Hourly PV Generation forecasting for Gran Canaria Island using different exogenous data

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Abstract. Global Solar Radiation gives us the possibility for determining electrical solar energy generation in a region. Maintain the balance between electrical power demand and supply requires a specific attention in order to integrate solar energy into the electrical grid. Indeed, the knowledge of solar radiation for different time horizons is the main tool for increasing the proportion of solar energy into the power system. The main objective of this paper is to improve PV Generation forecasting for the Island of Gran Canaria. Firstly, solar radiation forecasting is improved using statistical models with ground measurements and other exogenous variables as inputs. Based on the radiation data obtained in the forecasts, it is possible to obtain an estimate of electric power production for each hour of the day. The improvements obtained in forecasts for time horizons between one and six hours are very important for the electric power system. This helps reduce operating and maintenance costs by offering greater control and reducing uncertainty. These approaches may be used by electric power generators in order to improve interventions in the intraday market and allow them to revise management decisions with respect to the facilities.

Key words

Artificial Neural Networks, Forecasting, Solar Radiation, PV Generation, Satellite Data.

1. Introduction

Solar radiation forecasting is an important tool for increasing solar energy generation into the grid. In order to manage the demand and supply, the system operator and PV producers need solar radiation forecasting for different time horizons [1]. In case of Island grids, they should to produce all the electricity with their own resources. Moreover, Canary Islands present a solar radiation high variability because of the complicated orography. Depending on the purposes, solar radiation forecasting with different time horizons are required. Solar radiation models use different input parameters depending on each case [2, 3]. For time horizons shorter than an hour, ground-based sky images models forecast obtain high precision information about cloud cover conditions and movement [4]. On the other hand for hourly forecasting up to 6 hours ahead, cloud motion vectors models derived from geostationary satellite images show accurate results [5, 6]. Meteorological agencies developed different Numerical Weather Prediction (NWPs) models with several precisions depending on the time scale and the geographic area for the study, Heinemann [7]. In recent time, NWPs models associated with a post-processing method have been developed. These models use hourly ground measurements to improve NWPs results and show accurate results for predictions from 6 h onwards [8].

The work is focused on intra-day hourly solar radiation forecasting with time horizons from 1 hour to 6 hours ahead. Statistical models are commonly used for short-time forecasts from 5 min. to 6 h. In this paper, an artificial neuronal network (ANN) model is proposed to forecast the hourly Global Horizontal solar Irradiance (GHI) [9]. Bayesian probabilistic techniques have been used for analysing the complexity of the model for each simulation performed during the study [10]. ANNs are based using different input data sets, as ground measurement data, numerical weather prediction model data (from ECMWF) and satellite data (from Helioclim-3) [11, 7].

In this paper, PV Electrical Generation model has been used to show the useful of solar radiation. This model estimates PV Electrical Generation using solar radiation data, ambient temperature and different PV solar panels characteristics [12]. The performance of the model have been used in a generation plant with 480 solar panels situated in Pozo Izquierdo.

2. Available data

Ground measurement data were obtained from two stations located in Gran Canaria Island (Spain) and provided by the Canary Islands Technology Institute (Instituto Tecnológico de Canarias). Predominant Trade winds coming from north east produce a high climatic contrast between northern and southern area on the Island. Northern area present a higher cloudiness because the orography stops the clouds coming with predominant winds [13, 14]. Both stations represent the different climatic conditions around the Island.

Measurement stations use secondary standard pyranometer to acquire global horizontal irradiance (GHI). In this case we have the pyranometer CMP-11 of

Kipp & Zonen, with 3% accuracy for daily sum of GHI. Data are recorded for every 5 s, 1 min average, and later assembled into an hourly basis. One of the most important steps to obtain good results using ANNs is to assure the good quality of the data. In this case, we have used the SERI-QC control software for the quality assessment [15, 16]. This model filter out the global solar radiation data over top of the atmosphere radiation and values under zero.

To improve solar radiation forecasting obtained with ground measurements using ANNs models we added different exogenous data. In this study we worked with surface solar radiation data derived from satellite images and solar radiation and total cloud cover predicted with ECMWF model. Satellite information was retrieved from the Helioclim-3 database version 5 (HC3v5). All this information has been processed by converting the images taken from the Meteosat geostationary satellite network into solar radiation with Heliosat-2 method [17, 18]. Satellite derived data contain very high precision information for a great area around the Island and for a high temporal resolution. The defined area, in decimal degrees, is the coordinates latitude [+28.7500 to +27.2500], and longitude [-16.0000 to -14.5000], resulting in a grid of 61x55 pixels of information, where each pixel possesses a spatial resolution of 3x3 km^2. Satellite data were retrieved with a temporary resolution of 15 min. and later resumed into and hourly solar radiation database like ground data.

Moreover, we have used different data obtained with the ECMWF (European Center for Medium-Range Weather Forecast) numerical model. These data were granted by the Laboratoire de Physique et Ingénierie Mathématique pour l'Energie et l'environnement (PIMENT) from the Université de La Réunion. As well as satellite data, ECMWF data give us information about the whole area of the Island. This information was selected for an area located from 27.5º to 28.5º of latitude north, and 15º to 16º longitude west Fig. 2. For each pixel of the selected grid there is a spatial resolution of 16x16 km^2 and 21 vertical levels of resolution. ECMWF model provides a great number of meteorological variables, but in this study we only extracted the Total Cloud Cover (TCC) and the Surface Solar Radiation Downwards (SSRD).

3. Solar Forecasting Model

Statistical models training processes were handled with clear sky index series. To obtained clear sky index (Eq. (1)) we have used the clear sky model called Bird model. This model estimate solar radiation for a clear atmosphere using several parameters, as AOD, water steam and ozone.

$$\boldsymbol{k}^* = \frac{\boldsymbol{I_g}}{\boldsymbol{I_{cs}}} \qquad (1)$$

Otherwise, the results obtaining with the testing datasets are computed using global solar irradiances. In order to stablish the improvement obtained with the proposal models is very common in the literature use reference models. In this paper we compared ANNs models with one naïve model called Smart-persistence. This model estimate solar radiation forecasting for time horizon ‘h’ using the mean of the ‘h’ previous clear sky index data.

A. Model description

In this work, we used Artificial Neural Networks (ANNs) to improve solar radiation forecasting using different inputs. Artificial Neural Networks (ANNs) are statistical methods using to stablish a relation between input and output datasets. Each individual unit of the ANNs are called neurons and are connected by different weights. The ANNs used in this paper is the Multilayer Perceptron (MLP). This model is composed by an input layer, one hidden layer with non-linear neurons and an output layer. There are not any feedback connection between each layer. The input layer is composed by all the different inputs and the output layer contains only the solar radiation for the time horizon ‘h’. The general equation for the ANNs is as in Eq. (2).

$$\boldsymbol{y} = \boldsymbol{y}(\boldsymbol{x};\boldsymbol{w}) = \sum_{j=0}^{h}\left[\boldsymbol{w_j f}\left(\sum_{i=0}^{d}\boldsymbol{w_{ji}}\cdot\boldsymbol{x_i}\right)\right] \qquad (2)$$

At the beginning the weights are initialized randomly and later optimized with a cost function during the training process. The average of square difference between the computed output and the desired output in terms of clear sky index is the most common function Eq. (3)).

$$E(w) = \frac{1}{2}\sum_{i=1}^{N}(y_i - t_i)^2 \qquad (3)$$

The complexity of the model is one the most important issues to obtain improved results with ANNs. Networks with a high number of hidden units or inputs could obtain very good results with the training datasets but poor results when we used new testing dataset (overfitting problem). In order to avoid this kind of problem is very common to use different regularization methods. These methods normally control the complexity of the models and obtained generalized results [19, 20]. In this paper we proposed Bayesian regularization framework to control the architecture of the model [10, 21, 22]. Bayesian framework consider a probability density function over the weight space. So, the optimal ANN weight space correspond to the maximum of the probability density function. Finally, Bayesian framework introduces new hyperparameters to the cost function in order to control the complexity Eq. (4).

$$\boldsymbol{S}(\boldsymbol{w}) = \frac{\boldsymbol{\beta}}{\boldsymbol{2}}\sum_{i=1}^{N}(\boldsymbol{y_i} - \boldsymbol{t_i})^2 + \frac{\boldsymbol{\alpha}}{\boldsymbol{2}}\sum_{j=1}^{m}\boldsymbol{w_j}^2 \qquad (4)$$

Using the Bayesian framework the overfitting problem is avoid. In Fig. 1 the results obtained for C0-Pozo Izquierdo station are showed. This figure represents the results obtained with Bayesian Networks against the real solar radiation data for training and testing datasets. It is easily observed that the overfitting problem is not present in this forecasting.

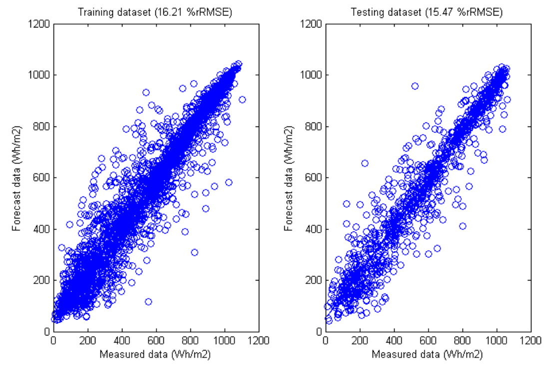

Fig. 1. Comparison of forecasted results with Bayesian Networks and real radiation ground data for C0-Pozo Izquierdo

B. *Forecasting model implementation*

In this paper we have trained ANNs with different inputs to improve solar radiation forecasting. Every cases work with different combination of inputs. Firstly, we trained ANNs only using six ground clear sky index in order to compute the improvement we get when we add exogenous data. The exogenous data used as inputs in the ANNs are solar radiation data derived from Helioclim-3 and solar radiation and total cloud cover (TCC) predictions from ECMWF. Indeed, the different ANN models computed are the following:

1) ANN model with only past ground data as inputs (denoted herein NN).
2) ANN model with past ground data and satellite data as inputs (denoted herein NN+SAT).
3) ANN model with ground data and ECMWF radiation data as inputs (denoted herein NN+ECMWF).
4) ANN model with ground data, satellite data and ECMWF radiation data as inputs (denoted herein NN+ECMWF+SAT).

Satellite data provide a high number of pixels for the whole area of Gran Canaria. So, select the best satellite pixel information is one of the most important decisions to improve hourly GHI forecasting. The selection of pixel have been carried out based on the calculation explained by Mazorra et al. [23]. The parameter used to establish the most related satellite pixels with the ground data is the Pearson Correlation. We computed the correlation between each satellite gridded pixels for different time lags and the ground measurement data for the present time. Consequently we could have information about the incoming events for 1, 2 and 3 hours before from the surroundings. The maximum number of satellite pixels was fixed in 30 to control the computational load of ANNs. Thus, satellite pixels selected as ANNs inputs show the highest relation with ground station data for each time lag.

In order to evaluate the performance of each method, we used a standard error metric widely used in the solar forecasting community: the Root Mean Square Error (RMSE) [24, 25]. Dividing by the average of the hourly GHI data we compute the relative metric (%rRMSE).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(GHI_{forecast,i} - GHI_{measured,i}\right)^2} \quad (5)$$

During the training process we computed different ANNs using six combinations of 30 satellite pixels and selected the optimal one. Once we selected the optimal selection of satellite data, all statistical models suggest in this paper were compared in terms of testing dataset error. All different ANN models, using different combinations of exogenous data, obtain better results than ANNs only with ground data. For station C0-Pozo Izquierdo, satellite data (NN+SAT) reproduced the best results for the first three hourly time horizons, while satellite data and ECMWF data (NN+ECMWF) provide similar results for the last three hours. In case of C1-Las Palmas station, NN+SAT model presents the most accurate results for time horizon lower than 3 h, while NN+ECMWF obtains the best results for the last time horizons. In both stations, the combination of both models, satellite and ECMWF data (NN+ECMWF+SAT) presents the best results for all time horizons. Thus, in this paper we recommend the use of NN+ECMWF+SAT model as the best one to improve solar radiation forecasting from 1 to 6 hours ahead in Gran Canaria Island.

Tables I-II present the forecast performance for both station in terms of %rRMSE from time horizon 1 to 6 using annual testing data set. Each row corresponds to the forecasting reference model, ANNs only using past ground radiation data (NN) and the optimal model proposed in this paper (NN+ECMWF+SAT). In all cases, forecasting models show worse %rRMSE error as time horizon increases. The Smart-Persistence increases from 15 %rRMSE in ‘h=1’ to 26 %rRMSE in ‘h=6’ at C0 station, while at C1 station error results oscillate between 27% and 42%. On the other hand, ANNs model proposed in this paper leads to error results around 15,5% at C0 and 24% at C1 for time horizon ‘h=1’ and 22% at C0 and 34% at C1 for time horizon ‘h=6’. It is easily observed than northern stations (C1) presents worse results than southern stations (around 12% difference for time horizon 6 hours). The climatic difference between both areas because of Trade winds effect is the main is the responsible of this accuracy difference.

We can also observe some difference between both stations if we study the improvements compared to the reference models. At station C0, proposal model shows and improvement between 1,5% and 4% compared to Smart-Persistence model for ‘h=1’ and ‘h=6’ and between 1% and almost 2% compared to NN. While at C1, NN+ECMWF+SAT model leads to a gain from 3% to 6% compared to Smart-persistence and between 1,5% and 3,5% compared to NN. Even if in southern stations, the results proposed model are better, the improvement shows very similar results for both areas.

TABLE I. - %rRMSE for testing dataset at station C0 – Pozo Izquierdo for different time horizons.

Model	1 h	2 h	3 h	4 h	5 h	6 h
SMART-PERS	17.03	22.95	25.80	26.60	26.05	25.54
NN	16.24	20.88	23.04	23.41	24.25	23.94
NN+ECMWF+SAT	**15.47**	**19.55**	**20.35**	**21.16**	**21.89**	**22.17**

TABLE II. - %rRMSE for testing dataset at station C1 – Las Palmas for different time horizons.

Model	1 h	2 h	3 h	4 h	5 h	6 h
SMART-PERS	27.42	38.98	43.96	45.03	43.85	42.00
NN	25.50	33.17	36.21	37.37	37.37	37.55
NN+ECMWF+SAT	**24.15**	**30.98**	**32.92**	**33.52**	**33.96**	**34.09**

4. PV Power Generation Model

Solar radiation prediction lets electrical system operators estimate power generation at different locations in Gran Canaria Island where there are installed PV Generation farms. In this study we have worked with a solar farm situated in C0-Pozo Izquierdo. The farm is composed by 480 MSK model TCF200-W photovoltaic panels and twelve Mini Sun Central 8000TL inverters. PV Solar models estimate electrical power generation using solar radiation data obtained both from measurement station and forecasting models. In this paper, to show the utility of solar forecasting, we have used the forecasting model results proposed and a generation model with PV panel described in [12].

This model compute electrical generation using solar radiation, temperature and different characteristics of PV panels. In order to estimate the production, we used a simple model for each cell array current:

$$I = N_P I_{PH} - N_P I_S \left[exp\left(\frac{qV}{N_S k T_C A}\right) - 1\right] \qquad (7)$$

Where N_P and N_S are the numbers of cells in pararell and in serie, I_{PH} is the photocurrent (eq. (8)), Tc is the operation temperature of the cell (eq. (9)) and I_S is the cell saturation of dark current (eq. (10).

$$I_{PH} = \left[I_{SC} + K_1\left(T_C - T_{ref}\right)\right]\lambda \qquad (8)$$

$$T_C = T_{amb+}\left[\frac{T_{NOCT}-20}{0.8}\right]\lambda \qquad (9)$$

$$I_S = I_{RS}\left(\frac{T_C}{T_{Ref}}\right)^3 exp\left[\frac{qE_G}{kA}\left(\frac{1}{T_{Ref}} - \frac{1}{T_C}\right)\right] \qquad (10)$$

Where I_{SC} is the cell short-circuit current at 25ºC and 1kW/m^2, T_{NOCT} is the nominal operating cell temperature, λ is solar radiation in kW/m^2, T_{amb} is the ambient temperature, T_{Ref} is the cell reference temperature and E_G is the bang-gap energy of the semiconductor. The test for the nominal operating cell temperature is made with 20ºC ambient temperature and 0.8 kW/m^2 irradiance level. IRS is the cell reverse saturation current using the temperature and solar radiation of reference:

$$I_{RS} = \frac{I_{SC}}{exp\left[\frac{qV_{OC}}{kA} - 1\right]} \qquad (11)$$

Where VOC is the open circuit voltage.

Fig. 2 represents the comparison between PV power generation estimated using global solar radiation measured in the area and the solar radiation forecasted with the proposed model. In this paper, we compared the results for time horizons 1 and 6 hours ahead using forecasting model NN+ECMWF+SAT. The compared day represent a clear sky day for station C0-Pozo Izquierdo. Both cases electrical power generation were estimated using photovoltaic model described in [12].

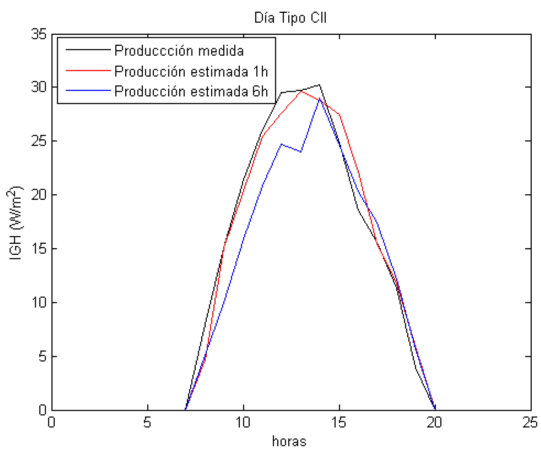

Fig. 2. Comparison of PV power generation measure and forecast for time horizons 1 and 6 hours ahead in C0-Pozo Izquierdo

We can consider the results obtained with the forecasting model proposed in this paper as an accurate tool for solar power generation forecasting. For time horizon 1 'h', we obtained better results, while for 6 hours ahead the model could not reproduce intraday variability. Taking into account daily generated energy, measurement data show a total electrical power generated of 234,23 kWh, while one hour ahead prediction model estimate a daily power generation of 234,33 kWh. On the other hand, for time horizon 6 hours the predicted model computed a daily PV power generation of 209,70 kWh. Indeed, the proposed model present an error of 0,04% in terms of daily energy with one hour ahead and an error of 10,47% for six hours ahead.

5. Conclusion

The influence of satellite data and data from ECMWF were first studied separately and in combination. For the first three hours forecast, satellite data (NN+SAT) obtained better results compared to ECMWF data. On the hand for the last three hours, similar and even better results were obtained by including ECMWF data (NN+ECMWF). The best results were obtained by combining both models (NN+ECMWF+SAT) as compared with NN.

Daily Electrical Generation profile estimated using solar radiation forecasting obtained from the proposed model (NN+ECMWF+SAT) was compared with the Electrical Generation profile measure in the plant. The proposed forecasting model reproduce useful results for estimating electrical solar energy generation. The results obtained for 1 hour ahead show very similar profiles between forecasting data and measure data, while for 6 hours ahead forecasting results fit the general trend. According to the Global Daily Solar Energy Generation for 1 hour ahead the forecasting model obtain an error around 0.04 %rRMSE compared to measured data. On the other hand, for 6 hours ahead the error obtained is around 10 %rRMSE in terms of daily energy.

The results obtained using the recommended models reproduce a daily radiation profile that can generally predict daily energy production. Nevertheless, the models do not reproduce hourly variations in solar radiation precisely. It is necessary to study the various forecasting techniques in order to obtain better results for short-term irradiance.

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References

[1] M. Wittmann, H. Breitkreuz, M. Schroedter-Homscheidt y M. Eck, «Case studies on the use of solar irradiance forecast for optimized operation strategies of solar thermal power plants,» *Selected Topics in Applied Earth Observations and Remote Sensing IEEE Journal,* vol. 1, nº 1, pp. 18-27, 2004.

[2] V. Kostylev and A. Pavlovski, “Solar Power Forecasting Performance –Toward Industry Standards,” in *Proceedings of the 1st International Workshop on the Integration of Solar Power into Power Systems*, October 24, Aarhus, Denmark., 2011.

[3] M. Sengupta, A. Habte, S. Kurtz, A. Dobos, S. Wilbert, E. Lorenz, T. Stoffel, D. Renné, C. Gueymard, D. Myers, S. Wilcox, P. Blanc y P. R., «Best Practices Handbook for the Collection and Use of Solar Resource Data for Solar Energy Applications,» Technical Report NREL/TP-5D00-63112 Contract No. DE-AC36-08GO28308, 2015.

[4] E. Lorenz and D. Heinemann, “Prediction of solar irradiance and photovoltaic power,” in *Comprehensive Renewable Energy*, Oxford, Elsevier, 2012, pp. 239-292.

[5] R. Perez, S. Kivalov, J. Schlemmer, K. Hemker Jr, D. Renné and T. Hoff, “Validation of short and medium therm operational solar radiation forecasts in the US,” *Solar Energy,* vol. 84, pp. 2161-2172, 2010.

[6] A. Hammer, D. Heinemann, E. Lorenz y B. Lückehe, «Short-term forecastingof solar radiation: a statistical approach using satellite data.,» *Solar Energy,* vol. 67, nº 1, pp. 139-150, 1999.

[7] D. Heinemann, E. Lorenz y M. Girodo, «Forecasting of solar radiation. Solar Energy resource managmente for electricity generation from local level to global scale.,» *New York: Nova Science Publishers*, 2006.

[8] M. Diagne, M. David, P. Lauret, J. Boland and Schmutz, “Review of solar irradiance forecasting methods and a proposition for small-scale insular grids,” *Renewable and Sustaineble Energy Reviews,* vol. 27, pp. 65-76, 2013.

[9] C. M. Bishop, Neural Networks for Pattern Recognition, Oxford: Clarendon Press, 1995.

[10] P. Lauret, M. David, E. Fock, A. Bastide and C. Riviere, “Bayesian and Sensitivity Analysis Approaches to Modeling the Direct Solar Irradiance,” *Solar Energy Engineering,* vol. 128, pp. 394-405, 2006.

[11] M. Diagne, M. David, J. Boland, N. Schmutz and P. Lauret, “Post-processing of solar irradiance forecasts from WRF model at Reunion Island,” *Solar Energy,* vol. 105, pp. 99-108, 2014.

[12] F. Díaz Reyes, Modelo numérico para la generación de mapas de radiación solar y u aplicación al aprovechamiento de energía solar fotovoltaica y termoeléctrica, Las Palmas de Gran Canaria: Tesis Doctoral Universidad de Las Palmas de Gran Canaria, 2013.

[13] F. Díaz, G. Montero, J. Escobar, E. Rodríguez and R. Montenegro, “An adaptive solar radiation numerical model,” *Journal of Computational and Applied*

Mathematics, vol. 236, no. 18, pp. 4611-4622, 2012.

[14] L. Mazorra, F. Díaz, G. Montero and R. Montenegro, “Typical Meteorological Year (TMY) evaluation for power generation in Gran Canaria Island, Spain,” in *Proceedings of the 25th European Photovoltaic Solar Energy Conference and*, Valencia, 2010.

[15] E. Maxwell, S. Wilcox and M. Rymes, “Users manual for SERI QC software, assessing the quality of solar radiation data,” NREL-TP-463-5608. 1617 Cole Boulevard, Golden, CO, National Renewable Energy Laboratory., 1993.

[16] S. Younes and T. Muneer, “Clear-sky classification procedures and models using a world-wide data-basee,” *Applied Energy,* vol. 84, pp. 623-645, 2007.

[17] C. Rigollier, M. Lefèvre y L. Wald, « The method Heliosat-2 for deriving shortwave solar radiation from satellite images,» . *Solar Energy 2004, 77, 159-169.,* vol. 77, pp. 159-169, 2004.

[18] P. Blanc, B. Gschwind, M. Lefèvre y L. Wald, «The HelioClim Project: Surface Solar Irradiance Data for Climate Applications,» *Remote Sensing*, vol. 3 , nº 2 , pp. 343-361, 2011.

[19] C. Bishop, Neural Networks for Pattern Recognition, Oxford: Oxford University Press, 1995.

[20] P. Lauret, E. Fock, R. Randrianarivony and J. Manicom-Ramsamy, “Bayesian neural network approach to short time load forecasting,” *Energy Conversion & Managment*, vol. 49, no. 5, pp. 1156-1166, 2008.

[21] P. Lauret, E. Fock and T. Mara, “A node pruning algorithm based on the Fourier amplitude sensitivity test method,” *IEEE Trans. Neural*, vol. 17, no. 2, pp. 273-293, 2006.

[22] D. Mackay, Information Theory, Inference, and Learning Algorithms, Cambridge: Cambridge university Press, 2003.

[23] L. Mazorra Aguiar, B. Pereira, M. David, F. Diaz y P. Lauret, «Use of satellite data to improve solar radiation forecasting with Bayesian Artificial Neural Networks,» *Solar Energy*, vol. 122, pp. 1309-1324, 2015.

[24] P. Lauret, C. Voyant, T. Soubdhan, M. David and P. Poggi, “A benchmarking of machine learning techniques for solar radiation forecasting in an insular context,” *Solar Energy,* vol. 112, pp. 446-457, 2015.

[25] C. Willmott and K. Matsuura, “Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance,” *Climate Research,* vol. 30, pp. 79-82, 2005.

[26] C. Coimbra, J. Kleissl and R. Marquez, “Overview of solar-forecasting methods and a metric for accuracy evaluation,” in *Solar Energy Forecasting and Resource Assessment.*, Elsevier,, 2013, pp. pp. 171-194.