17th International Conference on Renewable Energies and Power Quality(ICREPQ'19)
Tenerife, Spain, 10th to 12th April, 2019
Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, Volume No.17, July 2019

Radial Basis Function for Solar Irradiance Forecasting in Equatorial Areas

Marcello Anderson F. B. Lima[1], Paulo C. M. Carvalho[1], Arthur P. de S. Braga[1], Renata I. S. Pereira[1], Sandro C. S. Jucá[2], Luis M. Fernández-Ramírez[3], Josileudo R. Leite[4]

[1] Department of Electrical Engineering
Federal University of Ceará– UFC
Campus Pici, Av. Mister Hull, s/n - Pici, Fortaleza, 60455-760, Ceará (Brazil)
Phone: +558533669585, e-mail: **marcello@ifce.edu.br, carvalho@dee.ufc.br, arthurp@dee.ufc.br, renata@dee.ufc.br**

[2] Academic Master's Degree in Renewable Energy (PPGER)
Federal Institute of Ceará (IFCE)
Maracanaú Campus, Parque Central Av., s/n - Industrial District I, 61939-140, Ceará (Brazil)
Phone: +558538786333, Fax: +558538786300, e-mail: **sandrojuca@ifce.edu.br**

[3] Research Group in Electrical Technologies for Sustainable and Renewable Energy (PAIDI-TEP-023)
Department of Electrical Engineering,
University of Cadiz (UCA)
Escuela Politécnica Superior de Algeciras, Av. Ramón Puyol, s/n, Algeciras, 11202, Cádiz (Spain)
Phone/Fax number: +34956028166, e-mail: **luis.fernandez@uca.es**

[4] Department of Industrial Mechatronics
Federal Institute of Ceará (IFCE)
Limoeiro do Norte Campus, Rua Estevão Remígio de Freitas, 1145 - Monsenhor Otávio, Limoeiro do Norte, 62930-000, Ceará (Brazil)
Phone/Fax number: +558834476400, e-mail: **josileudorodrigues@hotmail.com**

Abstract. Photovoltaic (PV) solar generation is gaining an increasing attention due to technological advances such as higher efficiency and life of PV cells and cost reduction. Due to its vast territory, Brazil is composed of regions that can explore renewable energy sources for electricity generation, and the solar resource is found satisfactorily in several areas of the country. This article presents a solar irradiance prediction mechanism developed using data collected in Fortaleza-CE, Brazil. Due to the fact of its characteristic of unpredictability for this resource, many researchers look for several methods to take the generation of this type of energy. The predictions were performed using a Radial Basis Function (RBF) a computational model based on the human nervous system, it is a technical and effective for time series forecasting, which is a relatively complex problem, Artificial Neural Network (ANN) with the advancement of 1 hour. In the ANN performance, a total of 34.4% forecasts underestimated solar energy availability, 7% of the forecasts obtained error 0 and 58.6% of forecasts overestimated the solar resource. A total of 62.33% of forecasts was between -10% and 10% of forecast error. The prediction mean error was 5.93% and the Mean Absolute Percentage Error (MAPE) was 11.43%.

Key words

Solar Forecast, Solar Energy, Artificial Neural Network, Radial Base Function.

1. Introduction

With the current world population growth, in which the number of inhabitants must exceed 11 billion in 2100, the search for energy sources to supply the global electricity demand [1] is growing. In Brazil, for example, in the year 2017 there was an increase of approximately 2% in the units consuming electricity compared to 2016, going from 80,590 thousand to 82,236 thousand units. Considering specific consumer units, residential consumption had 2.2% increase, commercial units 0.8%, rural units 1.4%, and other sectors showed growth of 0.5% in consumer units. The number of industrial consumer units fell by -1.5% [2].

Several factors, such as climatic challenges, expansion of electric power consuming units and population habits involving the use of electricity, have been influencing the search for technologies capable of expanding and diversifying the world electricity matrix. Hence, energy sources, such as solar, have been gaining space for expansion. In 1973, non-hydro renewable sources held 0.6% of the world share of electricity production, while in 2015 the share increased to 7.1% [3].

In the Brazilian territory, solar energy has an average annual global irradiance between 1,200 and 2,400 kWh/ m². Compared with some countries, such as Spain and Germany, for example, which exploit strongly the solar potential, is quite high [4].

According to the technological development of the renewable sources, the proportion of use of these resources will increase in the application for electricity production in the next years. Photovoltaic (PV) solar generation is gaining an increasing attention due to technological advances such as higher efficiency and life of solar cells and reduction of electricity generation costs in the last decades [5].

In addition, a work [6] showed the importance of the prediction, where it was observed that a 25% improvement in the Mean Absolut Percent Error (MAPE) in the PV generation accuracy could lead to 1.56% (46.5 million dollars) of net reduction in the cost of generation in the simulated system [7].

Due to the influence of climatic factors, electricity production from the solar source is characterized as difficult to predict. As grid operators need to keep these variations under control to accommodate the input/output balance of the system, forecasting methods are needed to improve the connection of intermittent energy resources [5]. Hence, solar irradiance prediction is also necessary to enable prediction of the solar plants output power [8].

This becomes an important issue when faced with the fact that solar power plants are widely scattered and growing in most of today's energy systems in the world. The output power of a PV system is mainly related to the overall solar irradiance received in the module plane. But in many cases there is no measurement of this information as well as monitoring by methods of predictability [9].

Systems with high inclusion of solar energy also require strategies of production control and demand survey. In these systems, however, determining the correct levels of productive capacity requires a more probabilistic approach, because solar generators rely on phenomena that are not perfectly predictable. In the last decades, a growing number of methods have been implemented by many researchers because of the need to improve prediction of electrical systems with intermittent sources. Generally, these approaches can be broadly divided into three main classifications: conventional (statistical) methods [10], Artificial Intelligence (AI) techniques [11] - [14] and hybrid models [15].

One of these techniques used to solve the problem of predictability of the solar resource is the ANN RBF, because it is a technical and effective for time series forecasting, which is a relatively complex problem. Thus, RBFs have been used to model and predict daily global solar irradiance data, as well as other meteorological data such as air temperature, sunlight duration and relative humidity, among others [19].

Motivated by the increasing use of PV plants in Brazil, we propose the development of techniques for the use of ANN RBFto solar resource prediction in order to contribute to the reduction of predictability errors. Where the main cause is the variability in energy production. The performance of the forecasts seeks to guarantee how much a solar power plant can generate, by forecast the availability of the resource. Solar irradiance and ambient temperature data are collected in Fortaleza-CE (latitude: -03° 43 ', longitude: -38° 32', elevation: 21m (69 ft).

2. Radial Basis Function

ANN is a circuit composed of a large amount of simple processing units inspired by the animal neural system. RBF is an ANN with multiple layers, each of them with different activities:

1) The input layer (input neurons) is the ANN connection point with the data environment to be processed.
2) The second layer is a single layer, which applies a nonlinear transformation of the input space to a representation in the space generated by the neuron activations of the hidden layer.
3) The third layer is the ANN output.

RBF ANN structure is illustrated in Figure 1, where X0, X1 and X2 represent the input neurons, actually the input data of the system; ‘φ1’ and ‘φ2’ are the intermediate neurons, where each neuron has a radial base function; Y is the neuron that represents the ANN output; and the parameters w1 and w2 are the weights of the connections between intermediate and output layer.

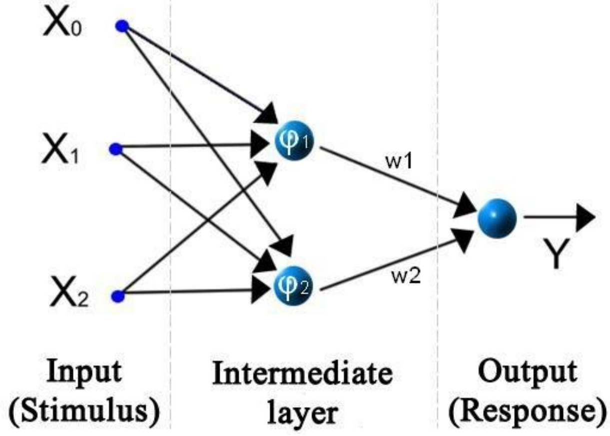

Fig. 1. RBF Structure. Source: adapted from [16].

The effect of using RBF is on the way the inputs are processed by the neurons in the middle layer. Instead of the internal activation of each neuron of the intermediate layer observes the dynamics by the use of the scalar product between the vector of inputs and the vector of weights, as in the case of perceptron, it is obtained from a weighted norm of the difference between both vectors [16].

RBF uses a methodology based on some types of biological neurons that are capable of selectively responding to data in a pre-established space. When an RBF is used to perform a complex task of pattern classification, the problem is basically solved by transforming the input space into a high-dimensional space non-linearly [16]. This is based on the Cover Theorem where it is stated that "a complex problem of classification of non-linearly arranged patterns in a space of high dimension is more likely to be linearly separable than in a space of low dimensionality". These ANN use activation functions with local receptive fields, as previously mentioned. Equations (1) and (2) were considered using the Gaussian function:

$$\varphi = \exp\left(-\frac{r^2}{2\sigma^2}\right) \tag{1}$$

$$r = \| x - t \| \tag{2}$$

where ‘φ’ is the output of each neuron of the hidden layer; ‘r’ is the difference between the input ‘x’ and the center ‘t’; and ‘σ’ is the measure of the curve scattering.

RBF output is formed by a single linear neuron, where the sum of each output of the hidden layer neurons is weighted by their respective weights, according to (3):

$$\mathrm{y} = \sum w_j \cdot \varphi_j \tag{3}$$

where ‘y’ is the output of ANN; and ‘w’ is the weight.

The location of the centers of each RBF neuron is defined at random from the ANN training set data. The chosen clustering algorithm was K-means. For the execution of K-means, a vector x is extracted from the training data, which is set to find the nearest center of the vector in evidence. The verification of the distance between centers and the vector in analysis is found using equation (4), where the information of the nearest center is also extracted.

$$y = \arg\min_k \| x_{(n)} - C_{k_{(n)}} \| \tag{4}$$

where ‘x’ is the vector in evidence; and ‘C_k’ is the neuron center.

Several research lines for predicting solar resources were observed using specific ANNs, such as [17]:

Multilayer Perceptron Networks (MLP) that can solve nonlinear problems and class standards;

Radial Base Function (RBFs) that can be used in problems of approximation of curves capable of learning complex patterns and solve non-linearly separable problems;

Support Vector Machine (SVM), which serves to separate patterns in a hyperplane, from the decision surface to the separation margin where it points negative and positive points.

A. Literature review

Several researchers have suggested model of computational technique and forecast methodologies for solar PV power generation forecast.
[18] Used the solar irradiance plus integration of 12 meteorological parameters that were used as input of the RBF was studied using the Pearson correlation coefficient period from 1998 to 2010, at four sites in the United States. [19] propose a RBF K-means and K-nearest neighbor (k-NN), to optimize the centers of neurons, radius and weights of the RBF. The proposed model is applied to predict the production of daily PV electricity in Palestine using PV panels already installed in the city of Jericho. [20] propose a new fault detection algorithm for PV systems based on ANN and fuzzy logic system interface. A daily prediction model based on the weather forecast information for solar power generation in Korea is proposed by [21].

[22] propose method to compare data classification, training, forecasting and forecasting updating stages. Using in first stage, a fuzzy k-means in Taiwan. [23] design a high concentrated photovoltaic output power prediction model based on the Fuzzy Clustering and RBF, uses the meteorological data which affect output power to classify the sample collection, selects the most similar two days' data and daily current average radiation exposure as the RBF neural network inputs. [24] propose a model was tested under different widely used data driven forecasting models, including Multilayer Perceptron (MLP), Support Vector Regression (SVR), kNN and decision tree regression. A multivariate neural network (NN) ensemble forecast framework is proposed by [25]. And [26] focus on the prediction of monthly mean daily global solar radiation (GSR) for different cities in India with most influencing input parameters identified using Waikato Environment for Knowledge Analysis (WEKA) software.

Table I shows the world development of solar resource forecasts based on ANNs.

Table I – ANNs methods using MLP, RBF, SMV

AUTHOR	PARAMETER	ANN	COUNTRY
Jiang, 2015 [18]	Solar Monthly Irradiance	RBF	EUA
Awad e Qasrawi, 2016 [19]	Daily Solar Irradiance	RBF	Palestine
Dhimish et al, 2018 [20]	Lack of power	RBF	UK

Kim et al, 2016 [21]	Solar irradiance every 5 minutes	SVM(RBF)	South Korea
Huang et al, 2015 [22]	Hourly solar Irradiance	RBF	Taiwan
Yan et al, 2014 [23]	Hourly solar Irradiance	RBF	China
Alfadda et al, 2018 [24]	Hourly solar Irradiance	MLP/SVM	Saudi Arabia
Raza et al, 2016 [25]	Daily Solar Irradiance	ELM/FNN/ BNA	Australia
Meenal e Selvakumar, 2017 [26]	Solar Monthly Irradiance	SVM	Italy

3. Methodology

The present study of the solar resource intermittence behavior used solar irradiance and temperature data. Irradiance data collection was performed by a pyranometer manufactured by NRG Systems Inc. (LI-200SZ line), which provides solar irradiance in W/m². Temperature data comes from a temperature sensor manufactured by NRG Systems Inc. (# 110S precision line), with ± 1.11ºC accuracy and a limit of -40ºC to 52.5ºC. Both sensors were installed at 6 meters high, at the ceiling of the Department of Electrical Engineering-DEE, Federal University of Ceará-UFC, in Fortaleza.

Data were collected and stored on spreadsheets at intervals of 10 min (obtained by arithmetic means from data processed every 2 s). Solar irradiance and temperature data were performed from May 2003 to April 2005, totaling 24 months of data collection, resulting in 61,404 measurements of solar irradiance and temperature, since the measurements were performed from 5:00 am to 6:00 pm. For ANN RBF training, 70% of all collected data of solar irradiance (512 days) was used.

For the RBF RNA training developed in the present thesis, 70% of all data collected from solar irradiance (512 days) was used. The algorithm was developed in the Matlab software by means of script, and predicts data of solar irradiance with one hour in advance, taking into account the events of the last 5 hours, 30 measurements, since the data are collected every 10 minutes.

The parameters used for the RBF developed in this article are: Matrix with 30 delays and 1 output; Gaussian function for neuron activation of the hidden layers and weighted sum for the neuron of the output layer; 30 neurons in the input layer; 6 neurons in the hidden layer; 1 neuron in the output layer; Learning rate of 0.7; the weights of the connections between hidden layer and output were initialized randomly. It is worth mentioning that the presented parameters were chosen based on a series of training sessions, where the best performance parameters were determined.

The training procedure carried out by RBF, developed in this work, can be summarized through Figure 2.

Procedure
1: Reading and preparing collected data
2: Initialization random of centers
while (stop criteria)
3: Extraction of the vector for analysis
4: Calculating the distances between vector and centers
5: Nearest center check
6: Update the nearest center
end while
while (stop criteria)
7: Hidden layer processing
8: Output layer processing
9: Calculation of forecast errors
10: Updating weights
end while
11: RNA test with final weights and bias

Fig. 2. RBF Procedure Used. Source: author (2018).

A. Prediction errors

To validate the AIs results, solar irradiance and temperature data reserved for the test period are used to characterize the operation of forecasting techniques and their respective solar resource forecasting capabilities. Comparing ANNs forecasting results and data collected in the same period, it is possible to calculate the percentage of errors. Solar prediction errors can be found at different times of day, i.e., at different levels of solar resource availability [27].

Hence, to adjust forecast errors and, at the same time, take into account the amplitude of solar resource availability, a filter called Impact Factor is applied, according to (5) and (6) [27]. D_p is the predicted data, D_m is the measured data, M_r represents the highest value of the resource under investigation in the period and F_i is the Factor Impact.

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

$$F_i = \frac{D_m}{M_r} \tag{6}$$

4. Results

Solar irradiance and ambient temperature data were collected from May 2003 to April 2005, totaling two years of collection. Figure 3 shows the behavior of the average daily irradiance in this period. Despite the great difference of behaviors between January and February 2005, in relation to January and February 2014, the solar availability behavior is presented as cyclical, with the resource highest availability found in the second semester. Solar availability peak was in September for the two used years of data.

Solar irradiance directly influences the electricity delivered to the load and, consequently, the productive impact of PV plants. Hence, it is necessary to understand the daily behavior of solar intermittence. Figure 4 presents the solar irradiance behavior over time for 5 days of data collection, from 5:00 am to 6:00 pm, emphasizing that the nocturnal period was disregarded.

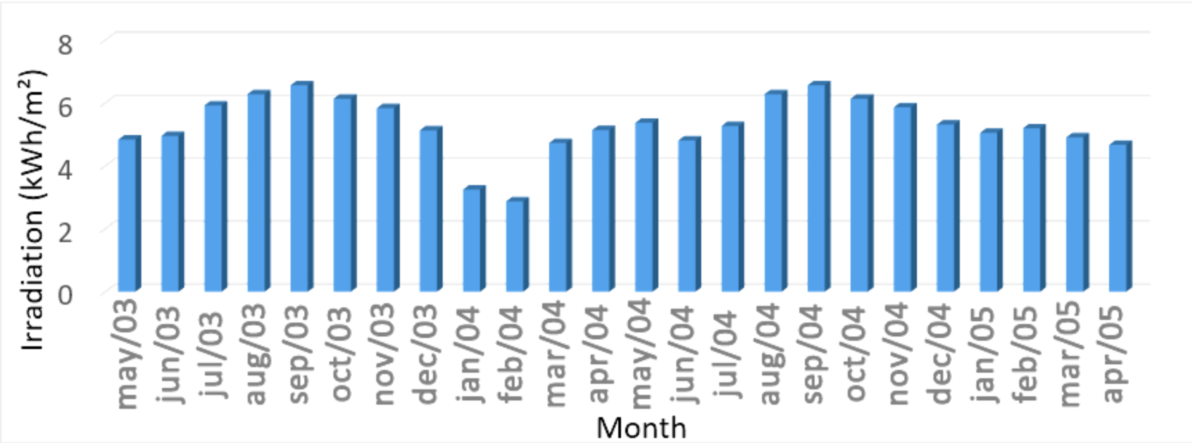

Fig. 3. Average daily solar irradiation in the analyzed period.

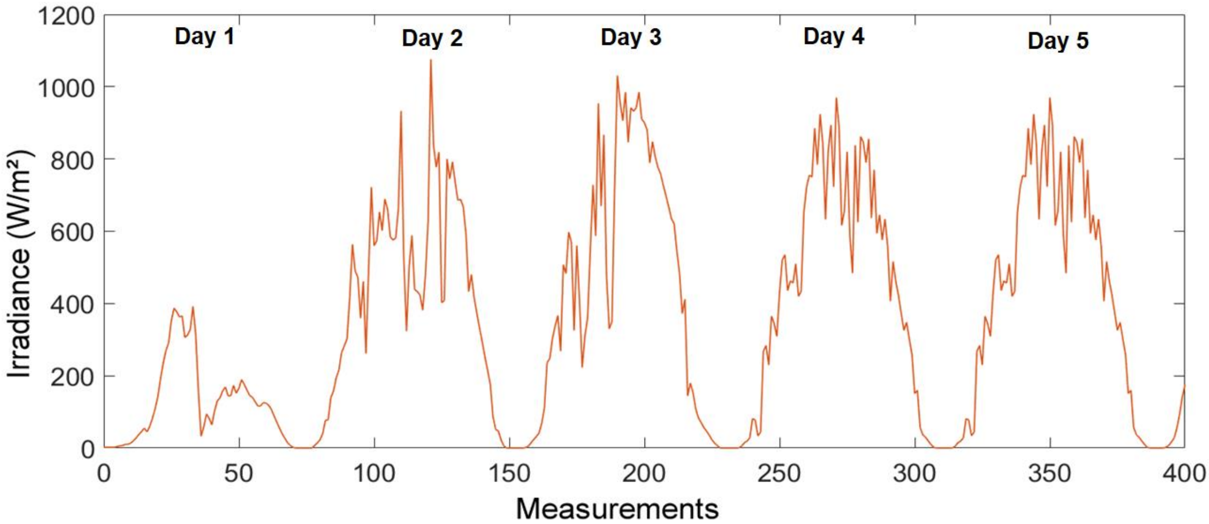

Fig. 4. Solar irradiance behavior, April 2003.

Figure 5 shows the behavior of the ambient temperature for the same period (April 2003). It is possible to verify that in four of the five days, the temperature had a behavior directly proportional to solar irradiance. However, day 4, a day with plenty of solar availability, showed lower temperatures compared to other days of high solar availability.

Considering the developed RBF prediction of solar resource, the behavior of the predicted and measured values of solar irradiance can be visualized in Figure 6, for a 5-day demonstration window, from October 24 to 28, 2004. RBF predictions were able to follow amplitude variations throughout the analyzed period. In general, the forecast remained stable, following the intermittent characteristic of the solar irradiance.

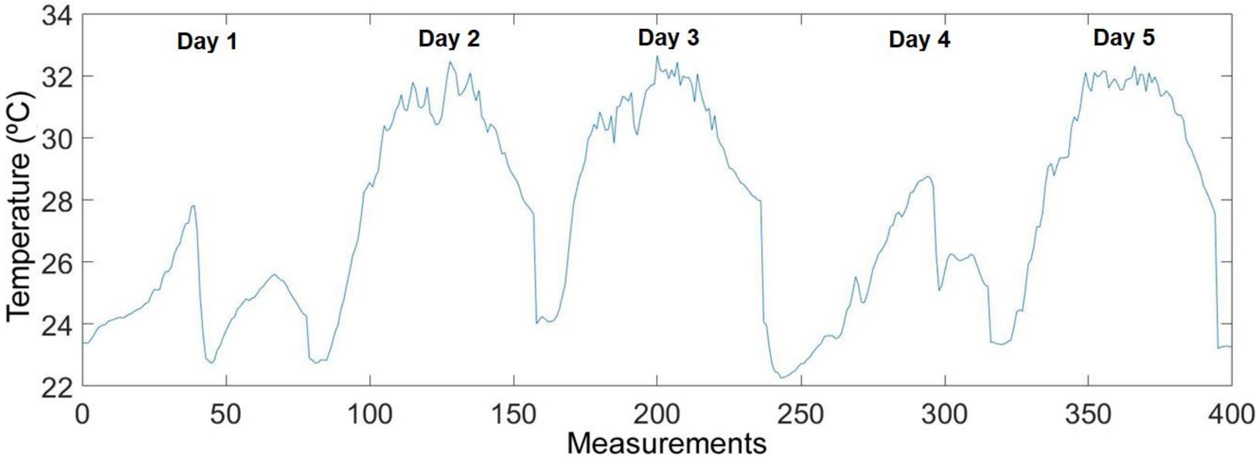

Fig. 5. Ambient temperature behavior, April 2003.

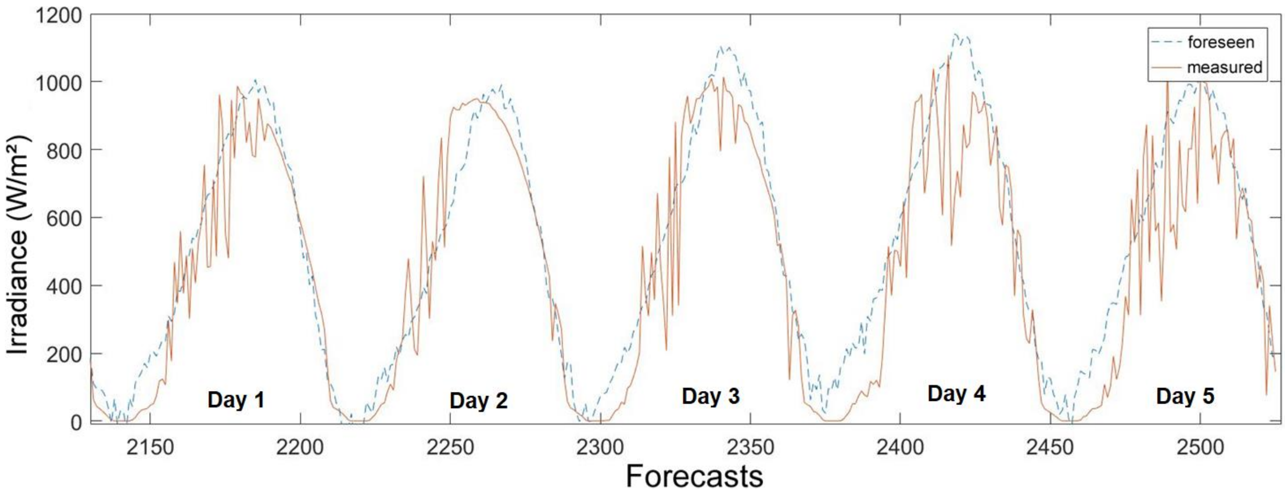

Fig. 6. Comparison between RBF predicted and measured solar irradiance.

Figure 7 shows the distribution of prediction errors during the ANN test period.

RBF underestimated a total of 34.4% solar energy availability forecasts, 7% of forecasts showed error 0 and 58.6% of the forecasts overestimated the solar resource. The most significant negative error was -36.06%, while the positive error was 101.4%. A total of 62.33% of forecasts were between -10% and 10% of forecast error and a total of 37.25% of the forecasts were between -5% and 5% of forecast error. The forecasts average error was 5.93% and the ANN Mean Absolute Percentage Error (MAPE) was 11.43%.

A Figure 8 presents the boxplot that can be used to understand the distribution of errors presented by RBF.The first quartile was defined as -3.16 (%), the third quartile was defined as the value of 11.08 (%), which means that the considerable number of forecasting errors remained within this range, with exception of the outiliers. The boundary characteristic of the quartiles represent the great predictive potential of the RBF during the test period, judging by the low value of the prediction errors. In addition, the figure demonstrates an apparent large number of outliers, but what should be interpreted as little in the universe of all predictions made (17,229 predictions).

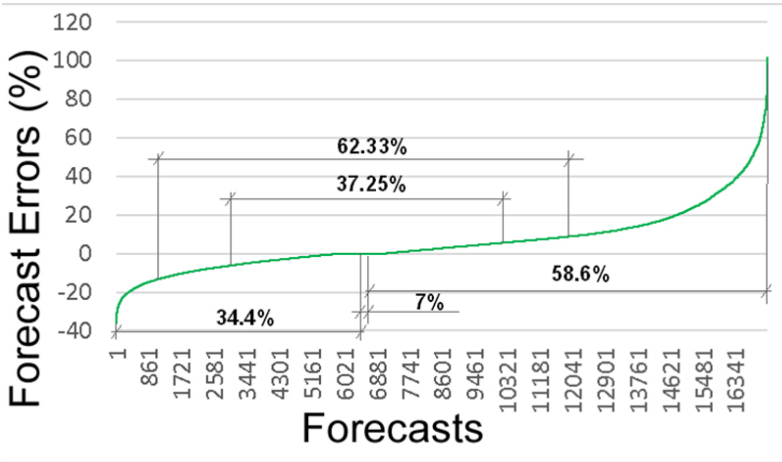

Fig. 7. Distribution of prediction errors during the ANN test period.

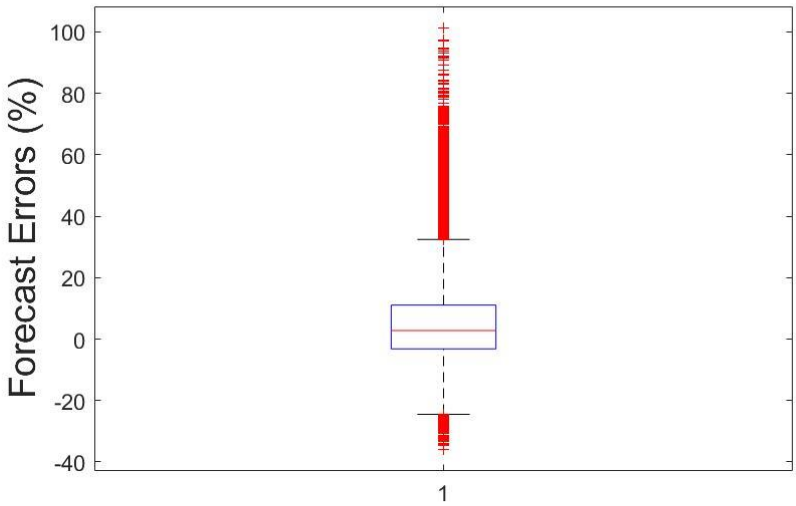

Fig.8. Boxplot of prediction errors during the ANN test period.

5. Conclusion

Consequences of solar electricity generation intermittence can be significantly reduced using an appropriate tool for solar resource availability prediction, thus lowering additional costs for the electricity sector. The proposed RBF ANN was able to perform predictions of solar irradiance with one hour in advance, obtaining satisfactory results. The prediction errors were considered good, considering the mechanisms of forecasting and the error rates found in previous studies (which reach 20%), since the found MAPE for the developed ANN RBF was 11.43%. Hence, the proposed RBF for the prediction of the solar resource can contribute to decrease predictability errors, reducing financial impacts resulting from such errors. The average forecast errors were 5.93%. These factors can guarantee a refining in the future forecasts, besides making applications in other regions of the planet and comparisons can be made with other techniques.

Acknowledgement

Authors would like to thank the Coordination for higher Education Staff Development (CAPES) and the National Council for Scientific and Technological Development (CNPq) for the sandwich doctorate scholarship awarded to the first author; the CNPq for researcher scholarship awarded to the second author; the *Deutscher Akademischer Austauschdienst* (DAAD) and CAPES for exchange scholarship at *TH Köln*-Germany and post-doctoral research scholarship (PNPD) awarded to the third author and *Fundación Carolina* for post-doctoral research at Uni Cádiz-Spain awarded to the fourth author.

References

[1] NAÇÕES UNIDAS. "Apesar de baixa fertilidade, mundo terá 9,8 bilhões de pessoas em 2050", DESENVOLVIMENTO SUSTENTÁVEL. Bruxelas, 22 June 2017. Available at: < https://nacoesunidas.org/apesar-de-baixa-fertilidade-mundo-tera-98-bilhoes-de-pessoas-em-2050/>. Access at: 30 August. 2018.

[2] MINISTÉRIO DE MINAS E ENERGIA – MME (Brasil) "Boletim Mensal de Monitoramento do sistema elétrico brasileiro", December de 2017, (2017). Available at: <http://www.mme.gov.br/documents/1138781/0/Boletim+de+Monitoramento+do+Sitema+El%C3%A9trico+-+Dezembro+-+2017.pdf/89e16453-fc2e-46fd-b5fd-aa6951daf934>. Access at: 30 August 2018.

[3] ITERNATIONAL ENERGY AGENCY – IEA. “Key world energy statistics 2017”, Paris (2017). Available at: <https://www.iea.org/publications/freepublications/publication/KeyWorld2017.pdf>.Acess at: 30 August 2016.

[4] M. A. F. B. Lima. “The Portifolio Theory applied to the forecasting of solar and wind resources”, Dissertation (Master in Electrical Engineering) - Department of Electrical Engineering, Federal University of Ceará, Fortaleza, (2016).

[5] P. Chaudhary, M. Rizwan, “Energy management supporting high penetration of solar photovoltaic generation for smart grid using solar forecasts and pumped hydro storage system”, Renewable Energy, Elsevier, v.118, April 2018, p. 928-946.

[6] C.B. Martínez-Anido, A. Florita, B. M. Hodge, “The impact of improved solar forecasts on bulk power system operations in ISO-NE”, Technical Report NREL/CP-5D00-62817. National Renewable Energy Laboratory, Golden, Colorado, (2017).

[7] G. M. Yagli, D. Yang, D. Srinivasan. “Reconciling solar forecasts: Sequential reconciliation”, Solar Energy, Elsevier, v.179, February 2019, p. 391-397.

[8] C. Voyant, G. Notton, S. Kalogirou, et al, “Machine learning methods for solar radiation forecasting: A review”, Renewable Energy, Elsevier, v.105, May 2017, p. 569-582.

[9] M. L. Aguiar, B. Pereira, P. Lauret, et al, “Combining solar irradiance measurements, satellite-derived data and a numerical weather prediction model to improve intra-day solar forecasting”, Renewable Energy, v.97, november 2016. p. 599-610.

[10] M. David, F. Ramahatana, P. J. Trombe, et al, “Probabilistic forecasting of the solar irradiance with recursive ARMA and GARCH models”, Solar Energy, Elsevier, v.133, August 2016, p. 55-72.

[11] L. Jiaming, J. K. Ward, J. Tong, et al, “Machine learning for solar irradiance forecasting of photovoltaic system”, Renewable Energy, Elsevier, v.90, May 2016, p. 542-553.

[12] A. T. Eseye, J. Zhang, D. Zheng, “Short-term Photovoltaic Solar Power Forecasting Using a Hybrid Wavelet-PSOSVM Model Based on SCADA and Meteorological Information”, Renewable Energy, Elsevier, v.118, April 2018, p. 357-367.

[13] H. Bouzgou, C. A. Gueymard, “Minimum redundancy – Maximum relevance with extreme learning machines for global solar radiation forecasting: Toward an optimized dimensionality reduction for solar time series”, Solar Energy, Elsevier, v.158, December 2017, p. 595-609.

[14] S. Suna, S.Wanga, G. Zhanga, et al, “A decomposition-clustering-ensemble learning approach for solar radiation forecasting”, Solar Energy, Elsevier, v.163, March 2018, pp. 189-199.

[15] D. Yanga, J. Kleisslb, C. A. Gueymard, et al, “History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining”, Solar Energy, Elsevier, v.168, July 2018, pp. 60-101.

[16] S. Haykin, “Redes Neurais: princípios e prática”, bookman, Porto Alegre (2001), pp.1-902.

[17] M. A. F. B. Lima, P. C. M. Carvalho, A. P. S. Braga, L. M. F. Ramírez, J. R. Leite, “MLP Back Propagation Artificial Neural Network for Solar Resource Forecasting in Equatorial Areas”, Renewable Energy and Power Quality Journal (RE&PQJ), (2018), pp.175-180.

[18] H. Jiang, Y. Dong, J. Wang, et al, “Intelligent optimization models based on hard-ridge penalty and RBF for forecasting global solar radiation”, Energy Conversion and Management, Elsevier, v.95, May 2015, pp. 42-58.

[19] M. Awad, I. Qasrawi, “Enhanced RBF neural network model for time series prediction of solar cells panel depending on climate conditions (temperature and irradiance)”, Neural Computing and Applications, Springer, v.30, September 2018, pp. 1757–1768.

[20] M. Dhimish, V. Holmes, B. Mehrdadi, et al, “Comparing Mamdani Sugeno fuzzy logic and RBF ANN network for PV fault detection”, Energy Conversion and Management, Elsevier, v.95, March 2018, pp. 257-274.

[21] J. G. Kim, D. H. Kim, W. S. Yoo, et al, “Daily prediction of solar power generation based on weather forecast information in Korea”, Renewable Power Generation, IET, v.11, Issue 10, March 2017, p. 1268-1273.

[22] C. M. Huang, S. J. Chen, S. P. Yang, C. J. Kuo, “One day ahead hourly forecasting for photovoltaic powercgeneration using an intelligent method with weather-based forecasting models”, Generation, Transmission e Distribuition, IET, v. 9, Issue 14, November 2015, p. 1874 – 1882.

[23] C. Yan, J. Xiu, C. Liu, Z. Yang, “A High Concentrated Photovoltaic Output Power Predictive Model Based on Fuzzy Clustering and RBF Neural Network”, Proceedings of CCIS2014, (2014), pp. 384-388.

[24] A. Alfadda, S. Rahman, M. Pipattanasomporn, “Solar irradiance forecast using aerosols measurements: A data driven approach”, Solar Energy, Elsevier, v. 170, August 2018, pp. 924-939.

[25] M. Q. Raza, N, Mithulananthan, A. Summerfield, “Solar output power forecast using an ensemble framework with neural predictors and Bayesian adaptive combination”, Solar Energy, Elsevier, May. 2018, v.166, p. 236-241.

[26] R. Meenal, A. I. Selvakumar, “Assessment of SVM, empirical and ANN based solar radiation prediction models with most influencing input parameters”, Solar Energy, Elsevier, June 2018, v.121, p. 324-343.

[27] M. A. B. F. Lima, P. C. M. Carvalho, T. C. Carneiro, et al, “Portfolio theory applied to solar and Wind Resources Forecast”, IET Renewable Power Generation, Vol. 11, Issue 7, June 2017, p. 973 – 978.