Power Curve Analytic for Wind Turbine Performance Monitoring and Prognostics

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ABSTRACT

The manufacturer-provided power curve for a wind turbine indicates the expected power output for a given wind speed and air density. This work presents a performance analytic that uses the measured power and the power curve to compute a residual power. Because the power curve is not site-specific, the residual is masked by it and other external factors as well as by degradation in performance of worn or failing components. We delineate operational regimes and develop statistical condition indicators to adaptively trend turbine performance and isolate failing components. The approach is extended to include legacy wind turbines for which we may not have a manufacturer's power curve. In such cases, an empirical approach is used to establish a baseline for the power curve. The approach is demonstrated using supervisory control and data acquisition (SCADA) system data from two wind turbines owned by different operators.

1. INTRODUCTION

High operations and maintenance costs for wind turbines reduce their overall cost effectiveness. One of the biggest drivers of maintenance cost is unscheduled maintenance due to unexpected failures. Using automated failure detection algorithms for continuous performance monitoring of wind turbine health can improve turbine reliability and reduce maintenance costs by detecting failures before they reach a catastrophic stage or cause damage that increases repair costs.

The power curve is a universal measure of wind turbine performance and an indicator of overall wind turbine health. Many failures and performance deterioration mechanisms can manifest in the measured power curve. By exploiting this measure with commonly collected supervisory control and data acquisition (SCADA) system information, we can provide early indications of failures or severe performance deterioration. This paper presents an approach to wind turbine diagnostics and prognostics that uses nominal power curves and operational data.

While early indication of failure is needed, it is equally important to minimize false warnings; therefore, it is important to determine data variability measures and bounds for normal and anomalous conditions. We use several statistical measures to establish separation between normal or baseline operation and deteriorated conditions.

2. WIND TURBINE PERFORMANCE MONITORING

Performance is described in the context of the underlying process physics of the equipment—in this case, the wind turbine. Wind turbines convert wind kinetic energy into useful electrical energy. As the turbine components deteriorate, the efficiency with which wind energy is converted to electrical energy decreases and the performance of the turbine decreases. Performance degradation can indicate problems such as blade aerodynamic degradation due to leading and trailing edge losses, dirt or ice buildup on blades, drivetrain misalignment, friction caused by bearing or gear faults, generator winding faults, or even pitch control system degradation.

SCADA or operating data of equipment is often used in other industries for accurate and timely detection, diagnostics, and prognostics of failures and performance problems (Bell & Foslien, 2005, Gorinevsky, Dittmar & Mylaraswamy, 2002, Kim & Mylaraswamy, 2006). For example, in turbine engine diagnostics, failures such as turbine degradation, compressor bleed band failure, fuel supply system faults, combustion liner burn-through, and in-range sensor faults can be automatically detected with appropriate diagnostic algorithms. SCADA data provides a rich source of continuous time observations, which can be exploited for overall turbine performance monitoring. With appropriate algorithms, performance monitoring can be matured into individual component fault isolation schemes.

The functional elements of performance monitoring are shown in Figure 1. A performance parameter is computed based on sensor measurements; this parameter can be raw sensor values, sensor values corrected for environmental conditions, residuals with respect to a wind turbine model, component efficiency or aerodynamic parameters. Anomaly detection uses one or more such parameters to test whether the wind turbine is behaving within normal bounds. If the root cause of the anomaly is further classified as a particular component failure, this provides diagnosis. Additional elements involve predictive trending and prognostics, wherein parameters or fault indicators are trended and time to failure is projected.

Use of SCADA data for performance monitoring or fault diagnostics in wind turbines is not as mature as in other industries, such as process and aerospace, where condition-based maintenance (CBM) is more widespread. In some cases, SCADA data, mainly temperature (bearing or generator-winding), have been used along with vibration data for fault detection (Wiggelinkhuizen, et al. 2008, Lekou, et al. 2009). Operating data is also used just to detrend or normalize the vibration or temperature data (Wiggelinkhuizen, et al. 2008). Zaher, McArthur, and Infield (2009) presented a method to use SCADA data for anomaly detection based on neural network models of normal operating modes. The use of power curve based performance monitoring is described in (Zaher & McArthur, 2007). The power curve agent uses a power curve learned from operating data for a healthy turbine. Two pairs of alarm limits are generated: inner and outer. The inner alarm curve is based on the standard deviation for each wind speed bin added to the average in each bin. The outer alarm is chosen by the study of several turbines operating normally.

Caselitz, Giebhardt, Kruger, and Mevenkamp (1996) showed the effectiveness of utilizing spectra of the electrical power output and the vibration measurements to detect the imbalanced rotor, the aerodynamic asymmetry, and the generator bearing faults.

Kusiak presented a method to predict the anomaly, the fault severity, and the fault isolation using data mining tech

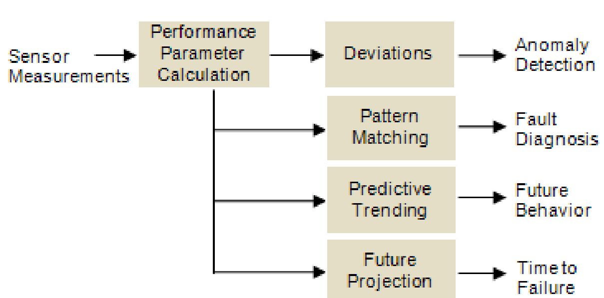

Figure 1. SCADA data-based monitoring

niques and prediction models based on wind speed and power output obtained from SCADA data (Kusiak, 2011).

Anomaly detection can be performed with a series of techniques that range from simple threshold checking to complex statistical analysis. Here, we focus on anomaly and fault detection methods for analyzing sensor data from individual wind turbines. Sensor data used in algorithm development and the approaches are described in the next sections.

3. POWER CURVE ANALYTIC

The power curve is a wind turbine performance specification provided by the manufacturer that indicates performance during operation at different wind speeds. For specific wind turbine operation, power curves are derived from non-dimensional C_p-λ (power coefficient versus tip speed ratio) performance curves of the wind turbine design. The nominal power curves are established by the wind turbine manufacturers following published guidelines. One widely-adopted international standard is published in IEC 61400-12-1: Power performance measurements of electricity producing wind turbines (IEC, 2005). The power curve is generally used to estimate the average energy production at a particular location for a given Rayleigh wind profile and to monitor the power production performance of installed wind turbines.

Typical power curves for different air densities for a wind turbine are shown in Figure 2. The operational speed range is between the cut-in speed and the cut-out speed. The cut-in speed is the wind speed at which the turbine begins to generate power. The cut-out speed is chosen to protect the turbine and structure from high loads.

The actual power curve may deviate from the nominal one due to site-specific factors (Tindal, 2008), complex wind regimes (Rareshide, 2009), or changes in component conditions. A complex terrain, as opposed to a benign one (as defined in the standards), and different meteorological

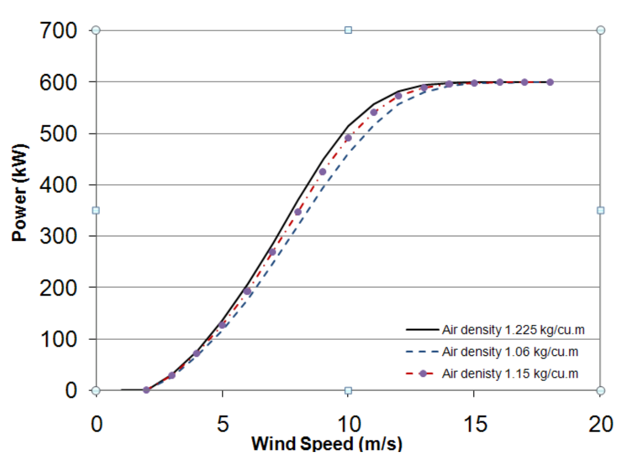

Figure 2. A typical power curve

conditions, such as varying wind direction, wind shear, and turbulence intensity can cause shifts in the power curve from the nominal.

To clearly account for factors affecting the power curve, the magnitude of the deviation from the baseline must first be assessed, and this deviation must then be further processed to generate various indicators that are relevant to different factors and critical wind turbine components.

3.1. Power Curve Generation

We use power curves provided by the manufacturer when available as the base power curve model. In the absence of a manufacturer-provided power curve (e.g., when the wind turbine is a refurbished machine or has undergone several component or control changes), SCADA data can be used to generate one. A number of data fitting approaches have been reported in the literature—from a simple polynomial fitting to a stochastic power curve generation (Milan, 2008) to a more symmetrical sigmoid function or a Gaussian CDF fitting (Yan, 2009). Since wind turbine designs and controllers are optimized for extracting maximum energy through a nonlinear phenomenon and the power coefficient C_p is not constant or symmetrical, we prefer to allow local optima instead of seeking overall symmetry. For this reason, we use polynomial fitting to generate the power curves when a manufacturer provided power curve is not available.

3.2. Power Residual Generation

The difference between the measured actual power and the power expected based on the power curve is called the power residual. Since generated power depends on the air mass as well, a family of power curves may be specified for different air densities. Hence, before we can calculate the power residual, we need to obtain the air density, which can be calculated using either of the following equations.

$$\rho = p / RT \tag{1}$$

or

$$\rho = (p_0 / RT) \exp(gz/RT) \tag{2}$$

where ρ is the air density at location in kg/m^3, p_0 is the standard sea level atmospheric pressure, p is the air pressure in Newtons/m^2, T is the ambient air temperature in Kelvin, z is the location altitude in meters, and R is the specific gas constant (287 J kg^{-1} Kelvin^{-1}).

When air density, wind speed, and, in turn, the expected power are available, the power residual can be readily calculated:

$$Power\_residual = Power\_actual - Power\_expected \tag{3}$$

3.3. Operational Metrics

Although the wind turbine is designed to operate between the cut-in and cut-out wind speeds, its power response to various factors discussed above is not identical across the wind speed range. Figure 3 visualizes the variation in the power residual with respect to wind speed, denoted by the blue dots. This plot illustrates the residual or power deviation of the baseline data from the power curve. Even in the case of baseline data (data used for power curve generation), there is variation in the distribution of residuals across wind speeds. The analysis presented in the following sections are based on characterizing these residual statistical metrics for the baseline and other cases—the difference in which can be visualized in plots, but need quantitative measures for automated analytics.

Notice that the variation starts small at low wind speeds, then expands in both positive and negative directions as the wind speed increases and tapers off once the rated power is reached, forming a bird-like shape which we call the Hummingbird model. To delineate the nominal and anomalous residuals with respect to the Hummingbird model, wind speed bins are defined and the standard deviation of the power residual for each bin is calculated. Three-sigma from the mean residual for each wind speed bin is used to set the upper and lower bounds on the residuals. The residual points that are outside these bounds for a particular wind speed bin are marked and used for anomaly detection as explained in the next section. Recall that the power curve shown in Figure 2 had first a concave segment followed by a convex segment. These two segments respond to increasing turbulence intensity in opposite manner—the power increases in the concave region while it decreases in the convex region as the turbulence intensity increases. Such factors determine the variability characteristics of the residuals at different wind speeds and provide a way to characterize the operational envelope.

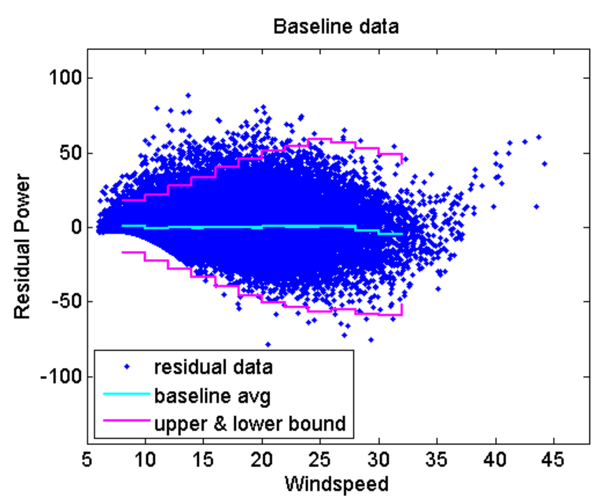

Figure 3. Power residual scatter plot of the baseline data

To model the operational envelope and be able to identify any data point that lies outside of it, Osadciw, Yan, Ye, Benson, and White used the Kaiser window fitting approach (Osadciw, et al. 2010). We prefer an industrial process control approach to define the operational parameters. This approach is naturally adaptive and easily accounts for performance changes due to normal component wear and other factors.

By adjusting the baseline period and the window size, changes in different time scales can be detected. For example, if the baseline is established using data collected from a newly installed wind turbine, any long-term changes in the turbine performance such as the deterioration of the aerodynamic performance of the rotor blades can be detected. However, using data only from a recent period to establish the baseline would mask any long-term performance degradation while exposing symptoms of an impending component failure.

In line with the standard practice of wind speed binning, we determine the power residuals for each bin and compute the corresponding bin statistics such as the mean and variance. For analysis, we also set a nominal operational boundary for each bin at some multiple of the standard deviation for that bin in the baseline data (3-sigma in this case). In Figure 3, the operational boundary is indicated by the staircase magenta lines surrounding the nominal variation (and defining the Hummingbird). Note that this operational boundary is not a 'threshold' in the anomaly detection sense. The n-sigma boundary provides insight into the variability of the residuals inside each bin and gives us an opportunity to characterize the shape of the residual distribution curve. This curve forms the basis for developing condition indicators that could separate nominal operation from faulty or deteriorated operation. Notice that although the Hummingbird in Figure 3 has a curvy shape, the nearly straight horizontal line in the middle indicates that the mean power residual for the baseline remains close to zero. Also note that at this early stage of development of an algorithm, we do not characterize the power curve model as accurate or not accurate with respect to the baseline data. We characterize only the baseline residual metrics and compare these metrics with subsequent time periods, including those with failure on the horizon.

3.4. Operational Regime Based Condition Indicators

Having defined the operational boundary, we can now generate various statistics and other parametric variables that we call condition indicators (CI). The CIs can be as simple as the mean of the power residual for a wind speed bin. We can also calculate higher statistics such as skewness to measure distribution symmetry and kurtosis to see how peaked or flat a distribution we obtain for each wind speed bin. These indicators can be computed using an appropriate set of data for the baseline to detect short- and long- term changes.

4. Test Cases

We have tested the power curve analytic approach with the SCADA data from two different wind turbines belonging to two different operators.

4.1. Data Set I

We obtained Data Set I from a mid-power wind turbine that supplies power to a university campus and sells excess power to the grid. It recently came out of 5-year warranty with the turbine manufacturer. The SCADA data is available in 10 minute and hourly intervals for 2006-2010.

Figures 4 and 5 show the power residuals plotted using the winter and summer 2008 data.

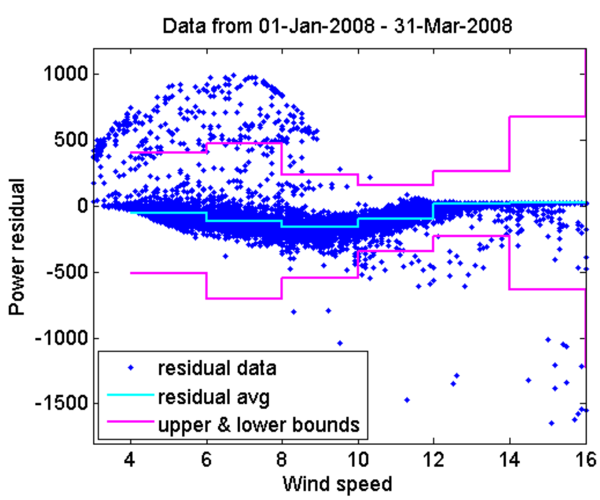

Figure 4. Power residuals in winter, 2008

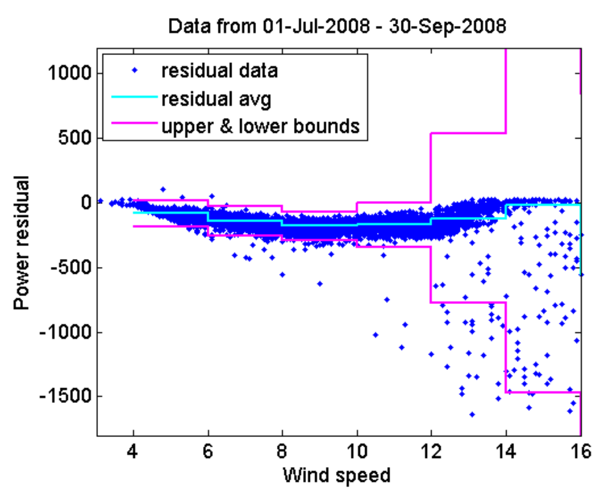

Figure 5. Power residuals in summer, 2008

Figure 6 shows a mean power residual condition indicator (CI_MPR) computed for each season in 2008 and 2009. Notice that CI_MPR is indistinguishable at low and high speeds, but it clearly shows a shift from 2008 to the next year at mid speeds. The shift indicates a noticeable improvement in the turbine performance in 2009. Unfortunately, the maintenance logs are not available from this wind turbine for us to verify the results or track the cause of the improvement to a particular maintenance action.

4.2. Data Set II

We collected Data Set II from a small, reconditioned wind turbine that provides power to the operator's office building, and the excess power is sold to the grid. The data is available at 1-min sampling rate.

This operator encountered an issue with the gearbox during routine, semi-annual maintenance in October, 2009. The low-speed gear was moving axially on the input shaft of the gearbox. To proactively repair this condition, the gearbox had to be removed from the turbine and taken to the rebuilding facility. The gearbox was disassembled and the low-speed shaft sizing was corrected to prevent the axial movement. The gearbox was then reassembled and reinstalled in the turbine.

This maintenance event provides a good test case for the power curve analytic approach. As a first step of our analysis, the data was split up by quarter for each year. The first quarter data from 2009 was used to establish the baseline. The power residuals were generated for the remaining quarters. Notice that the CI_MPR in Figure 7, plotted as a broken yellow line, drops further away from the baseline as the wind speed increases. Although this provides an indication of anomaly, it is not yet clear whether the drop in CI_MPR is the result of seasonal variations. Since we do not have many years' worth of data, this is hard to ascertain.

Building on this first indication of an anomaly, we compute two other condition indicators: Skewness (CI_SKEW) and kurtosis (CI_KURT). Figure 8 clearly shows that the power residual symmetry as measured by the CI_SKEW for the Q3_09 is much more skewed than the other quarters. Figure 9 provides more CI_KURT evidence for the anomaly. It is clear that seasonal variations are not a consideration for either of these indicators, and any small variations between datasets are completely dominated by the indicator curve for the quarter with the failure.

The preceding analysis is based on lumped data for certain quarters. Diagnostics and prognostics depend on the underlying measurements; very exclusive sensor measurements for particular failure modes provide more accurate and earlier warnings of that failure. Since power generated is a very broad measure, how early can any such deviations from normal be detected? We performed the same analysis for moving 30-day windows with 1-day progression intervals. Figures 10 and 11 show the variation of skewness and kurtosis of residual distribution in each wind speed bin. The moving window plots started deviating from the normal around Sept 30 to Oct 3.

Notice that in Figures 8-11, the biggest difference between the suspect data sets and the baselines occur at around 24 mph. By focusing on this wind speed bin, we can take a closer look at the data to see any early indication of the impending failure.

Figures 12 and 13 show the CI_SKEW and CI_KURT for the wind speed bin at 24 mph, computed daily, with the 30-day moving windows from the days preceding the failure. The last day that the data was collected before dismantling the turbine was October 22, 2009. In the figures, several days from the earlier periods are also included for comparison.

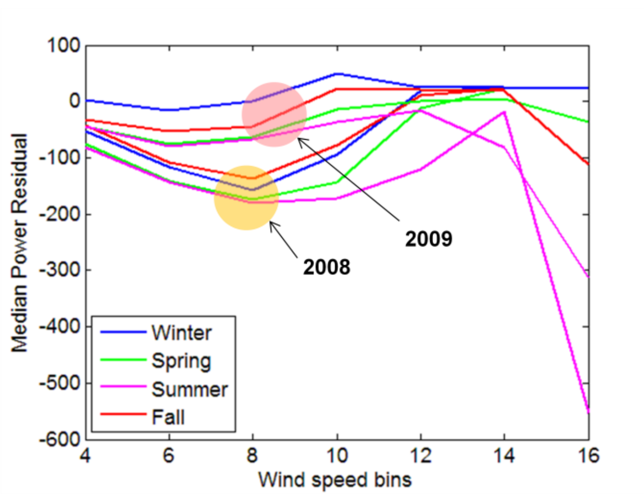

Figure 6. Improvement in WT performance at mid-range wind speeds.

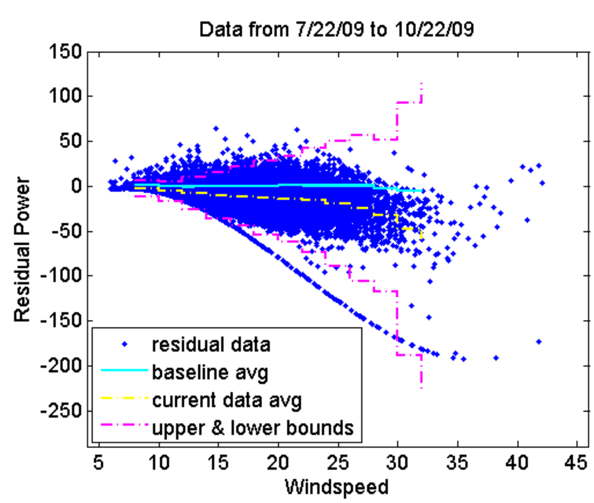

Figure 7. Power residuals in fall, 09

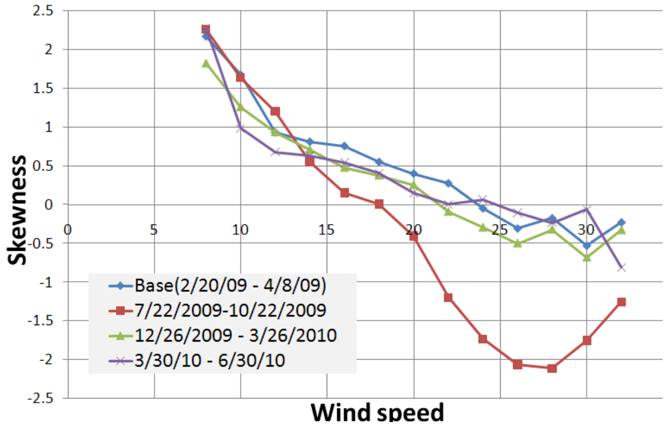

Figure 8. Skewness per quarter for each wind speed

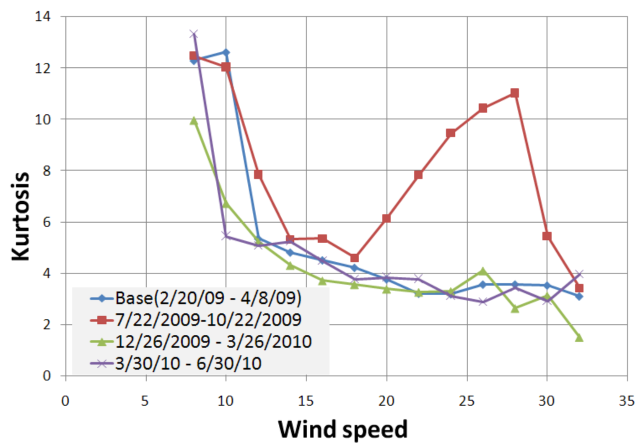

Figure 9. Kurtosis per quarter for each wind speed

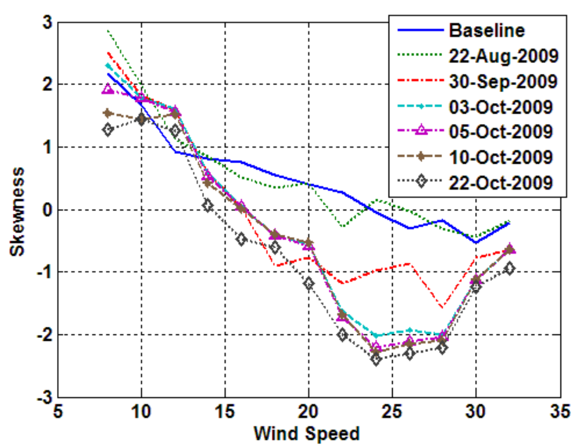

Figure 10. Skewness of power residual distribution in a 30-day moving window

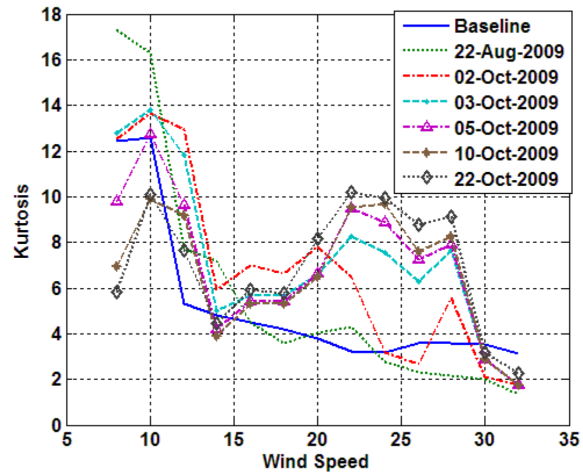

Figure 11. Kurtosis of power residual distribution in a 30-day moving window

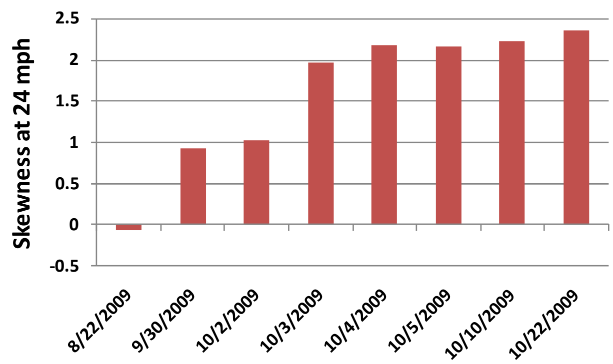

Figure 12. Skewness in days preceding the gearbox failure

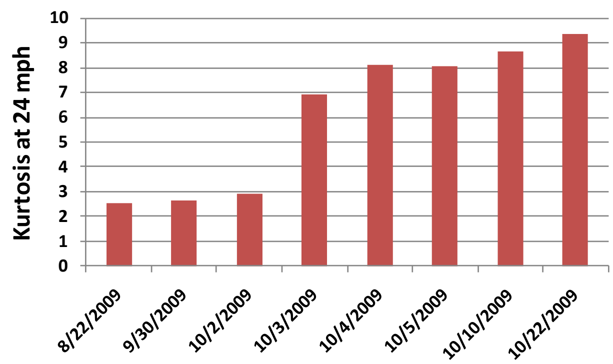

Figure 13. Kurtosis in days preceding the gearbox failure

Notice that on October 3, 2009 there is a significant rise in both CI_SKEW and CI_KURT, and the CIs remain at these new elevated levels until the failure. This shows that the first indication of the impending failure occurred about 20 days before the failure and that both indicators seem to be robust as demonstrated by the consistency in the elevated levels until the failure.

Note that these condition indicators can only quantify the wind turbine's difference in operation compared to the baseline or other periods of data. Our work analyzed the data with statistical measures to see whether the CIs capture approaching failures. At this stage, we cannot associate the anomaly to a particular failure—especially using a broad measure such as power. However, since the gearbox failure was noted and repaired and since no other major repairs or adjustments were performed during that timeframe, it is likely that the gearbox failure was manifested in the CIs. With additional data and experience, it may be possible to associate changes in CIs in particular bins to particular failure modes or operational changes.

In this gearbox failure case, the scheduled maintenance coincided with the developing failure. The operator was able to correct the problem in time and, in their own words, "it allowed us to salvage all gearing and shafts. Had the problem progressed, it would have damaged the components beyond repair and greatly increased the cost of the repair."

5. CONCLUSION

We showed that the wind turbine power curve analytic is useful for assessing wind turbine performance and generating robust indicators for component diagnostics and prognostics. The analytic takes advantage of a universal measure of wind turbine performance with commonly collected SCADA information and provides easy configuration based on process control approaches for condition-based monitoring. Condition-based rather than hours-based maintenance enables high reliability and low maintenance costs by eliminating unnecessary scheduled maintenance.

As demonstrated in the gearbox failure case in Data Set II, early detection of an impending failure can save an operator costly repairs and long downtimes.

The wind turbine performance analytic power curve analysis method clearly separates out pre-failure data from other normal operating data. Instead of simply assigning uniform thresholds for power curve deviation, our approach uses operational regime based condition indicators. Operational regime-based CIs prevent false alarms (recognizing unique regime variabilities) and increases the possibility of fault isolation (different faults may manifest at different regimes). It emphasizes detecting slow performance degradation caused by component wear as well as degradation due to an impending failure. Condition indicators that not only take into account the variability of the power residual, but also the distribution shape and symmetry, provide additional means of detecting and isolating failure cause.

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