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Censored spatial wind power prediction with random effects

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ABSTRACT

We investigate the importance of taking the spatial interaction of turbines inside a wind park into account for power forecasting. This paper provides two tests that check for spatial interdependence such as wake effects. Those effects are suspected to have a negative influence on wind power production. After that, we introduce a new modeling approach that is based on the generalized wind power prediction tool (GWPPT) and therefore respect both-sided censoring of the data. The new model makes use of a spatial lag model (SLM) specification and allows for random effects in the panel data. Finally, we provide a short empirical study that compares the forecasting accuracy of our model to the established models WPPT, GWPPT, and the naïve persistence predictor. We show that our new model provides significantly better forecasts than the established models.

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Contents

1. Introduction

As Ref. [1] points out, the worldwide wind power capacity continues to increase. Compared to other renewable sources of energy production, they find an economic advantage and competitiveness of wind energy, which leads to strengthening world wind energy markets. However, the prevailing of wind energy production depends on the obtained prices at the electricity markets. As wind power production itself is erratic, the yield of wind power is affected by the accuracy of wind power forecasts. Forecasts directly influence the pricing at international day-ahead electricity markets.

Lei et al. [2], and more recently, [3] as well as [4] present an overview of the manifold research on wind speed and wind power forecasting. The scope of wind power prediction models reaches from crude benchmarks (e.g. the so-called naïve predictor) to complex hybrid structure models. Two major classes of wind power forecasting are given by (a) physical approaches (see, e.g., [5]) and (b) stochastic modeling. The latter class contains conventional statistical approaches as well as artificial neural networks (ANNs) or support vector machines (SVMs). One state-of-the-art model for wind power predictions is the generalized wind power prediction tool (GWPPT), as introduced by Croonenbroeck and Dahl [6]. GWPPT is the recent generalization of the wind power prediction tool (WPPT) by Nielsen et al. [7], which has come to

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broad worldwide usage. While WPPT is based on a linear estimation of the relationship between wind speed and wind power (power curve), GWPPT additionally takes wind direction into account and also considers the non-linearity of the power curve by using a both-sided censored estimation procedure.

In recent research contributions, spatial wind power forecasting models are attaining increasing attention. With this paper we focus on a stochastic wind power forecasting approach that also incorporates the spatial correlation structure of a wind park. In this sense, we exploit information regarding the spatial arrangement of the turbines inside a wind park in order to take possibly present interaction effects between pairs of turbines into account. Interaction may be due to wake effects of the turbines: if two turbines are in a row (given the respective wind direction), there may be wake effects such as turbulence or energy reduction and we have to consider interaction.

This paper makes two major contributions: primarily, we introduce two straight-forward test approaches for an empirical wake effect analysis. Subsequently, we provide a new wind power forecasting model that takes spatial interdependence into account. We base our forecasting model on GWPPT, but introduce a spatial generalization of it that also allows for random effects. Thus, we show that our new model is capable of improving out-of-sample forecasting accuracy by a severe degree over the plain GWPPT model.

The paper is structured as follows. Section 2 provides a literature review of recent statistical modeling approaches. In Section 3, the wind park data set is described. We introduce our proposition for wake effects tests and the forecasting model. Section 4 sheds light on out-of-sample results and Section 5 concludes.

2. Literature review

Wind power forecasts can be performed for short-, medium- and long-term horizons. Although there is no clear consensus on how to define these horizon classes, Ref. [8] points out that short-term models cover forecasts minutes or few hours ahead. Medium-term forecasting refers to hours or few days ahead and long-term predictions deal with days to weeks to come. Here, we present an overview of several modeling approaches. We discuss the applicability of these models for the respective forecasting horizons (also see [9]) and put emphasis on modern spatial models.

Meteorological models focus on wind speed information and their impact on wind power production. Landberg [10] provides an early approach of this simple idea. Advancements of it led to the development of the model “Prediktor”, which is still in use nowadays. Lange and Focken [5] provide an overview of meteorological models. The ANEMOS.plus project aims at managing large-scale wind power generation based on meteorological inputs. The findings are reported regularly, the most recent issue is that of Giebel et al. [11]. After all, meteorological models work well in long-term scenarios, but lack the consideration of periodicity and persistence in the data. Therefore, they do not perform well in short-term settings. Purely statistical models however provide comparably well forecasts for short- to medium-term predictions.

ANNs, that usually process meteorological information, are algorithms for pattern recognition that can detect interdependencies between a multitude of input data and, based on that, select the model specification that fits the data best. Potter and Negnevitsky [12] provide an overview of methods of this class. One early application in the field of wind power forecasting is that of Beyer et al. [13]. Based on this idea, the WPMS (Wind Power Management System) was constructed. Since ANNs tend to overfitting, there are several approaches to compensate. Ernst and Rohrig [14] as well as Hong et al. [15] use “fuzzy” inputs, i.e. they provide deliberately diffuse data that are suitable to prevent meticulous fitting. As an alternative, an automatized, data-driven specification can be established using the methodology presented by Jursa and Rohrig [16]. Their artificial rigidity reduces overfitting, but also restricts the model's flexibility. To overcome this, Ref. [17] provides the idea of consensus forecasts. Therefore, a whole set of ANN based forecasts is generated. Based on that, a meta-forecast is generated in a second step, considering local conditions of the turbine. Catalao et al. [18] propose an ANN model in combination with wavelet transformations to cover periodicity while forecasting wind power in Portugal. A recently proposed hybrid model based on back propagation ANN and a genetic algorithm is presented by Huang et al. [19]. Lange and Focken [5] discuss a set of stochastic models and point out that the key to accurate short- to medium-term forecasts is in taking diurnal periodicity into account. WPPT, introduced by Nielsen et al. [7], does so. The WPPT is an autoregressive model with external regressors that considers short-term persistence modeling by a lag structure which is based on the desired forecasting horizon. The external regressors consist of a polynomial wind speed data input and a Fourier series to capture periodicity. The latter is based on an idea by Harvey and Koopman [20]. Alternatively, intermittency may also be modeled by basis spline functions as proposed by Lee [21]. WPPT, its generalization (GWPPT) and other models are compared by Croonenbroeck and Ambach [22]. They show that the GWPPT, taking the both-sided structure of the power curve into account, provides important additional information and improves the forecasts substantially.

Kusiak et al. [23] provide an overview of several time series approaches to predict the short-term power of a wind farm. An even broader comparison study is given by Taylor et al. [24]. Liu et al. [25] implement a new model which is based on autoregressive fractionally integrated moving average (ARFIMA) models and wavelet decomposition. They obtain accurate wind speed forecasts which are then used to predict wind power. The approach is compared to neural networks and other classical time series models. They find clear improvements of their model's accuracy over the classical benchmarks.

Li and Racine [26] provide an overview of advanced nonparametric kernel based regression methods. They show that the so-called “curse of dimensionality” can be overcome by using more advanced methods of bandwidth selection than that of Silverman [27]. A non-parametric wind power model is used by Khosravi and Nahavandi [28] to create suitable prediction intervals, as they argue that parametric approaches fail to provide precise prediction intervals.

Support vector machines, as proposed by Vapnik [29], are an attractive alternative to ANN models, as they are not prone to overfitting. Chitsaz et al. [30] use a stochastic support vector regression (SVR) approach for short-term wind power forecasts.

The spatial correlation of a wind park is a recent field of research, but only a few models exploit the spatial distribution of their target turbines. Alexiadis et al. [31] provide early work on the spatial correlation structure. Their ANN model provides wind speed and wind power forecasting enhancements. Damousis et al. [32] combine spatial modeling with a genetic algorithm to fit and predict their wind speed and wind power data. In the field of wind speed prediction, there are approaches that use spatial–temporal and regime switching models. Haslett and Raftery [33] provide one of the first spatial and temporal models to perform wind speed predictions for Ireland. They combine a kriging method with ARFIMA. The obtained long-term forecasts are used to evaluate the average wind power output of a given wind turbine. More recently, Ref. [34] set up a decomposition model for the temporal wind speed structure. After that, they use the obtained results to model the spatial structure by means of a Gaussian random field.

In spatial modeling, Ref. [35] contribute early work. Hering and Genton [36] provide a comparison of several kinds of multivariate

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