Fast Ice Detection for Wind Turbine Blades via the Langevin Equation

Haijun Fang, Linpeng Wang

Global Digital Energy Center, Envision Energy, 1201 Louisiana Street, Houston, Texas 77002, USA
E-mail: haijun.fang@envision-energy.com, linpeng.wang@envisioncn.com

Abstract. In this paper, a software-based algorithm for fast detection of ice on wind turbine blades is developed. The Langevin equation is used to create an entire or partial power curve with the high frequency data of wind speed and electrical power. Such a power curve is called the Langevin Power Curve (LPC). The LPC is obtained periodically. The period can be adjusted to be from 1 minute to 1 hour. For our application, the period is set to 5 minutes to allow enough data to generate an entire or partial LPC and then ice may be detected within a short period of time. The obtained LPC is compared to a reference power curve and then an ice index is calculated given that the condition for ice accretion is met. If the ice index is much higher or lower than 1, it may be concluded that there is ice on the anemometer or the blades of a wind turbine.

1. Introduction
The captured power of a wind turbine is calculated as

\[ P = \frac{1}{2} \rho A V^3 C_p, \tag{1} \]

where \( \rho \) is the air density, \( A \) is the sweeping area of blades of a wind turbine, \( V \) is the wind speed and \( C_p \) is the power efficiency. In cold regions or places at high altitudes, the captured power by a wind turbine can be higher because of higher air density \( \rho \) and/or wind speed \( V \). However, it is very possible that ice accrete on blades of wind turbines in these areas (Figure 1). The ice accretion may be due to the clouds around wind turbines at places of high altitude or snow and rain in cold regions. Ice usually results in negative impact on wind turbines in power production, wind turbine structure and safety. First, ice on blades may reduce the power efficiency, \( C_p \), or equivalently drag down the normalized power curve of a wind turbine. In some scenarios, the rotor speed of a wind turbine is very low even at high wind speed due to ice on blades so that a wind turbine generates very low power. In [3], 2D airfoil geometry coefficients, relative wind speed, angle of attack, relative humidity, liquid water content in air, mean water droplet diameter and icing duration are considered as inputs to the software \textit{LEWICE} [15] released by the National Aeronautics and Space Administration (NASA). Simulation shows ice profiles at different values of these inputs. It is concluded that ice results in reduction in the lift coefficient \( C_l \) and increase in the drag coefficient \( C_d \). Hence, the icing power curve is lower than that without ice. In Figure 2, we use real data from a wind turbine for the comparison.
between normalized power curves with ice and without ice. It is obvious that the normalized power curve shifts down due to the ice accretion. Moreover, it was observed that some wind turbines even barely generate power due to the ice. Secondly, there may be imbalance among blades due to different amounts of ice accretion on them. It may increase loads to the blades and even to the tower and then reduce the life expectancy of wind turbines. Thirdly, ice on blades can be dangerous to people and properties near wind turbines as well. Hence, anti-icing or de-icing functionality is very necessary for wind turbines that are set up in cold regions or places at high altitudes.

![Figure 1. Iced Blades](image1)

![Figure 2. Comparison between power curves without ice (black) and with ice (green)](image2)

The first step in the anti-icing or de-icing functionality is to detect ice on blades. The different methods of ice detection are summarized in [4, 9]. Basically, there are direct and indirect ice detection methods. In the direct methods, additional hardware sensors are put around blades. For example, the authors of [13] installed optical ice sensors in blades and used optical frequency domain reflectometry (OFDR) to detect ice. In OFDR, continuous laser light is measured with a swept frequency. It has shown in [7] that OFDR can have accuracy of $\pm 61\text{nm}$ in thickness.
and $\pm 2 \times 10^{-6}$ in the index of refraction. Hence, OFDR is used to detect ice accretion and thickness. With accurate measurement of the thickness of ice, the ice type can be determined as well. In [5], an approach for ice detection was originally designed for aircraft. Then the same idea is applied to detect ice on blades of a wind turbine as well. The idea is that a vibrating stick is placed on the surface of blades and it vibrates at its resonant frequency. The vibration frequency and amplitude will be changed due to the ice on blades. A sensor is used to detect the change in the vibrating frequency and amplitude and such a change indicates ice accretion. Obviously, direct methods may incur additional cost to wind turbines. Indirect methods are usually software-based and assumed to be cost effective. Researchers and engineers detect ice formation by monitoring abnormal values of physical signals impacted by ice. For example, in [11], it is found that a pulsation in electrical torque exists after ice is accumulated on blades. Such torque pulsation creates a frequency component in the output current of the electrical generator. By detecting the frequency component, ice accretion can be confirmed. In [12], the ice can be detected by monitoring the $1p$ frequency in the rotor speed. Ice accretion usually causes mass imbalance on blades. Hence, the torque on each blade may be different and then sinusoidal torque fluctuation exists. Such sinusoidal fluctuation, usually at the $1p$ frequency, can be seen in the rotor speed by spectrum analysis. Since this method can be used to detect mass imbalance caused by other factors such as dirt on blades, a supervisory system is needed to distinguish the mass imbalance by ice from that by other factors. The authors of [2] have investigated the change of power curves due to ice for ice detection. The concept of power threshold (PT) curves is used to compare power curves with ice and without ice. Three methodologies of PT are used: flat percentage, standard deviation and quantile. The effects of these three methods are compared as well.

In this paper, we will follow the idea in [2] and monitor the change of power curves for ice detection. However, by the design specification, we need to detect ice in a short time period (since ice accretion can be as short as 20 minutes) so that we are able to reduce the potential power loss or damage to wind turbines. For example, the blades have been seen with ice in some wind farms located in South China, where it is humid and the temperature can be below $0^\circ C$ in the night and above $0^\circ C$ in the day in winter. So ice accretes in the night and melts in the day in winter. However, the short duration of ice may still incur power loss. We are motivated to use the short time period data to describe the latest power generator performance of wind turbines as accurately as possible. Hence, we use the Langevin method [8] to create a power curve to monitor the power generation performance. In [10], the Langevin method is applied to monitor the whole wind farm power production as well. Using the Langevin equation, we can calculate the trend of power by linear regression and then predict the stable value of power at a given wind speed. Since the high frequency data is used in Langevin equation, we can quickly obtain an entire or partial LPC in a short time. With the new defined icing index that is based on LPCs, we can estimate if there is ice accretion on blades. In this research work, we assume that the power curve change is caused by ice accretion only. In the product implementation, we have a supervisory system to differentiate ice from other causes that impact the power curve similarly.

The rest of the paper is laid out as follows. In Section 2, we will introduce the Langevin equation and Langevin power curves as well. How to implement Langevin-based ice detection module will be described in Section 3. In Section 4, test results will show the effectiveness of the developed ice detection method. The conclusion will be drawn in Section 5.

2. Langevin Power Curves

A power curve describes the relationship between the wind speed and the generated electrical power. In [14], the average of 10 minutes of data is used to create the power curve. Such a standard is well accepted for the calculation of annual energy production (AEP). However, it
may take a long time to collect enough data to draw a power curve and then it is hard to observe the impact on the power curve by factors that last for only a short period of time, for example, ice on blades. The Langevin method has been applied to create a LPC with high frequency data. In [1], it is shown that the LPC is theoretically independent of the wind speed measurement device and the complexity of the terrain. In [6], the LPC is obtained with the data within a short period of time and it is used for power performance monitoring. In this paper, we will introduce how to implement the function of ice detection by using LPCs. In the following, we refer to [8] and simply explain how to create a LPC. More detailed explanation can be found in [8].

The Langevin equation is used to describe Brownian motion. So for wind turbines, we can think of the wind speed, $V_{\text{wind}}$, including two parts for a short of time,

$$V_{\text{wind}}(t) = V_0 + n(t),$$  \hspace{1cm} (2)

$V_0$ is a constant, representing the average wind speed during the considered time of period, and $n(t)$ describes the wind turbulence. $V_{\text{wind}}$ is the input to a wind turbine. The impact on the electrical power output can be described as

$$\frac{dP}{dt} = -\alpha(P, V_{\text{wind}})(P - P_L(V_0)) + \mathcal{R}(t).$$  \hspace{1cm} (3)

$\mathcal{R}(t)$ is the effect of $n(t)$. $P_L(V_0)$ is the stable power when $V_{\text{wind}} = V_0$ and is only dependent on $V_0$. Hence, if there is no wind turbulence, it is a relaxation process so that the electrical power output will converge to its stable value, $P_L$ (Figure 3). $\alpha$ describes the speed of convergence and is dependent on the current power, $P$, and the wind speed, $V_{\text{wind}}$. The first part on the left side is called the drift process and the second part is called the diffusion process.

![Figure 3. An LPC-based illustration of the Langevin dynamics](image)

Let the drift coefficient $D_{\text{drift}} = -\alpha(P, V_0)(P - P_L(V_0))$, then

$$D_{\text{drift}} = \lim_{\tau \to 0} \frac{1}{\tau} M_{ij}(P, \tau, V_{\text{wind}}),$$  \hspace{1cm} (4)

where $M_{ij}$ is the conditional moment,

$$M_{ij}(P, \tau, V_{\text{wind}}) = \langle (P(t + \tau) - P(t)) | P(t) = P_j, V_{\text{wind}} = V_i \rangle.$$  \hspace{1cm} (5)
and denote $\langle \rangle$ to be the average operation. Let $V_i, i \in [1, I]$ and $P_j, j \in [1, J]$ be the value of the selected wind speed and power, $I$ and $J$ are positive integers. Inside each bin,

$$V_i - \frac{1}{2}V_{bin} < V_{wind} \leq V_i + \frac{1}{2}V_{bin},$$

$$P_j - \frac{1}{2}P_{bin} < P \leq P_j + \frac{1}{2}P_{bin},$$

(6)

$P_{bin}$ and $V_{bin}$ are the size of power and wind speed in a bin. $V_{bin}$ is set to 0.5m/s following the IEC standard. $P_{bin}$ depends on wind turbulence. Smaller $V_{bin}$ or $P_{bin}$ can be selected to obtain higher accuracy in the LPC given that there is enough data in each bin. However, as $V_{bin}$ or $P_{bin}$ becomes smaller, there will be fewer data in each bin and the goal of higher accuracy in the LPC may not be achieved. Hence, the selection of the bin size in power and wind speed should be balanced between the accuracy and the available amount of data.

In [8], it is found that the sampling rate seems to not significantly impact the LPC. The authors of [8] collected 10Hz data from an ultrasonic anemometer. Then 1Hz data representing a cup anemometer was obtained by averaging every 10 points of 10Hz data. It is shown in [8] that similar $M_{ij}$ in (5) is obtained by 10Hz and 1Hz data. Meanwhile, data from LIDAR was used to create LPCs as well in [8]. The wind speed obtained from LIDAR is averaged over a horizontal range. Hence the sampling rate of the wind speed may be much less than 1Hz. Then the fast dynamics in power may not be reflected within some bins of wind speed. Some solutions to overcome the restriction of LIDAR data are provided in [8].

The LPC in [8] can also be used for condition monitoring. Since a LPC can be obtained with data from a short period of time, an abnormal operation can be observed quickly. The idea is that first a reference power curve is created when a wind turbine is in the normal operation. Then, a LPC is generated and compared to the reference power curve periodically. If anything abnormal occurs, a diagnosis should be done to find out the root cause of the issue. In [8], pitch failure is detected by observing that the power above the rated wind speed is greater than its normal value while yaw error is detected by observing that the power below the rated wind speed is less than its normal value.

Since ice will have an impact on the LPC too, we will use the LPC to detect ice on blades. The implementation of our approach is described in the next section.

3. Ice Detection by LPCs

The idea is that we first create a reference power curve. Then we compare the reference power curve to a LPC based on data from a specific period of time. The period can be from 5 minutes to 1 hour given that there is enough data in each bin. Through the comparison, an ice index is calculated. In normal operation, the ice index should be 1. It can deviate a little from 1 due to error in the sampled data and computations. However, when the ice index is much higher than 1, it indicates that there is ice on the anemometer so that the measured wind speed is much less than the actual wind speed. When the ice index is much lower than 1, it indicates that there is ice on the blades that negatively impacts the power characteristics of the wind turbine, which means that the wind turbine generates much less power than it does in normal operation.

3.1. Reference Power Curve

We first create a reference power curve to compare it with LPCs periodically for ice detection. Assuming that the performance of power generation of a wind turbine does not dramatically and permanently change in the near future, the reference power curve is created once and will be fixed and used throughout the winter season. The reference power curve can be generated by using high frequency data or 10 minute average data. The data should be collected when the condition for ice accretion is certainly not met. Meanwhile, the data should be collected
before the season when ice accretion occurs. Then the latest power generation performance of a wind turbine can be described by the reference power curve. In China, we usually generate the reference power curve for wind turbines based on two months of data collected in September and October. However the time duration of the data for the reference power curve depends on the type of wind turbines and their location so it may be different.

3.2. Data Collection for a LPC
We collect data from wind turbines located at two wind farms in China. The data sampling frequency is 20Hz. The blue line in Figure 4 shows the plots of wind speed and electrical power at 20Hz. The duration of the data is 1 hour in which there are 72000 data points. It can be seen that the wind speed spreads from 6m/s to 12m/s and the power is from 600kW to 1800kW. The bin size of wind speed and generator speed depends on how noisy both measured wind speed and power are. In our test, we calculate the average value of wind speed and power every 200 data points and filter out the high frequency noise in the data. Thus, the filtered data is at 0.5Hz and it is shown in the red line in Figure 4. As a result, the number of data points for a LPC is reduced from 72000 to 1800. Therefore, the bin size of wind speed and power is set to 0.5m/s and 200kW respectively to allow enough data in all or some bins. The number of filtered data data points in each bin is shown in Figure 5. It is obvious that an entire power curve cannot be created because of the limited range of the wind speed. Usually a partial LPC is obtained. We only compare it with the reference power curve at the wind speeds in the selected period of time.

![Figure 4.](image)

Figure 4. The left figure shows the one-hour data of wind speed and power and the right figure is a zoomed-in view of the left figure. The red line is the raw data at 20Hz and the blue line is the filtered data at 0.5Hz.

3.3. Creating a LPC
As the data is put into different bins, we first choose the value of $\tau$ and then calculate the moment $M_{ij}$ in (5). By the definition of $D_{drift}$ in (4), we need $\tau$ to be as small as possible. However, since a digital controller is used for wind turbines, the minimal value of $\tau$ is 1, which is equivalent to one period of the filtered data, $T_f = 2s$. Hence, we choose $\tau = [0, \cdots, N] \times T_f$ and calculate $\langle (P(t+\tau) - P(t)) \rangle$ at each bin. In the test, we have $N = 2$. If $N$ is a larger number the wind speed may fluctuate a lot during the time $[0, N \times T_f]$ so that it is not a relaxation process.
and the power does not head to its stable value $P_L$. Since $M_{ij} = 0$ if $\tau = 0$, we use the linear regression with zero intercept and get the value of $D_{drift_{ij}}$ in the bin,

$$D_{drift_{ij}} = \frac{\sum_{l=0}^{N}(\tau(l) \times M_{ij}(l))}{\sum_{l=0}^{N}(\tau(l)^2)}, l \in [1, N]. \quad (7)$$

Then for one wind speed, $V_i, i \in [1, I]$, we can have the drift coefficient at the power level, $P_j, j \in [1, J]$. We can use the linear regression again to get

$$D_{drift_{ij}} = k_i \times P_j + b_i. \quad (8)$$

Therefore to obtain the stable value of power, $P_{Li}$, at the wind speed $V_i$, $D_{drift_{ij}}$ should be 0, and we have

$$P_{Li} = -\frac{b_i}{k_i}. \quad (9)$$

Finally, we can draw a LPC based on the data $(V_i, P_{Li}, i \in [I_1, I_2, \cdots, I_H])$. $[I_1, I_2, \cdots, I_H] \subseteq [1, I]$ and $[I_1, I_2, \cdots, I_H]$ may not be equally spread. If $[I_1, I_2, \cdots, I_H] = [1, I]$, an entire LPC can be obtained over all selected wind speeds, $V_i, i \in [1, I]$. Otherwise, a partial LPC will be obtained. For example, in the right figure of Figure 6, there are only 3 wind speeds where $P_L$ is available.
Figure 6. The left figure shows the scatter plot (green dots) of the filtered data, on which the power curve (black) is based. The red and blue triangles mean that the sign of $D_{drift}$ is positive and negative respectively. The right figure shows the power curve based on the filtered data (blue) and a partial LPC (red).

### 3.4. Icing Index

From the previous section, we can obtain the stable power $P_{Li}$, at wind speed $V_i, i \in \{I_1, I_2, \ldots, I_H\}$. Then we define the icing index, $I_{ce}$, as

$$I_{ce} = \sum_{i=1}^{H} \alpha_i \frac{P_{Li}}{\bar{P}_i} \sum_{i=1}^{H} \alpha_i = 1,$$

where $\bar{P}_i$ is from the reference power curve at the wind speed, $V_i$. From the definition, we can see that ice will not impact much on power performance if $I_{ce}$ is equivalent or close to 1. However, if $I_{ce} \ll 1$, it indicates the power performance of the wind turbine is so negatively impacted by ice that a control action is necessary. if $I_{ce} \gg 1$, it indicates that there is much ice on the anemometer and the wind speed measurement is not accurate any more. For simplicity, we can set $\alpha_h = \frac{1}{H}$ so that $\frac{P_{Li}}{\bar{P}_i}$ at all wind speeds have the same weight on $I_{ce}$. But in reality, the same deviation between $P_{Li}$ and $\bar{P}_i$ at low wind speed results in a higher value of $\frac{P_{Li}}{\bar{P}_i}$ than that at high wind speed. Also, ice may cause more loss in power in high wind speeds than it does in low wind speeds. Hence, we can set $\alpha_{i1} > \alpha_{i2}$, when $V_{i1} > V_{i2}$, so that the impact on power at high wind speeds can be focused on.

### 4. Test Verification

In this section, we will apply the Langevin-based method to detect ice on blades. We select two turbines on which blade icing has been reported by wind farm field managers. We first choose wind turbines located in Wuwei County, Anhui Province, China. According to the historical weather report on November 24th, 2015, the average temperature in Wuwei was as low as $2^\circ C$ and there were snow and rain on that day ([16]). The beaufort scale was 3 and the wind speed was between 3.3m/s and 5.2m/s ([17]). The wind farm is in a small part of Wuwei. Hence, although the average temperature in Wuwei was $2^\circ C$, the local temperature in the wind farm...
can be lower than \(0^\circ C\) because of snow or freezing rain and wind. The rotation of the blades helps ice accretion as well. We use data from that day at 20Hz from the wind turbine and feed it into the icing detection module, which updates the icing index every 5 minutes. Figure 7 shows the results of the icing index. It can be seen that the icing index starts to decrease at about 5:00pm. We set 0.5 to be the threshold. If the icing index is greater than 0.5, we can still allow the wind turbine to work as usual; otherwise, the module will send out an alert to the controller for further action regarding the ice. In Figure 7, the icing detection module confirms the ice accretion because the icing index is less than 0.5 consecutively. The power performance of the wind turbine is greatly negatively impacted by ice.

![Icing index of a wind turbine in Anhui Province, China](image)

**Figure 7.** Icing index of a wind turbine in Anhui Province, China

Figure 8 shows the icing index value of another wind turbine in Shanxi Province, China, on November 9\(^{th}\), 2015. It can be seen that the value of the icing index is much higher than 1 at the beginning. It indicates that the measured wind speed is much less than its actual value. The reason is that there is ice on the anemometer, which cannot measure the wind speed correctly. The power generation of the wind turbine is still normal because the icing index is close to 1 later. As mentioned in Section 3, the icing index may deviate from 1 due to errors in sampled data and computation of the linear regression.

**Remark 1** Generally, when there is only ice on anemometer, the icing index will be greater than 1. The icing index will be less than 1 when there is only ice on blades. Hence, one interesting case is when there is ice on both anemometer and blades but the icing index is still around 1. It will be an interesting research topic to differentiate impact on the icing index from ice on the anemometer and ice on the blades based on the obtained LPC. One solution is to use a heated anemometer so that ice will not be on the anemometer and therefore we can focus only on the impact of ice on blades.

5. CONCLUSIONS
In this paper, we applied the Langevin equation to create a partial or entire power curve with the high frequency data. Using the method, the ice accretion can be detected in a short period of time. An off-line verification test has been done to show the effectiveness of the method. We will work on field tests in the coming winter and will show the results in another research article later.
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