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Power curve monitoring using weighted moving average control charts

P. Cambron [a,*], R. Lepvrier [a], C. Masson [a], A. Tahan [a], F. Pelletier [b]

[a] *École de Technologie Supérieure, 1100 Notre-Dame Ouest, Montréal, Québec, Canada*
[b] *Arista Renewable Energies, 2648 Av. Desjardins, Montréal, Québec, Canada*

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ABSTRACT

A method for the monitoring of a wind turbine generator is proposed, based on its power curve and using control charts. Exponentially Weighted Moving Average (EWMA) and Generally Weighted Moving Average (GWMA) control charts are used to detect underperformances such as blade surface erosion. These variations in production amount to a few percent per year. The reference power curve is modeled using the bin method. A validation bench using simulated shifts on data from an MW-class wind turbine generator is used to assess the performance of the proposed method. Results show great potential, with both the EWMA and GWMA control charts able to detect a 1% per year underperformance inside 300 days of operation, based on simulated data. A short example is also given of an application using data involving a real case of underperformance: this example illustrates both the applicability and potential of this method. In this case, a shift of 3.4% in annual energy production over a period of five years could have been detected in time to plan proper maintenance. The rate of false alarms observed is one for every 667 points, which demonstrate the method's robustness.

1. Introduction

Wind energy has grown considerably in recent decades. The world's approximate annual production of wind power has surged from 50 TWh in 2000 to 550 TWh in 2013 [1]. It is now common to encounter wind farms that have been operation for up to 10 years. With the aging of wind turbine generators (WTGs), issues related to the detection of failures and wear are now of interest [2]. Availability of turbines must be maximized by limiting the downtime required for repairing or changing components. Moreover, operation and maintenance (O&M) costs in wind energy are substantial. These expenses represent one tenth of the total cost of any project [3]: an ability to detect failures in a timely way combined with a knowledge of the state of wear can both improve O&M efficiency.

A great deal work has been done in WTG monitoring. Initially, work was done on condition monitoring systems (CMS) often based on vibration analysis with spectral methods like Fourier and wavelet transforms [4,5]. This offered various methods for detecting issues related to the WTG structure and the drive-train components. Since most of the CMS methods are needing the installation of additional sensors, methods based on the Supervisory Control and Data Acquisition (SCADA) system were also proposed [6].

The WTGs faults detection and prediction with SCADA data have also been studied using methods such as benchmark models [7], artificial neural networks [8,9]. Avoiding a fault or limiting the downtime of the WTG following a fault is a way to increase the availability of the WTG. However, faults are events occurring on a relatively short time scale and are focussed on only a component at the time.

Some work using the SCADA data and the power curve proposed ways to monitor the WTG's performance with the power curve using certain confidence intervals [10,11]. The power curve of a WTG is the relation between the wind speed and the produce power, but can also be regarded as an indicator of the performance of the WTG. A change in the WTG's behavior will result in a change in its power curve [10,12–14].

Often in related work on the topic of power curve monitoring an application a real change in the performance is covered. Control limits or confidence intervals are commonly used [11,13,15]. However, the sensibility of the proposed methods are not discussed. It is not clear which is the smallest shift in the power curve detectable and what is the time needed to be detect a shift of a certain level.

* Corresponding author.
E-mail address: philippe.cambron.1@ens.etsmtl.ca (P. Cambron).

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Not much attention has been paid, however, to cases of small and progressive underperformances over the long term (several years). One example of underperformance hard to detect is the erosion of the blades' surface coating, leading to the degradation of aerodynamic properties [16]. The rate of production loss for cases of underperformance is only a few percent per year; still, over time, this rate can reach critical values [17]. But, monitoring must be robust in order to suit the industry. This means, in Statistical Process Control terms (SPC), that Type I and Type II errors must be minimized. Type I error is defined as the detection of an underperformance when there is none and Type II error is to fail to find an actual underperformance [18].

This paper proposes a method for detecting of small underperformances in the production of a WTG, using its power curve and control charts. As mentioned above, a change in the behavior of the WTG will results in a change in the power curve. When used along with control charts, power curve monitoring can be a resourceful tool for operators. Control charts, used in Statistical Process Control (SPC), monitor processes in real time and can raise the alarm when a process goes out of control, i.e. when a process is statistically different from a fault-free reference. Here we will study the use of Exponentially Weighted Moving Average (EWMA) and the Generally Weighted Moving Average (GWMA).

2. Power curve

The relationship between the power produced (P) by a WTG and wind speed v is provided by the following equation:

$$P = \frac{1}{2}\rho c_p A v^3 \tag{1}$$

with ρ the air density; A the area swept by the rotor; and c_p the power coefficient of the WTG.

However, the shape of a WTG real power curve, as shown on Fig. 1, does not exactly follow this relationship. For wind speeds that are below the cut-in value (Zone I on Fig. 1), there is no power produced, since the wind does not have enough energy to move the rotor. At wind speeds above the nominal speed (Zone III), the power reaches its nominal value. Mechanisms such as pitch angle attenuation for active control turbines are used in order to maintain power at its nominal value. At extreme wind speeds, the WTG is stopped in order to ensure the structural integrity of the WTG (Zone IV). It is only between the cut-in speed and the nominal speed that a cubic relationship is observed (Zone II).

3. Statistical control charts

3.1. EWMA control chart

The EWMA control chart was introduced by Roberts [19]. It is a statistic that gives greater importance to recent data while still considering previous values. The weights used to the calculation of the moving average are distributed exponentially, with the most recent value having the most weight. The EWMA is expressed as follows:

$$Z_t = \lambda Y_t + (1-\lambda)Z_{t-1} \tag{2}$$

where Z_t is the EWMA at time t; Y_t the observed value being monitored; and λ a smoothing constant between 0 and 1.

Z_0 is the target value or the historical mean of the process. If λ is close to 1, the statistic has little memory, giving great deal of weight to the recent points, whereas if λ is close to 0, the statistic gives high importance to historical data. Moreover, if $\lambda = 1$, the chart becomes a Shewhart control chart [18]. Therefore, λ must be chosen as a function of the type of shift to be detected. The estimated variance of the EWMA is approximately the following:

$$s^2_{EWMA} = \frac{\lambda}{2-\lambda}s^2 \tag{3}$$

with s^2 the variance in historical data.

The central line of an EWMA chart is the target value or Z_0. The lower control limit (LCL) and the upper control limit (UCL) are defined by:

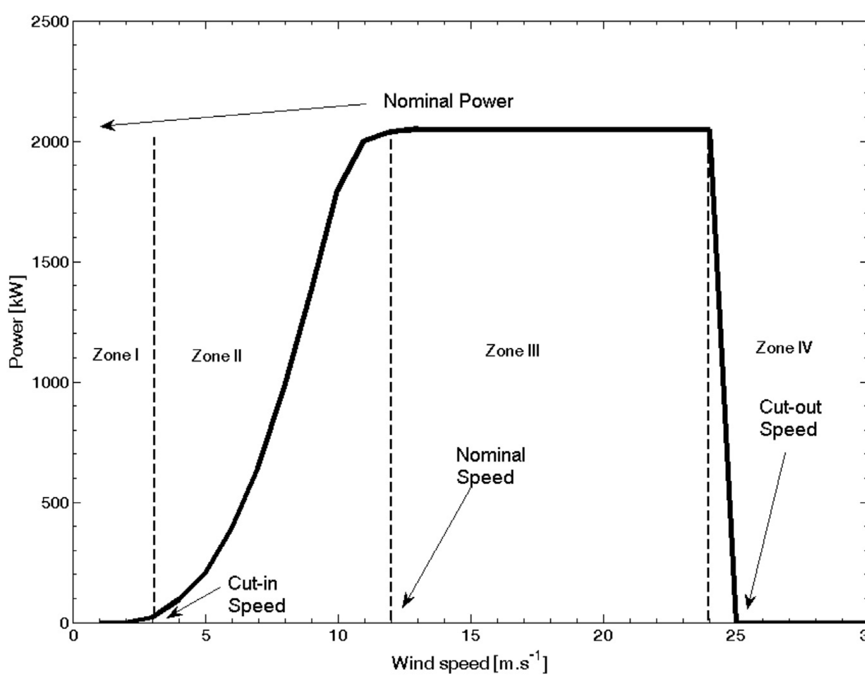

Fig. 1. Example of a power curve.