Energy 89 (2015) 793–802

Contents lists available at ScienceDirect

Energy

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

A statistical algorithm for predicting the energy storage capacity for baseload wind power generation in the future electric grids

Shahab Shokrzadeh [a, *], Mohammad Jafari Jozani [b], Eric Bibeau [a], Tom Molinski [c]

[a] Mechanical Engineering Department, University of Manitoba, Winnipeg, MB, R3T 2N2, Canada
[b] Department of Statistics, University of Manitoba, Winnipeg, MB, R3T 2N2, Canada
[c] Soft White 60 Corporation, Winnipeg, MB, R3T 0E4, Canada

ARTICLE INFO

Article history:
Received 16 December 2014
Received in revised form
17 April 2015
Accepted 25 May 2015
Available online 7 July 2015

Keywords:
Intermittent renewable energy
Baseload wind power
Energy storage sizing
Statistical parametric and nonparametric methods

ABSTRACT

We propose a statistical algorithm for sizing the energy storage system required for delivering baseload electricity to a selected confidence level for a wind farm. The proposed algorithm can be utilized by utilities to assess wind integration and to investigate better capacity credits for wind farms connected to the grid, by wind farm operators to potentially increase their return on investment by designing a baseload wind farm to a selected confidence level, and by financial institutions to calculate the confidence level for baseload wind farm projects. Methods introduced are based on parametric and nonparametric statistical models using wind resource assessment data and available wind turbine information that reflect different stages of a wind farm project—from site selection to operational status. To study the performance of each method, we apply these to a North America operational wind farm data set. We use averaged 10-min and hourly data to calculate and compare the firm capacity of the wind turbine for each proposed method. The results show that for different stages of the wind farm development, and depending on the available information, the proposed algorithm can properly estimate the energy storage capacity required to deliver constant power to a user selected confidence level.

1. Introduction

Electricity generation from non-hydro renewable energy sources like wind and solar is a key solution in addressing global energy concerns, and achieving the world's goal of limiting the earth's temperature increase to 2 °C in 2050 [1]. Utilities that have a significant portion of their generation from fossil fuel sources have realized that a move away from these sources will be required for a more sustainable future due to CO_2 and other harmful emissions [2]. Several studies have investigated high penetration of intermittent wind power into the electric grids, and have addressed the main challenge of accommodating high penetration of the intermittent sources, *i.e.*, the variability imposed on the power system [3–6]. Most robust grid systems today, no matter what the supply mix is, can likely accommodate approximately 25–30% intermittent sources such as wind power without any major changes to the grid [7,8]. Higher penetrations of wind and solar renewables on an energy basis may require the use of ESS (energy storage system) to integrate these intermittent renewables. The future electric grid can be made 100% renewable with utilizing intermittent renewables like wind and solar if their intermittent nature is addressed by the addition of an appropriate amount of ESS [8–10]. As postulated in this paper, these intermittent renewables can be "converted" to baseload generation by using appropriately sized ESS to smooth out their intermittency, allowing penetrations of more renewables.

Wind electricity generation is becoming more economically competitive, achieving the lowest marginal cost [11,12]. The declining costs of ESS can further support utilization of large scale ESS in power systems. The integration of ESS and wind energy to produce firm capacity of the generator for higher penetration of wind into the grid through repurposing electric vehicles batteries is discussed in Refs. [13,14]. The authors present a cost formula, and show how the size and cost of storage system affects the total cost of wind power production as a baseload generator unit.

Many publications have presented different methods to size the capacity of ESS in various electric grid applications [15–18]. We introduce a general algorithm for sizing the ESS integrated with wind power with the objective of firming the capacity of wind

* Corresponding author. Tel.: +1 2042307251.
E-mail addresses: shahab_shokrzadeh@umanitoba.ca (S. Shokrzadeh), M_Jafari_Jozani@umanitoba.ca (M. Jafari Jozani), Eric.Bibeau@umanitoba.ca (E. Bibeau), Tom.Molinski@mymts.net (T. Molinski).

http://dx.doi.org/10.1016/j.energy.2015.05.140

farms. The presented algorithm contributes towards our goal of converting intermittent wind to a baseload power generation source. This is a novel step towards the goal of using wind power plants in the future electric grids where higher penetration rates of intermittent wind energy are anticipated.

We calculate the size of ESS energy capacity in kWh required to generate constant power in kW, using enhanced parametric and nonparametric statistical methods based on available information of the wind power plant. Three methods are presented to perform the ESS sizing calculations each representing a scenario associated with (*i*) wind farm project conception, or, (*ii*) wind farm operation. In each method, we use statistical models to calculate the required ESS energy capacity. A data set of wind speed and power values for a wind farm in North America is used representing 10-min and hourly averaged data for a duration of six months in 2006 and 2007 to implement the methods and compare the influence of data resolution on the size of ESS. We also average the data to create different resolutions (*e.g.,* hourly) to assess the influence of data resolution on the size of ESS. A comparison of the calculated size of storage from each proposed method is then presented.

In this analysis, we attempt to achieve a flat output from the proposed system. However, we note that baseload power generation does not necessarily mean a 100% flat output. Furthermore, roundtrip efficiencies of different ESS technologies may apply to reflect a more realistic capacity of the storage system. However, in this analysis and for the purpose of developing the methodology of the proposed statistical algorithm, and comparison of the proposed methods, a flat output power and an efficiency of 100% are assumed for the analysis.

Section 2 describes the proposed ESS sizing algorithm. In Section 3, the first method is introduced for the scenario where the theoretical power curve is derived from available wind speed data. Within this method, three different approaches are presented which require prior knowledge of wind turbine parameters. Section 4 presents the ESS sizing case when the turbine is selected and the manufacturer power curve is known. Section 5 considers the case when the wind farm is operational and the operational wind power data are available. In Section 6, we apply these methods to wind resource and operation data of an actual wind farm. Concluding remarks as well as some suggested future work in this research direction are provided in Section 7.

2. Energy storage sizing algorithm

In this section, we present the general algorithm for calculating the size of ESS requirements when the goal is to produce the baseload power of a wind generator in a given location. We propose three different methods, denoted by M_1, M_2, and M_3, and expand on them using parametric and nonparametric statistical techniques. Each method represents a stage of development of a wind farm, from conception to operational.

The first method, M_1, is performed before the operation of the wind farm and uses only the wind resource assessment data of the location of study as well as some possible general information about the characteristics of a generic wind turbine such as cut-in (v_c), cut-out (v_s) and rated (v_r) speeds. A turbine starts generating power when the wind speed reaches v_c, and achieves its rated power, p_r, at the wind speed v_r. When the wind speed reaches v_s, the turbine is shut down to prevent damage [19]. In this method, M_{1A} represents the case where no information about the wind turbine is available. M_{1B} assumes that in addition to the time-domain wind data, v_c and v_s of a generic wind turbine are known. In M_{1C}, the rated speed of the generic turbine is also known.

The second method, M_2, is similar to M_1 except that we additionally have knowledge of the selected wind turbine power curve for the wind farm, which can be written as $p_i = f(v_i)$ where $f(\cdot)$ is known [20].

Method M_3 is performed when we have access to the actual operational data of the wind farm including the time series of the measured wind speeds and the corresponding generated power. Therefore, these methods cover all possible scenarios for estimating the capacity of ESS to generate baseload wind power to a selected confidence level.

In the proposed algorithm, the storage sizing procedure is performed using the following steps:

i. *Wind turbine firm capacity calculation*: The firm capacity of the wind turbine, p^*, is determined as the reference value with respect to which, the size of ESS is calculated. This is the average output power that the generator is producing intermittently.
ii. *Power imbalances calculation*: The net difference between the firm capacity of the turbine p^*, and the wind power, P_w, is calculated.
iii. *Energy imbalances calculation*: For each time interval, the individual energy imbalances are calculated by integrating the net power rating over the span of time *i*.
iv. *ESS sizing calculation*: The size of each energy charges and discharges is obtained by summing over consecutive occurrences of individual energy imbalances.
v. *Confidence levels*: The histogram of ESS charges and discharges is created to fit a suitable pdf (probability distribution function), and apply different statistical methods to obtain the size of ESS with different confidence levels. This represents a critical step in performing an economic assessment to determine the size of ESS.

3. M_1 based on wind resource assessment data

To obtain the firm capacity of the turbine, we first estimate the pdf of wind speeds by constructing the histogram of the wind speed data and estimating the parameters of the pdf of wind speeds. The Weibull distribution is often used to fit the wind speed data [21,22] as a unimodal, two parameter family of distribution functions with the following pdf

$$f_V(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k}; \quad v > 0, \tag{1}$$

where $c > 0$ is the scale parameter with the same unit as wind speed, and $k > 0$ is the dimensionless shape parameter of the distribution [23]. We use the notation $V \sim \text{Weibull}(c,k)$ to denote that V has the Weibull distribution with parameters c and k. The Weibull distribution with $c = 2$ reduces to the Rayleigh distribution which has also been widely used for fitting the wind speed data [24,25]. The mean and the variance of a Weibull random variable are obtained in terms of gamma functions as follow

$$\mu_V = c\mathscr{H}_k(1) \quad \text{and} \quad \sigma_V^2 = c^2\left\{\mathscr{H}_k(2) - \mathscr{H}_k^2(1)\right\} \tag{2}$$

where $\mathscr{H}_k(i) = \int_0^\infty x^{i/k} e^{-x} dx, \;\; i = 1, 2.$

There are several methods to estimate c and k in (1), including the ML (maximum likelihood) method, the MM (method of moments), and the LS (least square) method [26,27]. In this paper, we use the ML method to estimate c and k which has several desirable theoretical properties such as asymptotic optimality and efficiency for large sample sizes [28]. The ML estimates of c and k are uniquely determined as follow [29]: