MLP Back Propagation Artificial Neural Network for Solar Resource Forecasting in Equatorial Areas

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Abstract. Renewable energy (RE) resources such as solar are increasingly being used worldwide. Solar resource shows high availability, but presents an intermittent characteristic, causing oscillations in the electricity production. Intermittence is one of the main barriers for the use of solar plants in a system that needs to balance demand and electricity production. Aiming to contribute to a larger use of the solar resource in the world energy matrix, we propose a solar irradiance prediction methodology, developed from data collected in Fortaleza-CE (latitude: $-03^{\circ} 43'$, longitude: $-38^{\circ} 32'$). Predictions were developed using Multilayer Perceptron (MLP) Back propagation Artificial Neural Network (ANN) with the advance of 1 hour. In the best ANN performance, 41.9% of the predictions obtained up to 5% of error, 58.7% obtained errors lower than 10% and 68.6% obtained errors lower than 15%. MAPE (mean absolute percentage error) of 6.11% was found, which can be considered good, since errors found in previous works reached 20%.

Key words

Solar Predictability, Solar Energy, Artificial Neural Networks.

1. Introduction

There is a growing search for new sources of energy worldwide in order to complement the electricity supply. Additionally, according to United Nations projections [1], in 2050 the world population will increase approximately 29%, going from the current 7.55 billion inhabitants to 9.77 billion inhabitants [1]-[2], making it clear that energy demand will continue to expand. Therefore, better techniques are needed to produce, store and distribute

energy, taking into account technical, financial and environmental factors.

Considering environmental impacts, different ways of introducing RE in the world energy matrix are being developed, since countries such as Brazil, China, England, Canada, Germany, among others, have signed agreements to reduce global temperature increase by limiting at 1.5°C above pre-industrial levels [1].

RE resources, such as solar, are increasingly participating in the energy matrix of several countries. Worldwide photovoltaic (PV) power has grown by approximately 50%, from 228 GW in 2015 to 303 GW in 2016. This increase is due to policies that encourage PV panels cost reduction and technology improvement [3].

In Brazil, in 2014, the first auction to contract energy from centralized PV plants took place. In 2017, 891 MW of PV power is expected to be operational in the Northeast, Midwest and Southeast regions of the country. The 10-year Energy Expansion Plan (PDE 2024) forecasts that the installed capacity for solar generation will reach 8.3 GW in 2024, with 7 GW of centralized generation and 1.3 GW of distributed generation, representing 3.3% of the energy matrix [4].

Unlike the electricity generation from thermal sources, which can be increased or decreased according to consumption, solar generation presents intermittent characteristic. Intermittence and non-control of the generation can cause a lack or excess of electrical energy in the system [5].

Intermittence is one of the main barriers to the dissemination of PV parks in the electricity supply system. PV power is determined by local meteorological conditions and cannot be adjusted properly. As a

consequence, additional costs arise to level unforeseen fluctuations in electricity production. Hence, energy storage and/or sources integration are necessary to supply the demand. Consumption and RE based electricity generation forecasting are also employed [6]. In Germany, those responsible for the electricity generators have to report the planned production one day in advance. The information must be fulfilled, but in case of variation, other generation units are used to balance the system. From the perspective of costs, from March to October 2010, due to errors of solar and wind forecasting in the German market, the electricity production from these sources was 2 GWh lower than expected, resulting in an additional cost of €2.20 per MWh from wind and solar sources [7].

Several techniques are being used for the predictability of solar resource. Among them, ANN is widely used tool for forecasting time series. ANN is a processor in parallel composed of simple processing compartments, with natural propensity to store experimental knowledge and makes it accessible for use [8]. Motivated by the increasing use of PV plants in Brazil, we propose the development of techniques for the use of ANN to solar resource prediction in order to contribute to the reduction of predictability errors. Solar irradiance and ambient temperature data are collected in Fortaleza-CE (latitude: $-03^{\circ} 43'$, longitude: $-38^{\circ} 32'$, elevation: 21m (69 ft)).

2. Artificial Neural Network (ANN)

ANN is a circuit composed of a large amount of simple processing units inspired by the animal neural system. ANN using MLP model is a tool used successfully in networks that have a non - linearly separable pattern. Reason for good results is the network ability to follow the standards of each class or to predict data according to a time series pattern. MLP consists of a neural network organized in layers. Input layer refers to the data, output layer and hidden layers (hidden and intermediate) are composed of neurons capable of processing data, resulting in outputs assigned through inputs excitations and respective weights. Figure 1 shows a multi-layered network having three neurons in the input layer, two neurons in the hidden layer and one in the output layer.

Fig. 1. MLP network model, adapted from [9].

x are the input data, w the hidden layer neurons input weights, m the output layer neuron input weights and y is the network output. The algorithm is a generalization of

the Widrow & Hoff delta rule for Adaline training, called backpropagation because error propagation occurs in the reverse direction of the input signal. Widrow & Hoff Delta Rule generalization is used to adjust the weights and bias of the MLP network in order to minimize the error between the network output and the desired output. This procedure is performed for several epochs, in order to enable ANN to have adequate responses to the training data set, called network training. The weights settings, w, are also set from the output to the input.

Among the activation functions of the neurons, the activation function used for both the hidden neurons layer and the output layer was the logistic sigmoid, which generates values from 0 to 1. Equations (1) and (2) represent the function and its derivative, respectively.

$$y_i(t) = \frac{1}{1 + \exp[-u_i(t)]} \quad (1)$$

$$y'_i(t) = u_i(t)[1 - u_i(t)] \quad (2)$$

The weights updating of both the hidden and the output layer is given by equations (3) and (4).

$$w(t+1) = w(t) + \alpha \cdot \delta \cdot y_i(t) \quad (3)$$

$$b(t+1) = b(t) - \alpha \cdot \delta \quad (4)$$

Several lines of research for solar resource prediction have been observed with the use of ANN due to the low error rate (up to 20%) [10], [11], [12]. Specific types of ANN are used, such as:

- Multilayer Perceptron (MLP) networks that can solve nonlinear problems and class standards;
- Radial Basic Function Networks (RBF) that can be used in curve fitting (approximation) problems and are capable of learning complex patterns and solve nonlinearly separable problems;
- Support Vector Machine (SVM), which serves for separating patterns in a hyperplane [13]-[8].

Table I shows the development of solar resource forecasts using ANN worldwide.

Table I – ANN using MLP, RBF, SMV worldwide.

AUTHOR	PARAMETER	NETWORK	COUNTRY
Moustris et al., 2016 [13]	Hourly solar Irradiance	MLP	Greece
Valiki et al., 2015 [14]	Hourly solar Irradiance	MLP	Iran
Kumar and Kuar, 2015 [15]	Hourly solar Irradiance	MLP	India
Zhang et al., 2014 [16]	Solar Irradiance every 5 minutes	SVM	Canada
Huang et al., 2015 [17]	Hourly solar Irradiance	RBF	Taiwan
Yan et al., 2014 [18]	Hourly solar Irradiance	RBF	China
Pedro and Coimbra, 2012 [19]	Hourly solar Irradiance	MLP	USA
Neelamegame and Amirtham, 2016 [20]	Irradiance Solar Hour	MLP	India
Grimaccia et al., 2017 [21]	Irradiance Solar Hour	MLP	Italy

3. Methodology

To study the solar resource intermittence, solar irradiance and temperature data collected in Fortaleza were considered in the present analysis. Irradiance Data collection was performed using a pyranometer (NRG Systems, LI-200SZ). Temperature data were obtained from a temperature sensor (NRG Systems, # 110S), with an accuracy of $\pm 1.11^{\circ}\text{C}$ and operating between -40°C and 52.5°C .

Data were collected and stored by means of spreadsheets at intervals of 10 min, obtained by means of arithmetic means from data processed every 2 s. Solar irradiance and temperature data were collected from May 2003 to April 2005, totaling 24 months of data, resulting in 61,404 measurements for solar irradiance and the same for temperature, since measurements were from 05:00 hours to 18:00 hours. For MLP Backpropagation ANN training, 70% of the collected irradiance and temperature data (512 days, 43,008 measurements) were used. Figure 2 shows daily solar irradiation measurements in 2004.

Fig. 2. Daily solar irradiation (2004).

The weather in Fortaleza is characterized by a rainy and dry season, due to the presence of the Intertropical Convergence Zone. Dry period occurs in the second half of the year. Consequently, during this period there is a higher incidence of solar irradiation on the surface due to the absence of cloud cover. Rainy season, characterized by a lower solar irradiation, occurs in the first half of the year.

For validation of the ANN results, the rest of the data (30% of the collected data) of solar irradiance and temperature (219 days, 18,421 measurements) are used in order to verify the network operation for hitherto unknown inputs (generalization step). It is worth mentioning that, in the region of the study, the climate is well defined throughout the year, therefore, this climatic characteristic causes the neural network to be able to carry out predictions of later years.

With these results, weighted errors are calculated. Solar prediction errors are found at different times of the day, with different levels of solar resource availability [5]. If a solar prediction error happens at the end of the day, between 5 and 6 pm in Fortaleza, the impacts of these errors on the PV electricity generation are lower than errors at 12 am, period with greater solar potential. Aiming to adjust the prediction errors taking into account the solar resource availability, a filter called Impact Factor, according to equations (5) and (6) [6], is applied.

$$E_{pp} = \frac{(D_p - D_m) \times 100}{D_m} \times F_i \quad (5)$$

$$F_i = \frac{D_m}{M_r} \quad (6)$$

E_{pp} is the weighted prediction error, D_p and D_m are the predicted and measured data, respectively, M_r is the resource highest value and F_i the impact factor.

Solar irradiance prediction using data collected in Fortaleza was performed using an MLP ANN with backpropagation training algorithm. The developed algorithm provides solar irradiance data one hour in advance, taking into account the events of the last 10 hours (60 measurements). The characteristics of the implemented algorithm are:

- 1) Matrix with 60 delays and 1 output;
- 2) Sigmoidal function in the vectors of the hidden and output layers;
- 3) 10 neurons in the hidden layer;

- 4) 1 neuron in the output layer;
- 5) Learning rate of 0.1;
- 6) Hidden layer and output weights were initialized randomly;
- 7) Stop criterion was defined by the number of times, being used 10,000 times for each networking training.

Figure 3 shows the Process Flowchart.

Fig. 3. Process Flowchart.

4. Results

Figure 4 shows solar irradiance for 5 days in April 2003. During measurements there are sudden oscillations caused

Fig. 4. Data collected in April 2003.

Fig. 5. Network first training test (Demonstration window: September 24 to 28, 2004).

by clouds. Figures 5 and 6 show comparative tests between measured and predicted solar irradiance. Prediction uses MLP Backpropagation ANN from two different training sessions, with a time delay of 10 hours (window of 60 measured data). Structure characteristics and network initialization parameters were kept, with exception of the initial weights, which were different for each of the two trainings. All measurements consider one hour in advance, totaling 18,421 forecasts, or 219 forecast days. Test period was performed from September 23, 2004 to April 30, 2005.

Predictions of solar irradiance follow the behavior of the solar resource, demonstrating that the method is able to give values close to the observations in several hours of the period. The highest value of predicted solar irradiance for the 1st test was 1,144.2 W/m², while the measured value was 1,371 W/m², which is an understatement of 16.6 %. For the second test, the highest value of predicted solar irradiance was 1,449.33 W/m², characterizing an overestimation of 5.71%. For the first test, the largest difference between forecast and collected data was 99%, the lowest of 0% (no error). For the second test, the largest difference was 93.77% and the lowest of 0%.

In the first test, 41.9% of the predictions obtained up to 5% of error, 58.7% of the predictions obtained errors less than 10% and 68.6% of the predictions errors less than 15%.

In the second test, 34.87% of the predictions obtained up to 5% of error, 53.94% of the predictions obtained errors less than 10% and 67.42% of the predictions errors less than 15%. Figure 7 shows the prediction errors behavior for a 5 days window extracted from the 1st test, chosen for representation due to its better performance.

Fig. 6. Network second training test (Demonstration window: October 24 to 28, 2004).

Fig. 7. Prediction errors.

5. Conclusions

The proposed MLP network was able to perform solar irradiance predictions with 1 hour in advance obtaining satisfactory results for a site close to the Equator line. In the best network performance, 41.9% of the predictions obtained up to 5% of error, 58.7% obtained errors lower than 10% and 68.6% obtained errors lower than 15%. MAPE of 6.11% was found, a good value taking into account errors of previous works, which reached 20%. Hence, the proposed algorithm for solar resource prediction can contribute to predictability errors decrease, causing a smoothing in the financial impacts of RE projects.

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