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Ensemble forecast of photovoltaic power with online CRPS learning

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ABSTRACT

We provide probabilistic forecasts of photovoltaic (PV) production, for several PV plants located in France up to 6 days of lead time, with a 30-min timestep. First, we derive multiple forecasts from numerical weather predictions (ECMWF and Météo France), including ensemble forecasts. Second, our parameter-free online learning technique generates a weighted combination of the production forecasts for each PV plant. The weights are computed sequentially before each forecast using only past information. Our strategy is to minimize the Continuous Ranked Probability Score (CRPS). We show that our technique provides forecast improvements for both deterministic and probabilistic evaluation tools.

0. Introduction

Improved photovoltaic power integration needs better power forecasts. Forecasters may pursue efforts to improve meteorological models, weather-based power models or statistical post-processing methods. For our part, we focus on the following case: a forecaster, willing to provide probabilistic PV power forecasts, retrieves multiple meteorological forecasts (possibly from various sources). In this general setting, numerous state-of-the-art methods can be tested and combined.

Meteorological forecasts can either be deterministic single forecasts or an ensemble of forecasts, usually at coarser resolution. Inman, Pedro, and Coimbra (2013) provide a review of PV forecasting methods with deterministic forecasts. Ensemble forecasting and more generally probabilistic forecasting has been widely covered in the meteorological community (Gneiting & Katzfuss, 2014). Only recently, ensemble-based forecasting techniques are tested for PV (Zamo, Mestre, Arbogast, & Pannekoucke, 2014), while these techniques are more common for wind and wind power forecasting (Ren, Suganthan, & Srikanth, 2015).

A recent benchmark of deterministic and probabilistic PV forecasts is analyzed in Sperati, Alessandrini, Pinson, and Kariniotakis (2015), along with classical diagnostic tools. Probabilistic forecasts rely on the estimation of quantiles of the predicted probability density function (PDF). Quantile regression (Almeida, Perpiñán, & Narvarte, 2015) and analogs (Alessandrini, Delle Monache, Sperati, & Cervone, 2015; Huang & Perry, 2015) are amongst the most popular techniques for quantile estimation in PV. These techniques do not require an ensemble of forecasts as they can rely only on the historical variability of the forecasts and production data. The main drawback of most of the previously cited methods is that they use a single method and not a combination of several methods.

A forecaster having multiple forecasts hopefully wishes to combine them. In our case, we combine deterministic forecasts, quantile forecasts and ensemble forecasts, which is seldom the case. We combine these different types of forecasts to take advantage of their diversity. On the one hand, ensemble members describe several meteorological situations. On the other hand, quantile forecasts are built from the errors of a deterministic forecast, which describes

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a single meteorological situation with a finer resolution than the ensemble forecasts. Quantile forecasts estimate the inability of the forecaster to provide a perfect deterministic forecast.

The forecasts combination can be carried out in an optimal way. A batch process would not produce an estimation based on all available data but only on a limited learning data set. A batch process can be updated but it will only mimic an online learning technique. On the contrary, online learning techniques provide rules for combining forecasts, see the monograph (Cesa-Bianchi & Lugosi, 2006). The combination rules stemming from online learning depend only on the available past information at each forecast step and come with theoretical performance guarantee under essentially no assumptions (concerning prior weights, underlying stochastic process or distributions). The theoretical guarantee of the online learning algorithm can be seen as a long term performance guarantee without stationarity or ergodicity assumptions. Online learning techniques have been tested for several applications: electricity consumption, ozone concentration, wind and geopotential fields, and solar irradiance (Baudin, 2015; Devaine, Gaillard, Goude, & Stoltz, 2013; Mallet, 2010; Mallet, Stoltz, & Mauricette, 2009; Stoltz, 2010; Thorey, Mallet, Chaussin, Descamps, & Blanc, 2015).

This paper presents application results with our innovative approach (Thorey, Mallet, & Baudin, 2016), whose purpose is to combine multiple forecasters in a linear opinion pool (Genest & McConway, 1990; Geweke & Amisano, 2011). The originality of our technique is to use combination rules deriving from online learning techniques in order to minimize the CRPS of the weighted empirical distribution function. We stress here the fact that our method provides theoretical guarantee and that it does not rely on distribution assumptions. Besides, the algorithm has a low computational cost and is parameter-free. Our framework is inspired from the work of Gaillard, Goude, and Nedellec (2016), which focuses on quantile scoring functions.

Minimizing the CRPS is a common strategy in the meteorological literature to obtain calibrated probabilistic forecasts. However, standard techniques do not offer theoretical guarantees of robustness and usually resort to strong assumptions on the distributions. For example, Bayesian model averaging (BMA) techniques provide a mixture of parametric distributions, usually a Gaussian sum (Raftery, Gneiting, Balabdaoui, & Polakowski, 2005) or gamma distributions sum for wind and precipitation applications (Sloughter, Gneiting, & Raftery, 2010; Sloughter, Raftery, Gneiting, & Fraley, 2007). Non-homogeneous regression fits the parameters of a parameterized distribution using characteristics of the ensemble of forecasts (Gneiting, Raftery, Westveld III, & Goldman, 2005; Thorarinsdottir & Gneiting, 2010; Wilks, 2009). For instance, a Gaussian distribution is fitted using a linear model between the mean of the distribution and the mean of the forecasts. Besides, likelihood maximization with the logarithm loss is not an appropriate tool in our setting since it fails to produce satisfactory scores for a discrete probability distribution. A discussion on local scores such as the logarithm loss is addressed by Bröcker and Smith (2007b).

Table 1
Forecast availability with lead time. PEARP is the Météo France ensemble, Det defines the deterministic forecasts Arpège and HRES, and ENS is the ECMWF ensemble.

D	D + 1	D + 2	D + 3	D + 4	D + 5
PEARP	PEARP	x	x	x	x
Det	Det	Det	Det	x	x
ENS	ENS	ENS	ENS	ENS	ENS

The main contributions of this manuscript are twofold:

- We show probabilistic forecasts performance on a large data set comprising 219 PV power plants with deterministic, quantile and deterministic forecasts from two meteorological centers (ECMWF and Météo France). We evaluate PV forecasts that are used operationally at a country-scale.
- Our statistical postprocessing technique creates a weighted empirical distribution by CRPS minimization with theoretical guarantees under essentially no assumptions.

In Section 1, we introduce the production data sets and the forecasts from ECMWF and Météo France. We detail our method to generate deterministic, quantile and ensemble PV forecasts from ensemble and deterministic weather forecasts. We finish this section by describing linear opinion pools, or in other words, by describing how we build a probabilistic forecast from multiple pointwise forecasts. The evaluation tools are described in Section 2, with a focus on the CRPS. Our statistical post-processing method is explained in Section 3. We detail how the weights of the linear opinion pool are updated. Numerical results and discussions are developed in Section 4. The deterministic and probabilistic predictive skills of the present forecasts are computed. In particular, we highlight the benefits of using our online learning algorithm compared to simply using uniform weights.

1. Methods

1.1. Production and meteorological data

The production data cover 219 PV power plants in metropolitan France with 21 consecutive months (January 2012 to October 2013). The total power of the plants is referred to as France production. We wish to provide production forecasts for each power plant and for France production. The data are shown as load factor, i.e. scaled by the installed capacity. France production forecasts are the weighted sums of the plant forecasts w.r.t. the installed capacity of each plant.

Forecast data are summarized in Tables 1 and 2. We use data from two meteorological centers (ECMWF and Météo France), both deterministic forecasts and ensembles of forecasts: HRES and ENS for ECMWF, and ARPEGE and PEARP for Météo France (Courtier, Freydier, Geleyn, Rabier, & Rochas, 1991; Descamps et al., 2015; Palmer et al., 2009), up to a lead time of 6 days. Note that the deterministic forecasts are not the unperturbed members of the ensembles of forecasts but different forecasts, with better resolution.