Assessment of probabilistic PV production forecasts performance in an operational context

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***Abstract*— Nowadays, solar power (PV) capacity is undergoing a fast growth. The development of network management systems facilitating its penetration in the distribution network may rely on individual forecasts for each PV plant connected to the grid. This paper describes a probabilistic model for short-term forecasting of PV production which has been developed and tested under operational conditions in the frame of the Nice Grid demonstrator project in France. Detailed results on the performance of the forecasting tool are presented both in terms of deterministic and probabilistic forecasts for a portfolio of 35 PV installations. The results show that in general, even at the household producer level, the forecasts yield good performance.**

Keywords- Photovoltaic, probabilistic forecasting, models, evaluation analysis

I. Introduction

Power generated by photovoltaic (PV) plants is highly dependent on variable weather conditions. To operate a power system with high PV penetration in a secure and economical way, it is crucial to estimate the future PV production. In the literature several forecasting techniques have been developed for PV forecasting. These methods can be classified into 3 families: the statistical, the physical and the hybrid one. These methods use as input combinations of data such as historical measurements, Numerical Weather Prediction (NWP) forecasts, satellites or on-site cameras images.

Nice Grid is the first smart solar-energy district demonstration project to be conducted in France. It is one of the demo cases of the Grid4EU European project. Its objective is to develop a smart electricity grid that harmoniously integrates a high proportion of solar panels, energy storage batteries and intelligent power meters installed in the homes of volunteer participants. Forecasting PV generation accurately is one of the main challenges addressed in the Nice Grid project.

In this paper, we propose initially a short presentation of the state of the art on photovoltaic power forecasting techniques. Then, we describe the method proposed to generate short-term probabilistic PV production forecasts. This method is implemented into an operational forecasting system which is installed and evaluated under real conditions in the frame of the Nice Grid demonstrator. The paper presents the evaluation results for both deterministic (i.e. NBIAS, NMAE and NRMSE) and probabilistic criteria (reliability and sharpness diagrams). The evaluation results are given in comparison to two simple modules based on persistence module and on climatology. In this paper we also compare two sources of NWP models. One has a spatial resolution of 0.25° and a temporal resolution of 3 hours (GFS - NOAA) and the other one has a spatial resolution of 0.1° and a temporal resolution of 3 hours (ARPEGE – METEOFRANCE).

II. Forecasting models

A. A state of the art on short-term PV forecasts

Recent research work has undertaken the development of dedicated short-term (from a few hours to a few days ahead) PV forecasting models based on NWP, basically solar irradiation forecasts [1], [2], [3], [4], [5] and [6].

Detailed modelling of the electrical power output of a PV plant as a function of solar irradiance [1] has been investigated over the years. It generally relies on a parametric modelling of PV modules' efficiency with the incidental irradiance level and ambient temperature [7] and [8]. In a short-term forecasting context however, such a refined modelling may be unnecessary when considering the overall accuracy of other input variables like the NWP forecasts. Thus, a linear relationship between irradiance and power may be assumed [1]. When forecasting PV production from only past production data and solar irradiation forecasts, a statistical linear model may turn in fact, as performant as more complex nonlinear ones [9]. Nonlinear statistical models must nevertheless be useful if deciding to incorporate additional information such as temperature, air humidity or wind speed forecasts as input [2], [5] and [6]. More generally, they may be useful when considering any additional source of nonlinearity.

[1] One has to distinguish solar irradiation which represents the solar radiation energy by surface unit, from solar irradiance which is the solar power by surface unit (i.e. the solar radiation energy by unit of surface and unit of time). The latter is generally expressed in $W.m^{-2}$.

NWP solar irradiation forecasts are generally provided on horizontal plane. On the other hand, PV plants generally have tilted, potentially multiple, panels' orientation(s) [2] involving complex shading conditions. The relationship between irradiance levels, respectively on horizontal plane and on the panels' surface, may be complex and highly nonlinear [10], [11] and [12]. Thus, in some cases, a raw linear assumption between power and forecast irradiance may not be satisfying (even) for short-term forecasting purposes. Advanced non-linear statistical algorithms may perform NWPs' recalibration to PV plant's orientation automatically. An alternative can be to re-estimate solar irradiance forecasts from horizontal to PV plant's orientation, using dedicated models, before carrying the conversion into power forecasts [3] and [4]. In [13], the conversion from horizontal to PV plant's orientation is first applied to clear-sky irradiance estimates. Then, tilted clear-sky irradiance estimates are combined with NWP forecasts characterizing future sky-clarity conditions as input of a Neural-Network.

B. The proposed forecasting model

In this article, we describe a short-term probabilistic PV forecasting model incorporating PV plant's orientation data. As in [13], it relies on clear-sky irradiance estimates derived for the PV plant's orientation.

The considered forecasting approach is as follows: one considers a statistical model to forecast the PV production from surface solar irradiance's weather forecasts. Parameter's values are estimated depending on the time of day so as to capture interactions between the sun's course, the PV panels' orientation, potential shadowing effects, etc. It also allows capturing other effects from diurnal variations of meteorological parameters, such as the influence of temperature on modules' efficiency. Moreover the model's parameters are estimated adaptively using the most recent data available, so as to capture seasonal/climatic variations not explicitly modelled or even represented in the training data set (e.g. variations due to NWP model's updates, to ageing or dirt on PV panels, etc.).

The chosen statistical model is a non-parametric model which has been considered in estimating the whole power distribution at once. It is based on a kernel density estimator (KDE) and can be written as:

$$\hat{f}_{t+h}(p|I) = \frac{c_{I,k,h}}{b_{1,h}(k)} \sum_{i=1}^{N} w_{i,h}(I,k) \left\{ K\left(\frac{p - p_{t_i+h}}{b_{1,h}(k)}\right) + K\left(\frac{p + p_{t_i+h}}{b_{1,h}(k)}\right) + K\left(\frac{p + p_{t_i+h} - 2P_n}{b_{1,h}(k)}\right) \right\} \quad (1)$$

where P_n is the power plant's nominal capacity and the weights $w_{i,h}(I,k)$ are given by:

$$w_{i,h}(I,k) = \lambda^{\frac{t-t_i}{t_2-t_1}} K\left(\frac{I - \hat{I}_{t_i+h}}{b_{2,h}(k)}\right),$$
$$\text{and } c_{I,k,h} = 1/\sum_{i=1}^{N} w_{i,h}(I,k).$$

where $\hat{I}_{t+h}$ is the forecast surface solar irradiance on horizontal plan at time t for horizon h and λ is a fixed factor.

[2] We consider here plants with no sun-tracking system of any kind, thus with fixed panels' orientation.

The model proposed above is a conditional kernel density estimator of the power distribution estimated conditionally to the forecast irradiance level I. The bandwidth selection procedure is a k-nearest neighbours' procedure (see [14]), with the same value k assumed for both the variable p and the covariate I and selected through trials and errors[3].

III. CASE STUDY

The algorithm has been implemented as an operational module to produce PV production forecasts every day for the case study provided by the Nice Grid project. The project aims at developing a smart solar neighbourhood in the urban area of Carros near the city of Nice in the south of France. The network in the considered urban area has been chosen because of its exposure to two common problems: the expected growth of solar power production at the distribution level and the risk of disconnection from the transmission grid. The project, which started in January 2012 and ends in October 2016, includes a high proportion of solar-power panels connected to distributed energy storage systems.

The idea behind Nice Grid is to combine controllable distributed electricity and thermal storage devices with forecasts of solar power production and load in a local energy management system. The project is centred on a network energy management (NEM) system which enables financial transactions among the different actors of the power system. A schematic representation of the architecture being developed and deployed is presented in Figure 1. This paper is dedicated in the evaluation results of the PV production forecasts highlighted in red in the diagram.

The Nice Grid demonstrator involves different types of actors either in the residential or in the tertiary sector. More than 1500 consumers and 50 production sites equipped with PV panels are involved in this project. The total PV installed capacity represents more than 600 kW. Forecasts are calculated for both small producers (from the residential sector) equipped with Linky smart meters and large producers (from the tertiary sector) equipped with an Orange meter. The production data used as input to the forecasts are provided by the smart meters. The forecasts are delivered every day once a day for the next 48 hours with a temporal resolution of 30 minutes. It is required to deliver PV production forecasts to the "Network Constraints Prediction Tool" (NCPT) for all PV producers before 11.00 a.m. local time. The NCPT evaluates the network conditions for each future time step and estimates the flexibilities that have to be mobilized by the different actors like the storage aggregators or the domestic clients aggregators.

[3] Adaptive selection of an optimal value through cross-validation has been first considered but left apart because of the computational burden.

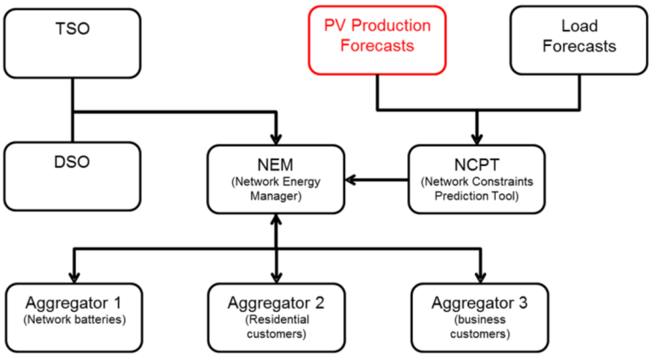

Figure 1. Nice Grid Architecture

IV. Evaluation Results

The objectives of this evaluation are multiple. First, it is necessary to assess whether the performance obtained by the predictive models developed are comparable to the performance of similar models in the literature. For this we adopt a set of evaluation criteria that are considered standard for the assessment of PV production. The assessment relates to both deterministic and probabilistic forecasts.

A. Evaluation Criteria

1) Deterministic forecasts

To evaluate deterministic forecasts, we chose to follow the standardized methodology proposed in different research projects like the SafeWind FP7 project or other international exercises on benchmarking for PV and wind power forecasts [15], [16], [17] and [18]. The criteria considered here are:

- Normalized mean Bias (NBIAS), for each forecast horizon *h*, expressed in percentage:

$$NBIAS(h) = \frac{1}{N \cdot P_{Max}} \sum_{t=1}^{N} \left(p_{t+h} - \hat{p}_{t+h/t}\right) \times 100 \quad (2)$$

- Normalized Mean Absolute Error (NMAE), for each forecast horizon *h*, expressed in percentage:

$$NMAE(h) = \frac{1}{N \cdot P_{Max}} \sum_{t=1}^{N} \left|p_{t+h} - \hat{p}_{t+h/t}\right| \times 100 \quad (3)$$

- Normalized Root Mean Squared Error (NRMSE), for each forecast horizon *h*, expressed in percentage:

$$NRMSE(h) = \frac{1}{P_{Max}} \sqrt{\frac{1}{N} \sum_{t=1}^{N} \left(p_{t+h} - \hat{p}_{t+h/t}\right)^2} \times 100 \quad (4)$$

Where:

$\hat{p}_{t+h/t}$ is the PV power forecast made at time t for horizon h

p_{t+h} is the observed PV power at time $t + h$

N is the number of considered values

P_{Max} is the peak power of the PV panel or plant

2) Probabilistic forecasts

To evaluate probabilistic forecasts, we chose to follow the methodology presented in [19] and [20]. The criteria considered here are:

- Reliability:

Reliability is a term dedicated to the assessment of probability forecasts that matches a criterion that measures the performance of quantile forecasts. It measures the similarity between predictions and observations. This criterion is obtained by calculating, for the evaluation period, the percentage of the measured values (observations) that exceed a certain quantile relative to the total number of observations. In other words, reliability here relates to the "bias" of quantile forecasts. If denoting $\hat{q}^{\alpha}_{t+h/t}$ a quantile forecast at time t for horizon h, the mathematical formulation of this criterion presented in [19] is as follows:

$$Rel^{\alpha}_{h} = \frac{1}{N} \sum_{t=1}^{N} \cdot\, p_{t+h} \leq \hat{q}^{\alpha}_{t+h/t} \quad (5)$$

This ratio should be as close as possible to the nominal value of the quantile. Deviations above approximately 3% on the nominal value of quantile indicate that this quantile forecast is unreliable. Reliability is evaluated for each forecast period separately. This criterion is fundamental when probabilistic forecasts are considered in a process of decision making that considers the uncertainty. Reliability is a property that can be improved by the calibration process of probabilistic prediction models.

- Sharpness:

The *sharpness* of probabilistic forecasts is a property that represents their ability to provide finely particular situations. It represents the degree of "concentration" of the expected distribution. A good forecast should have a very low value of this parameter. A model without "sharpness" is a standard "climate" model where uncertainty is expressed in a constant and independent way in regards to particular meteorological situations. For predicting PV this property is important because the level of uncertainty is different for sunny or cloudy days. The mathematical formulation for this criterion given in [19] is as follows:

$$Sharp^{\alpha}_{h} = \frac{1}{N} \sum_{t=1}^{N} \left(\hat{q}^{1-\alpha/2}_{t+h/t} - \hat{q}^{\alpha/2}_{t+h/t}\right) \quad (6)$$

Unlike the reliability, the sharpness is an inherent property of a forecasting system that cannot be improved by a calibration method [20].

B. PV production forecasts evaluation

This paper presents the evaluation results of the advanced KDE module, using as input the weather forecasts GFS (KDE-1) and ARPEGE (KDE-2). The evaluation results of the advanced KDE model are compared to two single reference methods which do not involve any mathematical model to generate predictions: the *persistence* and the *climatology* (mentioned as global_average in the diagrams below). A first condition for an advanced model is to have a better performance than persistence. *Persistence* characterizes the weather in the short term. Despite its simplicity the performance of this method is not always low. Persistence is obtained here using a forecast equal to the measured value of the previous day at the same time. *Climatology* considers that the forecast for any given time of the day is equal to the average of all the observed values at the same time of day over a long period (i.e. one year). This explains in particular that the value of the mean bias of the evaluation period is zero for climatology.

Probabilistic forecasts were generated for each time of day covering the entire distribution of PV production. These quantile forecasts are given in 10%-steps of the nominal probability. Predictive models are optimized with respect to the prediction that corresponds to the mean of the distribution. Hereby, the assessment using deterministic criteria is made using the average rather than the 50% quantile forecast (median).

The evaluation was conducted on 35 producers after eliminating time series productions for producers for which there were insufficient data. The evaluation covers the period from 01/11/2014 to 01/09/2015. During this period we received 96.7% of the measurement data and 99.9% of the PV forecasts are available. For practical use, in the figures below, we chose to show the evaluation results from a large PV producer which is representative of all of them as it represents almost 10% of the installed capacity of all PV plants.

1) Normalized BIAS

The bias is the average of prediction errors. A good forecast should have a bias close to zero. The chart from Figure 2. shows the evolution of the bias over the forecast horizons, for the two configurations of KDE model KDE-1 and KDE-2 with GFS and ARPEGE respectively, in comparison to the persistence and climatology models, for the PV producer taken into account during this assessment. The figure shows that both configurations of KDE model tend to have a bias slightly higher than the persistence. However this bias remains at low values, around 1%. In this figure, we can see that the ARPEGE forecasts help to improve the bias for the times of day that are critical for the grid operator.

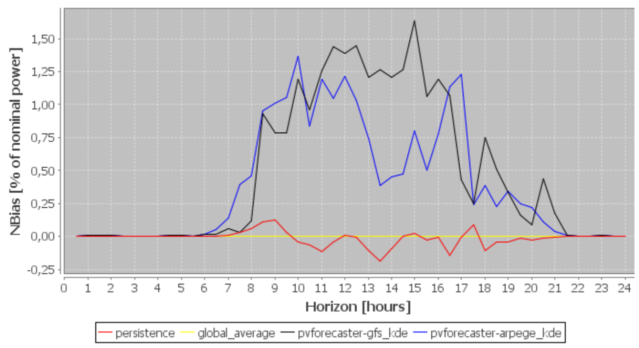

Figure 2. NBIAS over forecast horizons for both configurations of KDE in comparison to the persistence and the climatology

2) Normalized Mean Absolute Error

The NMAE is probably one of the most intuitive assessment criteria, representing the average deviation in absolute values between the forecasted values and the observed ones, normalized to the peak power of the producer. The chart from Figure 3. shows the evolution of NMAE over the forecast horizons, for both configurations of KDE model, persistence and climatology, for the PV producer taken into account during this assessment. The figure shows that the KDE-2 model still has a better performance.

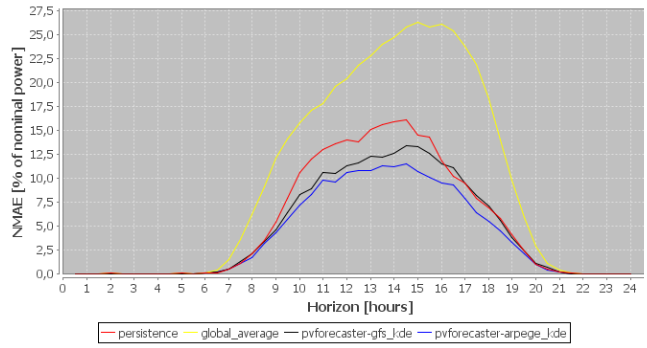

Figure 3. NMAE over forecast horizons for both configurations of KDE in comparison to the persistence and the climatology

3) Normalized Root Mean Squared Error

This criterion is the standard deviation of prediction errors, normalized to the peak power of the producer. Compared to NMAE, the NRMSE gives more weight to the errors with significant values. The chart from Figure 4. shows the evolution of NRMSE over the forecast horizons, for both configurations of KDE model, persistence and climatology, for the PV producer taken into account during this assessment. The diagram shows that the KDE-2 model still has a better performance. It also shows that the KDE-1 model gives a significant improvement in comparison to the persistence for all horizons during daylight hours. This indicates that even with a low spatial resolution's NWP model, weather forecasts help to improve significant errors.

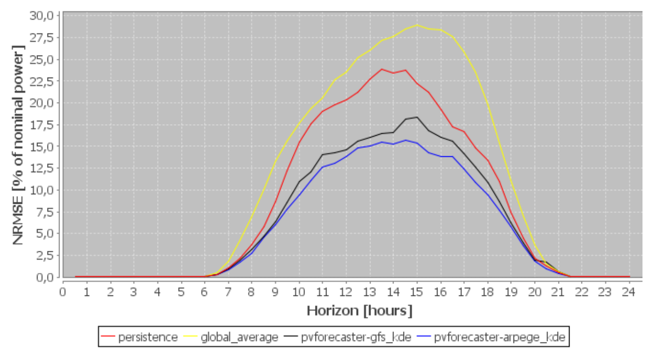

Figure 4. NRMSE over forecast horizons for both configurations of KDE in comparison to the persistence and the climatology

4) Reliability

Figure 5. shows the "reliability diagram" from which optimal reliability is the one corresponding to the diagonal. The diagram shows the reliability of PV forecasts for forecast horizons 9.00, 13.00 and 17.00 local time, for the considered PV producer. We note that overall all the models are "reliable" with better performance for the KDE-2 model. The deviations from the optimal value are limited. We can see that for this PV producer, the curves from horizons 9.00 and 17.00 overlap quite well with the reference diagonal line. This means that for horizons 9.00 and 17.00, we observed as many values as expected in each confidence interval.

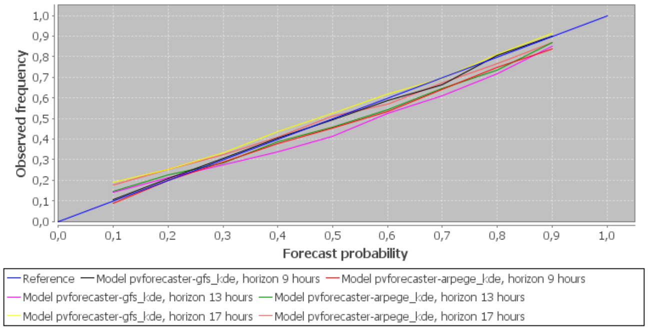

Figure 5. Reliability diagram for both KDE configurations for all 10%-steps quantiles for forecast horizons 9.00, 13.00 and 17.00 local time, in comparison to the persistence and the climatology

5) Sharpness

Sharpness measures the difference between two quantiles. In this case, considered quantiles are quantile 20% and quantile 80%. The chart from Figure 6. shows the evolution of sharpness for each forecast horizon of the day for the KDE model for the considered PV producer. We note that weather forecasts ARPEGE allow an improvement in this criterion.

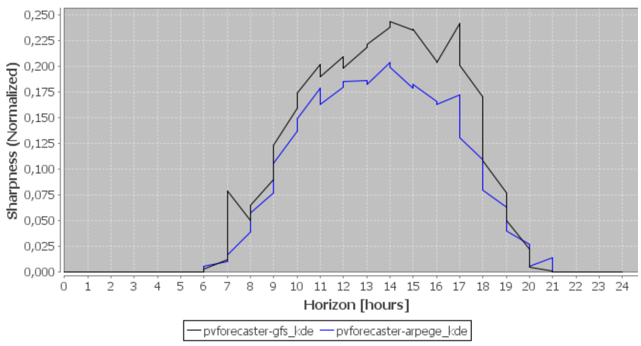

Figure 6. Sharpness criterion diagram over forecast horizons for both KDE configurations for prediction intervals defined by quantiles 20% and 80%, in comparison to the persistence and the climatology

6) Summarising evaluation results

The forecasts were evaluated using standard criteria for evaluating forecasts of renewable production. The values of these criteria were calculated for all producers and the results of this evaluation are summarized in TABLE I. for both configurations KDE-1 and KDE-2 of the advanced PV forecasting model, KDE. The evaluation results from this table only concern horizons between 9.00 and 17.00 local time, as it corresponds to daylight hours.

The work on probabilistic forecasting models led to the development of state of the art equivalent services even for household producers with very low power. In general, even at the household producer level, forecasts yield good performance, with a mean error of approximately 8% between 9.00 and 17.00 local time. This value is deemed satisfactory for practical applications.

TABLE I. OVERVIEW OF THE EVALUATION RESULTS

Criteria (9h-17h)	**Min**		**Average**		**Max**	
	KDE-1	***KDE-2***	***KDE-1***	***KDE-2***	***KDE-1***	***KDE-2***
NBIAS	0.06%	-0.2%	1.4%	1.2%	10.95%	10.4%
NMAE	3.64%	3.10%	8.85%	7.90%	16.62%	15.50%
NMRSE	5.19%	4.60%	12.23%	11.19%	19.73%	18.80%

Min: minimal values of evaluation criteria over all PV producers
Average: average value of evaluation criteria over all PV producers
Max: maximal values of evaluation criteria over all PV producers

V. CONCLUSION

The improvement obtained by the use of higher resolution weather forecasts is significant (i.e. the use of configuration KDE-2 in comparison to configuration KDE-1). This element is useful in a potential cost-benefit analysis of forecasts.

Eventually, in the improvement opportunities of the performance observed here we can mention the potential contribution of intraday forecasts using updated weather forecasts. Intraday forecasts would also allow the use of improved NWP model, such as METEOFRANCE's model AROME, with a spatial resolution of 0.025° and a temporal resolution of one hour. We can therefore reasonably expect improvements on the evaluation of PV production forecasts.

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