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Coordinator:	George Kariniotakis
Company:	ARMINES
Address:	BP 207 F-06904 Sophia Antipolis Cedex France
Telephone:	+33.4.93.95.75.01
Fax:	+33.4.93.95.75.35
Email:	georges.kariniotakis@mines-paristech.fr

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Coordination:	George Kariniotakis	Georges.kariniotakis@mines-paristech.fr
Authors:	José Luis Aznarte	ARMINES (France)
	Robin Girard	ARMINES (France)
	George Kariniotakis	ARMINES (France)
	Bella Espinar	ARMINES (France)
	Alfred Moussa	ARMINES (France)

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Short-term forecasting of photovoltaic power production

José Luis Aznarte M., Robin Girard,
Bella Espinar, Alfred M. Moussa and George Kariniotakis
ARMINES / Center for Energy and Processes (CEP), Mines ParisTech

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Abstract

Predicting solar irradiation or photovoltaic power production are two variants of the same problem, especially in the framework of the renewable energies integration into the electricity markets. Being a variable resource at the ground level, solar energy poses difficulties with respect to tradicional power sources, and therefore the availability of precise and reliable forecasts becomes an urgent need.

In this paper, we present a study on forecasting power production from a real photovoltaic installation, introducing the use of some unsupervised models to predict this production by relying on numerical weather predictions. Probabilistic forecasts, which predict the whole probability distribution of the data, are also provided.

Contents

1 Introduction

Photovoltaics (PV) for electricity generation is the fastest-growing energy technology since 2002, experiencing an average annual increase of 48% (1). The cumulative global installed capacity reaches 15,200MW, of which the majority are grid-connected systems (2). 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 (3) and in (ANEMOS-state of the art). 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.

In a solar panel at a fixed temperature, the power production is close to linear with respect to the global irradiance (4). Hence, the problem of predicting solar irradiance is not expected to be very different from the problem of predicting PV power. In this work, we will mainly refer to PV power, but the methods and results are readily applicable to irradiance.

1.1 State of the art

Numerial 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).

Numerical weather prediction 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 in forecasting solar irradiance for up to several days (5).

NWP has been used for short-term forecast, up to some days ahead. For example, (6) use three PV production models based on NWP: a linear combination of the values of three variables from ECMWF, a linear combination of clearness index kt (defined as the ratio of the observed solar aradiation to the maximum solar radiation) derived from these three values and finally, they also apply a kt depended bias correction to the former model. Forecast are up to three days with a hourly time resolution. As the authors explain, a common problem is that in general no detailed information of all PV systems for a control area is available. They propose a statistical method to select representative systems that adequately characterize the actually given ensemble. They obtein better results in terms of relative RMSE for 10 km^2, being of the same order than for wind prediction and enough to allow their safe penetration in the electricity marked.

Taking a comparative approach, (7) presents a comparison of short-term solar forecasting for 2 days ahead, for hourly irradiance from three different NWP models, ECMWF, National Digital Forecast Database (NDFD) and GFS/Weather Research and Forecasting (WRF). They evaluated the results with the RMSE value and the advanced Kolmogorv-Smirnov test (8). They studied the results from April to September 2007 for four stations in USA and, in their modelling process, they apply a correction of the results based on the bias value from the last four weeks. They concluded that the ECMWF was the better forecast model, followed by NDFD and GFS/WRF.

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 (9; 10).

Mesoscale models 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.

One of the most used mesoscale models is the PSU/NCAR model MM5, which is a regional-scale primitive equation model that can be configured hydrostatically or non-hydrostatically. It uses a terrain-following coordinate in pressure, solves its finite-difference equations with a time-split scheme and has multiple nesting capabilities. Parameterization of atmospheric radiation provides longwave and shortwave schemes that interact with the atmosphere including cloud and precipitation fields as well as with the surface (10).

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 (11; 12).

(10) have studied a case of using MM5 for forecasting surface solar irradiance for lead times of up to 48 hours for regions as well as for single locations was also carried out. Their results show the direct output from numerical macro- or mesoscale models for one- or two-day forecasts severe deviations between forecasted and real irradiance. They explain that with the role of radiant fluxes in numerical models, because they are important as a driver for atmospheric processes and but much less significant for the production of precise surface solar irradiances. The indirect use of these models by using forecasts of variables which influence surface irradiance as clouds or humidity can be a promising option. Also can be study the option of coupling of these data with radiative transfer models.

Other mesoscale models as HIRLAM (High Resolution Limited Area Model) or WRF (Weather Research and Forecasting Model) are used worldwide for the short-term forcasting of hourly and daily irradiance values. (13; 9; 14; 15). The results show that there is a strong dependence of the forecast accuracy on the climatic conditions. Also it is found a depence with the season in the year.

1.2 Classic approaches

Some of the existing approaches are stochastic in nature and others use some form of parameterization of known phenomena (16).

A priori, the physical modeling method could be less effective for the complex nonlinear systems such as the forecast of irradiation fluctuation, due to the fact that they need detailed system identification and data analysis. This way, a forecast method based on just a database on past meteorological data and no detailed system identification data is expeted to be more effective for the forecast of radiation fluctuation (17). In fact, the influence of the specific system is somehow implicit in the historical data.

We can classify the clasical approaches into three cathegories, time series based approaches, others based in the Model Output Statistics (MOS) and a set of other original formulations.

1.2.1 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) or weather station data (e.g. reference year based method) (18). Historical data, as well as the typical meteorological year (TMY) data which provide the data for typical months of a synthetic year, have proven to be useful in the past for PV array performance prediction. However, they 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 (16).

In this spirit, Brinkworth recognizes the sequential characteristics in the past solar irradiance data and introduces a stochastic model which generates future irradiance sequences (19). He uses the autocorrelation function of the irradiance time-series based on long-term averaged data. This model is dependent on a reference year of irradiance measurement and although useful for solar-thermal system design, may not be very useful for the photovoltaic performance study as pointed out in this paper.

The use of statistical markovian irradiance model for predicting the time-sequence of half-hour solar radiation values on a horizontal surface was introduced by (20). This author used the transition density function, which is a measure of the probability of the event at the next immediate hour of interest when the event at the present hour is given. He finds a half-hour transition density function from the hourly transition density function and predicts the joint cumulative distribution function for several successive normalized half-hour values.

Autorregresive Models (AR), Moving Average (MA) and Autorregresive Moving Averages (ARMA) models are frequently used to model linear dynamic structures, to depict linear relationships among lagged variables and to serve as vehicles for linear forecasting.

In the autoregressive model AR(p), the current value of the process is expressed as a linear combination of p previous values of the process and a random shock. In the moving average model MA(q), the current value of the process is expressed as a linear combination of previous random shocks. The general mixed autoregressive-moving average model ARMA(p,q) is a combination of these two approaches, but then, it can only be used to model stationary processes. 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. For these kind of models, a pre-whiten process the data is necessary to eliminate all periodicities (16).

ARMA models are one of the most frequently used families of parametric models in time series analysis. This is due to their flexibility in approximating many stationary processes (21).

This kind of approach has been used by (16) in the very short-term time forecast within one hour, with a statistical autoregressive ARIMA model to forecast sub-hourly irradiance, for 3 and 10 minutes step. They separate in advance the periodic component of the solar radiation in the surface and then forecast the ramdom component. With this formulation, randomness involved in suden extreme changes in the sun's intensity during a single interval will not be picked up by the forecast model. Otherwise, the results are independet of the geographical application, for radiation forecast and for PV output forecast, by means of VFORM model of Sandia National Laboratories.

Also for the very-short term power forecasting (13) have used AR models with and without exogeneus input variables (the temperature). Likewise they have studied the direct forecasting of power output through a transformation of NWP into prediction of stationary solar power series, as input for a AR model as well. The stationarization process is executed in a statistical way with recursive least squares with forgetting, contrary to clasical stationarization dividing by the extraterrestrial solar irradiance. They concluded that ARX cannot fully describe fluctuations caused by sudden changes incloud cover. Also, depending on the application of the forecasting system the most important variables in the model are different. For the very-short term forecast (less than 2h) observations of solar power are the most important variables. For further forecast up to 6h, both the NWP results and the observations of solar power can be chosen. For short-term forecast up to 36h, the most important inputs are the NWP forecast. They suggested a procedure based on quantile regression for calculating the varying intervals of the ucertainty of the solar power predictions and the results agree with other studies. Values of RMSE normalized to the mean solar power show for the three models a value rounding the unity for the fisrt 3h, lower than one between 3h and 6h and greater than one for next day forecasting.

In (22), the use of ARMA for the one day ahead hourly irradiance forecasting is shown, obtaining RMSE of about 40 Wm^{-2} for the period of study of 63 jours of spring of 1996. Their conclusion is that irradiance forecasting gave better results than clear index forecasting. Also they studied multivariate forecast models adding wind speed, wind direction, precipitation and temperature as input variables, obtaining better results than the univariate model.

Finally, (23) studies the ability of ARIMA for the very short-term solar forecast, from 5 minutes to 4h. The uncertainty in mean absolute relative error rounds the 15% for the 5-minutes forecast and 20% and 50% for the rest of the very short-term horizons.

1.2.2 Model Output Statistics (MOS)

The Model Output Statistics (MOS)(24) 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 (10; 16). The Glossary of Meteorology defines MOS as follows: *For a numerical weather prediction model, statistical relations between model-forecast variables and observed weather variables, used for either correction of model-forecast variables or prediction of variables not explicitly forecast by the model* (25). It accounts for some local effects and incorporates climatic considerations. By principle, it cannot predict events forced by mesoscale features (10).

NWP forecast can be the input for MOS and then, MOS objectively interprets NWP model output based on a historical sample and therefore only predicts events which are forced by synoptic-scale systems. It may correct certain systematic NWP model biases and quantify uncertainty in NWP model forecasts.

Also changes to NWP model components cannot be considered. Not every local effect may be accounted for as well as unusual climatic conditions (10).

The work of (26) was the first one to predict daily solar radiation for the short term, up to two days in advance, with the MOS technique. Approaches for clearness index, and irradiation directly, both for single station and regionalized were developed. He used output of limited are fine mesh model (LMF) as input for MOS and his results showed that MOS forecast was better than forecasts based on climatology. Regional forecast had also better results than local forecast, result confirmed by (27). And, finally, he had better results for prediction of the coefficient of transmittance kt than directly the irradiacion, contrary to (22).

MOS has been used for PV power forecasting (27; 28) as well as irradiance forecasting for the short-term forecast (10).

1.2.3 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 (17). PV power output against observed parameters is calculated by using past meteorological data in the database. That is, they search the data in the database whose parameters are similar to the observed ones. Their results in therms of relative error were 15% for clear days and 30% for mixed days (cloudy and clear periods within the day).

There are many solar irradiance based methods to forecast photovoltaic energy both for the short and long term. A popular method for short term forecasting is based on sky monitoring with cameras, to predict the amount of cloud coverage of the sun (29, in German).

1.3 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, because these models are a first approach which can be of great help to further estimate some of the parameters (21).

1.3.1 Neural networks

Neural networks 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. In effect, the net must run an iterative search at each stage of the estimation process.

In (23), neural networks were applied to forecasting solar radiation. The first specification issue is the number of hidden layers and input nodes. Several specifications were tried, including multiple hidden layers, but the simpler ones were able to converge more rapidly. As well, including the extraterrestrial horizontal component was not found to yield any improvement in forecast accuracy. The second specification issue was the convergence criterion. The criterion can be set using the R^2 (23).

A neural network based on backpropagation techniques, a deterministic atmospheric model and a fuzzy logic method were used by (30) in order to estimate hourly values of global solar radiation by using measured data. They concluded that the results were quite encouraging for developing a feedforward backpropagation neural network approach to simulate and predict future values of global solar radiation time series by extracting knowledge form their past values. Also, they investigated larger architectures constructed by adding more hidden layers or nodes and they concluded that they had longer converging times but did not significantly improve the network's prediction accuracy.

(22) focused on estimating hourly solar radiation by using two artifciial intelligence based techniques. These include linear, feed-forward, recurrent Elman's and radial basis neural networks, together with the adaptive neuro-fuzzy inference scheme. They concluded that non-lineal models were better in predicting solar radiation than linear ones. Also, better results are achieved for irradiance forecasting than clearness index kt forecasting and including meterological variables as input variables besides past irradiance values. Hourly forecasting of different solar sprectral bands has been also studied using NN by (31).

Nevertheless, if there are too much hidden layers, neural networks can over fit the noise and also converge to a local minimum instead of the global one. The number of hidden layers is critical to avoid this effects (23).

1.3.2 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 (32; 33; 34) which find favorable results for daily solar data. Also combination of a global or mesoscale NWP predictions with historic irradiance data or human interpretation fo NWP has been tested by (9). Their evaluation of results for Central European stations in terms of relative rmse ranges from 20% to 60%.

Combination of regressions and nerual networks 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 (23). This kind of models have been proposed by (35; 36; 37; 38; 39)

1.4 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 (5).

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 (4).

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 (40) 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 (41) is the determination of cloud strutures movement in previous images and then extrapolate it to predict the cloud positions for the next time step. As a consecuence, the local irradiance forecast is available. A multiresolution decomposition technique allowed to decompose the satellite image into local averages and gradients on various spatioal scales. Information included in both averages and gradients may be used for forecasting (42). However, the improvement over the persistent method is small, according to the authors (22).

1.5 Approaches comparison

(23) has compared different approaches, namely ARIMA in logs with time-varying coefficients, Unobserbed Components models, Transfer functions, neural networks 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. For the very short-term forecast up to 5 minutes the best model are NN and hybrid model (ARIMA + NN), and for horizon futher than 15 minutes, ARIMA , transfer function and hybrid models reveals the better results comparing to real data. . The uncertainty in mean absolute relative error rounds the 15% for the 5-minutes forecast and 20% and 50% for the rest of the very short-term horizons.

(22) have compared lineal (ARIMA) and non-lineal models (Feed-fordward 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 differences 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.

Most of the existing solar power prediction methods provide end-users with point forecasts, that is with 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. This paper evaluates several non-parametric statistical methods for point as well as probabilistic forecasting.

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 (43), for the optimal operation of combined wind-hydro power plants (44; 45) or for the design of optimal trading strategies in liberalized electricity pools (46).

2 Forecasting Models Description

In this work, we have considered a number of statistical non-parametric models for forecasting the output of a PV plant. Special attention was paid to include methods which can handle the case where there is a great number of available explanatory variables.

Two types of applications have been carried out: point forecasts and probabilistic forecasts. The chosen methods in each case are state-of-the-art developments whose robustness and accuracy has been acknowledged by the statistical community.

Publicly available implementations of these methods, included in the GNU's `R` software package (47), were used on each case.

2.1 Point forecasting models

Predicting the power output Y_{t+h} of a solar power plant at time t for h hours ahead involves finding a function f_h such that

$$Y_{t+h} = f_h(\boldsymbol{Y}_{t,h}^{\Delta}; \boldsymbol{Z}_{t,h}) + \varepsilon_{t+h} \tag{1}$$

where $\boldsymbol{Y}_{t,h}^{\Delta} = (Y_t, Y_{t-1}, \ldots, Y_{t-l},)$ is a vector of lagged values of the series to be predicted and $\boldsymbol{Z}_{t,h}$ is a vector of lagged exogenous variables. In the case of solar power forecasting $\boldsymbol{Z}_{t,h} = (\boldsymbol{N}_{t+h/t}, \boldsymbol{M}_{t,h})$ where $\boldsymbol{N}_{t+h/t}$ are NWP provided at time t for h hours ahead and $\boldsymbol{M}_{t,h}$ is a set of meteorological measurements informing about the instantaneous weather conditions around the plant.

The error term ε_{t+h} does not need to have specific statistical properties and hence equation (1) can summarize any forecasting process.

In most of the existing non-parametric methods, the variables which form $\boldsymbol{Y}_{t,h}^{\Delta}$ and $\boldsymbol{Z}_{t,h}$ must be carefully chosen to avoid what is known as *the curse of dimensionality* (48) (the difficulty of obtaining accurate estimates when there are many parameters to be estimated simultaneously). A wealth of variable or feature selection methods have been proposed in the literature, but in this case we chose to use models dealing with this selection automatically.

2.1.1 Neural-Networks

The multilayer perceptron, trained by the standard backpropagation algorithm, is the most widely used neural network (NN) approach for complex mappings between input and output. Its mathematical properties for non-linear function approximation are well-documented (49). In our case, a multilayer perceptron with one hidden layer was used (50).

2.1.2 Support Vector Machines for regression

The so called support vector machine (SVM) method for regression (51) is a well known nonparametric model designed to fit f_h in (1). In the SVM fitting procedure, f_h is obtained through an empirical loss minimization. For a good introduction to this algorithm, we suggest (52).

To explain the modelling process associated to SVM, we use the notation $X_{t,h} = (\boldsymbol{Y}_{t,h}^{\Delta}; \boldsymbol{Z}_{t,h})$. The particularity of the support vector machine for regression in our case is that it tries to find f_h within a subclass of functions that can be written

$$f_h : x \rightarrow \sum_{t=1}^{T} w_t^h K(x, X_{t,h}) + c \tag{2}$$

where $t = 1, \ldots, T$ is the range of the learning set and K is the kernel function measuring the proximity of x and $X_{h,t}$. The function K needs to be symetric and positive definite but the choice of the function K is very important and can be done with expert knowledge. A standard neutral choice, which was our choice in this paper, is to use the gaussian kernel $K(x, y) = e^{\|x-y\|_2^2}$.

2.1.3 Random forests

The Random Forests (RF) algorithm was proposed by Leo Breiman in 2001 (53) and it can be used for both regression and classification. Given a recursive partition, say $R_1, \ldots, R_l$ of the explanatory variables' space, in which the power output has low variations, a naive estimate of f_h in (1) over R_i ($i \in \{1, \ldots, l\}$) is obtained by averaging the power outputs that are associated to explanatory variables within R_i. The RF estimate of f_h is obtained from a random generation of partitions and a suitable aggregation of the associated naive estimates.

2.1.4 Generalized additive model

Suppose that $X_{t,h} = (X_{t,h}[1], \ldots, X_{t,h}[p])$ ($X_{t,h}$ is defined in the subsection 2.1.2), then generalized additive model (GAM) for f_h has the form

$$f_h(X_{t,h}) = c + \sum_{j=1}^{p} f_h^j(X_{t,h}[j]). \tag{3}$$

The estimation in the GAM model then depends on the assumptions that are made on functions f_h^j, and on the estimation procedure. In our numerical study, the functions $(f_h^j)_{j=1,\ldots,p}$ are estimated by likelihood based boosting algorithm using a b-spline decomposition and a binomial error distribution.

2.2 Probabilistic forecasting models

In this section we recall two of the previous methods, namely the Support Vector Machines (SVM) and the Random Forest (RF) methods which are adapted to obtain quantile forecasts. Let us recall that if α is given number in $[0,1]$ the α-quantile $q_{t+h|t}(\alpha)$ of Y_{t+h} given the information at time t is defined as the smallest value $q_{t+h|t}(\alpha)$ such that

$$P(Y_{t+h} \leq q_{t+h|t}(\alpha) | \boldsymbol{X}_{t,h}) \geq \alpha. \tag{4}$$

If F is the cumulative distribution function of Y_{t+h} given $\boldsymbol{X}_{t,h}$, and if F is increasing then $q_{t+h|t}(\alpha) = F^{-1}(\alpha)$. The quantile forecast at time t for horizon h is the forecast of $q_{t+h|t}(\alpha)$ which is denoted by $\hat{q}_{t+h|t}(\alpha)$.

2.2.1 Quantile Regression Forests

The random forest algorithm for quantile estimation is known as Quantile Regression Forest (QRF) (54), however it is only the application of the RF algorithm to the output $1_{Y_{t+h} \leq y}$ (instead of y_{t+h}) for different values of y (recall that for an event A, 1_A has the value 1 if A is true and 0 if A is not true). Because $E[1_{Y_{t+h} \leq y} | \boldsymbol{X}_{t,h}] = F(y)$ (E stands for the expectation) this gives an estimate of F which is then inverted to give a quantile forecast.

2.2.2 Support Vector Machine for quantile regression

Quantile regression with SVM (QSVM) was introduced in (55). With respect to SVM for regression, this quantile regression is obtained by using a different loss function, the *pinball loss* defined for $\alpha \in [0,1]$ by $l_\alpha(y) = y(\alpha - 1_{y<0})$ and also called quantile loss. It is motivated by the fact that

$$q_{t+h|t}(\alpha)(\boldsymbol{X}_{t,h}) = \arg\min_f E[l_\alpha(Y_{t+h} - f) | \boldsymbol{X}_{t,h}] \tag{5}$$

where the arg min is taken over all function f_h of $\boldsymbol{X}_{t,h}$.

This loss function will also be used in the evaluation of the results since according to equation (5), in the testing set, if $\hat{q}_{t+h|t}$ is the forecasted quantile,

$$ppl_\alpha(\hat{q}_{t+h|t}(\alpha)) = \frac{1}{T} \sum_t l_\alpha(Y_{t+h} - \hat{q}_{t+h|t}(\alpha)(\boldsymbol{X}_{t,h})) \tag{6}$$

should be small (T is the cardinal of the testing set). One can notice that this last criterion coincide with the mean absolute error (MAE) when $\alpha = 1/2$.

	Hours ahead								
Model	1	2	3	4	5	6	12	24	36
climat.	20.77	18.06	16.51	16.74	19.17	20.98	21.05	21.06	21.12
naive	36.64	37.73	27.17	14.12	33.59	37.81	17.60	18.50	19.15
GAM	8.62	10.26	10.57	10.05	11.03	11.53	11.22	12.53	12.08
NN	8.89	17.54	10.94	11.06	13.50	13.12	11.16	14.37	13.86
RF	8.51	10.09	10.28	10.00	11.00	11.12	11.08	12.26	11.75
SVM	8.33	10.27	10.67	9.57	11.06	11.25	11.15	12.72	12.53

Table 1: Normalized Root Mean Square Error (NRMSE) (% of Peak Capacity of the PV plant) for the models used in the point forecasting experiment.

	Hours ahead								
Model	1	2	3	4	5	6	12	24	36
climat.	12.87	10.75	10.52	10.15	11.66	13.44	13.49	13.50	13.56
naive	22.67	27.12	17.54	6.39	21.16	22.99	7.30	7.76	8.00
GAM	3.70	4.91	5.84	5.60	5.44	5.21	5.24	5.66	5.84
NN	4.05	10.22	6.34	6.38	7.36	6.29	5.12	6.54	6.47
RF	3.54	4.80	5.83	5.65	5.27	5.03	4.98	5.37	5.30
SVM	3.51	4.94	5.76	5.11	5.34	5.30	5.25	5.95	6.01

Table 2: Normalized Mean Absolute Error (NMAE) (% of Peak Capacity of the PV plant) for the models used in the point forecasting experiment.

3 Case study and results

3.1 Data

The dataset used in the study consists of measurements made at the solar power plant installed by the French association Soleil-Marguerite. It is located at Villeurbanne in the west central region of France, and its exact geographical position is at 45°78′N, 4°88′E. The capacity of the plant is 12,84kWc and is composed by three independent systems with a total of 128 panels from different manufacturers. The power values are obtained as the sum of the production of the three independent systems with a frequency of 15 minutes, covering the period from 11/01/2005 to 22/08/2006.

The PV power production is greatly affected by the status of the atmosphere around the plant. Variables like temperature, humidity, cloud cover, wind etc., have an effect on the energy that can be captured by the PV panel. Numerical weather predictions (NWP) of these variables can be used as explanatory variables when modelling PV power production.

In this study, we used NWPs provided by the ALADIN model of Méteo-France. These NWPs are hourly predictions for look-ahead times varying from 1h to 12h. They are updated every 6h at run times corresponding to 00:00, 06:00, 12:00 and 18:00.

From the wealth of variables offered by the ALADIN model, we selected those related with cloud coverage, wind speed, temperature and solar irradiation. These variables show the highest correlation with the power data.

In order to make the power data consistent with the NWP data, the original 15 minute power series were resampled using a linear interpolation to produce hourly series.

3.2 Results

Numerical weather predictions (NWP), as described in section 3.1, and lagged power measures are used as input data. In our case, we considered $\boldsymbol{Z}_{t,h} = \boldsymbol{N}_{t+h/t}$, that is, no instantaneous meteorological information was used. If t is the time at which the model is run and $t+h$ is the lead time, the set of NWP selected in our case is

$$\boldsymbol{N}_{t+h|t} = \left(R_{t+h|t}, T_{t+h|t}, W_{t+h|t}, n_{t+h|t}\right) . \tag{7}$$

where $R_{t+h|t}$ is the global solar irradiation, $T_{t+h|t}$ is the 10m temperature, $W_{t+h|t}$ is the 10m wind speed and $n_{t+h|t}$ is the total cloud cover index.

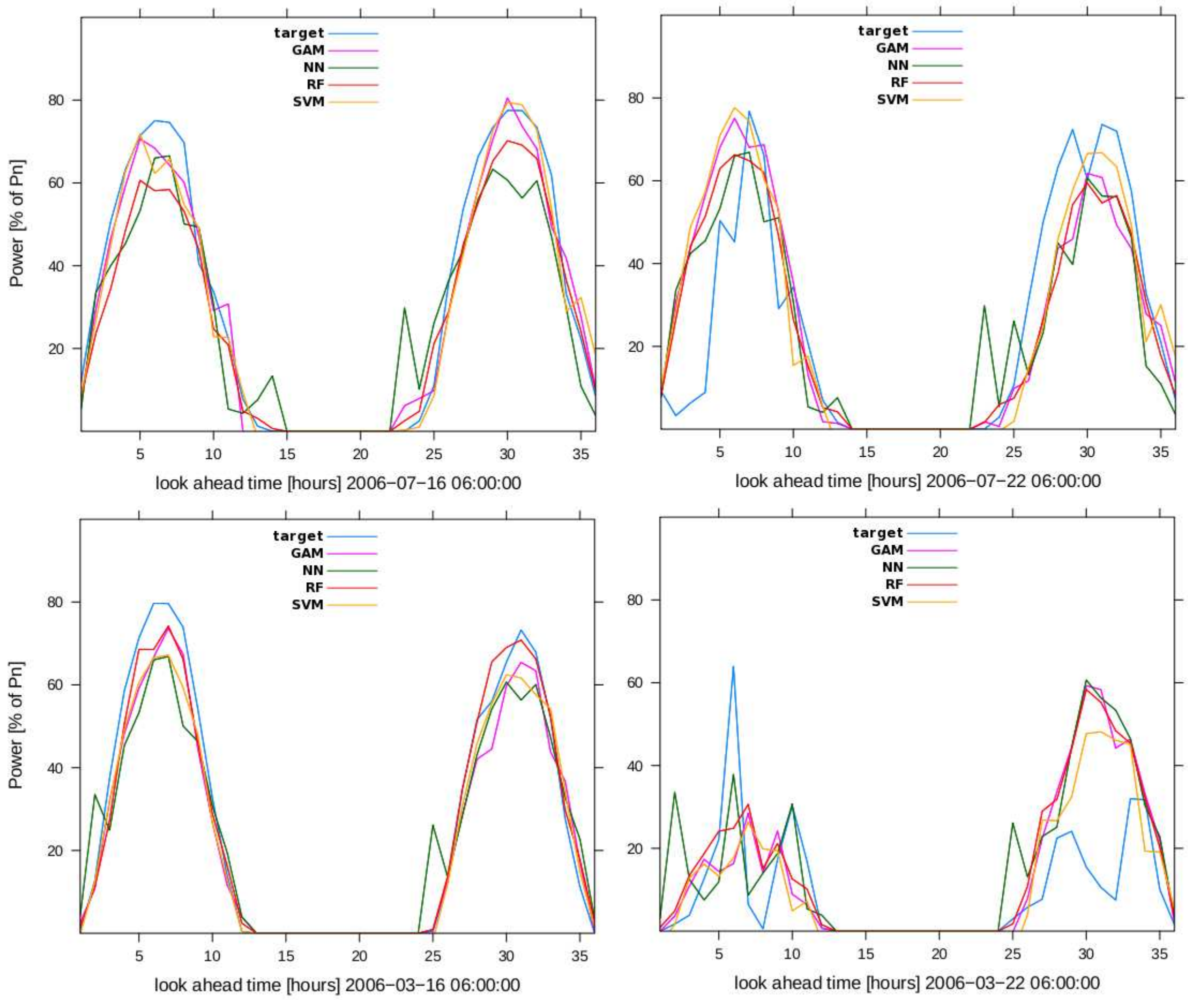


Figure 1: Examples of the results obtained by point forecasting methods. Left column shows predictions performed during two sunny periods while right column shows the same for cloudy periods.

Concerning lagged power measures, we selected values at time t and the same hour of the day before:

$$\boldsymbol{Y}^{\Delta}_{t+h|t} = \begin{cases} (Y_t, Y_{t+h-24}) & \text{if } 0 < h \leq 24, \\ (Y_t, Y_{t+h-48}) & \text{if } 24 < h \leq 48. \end{cases} \tag{8}$$

In the experiments described in this work, we used $\boldsymbol{M}_{t+h|t}$ and $\boldsymbol{Y}^{\Delta}_{t+h|t}$ as inputs for both the point forecasting models (section 2.1) and for the probabilistic models (2.2).

Given the fact that the available data spanned a relatively short period of 20 months, and considering the annual periodic nature of PV power series, we split our dataset into training and testing periods by reserving the first 12 months for training and the last 8 months for testing.

Once the models were trained, we used them to predict the data included in the testing set. The following section presents the criteria considered for the evaluation of the results.

3.3 Evaluation of point forecasting models

The evaluation framework in the point forecasting case follows closely the indications from (56) in the area of wind power forecasting. The selected evaluation criteria are the normalized mean absolute error (NMAE) and the normalized root mean square error (NRMSE). In both case, the normalisation factor is the peak power of the solar power plant.

In order to assess the usefulness and accuracy of the considered advanced models, reference models are needed. The first reference model used is a naive predictor, namely the diurnal-persistence model, defined as

$$\hat{Y}_{t+h/t} = \begin{cases} Y_{t+h-24} & \text{if } 0 < h \leq 24 \\ Y_{t+h-48} & \text{if } 24 < h \leq 48 \end{cases}. \tag{9}$$

The second reference model considered is the so-called climatology, which uses the mean of the time series as predictor for every time step in the future.

Tables 1 and 2 show the results respectively in NRMSE and NMAE for the six models considered: the reference naive and climatology predictors, as well as RF, GAM NN and SVM. From those tables, the benefits of using the advanced models compared to the simple predictors for point forecasting become clear. The results of SVM an RF are significantly better than those of the reference models, both for the nearest horizons (1 to 3 h), where the advanced models show their best performance and for longer horizons, where the worst results for RF and SVM are still much better than those of the reference models.

In figure 1, we can see representative examples of how the considered models behave in four different situations. On the top left, a summer sunny day is underestimated by NN and RF, while GAM and SVM succeed in forecasting the PV power production with a remarkable precision. This fact is still more significant when considering the longer term prediction horizons, over one day ahead.

The graph on top right shows another summer day, in this case a cloudy one. In general, all the models find it more difficult to forecast in this context, especially in the first 6 hours where an unexpected cloud cover resulted in bigger forecasting errors.

The bottom left graph shows the results of the models for a sunny spring day which are similar to those of the summer sunny day. The main difference is that, in this case, the RF and GAM models outperform the rest, whereas SVM falls to the lower precision level of NN.

Finally, from the bottom right graph we can see how the models behave in the more unstable atmospheric conditions of a typical spring day. Surprisingly, only the NN model succeeds in forecasting the two peaks of production observed in the first 6 and 10 hours, although it misses the cloudy beginning of the day. The rest of the models produce a similar curve and hence similar prediction errors. For the period covering more than 24 hours ahead, all four models fail to predict the cloudy hours of the middle of the day (around hours 30-32), which suggests that this situation was not correctly forecast by the NWPs.

Of course, it is impossible to determine the percentage of the error that is due to the NWPs themselves and the percentage that is due to the proposed models. However, studying the errors by classifying them in different types of meteorological situations might yield a better understanding about the forecasting abilities of each model.

3.4 Probabilistic forecasts

In order to test the models outlined in section 2.2, we run them over the same data used in the point forecasting case. However, for the evaluation of probabilistic forecasts, error measures such as the NRMSE or the NMAE are not appropriate. By definition, such measures are only applicable to models that predict exclusively the mean of the distribution of the stochastic process under study.

Specially defined evaluation criteria for probabilistic forecasting exist, and we selected the following amongst them:

- *Reliability* relates to the ability of probabilistic forecasts to respect nominal probabilities. Under a large number of, for example, 20% forecasted quantiles, we should observe 20% of the power output, not more, not less. In this paper reliability is measured by the deviation of the observed proportion from the theoretical proportion.

- *Sharpness* is defined as the ability of a probabilistic forecast to concentrate the probability of a future outcome. In this paper, the sharpness of a set of predicted quantiles $\hat{q}_{t+h}$ is measured by the length
$$l(\alpha) = \hat{q}_{t+h}(1 - \alpha/2) - \hat{q}_{t+h}(1 - \alpha/2)$$
of confidence interval with coverage rate $\alpha \in [0; 1]$.

- The *pinball loss*: $ppl_\alpha(\hat{q}_{t+h}(\alpha))$ as defined in (6). Being a loss function, this value has to be as close to zero as possible and when $\alpha = 1/2$, $ppl_\alpha(\hat{q}_{t+h}(\alpha)) = \text{NMAE}$.

In a probabilistic context it is also a challenge to define simple reference models. Here, a climatology model is used as reference. This corresponds to using the distribution of the time series obtained over

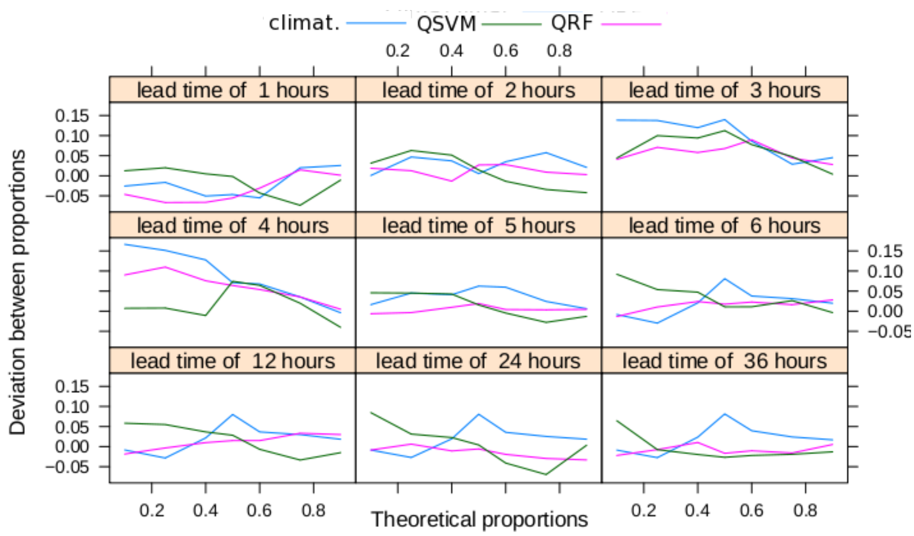


Figure 2: Reliability of probabilistic forecasts obtained by the two proposed models and the climatology for different horizons.

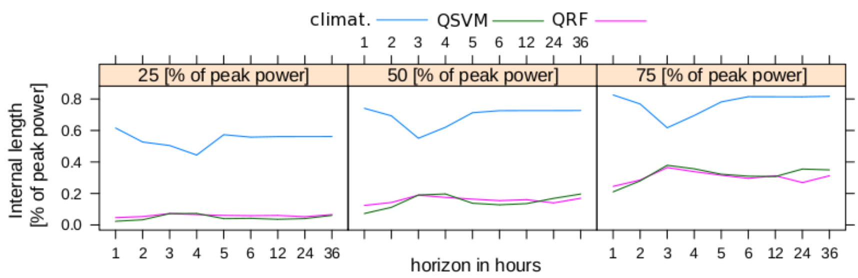


Figure 3: Sharpness of probabilistic forecasts obtained by the two proposed models and the climatology for three different levels of probability.

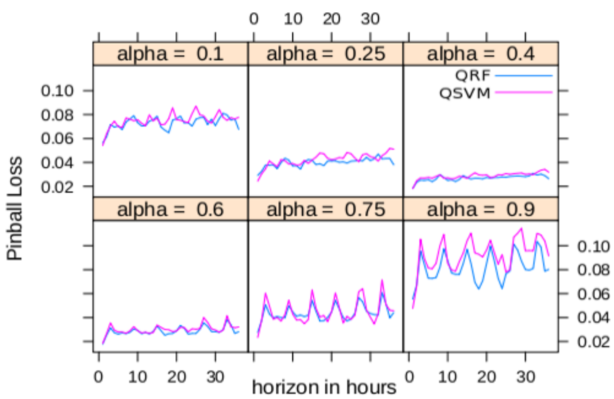


Figure 4: Pinball loss values obtained by the two proposed models for different values of α.

	Hours ahead									
Model	0	1	2	3	4	5	6	12	24	240
climat.	19.16	18.03	16.27	13.71	10.25	6.24	2.02	19.16	19.17	18.83
naive	51.40	17.22	43.74	13.41	23.05	5.48	3.01	51.46	51.51	52.06
RF	4.47	8.49	8.99	7.38	5.45	3.28	1.26	13.84	13.82	16.74
SVM	20.32	8.50	8.81	7.40	5.68	3.48	1.29	20.33	13.73	16.98
NN	1.05	8.37	8.80	7.41	5.55	3.59	1.34	13.66	13.78	16.14

Table 3: Normalized Root Mean Square Error (NRMSE) (% of Peak Capacity of the PV plant) for the models used in the CESI Ricerca point forecasting experiment.

a long historical record as predicted pdf for each time step in the future. Recalling that climatology is the forecast obtained using no information from the present, it is expected to be fully reliable (through a sufficiently long period) but to have no sharpness whatsoever.

A diagnostic tool for the assessment of the reliability of probabilistic forecasts is the reliability diagram. We used the type of diagrams proposed in (**?**) as shown in Figure 2. In this figure, we can see that results are mixed in terms of reliability, being the two proposed models quite close to the climatology reference. However, the further the horizon, the better the advanced models behave, leaving the climatology curve on top most of the time.

Given the fact that reliability measures are not sufficient to evaluate a probabilistic forecast (**?**), we used sharpness measures to determine the behaviour of each model. Figure 3 shows the obtained sharpness for different probability levels, and there it becomes clear that our proposal consistently outperforms the reference model. It is also noticeable that both the QRF approach and the QSVM approach are almost indistinguishable.

To assess in a more detailed way the relative performance of the two proposed methods we can use the graphical representation of the pinball loss function. As we can see in Figure 4, the QRF model clearly outperforms QSVM when $\alpha = 0.9$, while for other values the difference is smaller albeit noticeable.

From these three evaluation criteria we can conclude that both proposed models are of interest for the problem of probabilistic forecasting for PV power.

In order to show the forecasts in the way the final user would see them, we compared the performance of both models on a set of four representative days in Figures 5(a) and 5(b). The criteria for selecting the days was to have two sunny and two cloudy periods of different periods, and, we randomly selected two days of November, 2005 and two days of July 2006.

The first and last column of both figures show two sunny periods. From the results of both models we can say that both of them managed to properly predict what finally happened, although QRF performed slightly better. This becomes especially clear in column 4, which shows the period starting at 06:00 hours on the 17/07/2006. During the first 12 hours of that period, QRF obtained a prediction which can be considered as perfect, whilst the results of QSVM are clearly less accurate.

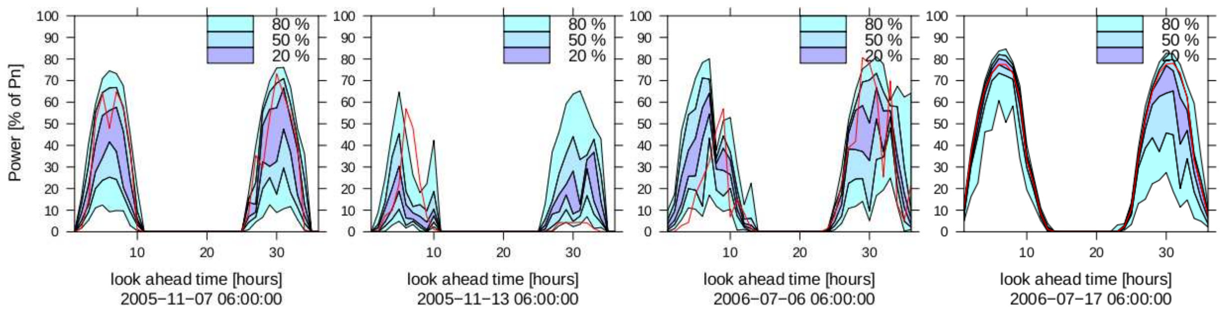
Facing cloudy and unstable days, the models found more difficulties indeed. Columns 2 and 3 of both figures show these kind of cloudy days, and there it is clear that the models did not succeed in forecasting the behaviour of the atmosphere. This is especially true in the last hours of the period starting at 06:00 on the 13/11/2005, where effective power produced was reduced to a minimum and both models overestimated it.

4 Dataset from CESI Ricerca

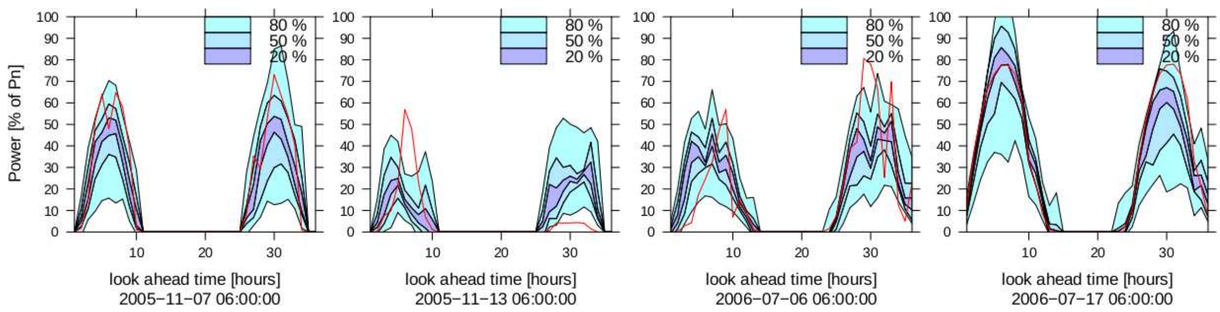
Probabilistic forecasts as well as point forecasts were performed at a different site, namely the CESI Ricerca PV station, situated in Milano and having a record of power data for 2 years. The first year was used for learning and the second year for testing. Results are presented in Figures 6 7 8 (Visualization of the predictions for sample days), Table 3 4 (NMAE and NRMSE) and Figures 910 for reliability and sharpness of the probabilistic forecast.

5 Conclusions

In this paper the aim was to assess the capacity of state of the art statistical non-parametric methods to predict the power output of a solar plant. The models considered both power measurements as well as



(a) QRF



(b) QSVM

Figure 5: Probabilistic forecasts for selected days obtained using QRF (top row) and QSVM (bottom row).

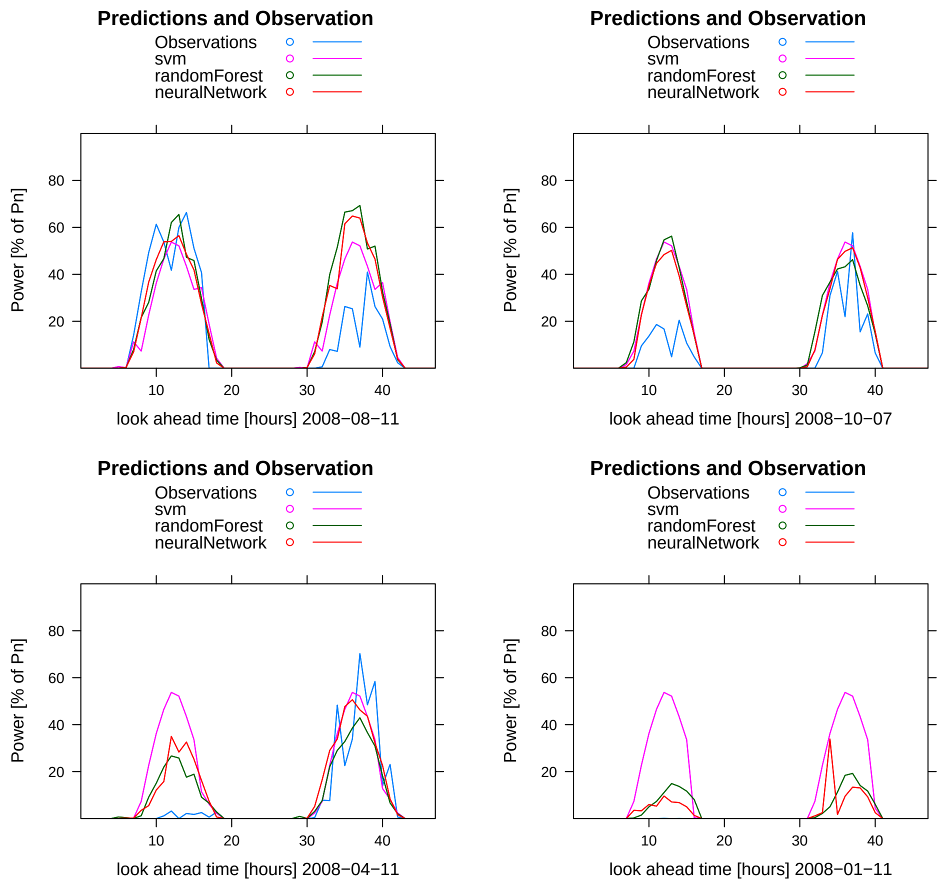


Figure 6: Point Forecast for CESI, cloudy days

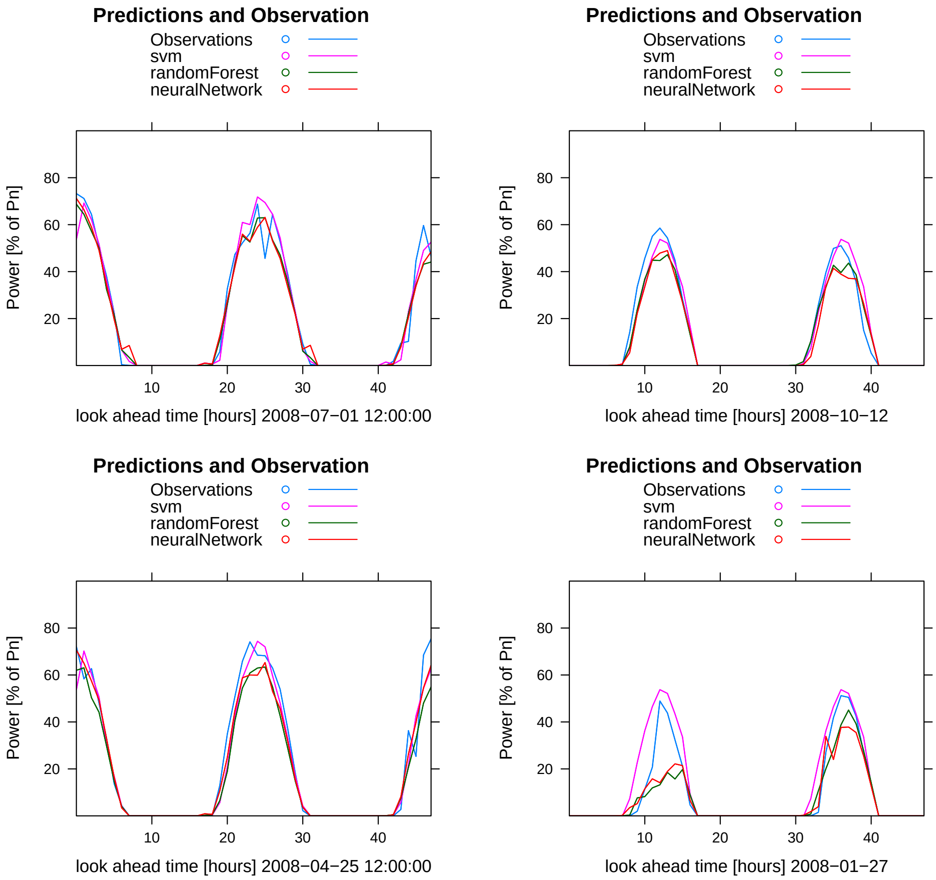


Figure 7: Point Forecast for CESI, sunny Days

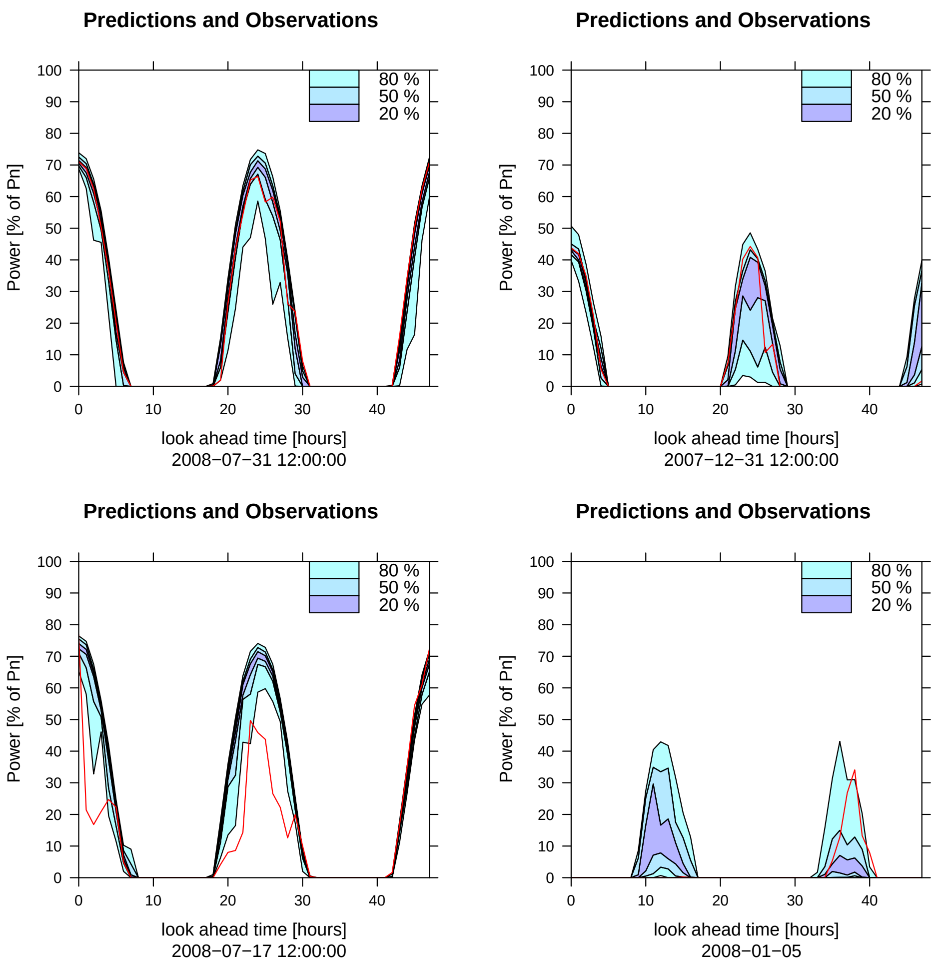


Figure 8: Probabilistic Forecast for CESI (Sunny days on top row and cloudy days on bottom row) using procedure quantile regression forest

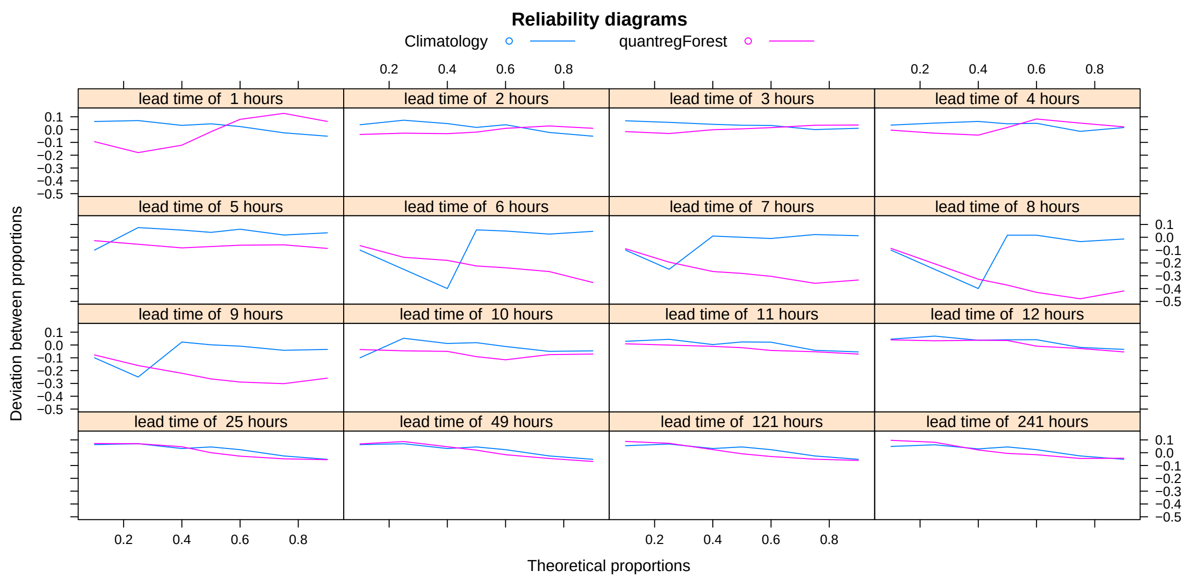


Figure 9: Probabilistic Forecast for CESI: reliability (the poor reliability for climatology as well as quantile regression forest for lead time of 6-7-8 hours is due to night values)

	Hours ahead									
Model	0	1	2	3	4	5	6	12	24	240
climat.	11.77	10.85	9.96	8.49	6.40	4.09	1.19	11.78	11.77	11.57
naive	43.73	8.43	37.29	6.80	17.93	2.27	1.55	43.87	44.02	45.08
RF	2.30	4.26	4.73	3.78	2.75	1.40	0.56	8.04	8.02	9.96
SVM	11.79	3.46	4.01	3.49	2.81	1.56	0.60	11.81	7.66	9.51
NN	0.62	4.06	4.49	3.75	2.79	1.55	0.58	7.79	8.28	9.63

Table 4: Normalized Mean Absolute Error (NMAE) (% of Peak Capacity of the PV plant) for the models used in the CESI Ricerca point forecasting experiment.

numerical weather predictions as inputs in order to forecast future values of photovoltaic production at different time horizons. Both point and probabilistic forecasting models have been considered.

Regarding the proposed point forecast models, we shown that they managed to properly predict sunny days up to a satisfactory accuracy degree, whereas cloudy or unstable days pose more difficulties to be forecasted. 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 (wind predictability decreases with terrain complexity).

With regard to probabilistic models, we have shown how the proposed models improve the reference model and give results which are more interpretable and of a higher value than the standard point forecasting models. This sets a promising path towards more useable forecasting modules that are of interest for the electricity industry.

This study supports the validity of the non-parametric approach towards the forecasting of photovoltaic power. Forthcoming improvements include the proposal for a classification of usual meteorological situations and the advance in the probabilistic prediction of photovoltaic power.

Aknowledgements

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The `R` packages used to perform the experiments are: `e1071` (57), `kernlab` (58), `randomForest` (59), `GAMBoost` (60), `kqr` (61).

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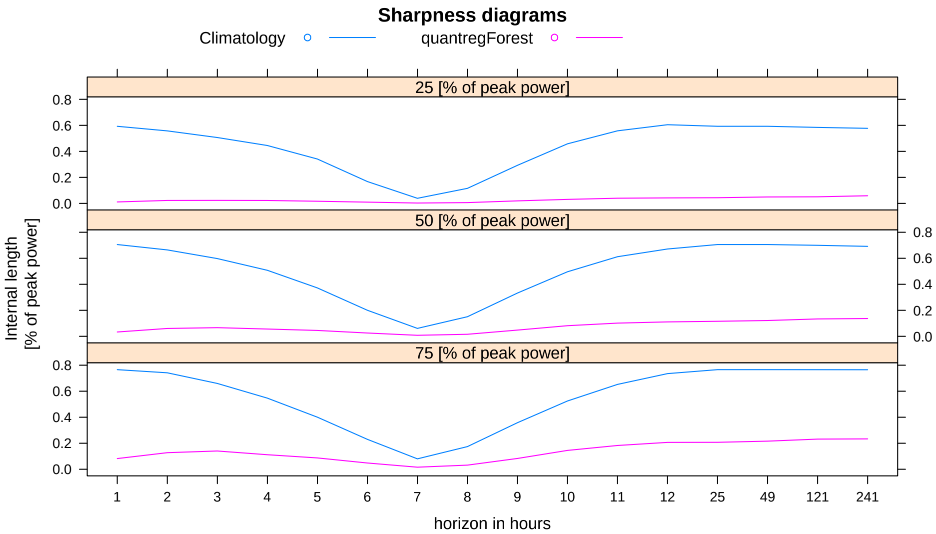

Figure 10: Probabilistic Forecast for CESI: Sharpness