Photovoltaic Forecasting: A state of the art

Bella Espinar, José-Luis Aznarte, Robin Girard, Alfred Mbairadjim Moussa, Georges Kariniotakis

Photovoltaic Forecasting: A state of the art

B. Espinar, J.L. Aznarte, R. Girard, A.M. Moussa and G. Kariniotakis

MINES ParisTech (CEP), B.P. 207, 1 rue Claude Daunesse,F-06904 Sophia Antipolis Cedex
Tel. +33(0)493678967; FAX: +33 (0)493957535,bella.espinar@mines-paristech.fr

Abstract

Photovoltaic (PV) energy, together with other renewable energy sources, has been undergoing a rapid development in recent years. Integration of intermittent energy sources as PV or wind power is challenging in terms of power system management in large scale systems as well as in small grids. Indeed, PV energy is a variable resource that is difficult to predict due to meteorological uncertainty. To facilitate the penetration of PV energy, forecasting methods and techniques have been used. Being able to predict the future behavior of a PV plant is very important in order to schedule and manage the alternative supplies and the reserves. In this paper we presented an overview aiming at a classification attending to the different techniques of forecasting methods used for PV or solar prediction. Finally, recent new approaches that take into account the uncertainty of the estimation are introduced. First results of these kind of models are presented.

1 Introduction

Photovoltaics (PV) for electricity generation is the fastest-growing energy technology since 2002, experiencing an average annual increase of 48% [21]. The cumulative global installed capacity reaches 15200 MW, of which the majority are grid-connected systems [39]. In some power systems, like in the case of islands, PV penetration reaches already high levels and the management of the PV production is becoming an issue for the system operators.

The main challenge of PV power is its variability. Conventional power sources, apart from occasional technical failures, are easily dispatchable in the sense that future production can be precisely planned beforehand. This is not the case with wind or PV power generation, which closely depend on the weather conditions.

Subsequently, forecasting the power output of a PV plant for the next hours or days is necessary for the optimal integration of this production into power systems. This is similar to the case of wind energy where short-term forecasting tools are widely used nowadays. Two extensive reviews of the state of the art in wind power forecasting are available in [15] and in [18]. Forecasts of the renewable production can be useful to estimate reserves, for scheduling the power system, for congestion management, for coordinating renewable with storage, or for trading in the electricity markets. Although extensive research has been carried out since mid '80s on wind power forecasting, the situation is quite different for the case of photovoltaics. Research in the last decades has concentrated on forecasting solar irradiation, while few works focus on prediction of PV production and even less on uncertainty estimation of the predictions. As in a solar panel at a fixed temperature, the power production is close linear depended on global irradiance [31], then predicting solar irradiance is not expected to be very different from predicting PV power.

Numerical Weather Predictions (NWP). Amongst the different forecasting approaches, making use of a global numerical weather prediction (NWP) models is a common strategy. Amongst the most used NWP services are found the global model of the European Centre for Medium-Range Weather Forecasts (ECMWF) or the Global Forecast System (GFS) model of the National Centers for Environmental Prediction (NCEP).

NWP uses current weather conditions as input into mathematical models of the atmosphere to predict the weather. NWP models are expected to have the potential to satisfy the requirements and have been used in forecasting solar irradiance for up to several days [29, 37, 23].

These NWP global models have a coarse temporal and spatial resolution and do not allow for a detailed mapping of small-scale features. Different methods to derive optimized hourly and site specific irradiance forecasts have been proposed: the use of mesoscale models, as the MM5 regional climate model, developed at the Penn State University / National Center for Atmospheric Research (PSU/NCAR), the application of statistical post-processing tools or a combination of both, and also a synoptic approach combining different forecasting models [30, 24].

Mesoscale models are three-dimensional regional models based on primitive equations. They usually use staggered grids, terrain-following vertical coordinates, and four-dimensional data assimilation using nudging. They include parameterizations for several processes, e.g., turbulence and radiation. The accuracy of MM5 forecasts of solar irradiance and the dependency on different MM5 configurations as well as on different input data is still not known in detail. Only a few studies have investigated MM5 estimations of solar irradiance for single locations and extended studies on regional forecasts of solar irradiance are still pending [44, 3].

Other mesoscale models as HIRLAM (High Resolution Limited Area Model) or WRF (Weather Research and Forecasting Model) are used worldwide for the short-term forecasting of hourly and daily irradiance values [6, 30, 38, 19]. The results show that there is a strong dependence of the forecast accuracy on the climatic conditions. Also it is found a dependency with the season in the year.

2 Classic approaches

Some of the existing approaches are stochastic in nature and others use some form of parameterization of known phenomena [14]. We can classify the clasical approaches into three categories, time series based approaches, others based in the Model Output Statistics (MOS) and a set of other original formulations.

Time series approach. The traditional forecast of PV energy is based on the time series of solar energy and weather conditions, which are used to calculate the electrical energy of PV systems. For long term forecasting the methods are based on climate time series (e.g. markov chain based methods [35]) or weather station data (e.g. reference year based method [8, 10]). Historical data, as well as the typical meteorological year (TMY) data which provide the data for typical months of a synthetic year are only useful to predict the average monthly or even daily PV array performance. A time scale smaller than the day requires knowledge of the cloud cover and their expected instantaneous changes [14]. Autorregresive Models (AR) [6], Moving Average (MA) and Autorregresive Moving Averages (ARMA) models are frequently used to model linear dynamic structures [42], to depict linear relationships among lagged variables and to serve as vehicles for linear forecasting. Non-stationary processes can be modeled by differencing the original process to obtain a stationary process. Multiple differencing may sometimes be required in order to achieve stationarity. This results in an autoregressive integrated moving average ARIMA(p,d,q) model [36, 14].

Model Output Statistics (MOS). The Model Output Statistics (MOS) [20] was also used in the early attempts in irradiance forecasting. MOS is a post-processing technique used to objectively interpret numerical model output. It determines statistical relationship between observed weather elements and variables forecast by a numerical model at some projection time [24, 14]. The work of

[26] was the first application of MOS technique to predict daily solar radiation for the short term, up to two days in advance. [28, 24, 9, 42] are more recent references that have use it for forecasting.

Other approaches. There are other original approaches which try to predict solar radiation or PV production in a different way. For example, using the Euclidean distances for a just-in-time model [43]. A popular method for the very short term forecasting is based on sky monitoring with cameras, to predict the amount of cloud coverage of the sun [40, in German].

3 Advanced models

Given the limitations of the basic models seen above, in the last years much research has been devoted to nonlinear models. Different studies show that nonlinear and non-stationary models are more flexible in capturing the characteristics of data and that, in some cases, are better in terms of estimation and forecasting. These advances do not rule out linear models at all, since these models are a first approach which can be of great help to further estimate some of the parameters [5].

Neural networks. Neural Networks (NN) are a class of nonlinear functional forms which have been developed separately from standard regression techniques. Fitting the network involves training the model over known input and output values; the algorithm adjusts the hidden and output node weights until the output approximates the actual data within a given threshold. Training is accomplished using a back-propagation algorithm, which is analogous to the steepest descent algorithms used in nonlinear regression, except that the derivatives for each weight are adjusted separately. For this reason, the time involved in training can be considerable. Forecast studies with NN are found in [36, 41, 42], in the two last of them, together with fuzzy logic method. Hourly forecasting of different solar spectral bands has been also studied using NN by [17].

Hybrid models. Other classes of models combining nets with other techniques have been proposed in order to overcome the shortcomings of neural nets. They are known as *hybrid models*. We can find models that combine NN with wavelets [12, 11, 32]. Also combination of a global or mesoscale NWP predictions with historic irradiance data or human interpretation for NWP has been tested by [30]. Combination of regressions and NN is another possibility. In these hybrid models, normally an initial regression or ARIMA is estimated, and the residuals are then processed using a neural net. The forecasts from the two separate stages are then combined [36]. These kind of models have been proposed by [1, 25, 46, 45, 33].

4 The use of satellite images

In order to forecast time horizons from a few minutes to hours, it is important to incorporate information on the actual atmospheric state. Data of the European Meteosat satellites are a high quality source for irradiance and cloud information because of their excellent temporal and spatial resolution [23]. The possibility of using irradiance values derived from satellite images for predicting PV production and its performance has been considered. Results indicate that the achievable accuracy is enough to use this kind of data [31].

Geostationary satellites are those than take images always over the same area in the Earth surface. Images from these kind of satellites, as Meteosat, have been used for the forecasting of local solar radiation conditions. In early 90's [27] used a statistical approach for the prediction of cloud motion in Meteosat images. Results were encouraging for the time scale of one hour, but the numerical effort was significant. The basis of the method of [7] is the determination of cloud structures movement in previous images and then extrapolate it to predict the cloud positions for the next time step. As a consequence, the local irradiance forecast is available. A multiresolution decomposition technique allowed to decompose the satellite image into local averages and gradients on various spatial scales for forecasting [22].

5 Approaches comparison

[36] has compared different approaches, namely ARIMA in logs with time-varying coefficients, Unobserved Components models, Transfer functions, NN and hybrid models, for the short-term forecast up to 4h in a time step of 5, 10, 15, 30 and 60 minutes. After the comparison for a period of some years and several geographic locations in USA, results show that there is no universal forecasting method but the choice of the model depends critically on the wanted resolution.

[42] have compared lineal (ARIMA) and non-lineal models (Feed-forward Neural Network, Radial-Basic function network, ELMANN recurrent network and Adaptative neuro-fuzzy inference systems ANFIS) for one day ahead hourly forecasting. The models were evaluated by the RMS difference value, resulting from 30 Wm^{-2} to 40 Wm^{-2} for non-lineal models, nearly 30 Wm^{-2} for ANFIS and about 40 Wm^{-2} for ARIMA.

6 New approaches

Most of the existing solar power prediction methods provide point forecasts, that is a single value of the PV production in each predicted horizon. However, associating uncertainty estimates to these point forecasts is crucial for end-users. They may take the form of quantile, interval or density forecasts. These models are altogether referred to as *probabilistic forecasts*.

Uncertainty forecasts, when appropriately incorporated in decision-making methods, are expected to contribute in increasing the value of solar generation. Recent developments in that direction within the field of wind power include, amongst others, models and methods for dynamic reserve quantification [16], for the optimal operation of combined wind-hydro power plants [13, 2] or for the design of optimal trading strategies in liberalized electricity pools [34].

Recently, [4] have evaluated two advanced non-parametric statistical methods (Random Forest and Support Vector Machine) for point forecasting, as well as their probabilistic forecasting version (Quantile regression Forest and Support Vector Machine for Quantile Regression). Regarding the proposed point forecast models, in their application to the data obtained from a real, grid-connected PV power station located in France, they have shown that these models managed to properly predict sunny days up to a satisfactory accuracy degree, whereas cloudy or unstable days pose more difficulties to be forecast. It is worth noticing that the overall performance obtained is twice better the typical performance obtained for the case of wind farms at flat terrain.

With regard to probabilistic models, they have shown that these models give results which are more interpretable and of a higher value than the standard point forecasting models, while retaining the same accuracy levels. This sets a promising path towards more usable forecasting modules that are of interest for the electricity industry.

These results support the validity of the non-parametric approach towards the forecasting of photovoltaic power.

References

[1] L. Aburto and R. Weber. Improved supply chain management based on hybrid demand forecasts. *Applied Soft Computing*, 7:136–144, 2007.

[2] J. Angarita and J. Usaola. Combining hydro-generation and wind energy biddings and operation on spot electricity markets. *Electric Power Systems Research*, 77(5-6):393–400, 2007.

[3] M. Armstrong. Comparison of MM5 forecast shortwave radiation with data obtained from the Atmospheric Radiation Measurement Program. Master of Science Scholarly Paper, 2000. University of Maryland (USA).

[4] J. Aznarte, R. Girard, B. Espinar, and G. Kariniotakis. Short-term forecasting and uncertainty management of solar power production. *IEEE Transactions on Energy Conversion*, 2010. Submitted.

[5] J. L. Aznarte M. *Modelling time series through fuzzy rule based models: a statistical approach*. PhD thesis, Universidad de Granada, 2008.

[6] P. Bacher, H. Madsen, and H. A. Nielsen. Online short-term solar power forecasting. *Solar Energy*, 83(10):1772–1783, 2009.

[7] H. Beyer, C. Costanzo, D. Heinemann, and C. Reise. Short range forecast of PV energy production using satellite image analysis. In *12th European Photovoltaic Solar Energy Conference*, pages 1718–1721, Amsterdam (Netherlands), 1994.

[8] T. Bien and H. Musikowski. Forecasting photovoltaic energy using a fourier series based method. In *23rd European Photovoltaic Solar Energy Conference*, pages 3088–3091, Valencia (Spain), 1st-5th September 2008.

[9] S. Bofinger and G. Heilscher. Solar electricity forecast - approaches and first results. In *21th PV Conference*, Dresden (Germany), 4th-8th September 2006.

[10] B. Brinkworth. Autocorrelation and stochastic modelling of insolation sequences. *Solar Energy*, 19:343–347, 1977.

[11] J. Cao and S. Cao. Forecast of solar irradiance using recurrent neural networks combined with wavelet analysis. *Applied Thermal Engineering*, 25:161–172, 2005.

[12] J. Cao and S. Cao. Study of forecasting solar irradiance using neural networks with preprocessing sambple data by wavelet analysis. *Energy*, 31:3435–3445, 2006.

[13] E. Castronuovo and J. Pecas Lopes. On the optimization of the daily operation of a wind-hydro power plant. *IEEE Transactions on Power Systems*, 19(3):1599–1606, 2004.

[14] B. Chowdhury and S. Rahman. Forecasting sub-hourly solar irradiance for prediction of photovoltaic output. In *IEEE Phtovoltaic Specialist Conference*, pages 171–176, New Orleans (USA), 1987.

[15] A. Costa, A. Crespo, J. Navarro, G. Lizcano, H. Madsen, and E. Feitona. A review on the young history of wind power short-term prediction. *Renewable and Sustainable Energy Reviews*, 12(6):1725–1744, 2008.

[16] R. Doherty and M. O'Malley. A new approach to quantify reserve demand in systems with significant installed wind capacity. *IEEE Transactions on Power Systems*, 20(2):587–595, 2005.

[17] H. K. Elminir, F. F. Areed, and T. S. Elsayed. Estimation of solar radiation components incident on Helwan site using neural networks. *Solar Energy*, 79:270–279, 2005.

[18] R. B. G. Giebel and G. Kariniotakis. The state-of-the-art in short-term prediction of wind power. Technical report, European Commission (Project ANEMOS, Development of a Next Generation Wind Resource Forecasting System for the Large-Scale Integration of Onshore and Offshore Wind Farms), 2003.

[19] C. Geijo Guerrero and B. Orfila Estrada. Verificación de predicciones a corto plazo de energía solar mediante datos de piranómetros y observaciones de satélite. In *XIX Jornadas Científicas de la Asociación Meteorológica Española y VII Encuentro Hispano Luso de Meteorología*, Pamplona (Spain), 2006.

[20] H. Glahn and D. Lowry. The use of Model Output Statistics (MOS) in objective weather forecasting. *Journal of Applied Meteorology*, 11:1203–1211, 1972.

[21] Globaldata. Global solar photovoltaic market analysis and forecasts to 2020. Technical report, Globaldata, 2009.

[22] A. Hammer, D. Heinemann, C. Hoyer, and E. Lorenz. Satellite based short-term forecasting of solar irradiance - Comparison of methods and error analysis. In *Proceedings of the EUMETSAT Meteorological Satellite Data Users' Conference*, Antalya (Turkey), 1st-5th October 2001.

[23] A. Hammer, D. Heinemann, C. Hoyer-Klick, E. Lorenz, B. Mayer, and M. Schroedter-Homscheidt. Remote sensing and atmospheric physics for an efficient use of renewable energies. Status Report 2004-2007. Technical report, Virtual Institute of Energy Meteorology, 2007.

[24] D. Heinemann, E. Lorenz, and M. Girodo. Forecasting of solar radiation. In E. Dunlop, L. Wald, and M. Suri, editors, *Solar Energy Resource Management for Electricity Generation from Local Level to Global Scale*, Nova Science Publishers, Hauppauge, 2006.

[25] M. Hibon and T. Evgeniou. To combine or not to combine: selecting among forecast and their combinations. *International Journal of Forecasting*, 21:15–24, 2005.

[26] J. Jensenius and G. Cotton. The development and testing of automated solar energy forecasts based on the Model Output Statistics (MOS) technique. In *1st Workshop on terrestrial solar resource forecasting and on use of satellites for terrestrial solar resource assessment*, Washington, D.C., 1981.

[27] A. Kaifel and P. Jesemann. An adaptive filtering algorithm for very short-range forecast of cloudiness applied to Meteosat data. In *9th Metosat Users Meeting*, Locarno, 1992.

[28] E. Lorenz, D. Heinemann, H. Wickramarathne, H. Beyer, and S. Bofinger. Forecast of ensemble power production by grid-connected PV systems. In *22nd European Photovoltaic Solar Energy Conference*, Milano (Italy), 3rd-7th September 2007.

[29] E. Lorenz, J. Hurka, G. Karampela, D. Heinemann, H. Beyer, and M. Schneider. Qualified forecast of ensemble power production by spatially dispersed grid-connected PV systems. In *23rd European Photovoltaic Solar Energy Conference*, pages 3285–3291, Valencia (Spain), 1st-5th September 2008.

[30] E. Lorenz, J. Remund, S. Müller, W. Traunmüller, G. Steinmaurer, D. Pozo, V. Lara Fanego, L. Ramírez, M. Gastón Romeo, C. Kurz, L. Martín Pomares, and C. Geijo Guerrero. Benchmarking of different apporaches to forecast solar irradiance. In *24th European Photovoltaic Solar Energy Conference*, Hamburg (Germany), 21st-25th September 2009.

[31] D. Mayer, L. Wald, Y. Poissant, and S. Pelland. Performance prediction of grid-connected photovoltaic systems using remote sensing. Technical Report IEA-PVPS T2-07:2008, International Energy Agency - Photovoltaic Power Systems Programme (IEA - PVPS Task 2), March 2008.

[32] A. Mellit, M. Benghanem, and S. A. Kalogirou. An adaptive wavelet-network model for forecasting daily total solar-radiation. *Applied Energy*, 83(7):705–722, 2006.

[33] M. Nelson, T. Hills, W. Remus, and M. O'Connor. Time series forecasting using neural networks: Should the data be deseasonalized first? *Journal of Forecasting*, 18:359–367, 1999.

[34] P. Pinson, C. Chevallier, and G. Kariniotakis. Trading wind generation from short-term probabilistic forecasts of wind power. *IEEE Transactions on Power Systems*, 22(3):1148–1156, 2007.

[35] V. Puri. Estimation of half-hour solar radiation values from hourly values. *Solar Energy*, 21:409–414, 1978.

[36] G. Reikard. Predicting solar radiation at high resolutions: A comparison of time series forecast. *Solar Energy*, 83:342–349, 2009.

[37] J. Remund, R. Perez, and E. Lorenz. Comparison of solar radiation forecats for the USA. In *23rd European Photovoltaic Solar Energy Conference*, pages 3141–3143, Valencia (Spain), 1st-5th September 2008.

[38] J. Remund, C. Schilter, S. Dierer, S. Stettler, and P. Toggweiler. Operational forecast PV production. In *23rd European Photovoltaic Solar Energy Conference*, pages 3138–3140, Valencia (Spain), 1st-5th September 2008.

[39] REN21. Renewables global status report: 2009 update. Technical report, REN21 Secretariat, 2009.

[40] P. Ritzenhoff. Strahlungssimulation und vorhersage der strahlungsenergie der sonne zur regelung solarer energieversorgungssysteme. Forschungszentrum Jülich, november 1995.

[41] M. Santamouris, G. Mihalakakou, B. Psiloglou, G. Eftaxias, and D. N. Asimmakopoulos. Modeling the global solar radiation on the earth surface using atmospheric deterministic and intelligent data driven techniques. *Journal of Climate*, 12:3105–3116, 1999.

[42] A. Sfetsos and A. H. Coonick. Univariate and multivariate forecasting of hourly solar radiation with artificial intelligence techniques. *Solar Energy*, 68(2):169–178, 2000.

[43] H. Suzuki, Y. Watanabe, and S. Wakao. Short-term output forecast using just-in-time modeling. In *23rd European Photovoltaic Solar Energy Conference*, pages 3406–3408, Valencia (Spain), 1st-5th September 2008.

[44] R. J. Zamora, S. Solomon, E. G. Dutton, J. W. Bao, M. Trainer, R. W. Portmann, A. B. White, D. W. Nelson, and R. T. Mc Nider. Comparing MM5 radiative fluxes with observations gathered during the 1995 and 1999 Nashville Sourthern oxidant studies. *Journal of Geophysical Research D: Atmospheres*, 108:ACL 9–1 ACL 9–13, 2003.

[45] G. P. Zhang. Time series forecasting using a hybrid ARIMA and neural network model. *Neurocomputing*, 50:159–175, 2003.

[46] G. P. Zhang and M. Qi. Neural network forecasting for seasonal and trend time series. *European Journal of Operational Research*, 160:501–514, 2005.