelfa, Algeria,” presented at the International Conference on Composite Materials & Renewable Energy Applications (ICCMREA), Sousse, Tunisia, 22-24 Jan. 2014.

[5] H. Nazaripouya, B. Wang, Y. Wang, P. Chu, H.R. Pota, and R. Gadh, “Univariate time series prediction of solar power using a hybrid wavelet-ARMA-NARX Prediction Method,”presented at the IEEE/PES Transmission and Distribution Conference and Exposition (T&D), Dallas, TX, USA, 3-5 May 2016.

[6] M. J. Reno, C. W. Hansen, and J. S. Stein “Global Horizontal Irradiance Clear Sky Models: Implementation and Analysis,” *Sandia Report Sand* 2012-2389, Unlimited Release Printed, March 2012.

[7] F. Kasten “The linke turbidity factor based on improved values of the integral Rayleigh optical thickness,” *Solar Energy*, num. 56(3), pp. 239-244, 1996.

[8] B. Molineaux, P. Ineichen, and O. N. Neill, “Equivalence of pyrheliometric and monochromatic aerosol optical depths at a single key wavelength,” *Applied Optics*, num. 37(30), pp. 7008-7018, 1998.

[9] R. W. Mueller, K. F. Dagestad, P. Ineichen, M. Schroedter-Homscheidt, S. Cros, C. Reise, L. Wald and D. Heinemann “Rethinking satellite-based solar irradiance modelling: The *SOLIS* clear-sky module,” *Remote Sensing of Environment*, num. 91(2), pp. 160-174, 2004.

[10] P. Ineichen “Comparison of eight clear sky broadband models against 16 independent data banks,” *Solar Energy*, num. 80(4), pp. 468-478, 2006.