Renewable Energy 101 (2017) 1067–1074

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Short-term wind power prediction based on spatial model

Lin Ye*, Yongning Zhao, Cheng Zeng, Cihang Zhang

Department of Electric Power Systems, College of Information and Electrical Engineering, China Agricultural University, P.O. Box 210, Beijing 100083, PR China

ARTICLE INFO

Article history:
Received 24 October 2015
Received in revised form
25 July 2016
Accepted 26 September 2016

Keywords:
Wind farm
Power prediction
Spatial correlation model
Wake effect
Finite volume method (FVM)

ABSTRACT

Large-scale integration of wind energy into power systems may cause operational problems due to the stochastic nature of wind. A short-term wind power prediction model based on physical approach and spatial correlation is proposed to characterize the uncertainty and dependence structure of wind turbines' outputs in the wind farm. Firstly, continuous partial differential equation of each wind turbine has been developed according to its specific spatial location and the layout of its neighboring correlated wind turbines. Then, spatial correlation matrix of wind speed is derived by discretizing differential equation at each wind turbine using a finite volume method (FVM). Wind speed at each turbine is acquired by solving the relevant differential equation under given boundary conditions. Finally, the wind speed is converted to wind power production via a practical power curve model. Prediction results showed that the spatial correlation model can accurately characterize the correlations among outputs of wind turbines and reduce the error of short-term wind power prediction.

1. Introduction

To deal with environmental problems and energy crisis, wind power has been one of the most rapidly growing renewable energy over the last decades. The cumulative installed wind power capacity around the world reached 432.9 GW at the end of 2015 [1]. Unlike the conventional power generation, wind power is non-dispatchable due to the inherent stochastic and intermittent nature of wind [2]. Thus, high penetration of wind power in power systems has great impact on stability of systems operations [3]. Wind power prediction is an effective tool to cope with the uncertainty of wind farm output and minimize scheduling errors in power systems. Extensive work have been devoted to wind power prediction and many different methods have been proposed to help power system operator make decisions in scheduling and trading wind power [4].

In general, wind power prediction methods can be classified into two groups [5]: physical and statistical ones, which have been comprehensively reported in several literature [6–8].

It should be noted that most of state-of-the-art methods are focused on the wind power prediction at a specific turbine site, without properly accounting for the spatial dependence structure in the wind power generation field. That is, traditional inputs to prediction models only consist of on-site observations (wind power measurements, wind speed and direction) and/or meteorological forecasts, i.e. Numerical Weather Prediction (NWP). Information related to the physical phenomenon or neighboring territories is not adequately considered [9], which may lead to low prediction accuracy. On the other hand, with the development of wind power, hundreds of wind turbines may be installed in a wind farm. Wan [10] outlined a report that analyzed the characteristics of wind power fluctuations on different timescales. In this study, wind characteristics at 1s, 1min and 1 h timescales were analyzed respectively by utilizing data from 3 sites in Texas, Iowa and Minnesota at resolution of 1s. It was shown that the use of a single wind turbine to characterize the behavior of a wind farm or fleet of wind farms is erroneous, since single wind turbine exhibits increasing variability compared with that of an entire wind farm. Typical statistical properties of individual turbine output such as non-stationarity, a slowly decreasing autocorrelation curve, and weak diurnal variation are no longer helpful to characterize the outputs of all the turbines in a wind farm [11], so it is necessary to take more factors into consideration for accurate wind power prediction.

In this perspective, some previous research turned to spatial correlation studies of wind speeds. Considering the amplitude attenuation of the equivalent wind speed and the phase shift of the wave properties, Sørensen et al. [12] derived a correlation matrix in

* Corresponding author.
E-mail addresses: yelin@cau.edu.cn (L. Ye), zyn@cau.edu.cn (Y. Zhao), zhangch@cau.edu.cn (C. Zhang).

http://dx.doi.org/10.1016/j.renene.2016.09.069
0960-1481/

the frequency domain to describe the interdependent characteristics among the wind turbines in the wind farm. The model was used to simulate wind speed fluctuation of the wind turbines at hub height in large wind farm in the frequency domain. In Ref. [13], a new Storpark Analytical Model was developed and evaluated for wake effect, and a recursive equation was derived to describe the spatial correlation between the input wind speeds of two wind turbines. The correlation between the power outputs of wind turbines at different separation distances was also examined to explain the effect of decreasing variability with geographic aggregation. The output power of wind farms spaced less than 100 km apart was found to be highly correlated and spaced more than 200 km apart was found to only be weakly correlated [14].

Several research works have been carried out with emphasis on wind speed and power prediction using spatial correlation approaches. A technique based on Artificial Neural Network (ANN) was put forward by Alexiadis et al. [15] to predict wind speed and power output based on cross-correlated and upwind information from neighboring sites. It is demonstrated this model exhibits significant improvement compared with the persistent method. A Fuzzy Inference System with wind speed and direction as input variables was proposed as well in Ref. [11]. The model parameters were optimized using a genetic algorithm. The model used training data measured at various stations in and around the wind park. Thus, the autocorrelation and cross-correlation between local and remote wind speed time series were exploited to improve the accuracy of short-term prediction ranging from a few minutes to several hours ahead. Similarly, Barbounis and Theocharis [16] employed local recurrent neural networks for multi-step wind predictions at the park site for up to 3 h ahead, using wind data measured at neighboring sites up to 30 km away.

Gneiting et al. [17] proposed a Regime-Switching Space-Time method accounting for two dominant directions to discriminate between situations when wind blows from two different directions. Geographically dispersed meteorological observations in the vicinity of the wind farm were used as off-site predictors. In Ref. [18] the authors proposed a modified regime-switching space-time wind speed forecasting model that allows the forecast regimes to vary with the dominant wind direction and with the seasons, avoiding a subjective choice of regimes. Sanandaji et al. [19] built a low-cost sparse spatial-temporal predictor inspired by techniques from compressive sensing taking into consideration the numerical robustness and computational efficiency for large scale spatial forecasting. In Ref. [20] Dowell et al. modelled the wind speed and direction as magnitude and phase of a complex-valued time series. A multichannel adaptive filter was set to predict this signal on the basis of its past values and the spatial-temporal correlation between wind signals measured at numerous geographical locations. Tastu et al. [21] demonstrated the underlying correlation patterns for spatial propagation of forecasting errors. It is found that a forecast error made at a given point in space and time will be related to forecast errors at other points in space in the following period. In Refs. [22] and [23] spatial information of forecasting errors and uncertainty were incorporated into the probabilistic forecasting models to gain the potential benefits.

The above mentioned models still focused on prediction of specific site, though spatial correlation is incorporated. That is, in each prediction case, only the wind speed or power at target site is predicted, using the information from neighboring correlated sites. If it is required to predict the regional aggregated generation, each site should be selected as the target site in turn and be predicted individually using its neighboring sites. The prediction model for each site is with specifically tuned parameters which are different from that of other sites. This procedure is complicated and impracticable, especially for regions with a large number of wind turbines.

In this paper, a novel wind power prediction model is proposed based on physical approach and spatial correlation. In order to characterize the spatial dependence structure of wind turbines' outputs in a wind farm, a novel spatial correlation matrix is derived from Computational Fluid Dynamics (CFD) methods. The correlations among wind turbines can be mathematically described with this matrix. By using this spatial correlation model along with predicted speed of upwind turbines and power curve model, the wind power prediction for all turbines in a wind farm can be effectively obtained in one calculation, without building models for each wind turbine.

The structure of the paper is organized as follows: In Section 2, overview of the proposed wind power prediction methods based on spatial correlation is described. Section 3 introduces detailed derivation process of spatial correlation model. Section 4 is devoted to a case study based on spatial correlation model. Conclusions are given in Section 5.

2. Wind power prediction based on spatial correlation

A large wind farm may contain hundreds of wind turbines. Due to the wide distribution of the turbines, wind energy in different spatial locations of wind farm may be different, which is determined by the wind farm location, wind turbines layout, terrain and so on. Characteristic of wind turbine output is different from that of another. The wind farm output cannot be precisely assessed by simply multiplying individual turbine output by the number of the wind turbines, because this method will lead high uncertainty. Thus, a novel model which can reflect the spatial distribution of wind power characteristics is developed in this paper.

The spatial correlation model is derived based on CFD. Firstly, continuous partial differential equation of each wind turbine has been developed according to its specific spatial location and layout of surrounding correlated wind turbines. Then, spatial correlation matrix of wind speed is derived by discretizing differential equation at each wind turbine through a finite volume method (FVM). Wind speed at hub height for each turbine is obtained by solving the relevant differential equation under given boundary conditions.

In the wind power prediction based on the derived spatial correlation model, the wind speed at hub height of the upwind wind turbines is predicted firstly, using traditional statistical or physical methods. Then the predicted wind speed is input into spatial correlation model to derive wind speeds for other wind turbines in the wind farm. Finally, the wind speed is converted to wind power prediction via wind power curve model. Wind farm power prediction is acquired by summing up all of turbines' outputs. The wind power prediction based on spatial correlation is illustrated in Fig. 1.

The wind power prediction using spatial correlation model is a two-step prediction procedure, i.e. wind speed prediction at hub height is determined firstly and then converted to wind power prediction via a wind turbine power curve model. Wind power is a function of wind speed. Time series of speed v can be transformed into time series of power P_M using the power curve model as follows [24].

$$P_M = \begin{cases} 0, & v < v_{cut\_in} \quad or \quad v \geq v_{cut\_out} \\ P(v), & v_{cut\_in} \leq v \leq v_r \\ P_r, & v_r \leq v \leq v_{cut\_out} \end{cases} \tag{1}$$

where v_{cut_in} is the cut-in speed at which the wind turbine starts to generate power; v_{cut_out} is the cut-out speed at which the wind turbine stops generating power for mechanical protection; v_r is the rated speed at which wind turbine generates its rated power of P_r. A