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Probabilistic wind power forecasting and its application in the scheduling of gas-fired generators

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HIGHLIGHTS

- Accurate wind forecast is essential for integration of wind farms to power systems.
- This paper presents a methodology for producing wind power forecast scenarios.
- The impact of the wind uncertainty on the operation of gas plants was investigated.

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ABSTRACT

Accurate information regarding the uncertainty of short-term forecast for aggregate wind power is a key to efficient and cost effective integration of wind farms into power systems. This paper presents a methodology for producing wind power forecast scenarios. Using historical wind power time series data and the Kernel Density Estimator (KDE), probabilistic wind power forecast scenarios were generated according to a rolling process. The improvement achieved in the accuracy of forecasts through frequent updating of the forecasts taking into account the latest realized wind power was quantified. The forecast scenarios produced by the proposed method were used as inputs to a unit commitment and optimal dispatch model in order to investigate how the uncertainty in wind forecast affect the operation of power system and in particular gas-fired generators.

1. Introduction

Many countries are committed to reduce their greenhouse gases (GHG) emissions by at least 80% by 2050, from 1990 levels [1]. Therefore ambitious plans have been set to deploy low carbon and renewable sources of energy. The large scale integration of wind generation into power systems of the countries in west of Europe is perceived to be an efficient strategy in response to the short term as well as long term emissions and renewable targets [2]. For example, in UK, according to a number of low carbon scenarios developed by industry and governmental bodies, capacity of wind generation in 2030 is expected to span between 48 GW and 65 GW [3,4].

The uncertainty of wind power forecasts makes the balancing of electricity supply and demand more challenging [5], as such, larger level of flexibility is required in the system to compensate for the forecasts errors. The additional investment and operating costs required for employing flexibility options (such as fast ramping back-up generators and electrical storage) can be minimised through obtaining accurate information about possible day-ahead wind power generation.

During the past decade many methods have been developed for forecasting of wind power. Generally, these approaches can be classified into two broad categories, namely physical methods and time series methods [6]. Physical methods use physical and meteorological information, including description of orography, roughness, obstacles, pressure and temperature to model wind power and forecast its future values. These approaches perform satisfactory for long-term prediction of wind power [7]. On the other hand, time series approaches require a smaller volume of data and information, compared to physical methods. Some of key meteorological variables such as wind speed and direction are needed by a time series approach to build a wind forecast model [8]. The historical data of wind power generation can also be used directly by the time series models to forecast wind power

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Nomenclature

Sets

t	time steps (30 min)
i	power generating units
b	electric busbars

Parameters

P_{t+k}	the aggregate wind power time series value at time t + k
$P_{\max}$	the maximum value of aggregate wind power time series
N	the number of prediction errors used for method evaluation
C^{fuel}	fuel cost of generators (£/MW he)
C^{var}	variable O&M cost of generators (£/MW he)
ts	duration of time step (30 min)
C^{eshed}	cost of electricity shedding (£)
C^{sd}	shut down cost for generators (£)
C^{su}	start up cost for generators (£)
R	ramp rate for generators (MW/h)
η	efficiency of generators (%)
H	gas heating value (39 MJ/m^3)
$\overline{Power}$	upper limit of power generation
$\underline{Power}$	minimum stable generation
UT	minimum up time
DT	minimum down time

Variables

e	wind power forecast error
$\bar{e}$	mean error
$\widehat{P}_{t+k}$	the value of aggregate wind power forecast for time t + k made at time t
μ_e	systematic error in forecasts
χ_e	random error in forecasts
v	ON and OFF state of thermal generating unit (1/0)
$Power$	power generation (MW)
P^{eshed}	unserved electric power (MW)
Q	volumetric gas flow rate (m^3/s)

Abbreviations

ME	Mean Error
NMAE	Normalized Mean Absolute Error
MAPE	Mean Absolute Percentage Error
SDE	Standard Deviation of the Errors
UC&ED	Unit Commitment and Economic Dispatch

[8]. Conventional statistical models such as auto-regressive (AR) models [9] and auto-regressive integrated moving average (ARIMA) models have been proposed for wind speed and wind power forecasting.

A number of recently reported methods for wind power forecasting are mentioned in the following. A Markov-switching method for forecasting wind speed is examined by [10] which is able to produce both point forecast as well as interval forecast for wind speed. In [11], a recursive model for short term (1–24 h) forecast of wind speed is reported. The model was developed based on Hammerstein model, and is capable of capturing chaotic dynamics of wind speed time series. A wind speed forecasting method based on secondary decomposition algorithm and Elman neural networks is reported in [12]. An approach based on backward extreme learning machine (ELM) forecasting was proposed by [13] to address the issue of ultra-short term wind power time series forecasting. For a detailed review of wind power forecasting models refer to [14].

From the system operators' point of view, forecast values and the associated uncertainty of aggregated wind power from wind farms in a region is of high importance. These information are important for optimal scheduling of storage and thermal units as well as determining the required level of reserve to deal with uncertainty in wind and load forecasts [15–17]. Most of the wind power forecasting models generate a single forecast thus do not provide information about the uncertainty of the wind power forecasts. In an effort to enhance the information provided by the forecasters, probabilistic forecasting has been a recent area of development in wind power forecasting [18–20]. Probabilistic predictions can be either derived from meteorological ensembles [21] based on physical considerations [22], or finally produced from one of the numerous statistical methods that have appeared in the literature, see [23–28] among others.

The models producing probabilistic wind power forecasts, provide useful information for studying power system impacts of wind energy. In [28], the impact of wind power forecasting on the market integration of wind energy in Spain is studied using time series analysis. The impact of wind power forecast uncertainty on unit commitments was investigated in [29], however the value of improved forecasts has not been quantified.

The main objective of this study is to propose a framework for generating probabilistic aggregate wind power forecast scenarios using historical wind power time series data. The advantage of the proposed forecasting model is its independency on additional attributes (i.e. weather data) for the training process. Real aggregate power from wind farms across Great Britain were used to examine the performance of this model. The time granularity for historical data and generated forecasts is 30 min. The historical values for wind power were classified based on their normalized values and trend. Data in the same classes were used to create probability density functions based on kernel density estimators. These probability density distributions were used to generate forecast scenarios using a rolling process. In order to demonstrate the application of the proposed forecasting approach, the wind forecast scenarios were used in an optimal unit commitment and economic dispatch model to investigate the impacts of wind forecast uncertainty on the operation of gas-fired generators.

The rest of the paper is organized as follows. In Section 2 the forecasting methodology is illustrated. In Section 3, a case study is presented to demonstrate the performance of the forecasting model using real data from wind farms in UK. Section 4 discusses the impact of forecasting errors on the unit commitment of gas-fired generators. Conclusions are drawn in Section 5.

2. Methodology

A probabilistic forecasting model was developed to generate wind power forecast scenarios and provide insights on the uncertainty of forecasts. As shown in Fig. 1, the model consists of three stages: *Data pre-processing*, *Training* and *Forecasting*.

2.1. Data pre-processing stage

A data pre-processing stage is required to prepare the inputs for the forecasting model. In this stage, the time series of the wind power data are normalized between zero and one, according to the installed wind generation capacity. Then, the normalized data were separated into two datasets, namely *Training* and *Testing* dataset. The *Training* dataset was used in the Training process