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A new merit function to accommodate high wind power penetration of WGRs (wind generating resources)

J. Hur [a, *], R. Baldick [b]

[a] Dept. of Energy Grid, Sangmyung University, 20 Hongjumun 2-gil, Jongno-gu, Seoul, 110743, Republic of Korea
[b] Dept. of Electrical and Computer Engineering, Engineering Science Building ENS 502, The University of Texas at Austin, Austin, TX 78712-1084, USA

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ABSTRACT

In this paper, we propose a new merit function to provide practical information to find optimal wind farm locations and projects based on spatial wind farm output prediction, including correlation with other wind farms. Our approach can predict what will happen when a new wind farm is added at various locations. Spatial power prediction of geographically distributed wind farms and their statistics through the proposed prediction model based on Kriging techniques will be presented. Using the proposed prediction model of wind generating resources, the performance of the spatial merit function in the context of the McCamey areas of ERCOT (Electric Reliability Council of Texas) will be provided. A new merit function through the prediction of wind farm outputs can play a key role to accommodate high wind power penetration from spatially distributed wind farms in power system planning models. In addition, we also propose the Kriged Wind Farm-SMES (Superconducting Magnetic Energy Storage System) hybrid model to enhance the higher wind power penetration levels using a new merit function. The proposed merit function requires only the existing data of wind generating resources around the candidate wind farm sites in order to reduce the time and costs for the installation of an anemometry tower as a practical method of wind resource assessment study compared to MCP (Measure-Correlate-Predict).

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1. Introduction

Large scale wind farm penetration to existing power systems provides many challenging environments to ISOs (Independent System Operators) these days. Recently, wind developers are installing more advanced wind turbines with better dynamic response capability. If ISOs cannot handle those wind farms properly, it will create a lot of inefficiencies in system operations [1–9]. As a result, many ISOs are concerned about the reliability and stability impact on the power system because wind generating resources are the inherent unpredictability and variability.

Wind power is one of the most promising clean energy sources, since it can be easily captured by wind generators with higher power capacity compared to other renewable energy sources. Recent development in power electronics, digital signal processors and variable speed wind turbine technologies enables the rapid increase in global wind energy capacity and wind has become the fastest growing renewable energy technology. However, the main problem of wind energy system is its intermittent nature. Fig. 1 illustrates wind farm outputs in MW sampled with 1 min resolution for May 2009. As shown in the figure, wind farm outputs vary with time, as is well known, and the variability of production from a single wind farm is very high. As wind is fluctuating in nature, power variations may occur that can affect the system operations and planning.

In order to examine wind project viability, wind resource assessments are performed for a longer term system resource planning. During the process of wind resources assessments, wind developers have to determine project location and size, tower height, turbine selection and layout, energy production, and so on [1–3]. Basically, the wind resource assessment process involves the following steps: First, we identify attractive candidate sites and collect long term wind data using tall anemometry towers. Second, we adjust data for height and for long-term climatic conditions and use a model to extrapolate measurements to all proposed wind turbine locations. Third, we can predict energy output from turbines and also quantify uncertainties. As a practical example of

* Corresponding author.
E-mail addresses: jinhur@smu.ac.kr (J. Hur), baldick@ece.utexas.edu (R. Baldick).

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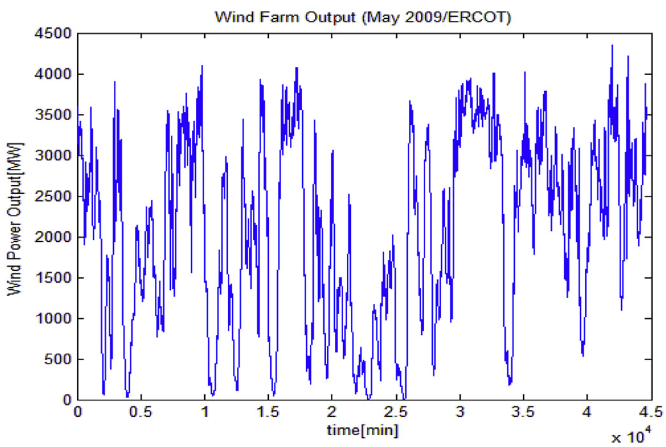

Fig. 1. Wind farm outputs sampled with 1 min resolution.

wind resource assessment study, we mention the wind generation resource assessments performed by the NREL (National Renewable Energy Laboratory) and SNL (Sandia National Laboratories) [3]. MCP (Measure-Correlate-Predict) method is used in their methodology to predict wind resources after the process of data validation. The MCP method is commonly used for the evaluation of long term wind resource at the candidate wind farm sites for wind power development [4,5]. The MCP method requires the installation of an anemometry tower to obtain the data such as wind speed at the candidate wind farm sites.

Wind generating resources are variable, uncontrollable, and uncertain compared to traditional generating resources. Analysis of wind farm output fluctuation provides useful information for studying the planning and operations of power systems, especially when a large amount of wind generating resources is concentrated in a specific geographical area such as the west area of ERCOT (Electric Reliability Council of Texas) in Texas. The study of wind farm output fluctuations can also contribute to development of new electric power system operation models and planning tools to handle variable wind generating resources and it is also required to maintain system reliability.

Generally, wind power prediction can be performed by three kinds of approaches such as statistical, physical, and hybrid methods as shown in Fig. 2. A lot of works [10–20] have been used only as a statistic model based on time series of wind power [10]. Numerical weather prediction model [11] is integrated with wind speed forecasting system and then the forecasted wind speed is converted to electrical power output through a power curve of a wind turbine. Hybrid model combined statistical model with the weather prediction model adopts neural network system with fuzz

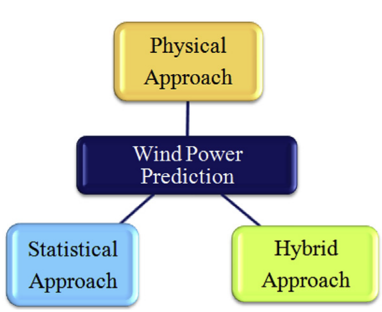

Fig. 2. Wind power prediction method focused on temporal approach.

data to enhance wind power prediction [14–16]. The previous works are focusing on temporal approach which is not reflecting spatial characteristics of wind generating resources. On the other hand, the proposed work is focused on spatial approaches to enhance wind power prediction.

The variability of wind generating resources across different geographical locations can increase the system operating costs for the traditional generating resources contributing to covering the net load. It can also increase the reserve quantities required to maintain system reliability. The analysis of power output fluctuation of geographically distributed wind farms is the first step to understand the variation patterns and characteristics of wind farm outputs in order to identify the correlation decay length to check spatial distribution of measured wind farm outputs and to develop the spatial correlation model. The spatial correlation model, represented by a semivariogram [25] between the existing wind farms, is a key function to predict wind farm outputs at unmeasured or new wind farm locations [24–33].

In our proposed work, we propose the Kriging-based Model to predict power outputs at unmeasured or new wind farm sites. The proposed model can alleviate the data requirement problem of the MCP method [21–23] when sufficient wind farms already exist in the region, as is the case, for example, for the McCamey region in West Texas. The method predicts wind production at unmeasured locations by implementing the spatial correlation model using data from measured wind farm sites. In our application, the historical data at unmeasured locations is not required to predict wind power productions. Spatial analysis based on the Kriging-based Model focuses on estimating longer term statistics of wind generating resources. The previous works on predicting future wind production is typically performed by scaling up power levels. For example, the higher power levels of future wind productions are represented by simply scaling up capacity factors. As the proposed spatial prediction model can provide practical information to find optimal wind farm sites, our approach is more subtle in that it can predict what will happen when a new wind farm is added at a particular location.

Energy storage system is urgently required to adapt with the mismatch between the variable generating production and the time distribution of load demands. SMES (Superconducting Magnetic Energy Storage) system is considered as a strong candidate to smooth the power outputs of wind farms controlling the ramp rate of wind turbines with SMES system as SMES's time delay is quite short during charge and discharge. Superconducting magnetic energy storage is surely one of the key technologies to overcome the wind variability problem [37,38].

In this paper, we propose a merit function to provide practical information to find optimal wind farm sites based on spatial wind farm output prediction, including correlation with other wind farms. Our approach can predict what will happen when a new wind farm is added at various locations. The proposed merit function is applied to the McCamey area of ERCOT (Electric Reliability Council of Texas) in Texas. In addition, we also propose the Kriged Wind Farm-SMES hybrid model to enhance the higher wind power penetration levels using a new merit function.

2. Spatial characteristics of wind farms

2.1. Spatial anlaysis for optimal strategy of wind farm projects

As wind farm output depends on stochastic wind resources that vary over space and time, wind farm output is random. It is very difficult to model the spatial variation of power output produced from spatially distributed wind farms by a simple function. Spatial variation can be better represented by a

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