SASEC2015
Third Southern African Solar Energy Conference
11 – 13 May 2015
Kruger National Park, South Africa

DAY AHEAD SOLAR FORECASTING APPLIED TO AN INSULAR SITE

David M.*, Lauret P., and Tapachés E.
*Author for correspondence
PIMENT laboratory,
University of La Reunion,
15, avenue René Cassin, 97715,
Saint-Denis,
E-mail: mathieu.david@univ-reunion.fr

ABSTRACT

Some small territories, like islands and isolated areas, actually experience a high penetration rate of PV inside a small electricity grid. Moreover, the high amplitude fluctuations of PV outputs can destabilize the grid stability. In order to avoid the risk of blackout, some countries set up regulatory limits of PV integration. In this context, the forecasting of the PV output is necessary for the supply-demand balance and for the increase of the penetration rate of PV. Previous works on this topic were mainly done for large-scale continental grids. Due to the small scale of the climatic phenomena, forecasting the solar irradiance in insular territories addresses new issues. In order to cope with specific plant operations, forecasts must be provided with different granularities and horizons. In this work, we will focus on day ahead forecasts with an hourly granularity. Day-ahead forecasts are produced for scheduling of resources and commitment of units of production. This paper presents a comparison of two post processing models. A Model Output Statistics (MOS) and an Artificial Neural Network (ANN) are applied to the IFS (Integrated Forecast System) forecasts for the insular site of Saint-Pierre in Reunion Island. The small scale of the climatic phenomena requires to set up these post processing methods differently than in the continental areas.

INTRODUCTION

Between 2005 and 2011, the French government set up an incentive policy in order to develop the electricity production from photovoltaic. During this period, the feed-in tariffs proposed were specifically high in the overseas territories, as Reunion Island [1]. It resulted an exponential increase of the installed PV systems. For these small grids, an important penetration rate of such a variable means of production can destabilize the supply-demand balance. A regulatory limit of 30% of the instantaneous power produced from intermittent renewables (solar, wind and waves) was defined in order to avoid this risk [2]. This legal constraint was reached in 2012 in Reunion. In this context, the forecast of the PV output power is essential in order to guarantee the supply-demand balance. First, it will help the grid operator and the PV producers to better manage the means of production and storage. Second, it will permit to stretch the mandatory limit of 30% and so to increase the penetration rate of PV.

In order to cope with specific plant operations, forecasts must be provided with different granularities and horizons [3]. In this work, we will focus on day ahead forecasts with an hourly granularity, so called short term forecasts. Day-ahead forecasts are produced for scheduling of resources and commitment of units of production.

Forecasting of global horizontal irradiance (GHI) is the first and most essential step in most PV power prediction systems [4]. Common operational approaches to short-term solar radiation forecasting is the use of numerical weather prediction (NWP) models that infer local cloud information – hence, indirectly, transmitted radiation – through the dynamic modeling of the atmosphere up to several days ahead [5]. The NWPs are used worldwide to forecast the weather and they are not initially designed to produce accurate solar irradiance forecasts for PV applications. In order to refine the forecasts of the NWP, post-processing methods have been applied to the global models IFS [6] and GEM [7]. These works were done for continental areas. The coarse spatial resolution of the global NWP is potentially an issue for the forecasting of solar irradiance in insular territories that experience numerous microclimates in a reduced area.

The aim of this work is to compare two different methods of post-processing applied to the solar forecasts provided by the European Centre of Medium-Range Weather Forecasts (ECMWF) for the insular site of Saint-Pierre in Reunion Island. These two models of post-processing are the wellknown MOS developed by Lorenz et al. [6] and a artificial Neural Network (NN) designed by our team.

GROUND DATA MEASUREMENTS AND PRE-PROCESSING

Solar irradiance measurements

The weather station is located at Saint-Pierre (21°20 South, 55°29 East, 75 meters of elevation) in the southern coastal part of Reunion Island. The station measures the Global Horizontal Irradiance (GHI) every six seconds and the 1-minute averages are recorded. The hourly used data correspond to the average of the previous 60 minutes of measurements. The solar irradiance is measured with a secondary standard pyrometer (CMP11 Kipp & Zonen).

Two years of records without missing data, 2012 and 2013, were provided for this work. The year 2012 was used for the calibration of the models and the year 2013 was used to test the models. So all the results presented further in this paper correspond to the test year 2013.

Clear sky index

Solar irradiance is characterized by diurnal and seasonal variations. The clear sky index (k_t*) is commonly used to remove this deterministic component of the GHI. It corresponds to the ratio of the measured GHI to the theorical GHI observed under clear sky conditions.

The clear sky irradiance is generated with the BIRD model [8]. This simple model performs estimates with acceptable accuracy and with only few inputs [9]. The input parameters of the BIRD model are set to their climatological means and they remain constant. The optical depth of the atmosphere components corresponding to Reunion Island were retrieved from the AERONET website [10].

Zenith angle filtering

Low solar elevations induce complex reflections phenomenon and the values of the measured GHI are often not reliable. Furthermore, the amount of solar energy received at ground level in this condition is not significant. As a consequence, data corresponding to a zenith angle (θ_z) superior to 85° are removed. So night times and low solar elevations were not taken into account for the calibration and the test of the models.

MEASURES OF ACCURACY

In this paper, we focus on a few measures of accuracy that are considered to be the most relevant for the solar forecasting [11,12]. We used the mean bias error (MBE – eq. 1), the root mean square error (RMSE – eq. 2) and the mean absolute error (MAE – eq. 3). In equation 1 to 3, $X_{forecast,i}$ and $X_{measure,i}$ correspond respectively to the forecasted GHI and the measured GHI at time i.

$$MBE = \frac{1}{N}\sum_i^N\left(X_{forcast,i} - X_{measure,i}\right) \qquad (1)$$

$$MAE = \frac{1}{N}\sum_i^N\left|X_{forcast,i} - X_{measure,i}\right| \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_i^N\left(X_{forcast,i} - X_{measure,i}\right)^2} \qquad (3)$$

Relative values of the error measures (rMBE,rRMSE and rMAE) will be given in the following sections. Normalization is done with respect to mean ground measured irradiance of the considered period.

DAY-AHEAD FORECASTING

Initial ECMWF forecast

The European Centre for Medium-Range Weather Forecasts (ECMWF) is an intergovernmental organization that provides operational forecasts. It maintains and runs the numerical weather prediction (NWP) model named Integrated Forecast System (IFS). NWP models give relatively accurate forecasts for horizon superior to 6 hours [5,13]. Initial day-ahead forecasts of GHI are the uncorrected values provided by the ECMWF.

In order to supply forecasts that can be used by the grid operator for day-ahead scheduling, we retrieved the data generated by the IFS at 12h00 UTC (16h00 in Reunion). The forecasts correspond to hourly data with a spatial resolution of 0.125° x 0.125° (approximately 14km x 14km in Reunion).

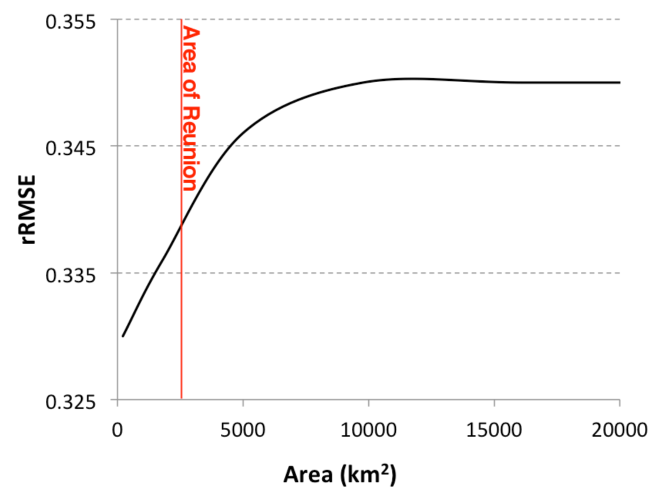
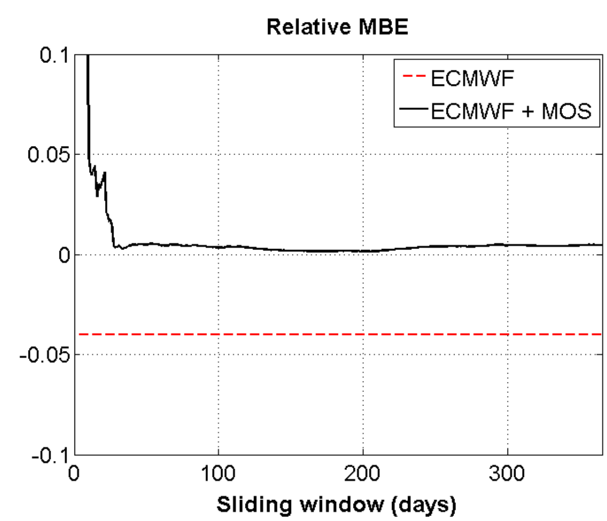


Figure 1 Day-ahead forecast error over spatial averaging of ECMWF around Saint-Pierre



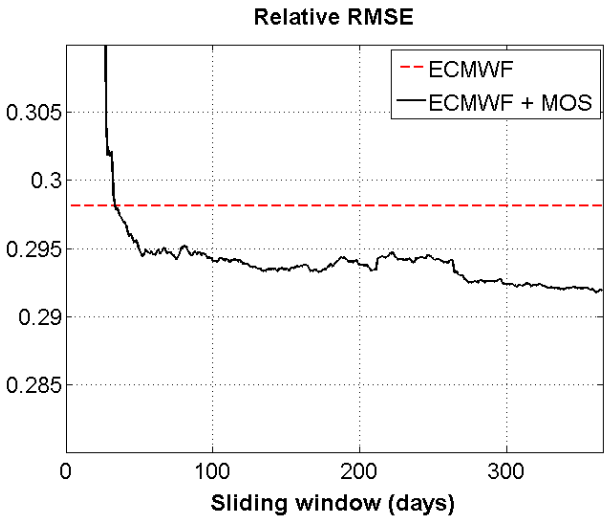


Figure 2 Day-ahead forecast error over the size of the sliding window for the calibration of the polynomial function of fourth order

MOS post-processing

Lorenz et al. showed that the ECMWF forecasts can be refined with model output statics (MOS) techniques [6]. Three steps of correction are proposed in their work in order to reduce the error of the forecast.

First, the arithmetic average of surrounding pixels can potentially reduce the RMSE. For the site of Saint-Pierre, the spatial averaging does not improve the forecast accuracy (Fig. 1). The lowest RMSE is obtained for the nearest pixel. Due to the coarse spatial resolution of the ECMWF, each forecast point is related to a different microclimate and a very different level of irradiance. So the spatial averaging will not be applied.

Second, for very a low total cloud cover (*TCC*), the forecasted GHI is underestimated. In these conditions, a forecast provided with a clear sky model enables to reduce the bias.

Finally, the bias is modeled by a polynomial function of fourth order in the clear sky index (k_t*) and the cosine of the zenith angle ($cos\theta_z$). The calibration of the polynomial function can be done with the historical data [6] or with a sliding window covering the last days of measurements [14]. These two approaches were compared. The longer is the size of the sliding window used to calibrate the polynomial function the better is the RMSE (Fig. 2). Thus, the calibration of the model was done with the historical data of year 2012 and the test was done with the data of the year 2013.

Neural Network post-processing

Artificial Neural Networks (NNs) are data driven approaches capable of performing a non-linear mapping between sets of input and output variables. A NN with d inputs, m hidden neurons and a single linear output unit defines a non-linear parameterized mapping from an input vector x to an output y given by the following relationship:

$$y = y(x; w) = \sum_{j=1}^{m} w_j\, f\left(\sum_{i=1}^{d} w_{ji}\, x_i\right) \qquad (4)$$

Each of the m hidden units are related to the tangent hyperbolic function $f(x) = (e^x - e^{-x})/(e^x + e^{-x})$. The parameter vector $w = (\{w_j\}, \{w_{ji}\})$ governs the non-linear mapping and is estimated during a phase called the training or learning phase. During this phase, the NN is trained using a dataset (called training set) of n input and output examples. The second phase, called the generalization phase, consists of evaluating the ability of the NN to generalize, that is to say, to give correct outputs when it is confronted with examples that were not seen during the training phase.

Careful attention must be put on the building of the model, as a too complex ANN will easily overfit the training data. Several techniques like pruning or Bayesian regularization [15] can be employed to control the NN complexity. In this work, we used the Bayesian Technique in order to automatically control the NN complexity and therefore improve the generalization capability of the model [16].

In our context, a NN is used to model the bias of the NWP forecasts in relation with the clear sky index (k_t*) and the cosine of the zenith angle ($cos\theta_z$). The MOS-corrected ECMWF forecasts are obtained by subtracting the modeled bias from the original ECMWF forecasts.

RESULTS

The computational time of the two tested methods is very low and the post-processing of a day-ahead forecast can be produced in less than 1 second. Post-processing of the day-ahead forecasts produced by a NWP permits to improve their quality. The bias is efficiently reduced to a value close to 0. However the quadratic error is only slightly improved (Table 1).

Relative error (%)	MBE	RMSE	MAE
Initial ECMWF	-3.99	29.8	21.0
ECMWF + MOS	0.96	29.3	20.2
ECMWF + NN	0.81	28.9	20.0

Table 1 Relative errors of day-ahead forecast (mean GHI = 498.2 W.m-2)

Figure 3 shows the percentage of "good" forecasts for the initial ECMWF data and for the two post-processing methods. A "good" forecast corresponds to a forecast that enters in the same range of clear sky indices as the measured data. Three range of clear sky indices are defined. Boundaries of the different sky conditions were defined by Reindl et al. for the clearness index [17]. In our study, we used the same boundaries but they are applied to the clear sky index. They are representative of the three types of sky conditions : clear sky, cloudy sky and overcast sky. On average, the ECMWF model underestimates the solar irradiance with a negative bias (Table 1). The post-processing techniques allowed to reduce this bias by increasing the number of forecasted clear sky hours. But unfortunately, the MOS techniques also reduced the percentage of good forecasts in case of cloudy or overcast skies.

The MOS technique based on the 4th order polynomial model is a linear parameterized model while the NN model is able to reproduce more complex non-linear relationships between the inputs and the output. The better results obtained with the NN confirms that non-linear relationships probably exist between the error of the ECMWF model and the selected inputs (i.e. K_t* and $\cos\theta_z$).

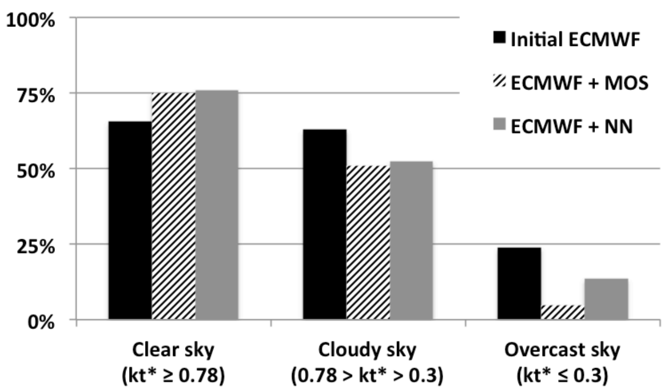


Figure 3 Rate of "good" forecast before and after the post-processing for the 3 different sky conditions

CONCLUSION

Forecasting the solar irradiance is mandatory for the non interconnected grids that experience an important penetration rate of PV. It allows the distribution system operator to anticipate the sudden variations of the PV power output and to schedule the management of the ressources.

Day-ahead forecasts are initially produced by NWP models. Their accuracy can be refined by using post-processing techniques. Two models of post-processing have been applied to the ECMWF day-ahead forecasts: MOS and NN. The bias of the NWP forecasts is modeled with the clear sky index (K_t*) and the cosine of the solar zenith angle ($\cos\theta_z$). Using these inputs, both models allow to reduce efficiently the bias of the initial solar irradiance forecasted by the NWP. However, this correction improves slightly the RMSE. Even if the NN model performs better than the MOS, their accuracy remains however very close for the study case of la Reunion.

ACKNOWLEDGMENT

The authors would like to thank the European Centre for Medium-Range Weather Forecasts (ECMWF) for providing forecast data.

REFERENCES

[1] Praene J.P., David M., Sinama F., Morau D., Marc O., Renewable energy: Progressing towards a net zero energy island, the case of Reunion Island Review, *Renewable and Sustainable Energy Reviews*, Vol. 16, 2012, pp. 426-442

[2] Arrêté du 23 avril 2008 relatif aux prescriptions techniques de conception et de fonctionnement pour le raccordement à un réseau public de distribution d'électricité en basse tension ou en moyenne tension d'une installation de production d'énergie électrique, *JORF*, 2008, pp. 6920-6930

[3] Kostylev V., Pavlovski A., Solar power forecasting performance – towards industry standards, *Proceedings of the First international workshop on the integration of solar power into power systems*, Aarhus, Denmark, 2011.

[4] Diagne M., David M., Lauret P., Boland J., Schmutz N., Review of solar irradiance forecasting methods and a proposition for small-scale insular grids, *Renewable and Sustainable Energy Reviews*, Vol. 27, 2013, pp. 65–76

[5] Perez R., Lorenz E., Pelland S., Beauharnois M., Van Knowe G., Hemker K., Heinemann D., Remund J., Müller S.C., Traunmüller W., Steinmauer G., Pozo D. Ruiz-Arias J.A., Lara-Fanego V., Ramirez-Santigosa L., Gaston-Romero M., Pomares L.M., Comparison of numerical weather prediction solar irradiance forecasts in the US, Canada and Europe, *Solar Energy*. Vol. 94, 2013, 305–326.

[6] Lorenz E., Hurka J., Heinemann D., Beyer H.G., Irradiance Forecasting for the Power Prediction of Grid-Connected Photovoltaic Systems, *IEEE Journal of selected topics in applied earth observation and remote sensing*, Vol. 2, 2009, pp. 2-10

[7] Pelland S., Galanis G., Kallos G., Solar and photovoltaic forecasting through post-processing of the Global Environmental Multiscale numerical weather prediction model: Solar and photovoltaic forecasting, *Progress in Photovoltaics: Research and Applications*, Vol. 21, 2013, pp. 284–296

[8] Bird R.E., Hulstrom R.L., Simplified Clear Sky Model for Direct and Diffuse Insolation on Horizontal Surfaces, *Technical Report No. SERI/TR-642-761*, Golden, CO: Solar Energy Research Institute, 1981

[9] badescu V., Gueymard C.A., Cheval S., Opera C., Baciu M., Dumitrescu A., Iacobescu F., Milos I., Rada C., Accuracy analysis for fifty-four clear-sky solar radiation models using routine hourly global irradiance measurements in Romania, *Renewable Energy*, Vol. 55, 2013, pp. 85-103

[10] http://aeronet.gsfc.nasa.gov/

[11] Glassley W., Kleissl J., Van Dam C.P., Shiu H., Huang J., Braun G., Holland R., Current state of the art in solar forecasting, *Final report, Appendix A, California Renewable Energy Forecasting, Resource Data and Mapping*, California Institute for Energy and Environment, 2010

[12] David M., Diagne M., Lauret P., Output and errors indicators for solar forecasting models, *Proceedings of World Renewable Energy Forum (WREF) 2012*, American Solar Energy Society, Denver, Colorado, USA, 2012, pp. 831–836

[13] Perez R., Kivalov S., Schlemmer J., Hemker K. Jr., Renne D., Hoff T.E., Validation of short and medium term operational solar radiation forecasts in the US , *Solar Energy*, Vol. 84, 2010, pp. 2161-2172

[14] Lorenz E., Scheidsteger T., Hurka J., Heinemann D., Kurz C., Regional PV power prediction for improved grid integration, *Progress in photovoltaics: Research and Applications*, Vol. 19, 2010, pp. 757-771

[15] MacKay DJC., A practical Bayesian framework for back-propagation networks, *Neural Computation*, Vol. 4, 1992, pp. 448–72.

[16] Lauret P., Fock E., Randrianarivony R.N., Manicom-Ramsamy J.F., Bayesian neural network approach to short time load forecasting, *Energy Conversion and Management*, Vol. 49, 2008, pp. 1156-1166

[17] Reindl D.T., Beckman W.A., Duffie J.A., Evaluation of hourly tilted surface radiation models, *Solar Energy*, Vol. 45, 1990, pp. 9–17