Improving Wind Power Forecasting through Cooperation: A Case-Study on Operating Farms

Extended Abstract

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ABSTRACT

Concerns about climate change have never been so strong at the global level. One of the major challenges of the energy transition is dealing with the variability of renewable energies. Providing accurate production forecasts has become an important issue for the future, notably for wind energy. This paper proposes a method for wind power forecasting that focuses on interactions between neighboring wind turbines. The model is a multi-agent system based on a cooperative approach to improve an initial forecast. This work was carried out jointly with meteo*swift, a company specialized in wind power forecasting. The model was evaluated under real conditions on five wind farms currently operated by power producers. An improvement in forecast accuracy was observed compared to the model initially used by the company.

KEYWORDS

Multi-Agent System; Wind Power Forecasting; Cooperation; Wind Energy; Forecasting

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1 INTRODUCTION

Wind power will play a key role in the energy transition because the source of energy is unlimited and the exploitation of this resource does not emit greenhouse gases during electricity production. In order to obtain an efficient energy mix, a precise estimate of electricity production and consumption is required to regulate the electricity grid [10].

Wind power forecasts have been used industrially for over 20 years and this field is approaching technological maturity following a concerted research effort reviewed comprehensively in [11] and [4]. However, the scientific community is still showing a significant interest in the field of forecasting. Forecast errors are still high and there are several pointers to reduce them. This paper focuses on modeling the dependencies between the productions of close turbines in order to improve the overall forecast.

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This paper presents a forecasting model based on a cooperative approach. Wind turbines are considered as agents in a multi-agent system. Based on initial forecasts and constraints learned from weather and production forecasting historical data, they can modify their forecasts to make them consistent with nearby wind turbines. The model presented in this paper, faced with an operational method currently used by the company, was evaluated on actual data provided by power producers. This paper continues the work started in [2] by enhancing the way the forecasts are made and evaluating the results on a heterogeneous set of wind farms.

2 WIND POWER FORECASTING

According to theoretical studies [9], the power P delivered by a wind turbine follows the equation:

$$P = \frac{1}{2}\rho S C_p W_s^3 \tag{1}$$

where W_s is the wind speed, ρ is the air density, S is the rotor surface (the area swept by the blades) and C_p is the power coefficient (the fraction of wind energy that the wind turbine is able to extract).

In practice, the relationship between wind speed and production is difficult to model due to many external factors affecting the conversion process. Moreover, the wind speed at the exact blades location depends on the topography and the interactions between turbines. A typical theoretical power curve for an operational wind turbine is sketched in Figure 1. The observed production is also plotted as a function of the 100m-high wind speed forecast, the wide disparity of the points demonstrates the difficulty of modeling the relationship.

As a result, theoretical models constitute a preliminary approximation of the production but they introduce uncertainty. They are mostly used when a wind speed or production history is not available, e.g. for recently installed turbines.

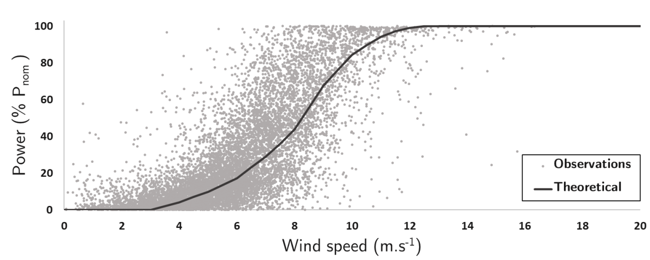

Figure 1: Production and wind speed relationship

Wind power forecasting methods are essentially based on statistical approaches which use previous historical data to train a model representing the relation between wind power and explanatory variables including Numerical Weather Prediction (NWP) and on-line measured data [7]. Approaches based on machine learning methods such as boosted regression trees [8], neural networks [14] or deep learning [16] are at the forefront of the technology, with gradient boosting methods winning two Global Energy Forecasting Competitions [5], [6]. Despite the performance of these approaches, they do not take into account the information available relating to the relationships between wind turbines.

Indeed, since a wind turbine generates electricity from the energy in the wind, the wind leaving the turbine has a lower energy content than the wind arriving in front of the turbine. A wind turbine thus interferes with its neighbors and can cause a production decrease on the turbines located behind it downwind. This phenomenon is called the wake effect [13]. This additional information has to be taken into account in the forecast process with the aim of improving the prediction accuracy. Therefore, the problem is to forecast the production at wind farm level by considering local constraints between turbines.

3 A MAS FOR WIND POWER FORECASTING

This problem requires modelling a distributed, dynamic system that has inter-dependencies between its elements. These characteristics correspond to a Multi-Agent System able to adapt to its environment in an autonomous way, such as those studied in [1].

The criticality of an agent expresses its degree of dissatisfaction [12] and its cooperative social attitude consists in always helping the most critical agent in its (limited) neighborhood (without being altruistic i.e. without becoming the most critical agent). The actions of the agents aim to reduce as much as possible the criticality of all the agents in the system without needing any global knowledge.

The proposed system is composed of Turbine Forecaster Hour (TFH) agents. Each agent is responsible of the forecast of a wind turbine production at a given hour. Each agent has access to weather forecasts and production data history. The neighborhood of a TFH agent is based on physical closeness: at a given hour, a TFH agent is related to, at most, the two closest TFH agents.

The behavior of an agent follows a Perception-Decision-Action life cycle. The agent starts with an initial forecast and can modify it at the end of each cycle. The behavior of an agent is summed up in Algorithm 1.

Algorithm 1 Life-Cycle of a TFH agent

repeat
  Perceive: Store its own forecast and criticality and those of its neighbors
  Decide: Compute the criticality of each possible action (increase, decrease or not change the forecast) and decide cooperatively the action that minimizes the highest criticality of its neighbors and its own
  Act: Perform the decided action and inform its neighbors of its new criticality
until Global criticality convergence *or* limit number of cycles exceeded

The quality of the forecast made by a TFH agent depends on the consistency of its forecast with both its own past productions and the neighboring agents forecast. Compliance with these constraints appears through Local and Neighboring criticalities. The final criticality of a TFH agent corresponds to the maximum between its local criticality and each neighboring criticality. This choice enables not to give an advantage to one criticality over the other, they are considered equivalent. The functions representing the criticalities are obtained from forecasted Probability Density Functions (PDF). A high probability corresponds to a low criticality while a low probability corresponds to a high criticality.

4 EXPERIMENTS AND ANALYSIS

The experiment consists in making a first forecast with Gradient Boosting Model (GBM) [3], a reference algorithm. Then our proposed system is used to possibly correct this. The model is validated by a 10-fold cross-validation. To evaluate forecasts performance two standard measures were used: the Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE).

The study was carried out on five wind farms in France. These farms were chosen because they are located in different wind zones and on land with different topographies. Weather forecasts are provided by the Météo-France AROME [15] high-resolution forecast model for the entire next day (with time horizon from 21h to 45h). The experiment covers a large period thanks to a nearly three-year history of wind power and weather forecasts from 01/2014 to 09/2017. In order to obtain the PDF and build the criticality functions, another GBM was trained with the parameters related to Equation 1, at 100m: wind speed, wind direction, temperature, pressure and relative humidity. The increase and decrease value specified in Algorithm 1 has been set to 1kW.

Finally, over the evaluation period, the improvement reaches on average 1% on MAE and 0.9% on RMSE compared to a reference algorithm. Although low, this decrease in error can avoid significant financial penalties for the wind operator on the electricity market, especially when the forecasts concern several wind farms. Moreover, the improvement was observed individually for the five wind farms evaluated. Plotting the criticality of agents shows that the local behavior of agents leads to a decrease in the overall criticality of the system. The cooperative behavior of the agents allowed a global resolution of the problem. As weather forecasts are uncertain, the decrease in criticality is not always correlated with a decrease in error. However, the results show an overall decrease in error.

Since there are also time dependencies in productions, the next step will be to connect each agent to its neighbors at hours h-1 and h+1. The model should also be tested on a larger scale on offshore wind farms where the wake effect is greater. Testing the model on other farms may also provide a better understanding of the impact of farm characteristics on the results.

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