White Paper

A Multi-Project Validation Study of Vaisala's Wake Loss Estimation Method

August 2019 | Mark Stoelinga, Senior Scientist

Executive Summary

Vaisala has conducted a multi-project validation study of its unique wake loss estimation method, using one year of post-construction operational data from seven North American onshore wind energy projects in flat terrain. Observed wake losses were derived from the wind project SCADA data using a "reference set" approach to estimate the unwaked power. A mesoscale model simulation was used to determine the spatial variability of the unwaked wind field so that its signature could be removed from the observed estimate of wake losses. The pre-construction wake loss estimates were made with Vaisala's time series-based method utilizing the Larsen single turbine wake model. Finally, error metrics were calculated describing the difference between the modeled and observed wake losses. The results showed that the observed wake losses were 21% larger than predicted, on average, indicating the need for a calibrative correction to the wake loss estimate. If the 21% bias is removed, the standard deviation of the remaining project-to-project random error is 16% of the observed wake loss. This is an encouraging result, considering that consultants typically assume uncertainties ranging from 20% to 30% of the total estimated wake loss. A caveat to both the mean bias and uncertainty results is that it is based on a relatively small sample size of seven projects, which yields large 90% confidence intervals on each statistic: +11% to +30% for the mean bias error, and also 11% to 30% for the uncertainty. Going forward, Vaisala intends to update the study with a larger sample size by adding new operational projects to the validation data set and thereby decrease uncertainty in the results.

Introduction

When wind flows past a wind turbine, the turbine produces a wake of reduced wind speed and enhanced turbulence, which can persist tens of kilometers downwind. In a wind project, wakes from upwind turbines often align with downwind turbines, and thereby decrease the energy produced by the waked downwind turbines. Three different depictions of wind turbine wakes, as condensation plumes visible to the eye, as radar-measured deficits in wind speed, and as modeled deficits in wind speed, are shown in **Fig. 1** (for different wind projects).

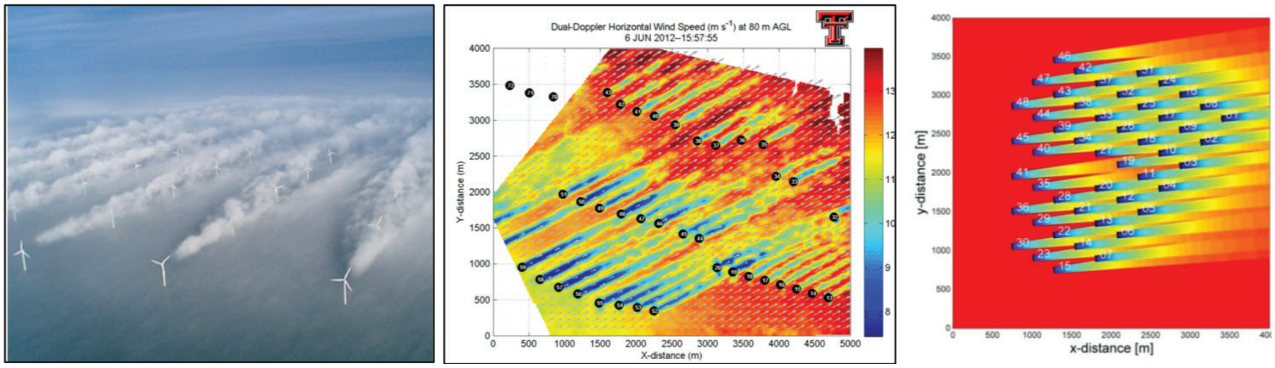


Figure 1. Three depictions of wind turbine wakes. Left: Condensation plumes produced by turbulence within turbine wakes in the Horns Rev offshore wind project in the North Sea. Photo: Christian Steiness, Vattenfall. Middle: Wind speed deficits within turbine wakes measured with the Texas Tech University Doppler Ka-band radar at a wind project in Texas. Downloaded from depts.ttu.edu/nwi/research/radar-research. Right: Wind speed deficits simulated for the Lillgrund offshore wind project in the Øresund, using the Jensen (1983) model with wake decay constant of 0.04 (from Smith et al. 2012).

Depending on the layout and environmental conditions, the associated long-term average energy loss due to wakes can be >10% of the project's gross energy production. In fact, the wake loss is often the single largest energy loss for a wind project, so accurate estimation of the wake loss is paramount for reliable pre-construction energy yield estimates. However, the wake loss is a challenging calculation that depends on accurate prediction of the flow meteorology (wind speed and direction, stability, and turbulence), as well as accurate modeling of wake behavior (including wake generation, expansion and dissipation, and combination with other wakes). The difficulty in estimating wake losses is reflected in the large uncertainty typically assigned to wake losses. Nygaard (2015) found from a survey of consultants that uncertainties for European offshore projects range from 25% to 60% of the estimated wake loss. For onshore projects in North America, consultants assign somewhat lower uncertainties, typically 20% to 30% of the estimated wake loss.

In light of the importance of the wake loss to pre-construction energy yield estimates, the challenge in calculating it, and the large uncertainty assigned to it, wake loss estimation methods must be accompanied by well-designed validation studies to establish the industry's confidence in the methods. Many such studies can be found in the literature and conference presentations. These studies fall loosely into three categories: single turbine, aligned turbine, and full project studies. Single turbine studies use wind speed or power measurements in the wake of a single turbine, in specific wind speed, direction and turbulence conditions, to study wake behavior and to validate the outputs of single turbine wake models. Similarly, aligned turbine studies look at wakes aligned along or across straight, regularly spaced rows of turbines, to examine how interacting wakes behave, and how this behavior is captured by wake loss models applied to multiple turbines. As with single turbine studies, the data in these studies is filtered for specific speed, direction, and turbulence conditions, to pinpoint how the model behaves as a function of those conditions. A recent validation study by Archer (2018) provides a good review of the results of several single turbine and aligned turbine studies that were used to compare the most regularly used engineering wake models.

Far less common are studies in the the third category, the full project study, especially those that validate wake loss estimates at three or more projects. A full project study is one in which SCADA data is analyzed, for periods of approximately a year or more, to estimate the actual, long-term energy loss due to wakes, under the full range of conditions the wind project encounters during that time period; and then compare the observed wake loss to the pre-construction wake loss estimate. These studies are uncommon for several reasons.

First, they are difficult to carry out. SCADA data is difficult to obtain and work with, and varies in format and quality from project to project. Additionally, wake losses are difficult to tease out of the SCADA data under the full diversity of wind flow and weather that occurs throughout the year, for arbitrary project layouts. Wake losses are especially cumbersome to extract from onshore projects, with irregular layouts and the added complication of spatial wind variability due to terrain and land surface effects. The particular challenge of validating wake losses for onshore projects explains why the vast majority of wake studies (of all three categories) are performed at offshore sites, where unwaked winds are more uniform and wake signatures more identifiable. Yet onshore wind still comprises a large majority of both established and newly developed wind energy capacity worldwide, and validation studies should reflect this reality with representative cases of onshore wake behavior. Finally, multi-project studies derive their value not from detailed insights into the actual or modeled behavior of wakes (as with single or aligned turbine studies), but by establishing a statistical error distribution of wind project wake loss estimates. The conventional approach to estimating uncertainty is the "forward mode," in which component uncertainties are propagated through the entire wake loss estimation process. However, that approach typically requires many guesses at unknown component uncertainties (Nygaard 2015). The alternative is the empirical approach advocated here, made possible by a multi-project validation study. The mean of the observed error distribution indicates the overall bias in the wake loss method (which, if desired, can be removed through calibration); and the standard deviation indicates the project-to-project uncertainty. Of course, the confidence intervals on such estimates is inversely related to the sample size, which presents the final difficulty: one must perform the validation not for one or two projects, but ideally on a great number of projects. This has proved impractical to date, and currently the bar is set by Nygaard (2015), who accumulated a data set from ten offshore projects. After that, the sample sizes of other studies drops off rapidly. Walker (2016) examined three offshore sites and Angot (2017) studied two offshore sites. Nygaard's and Walker's studies both showed tantalizing evidence that actual uncertainties are not as large as consultants have been assuming and may actually be <20% of the estimated wake loss.

The purpose of the present study is to validate a specific wake loss estimation method: the time-series wake loss method currently used by Vaisala for project wind energy yield assessment. To contrast the dearth of onshore projects included in previous multi-project studies, this study examined exclusively onshore sites. It used a NWP-based approach to quantify non-wake-induced (primarily terrain-induced) horizontal variability of wind resource, and to eliminate its contaminating signature from the SCADA-based estimates of measured project wake losses. The sample size in this study was seven projects, though that is anticipated to grow, now that the methodology has been established. Seven projects are not sufficient to precisely quantify the bias and uncertainty of Vaisala's method, but can yield indicative results. Confidence intervals on both bias and uncertainty error statistics are included and account for the relatively small sample size of the study.

Vaisala's Wake Loss Estimation Method

Vaisala's method for estimating project wake losses is summarized in Table 1.

Vaisala Wake Loss Estimation	
Single turbine wake model	Larsen (1988)
Calculation	Upwind-to-downwind, considering both ambient and waked TI in wake recovery
Wake combination	Root mean-squared summation
Temporal aggregation	Time series calculation, using hourly output from ~30-year mesoscale numerical weather prediction simulation
Static inputs	Turbine coordinates, rotor diameter, hub height, and thrust curve
Time varying inputs	Hub-height wind speed, wind direction, and ambient turbulence intensity

Table 1. Specifications of Vaisala's wake loss estimation method.

The unique aspect of the approach is the calculation of wakes in a full time series framework, where the wake model is run using specific conditions of wind speed, wind direction, and turbulence intensity (TI) at each hourly time point of a ~30-year historical period. The time series framework requires more computation than the conventional method of running the wake model for a limited set of wind speed and direction conditions and taking a weighted aggregate of those results using the speed histogram and wind rose bin frequencies. The benefit of the time series method is the specification of exact meteorological conditions at each time point. In particular, the ability to include the full time variability of TI leads to a more accurate representation of the nonlinear relationship of wakes to TI. The Vaisala wake model employs the single-turbine model developed by Larsen (1988) (**Fig. 2a**), which has the desirable feature that wake recovery is directly dependent on TI, in contrast to the more commonly used Jensen (1983) model that has a user-set wake decay constant.

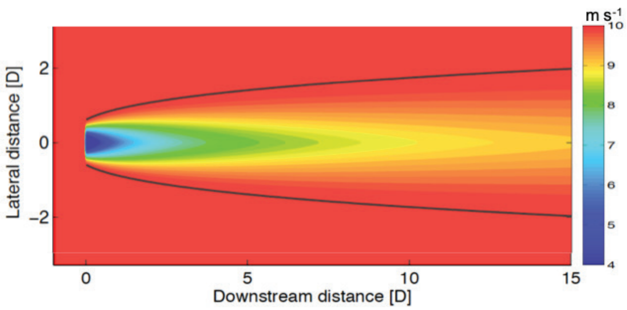


Figure 2. (a) The wind speed deficit pattern in the Larsen (1988) single turbine wake model (adapted from Renkema 2007).

Overlapping wakes in Vaisala's method are combined with a root-sum-squared addition. This generally leads to amplified wind speed deficits where many wakes combine (e.g., in the top right section of **Fig. 2b**), compared to the more common "choose the largest" approach.

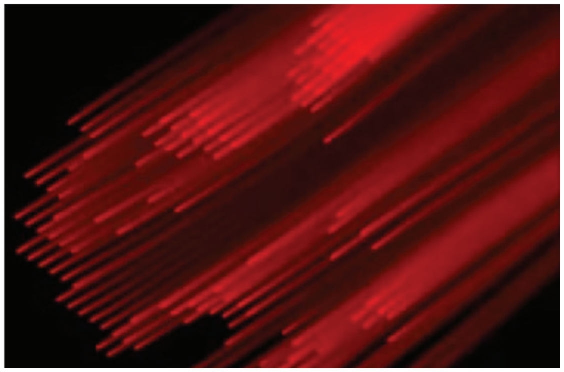


Figure 2. (b) A depiction of wind speed deficits for an entire wind project, using Vaisala's Larsen-based wake model.

Gunn (2016) suggests that while "choose the largest" may work best for wakes aligned along a linear row of turbines, it may not be appropriate for arbitrary layouts and wind directions. Vaisala does not employ an additional "large array" reduction to the waked wind speed. This choice was based on early validation work at a large North American wind project (McCaa 2013), where Vaisala found that wake model errors at deep interior turbines were not biased relative to those at shallow interior turbines.

Validation Method

Wind projects

The study data set consists of seven projects, all over flat agricultural or prairie terrain in central North America. Due to nondisclosure agreements, we cannot provide project-specific characteristics. As a whole, the projects ranged in nameplate capacity from 60 to 500 MW, and in turbine count from 30 to 300. Five of the projects had elongated layouts, and two had more circular or confined layouts. Data from the projects consisted of approximately one year of turbine power, nacelle wind speed and direction, and wind speed and direction from one or more permanent met towers or remote sensing devices. Temperature and pressure data were either provided by the project owner or extracted from MERRA2 reanalysis data.

Data preparation

Basic quality control (QC) checks were applied to the meteorological data, such as range bounds and flat-line removal. Air density (needed for conversions between wind speed and power) was estimated at every turbine and time point using temperature and pressure measurements, and an adjustment for elevation and hub height. A time series of project-average wind direction was derived from a weighted median of nacelle orientations and met tower vane measurements. Using that project-average wind direction, unwaked met towers and turbines were identified at each time point, and a project-average unwaked wind speed time series was derived, also using a weighted median of available wind speeds from unwaked met towers and turbines. While many turbines clearly report inaccurate speed and direction values, there is typically a cluster of values around the correct value, and so the median performs well at selecting a reliable representative value.

QC of the power data was performed as follows. Ideally, SCADA data would identify times when turbines were not in a state of normal operation. However, SCADA flags for different operational states were often missing, not clearly defined, or inaccurate. Nacelle wind speeds were also frequently missing or inaccurate. Therefore, QC'ing the power data based on either SCADA flags, or based on bad points on a scatter plot of turbine power vs. nacelle speed, was found to be either unreliable or too aggressive in eliminating good power data. Therefore, it was decided to QC the turbine power data based only on the power itself, and its relationship to the more reliable project-average unwaked wind speed estimate described above. Any turbine power values that were clearly derated (i.e., the appearance of a derating "shelf" on the power versus speed scatter plot) were flagged as invalid. Additionally, polygons were defined that enclosed plausible values on the turbine power versus project-average unwaked wind speed scatter plot, allowing liberal room beneath the power curve for wake-reduced power. All turbine power values outside the plausible area were flagged as invalid. Finally, all turbine reports of zero power were flagged as invalid. Most of these zero power reports were likely correctly reported times of below cut-in windspeed, but many occurred when wind speeds were well above cut-in, meaning the turbine was either not operating or not properly reporting its power, and it was difficult to distinguish these cases. Therefore, we chose the more aggressive approach of flagging all zero power instances as invalid. The implications of this decision are discussed a bit later.

Estimation of observed unwaked and waked power

With the power data QC completed, the next step is to define the project unwaked and waked power at each time point. The waked power is just the sum of all valid power values in the wind project. At least 90% of the turbines had to report a valid power, or else that time point was invalidated. The unwaked power is estimated by a method similar to that used in Nygaard (2015), Walker (2016), and Angot (2017). Based on the project-average wind direction, a "reference set" of turbines is defined, which are unwaked and have valid power at that time, as illustrated in **Fig. 3**. The reference set had to include a minimum of 5 unwaked turbines with valid power data, or else that time point was invalidated. The unwaked power at that time point was then defined as the mean power of the reference set, times the total number of valid turbines in the wind project farm at that time point. Two additional time filters were applied: a time point was invalidated if either the air density or project-average wind speed could not be estimated from available data at that time point.

Effects of data filtering

The effects of the power data filtering are summarized in **Table 2**.

Filtering step	Percent of turbine time points remaining	Percent of energy remaining
After removal of missing and out of range power values:	**98%**	**100%**
After removal of de-rated power values:	**97%**	**99%**
After removal of all turbine time points for which power is inconsistent with project-average wind speed:	**90%**	**95%**
After removal of all turbine time points with zero power:	**74%**	**95%**
After removal of times lacking minimum number of valid turbines in either the full project or reference set:	**66%**	**87%**

Table 2. Effects of various data filtering steps, in terms of percent of total turbine time points remaining, and total energy remaining, after the filtering step is applied.

Missing and out of range power values were relatively infrequent, so their removal eliminated only 2% of turbine time points. Removal of clearly de-rated power values removed and additional 1% of turbine time points and of total energy. More substantial was the removal of power values that were inconsistent with the project-average unwaked wind speed, but this step still left 90% of turbine time points and 95% of total energy. Invalidation of all zero-power turbine time points reduced the

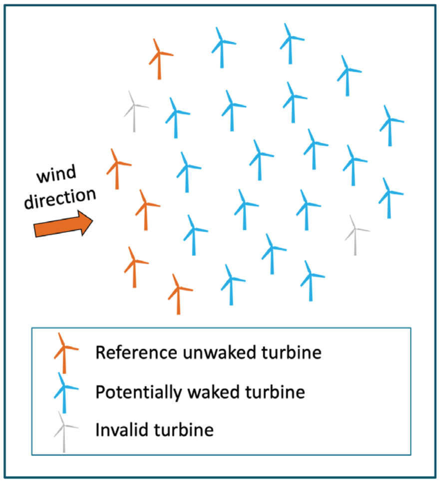


Figure 3. A schematic illustrating the "reference set" method for estimating unwaked wind speed. A reference set of unwaked turbines are chosen if they occupy an unwaked location relative to the current wind direction, and have a valid power measurement at the current time.

turbine time points to 76% of the full period of record, a considerable reduction, but of course had no effect on removed energy. Finally, time filtering based on a minimum number of valid turbines in the project as a whole (at least 90% of total turbines) and in the reference set (at least 5 turbines) reduced both turbine time points and total energy by and additional 8%. It was at this step that we were concerned that the aggressive invalidation of all zero-power turbine time points might push too many of the time points below these two availability thresholds, and leave too few valid time points. However, 2/3 of the time points remained, and nearly 90% of the energy remained in the data set after this filtering step was taken, so it was deemed to be a sound approach.

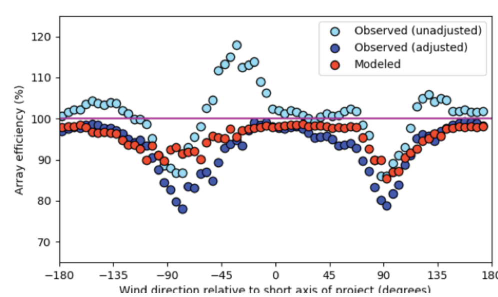
Wake loss metrics

Following previous studies, we express wake losses in two ways. The first is termed "relative power" or "array efficiency", and is the ratio of energy the wind project actually produces with wake effects included to the energy it would produce if all turbines experienced unwaked winds, or $E_{waked}/E_{unwaked}$. It can either be given as a dimensionless ratio or a percent, with a value less than 1.0 or 100% indicating waking. The second is termed the "wake loss", which is the difference between the unwaked and waked energy, as a fraction of the unwaked energy, or $(E_{unwaked} - E_{waked})/E_{unwaked}$. It is usually given as a percent, with a positive value indicating waking. Both quantities can refer to the wind project power at an instant in time, or to the energy aggregated over some period of time. They can also be calculated for data binned by other variables, such as wind direction. However, to aggregate a correct long-term value for the wind project as a whole, the order of operations is important. First the waked and unwaked energies should be aggregated, then the ratios computed.

Examples of the array efficiency calculation for two projects ("#3" and "#6"), binned by wind direction, are depicted as light blue dots in **Fig. 4**. Both projects have elongated turbine layouts, and to keep the projects anonymous, the wind direction is shown relative to the orientation of the short axis of the project, rather than relative to north. As expected, the strongest waking (lowest values of array efficiency) occurs for directions roughly plus and minus 90 degrees from the short axis, or in other words, when the air flow is along the long axis of the project. However, there are many directions (especially for project #3) for which the array efficiency is > 1.0, which is not physically plausible if the array efficiency (as defined above) is being affected only by wakes.

Spatial adjustment

The explanation for the apparent array efficiencies > 1.0 is that the array efficiency is not being affected only by wakes. Despite our best efforts to choose projects for the validation study over flat terrain, the reality is that most projects are built on some sort of local topographic maximum, however subtle, where wind speed is slightly higher than over the surroundings. To investigate the effects of horizontal variability of unwaked wind resource, Vaisala conducted high-resolution mesoscale numerical weather prediction (NWP) simulations of each project for 1 year. These simulations revealed that, in addition to the expected speed maximum at the top of the topographic maximum, there was also a distinct tendency for unwaked wind speeds to decelerate on the windward side of the topographic maximum (where the "front row" turbines are located), and to accelerate on the leeward side (where the rear-most turbines are located). This wind pattern is familiar to meteorologists as "windward blocking" and "downslope acceleration," an expected dynamical response to stable flow over a mountain barrier. Here, the "mountain barrier" is



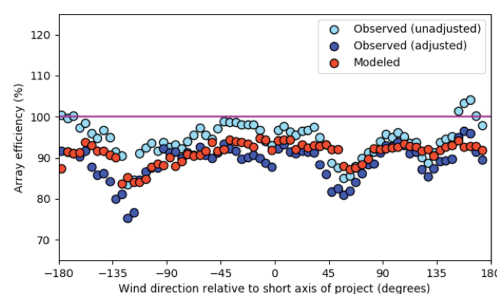
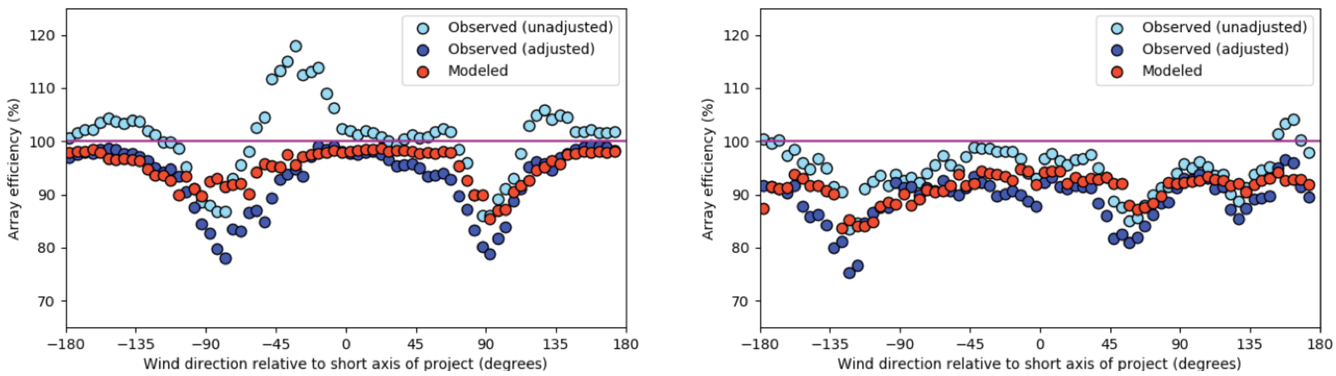


Figure 4. Array efficiency as a function of project-average wind direction, for two sample wind projects in the study. Blue dots: Estimates of observed array efficiency using SCADA data, before (light blue) and after (dark blue) the adjustment for spatial variability of unwaked wind resource. Red dots: Model predicted array efficiency.

an almost imperceptible topographic ridge or rise, but produces mean speed deviations of up to ±10% in some cases. The pattern tends to counteract the typical pattern of waking, and thereby contaminates our observed wake loss metric by lowering the estimated unwaked power (by lowering the power of the reference set) and increasing the estimated waked power (by increasing the power of the rear turbines). A similar pattern occurs for every wind direction to varying degrees, so the tendency is to reduce the wake loss (or even produce "wake gain") to some degree in every direction.

To account for this effect, we applied a correction that is somewhat similar to the approach described in Peña et al. (2018). First, we used the same mesoscale NWP simulations described above to develop a sector-wise speed-up ratio for every turbine (relative to the mean unwaked wind speed at all turbines). We then used an inverse power curve to convert turbine power values to wind speed, and divided that wind speed by the sector-appropriate speed-up ratio at each time, to estimate a new wind speed that is due only to wakes and not to horizontal variability of unwaked wind speed. Finally, we used the forward power curve to convert the adjusted speed back to power, now adjusted for the sector-wise mean spatial wind pattern. This was done for every valid turbine power value at every time point. We then recalculated the wake metric, and the results for projects #3 and #6 are shown as the dark blue dots in **Fig. 4**. Several improvements can be seen. At both projects, the array efficiency is now ≤100% in all direction sectors, as expected. At project #3, which is a narrow project with just a few long rows of turbines that are infrequently waked when the wind flows across the rows, the efficiencies are just below 1.0 for directions between -45 and +45 degrees, as expected, instead of the erratic behavior of the unadjusted array efficiency metric. Based on these results, we proceeded under the assumption that with this spatial adjustment, we were able to produce a reasonable estimate of the observed project wake loss that could be used for validation of Vaisala's predicted wake losses.



Comparison of observed and modeled array efficiencies

We ran our standard energy yield assessment process for the seven projects in the study. This process included both a mesoscale model simulation to map out the spatial variability of wind speed, as well as an application of the wake model in a time series mode, as described in section 2. This combination of modeling yielded time series of predicted waked and unwaked wind speeds at every turbine location, which were then passed into a power curve to convert to time series of power at each turbine location, and then aggregated across the entire project. The spatial variability of unwaked wind speed described above, which contaminated the observed estimate of wake loss, is already accounted for in the model estimated wake loss, so there is no need to apply a speed-up ratio-based adjustment for the modeled wake loss. The predicted wake loss metrics are then computed from the modeled power time series as described in section e above. The associated directionally binned array efficiencies from the modeled wakes are shown as red dots in **Fig. 4**. They tend to be slightly biased toward weaker wake losses, which will be discussed in the overall validation results in the next section. The directional details of the wake pattern, with maximum wake losses identified when the wind flow is along the long axis of the project, is generally captured, although the model estimate does not capture the full magnitude of the array efficiency "valleys." Some of these differences in the details can be attributed to the wake model or its implementation, but some are also likely to result from errors in our estimates of the observed wake loss, which was produced by a complicated processing of SCADA data, and adjusted with imperfect simulations of the spatial variability of unwaked winds.

Multi-Project Validation Results

The modeled and observed waked and unwaked energy can be aggregated over the entire period of record of production data for each of the seven projects in the validation study, to produce observed and modeled long-term wake losses for each project. These validation results are shown in **Fig. 5**, as a scatter plot of observed (y) versus modeled (x) wake losses. The 1-to-1 line, representing a perfect match between the model and observed, is shown for reference as a gray line. Most of the projects show the observed wake loss is stronger than the modeled wake loss, or in other words, the model underpredicted the strength of the wake loss. The slope of the best fit line is 1.2631.

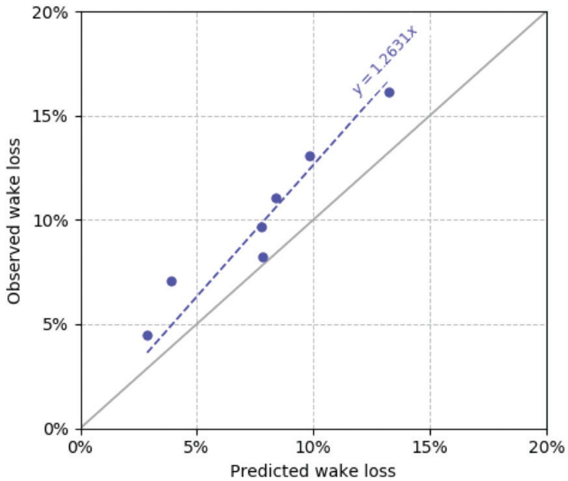


Figure 5. Scatter plot of observed project wake loss (y) versus predicted wake loss (x). Best-fit line forced through the origin (blue dashed line), as well as the associated equation, are also shown. Gray line is the 1-to-1 ("perfect prediction") line, for reference.

As in Nygaard (2015) and Peña et al. (2018), we define the relative wake model error as the difference between the observed and modeled wake loss, as a fraction of the observed wake loss, or $\varepsilon = (L_{observed} - L_{modeled})/L_{observed}$, where L is the wake loss as defined in section 3e. Based on this definition, the relative wake model error is related to the slope (m) of the best-fit line in **Fig. 5** by the formula $\varepsilon = 1 - \frac{1}{m}$. Using this formula, the mean relative wake model error implied by the 7-project result is 1 – 1/1.2631, or +21%. In other words, observed wake losses are, on average, 21% stronger than predicted. As an example, for a project with a true wake loss of 10.0%, the pre-construction wake loss estimate with Vaisala's current method would likely be 7.9%, resulting in an underperformance of 2.1% relative to the true gross energy.

Based on these results, Vaisala is in the process of determining an adjustment to its wake loss method to calibrate and better align its estimates with observed wake losses as shown in this study. An important caveat is that this study has a small sample size of seven projects, which implies a large statistical uncertainty to the result. Using the standard Student's t-based estimate of the 90% confidence interval for the population mean based on a sample mean of seven, the result is that the mean relative wake model error probably lies within the range +11% to +30%.

Finally, we consider the uncertainty of the wake loss estimate. Although the wake loss estimates are biased too weak compared to observed by 21%, the remaining random error is actually quite small. The standard deviation of the relative wake model errors for the seven projects is 16%. This is considerably lower than the 20%–30% range of uncertainty typically assigned by consultants for North American onshore wind projects. This is an encouraging result, and echoes recent similarly encouraging findings in validation studies by Nygaard (2015) and Walker (2016). However, there are several reasons for caution. First, the small sample size implies a large confidence interval on the standard deviation. A Chi-squared calculation yields a 90% confidence interval for the standard deviation of 11%–30%. Second, the projects are all located onshore in North America, over flat agricultural and prairie terrain, so the validation data set is currently not very diverse. As the data set grows through ongoing accumulation of operational project data, we will specifically seek offshore sites and locations on other continents. A larger, more diverse data set will increase our confidence in the representativeness of the validation statistics, and will narrow the confidence interval on the uncertainty, perhaps enough to warrant decreasing the uncertainty of Vaisala's wake loss estimation in the near future.

Conclusions

Vaisala has conducted a multi-project validation study of its time-series based wake loss estimation method, to provide indicative visibility into the overall bias and uncertainty in that method. The study included seven onshore wind projects of varying size, all in the generally flat central part of North America. Observed wake losses were calculated using the "reference set" method for estimating unwaked power. Due to subtle terrain-induced effects that tended to reduce wind speeds at the leading edge of the project and enhance wind speeds at the rear of the project, the observed wake estimation method required a correction to remove this effect, which was accomplished using sectorized speed-up ratios for unwaked wind speeds derived from mesoscale model simulations. Once the horizontal pattern in unwaked wind speed was accounted for, the resultant wake loss estimate provided a good basis for model validation.

When compared to the observed wakes, the model-estimated wakes roughly captured the observed directional pattern of turbine array efficiency, although with some differences in the wake loss details by sector. The difference between observed and modeled wake loss at all seven projects, as a percent of the observed wake loss, was +21%, meaning the model was under-predicting the strength of the wakes (with a 90% confidence range of 11% to +30%). Vaisala is in the process of determining an adjustment to its wake loss method to calibrate and better align its estimates with observed wake losses as shown in this study.

The validation results showed that, if the bias is removed, the remaining project to project random error in the wake loss estimates (as represented by the standard deviation of the project relative wake model errors) is 16%, with a 90% confidence interval of 11% to 30%. This is an encouraging result, considering that the wind energy consulting industry currently assigns uncertainties of 20% to 30% to the wake loss estimate for North American onshore wind projects. Vaisala hopes to increase its validation project sample size and diversity, so that we can eventually be confident in reducing our standard wake loss uncertainty below its current value of 20%.

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