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ECONOMIC VALUE OF SOLAR FORECASTS FOR DIRECT MARKETING OF PV PRODUCTION

Summary

Energy market operation strongly depends on the accuracy of PV power forecasting. Forecasting errors affect the smooth integration of solar energy into the grid because they influence market balance and, therefore, the revenues of energy producers. This paper investigates the impact of different levels of forecasting errors on the producers' income in the Californian market settlements. To this end, a PV system was simulated in this region along with forecasts generated using persistence models and a numerical weather prediction (NWP) model. Also, the benefits of participating in the intraday market compared to relying exclusively on the day-ahead market are assessed for this market structure. Forecast performance is evaluated using standard error metrics, revealing correlations between forecast mean bias and the imbalance penalties. Advanced forecasting approaches such as NWP models reduce forecasting errors and increase market revenues compared with persistence models, while systematic overestimation of production can be economically advantageous depending on market structure.

Keywords: PV power forecasting, Market structure, Intraday market, Forecasting errors

Field of application for the findings: Electricity grid operation, Solar production management

Addressed audience: Solar power producers, Solar forecasters, Grid operators

1. Introduction

As the number of PV installations increases, new challenges arise for energy market operators. One of them is the intermittency of solar energy. This can lead to negative pricing when the PV production exceeds grid demand or high penalties when production falls below the producers' bids [1]. Forecasts are then introduced to mitigate the intermittency of this energy source. Depending on the forecasting horizon, solar forecasts can be produced using numerical weather prediction (NWP) models, statistical and time-series methods and machine learning. The forecast quality, which refers to the accuracy of the predictions (i.e. how close the forecasted values are to the corresponding observations), is assessed using suitable error metrics. Good forecast quality should result in a higher value, which can be either economic, environmental or logistic. However, in the literature, there is no clear link between forecast quality and its associated value.

As most of the works on the value of solar forecasts generally focus on the economic value of solar forecasts, we decided to study this type of value. To investigate how the economic value evolves depending on forecast errors, we use different forecasting techniques, including naive models and NWP. Furthermore, energy markets have to balance their supply and demand. To do so, they apply market rules on prices and penalty terms. Therefore, it is also important to investigate how these rules can influence the link between the quality of a forecast and its associated value. To this end, this study is conducted using the Californian market rules and prices. This choice of market was motivated by previous works done on these energy markets, but also by the accessibility of price data [2]. When participating in the aforementioned energy market, the solar energy producers can rely on the intraday market to meet their planned production for the day-ahead market in case of a sudden change. Hence, this paper will also explore the impact of the integration of intraday forecasts and how it can affect economic value. Thus, two types of market operations will be simulated: one functioning purely as a day-ahead market and the other combining the day-ahead market with the intraday market.

2. Energy market structure and economic model

Most energy markets use the intraday forecast to calculate the producer's revenue accurately. The intraday process enables the market operator to pay energy producers according to the magnitude of the error between the forecast and actual production. The following equation uses an imbalance penalty P_{dev} instructed by the market operator to penalize the producer or not according to the energy imbalance [3]. The income for PV producers is calculated as :

$$R = \sum_{i=1}^{H} F_{DA} \times P_{DA} + \delta(F_{ID} - F_{DA}) \times P_{ID} + F_{dev} \times P_{dev} \tag{1}$$

where P_{DA} and P_{ID} are the energy prices submitted on the day-ahead and intraday markets, F_{DA} and F_{ID} the associated day-ahead and intraday forecasts. In the presence of intraday trades, δ is set to 1, otherwise δ is set to 0. The energy imbalance, which the system would have to regulate, F_{dev}, is calculated using Equation 2. This imbalance is then penalized using P_{dev}.

$$F_{dev} = O - F_{DA} - \delta(F_{ID} - F_{DA}) \tag{2}$$

With intraday trades, the imbalance becomes the difference between the actual generation O and the intraday forecast F_{ID}. In addition to the penalty, the energy market applies curtailments on prices and energy to maintain market balance. To ensure that negative day-ahead prices are not unfairly beneficial, energy is never allowed to be sold at a negative price. In case of oversupply, the market compensates the producers for cutting their production [2]. Economic scenarios combined with solar forecasts of different qualities are used to show the effect of quality on revenue. Then, it will be possible to link forecast quality to economic value of solar forecasting.

3. Data generation

Due to limited access to production data, photovoltaic generation is simulated using satellite-derived solar irradiance and the PV model named PV Watts [4]. For this study, solar power production was simulated for a 1 MWp PV plant located in Northern California. For this region, the meteorological and solar irradiance datasets were extracted from NSRDB database [5]. The PV system was defined using the coordinates of an existing PV plant in Northern California along with the corresponding optimal tilt and azimuth. The irradiance for the plane of array is then determined [6]. Finally, this value is used as input to the PV model which calculates the power output for the studied PV system for a period of one year with an hourly time step.

From the solar power simulation, different sets of deterministic forecasts are produced. The persistence model is a simple benchmark method in which the future solar generation at time $t + \Delta t$ is assumed to be equal to the observed value at time t. Although this method is simple, it generally performs poorly under rapidly changing weather conditions.

The study also considers more advanced forecasts based on NWP models. The European Centre for Medium-Range Weather Forecasts (ECMWF) provides access to operational forecasts. To analyze the correlation between forecast value and quality, a large number of forecasts are required. To achieve this, spatial variation has been used to create different forecasts [7]. It is assumed that a forecast produced for a point close to the studied site will be more accurate than a forecast produced very far from the same site. To generate a large number of forecasts, the simulation was run for each point around the site in a 0.5 degrees of latitude-longitude radius, which enables the production of 80 forecasts.

4. Revenue and quality assessment

The revenue of our solar PV system is calculated using the price data from the Californian market operator for the selected year. The same process is then applied to the corresponding forecasts. Given that one of the objectives of this study is to assess the impact of integrating intraday forecasts on revenues, two revenue scenarios were calculated. A first revenue calculation taking into account only the day-ahead market ($\delta = 0$) and a second one integrating the intraday trades ($\delta = 1$) were applied to the selected PV system. For this second application, a persistence forecast was selected as the intraday forecast.

To evaluate the quality of the different forecasts, the most common error metrics were selected: the root mean square error (RMSE), the mean absolute error (MAE) and the mean bias error (MBE) [8].

In the Californian market, a clear correlation is observed between the income associated with the different forecasts and their MBE. Figure 1 shows this correlation for our application in the day-ahead market only. The same correlation can be observed between their associated penalty terms $F_{dev} \times P_{dev}$ and their MBE.

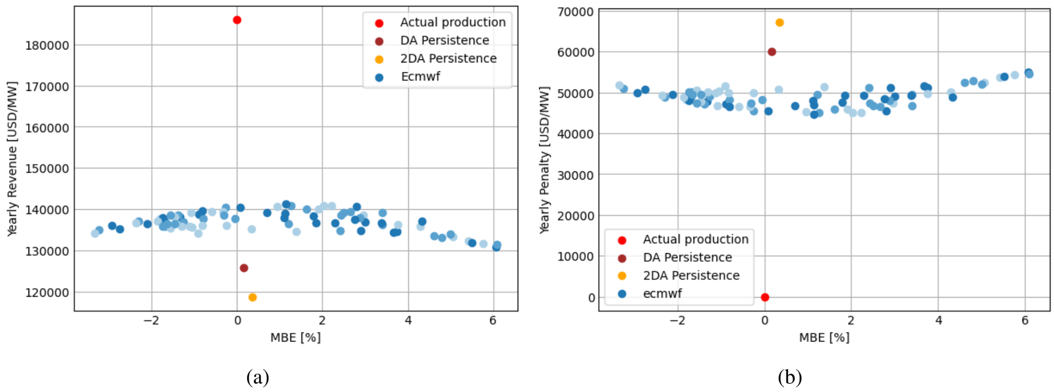

Fig. 1: Correlation between the MBE and yearly revenues (a) and yearly penalties (b) for a Californian PV plant operating in the day-ahead market

The value of forecasts depends heavily on market structure. Markets with strict imbalance penalties or high price volatility increase the economic benefits of accurate forecasts, while flexible balancing mechanisms reduce the financial impact of forecasting errors. Simple forecasting methods, such as persistence, lead to lower revenues due to their limited accuracy, whereas advanced methods based on NWP tend to reduce errors and improve market performance. Furthermore, we studied the integration of the intraday term in the revenue Equation 1 ($\delta = 1$). Since the difference between the actual generation and the intraday forecast remains constant over the year, the yearly revenue depends on the difference between the day-ahead forecasts and the intraday forecast. Hence, with intraday trades, overestimating the production can be more beneficial for the producer.

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