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Impact of wind power uncertainty forecasting on the market integration of wind energy in Spain ☆

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HIGHLIGHTS

- Reduction wind power forecasting uncertainty for day ahead and intraday markets.
- Statistical relationship between total load and wind power generation.
- Accurately forecast expected revenues from wind producer's perspective.

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ABSTRACT

The growing share of electricity production from variable renewable energy sources increases the stochastic nature of the power system. This has repercussions on the markets for electricity. Deviations from forecasted production schedules require balancing of a generator's position within a day. Short term products that are traded on power and/or reserve markets have been developed for this purpose, providing opportunities to actors who can offer flexibility in the short term. The value of flexibility is typically modelled using stochastic scenario extensions of dispatch models which requires, as a first step, understanding the nature of forecast uncertainties. This study provides a new approach for determining the forecast errors of wind power generation in the time period between the closure of the day ahead and the opening of the first intraday session using Spain as an example. The methodology has been developed using time series analysis for the years 2010–2013 to find the explanatory variables of the wind error variability by applying clustering techniques to reduce the range of uncertainty, and regressive techniques to forecast the probability density functions of the intra-day price. This methodology has been tested considering different system actions showing its suitability for developing intra-day bidding strategies and also for the generation of electricity generated from Renewable Energy Sources scenarios. This methodology could help a wind power producer to optimally bid into the intraday market based on more accurate scenarios, increasing their revenues and the system value of wind.

1. Introduction

In the European Union, the share of electricity generated from Renewable Energy Sources (RES-E) has grown significantly during the last decade. As a result the European Commission considers RES-E to be an "important and growing player" and suggests that, as a result of ongoing investments in RES-E, their share of total energy supply would increase from 21% today to at least 45% in 2030 [1,2]. The growing share of electricity production from wind and solar PV increases the stochastic nature of the power system and thus has repercussions on the markets for electricity. Case studies for power systems with a growing share of intermittent RES-E highlight the importance of RES-E forecasting and market mechanisms to react to deviations from forecasts in real time [3]. The obligations to balance a production portfolio deviate significantly between different power markets within the European Union. The European Commission has issued a preference for RES-E generators to bear balancing responsibility; however RES-E generators are currently obliged to fully balance their production in only a few markets [4,5].

Addressing RES-E forecast deviations is important for both the power system as a whole as well as for the balancing responsible party. The adjustments needed to balance power supply and demand after the closure of the day-ahead market are typically

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done through transactions on intraday and reserve markets. From a system point of view, most of the adjustments would ideally be done in the intraday market to avoid the use of the more expensive reserve products. On the other hand, the existence of forecast errors provides opportunities to actors who can offer flexibility in the short term. Flexibility products (traded on intraday and reserve markets) have been identified as an important source of income for electricity storage in a number of studies [6].

Of all RES-E, wind power forecasts have the highest uncertainties mainly due to the temporal and spatial variability and predictability of the wind field. The studies available in the literature so far, are devoted to:

(1) Developing more accurate numerical and statistical wind power forecasting techniques or,
(2) Studying the Wind Power Forecasting Error (WPFE) as a single probability density function, describing the error variability as a range from the lowest to the highest value of the distribution in the historical records.

In the first classification, the cascade of uncertainties of the wind power forecasting techniques comes from different parts of the methodology and tools to obtain the forecasted wind power (i.e. transforming a meteorological variable into wind power as [7] highlighted). The main sources of uncertainty are:

- If the meteorological variable (in this case the wind field) is selected from a Numerical Weather Prediction (NWP) model. The NWP model performances add a bias in the wind fields (at 10 m height or at other pressure levels) because the physical parameterizations of the model do not perfectly simulate the dynamics of the lower atmosphere.
- The selection of the wind fields at 10 m height or at other pressure levels needs to be corrected to the hub height of the wind farm. This interpolation method also contributes to the uncertainty [8].
- The selection of the power curve is also a controversial issue since each type of turbine has a different power curve. The area, geographical position of the wind farm, and the number and location of the turbines within the wind farm also play an important role in the accuracy forecasting (see for example [9]).

A detailed review about the methods and advances in forecasting wind power generation can be found in [10] and the recently published [7] improved the probabilistic wind power forecasting techniques applying an Analogue Ensemble method to the output of an ensemble of NWP predictions. Further, Junk et al. [11] explored several predictor-weighting techniques to improve the analogue ensemble methodology.

In the second classification, WPFE can be addressed using probabilistic techniques that identify probability distribution of random variables and calculate their distribution parameters based upon historical trends. Probability distribution functions of WPFE have been studied for different purposes. Bruninx and Delarue [12] and Bludszuweit and Dominguez-Navarro [13] analysed the variability of the WPFE distribution for multiple power systems from different countries, fitting the hourly time series of the error to a specific distribution in order to improve the probabilistic total reserve sizing. Schertzer [14] built a prediction model to calculate the wind power uncertainty for the 24 h of the following day and for the hour ahead for the French power system. A detailed literature review of numerical (physical), statistical and a combination of both wind power forecasting approaches can be found in [15–17], respectively. For example, Hodge et al. [18] investigated the WPFE variability for different countries to understand the temporal variations and to help power system actors determine appropriate corrections beforehand. The implications of integrating wind energy on day-ahead and intraday markets and the related price fluctuations have been subject to several studies in the last decade (e.g. [19–23]). Rahimiyan [24] proposed a statistical cognitive model to assess the impact of wind uncertainty on market behaviour in a pool-based day-ahead market. Wang et al. [25] generated wind power scenarios for a unit commitment model providing information about prediction errors by applying a Gaussian distribution to the time series. The short term relationships between wind generation and electricity prices were analysed by [26], who developed a model to derive optimal day-ahead bids for wind power producers taking into account one probabilistic density function of the WPFE. The study dealing with the reduction of the time series uncertainties is done by [27] who made an attempt to use short-term wind-power predictions using forecasting techniques to provide quantitatively an uncertainty estimate of the wind power output. They developed prediction risk indices (five classes) to evaluate the weather stability and the probabilities of the occurrence of high prediction errors according to the index, but the research was limited to estimating the short-term error as a function of the forecasted wind speed or other power market variables such as the total load. Lange [28] focused on the WPFE from the forecasted wind speed and evaluated the probability density function (PDF) of deviations between the predicted and the measured wind speeds. In addition, since the wind power prediction is not only dependent on external wind conditions but also on the structural and mechanical performance of the wind turbines systems, Tavner et al. [29] quantified the uncertainty of overall wind energy potential prior to the construction of a wind turbine. Kwon [30] studied the uncertainty caused by the variability of natural wind and power performance in the assessment of wind energy potential at a site.

As a consequence, these models and analyses are based on the highest range of uncertainty observed; while not taking into account that the wind error does not necessarily have the same range in every moment in time. There is only very limited research that explores the characteristics of the wind power forecast errors and explores their dependency and influence on the power market prices fluctuations and in the system actor decisions, before building models or generating stochastic scenarios.

Moreover, despite the continuous improvement of wind power forecasts, the uncertainty about predicting the absolute volume of wind output day-ahead increases with growing wind penetration [15–17]. Therefore, in the short-term, improved wind forecasts alone or studies for the distribution of the errors will not be enough to deal with the uncertainty involved in the power markets (day-ahead, reserve and intra-day markets) – other options need to be considered for managing the forecast deviations deriving in more volatile intraday prices and to balance the power supply and demand.

The novelty of our approach to deal with this issue consists in assuming that the WPFE has different characteristics in each time step, which allows us to classify them into different spreads as a function of other variables (e.g. day-ahead and intraday price and load), playing a key role in the power market bidding strategies. The contribution of this study is to quantify the range of uncertainty of the wind power forecasting used by a transmission operating system, assessing their influence on the power market prices and therefore, the impact on the power system actor decisions. The methodology presented in this study is used to reduce the wind power forecasting uncertainty range when the wind power forecasting is performed in the time period between the closure of the day-ahead market (11:00 h) and the first intraday bidding session (20:00 h), having a direct link with other variables such as the wind power generation and the total load. As a consequence, a data driven diagnosis model is developed to capture the strong influence that variability of the WPFE has on the fluctuations of the intra-day price. The methodology is presented in three steps: