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Deep belief network based deterministic and probabilistic wind speed forecasting approach

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HIGHLIGHTS

- For the first time, deep belief network is designed for wind speed forecast (WSF).
- The nonlinear features in wind speed are used to improve forecast accuracy.
- The uncertainties of wind speed are evaluated using quantile regression.
- The competitive performance and high-stability of the proposed method were proved.

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ABSTRACT

With the rapid growth of wind power penetration into modern power grids, wind speed forecasting (WSF) plays an increasingly significant role in the planning and operation of electric power and energy systems. However, the wind speed time series always exhibits nonlinear and non-stationary features, making it very difficult to be predicted accurately. Recognizing this challenge, a novel deep learning based approach is proposed for deterministic and probabilistic WSF. The approach is a hybrid of wavelet transform (WT), deep belief network (DBN) and spine quantile regression (QR). WT is employed to decompose raw wind speed data into different frequency series with better behaviors. The nonlinear features and invariant structures of each frequency are completely extracted by layer-wise pre-training based DBN. Then, the uncertainties in wind speed are statistically synthesized via the QR method. Case studies using real wind farm data from China and Australia have been presented. The comparative results demonstrate that the high-level nonlinear and non-stationary feature in the wind speed series can be learned better, and competitive performance can thus be obtained. It is therefore convinced that the proposed method has a high potential for practical applications in electric power and energy systems.

1. Introduction

To mitigate climate change and reduce environmental pollution, new regulatory acts that encourage the use of renewable energy have been established worldwide [1]. Among renewable energy sources, wind power, as an alternative to fossil fuel-generated electricity, has been accepted as one of the most promising sources because it is clean, widely distributed, and emits no greenhouses gas during operation. Meanwhile, together with its mature and competitive technologies, wind power has gone through an unexpectedly high growth in recent years. It is, therefore, essential and desirable for high-accurate WSF to maximize the benefits of the high penetration of wind energy into electric power and energy systems [2] because the optimal solutions for almost every problem in power systems, e.g., the operating strategies, unit commitment, capacity planning and load balancing, are more or less associated with the accuracy of WSF [3]. However, the weather system always exhibits a chaotic nature, making it very difficult to achieve accurate and reliable WSF.

Traditionally, wind speed is predicted by deterministic forecast, short for deterministic point forecast. To date, four types of methodologies have been proposed in the literature for deterministic WSF, including the persistence method, physical modelling methods, statistical models, and soft-computing based approaches. The persistence method operates an assumption that any future wind speed value will be equal to the last known value due to the high autocorrelation shown in wind speed series [3]. Thus, the persistence method is generally applied as a benchmark for WSF to baseline the performance of newly developed forecasters [4]. Physical

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methods manage to utilize several meteorological parameters, such as the temperature, pressure, and orography, to establish a mathematical model of WSF [5]. However, due to the high computational cost, these methods may not be suitable for practical real-time WSF in electric power and energy systems. Statistical models, such as Autoregressive Integrated Moving Average (ARIMA), grey predictor, and exponential smoothing, try to approximate the WSF model by using historical samples with error minimization [6,7]. In addition, with the development of soft-computing techniques, various new WSF methods, such as artificial neural network (ANN) [8], neuro-fuzzy inference system [9], and Kalman filtering [10], have been proposed. Generally, the soft-computing based methods always provide a more competitive performance than the other three types of methodologies because of their potential abilities for data-mining and feature-extracting [11].

Due to the volatile and erratic nature of weather systems, the individual methods mentioned above may not comprehensively represent the inner stochastic traits of wind speed series. As a remedy, many hybrid methods in combination with different forecast models have been mooted for deterministic point WSF. In [12], a novel hybrid approach based on ANN and fifth generation mesoscale model was proposed. The numerical results demonstrated that this method outperforms physical methods and pure ANN. In [13], a hybrid architecture based on an unscented Kalman filter and support vector regression was presented. In [14], a novel hybrid approach based on wavelet packet transform (WPT), particle swarm optimization (PSO), and fuzzy inference system was proposed to mitigate the volatility and intermittency in wind speed series, and its efficiency was demonstrated in wind farms in Portugal. In [15], a general framework in combination with extreme learning machine and PSO was developed to approximate the WSF model. In [16], a multi-layer feed-forward neural network method proposed to extract the stochastic feature in wind speed series was well-trained by the perturbation stochastic approximation algorithm. In [17], the first/second order adaptive coefficient was employed to establish the WSF model, and its forecast error was minimized by PSO. In [18], to achieve better performance, WPT and least square support vector machine were utilized to effectively alleviate the randomness and uncertainties exhibited in wind speed series.

However, deterministic forecasts, i.e., point forecasts, fail to estimate the uncertainties associated with a given prediction of WSF [4]. These uncertainties play a key role in improving the economic benefits of day-ahead energy bidding and reserve scheduling [4]. Therefore, probabilistic WSF that can describe the uncertainties involved in wind speed data has attracted much more attentions in recent years. Generally, probabilistic uncertainty in wind speed series can be effectively formulated using an ensemble of point forecasts. In [19], an ensemble of mixture density ANN was proposed for probabilistic WSF, and the uncertainties in model mis-specification were numerically evaluated. In [20,21], the uncertainties in wind power series were fully captured by modelling probabilistic forecasts as an ANN-based optimal prediction interval (PI) problem. In [22], the optimal PI was directly constructed via an extreme learning machine-based ensemble approach and was solved by PSO. The main demerit of ensemble-based probabilistic forecasts is their high computational cost, which may cause a problem for real-time implementation. Another mainstream method for obtaining probabilistic information is to extend the point forecast into a probabilistic form by using parametric method [23], non-parametric method [24] and quantile regression [25]. In [26], an adaptive sparse Bayesian model for probabilistic wind power forecast was proposed and its computational cost was effectively mitigated via a sparsification method. An overview of probabilistic WSF and wind power prediction was presented in [27].

However, the deterministic and probabilistic approaches for WSF presented above usually adopt shallow models as their core of learning principle. As noted in [28], the deep nonlinear features of data series may not be fully extracted by these shallow models. Furthermore, the widespread use of environmental sensors and other relevant technologies drives us into the era of big data, which makes it even harder to extract the deep variability and volatility features in wind speeds [29]. Therefore, the unsatisfactory feature mining of shallow models inspires us to rethink the WSF problem based on deep learning architecture.

Recently, deep learning, as a new branch of machine learning, has been growing rapidly and has been employed in a variety of fields, including classification tasks, data mining, dimensionality reduction and image processing [30]. Previous studies have proven that compared with the shallow models, deep learning can discover the inherent abstract features and hidden invariant structures in data from the lowest level to the highest level. Considering the wind speed series complicated in nature, deep learning can represent the inner structures and features without any prior knowledge. Therefore, the performance of deep learning exhibits superiority and higher accuracy in WSF problems, and the characteristics specific to feature extraction make deep learning much more attractive [31]. The classical deep learning algorithm mainly includes stacked auto-encoder (SAE), and DBN. Earlier implementation of SAE tailored for WSF was reported in [28,32]. Nevertheless, to date, DBN designed for WSF has not yet been considered in the published literature. Therefore, this work, which investigates a deep WSF framework and a hybrid intelligent approach based on WT, DBN and QR, is originally proposed to enhance WSF performance and prediction efficiency. The main contributions of this paper are presented as follows:

- For the first time, deep belief network is introduced and tailored to comprehensively extract the deep invariant structures and hidden high-level nonlinear features exhibited in any wind speed frequency.
- A novel deterministic WSF approach in combination with DBN and WT is proposed to mitigate the effects of invariant structure and nonlinearity features that exist in wind speed series on prediction accuracy.
- A probabilistic WSF framework is formulated based on WT, DBN and QR to accurately evaluate the randomness and uncertainty in wind speed series from the perspective of sharpness, reliability and overall skills.

The proposed hybrid deep architecture for WSF has been thoroughly tested and benchmarked on real wind speed data from China and Australia under various time-scales and operation scenarios.

2. Deep belief network

In this section, the DBN architecture is presented. DBN was initially invented by Hinton [33] and has been implemented successfully in feature learning, classification and collaborative filtering [30]. DBN mainly contains an unsupervised learning subpart using restricted Boltzmann machines (RBMs) as its building blocks and a logistic regression layer for prediction.

2.1. Restricted Boltzmann machine

Restricted Boltzmann machine is a stochastic neural network that can learn a distribution over its set of inputs. The network generally consists of one layer of binary-valued visible neurons and one layer of Boolean hidden units. In a RBM, no connections