Paper: wes-2016-16
Title: Monitoring offshore wind farm power performance with SCADA data and advanced wake model
Authors: Niko Mittelmeier et al.

Answers to comments of anonymous Referee #2 by

Niko Mittelmeier et al. July 26, 2016

Dear Referee,
Thank you very much for reviewing our paper and sharing your experience. It is of great value for us and we hope to have answered your questions and comments sufficiently. Your comments helped us to identify the sections, where certainly more explanations are necessary and it will help to improve the paper.
Our responses to your comments are marked as ***/ Response /***.

It is an interesting paper, introducing a new validation method for identifying wind farm underproduction. Such methods are highly needed with the large amount of wind turbines are installed in wind farms. The precondition for my review is that the method should also be applicable for implementation and not only be an theoretical exercise. The method, which seems to be a spin-off from an EERA project named ClusterDesign, refers to an ideal determination of the inflow conditions. The proposed method uses wake models estimates as reference, which seems to make a robust estimate of the underproduction. The accumulated uncertainty for the inflow conditions has been estimated to 7% and this number seems realistic when using recent calibrated instruments (cup and vane). This number is not realistic when using derived inflow conditions based on nacelle anemometry, electric power and wind turbine yaw position for periods longer than 1 year according to my experience.

***/ You are right, this result would not be realistic if it was based on absolute AEP values. But we have obtained 7% combined uncertainty based on normalised reference values compared between model and measurement. We see the advantage of the proposed method in the fact, that a precise wind speed measurement is less important compared to the IEC 61400-12-1 or IEC 61400-12-2. The sensitivity factor for wind speed uncertainty is taken from the slop of the power curve. When we normalize the power curve with the power of the same turbine type, Type B uncertainties become 0 in free flow conditions. The second thing we find helpful to reduce the know disadvantages from nacelle wind speed measurements is the fact, that we average all devices from turbines in free flow conditions. The variation among these signals is then represented in the uncertainty estimation.

We can confirm your concern, that yaw positions (nacelle positions) are prone to errors over time if no care is taken. For our monitoring model we are using the absolute wind direction signal from each turbine which is defined as

$$\vartheta = nacelle\ position + wind\ vane\ position$$

The nacelle position is the angle between the rotor axis and a marking for true north. This marking is calibrated as part of the commissioning. But often this signal is not maintained well during operation, because it has no effect on turbine performance. This causes the necessity to apply a bias correction to this signal before using it for reanalysis purposes. The wind vane position indicates the angle of the flow to the rotor axis. It directly provides a value for the yaw error. The turbine controller uses this signal to control the yaw activity. We have recalibrated ϑ by looking at the maximum wake deficit behind the turbine 26. This offset has been used to recalibrate all nacelle positions in the farm. /***

Problem: The determination of the wind farm inflow (environmental) conditions (wind speed and wind direction) seems not to be aligned with the state-of-art wind farm signals.

/ One of our main objectives was to establish a method that can be applied with no need for additional hardware installations. Therefor we have used the available SCADA data and a pre-process to derive the wind farm inflow conditions. We agree, with LiDAR techniques improvements may be possible./

In section 2.1.1 the wind direction is derived, but without any reference to how this is done. The wind direction measured on the nacelle is only used for yaw control, where the strategy is the keep the rotor aligned with the wind direction to minimize the yaw-misalignment. This signal can also identify a "forced" yaw misalignment used to determine the "wake drift"? The optimal readings from this instrument is 0, and will not reveal anything about the actual flow direction, which only can be identified from the wind turbine yaw position. The wind turbine yaw position not used by the controller, only when wind farm has sector management (proposed but never seen). The yaw position is usually not calibrated or has a wrong offset, which need to be identified.

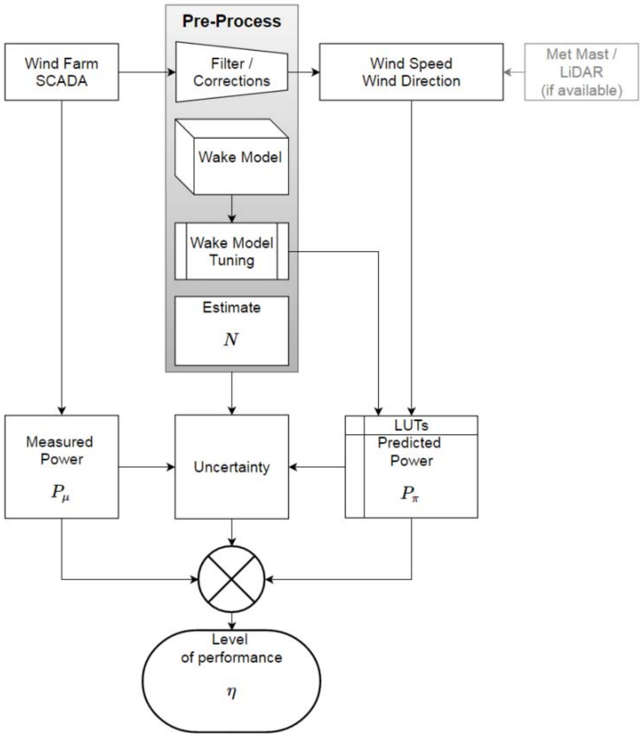
***/ Thanks for pointing this out. We see the need to provide more clarification in this section. We will add the following explanations:

"The first step is to derive a wind direction ϑ for each 10 min interval. For our monitoring model we are using the absolute wind direction signal from each turbine which is defined as

$$\vartheta = nacelle\ position + wind\ vane\ position \tag{4}$$

The nacelle position is the angle between the rotor axis and a marking for true north. This marking is calibrated as part of the commissioning. But often this signal is not maintained well during operation, because it has no effect on turbine performance. This causes the necessity to apply an offset correction to this signal before using it for reanalysis purposes. The wind vane position indicates the angle of the flow to the rotor axis. It directly provides a value for the yaw error. The turbine controller uses this signal to control the yaw activity.
Within the Pre-Process (Fig.1) of the monitoring model we estimate the north marking offset for one turbine by checking the location of the maximum wake deficit with respect to the true north. Then we compare the average wind direction between corrected turbines and neighbouring turbines to estimate the remaining offset for all turbines. After applying this offset correction, the wind direction from all wind vanes are averaged in the complex plane to account for the wind direction discontinuity at the beginning/end of the value range, after removing outliers outside ±1.5 IQR (interquartile range)."

Furthermore, we will update Fig. 1 as below, to show the Pre-Process which is necessary to derive the right wind direction signal.



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Section 2.1.2 states to use nacelle anemometry to determine the wind speed; correct this is the only accessible wind speed measured on a wind turbine. This is measured with either a cup anemometer or sonic, located on the nacelle (behind the rotor).
The signal is recorded through the controller and stored in SCADA system, but lacks documentation and uncertainty estimation. A correlation check between a number of identical wind turbines reveals a large scatter in the binned power curves. The scatter increases when the turbine operates in a wake compared to free inflow.
Conclusion:
the nacelle wind speed signal is biased. Furthermore the nacelle anemometer changes over years e.g. due to degradation. Even a NTF based wind speed (IEC 61400-12-2) is only applicable for free, undisturbed inflow.

***/ We absolutely agree with you conclusion. But as described in our response above, the monitoring method is less sensitive to wind speed measurements compared to IEC 61400-12-1 and IEC 61400-12-2 cause comparison is based on normalized power curves.
Secondly, the derived wind speed consists of only free and undisturbed nacelle wind speed signals and the variation among the devices is reflected by the uncertainty (one standard deviation) /***

Conclusion on inflow conditions: the stated uncertainty, for wind speed and wind direction does not meet the requirements given in IEC 61400-12-1 and this need to be addressed both in the method and in the example.

***/ We will add clarification about that in the last paragraph of Section 4 (Discussion):
"The stated uncertainties for wind speed and wind direction may be sufficient for the relative comparison to detect underperformance between turbines but it does not meet the requirements for an absolute performance validation according to IEC 61400-12-1(2005) or IEC 61400-12-2 (2013). One could perform power curve verification test in accordance with the mentioned standards at turbines where its applicable and those turbines being reference turbines in the monitoring method would increase the confidence in underperformance detection. At least for the concurrent period."
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Comments to the figures: all figures should include proper captions readable out of context. The caption of the figures are not sufficient e.g. while Figure 2b is not a addressed in the caption.

***/ Thanks for this advice. Below we provide new captions for each figure so that its understandable out of the context:

Figure 1: Flowchart of the Performance Monitoring Model. Wind speed and wind direction are derived from SCADA data after an offset correction of each wind direction signal and outlier filtering. Wake model calculations and tuning as well as the estimation of the number N of 10-min samples for averaging are pre-processed. N, P_π and P_μ are input values for the uncertainty calculation. An underperformance indicator η lower than the uncertainties indicates underperformance.

Figure 2: Impact of different key tuning aspects on the wake model results step by step. An increasing atmospheric stability increases the wake deficit (from red rhombus to black triangles). Wind direction uncertainty flattens the wake deficit (orange points), and a wind direction bias shifts the deficit horizontally (green squares). The left plot shows the power of the turbine in the wake divided by the power of a turbine in free flow conditions as function of the wind direction. The right plot displays the same power ratio as function of the normalized wind speed. (normalized power curve)

Figure 3: Determination of free flow turbines for wind speed averaging. The turbine at (x0,y0) produces a wake on the turbine at (x,y) for the displayed wind direction ϑ. β is the angle between the orientation of the turbines and the true north. α is the angle of the disturbed sector in accordance with IEC 61400-12-1.

Figure 4: Underperformance indicator η with uncertainty margin as function of the number of measurement values N. Derived with the calibrated model at a turbine in triple wake.

Figure 5: Layout of wind farm Ormonde. The 30 turbines of 5MW class are located in the Irish Sea 10km west of the Isle of Walney. For a wind direction of 207° the single wake, double wake and triple wake behind OR26 has been selected as underperformance demonstration cases.

Figure 6: Estimation of uncertainty of the artificial wind direction. Histogram of the deviation of 30 individual wind vanes from the average wind direction for the full data set filtered for wind speeds > 5m/s with a sector of 30° centring the full wake condition. The red curve represents a Gaussian fit with a standard deviation of 3.6°.

Figure 7: Wind farm averaged wind speed with wake effects normalised with wind farm averaged wind speed without wake effects plotted versus averaged wind farm wind direction. Black dots show the measurements from SCADA and the green solid line represents the results from Fuga with a Gauss averaging for standard deviation of 4°. An offset of the wind direction between model and SCADA can be observed. At 207° the offset is approximately 2.2° and it increases up to 5° for wind directions (132° and 312°) with the largest wake effects. An explanation and correction for this "wake drift" is proposed in section 2.2.

Figure 8: Estimation of uncertainty of the artificial wind speed. Histogram of the wind speed difference of a single anemometer to the average wind speed of all free flow anemometers. The displayed Gaussian distribution (red line) has the standard deviation of 0.46 m/s. A sector of 30° centring full wake alignment has been selected.

Figure 9: Tuning of the wake model results.(left column) Power normalized by the power of the free flow turbine as function of the wind direction centred at full wake for 8 ± 1 m/s wind speed. (right column) Power normalized by the power of the free flow turbine as function of the wind speed normalized by wind speed at rated power for the waked turbine. Black dots represent the measured and binned SCADA data with error bars of one standard deviation. The red triangles show wake model results with Fuga standard settings ($\zeta_0 = 0$, no Gaussian averaging) and the green diamonds provide the tuned results. ($\zeta_0 = 2.72E - 7$, Gaussian averaging as function of the wind speed and applying the wind direction offset to account for the wake drift).

Figure 10: Scatterplot with normalized power as function of the normalized wind speed for four turbines in one row with two error test cases. Green dots are the measured power values and represent optimal operation. 8% degradation of the power output is shown with yellow dots. A curtailment at 58% is shown in red.

Figure 11: Underperformance detection for curtailment (right column) and degradation (left column) at turbines with different levels of wake influence. The displayed values represent the underperformance indicator η as function of the number of values N. We highlight the first time of underperformance detection when the green dotted line is outside of the grey uncertainty bandwidth.

Figure 12: Uncertainties for the underperformance indicator u(η) as function of N values for free flow, single wake, double wake and triple wake situation. Uncertainties for free flow conditions (green) are much lower that the uncertainties for the waked turbines.

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The description of the method seems to be adequate, but the "wake drift" in section 2.2 is not well defined, I assume this refers to periods with active wake control, which I do not expect has been implemented yet?

***/ The data for our demonstration is without active wake control. We cannot fully rule out the possibility of an unwanted yaw misalignment as the uncertainties within this process of aligning the turbine lies within 3° (IEC 61400-12-2, 2013).

We rather think, that a small wake drift is also possible for a perfectly aligned turbine. Therefore we will add the following explanations and references to provide better explanations of the observed phenomenon.

"The third tuning parameter is applying a simple offset on the wind direction of the LUTs to account for a drift of the wake. We call this phenomena from here on "wake drift". Fleming (2013) has studied the effects of active wake control and in his baseline simulation (no yaw error) a small wake drift to the right can be observed when looking downwind. In the LES study of Vollmer et al. (2016) the wake drift increases from neutral to stable conditions also for 0° yaw angle. Gebraad (2014, p86) gives an explanation for the observations from the simulations by Fleming (2013). The flow reacting on the rotation of the rotor causes the wake to rotate counter clockwise (looking downstream). Higher wind speeds from the upper layer are transported downwards (on the

left side) and lower wind speeds from the lower layer are pushed upward on the right side of the wake. As a result the velocity deficit at the right part of the wake increases, so the wake deflects to the right.
Marathe et al. (2015) could show in their field measurement campaign with a dual-doppler radar the wake drifting to the right, as expected by the theory. But in the far wake they registered a movement to the left. The authors state the hypothesis that this contradicting phenomenon may be caused by atmospheric streaks. In an offshore field experiment by Beck et al. (2015) further evidence is provided that wakes are moving out of the centre line. This wake drift is currently not modelled in Fuga and therefore applied in a further step of the pre-process (Fig. 1).“

References for this paragraph:
Beck, H., Trujillo, J. J., Wolken-möhlmann, G., Gottschall, J., Schmidt, J., Peña, A., Gomes, V., Lange, B., Hasager, C. and Kühn, M.: Comparison of simulations of the far wake of alpha ventus against ship-based LiDAR measurements, in RAVE Conference., 2015.

Fleming, P. A., Gebraad, P. M. O., Lee, S., van Wingerden, J. W., Johnson, K., Churchfield, M., Michalakes, J., Spalart, P. and Moriarty, P.: Evaluating techniques for redirecting turbine wakes using SOWFA, in ICOWES2013 Conference., 2013.

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Marathe, N., Swift, A., Hirth, B., Walker, R. and Schroeder, J.: Characterizing power performance and wake of a wind turbine under yaw and blade pitch, , doi:10.1002/we, 2015.

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