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Wind farm power production in the changing wind: Robustness quantification and layout optimization

Ju Feng *, Wen Zhong Shen

Department of Wind Energy, Technical University of Denmark, DK-2800 Lyngby, Denmark

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ABSTRACT

Wind farms operate often in the changing wind. The wind condition variations in a wide range of time scales lead to the variability of wind farms' power production. This imposes a major challenge to the power system operators who are facing a higher and higher penetration level of wind power. Thus, wind farm developers/owners need to take the variability into consideration in the designing/planning stage, in addition to the conventional main objective of maximizing the expected power output under a fixed wind distribution. In this study, we first propose a new metric to evaluate the variability of wind power based on the characteristics of the wind farm and its local wind conditions. Then a series of robustness metrics are proposed to quantify wind farm's ability to produce power with high mean value and low variability under changing wind, considering both short-term and long-term wind condition variations. Based on these metrics, wind farm layout optimization is performed to maximize the robustness of a real offshore wind farm in Denmark. The results demonstrate that the robustness metrics are more flexible and complete than the conventional metrics for characterizing wind farm power production, such as mean power output or wind power variability alone, and it is feasible to design wind farms to produce power with high mean value and low variability.

1. Introduction

In the past two decades, wind energy has grown into a mature and important player in the global energy mixture, especially in the countries where environmental concerns and sustainability have received a high priority in their development goals. For example, in Denmark, one of the pioneering countries supporting wind power development, the penetration of wind energy production in the total electricity consumption has grown from 17% in 2006 to 42% in 2015 [1]. With the higher and higher penetration level of wind power, the integration challenges faced by the electrical power system are becoming more and more critical.

From the perspective of power system operators, the power variability is one of the most crucial challenges brought by the high wind power penetration. The wind power variability is a direct consequence of the fluctuating nature of wind and makes the wind power difficult or generally impossible to dispatch like other conventional powers. This imposes negative impacts on the reliability, stability, operations, ancillary services and cost of the power system [2].

The variability of wind power has been the subject of many studies. Most of these studies focus on the short-term variability and are mainly based on the study of the wind power time-series. For example, Katzenstein et al. [3] developed a metric to quantify the sub-hourly variability cost of individual wind farms (WFs). Kivilouma et al. [4] studied the characteristics of wind power variability using real data from multiple regions and divided these regions into low, medium and high variability regions according to the maximum 1 h wind power ramps relative to the nominal capacity. The metric they used to quantify the short-term variability consists of values of the ramp duration and the exceedance level of the ramp magnitude. Boutsika et al. [5] proposed a conditional range metric to quantify the intra-hour wind power variability and extended it to consider scarce or noisy data situations in a recent study [6]. Power spectral density has also been applied in other variability metrics [7,8].

Several methods have also been proposed to mitigate the negative impacts brought by the short-term variability of wind power, including: interconnecting WFs [8], optimizing regional spatial distribution of WFs [9] and optimizing wind turbine (WT) control strategy [10]. Better wind power forecasting can also contribute in solving the short-term variability challenges, as suggested in several recent studies, such as in [11,12].

* Corresponding author.
E-mail address: jufen@dtu.dk (J. Feng).

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Nomenclature

Acronyms

WF	wind farm
WT	wind turbine
AEP	annual energy production
TRI	terrain ruggedness index

Symbols

v	wind speed [m/s]
θ	wind direction [°]
P	power output [MW]
$\bar{v}$, $\bar{\theta}$, $\bar{P}$	non-dimensionalized wind speed, wind direction and power [–]
A_k	scale factor of Weibull distribution for the kth sector [m/s]
c_k	shape factor of Weibull distribution for the kth sector [–]
f_k	frequency of occurrence for the kth sector [–]
θ_k	wind direction for the center of the kth sector [°]
P_{mean}	mean power output of the WF [MW]
P_{rated}	nameplate capacity of the WF [MW]
v_{in}, v_{out}	minimal and maximal wind speeds the WF produces power [m/s]
$PSRI$	power surface ruggedness index [–]
VoP	variability of power [–]
P_{mean}^{ref}	mean power output of the reference WF [MW]
VoP^{ref}	variability of power of the reference WF [–]
$\tilde{A}_k$, $\tilde{c}_k$, $\tilde{f}_k$	variated version of A_k, c_k and f_k to account for long term wind variations
ξ_k^A, ξ_k^c, ξ_k^f	independent random variables to characterize the parametric variations of A_k, c_k and f_k
VR_A, VR_c, VR_f	maximal variation percentages of A_k, c_k and f_k [–]
p_λ	probability density function of the λ-PDF distribution [–]
λ	shape parameter of the λ-PDF distribution [–]
a_λ	normalizing parameter of the λ-PDF distribution [–]
N_{sample}	number of variated wind condition samples [–]
P_{mean}^{l}	mean power output of the WF under the lth variated wind condition sample [MW]
R_{short}, R_{long}, $R_{overall}$	short-term, long-term and overall robustness metrics [–]
α, β, γ	weighting parameters in R_{short}, R_{long} and $R_{overall}$ [–]
N_{wt}	number of WTs in the WF [–]
$\boldsymbol{X}$, $\boldsymbol{Y}$	vectors of x and y coordinates describing all WTs' locations [m]

In the meanwhile, the long-term variability of wind power has received less attention, mainly due to the lack of wind power time series that is long enough for long-term variability analysis. Recently, Kirchner-Bossi et al. [13] analyzed the long-term variability of wind power output from a real WT in the period 1871–2009 for two locations in Spain. They found that the simulated annual power output from a WT variates largely from year to year. For example, in one of the sites, its maximal annual value was 644 kW in 1978 while the minimal value was 485 kW in 1911. In general, predicting the long-term variation of wind power is extremely challenging, as there are no accurate methods to predict the long-term variation of wind conditions. As pointed out by Watson [14], general circulation models can predict possible future decadal fluctuations of wind conditions, but large uncertainties still exist.

All the studies referred above focused on the variability of wind power, which is of major concern to the power system operators. However, from the perspective of WF developers/owners, the annual energy production (AEP) of a WF is far more important than its variability, since it directly determines the WF's income. Thus, maximizing AEP is usually one of the most important objectives for any WF designer [15].

In the designing/planning stage, AEP of a WF is calculated as an expected value based on the local wind distribution, which is derived from a certain period of wind measurement data [16]. Most of the studies on WF layout optimization assumed a fixed wind distribution and thus didn't take the long-term variability into consideration [15]. Although the short-term variability has been considered for WF operation and control [10], it is seldom considered in the designing/planning stage. One exception is a recent study by Song et al. [17]. In this study, they defined a sensitivity index to evaluate the variation of a given WF's power output under varying wind directions. After a first stage optimization of maximizing the mean power output, they then carried out a second stage local adjustment of the layout to minimize the sensitivity of power to the changing wind direction.

Ideally, it is desirable to have the mean value of WF's power output as high as possible while keeping its variability under both short-term and long-term wind variations as low as possible. A lot of studies in the literature have focused on maximizing the power output, through both wind farm layout optimization [18,19] and wind farm control [20,21]. However, to the authors' knowledge, there hasn't been a metric in the literature that can be used to address both aspects in the same time, i.e., maximizing the mean power output and minimizing its variability.

In this study, we propose a series of robustness metrics to quantify WF's ability to produce power with high mean value and low variability under changing wind. A new metric for the variability of power is first proposed to quantify the sensitivity of a given WF's power output to the possible short-term wind condition variations, weighted by the local joint distribution of wind speed and wind direction. Then, the short-term robustness is defined by WF's mean power output and its variability of power. The long-term robustness is computed by modelling the possible long-term wind condition variations and investigating WF's power outputs under such variating/fluctuating wind conditions. Finally, the overall robustness is defined as a weighted sum of these two robustness metrics and a layout optimization study is then carried out to maximize it for the Horns Rev 1 WF using the random search algorithm [19].

2. Wind farm power output

A WF is a group of WTs located at a site to generate power from the wind. It can be viewed as a system that transforms the wind energy into power. At any given moment, the power output of a WF depends mainly on the characteristics of the inflow wind and the state of the WF itself.

The most essential characteristics of the inflow wind are wind speed v and wind direction θ at hub height. Although other characteristics such as turbulence intensity, atmospheric stability also have impacts on the power output, their influence on WF's long-term mean performance can be neglected.

In order to calculate the mean power output of a WT or a WF, we usually model the wind with a certain probability distribution for wind speed. While different types of distributions are available