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Aggregated wind power generation probabilistic forecasting based on particle filter

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ABSTRACT

Probability distribution of aggregated wind power generation in a region is one of important issues for power system daily operation. This paper presents a novel method to forecast the predictive densities of the aggregated wind power generation from several geographically distributed wind farms, considering the non-Gaussian and non-stationary characteristics in wind power uncertainties. Based on a mesoscale numerical weather prediction model, a dynamic system is established to formulate the relationship between the atmospheric and near-surface wind fields of geographically distributed wind farms. A recursively backtracking framework based on the particle filter is applied to estimate the atmospheric state with the near-surface wind power generation measurements, and to forecast the possible samples of the aggregated wind power generation. The predictive densities of the aggregated wind power generation are then estimated based on these predicted samples by a kernel density estimator. In case studies, the new method presented is tested on a 9 wind farms system in Midwestern United States. The testing results that the new method can provide competitive interval forecasts for the aggregated wind power generation with conventional statistical based models, which validates the effectiveness of the new method.

1. Introduction

As the most promising renewable energy to replace the conventional fossil energy, wind energy has experienced a rapid growth around the world in the past decades [1]. However, due to the stochastic nature of wind, the variability and intermittency in wind energy pose great challenges to power system operations [2]. The integration of energy storage system (ESS), especially the distributed ESSs such as plug-in hybrid electric vehicle (PHEV), is one of the effective solutions to remedy this problem [3]. It is validated in [4] that the optimal storage size of ESS is strongly affected by the wind power forecast error, which leads to a need of accurately forecasting wind power generation. Moreover, with the rapidly increasing wind power installation, forecasting the aggregated wind power generation in a region becomes one of important issues for power system daily operation [5].

Some works have been investigated to forecast the aggregated wind power generation of regional wind farms. Pinson et al. [6] employed the upscaling technique to extrapolate the aggregated wind power generation from the wind power predictions of reference wind farms. Another way to predict the aggregated wind power generation is to use the smoothing techniques, e.g. Lobo and Sanchez [7] used the smoothing techniques to construct the predictions of the aggregated wind generation from historical wind speed predictions and the associated wind generation measurements. These approaches provide deterministic predictions and are convenient to implement. Nevertheless, due to the stochastic nature of wind, there are inherent and inevitable wind power forecasting errors with the deterministic predictions [8]. In this case, probabilistic forecasting of the wind power is much more meaningful.

Wind power probabilistic forecasting approaches can quantify the uncertainties associated with the wind power predictions. Such additional uncertainty information can help system operators make more reliable and economical decisions in optimization management of wind power [9]. Existing wind power probabilistic forecasting approaches can be divided into two main categories: statistical approaches [10–14] and physical approaches [15–17]. Statistical approaches use the historical wind generation and numerical weather predictions (NWPs) as inputs and employ machine learning models to provide wind power prediction intervals or predictive densities. Nielsen et al. [10] used the quantile regression method to provide wind power prediction intervals. Juban et al. [11] employed a kernel density estimator to predict

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the conditional probabilistic density function (pdf) of wind generation. Pinson et al. [12] estimated the empirical distributions of wind power forecasting errors and adopts a fuzzy inference model and bootstrap resampling technology to generate the prediction intervals from the empirical distributions. Sideratos and Hatziargyriou [13] used a neural network model to predict the uncertainty information of wind generation based on the point forecasts. Wan et al. [14] proposed a novel hybrid intelligent algorithm approach to formulate the prediction intervals of wind generation based on extreme learning machine and particle swarm optimization. The physical approaches are mainly based on numerical weather prediction (NWP) models. Talyor et al. [15] and Pinson et al. [16] employed weather ensemble predictions to predict the wind power uncertainties. Chen et al. [17] combined the NWP model with a Gaussian process for day-ahead wind power prediction. An overview of state-of-the-art approaches in wind power probabilistic forecasting can be found in [18].

The aforementioned models mainly focus on wind power probabilistic forecasting at the single wind farm level. To forecast the aggregated wind generation of several wind farms, it will be more complicated. One of key points need to be considered is to incorporate the spatial and temporal correlations between the geographically distributed wind farms. It is validated in [19] that a good understanding of the spatial and temporal correlations between the geographically distributed wind farms can help to improve the forecasting accuracy of their aggregated wind power generation. In addition, a favorable phenomenon caused by these correlations is the spatial smoothing effect that the variability of the aggregated wind power generation is less than that of a single wind farm [20]. These correlations are inherently induced by the motions of the atmosphere, e.g. the inertia of the same mesoscale or synoptic scale weather systems [21]. Thus a fundamental way to incorporate these inherent correlations is to use the NWP models. The NWP models are established based on the primitive equations, which formulate the physical laws of conservation of mass, momentum, and energy, and for wind farms distributed over thousands of miles, a mesoscale NWP model which omits the small scale turbulence is suitable in the scale [22].

Furthermore, a good wind power probabilistic forecasting model should be able to represent the non-Gaussian and non-stationary characteristics in wind power uncertainties [23]. The non-Gaussianity is mainly caused by the nonlinear transformation between the wind speed and wind power generation [24]. To address this issue, researchers usually approximate this nonlinear transformation by the individual turbine's power curve [18]. The non-stationary characteristic in wind power uncertainties is mainly induced by the time-varying meteorological conditions, e.g. the wind speed, air density, temperature and humidity, and the dynamic behavior of wind turbines caused by the factors of shadowing effects, aging and maintenance. To capture these non-stationary changes in wind power uncertainties, some researchers employ online learning algorithms for wind power probabilistic forecasting [25–27]. Moller et al. [25] gave a time-adaptive quantile regression model to provide interval forecasts. Bessa et al. [26] proposed a time-adaptive quantile-copula kernel density estimator to obtain the predictive densities of wind power generation by introducing a forgetting factor for the old input data. Kou et al. [27] employed an ensemble model based on the warped Gaussian process under an online model selection regime to provide the non-Gaussian predictive distribution of the wind power generation. It is validated in [25–27] that with the online scheme based models can well capture the non-stationarity in wind power uncertainties and yield better performances than offline models.

To address above issues, this paper presents a novel method for probabilistic forecasting of the aggregated wind power generation from geographically distributed wind farms. Based on a mesoscale NWP model and a wind speed downscaling model, a stochastic dynamic system is formulated to describe the relationship between atmospheric and near-surface wind fields. In the dynamic system, the atmospheric conditions over the geographically distributed wind farms are modeled as the system state, and the system output consists of the wind power generation of each individual wind farms. To cope with the non-Gaussian uncertainties, a recursively backtracking framework based on the particle filter (PF) algorithm is applied to estimate the atmospheric state and to forecast power generation of each wind farm. PF is a sequential Monte Carlo method used for recursive nonlinear filtering and prediction problems [28]. Unlike the traditional Kalman filter (KF), PF estimates the posterior densities of the system state and system output by a set of random samples (particles) and it is not restricted by the linear and Gaussian assumption. In PF algorithm, a series of random samples are generated from the uncertain atmospheric state. These random samples are propagated and updated to obtain the predictive samples of wind power generation according to the dynamic model and the new received wind power generation measurements. The predictive density of the aggregated wind power generation is estimated by a non-parametric kernel density estimator (KDE) based on the predicted samples.

The rest of this paper is organized as follows: Section 2 shows the procedure of modeling the stochastic dynamic system. Section 3 presents the details of forecasting the probabilistic densities of the aggregated wind power generation. The case studies are shown in Section 4 and conclusions are given in Section 5.

2. Establishing stochastic dynamic system

In this section, a stochastic dynamic system is formulated to describe the relationship between the atmospheric and near-surface wind fields of geographically distributed wind farms. As illustrated in Fig. 1, a dynamic equation is firstly formulated to predict the atmospheric wind speeds based on a mesoscale NWP model. Then the output equation converts the atmospheric wind speeds to the power generation for each wind farms. The foundation of this dynamic system is explained in detail as follows.

2.1. Modeling stochastic dynamic equation for atmospheric boundary layer

The stochastic dynamic equation is established based on a mesoscale NWP model. According to the atmosphere dynamics, evolution of the atmosphere can be described by the following baroclinic primitive equations [22]:

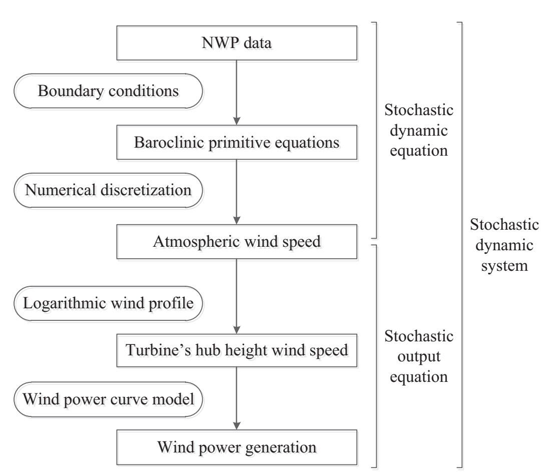

Fig. 1. Flowchart of establishing the stochastic dynamic system.