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Forecasting volatility of wind power production

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HIGHLIGHTS

- An increasing share of wind energy requires assessing the wind power volatility.
- Volatility forecasting with different GARCH models for wind power is examined.
- We introduce realized volatility of wind power as a benchmark for latent volatility.
- Markov regime switching GARCH model significantly outperforms classical GARCH models.

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ABSTRACT

Given the increasing share of wind energy in the portfolio of energy sources, there is the need for a more thorough understanding of its uncertainties due to changing weather conditions. To account for the uncertainty in predicting wind power production, this article examines the volatility forecasting abilities of different GARCH-type models for wind power production. Moreover, due to characteristic features of the wind power process, such as heteroscedasticity and nonlinearity, we also investigate the use of a Markov regime-switching GARCH (MRS-GARCH) model on forecasting volatility of wind power. Realized volatility, which is derived from lower-scale data, serves as a benchmark for latent volatility. We find that the MRS-GARCH model significantly outperforms traditional GARCH models in predicting the volatility of wind power, while the exponential GARCH model is superior among traditional GARCH models.

1. Introduction

Increasing energy demand and the negative impact of fossil energy consumption on climate change impacts have led to a worldwide boom of renewable energies, including wind energy. The global cumulative installed wind energy capacity increased from 24 GW in 2001 to 370 GW in 2014 and is expected to reach 596 GW in 2018 [1]. However, relying on renewable energy to meet increasing energy demand is still problematic. One of the main concerns of renewable energy production is its riskiness due to changing weather conditions. This is particularly true for wind energy production, which is one of the most rapidly expanding energy source. Volume risk is an important economic issue since energy is a non-storable commodity. In light of the increasing share of risky renewable energies in the portfolio of energy sources, a quantification of the production risk has gained considerable attention.[1] Interest in the prediction of wind energy production is diverse: In the long run (several years), investors want to predict their returns on investments in wind energy production. In the short run (several hours to days), grid operators have to make decisions about energy scheduling to balance supply and demand for a regional or national grid. Moreover, energy traders want to make informed decisions on how much they can offer or bid in the next trading cycle. This requires reliable forecasts of the output of wind energy farms.

There are several main streams of approaches and models that have been proposed to generate wind power forecasts. The first

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[1] The Economist Intelligence Unit [2] reports from a survey among 280 executives and investors in the renewable energy industry that 66% of respondents are concerned about volumetric risk in wind energy production.

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type is physical or meteorological models. These models rely on Numerical Weather Prediction (NWP) models to determine meteorological wind speed forecasts, which are then transformed into wind power forecasts via a power curve [3]. However, numerical weather prediction models is rather difficult to apply since it requires rich physical or metrological background knowledge for areas of interest. The second type is statistical approaches, which use statistical time series models to identify the spatial–temporal relationship of wind power productions/wind speeds [4–6]. Based on this relationship, wind power forecasts are estimated from the observed explanatory variables. Widely used time series models, such as autoregressive models, are normally linear. To model nonlinearity, Markov regime-switching time series models have been proposed [7,8]. The third type comprises data-driven/data mining models, such as neural networks or support vector machines, that have been intensively investigated recently [9–11]. In addition, some researchers also propose a hybrid model that integrates NWP and statistical models to derive more accurate forecasts [12]. The strengths of various models rely upon their different forecast horizons. An overview on the various modeling approaches can be found in [13,14]. In this paper, we focus on directly modeling wind power production for the short-term volatility forecasting via statistical approaches since statistical modeling of wind power production normally outperforms meteorological approaches for short-term forecasting, such as less than a few hours [13]. Moreover, meteorological approaches are subject to two estimation uncertainties: the uncertainty of the wind speed model and that of the power curve [15]. Therefore, the direct modeling of wind power production is common in the literature (cf. [16–19]).

Two kinds of forecasts can be considered, regardless of the approach and model. Early research focused on point forecasts of wind energy production, i.e., a single value of conditional expectation of wind power production is predicted. To make optimal decisions for energy participants, however, it is not sufficient to know only the expected wind power production. Actual production most likely deviates from forecasts and their difference causes imbalance costs for market participants. Therefore, participants in the energy market need an assessment of the uncertainty involved in the prediction. To account for the uncertainty of wind power production, probabilistic forecasts of wind energy production have been proposed [17,20,21]. Probabilistic forecasts are more flexible than point forecasts and can be quantile or interval forecasts [19,20] or full predictive density forecasts [16].

Volatility is a crucial parameter that captures the uncertainty of wind power production in wind power forecasting. It complements the point forecast to determine the distribution of probabilistic forecast. This distribution enables interval forecasts or quantile forecasts to be made feasible, which best serve the energy operator in decision-making [22,23]. From the point of view of an energy producer participating in the day-ahead electricity market, the uncertainty of wind power production results in imbalance costs or operating reserve cost. When the forecast has less uncertainty, fewer reserves need to be held and thus less imbalance cost will occur [24,25]. Volatility is also a determinant of financial risk measures, such as (conditional) Value at Risk (VaR, CVaR), and risk management instruments, such as insurance or wind derivatives. In fact, the (conditional) Value at Risk has been incorporated as an important indicator of risk assessment in the wind energy system. Based on these downside risk measures (VaR or CVaR), energy operators would be able to adjust their energy operation strategy and maximize profit in the energy market [26–28].

To measure the volatility of wind power production, characteristic features of wind data have to be taken into account. First of all, it has to be recognized that not only wind speed, but also wind volatility is usually time-varying. In a medium term perspective, seasonal effects of wind activity have to be considered [29]. In addition, one can observe stochastically time-varying heteroscedasticity similar to that in financial markets [16]. Moreover, wind power production can be affected by ramp events, i.e., when energy output changes by a substantial fraction of the capacity within a short time. Ramp events can be caused by a passage of large scale weather systems or thunderstorms. As a result, high wind speed shutdowns may occur, causing a rapid decrease in wind power production.

So far, a variety of volatility models have been applied either to wind speed data or to wind power data to capture time-varying heteroscedasticity. Alexandridis and Zapranis [30] estimate an ARIMA model for daily average wind speed data and model seasonal variation of the volatility with a truncated Fourier series. The prevalent models, however, are autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models. Tastu et al. [31] use an ARCH model to generate variances in probabilistic forecasts of wind power production for an offshore wind farm in Denmark. Liu et al. [22] evaluate the effectiveness of ARMA–GARCH approaches for modeling the mean and volatility of wind speed, including different GARCH models such as exponential GARCH and threshold GARCH models. Lau and McSharry [16] identify an ARIMA-EGARCH model for aggregated wind power data in Ireland and produce forecasts of the wind power density up to 24 h ahead. However, wind speed or wind power data exhibit random breaks and nonlinear behaviors. The classic ARMA and ARMA–GARCH models may be too restrictive to capture such nonlinear dynamic process. Recently, a Markov regime-switching model has been proposed and found suitable to model the dynamic behavior of wind power [7] and wind speed [8]. An advantage of this model is that it allows for incorporating the impact of random external factors since the regime switching process is driven by a Markov chain. To account for the nonlinearity and heteroscedasticity of volatility, we propose the use of the Markov regime-switching GARCH (MRS-GARCH) model as an alternative for modeling the volatility of wind power production.

In contrast to previous studies that aim to forecast wind power production, this paper focuses on volatility forecasts and explores the performance of volatility forecasting within the class of GARCH models including MRS-GARCH. A volatility forecast comparison can be difficult since the true, latent volatility is unobservable. As a result, the predicted value must be compared with an *ex post* proxy of volatility, e.g., realized volatility. The concept of realized volatility was introduced in financial markets due to the availability of high frequency financial data [32]. The daily volatility of stock prices is calculated by summing squared intraday returns. As a model-free estimator, realized volatility has often been used as an *ex post* proxy to evaluate the volatility of forecast models in financial and energy markets [33–35]. To the best of our knowledge, realized volatility has not yet been exploited in the analysis of wind power production.

In this article we use wind power production from a wind farm in Germany. Since energy market participants traditionally reply on hourly forecasts for bids that are set for each delivery hour in the market, e.g., Nord Pool Spot market [36,37], the hourly resolution of wind power production is chosen to generate the hourly volatility forecast through the considered models. To evaluate forecasted volatility, we examine higher frequency data of wind power production reported at10-min intervals to derive realized volatility as the *ex post* proxy of hourly volatility.

The contribution of this article to the existing literature is fourfold. First, we develop a MRS-GARCH model to describe the time-varying volatility of wind power production. This model allows us to capture the nonlinearity of wind power production due to changing weather conditions. Second, there is no consensus on the usage of volatility models in the application of wind energy.