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Probabilistic wind power forecasting based on logarithmic transformation and boundary kernel

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ABSTRACTS

Probabilistic wind power forecasting not only produces the expectation of wind power output, but also gives quantitative information on the associated uncertainty, which is essential for making better decisions about power system and market operations with the increasing penetration of wind power generation. This paper presents a novel kernel density estimator for probabilistic wind power forecasting, addressing two characteristics of wind power which have adverse impacts on the forecast accuracy, namely, the heavily skewed and double-bounded nature of wind power density. Logarithmic transformation is used to reduce the skewness of wind power density, which improves the effectiveness of the kernel density estimator in a transformed scale. Transformations partially relieve the boundary effect problem of the kernel density estimator caused by the double-bounded nature of wind power density. However, the case study shows that there are still some serious problems of density leakage after the transformation. In order to solve this problem in the transformed scale, a boundary kernel method is employed to eliminate the density leak at the bounds of wind power distribution. The improvement of the proposed method over the standard kernel density estimator is demonstrated by short-term probabilistic forecasting results based on the data from an actual wind farm. Then, a detailed comparison is carried out of the proposed method and some existing probabilistic forecasting methods.

1. Introduction

Efficiently integrating wind power generation with the nature of randomness and intermittence in power system and market operations necessitates wind power forecasting (WPF). The widely-used WPF method produces only a conditional expectation of wind power output, and is a deterministic prediction (or spot prediction) [1]. However, studies have indicated that wind power generation is a non-linear and non-stationary process. A large portion of the forecasting error comes from meteorological variables, especially wind speed, which have low predictability [2]. Therefore, the accuracy of WPF varies with time, with significant uncertainty involved [3–5].

Compared with deterministic forecasting, probabilistic wind power forecasts not only produce the expectation of wind power output, but also give quantitative information on the associated uncertainty [6]. This method has been applied to a wide range of decision-making problems related to power system operations, such as reserve requirement determination [7], economic dispatch [8], unit commitment [9] and energy storage sizing [10]. In addition, probabilistic wind power forecasting could help power market operators and market participants make sound decisions in uncertain electricity markets, which can hardly be achieved by deterministic wind power forecasting [11,12]. For instance, Pinson et al. [13] reported an optimal bidding strategy for wind power producers based on probabilistic forecasting. Simulation results showed that the new bidding strategy allowed a multi-MW wind farm to increase its revenue by 10–20%.

For continuous random variables such as wind power output, probabilistic forecasting usually takes the form of quantiles, prediction intervals, risk indices or the probability density function (PDF) [14]. The two main choices in constructing the probabilistic forecasting of wind power output are the parametric and non-parametric approaches. The parametric approach is based on assuming a predefined shape of predictive distribution, as in Weibull or Gaussian [15,16]. However, the assumption about the wind power distribution shape may be not reasonable, which may influence the effectiveness of the approach. Without any assumption of density shape, in the non-parametric framework, wind power density is estimated at a finite number of points.

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A series of non-parametric approaches have been applied in probabilistic wind power forecasting, for example, adaptive resampling [17], quantile regression [18–20] and kernel density estimation (KDE) [21–23].

The KDE method is popular among non-parametric approaches. It can not only provide entire information about wind power's predictive distribution, but can also easily deal with multi-modal wind power density. However, there are still some problems in the direct application of the standard KDE for probabilistic forecasting. Statisticians have found that the KDE method has worked well for near-Gaussian distributions, but not for ones that are significantly different from Gaussian density [24]. It is known that the distribution of wind power forecasting error is heavily skewed and heavy-tailed, resulting in a higher possibility of forecasting error in the tail of the density [25]. Therefore, wind power density is different from Gaussian. It is difficult to accurately estimate such a heavily skewed distribution with the standard KDE method. Bessa et al. [26] proposed a novel time-adaptive quantile-copula KDE method that produced more accurate probabilistic forecasting. Jeon and Taylor [23] applied the conditional KDE method to model the stochastic nature of the conversion from wind speed into wind power. In this paper, we introduce a transformation-based KDE method to address the heavily skewed wind power density. Transforming a variable to facilitate the model estimation is a commonly used approach in statistical analyses [27]. For modeling the non-linear nature of wind power generation, several transformation approaches have been investigated. Pinson [28] introduced the logit transformation into very-short term probabilistic wind power forecasting. Messner et al. [20] proposed to transform the observed wind power into wind speed via the inverse power curve of the wind turbine. In this paper, the proposed logarithmic transformation is focused on reducing the skewness of wind power density. The resulting new distribution in the transferred scale is much closer to the Gaussian distribution. The essence of this scheme is to transform the data to a scale on which it is more appropriate to apply the standard statistical tools, for instance, KDE. This transformation also benefits the bias reduction of the KDE method.

Another notable characteristic of the wind power variable is that it is double-bounded between the minimum output of zero and the maximum output of the installed capacity of the wind farm. Therefore, the wind power density is restricted within a compact support, resulting in the boundary effect problem of probabilistic forecasting. The boundary effect problem has had much attention in recent years. Pinson [28] introduced two discrete probability masses to represent the potential concentration of probability at the bounds of the compact support. Messner et al. [20] presented a censored regression model that solved the problems caused by censored wind power data. Probabilistic wind power forecasting based on the KDE method also suffers from the boundary effect problem [29]; that is, the kernel density estimator is biased downward near the boundary. This problem is caused by the discontinuity of wind power density across the boundary [30], which has an adverse impact on the performance of the KDE method. Pinson and Madsen [31] proposed a mean-variance model to model the shape of kernel functions associated with each of the ensemble members. Bessa et al. [21] suggested that the beta kernel function can be used for an interval-bounded variable (i.e. wind power), and the gamma kernel function is suitable for a one-sided bounded variable (i.e. wind speed). In our research, after the proposed transformation, there still remains a serious problem of density leakage in the transformed scale for the standard KDE method. To solve this problem, a boundary kernel method is proposed to eliminate the density leak at the bounds of the wind power distribution. The boundary kernel is a linear combination of two types of kernel function. As a result, the density estimate would not leak outside the boundary of wind power distribution.

This paper is organized as follows. Section 2 describes the theoretical methodology of the proposed KDE approach to probabilistic wind power forecasting, including logarithmic transformation and boundary kernel. Section 3 introduces an evaluation framework for verification of the effectiveness of the proposed method. The test results of the proposed method with real-world data under the evaluation framework are given in Section 4. This paper ends with a discussion and conclusions in Sections 5 and 6, with remarks on the future development of probabilistic wind power forecasting.

2. Methodology

2.1. KDE-based probabilistic wind power forecasting

KDE is a data-driven and non-parametric estimator of density function. Given independent and identically distributed (i.i.d.) data $X_1, \ldots, X_N$ following an unknown density function f_X, the univariate KDE is given by [30]

$$\hat{f}_X(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{x - X_i}{h}\right) \tag{1}$$

where $K(\cdot)$ is a kernel function and N is the number of samples. Bandwidth parameter h can be estimated by plug-in bandwidth selectors [32]. A density curve $K(\cdot)$ is placed at each data point, and represents the contribution of the data point to probability density. The corresponding density estimate can be obtained by adding up the N kernel functions.

Given i.i.d. multivariate data $X_{i1}, \ldots, X_{id}$ ($i = 1, \ldots, N$) from d different variables $x_1, \ldots, x_d$ following an unknown multivariate density $f_{X_1,\ldots,X_d}$, the multivariate KDE is as follows [30]:

$$\hat{f}_{X_1,\ldots,X_d}(x_1, \ldots, x_d) = \frac{1}{Nh_1 \cdots h_d}\sum_{i=1}^{N}\prod_{j=1}^{d} K_j\left(\frac{x_j - X_{ij}}{h_j}\right) \tag{2}$$

where $h_1, \ldots, h_d$ are bandwidth parameters and $K_j(\cdot)$ is the kernel function corresponding to the variable $x_j (j = 1, \ldots, d)$.

The conditional PDF model is used in probabilistic wind power forecasting, that is, in predicting wind power distribution when knowing the value of the conditional variable. Conditional variables are chosen from the prediction information of Numerical Weather Prediction (NWP), such as wind speed, wind direction and temperature. Then, the wind power output density given at time t for look-ahead time k can be formulated as:

$$f_P(p_{t+k}|X = x_{t+k|t}) = \frac{f_{P,X}(p_{t+k}, x_{t+k|t})}{f_X(x_{t+k|t})} \tag{3}$$

where $x_{t+k|t}$ is the wind speed prediction at time t for look-ahead time k, p_{t+k} is the wind power output at time $t + k$, f_P is the density of wind power output, $f_{P,X}$ is the joint probability density of wind speed and wind power and f_X is the marginal probability distribution of wind speed. This density f_X has also been modeled successfully in a parametric way by Weibull [33] or by log-normal [34] distribution. In order to maintain the nonparametric property, we chose to use the KDE method, which is also very easy to complete in practice.

Using (1) and (2) to estimate f_X and $f_{P,X}$, respectively, we can derive a probabilistic wind power forecast based on the standard KDE method:

$$\hat{f}_P(p_{t+k}|X = x_{t+k|t}) = \frac{\frac{1}{Nh_1h_2}\sum_{i=1}^{N} K_1\left(\frac{p_{t+k}-P_i}{h_1}\right) K_2\left(\frac{x_{t+k|t}-X_i}{h_2}\right)}{\frac{1}{Nh_2}\sum_{i=1}^{N} K_2\left(\frac{x_{t+k|t}-X_i}{h_2}\right)} \tag{4}$$