

Towards a more robust understanding of the uncertainty of wind farm reliability

C.H. Westergaard^{a,b,1}, S.B. Martin^b, J.R. White^b, C. Carter^b and B. Karlson^b

^a*Texas Tech University, Lubbock, Texas, USA*

^b*Sandia National Laboratories, Albuquerque, New Mexico, USA*

Abstract. Understanding wind farm reliability from various data sources is highly complex because the boundary conditions for the data often are undocumented and impact the outcome of aggregation significantly. Sandia National Laboratories has been investigating reliability of wind farms through the Continuous Reliability Enhancement Wind (CREW) project since 2007 through the use of Supervisory Control and Data Acquisition (SCADA) data from multiple wind farms in the fleet of the USA. However, data streaming from sample wind farms does not lead to better understanding, as it is merely a generic status of those samples. Economic type benchmark studies are used in the industry, but these does not yield much technical understanding and gives only a managerial cost perspective. Further, it is evident that there are many situations in which average benchmark data cannot be presented in a meaningful way due to discrete events, especially when the data is only based on smaller samples relative to probability of the events and sample size. The discrete events and insufficient descriptive tagging contributes significantly to the uncertainty of a fleet average and even impair the way we communicate reliability. These aspects will be discussed. It is speculated that some aspects of reliability can be understood better through SCADA data-mining techniques, considering the real operating environment, as it will be shown, that there is no particular reason two identical wind turbines in the same wind farm should have identical reliability performance. The operation and the actual environmental impact on the turbine level are major parameters in determining the remaining useful life. Methods to normalize historical data for future predictions need to be developed, both for discrete events and for general operational conditions.

Keywords. Wind farms, reliability, SCADA data, wakes, vibration

1. Introduction

The wind industry has improved its operational practices tremendously over the past decades leading to tremendous global and local successes. According to the Global Wind Energy Council (GWEC) a total of 370 GW was installed by the end of 2014, hereof approximately 66 GW in the USA. The fifth largest territory in the world is Texas, which according to recent numbers, ref. [1], gets 11.7% of its energy from a wind fleet of 16 GW worth of wind turbines. The wind energy power price in the interior of the USA is low and competitive, only \$23/MWh, ref. [2], making new installed wind equally attractive to new installed gas generation. The two sources, wind and gas, approximately each have half the market of new capacity installed in the past years.

¹ Carsten H. Westergaard, Texas Tech University, carsten.westergaard@ttu.edu.

A big contribution to the success of wind energy is new technology introduced in many of the components of the wind turbines, ref. [3], which has driven down cost and increased efficiency. The huge rotor size is the most noticeable development, the size has doubled in the past 15 years, so more than 80% of the rotors entering the market are over 100 meter in diameter, with an average nameplate rating of 2 MW, ref.[2]. This improvement results in capacity factors approaching 50%.

A second contributor to improved cost is increased reliability and operational practices. In the early 80's, reliability was low and availability as low as 20%, ref. [4]. Costs were unreasonably high, but today the O&M costs of new projects are of the order of \$8/MWh, ref. [2]. The availability is beyond 98%, ref. [5]. This has been achieved by intensive monitoring from large operation centers, where owners of wind farms have reduced downtime significantly by fast response and secured availability for new spare equipment. The improved O&M cost also reflects on technology and design procedure improvements.

In spite of these improvements owners often comment that O&M expenditures either have increased or are too high. This can in part be understood from the large spread of O&M cost one can observe, see for example ref. [2]. Individual wind farm projects do not behave similarly, meaning that unplanned events are an important part of O&M cost; and, thereby the reliability of the wind farm.

Three elements contribute to unplanned reliability events. First, new turbine technology is constantly entering the market, manufacturing flaws (acceptable and unacceptable) are present and new and/or unexpected failure modes occur. These types of failures typically show up in the initial life of the wind farm and contribute to the beginning of the classical bathtub curve. The failure modes often are covered under warranty and thus are of proprietary nature, therefore the cost and corrective action is not documented for future use. Frequently, the flaws are overestimated in future planning or studies for the same reason. The second contributor is poor operational practice and lack of consistent documentation, including tagging of reliability events. However, significant resources have been put into improvements. The third contributor is truly unforeseen events or systematic bias. The frequency and nature of the events is typically not accounted for.

Removing reliability events of proprietary nature from statistics will remove technical bias in our understanding. From a managerial perspective such events should be allocated separately. Better tagging and description of the events could lead to more opportunity for description of rare but costly unforeseen events to be investigated. Those are, for example, driven by external environmental conditions and operational practices. Finally, a data driven description of each turbine's expected reliability performance could support a more accurate description of future expectations.

In this article it will be discussed how important data quality and tagging is before aggregating. Further, it will be discussed how the boundary conditions, especially the external environmental impact, also need to be included with the data collection, in order for the data comparison to be useful. Finally, it will be shown that SCADA data provides insight to some of these external impacts and how this knowledge can support improvement of monitoring of wind farms.

2. The challenge of collecting data

The largest single challenge in collecting reliability data from wind farms is the proprietary nature of the data. The second largest challenge is that no one single participant has an overarching understanding of the entire fleet. Turbine suppliers know their own products and may be collecting data from those in the first few years of the wind farm life while the assets are still under warranty. However, the turbine suppliers do not typically have much knowledge in the remaining time of the turbine life. The owners often know little about the first years of operations, because the wind farm is under service agreement with the turbine supplier, but they do, on the other hand, have 20 years of operational experience with multiple turbine platforms; knowledge which is often partially shared with the independent service providers (ISP), see figure 1.

However, the turbine supplier often has access to data that the owner does not, such as detailed design documentation and high speed turbine controls data (not to be confused with the SCADA data). The component supplier knows everything about their products and the physics of the product, but only little about the physical conditions which their product component is subjected to. Efforts like the Gearbox Reliability Collaborative (GRC), run by National Renewable Energy Laboratory (NREL), help close the gap for a narrow set of challenges, such as initially described in ref. [6]. A similar initiative exists for blades called the Blade Reliability collaborative (BRC) is run by Sandia National Laboratories. The efforts are focused on bringing the physics of materials, parts and physical conditions together with testing and monitoring, including condition monitoring or predictive health monitoring.

The Continuous Reliability Enhancement for Wind (CREW) efforts, ref. [5, 7, 8, 9], also run by Sandia National Laboratories, are aimed at generating macroscopic technical data to better understand the system as a whole, in particular to develop methods which can be used to describe the external boundary conditions of the wind farm operation down to the turbine level. This is particularly challenging, because of large individual variability from turbine to turbine and because the individual event data set may be extremely sparse. Further, the descriptive characteristics from event to event can be quite inconsistent. A pathway to a more robust approach is described in ref. [9].

Other overarching data bases do exist or are in preparation for other purposes, such as grid compliance by North American Reliability Council (NERC) or economic studies typically performed by private fee based organizations. Again, such data is generally not sufficiently technically detailed to be useful understanding technical trends.

As discussed above quantifying the reliability in general terms is difficult. Based on many different sources, such as ref. [2, 5, 10, 11, 12, 14], experience and conversations with different organizations, Table 1 reflects an indicative weighted approach indicating state-of-the-art for a fictive 2MW geared turbine. While it is common wisdom in the community that gear and bearings have caused challenges in the past, blades have at large been ignored. As seen, the cost of blade failures is similar to that of gear and bearings, which is one reason it is expected to see more focus on blades in the coming years.

3. Unplanned discrete events

As discussed in the introduction, reliability events of proprietary nature are, generally speaking, inaccurate indicators of future behavior either because they are associated with initial failures due to, for example, manufacturing flaws or because they are associated with some sort of upgrade by the manufacturer. It can be difficult to separate such events purely on a time basis. A recent presentation, ref. [11], showed blade failure sorted by blade types across an 8 GW fleet. One particular blade type showed a large number of events three years into the data, approximately four times larger than the average over six years, but no failure at the end of the six year period. Presumably this was associated with events of proprietary nature. Further, one has to be aware that blade inspections are a manual and labor intensive process, which may only be executed every three years. Therefore, the probability of detecting flaws can include significant delays from the origin of the damage.

Comparing blade failures reported in ref. [11] and [12] from two different wind farm owners, it is apparent that similar physical symptoms of blade failures are not tagged in a similar manner. This has, in part, to do with lack of standards but also practical difficulties actually tracking work orders and field reports. As an example, one of the reports calls out blade damages from lightning, which often results in damages near the tip of the blades and frequently near the trailing edge in the tip region. The second report however, does not call out lightning and only reported trailing edge damages in general, which could have many different root causes. Although this seems like a very simple case, the operational complexity of collecting such data from across many geographical locations and a diverse workforce, cannot be ignored. The uncertainty is real and it makes it difficult, if not impossible to aggregate statistical data without unnecessary uncertainty.

Even if the above blade failure data could be accurately aggregated precisely for lightning damages, one has to be very careful in the interpretation of the data as common averages do not describe the issues at hand. Firstly, the number of thunderstorm days has large regional differences. For the US, this ranges from almost no days in California and up to 75 days in the mid-west. It would not be reasonable to assume a fleet average directly across these regions with such big difference in exposure to risk. Secondly, landscape exposure and turbine height plays an important role. The IEC standard, ref. [13], reports a height square sensitivity, but in ref. [10] a turbine manufacturer examines their historical fleet performance from very small turbines to large modern turbines, disclosing a probability of strike sensitive to the height in the fourth power (with or without failures occurring). Now this sensitivity would entail that newer turbines should be extremely exposed as they are much larger than just a decade ago. Although lightning damages in blades are significant (about 15% of all blade failures according to ref. [11]), the technical improvement of lightning diverter systems has mitigated this large sensitivity.

The above examples highlight the difficulties in quantifying the reliability of wind turbine components because both the boundary conditions for the observations and the failure mechanisms are unknown or inaccurately reported. Resorting to reducing the samples to very specific elements may further be challenging because the number of samples are low. If, for example, the annual blade failure rate is 16%, see table 1, and this is distributed evenly on 20 major failure modes in a fleet of 1000 turbines, then only 8 event samples is retrieved per year. Out of these 8 samples, it will still be necessary to quantify the similarities in boundary conditions and failure modes, so

aggregation becomes reasonable. If all data from the USA fleet were collected, we would have about 250 events per failure mode per year on record if all market players were contributing their data to the same standards.

It is clear from this discussion that meaningful aggregation of reliability data begins with a systematic inclusion of the boundary conditions of the failures:

- Extreme wind with static loading
- Extreme wind with dynamic events, such as vibration
- Lightning characteristics
- Environmentally induced erosion, corrosion or similar deterioration
- Ice and extreme cold
- Operation or maintenance variance

4. SCADA data mining and modeling potential

Modern wind farms are instrumented with a large number of sensors, as many as 250 sensors per turbine, which can be accessed in different ways. In general, SCADA data is available at least as 10 minutes averages and can provide an overview of the historical reliability events such as shown in ref. [5, 14]. This approach may reveal reliability issues like sensor faults, but even if these are frequent, the associated costs may not be of big consequence. In the previous section it was discussed how discrete events needs better clarification on the boundary conditions, but what about the average operational parameters which induce the wear and tear, are they similar between even two neighboring wind turbines in a wind farm? The answer is no, but we can use SCADA data to understand turbine to turbine variations and possibly develop models from such mappings.

Recently, Martin et. al. [7, 8] investigated 1.5 years of SCADA data from 67 wind turbines in the mid-west of the USA in order to quantify the impact of turbines shadowing each other with their wakes by mapping the normalized performance in narrow directional sectors. The study found that turbines waking each other indeed impose power deficits and increased power variability when a turbine is directly waked by another turbine. This scenario is generally covered by the design foundation in wind turbine design, where an increased turbulence level will be used for computing turbine loads. However, the study also found that certain combinations of upstream turbine locations actually caused the downstream turbine to produce much higher power than its peers. Counter-intuitively these high power situations were associated with low power variability. The effects could affect turbine reliability both in positive and negative way. Figure 2 shows the power variability across the entire wind farm. It is clear that none of the turbines had the same experience in the 1.5 years of investigation, so it should not be expected that the drive train in each of these machines to exhibit the same lifetime wear. Further this illustrates that cannot consider a simple fleet average to compare drivetrain reliability performance.

In figure 3, three turbines are selected from the upper middle part of the wind farm. The power variability shows the clear characteristics just discussed. In the right hand part of the figure the average tower vibration over 1.5 years is plotted. A similar pattern is seen across the wind farm. The vibrations show similar trends, compared to the power variance, in particular in the wake situation. In addition to individual wake deficit profiles, a generic wake deficit effect can be observed across the entire wind

farm. To see this effect, 854 turbine pairs were selected within 25 rotor diameters and an undistributed direct path between them (to observe potential wake effects). From these pairs, the maximum power variance and maximum tower vibration level of the downwind turbine is shown in figure 4 versus distance between turbine pairs.

In ref. [8] a simple directional analysis model is demonstrated for power and power variability to effectively map the inter-turbine variability only based on the geometrical layout of the wind farm. A similar model could potentially be built for tower, blades and other main components in order to reduce the uncertainty imposed on the analysis of reliability data.

As a last step in this investigation showing large inter-turbine variability, the number of faults reported in the SCADA system was plotted as a function of direction. In figure 5, a subset of the wind farm is shown. As a first observation, it is clear that none of the turbines exhibit similar fault behavior. It is also surprising that the majority of faults are not aligned with the two main wind directions (NE and SSE), but seem to be rather randomly oriented. A deeper analysis could potentially help understand these patterns, but very little validation opportunity exists for this particular data set, so this has not been pursued further.

The directional analysis confirms that even for a simple flat site in the mid-west, higher fidelity analysis provides great insight to the reliability performance of each turbine and that bulk averaging may not be a suitable approach. This type of analysis would be useful in complex landscapes where the turbine performance is heavily influenced by the landscape features. Methods to normalize historical data for future predictions of reliability are definitely possible.

5. Conclusion

Discrete events of proprietary nature need to be isolated from technical benchmarking as they do not support the prediction of the future. Further, it is clear that environmentally induced reliability issues, originating from wind, ice, moisture, lightning, erosion, corrosion etc., are relatively undocumented, in part due to lack of attention and inspection methods; and, common tagging methods. The discrete events are relatively rare so large amounts of data is required, which in terms suggest a national effort is required if meaningful technical information is to be retrieved for future modeling. Methods for normalization with respect to physical processes (size, technology, location, environment etc.) need to be included in such efforts. The CREW project was initiated to facilitate this national effort to collect, normalize, analyze, and benchmark this type of data essential for understanding wind turbine fleet reliability trends and issues. However, success of the CREW project will be determined by willingness of owners to participate and share data with Sandia National Laboratories under the protection of a non-disclosure agreement that ensures the safeguarding of all proprietary data.

A novel directional analysis has been developed for power and power variance, showing that individual turbines performance is linked to their location. It is shown that similar analysis of sensors relating to loading on main components could be successful in modeling the common wear and tear on the individual turbines rather than using common average approaches.

Finally, a directional analysis of faults occurring in the wind farm may prove extremely useful and reveal these individualities from turbine to turbine. Deviation from expected patterns could yield more accurate detection and accommodation.

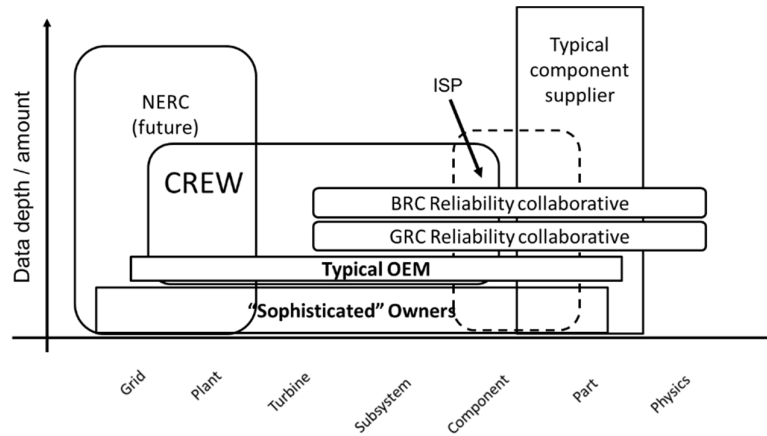


Figure 1. Knowledge in the reliability space

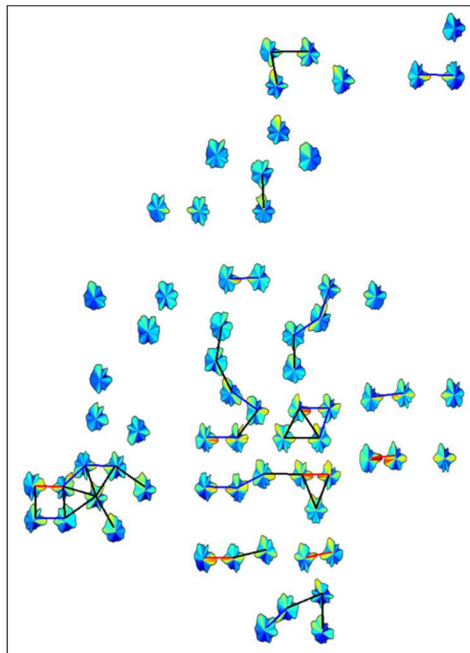


Figure 2. Directional power variability in an entire wind farm mapped over 1.5 year, ref. [7,8]. The colored lines show turbine which are closely spaced.

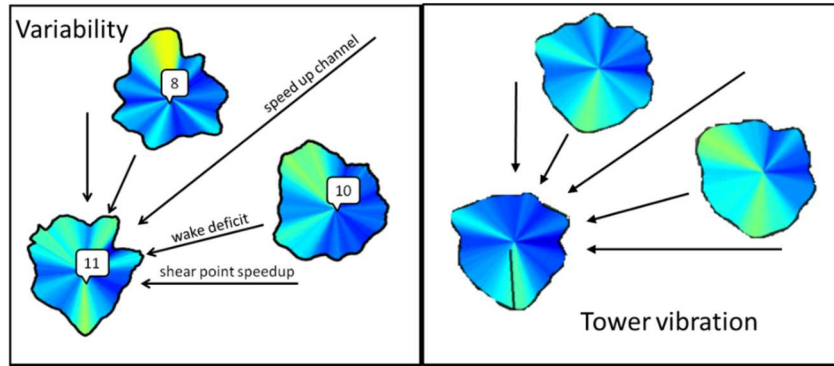


Figure 3. Left: Power variability from 3 turbines in the upper middle in figure 1. Right: Corresponding average tower vibration levels recorded over 1.5 years, similarly to that of the power variability. Arrows indicate wind farm flow effects identified in ref [7, 8]

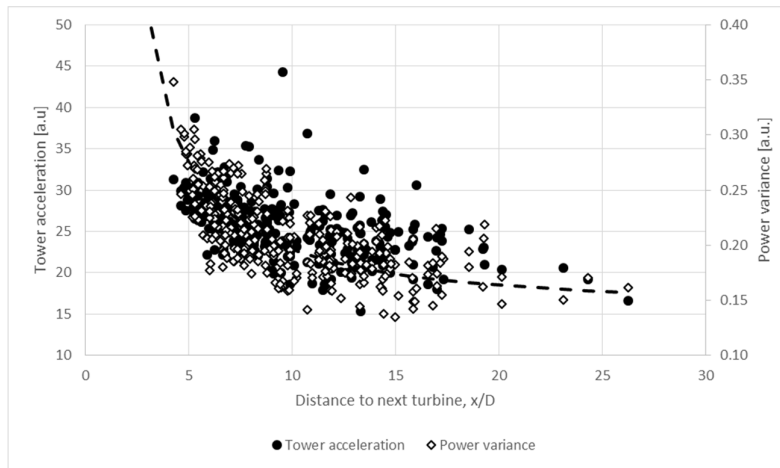


Figure 4. Power variability at direction of any neighboring turbine (waked turbine) from figure 3 compared to tower vibration in the same direction. Data is 1.5 years of duration.

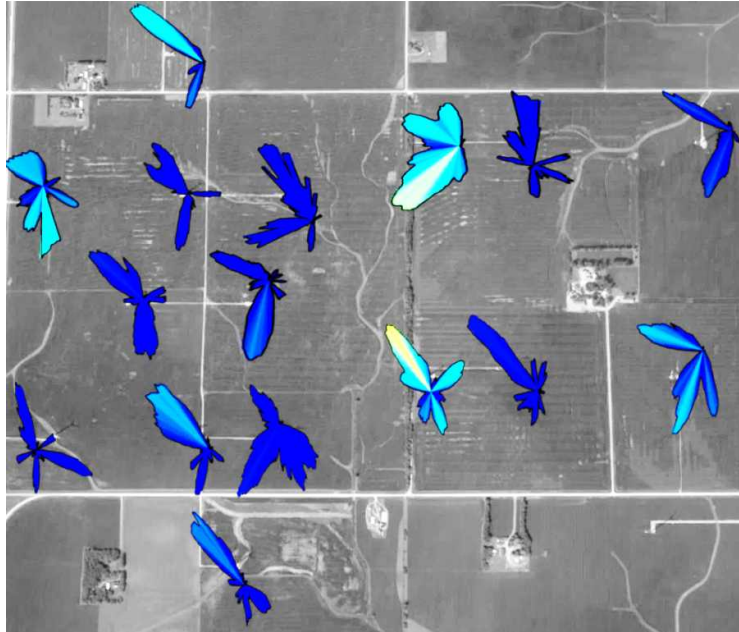


Figure 5. All fault counts by direction over 1.5 years in subset of the wind farm shown in figure 1. It is noticeable that the faults do generally not align with the main wind directions (NE and SSE)

Table 1. Indicative cost and occurrence of unplanned reliability for a fictive 2 MW turbine in the USA territory. The total lifetime cost is \$516,000, whereof \$330,000 is replacement cost. The cost accumulates to approximately \$5/MWh produced energy. The unplanned cost is about half of the total cost. The objective of this table is not to give accurate numbers, but an order of magnitude.

Item	Relative cost	Annual failure rate of repairable items	Fraction of fleet which will experience major replacement in lifetime
Blades	29%	16%	14%
Gear and bearings	36%	6%	42%
Generator	22%	3%	29%
Other	9%	39%	
Force outage or resets	4%		

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