An Overview of Wind Energy Production Prediction Bias, Losses, and Uncertainties

Joseph C. Y. Lee[1] and M. Jason Fields[1]

[1]National Wind Technology Center, National Renewable Energy Laboratory, Golden, Colorado 80401, USA

5   *Correspondence to*: Joseph C. Y. Lee (joseph.lee@nrel.gov)

Abstract. The financing of a wind farm directly relates to the preconstruction energy yield assessments which estimate the annual energy production for the farm. The accuracy and the precision of the preconstruction energy estimates can dictate the profitability of the wind project. Historically, the wind industry tended to overpredict the annual energy production of wind farms. Experts have been dedicated to eliminating such prediction errors in the past decade, and recently the industry is
10   recording near-zero average energy prediction bias. Herein, we present an overview of the energy yield assessment errors across the global wind energy industry. We identify a long-term trend of reduction in the overprediction bias, whereas the uncertainty associated with the prediction error is prominent. We also summarize the recent advancements of the wind resource assessment process that justify the bias reduction, including the improvements in modeling and measurement techniques. Additionally, because the energy losses and uncertainties substantially influence the prediction error, we document and
15   examine the estimated and observed loss and uncertainty values from the literature, according to the proposed framework in the International Electrotechnical Commission 61400-15 wind resource assessment standard. From our findings, we highlight the opportunities for the industry to move forward, such as the validation and reduction of prediction uncertainty, and the prevention of energy losses caused by wake effect and environmental events. Overall, this study provides a summary on how the wind energy industry has been quantifying and reducing prediction errors, energy losses, and production uncertainties.
20   Finally, for this work to be as reproducible as possible, we include all of the data used in the analysis in appendices to the manuscript.

1 Introduction

Determining the range of annual energy production (AEP), or the energy yield assessment (EYA), has been a key part of the wind resource assessment (WRA) process. The predicted median AEP is also known as the P50, where the actual
25   AEP would exceed that threshold 50% of the time. For years, the experts in the field have been discussing the difference between the predicted P50 and the actual AEP, where the industry often overestimates the energy production of a wind farm (Hale, 2017; Hendrickson, 2009, 2019; Johnson et al., 2008). A recent study conducted by the researchers at the National Renewable Energy Laboratory (NREL) concludes 3.5% to 4.5% of average P50 overprediction bias, based on a subset of wind farms in the United States, after accounting for curtailment (Lunacek et al., 2018).

30   The financial implication of such P50 overestimation is influential. Healer (2018) states that if a wind project produces a certain percentage lower than the P50 on a 2-year rolling basis, the energy buyer, also known as the offtaker, has the option to terminate the contract. For a 20-year contract, if a wind farm has a 1% chance of such underproduction within 2 years, the probability of such event taking place within the 18 2-year rolling periods is 16.5%, where $100\% - (100\% - 1\%)^{18} = 16.5\%$ (Healer, 2018), assuming each 2-year rolling period is independent. Therefore, projects with substantial energy-production
35   uncertainty experience the financial risk from modern energy contracting.

The WRA process governs the accuracy and precision of the P50, and a key component in WRA constitutes the estimation of energy-production losses and uncertainties. Wind energy experts have been using different nomenclature for in WRA, and inconsistent definitions and methodologies exist. To consolidate and ameliorate the assessment process, the International Electrotechnical Commission (IEC) 61400-15 working group has proposed a framework to classify various types
40   of energy-production losses and uncertainties (Filippelli et al., 2018, adapted in Appendix A). We illustrate the categorical and subcategorical losses and uncertainties in Figs. 1 and 2. Note that the proposed framework is not an exclusive list of losses and uncertainties because some institution-specific practices may not fit into the proposed standard.

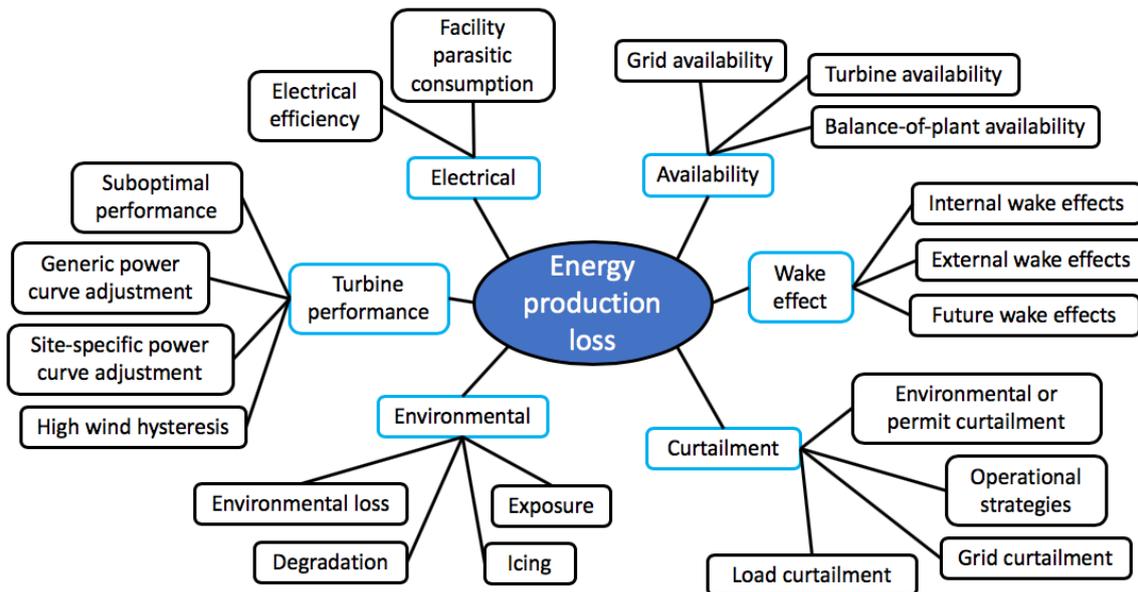



Figure 1: Mind map of energy production loss, according to the IEC 61400-15 proposed framework. The blue and black rounded
45   **rectangles represent the categorial and subcategorical losses, respectively. Details of each loss category and subcategory are discussed in Table A1.**

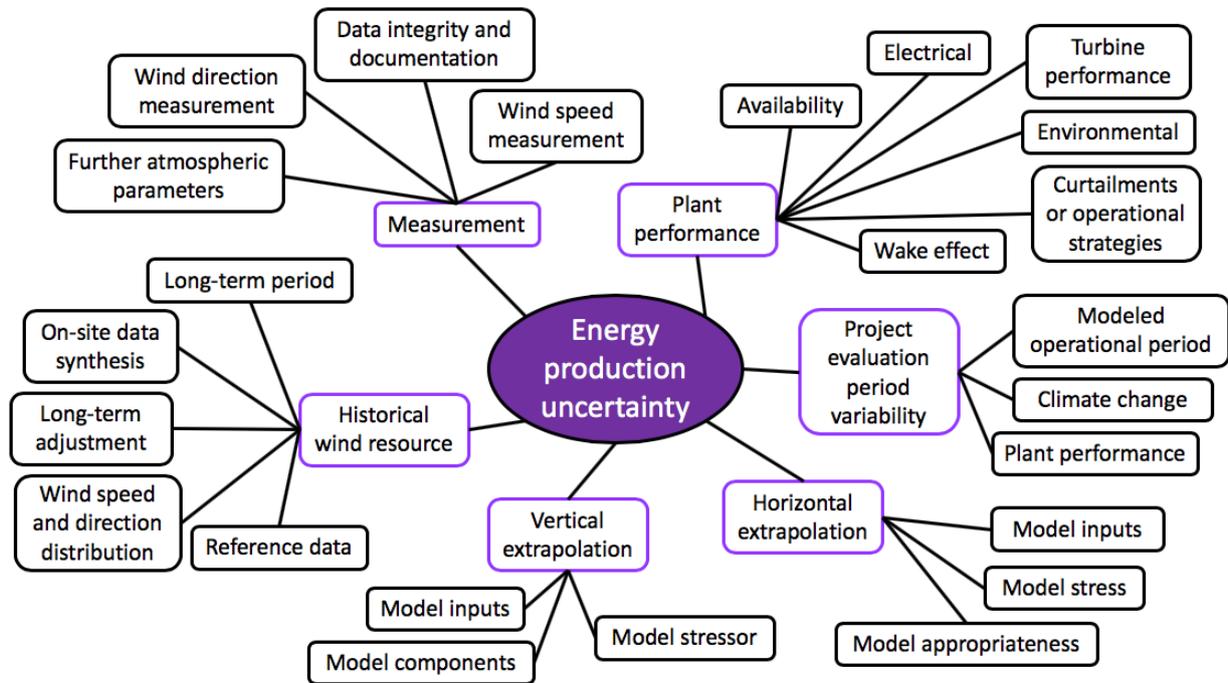



Figure 2: Mind map of energy production uncertainty, according to the IEC 61400-15 proposed framework. The purple and black rounded rectangles represent the categorial and subcategorical uncertainties, respectively. Details of each uncertainty category and subcategory are discussed in Table A2.

The wind energy industry has been experiencing the monetary impacts caused by the challenges and difficulties in predicting energy-production losses and uncertainties over the lifetime of a modern wind project, which can continue to operate beyond 20 years:

- For the financial impact of P50 prediction error, losing 1 GWh translates to about 50,000 to 70,000 Euros lost in the industry (Papadopoulos, 2019).

- Regarding the uncertainty of wind energy production, reducing 1% of energy uncertainty can result in $0.5 to $2 millions of economic benefits, depending on the situation and the financial model (Brower et al., 2015; Halberg, 2017).

- In one study that quantifies the economic influence of wind speed uncertainty, changing 1% of such uncertainty can lead to 3% to 5% change in net present value of a wind farm (Kline, 2019).

Experts in the industry have presented many studies on the P50 prediction error, energy loss, and uncertainty for years, and the purpose of this evaluation of past literature is to assemble previous research and deliver a meaningful narrative. This manuscript is unique and impactful because this is the first comprehensive review and analysis of the key parameters in the WRA process across the industry. The three main research questions of this study include:

- Is the P50 prediction bias changing over time, and what are the reasons for the changes?

- What are the ranges of different categories of energy-production losses and uncertainties?

- Given our understanding on losses and uncertainties, what are the opportunities for improvements in the industry? From past research, in addition to the energy-production uncertainties, we discover the industry has been quantifying various wind speed uncertainties, particularly from wind measurements, extrapolation methods, and modeling. We also compile and present the wind speed results herein.

We present this manuscript with the following sections: Sect. 2 documents the data and the methodology of data filtering; Sect. 3 focuses on P50 prediction bias, including its trend and various reasons of bias improvement; Sect. 4 and Sect. 5, respectively, illustrate the energy-production loss and uncertainty, according to the IEC proposed framework; Sect. 6 describes the numerical ranges of various wind speed uncertainties; Sect. 7 discusses the implications and future outlook based on our findings; Sect. 8 provides our conclusion; Appendix A outlines the energy loss and uncertainty frameworks proposed by the IEC 61400-15 working group; Appendix B compiles the data used in this analysis.

2 Data and methodology

We conduct our literature review over a broad spectrum of global sources. The literature includes the presentations at academic, industry, and professional conferences, particularly the Wind Resource and Project Energy Assessment workshops hosted by the American Wind Energy Association (AWEA) and the WindEurope as they are the key annual gatherings for wind resource experts. Additionally, we examine data from industry technical reports and white papers; publicly available user manuals of wind energy numerical models; technical reports from government agencies, national laboratories, and research and academic institutions; and peer-reviewed journal articles. Many of the literature sources originate in North America and Europe. Meanwhile, many of the regional corporations we cited in this manuscript have become global businesses after mergers and acquisitions; hence, their presentations and reports also represent international practices.

In most cases, we label the data source with the published year of the study, unless the author highlights a method change in a specific time. For example, if an organization publishes a study in 2012 and reports their improvements on P50 prediction bias by comparing their "current" method with their "previous set of methodology before 2012", the two P50 biases are recorded as 2012 and 2011, respectively. Moreover, for the same study that documents multiple P50 prediction errors in the same year, we select the one closest to zero, because those numbers reflect the state of the art of P50 validation of that year (Fig. 3). Along the same line, we use the paired P50 errors to indicate the effects from method adjustments (Fig. 4). To track the bias impact of technique changes from different organizations, we combine the closely related, ongoing series of studies from a single organization, usually by the same authors from the same institutions (each line in Fig. 4).

We also derive the trend of P50 prediction errors using linear regression and investigate the reasons behind such trend. In the linear regressions presented in this article (Figs. 3, 8, and C1), we implement the 95% confidence interval, generated via a bootstrap, using the regplot function in the Seaborn Python library (Waskom et al., 2020). The confidence interval describes the bounds of the regression slope and intercept with 95% confidence. Furthermore, we present the 95% prediction interval in Fig. 3, which depicts the range of the predicted values (e.g. the P50 prediction bias in Fig. 3) with 95% confidence, given the

100   existing data and regression model. In short, the confidence interval illustrates the uncertainty of the regression function, whereas the prediction interval represents the uncertainty of the estimated values of the predictand. In addition, we evaluate the regression analysis with the coefficient of determination (R^2), which represents the proportion of the variance of the predictand explained by the regression.

    For loss and uncertainty, we need to interpret a small subset of the data, because these data are only sparsely available.
105   When a source does not provide an average value, we perform a simple arithmetic mean when both the upper and lower bounds are listed. For instance, when the average wake loss is between 5% and 15%, we project the average of 10% in Fig. 6, and we present all the original values in Appendix B. If only the upper bound is found, then we project the data point as a maximum: the crosses in Fig. 6 are used as an example.

    We categorize the data to the best of our knowledge to synthesize a holistic analysis. On one hand, if the type of loss
110   and uncertainty from a source uses marginally different terminology from the IEC proposed framework, we first attempt to classify it within the IEC framework, we gather other values in the same category or subcategory from the same data source, and we select the minimum and the maximum. As an illustration, if the total electrical losses from the substation and the transmission line are, respectively, 1% and 2%, we then label the total electrical loss with the range of 1% to 2%. On the other hand, when the type of loss and uncertainty illustrated in the literature largely differ from the IEC framework, we label them
115   separately (Figs. 7 and 11). Because a few studies contrast wake loss and nonwake loss, where nonwake loss represents every other type of energy loss, we also include nonwake loss in this study (Figs. 6 and 10). When a type of uncertainty is recorded as simply "extrapolation," we label it as both horizontal and vertical extrapolation uncertainties. We also divide the reported losses and uncertainties into two groups, the "estimated" and the "observed", where the former are based on simulations and modeling studies, and the latter are quantified via field measurements.

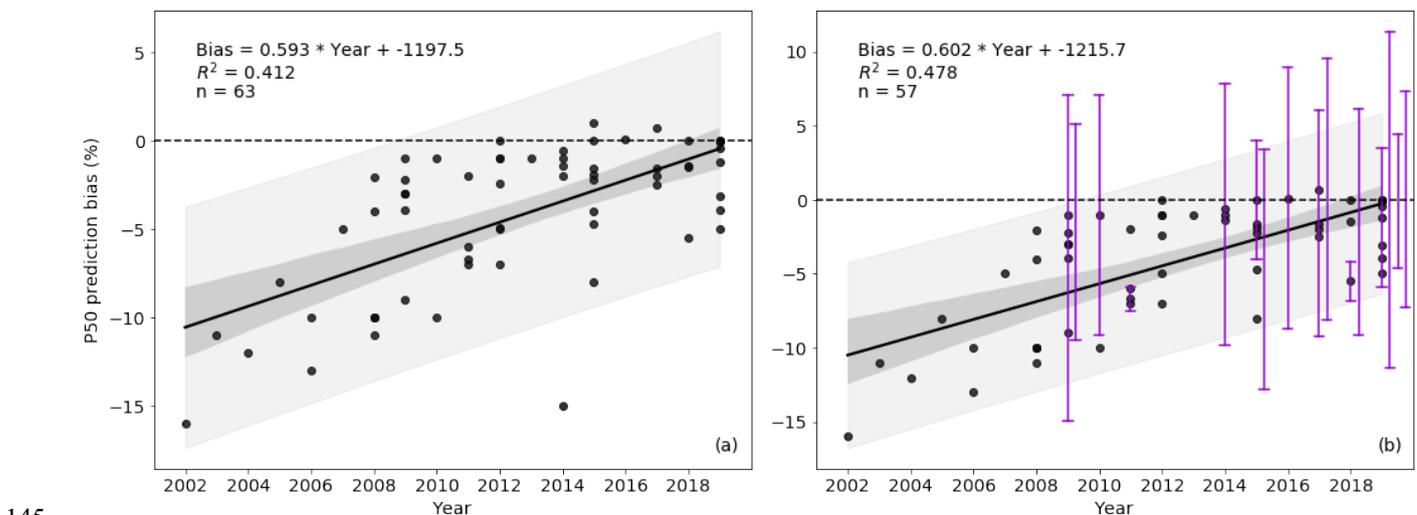
120   Unless specifically stated otherwise in Appendix B, we present a loss value as the percentage of production loss per year, and we document an uncertainty number as the single standard deviation in energy percentage in the long term, usually for 10 years or 20 years. The wind speed uncertainty is stated as a percentage of wind speed in m s^{-1}, and the uncertainty of an energy loss has the units of percent of a loss percentage.

    This manuscript evaluates a compilation of averages, where each data point represents an independent number. The
125   metadata for each study in the literature vary, in which the resultant P50 prediction errors, losses, and uncertainties come from diverse collections of wind farms with different commercial operation dates in various geographical regions and terrains. Therefore, readers should not compare a specific data point with another. In this study, we aim to discuss the WRA process from a broad perspective. Other caveats of this analysis include the potentially inaccurate classification of the data into the proposed IEC framework; the prime focus on P50 rather than P90, which also has a strong financial implication; and the
130   tendency to report extreme losses and uncertainties caused by extraordinary events, such as availability loss and icing loss, in the literature. Our data sources are also only limited to publicly available data or those accessible at NREL. We perform a rigorous literature review from approximately 170 sources, and the results presented in this manuscript adequately display the current state of the wind energy industry.

3 P50 prediction bias

135 ### 3.1 Bias trend

We identify an improving trend of the mean P50 prediction bias, where the overprediction of energy production is gradually decreasing over time (Fig. 3), and the narrow 95% confidence interval of the regression fit justifies the long-term trend. Such an improving trend is not strictly statistically significant (Fig. 3a), even after removing the studies based on small wind farm sample sizes (Fig. 3b). However, the low R^2 implies that less than half of the variance in bias can be described by

140 the regression, and more than half of the variance is caused by the inherent uncertainty between validation studies that does not change over time. The average bias magnitude also does not correlate with the size of the study, either in wind farm sample size or wind farm year length (not shown). Note that in some early studies, the reported biases measured in wind farm differ from those using wind farm year from the same source; we select the error closest to zero for each independent reference because the bias units are the same (Sect. 2).

145
Figure 3: The trend of P50 prediction bias: (a) scatterplot of 63 independent P50 prediction error values, where R² is the coefficient of determination and n is the sample size. Negative bias means the predicted AEP is higher than the measured AEP, and vice versa for positive bias. The black solid line represents the simple linear regression, the dark grey cone displays the 95% confidence interval of the regression line, the light grey cone depicts the 95% prediction interval, the horizontal black dashed line marks the zero P50
150 **prediction error. (b) as in (a), but only for 57 studies that use more than 10 wind farms in the analyses. The vertical violet bars represent the estimated uncertainty bounds (typically presented as one standard deviation from the mean) of the mean P50 prediction errors in 16 of the 57 samples. Table B1 summarizes the bias data illustrated herein.**

The uncertainty of the average P50 prediction error quantified by the studies remains large, in which the mean standard deviation is 6.88% of the 16 data sources' reported estimated P50 uncertainty (violet bars in Fig. 3b). The industry

155 started to report the standard deviations of their P50 validation studies in 2009 and it is becoming more common. With only 16 data points, we cannot identify a temporal trend of the uncertainty in P50 prediction bias. Even though the mean P50 prediction bias is approaching zero, the industry appears to overestimate or underpredict the AEP for many individual wind projects.

3.2 Reasons of bias changes

160   To correct for the historical P50 prediction errors, some organizations publicize the research and the adjustments they have been conducting for their WRA processes. We summarize the major modifications of the WRA procedure in Table 1. Most studies demonstrate mean P50 bias improvement over time (Fig. 4), and the magnitude of such bias reduction varies. In two studies, the authors examine the impact of accounting for windiness, which is the quantification of long-term wind speed variability, in their WRA methodologies. They acknowledge the difficulty in quantifying interannual wind speed variability

165   accurately, and their P50 prediction errors worsen after embedded this uncertainty in their WRA process (vertical dash lines in Fig. 4).

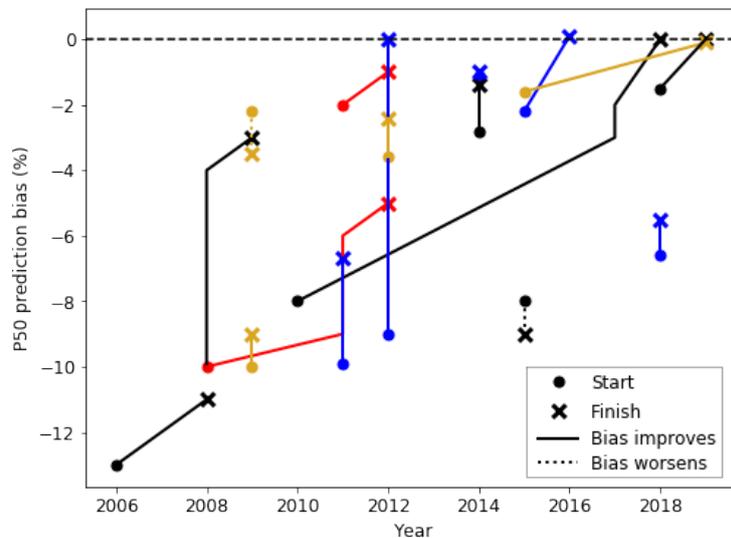



Figure 4: Illustration of P50 bias changes over time after method modifications in 17 studies. The dot and the cross, respectively, represent the starting point and the finish point of the P50 prediction error because of method adjustments. The solid line indicates

170   **the P50 bias reduces after the method change, and the dotted line displays the opposite. The different colors are solely used to differentiate the lines and represent no meaning. The paired data are presented in Table B2.**

Table 1: Categories of method adjustments to improve the wind resource assessment process and the respective data sources.

Method change	Source
Account for additional factors in wind resource assessment and operation e.g., • windiness or long-term correction of wind data, • suboptimal operation, • external wake effect, and	AWS Truepower, 2009; Johnson, 2012

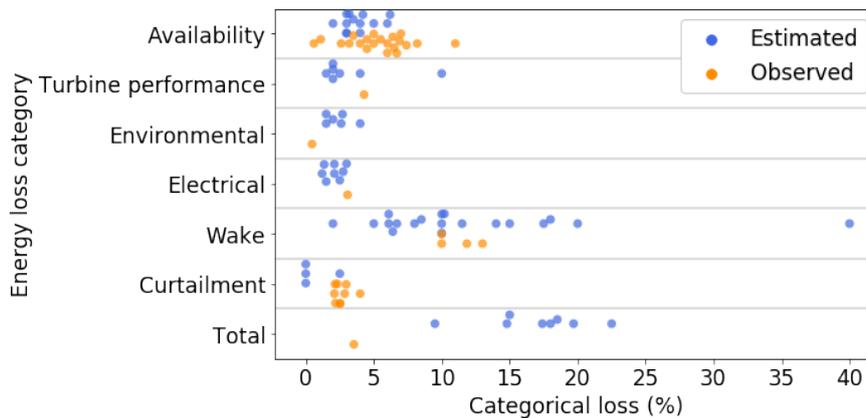
• degradation of long-term meteorological masts.	
Consider meteorological effects on power production e.g., • wind shear, • turbulence, • air inflow angle, and • atmospheric stability.	AWS Truepower, 2009; Brower et al., 2012; Elkinton, 2013; Johnson, 2012; Ostridge, 2017
Improve modeling techniques e.g., • turbine performance, • wind flow, • wake, • complex terrain flow, • surface roughness, and • wind farm roughness.	Elkinton, 2013; Johnson, 2012; Ostridge, 2017; Papadopoulos, 2019
Improve in measurement and reduce in measurement bias e.g., adjust for dry friction whip of anemometers	AWS Truepower, 2009; Johnson, 2012; Ostridge, 2017; Papadopoulos, 2019
Correct for previous methodology shortcomings e.g., • loss assumptions, and • shear extrapolation	Ostridge, 2017; Papadopoulos, 2019

4 Energy-production loss

175

The prediction and observation of production losses are tightly related to the P50 prediction accuracy; hence, we contrast the estimated and measured losses in various categories and benchmark their magnitude (Figs. 5, 6 and 7). The total energy loss is calculated from the difference between the gross energy estimate and the product of gross energy prediction and various categorical production efficiencies, where each efficiency is one minus a categorical energy loss (Brower, 2012). Of

180 the total categorical losses, we record the largest number of data points from availability loss, and wake loss display the largest variability among studies (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 6a). The turbine availability loss appears to be larger than the balance of plant and grid availability losses; however, more data points are needed to validate those estimates (Fig. 6a). Except for one outlier, the turbine performance losses, in both predictions and observations, are about or under 5% (Fig. 6b). Large ranges of environment losses

185   exist, particularly for icing and degradation losses, which can extremely deplete AEP (Fig. 6c). Note that some of the icing
       losses indicated in the literature represent the fractional production loss from the abnormal production halts for an extended
       period in the winter, rather than a typical energy loss percentage for a calendar year. Electrical loss has been assured as a
       routine energy reduction with high certainty and relatively low magnitude (Fig. 6d). Of all the categories, wind turbine wake
       results in a substantial portion of energy loss, and its estimations demonstrate large variations (Fig. 6e). The magnitude of
190   estimated wake loss is larger than that of the predicted nonwake loss, which consists of other categorical losses (Fig. 6e). The
       observed total curtailment loss exhibits lower variability, yet with larger magnitude than its estimation (Fig. 6f). From the eight
       studies that report total loss, the predictions range from 9.5% to 22.5% (Fig. 6g). We do not encounter any operational strategies
       loss under curtailment loss in the literature, and thus the subcategories in Fig. 6 do not cover every subcategory in Table A1.

195   **Figure 5: Ranges of total energy-production losses in different categories, according to the proposed framework of the IEC 61400-
       15 standard. Each blue and orange dot, respectively, represent the mean estimated loss and mean observed loss documented in each
       independent reference. The units of losses are in AEP percent. For clarity, the grey horizontal lines separate data from each category.
       Table B3 catalogs the categorical losses plotted herein.**

200

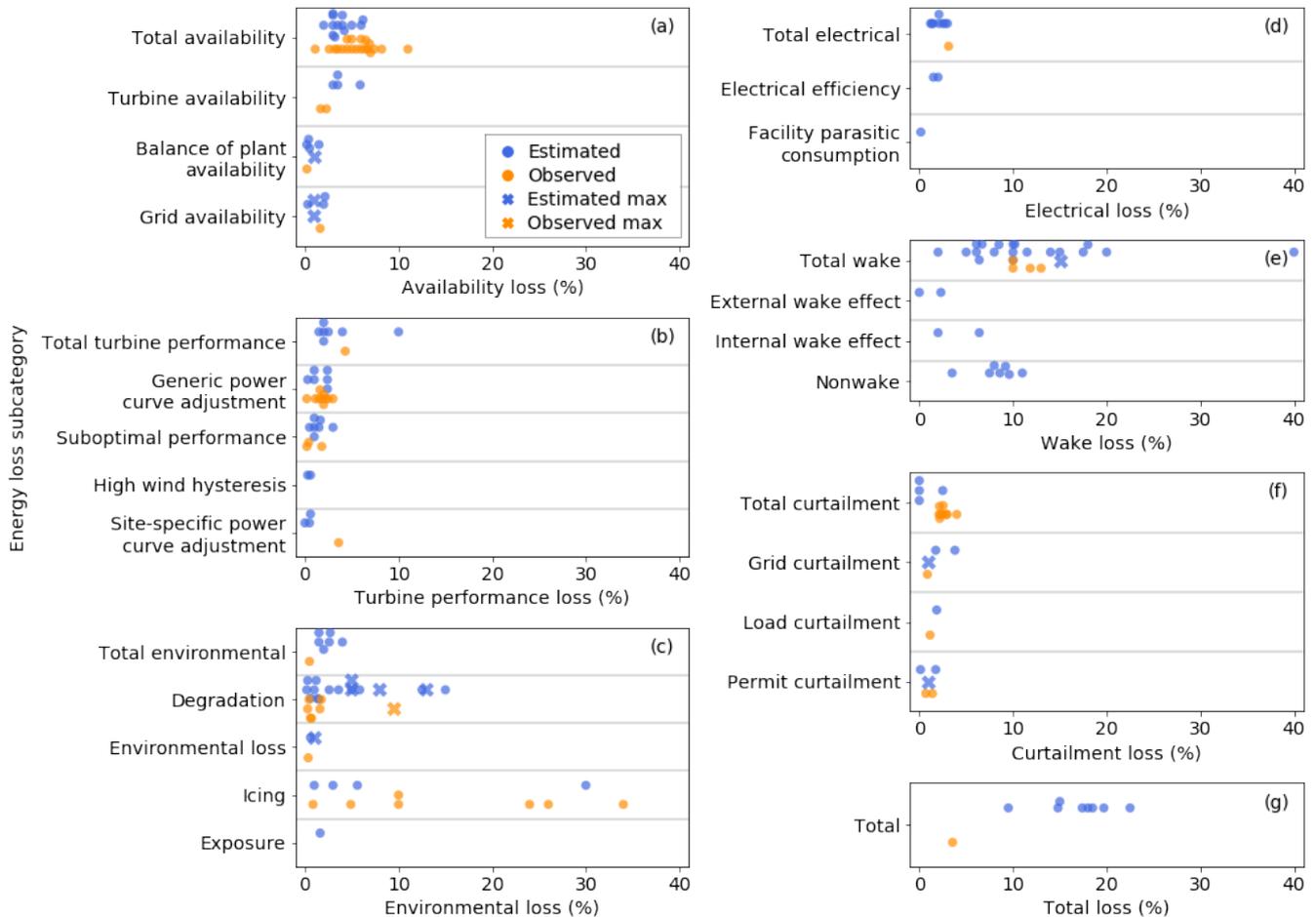



Figure 6: Ranges of energy-production losses in different categories and subcategories, according to the proposed framework of the IEC 61400-15 standard, except for nonwake in (e), which is an extra subcategory summarizing other nonwake categories. Each blue and orange dot, respectively, represent the mean estimated loss and mean observed loss documented in each independent study. The
205 **blue and orange crosses, respectively, indicate the maximum of estimated loss and the maximum of observed loss reported, where the minima are not reported, and thus the averages cannot be calculated. The units are in AEP percent. For clarity, the grey horizontal lines separate data from each subcategory. Table B3 catalogs the categorical and subcategorical losses plotted herein.**

Losses that inhibit wind farm operations have considerable monetary impacts. For example, blade degradation can lead to a maximum of 6.8% AEP loss that translates to $43,000 of annual loss for a single turbine in the IEC Class II wind

210 regime (Wilcox et al., 2017), where the maximum annual average wind speed is 8.5 m s^{-1}. Generally, the typical turbine failure rate is about 6%, where 1% reduction in turbine failure rate can lead to around $2 billion of global savings in operation and maintenance (Faubel, 2019). In practice, the savings may exclude the cost of preventative measures for turbine failure, such as hydraulic oil changes and turbine inspections.

We categorize two types of energy-production losses additional to the proposed IEC framework, namely first few
215 years of operation and blockage effect (Fig. 7). For the former loss, a newly constructed wind farm typically does not produce to its full capacity for the first few months, or even for the first 2 years. The loss from the first few years of operation captures

this time-specific and availability-related production loss. Regarding the later loss, the blockage effect describes the wind speed slowdown upwind of a wind farm (Bleeg et al., 2018). Wind farm blockage is not a new topic (mentioned in Johnson et al., 2008) and has been heavily discussed in recent years (Bleeg et al., 2018; Lee, 2019; Papadopoulos, 2019; Robinson, 2019;

220   Spalding, 2019). Compared to some of the losses in Fig. 6, the loss magnitude of first few years of operation and blockage is relatively small, where they contribute to less than 5% of AEP reduction per year (Fig. 7).

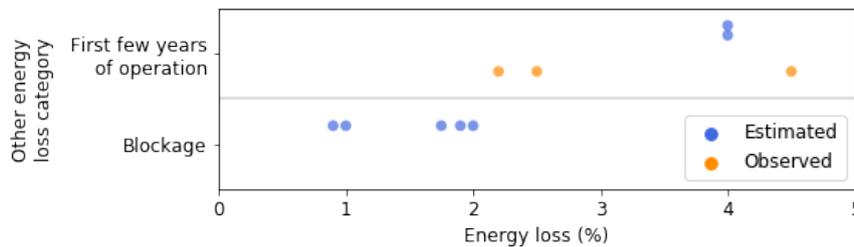



Figure 7: As in Fig. 6, but for the loss categories outside of the proposed IEC framework, as listed in Table B4.

For trend analysis, we linearly regress every subcategorical energy loss (Fig. 6 and Table B3) on time, and we only

225   find two loss subcategories demonstrate notable and statistically confident trends (Fig. 8). The measured curtailment loss and the observed generic power curve adjustment loss steadily decrease over time, and the reductions have reasonable R^2 (Fig. 8). No other reported losses with a reasonable number of data samples display remarkable trends (Fig. C1).

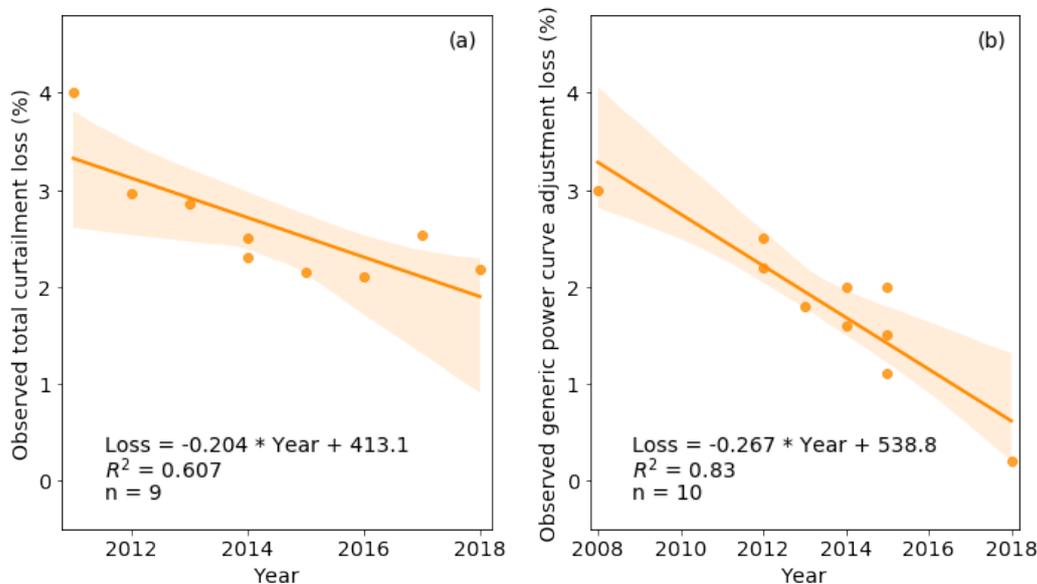



Figure 8: Trend in observed energy-production loss: (a) total curtailment loss and (b) generic power curve adjustment loss. The
230   **annotations correspond to those in Fig. 3, where the orange solid line represents simple linear regression, the light orange cone illustrates the 95% confidence interval, R^2 is the coefficient of determination, and n is sample size.**

Past research further documents the uncertainties of AEP losses. Except for an outlier of measuring 80% uncertainty in wake loss, the magnitude of the uncertainty of wake loss is analogous to that of nonwake loss (Fig. 9). Moreover, the industry tends to report the uncertainty of wake loss according to the larger number of data sources (Fig. 9). One data source reported

235 that intermonthly variability can alter AEP losses for more than 10% (Fig. 9). Note that the results in Fig. 9 represent the
uncertainty of the respective production loss percentages in Fig. 6 and Table B3, rather than the AEP uncertainty.

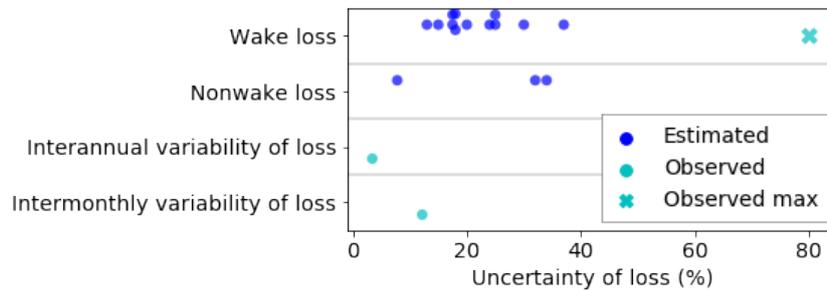



Figure 9: Uncertainty of energy-production losses, where the magnitude corresponds to the AEP loss percentages listed in Fig. 6 and
240 **Table B3. Each dark blue dot, turquoise dot, and turquoise cross represents the estimated uncertainty, the observed uncertainty,**
and the maximum observed uncertainty of losses, respectively. The units are the percent of uncertainty in terms of the loss
percentage. For clarity, the grey horizontal lines separate data from each uncertainty. Table B5 records the uncertainties displayed
herein.

5 Energy-production uncertainty

245 The individual energy-production uncertainties directly influence the uncertainty of P50 prediction. Total uncertainty
is the root-sum-square of the categorical uncertainties; the assumption of correlation between categories can reduce the overall
uncertainty, and this assumption is typically consultant- and method-specific. (Brower, 2012). Except for a few outliers, the
magnitude of the individual energy-production uncertainties across categories and subcategories is about or below 10% (Fig.
10). The energy uncertainties from wind measurements range below 5%, after omitting two extreme data points (Fig. 10a).
250 The estimated long-term period uncertainty varies the most in historical wind resource (Fig. 10b), which indicates the
representativeness of historical reference data (Table A2). Horizontal extrapolation generally yields higher energy-production
uncertainty than vertical extrapolation (Fig. 10c and d). For plant performance, each subcategorical uncertainty corresponds
to the respective AEP loss (Fig. 6 and Table A1). The range of the predicted energy uncertainty caused by wake effect is about
6% (Fig. 10e). The estimated uncertainty of turbine performance loss and total project evaluation period match with those
255 observed (Fig. 10e and f). Overall, the average estimated total uncertainty varies by about 10%, whereas the observed total
uncertainty appears to record a narrower bound, after excluding an outlier (Fig. 10g).

In the literature, we cannot identify all the uncertainty types listed in the proposed IEC framework; hence, the
following AEP uncertainty subcategories in Table A2 are omitted in Fig. 10: wind direction measurement in measurement;
on-site data synthesis in historical wind resource; model inputs and model appropriateness in horizontal extrapolation; model
260 components and model stressor in vertical extrapolation; and environmental loss in plant performance.

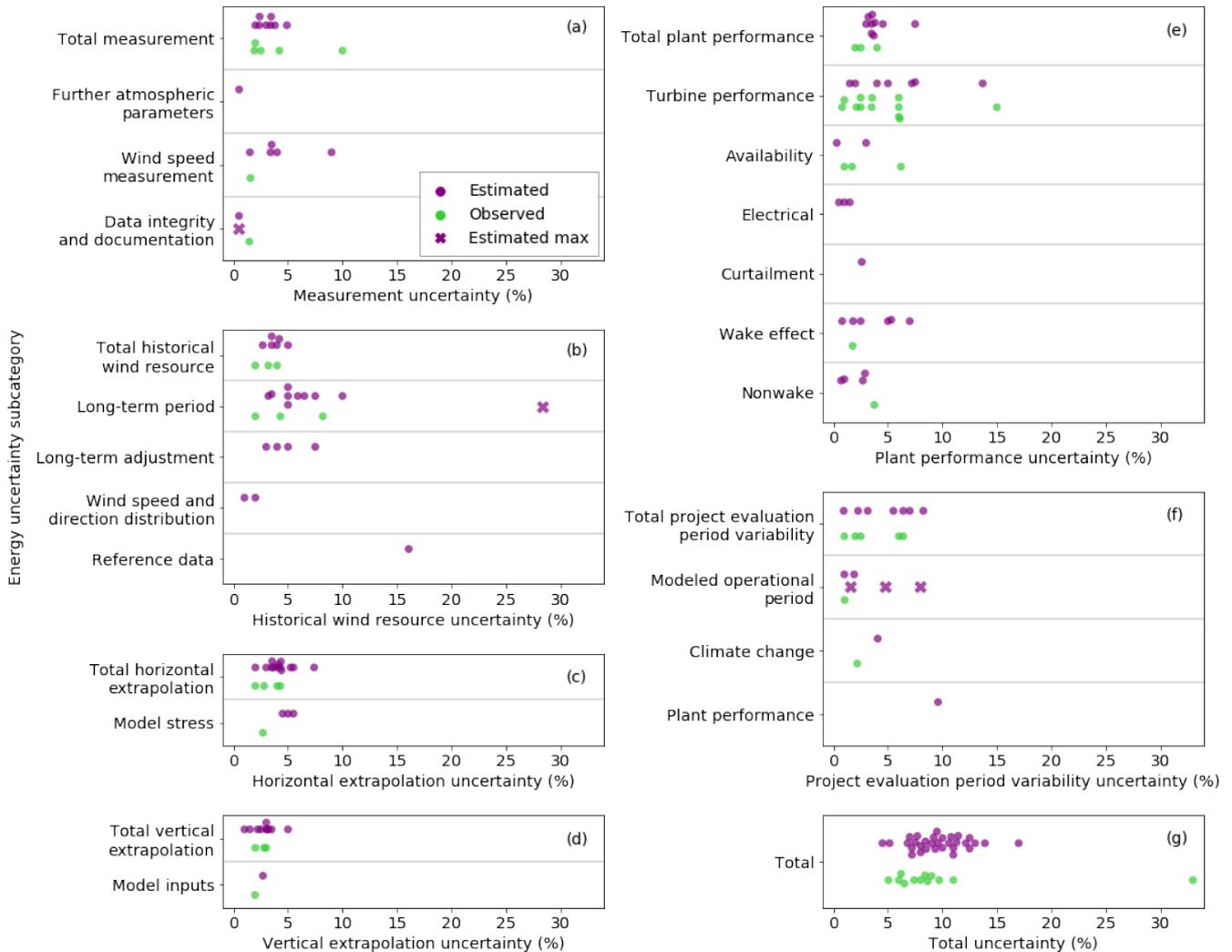



Figure 10: Ranges of energy-production uncertainties in different categories and subcategories, according to the proposed framework of the IEC 61400-15 standard. The annotations correspond to those in Fig. 6, where each purple dot, green dot, and purple cross represent the mean estimated uncertainty, the mean observed uncertainty, and the maximum of estimated uncertainty from each independent reference, respectively. The units are in AEP percent. For clarity, the grey horizontal lines separate data from each subcategory. Table B6 numerates the production uncertainties.

Similar to energy losses, other types of AEP uncertainties not in the proposed IEC framework emerge. The magnitude of the uncertainties in Fig. 11 is comparable to the uncertainties in Fig. 10. The power curve measurement uncertainty in Fig. 11, specifically mentioned in the data sources, could be interpreted as the uncertainty from the turbine performance loss.

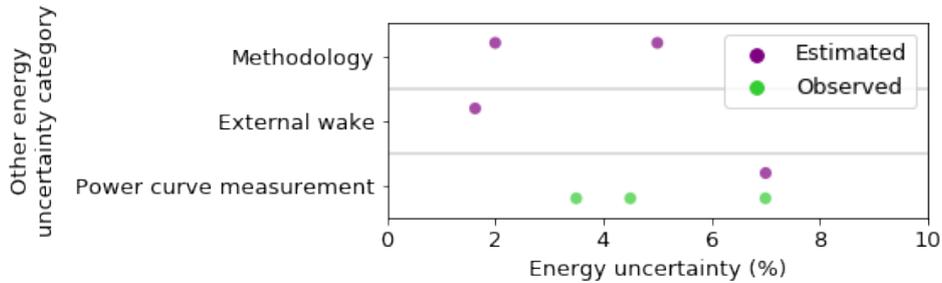



Figure 11: As in Fig. 10, but for the uncertainty categories outside of the proposed IEC framework, as listed in Table B7.

The energy-production uncertainty from air density and vertical extrapolation depends on the geography of the site. For instance, the elevation differences between sea level and the site altitude, as well as the elevation differences between the mast height and turbine hub height affect the AEP uncertainty (Nielsen et al., 2010). For simple terrain, the vertical extrapolation uncertainty can be estimated to increase linearly with elevation (Nielsen et al., 2010). A common industry practice is to assign 1% of energy uncertainty for each 10 m of vertical extrapolation, which could overestimate the uncertainty, except for forested locations (Langreder, 2017).

6 Wind speed uncertainty

Energy production of a wind turbine is a function of wind speed to its third power. Considering wind speed, either measured, derived, or simulated, is a critical input to an energy estimation model, the uncertainty of wind speed plays an important role in the WRA process. We present various groups of wind speed uncertainties in the literature herein (Fig. 12). The bulk of the wind speed uncertainties are about or less than 10% in wind speed. Many studies report estimated uncertainty from wind speed measurement, however its magnitude and discrepancy among the sources are not as large as those from wind speed modeling or interannual variability (Fig. 12). Notice that some of the wind speed categories coincide with the IEC proposed framework of energy uncertainty, and others do not. The absence of standardized classification of wind speed uncertainties increases the ambiguity in the findings from the literature and poses challenges to the interpretation of the results in Fig. 12. We also lack sufficient samples of measured wind speed uncertainties to validate the estimates.

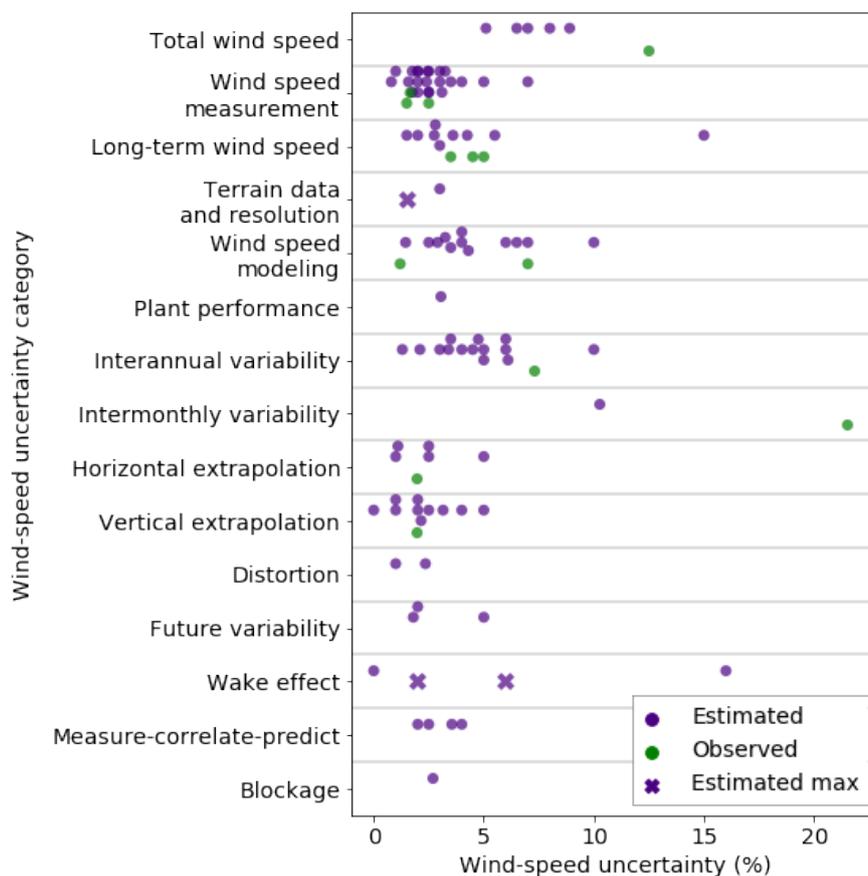



Figure 12: Ranges of wind speed uncertainties in different categories. The annotations correspond to those in Fig. 10, where each dark purple dot, dark green dot, and dark purple cross represent the mean estimated wind speed uncertainty, the mean observed wind speed uncertainty, and the maximum of estimated wind speed uncertainty from each independent study respectively. The units are in percent of wind speed. For clarity, the grey horizontal lines separate data from each category. Table B8 documents the wind speed uncertainties displayed.

Wind speed uncertainty greatly impacts AEP uncertainty, and the method of translating wind speed uncertainty into AEP uncertainty also differ between organizations. For example, 1% increase of wind speed uncertainty can lead to either 1.6% (AWS Truepower, 2014) or 1.8% increase in energy production uncertainty (Holtslag, 2013; Johnson et al., 2008; White, 2008b). Local wind regimes can also affect this ratio. For low wind locations, AEP uncertainty can be three times the wind speed uncertainty, while such ratio drops to 1.5 at high wind sites (Nielsen et al., 2010). Reduction in wind speed measurement uncertainty of 0.28% could reduce project-production uncertainty by about 0.15% (Medley and Smith, 2019). Using a computational fluid dynamics model to simulate airflow around meteorological masts can reduce wind speed measurement uncertainty from 2.68% to 2.23%, which translates to 1.2 million British pounds of equity savings for a 1-GW offshore wind farm in the United Kingdom (Crease, 2019).

7 Opportunities for improvements

305   Instead of the magnitude of the prediction errors, the uncertainties immersed in the WRA process dominates the accuracy of AEP prediction. Different organizations have been improving their techniques over time to eliminate the P50 bias (Table 1), and as a whole we celebrate such advancements; nevertheless, challenges still exist for validation and reduction of the AEP losses and uncertainties. Even though the average P50 prediction bias approaches zero, the associated mean P50 uncertainty remains at over 6%, even for the studies reported after 2016 (Fig. 3b). For a validation study that involves a

310   collection of wind farms, such uncertainty bound implies that sizable P50 predication errors for particular wind projects can emerge. In other words, statistically, the AEP prediction is becoming more accurate yet is imprecise. Moreover, from an industry-wide perspective that aggregates different analyses, the variability on the mean P50 bias estimates is notable, which obscures the overall bias-reducing trend (R^2 below 0.5 in Fig. 3). Specifically, the magnitude of the 95% prediction interval at over 10% average P50 estimation error (Fig. 3b) suggests a considerable range of possible mean biases in future validation

315   studies. Additionally, the uncertainties are still substantial in specific AEP losses (Fig. 9), AEP itself (Figs. 10 and 11), and wind speed (Fig. 12). Therefore, the quantification, validation, and reduction of uncertainties requires the attention of the industry collectively.

        To reduce the overall AEP uncertainty, the industry should continue to assess the energy impacts of plant performance losses, especially those from wake effect and environmental events. On one hand, Wake effect, as part of a grand challenge in

320   wind energy meteorology (Veers et al., 2019), has been estimated as one of the largest energy losses (Fig. 6e). The AEP loss caused by wake effect also varies, estimated between 15% and 40% (Fig. 9), and the unpredictability of wakes contributes to the AEP uncertainty on plant performance (Fig. 10e) and the wind speed uncertainty (Fig. 12). Although the industry has been simulating and measuring the substantial energy depletion caused by wake effect, its site-specific impact on AEP for the whole wind farm as well as its time-varying production impact on downwind turbines remains largely uncertain. From a macro point

325   of view, compared to internal wake effect, external wake effect from neighboring wind farms is a bigger known unknown because of the lack of data and research. On the other hand, environmental losses display broad range of values, particularly from icing events and turbine degradation (Fig. 6c). In general, the icing problem halts energy production in the short run, and blade degradation undermines turbine performance in the long run. Diagnosing and mitigating such substantial environmental losses would reduce both loss and uncertainty on AEP. Overall, the prediction and prevention of environmental events are

330   critical, and the production downtime during high electricity demand can lead to substantial financial losses.

        Additionally, the industry recognizes the role of remote-sensing instruments in reducing the uncertainty of energy production and wind speed from extrapolation, such as profiling lidars, scanning lidars, and airborne drones (Faghani et al., 2008; Holtslag, 2013; Peyre, 2019; Rogers, 2010). The latter can also be used to inspect turbine blades (Shihavuddin et al., 2019) to reduce unexpected blade degradation loss over time. Industrywide collaborations such as the International Energy

335   Agency Wind Task 32 and the Consortium For Advancement of Remote Sensing, have been promoting remote-sensing implementation in WRA.

Experts in the field have been introducing contemporary perspectives and innovative techniques to improve the WRA process, including time-varying and correlating losses and uncertainties. Instead of treating energy loss and uncertainty as a static property, experts have studied time-varying AEP losses and uncertainties (Brower et al., 2012), especially when wind plants produce less energy with greater uncertainty in later operational years (Istchenko, 2015). Furthermore, when different types of energy-production losses or uncertainties interact and correlate with each other, the resultant compound effect can become larger than the total value from a linear (Brower, 2011) or root-sum-square approach (Istchenko, 2015). For example, an icing event can block site access and decrease turbine availability, and even lead to longer-term maintenance problems (Istchenko, 2015).

Overall, more observations are necessary to validate the estimates listed in this article. In this article, the ratios between the measured and predicted values are 1 to 1.9, 2.3, and 7.3, for energy loss, energy uncertainty, and wind speed uncertainty, respectively. The small number of references on measured uncertainties indicate that we need more evidence to further evaluate our uncertainty estimates. Public disclosure of summary statistics would continually improve insight into the WRA process and increase the AEP estimation accuracy for the industry as a whole, even when the data are site-specific or organization-centric.

8 Conclusions

In this analysis, we compile and present the ranges and the trends of predicted P50 (i.e. median annual energy production) errors, as well as the estimated and observed energy losses, energy uncertainties, and wind speed uncertainties embedded in the wind resource assessment process. Although the mean P50 bias demonstrates a statistical trend that it approaches zero over time, the notable uncertainty of the mean prediction error reveals the imprecise prediction of annual energy production. The dominant effect of prediction uncertainty over the bias magnitude calls for further improvements on the prediction methodologies. To reduce the mean bias, the industry experts have made method adjustments in recent years that minimize the energy-production prediction bias, such as the applications of remote sensing devices and the modeling advancements of meteorological phenomena.

We present the wind energy production losses and uncertainties according to the proposed framework by the International Electrotechnical Commission (IEC) 61400-15 working group. Wake effect and environmental events undermine wind plant performance and constitute the largest loss in energy production, and validating the wake and environmental loss predictions requires more field measurements and detailed research. Moreover, the variability of observed total availability loss is larger than its estimates. Meanwhile, the decreasing trends of measured curtailment loss and observed generic power curve adjustment loss indicate the continuing industry effort to optimize wind energy production. Additionally, different categorical energy uncertainties and wind speed uncertainties demonstrate similar magnitude, with a majority of the data below 10%. More observations are the solution to better understand and further lower these uncertainties.

In our findings, we highlight the potential future progress, including the importance of accurately predicting and validating energy-production uncertainty, the impact of wake effect, and innovative approaches in the wind resource assessment process. This work also includes a summary of the data collected and used in this analysis. As the industry evolves with improved data sharing and rigorous research, we will increasingly be able to maximize energy production and reduce its uncertainty for all project stakeholders.

Data availability

Appendix B includes all the data used to generate the plots in this manuscript.

Appendix A

Table A1: Consensus energy-production loss framework for wind resource assessment proposed by the International Electrotechnical Commission (IEC) 61400-15 working group (Filippelli et al., 2018).

Loss category	Loss subcategory	Notes
Wake effect	Internal wake effects	Wake effects internal to the wind plant
	External wake effects	Wake effects generated externally to the wind plant
	Future wake effects	Wake effects that will impact future energy projections based on either confirmed or predicted new project development or decommissioning
Availability	Turbine availability	Including warranted availability, noncontractual availability, restart after grid outage, site access, downtime (or speed) to energy ratio, first-year or plant start-up availability
	Balance-of-plant availability	Availability of substation and collection system, other nonturbine availability, warranted availability, site access, first-year or plant start-up availability
	Grid availability	Grid being outside the grid connection agreement operational parameters, actual grid downtime, delays in restart after grid outages
Electrical	Electrical efficiency	Electrical losses between low- or medium-voltage side of the transformer of wind turbine and the energy measurement point
	Facility parasitic consumption	Turbine extreme weather packages, other turbine and/or plant parasitic electrical losses (while operating or not operating)
Turbine performance	Suboptimal performance	Performance deviations from the optimal wind plant performance caused by software, instrumentation, and control setting issue
	Generic power curve adjustment	Expected deviation between advertised power curve and actual power performance in standard conditions ("inner range")
	Site-specific power curve adjustment	Accommodating for inclined flow, turbulence intensity, density, shear, and other site or project-specific adjustments ("outer range")
	High wind hysteresis	Energy lost in hysteresis loop between high wind speed cut-out and recut-in
Environmental	Icing	Performance degradation and shutdown caused by icing
	Degradation	Blade fouling, efficiency losses, and other environmentally driven performance degradation

	Environmental loss	High- or low-temperature shutdown or derate, lightning, hail, and other environmental shutdowns
	Exposure	Tree growth or logging, other building development
Curtailments (or Operational strategies)	Load curtailment	Speed and/or direction curtailments to mitigate loads
	Grid curtailment	Power-purchase-agreement or off-taker curtailments, grid limitations
	Environmental/permit curtailment	Birds, bats, marine mammals, flicker, noise (when not captured in the power curve)
	Operational strategies	Any periodic uprating, downrating, optimization, or shutdown not captured in the power curve or availability carveouts

380

Table A2: Consensus energy-production uncertainty framework for wind resource assessment proposed by the IEC 61400-15 working group (Filippelli et al., 2018).

Uncertainty category	Uncertainty subcategory	Notes
Historical wind resource	Long-term period	What is the statistical representativeness of the chosen historical and/or site data period? In other words, the interannual variability (coefficient of variation) of the historical reference data period in years
	Reference data	How accurate or reliable is the chosen reference data source? In other words, historical data consistency (e.g., are there possible underlying trends in the data?)
	Long-term adjustment	What is the uncertainty associated with the prediction process? Statistical or empirical uncertainty in establishing a correlation or carrying out a prediction, which may be conditioned upon the correlation method and span or the quantity of concurrent data period
	Wind speed and direction distribution	Mean wind speed aside, how representative is the measured or predicted distribution and wind rose or energy rose shape of the long term?
	On-site data synthesis	Uncertainty associated with gap-filling missing data periods. Usually done using directional correlations or the measure-correlate-predict process. and, hence, long-term and reference data categories may apply.
Project evaluation period variability	Modeled operational period	The statistical uncertainty associated with how closely the wind resource over the modeled operational period (i.e., 1 year or 10 year) may match the long-term site average
	Climate change	When an impact of climate change can be assessed, then this may be considered as an uncertainty.
	Plant performance	The statistical uncertainty associated with how closely the plant performance over the modeled operational period (i.e., 1 year or 10 year) may match the long-term site average.
Measurement	Wind speed measurement	Including effects for wind speed sensor characteristics (cup or sonic), wind speed sensor mounting or deployment (cup or sonic), wind speed sensor data handling and processing characteristics (e.g., tower shadow, icing, and degradation), system motion, consistency and exposure, data acquisition, and data handling. Additionally, the reduction in uncertainty caused by sensor combination is considered.

	Data integrity and documentation	Documentation, verification, and traceability of the data
	Wind direction measurement	Sensor type or quality, operational characteristics, mounting effects, alignment, acquisition, long-term representativeness
	Further atmospheric parameters	Air temperature, pressure, relative humidity, and other atmospheric parameters
Vertical extrapolation	Model inputs	Terrain surface characterization, wind data measurement heights, wind statistics or shear, measurement uncertainty
	Model components	Representativeness per height or terrain, profile fit
	Model stressor	Large extrapolation distance, complex terrain (measurement height relative to terrain complexity)
Horizontal extrapolation	Model inputs	Fidelity and appropriateness, given sensitivity of model to terrain data, roughness, forestry information, atmospheric conditions
	Model stress	Representativeness of initiation points relative to turbine locations in terms of complicating factors (e.g., forestry, stability, steep slopes, distance, elevation, veer); the intensity of and sensitivity to complicating factors
	Model appropriateness	Physical scientific plausibility of model to capture complicating factors; validation of implementation of model: published validation of specific implementation and relevance to complicating factors present on-site; on-site model verification: site to site (untuned, blind); consider the quality of any shear verification
Plant performance	Wake effect	Refer to Table A1
	Availability	
	Electrical	
	Turbine performance	
	Environmental	
	Curtailments or operational strategies	

385

Appendix B

For the P50 prediction error, Fig. 3 and Fig. 4 use the data from Table B1 and Table B2, respectively. For the various categories and subcategories of losses, Figs. 5, 6, 8 and C1 portray the values in Table B3. Fig. 7 illustrates the losses outside of the IEC proposed framework listed in Table B4. Fig. 9 summarizes the uncertainty of production loss percentages in Table B5. Figs. 10 and 11 represent the AEP uncertainty data included in Table B6 and Table B7, respectively. Fig. 12 displays the wind speed uncertainty data in Table B8.

Table B1: List of P50 biases in the literature, which is necessary to generate Fig. 3. The "Bias (%)" column represents the average P50 bias, where a negative number indicates an overestimation of actual energy production. The "Uncertainty (%)" column usually illustrates one standard deviation from the mean.

Year	Wind Farm	Wind Farm Year	Bias (%)	Uncertainty (%)	Notes	Source
2002	12		-16			Mönnich et al., 2016
2003	10		-11			Mönnich et al., 2016
2004	19		-12			Mönnich et al., 2016
2005	37		-8			Mönnich et al., 2016
2006			-13			Johnson et al., 2008
2006	21		-10			Mönnich et al., 2016
2007	23		-5			Mönnich et al., 2016
2008	59	243	-11			Johnson et al., 2008; Jones, 2008
2008	41	113	-4			Johnson et al., 2008
2008	56	112	-10			White, 2009
2008	36	62	-2.1			Johnson, 2012
2008			-10		Industry average	White, 2009
2008	17		-10			Mönnich et al., 2016
2009		255	-1			Horn, 2009
2009			-9			Hendrickson, 2009
2009		43	-3			Hendrickson, 2009
2009		53	-3.9	11		Derrick, 2009
2009	11	45	-2.2	7.3		White, 2009
2009	18		-3			Mönnich et al., 2016

2010			-1	8.1	From 1,806 wind turbines	Nielsen et al., 2010
2010	11		-10			Mönnich et al., 2016
2011	1			2.4	Comparison of 15 analysts	Hendrickson, 2011
2011	89		-6		Industry average: 2000–2011	Drunsic, 2012
2011			-2			Drunsic, 2012
2011	18		-7			Mönnich et al., 2016
2011			-6.7	0.8		Lunacek et al., 2018
2012			-5		Industry average: 2005–2011	Drunsic, 2012
2012			-1			Drunsic, 2012
2012			-1			Brower et al., 2012
2012	125	382	0			Johnson, 2012
2012			-2.4			Bernadett et al., 2012
2012	11		-7			Mönnich et al., 2016
2012	6		-4.9			Pullinger et al., 2019
2013	14		-1			Mönnich et al., 2016
2014	24	106	-1	8.8		Brower, 2014
2014	31	101	-1.4			Istchenko, 2014
2014			-0.6			Geer, 2014
2014	9		-15			Redouane, 2014
2014	4		-2			Mönnich et al., 2016
2015			-1.9			Istchenko, 2015
2015	10		0	4		Sieg, 2015
2015	1		-4	3	Comparison of 20 analysts	Mortensen et al., 2015
2015	1		1			Mönnich et al., 2016
2015	25	91	-8			Cox, 2015
2015	30	127	-2.2			Stoelinga and Hendrickson, 2015
2015	18	58	-1.6			Hendrickson, 2019
2015	23		-4.7	8.1		Hatlee, 2015
2016	30	127	0.1	8.8		Baughman, 2016
2017		140	-2		Projects from 2011–2016	Elkinton, 2017; Hale, 2017

2017	61		-1.6	7.6	Most projects from 2008–2012	Brower, 2017; Hale, 2017
2017			-2.5			Hale, 2017
2017	30	127	0.7	8.8		Perry, 2017
2018	56	294	-5.5	1.3		Lunacek et al., 2018
2018	50		0			Hendrickson, 2019
2018			-1.5	7.6		Hendrickson, 2019
2018	6		-1.4			Pullinger et al., 2019
2019	31	212	-1.2	4.7		Crescenti et al., 2019
2019	30	144	0	11.37		Hendrickson, 2019
2019	30	111	-0.1	4.5		Hendrickson, 2019
2019			0	7.3		Hendrickson, 2019
2019	87	570	-3.1			Papadopoulos, 2019
2019	25	146	-5			Papadopoulos, 2019
2019	11	59	-0.4			Papadopoulos, 2019
2019	11	24	-3.9			Papadopoulos, 2019

395

Table B2: List of P50 bias groups for Fig. 4, expanding from Table B1. Different groups (the "Group" column) are represented by different line colors in Fig. 4.

Group	Year	Wind Farm	Wind Farm Year	Bias (%)	Uncertainty (%)	Notes	Source
1	2006			-13			Johnson et al., 2008; Jones, 2008
1	2008	59	243	-11			Johnson et al., 2008; Jones, 2008
2	2008	41	113	-10			Johnson et al., 2008
2	2008	41	113	-4		Adjust for windiness and availability	Johnson et al., 2008
2	2009		43	-3			Hendrickson, 2009
3	2008			-10		Industry average	White, 2009
3	2011		476	-9		Industry average	Drunsic, 2012
3	2011	89		-6		Industry average: 2000–2011	Drunsic, 2012
3	2012			-5		Industry average: 2005–2011	Drunsic, 2012
4	2009			-10			Hendrickson, 2009
4	2009			-9		Exclude Texas projects	Hendrickson, 2009
5	2009	11	45	-2.2	7.3		White, 2009
5	2009	11	45	-3.5	7	Accounting for windiness	White, 2009
6	2010			-8		Projects from 2000–2010	Ostridge, 2017
6	2017	50		-3		Projects from 2011–2016	Elkinton, 2017; Hale, 2017
6	2017		140	-2		Adjusted for curtailment and windiness, and so on.	Elkinton, 2017; Hale, 2017
6	2018	50		0			Hendrickson, 2019
7	2011		294	-9.9			Lunacek et al., 2018
7	2011	56		-9.2			Lunacek et al., 2018)
7	2011			-6.7	0.8	Long-term correction, R^2-filtered	Lunacek et al., 2018
8	2011			-2		Projects from 2000–2011	Drunsic, 2012

8	2012			-1		Projects from 2005–2011	Drunsic, 2012
9	2012	125	382	-9			Johnson, 2012
9	2012	125	382	0			Johnson, 2012
10	2012	24	106	-3.6	1.4		Bernadett et al., 2012
10	2012			-2.4			Bernadett et al., 2012
11	2014	31	101	-2.8		1 year	Istchenko, 2014
11	2014	31	101	-1.4		10 year	Istchenko, 2014
12	2014	24	106	-1.1	7.5		Brower, 2014
12	2014	24	106	-1	8.8	Correct for windiness	Brower, 2014
13	2015	25	91	-8			Cox, 2015
13	2015	25	91	-9		Correct for windiness	Cox, 2015
14	2015	30	127	-2.2		Adjust for windiness and availability	Stoelinga and Hendrickson, 2015
14	2016	30	127	0.1	8.8		Baughman, 2016
15	2015	18	58	-1.6	4.4		Hendrickson, 2019
15	2019	30	111	-0.1	4.5		Hendrickson, 2019
16	2018		65	-6.6		Projects after 2011	Lunacek et al., 2018
16	2018	23		-6.4		Projects after 2011	Lunacek et al., 2018
16	2018			-5.5	1.28	Long-term correction, R^2-filtered	Lunacek et al., 2018
17	2018			-1.5	7.6		Hendrickson, 2019
17	2019			0	7.3		Hendrickson, 2019

400

Table B3: List of energy losses, corresponding to Figs. 6 and 8. The "e" and "o" in the "Est/Obs" column represent estimated and observed values, respectively. The energy loss categories and subcategories align with those in Table A1. The "Avg (%)," "Min (%)," and "Max (%) indicate the average, minimum, and maximum energy loss percentages, respectively. The same column-name abbreviations apply to the following tables in Appendix B.

405

Year	Est/Obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2010	e	Availability	Balance of plant		1	2		Clive, 2010
2013	e	Availability	Balance of plant			1	Typical Northwest European onshore	Mortensen, 2013
2014	e	Availability	Balance of plant	0.2	0.2	0.4	Typical North America onshore, collection and substation	AWS Truepower, 2014
2016	e	Availability	Balance of plant	0.5			Substation	Clifton et al., 2016
2017	e	Availability	Balance of plant		0.3	0.5	Onshore: 0.5; Offshore: 0.3	Papadopoulos, 2019
2011	o	Availability	Balance of plant	0.2				Johnson, 2011
2010	e	Availability	Grid	2	1	3	WindPro 2.7	Nielsen et al., 2010
2013	e	Availability	Grid			1	Typical Northwest European onshore	Mortensen, 2013
2014	e	Availability	Grid	0.3	0.3	0.6	Typical North America onshore, utility grid	AWS Truepower, 2014
2016	e	Availability	Grid			1	Transmission	Clifton et al., 2016
2019	e	Availability	Grid availability		1	3.3		Hill et al., 2019
2008	o	Availability	Grid		0.7	2.5		Spengemann and Borget, 2008
2008	e	Availability	Total availability	3			Outside North America	Graves et al., 2008

2008	e	Availability	Total availability		3	5	Include first-year operation, also stated in Table B4	Johnson et al., 2008; White, 2008a
2009	e	Availability	Total availability	3	2	3		Randall, 2009
2009	e	Availability	Total availability		3	5	United States.: southern states: 3; northern states: 5	Horn, 2009
2011	e	Availability	Total availability	5			Analyst comparison	Hendrickson, 2011
2012	e	Availability	Total availability	3				Drunsic, 2012
2012	e	Availability	Total availability	6	2	10		Brower, 2012
2013	e	Availability	Total availability	3.2			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Availability	Total availability	6.2			Typical North America onshore	AWS Truepower, 2014
2016	e	Availability	Total availability		2	5	For plants built in 2010 to 2015	Clifton et al., 2016
2016	e	Availability	Total availability	4.2				Beaucage et al., 2016
2016	e	Availability	Total availability		2	4		Bernadett et al., 2016
2018	e	Availability	Total availability	2			Onshore	Stehly et al., 2018
2007	o	Availability	Total availability	7.4				Johnson, 2011
2008	o	Availability	Total availability	4.5			North America	Graves et al., 2008
2008	o	Availability	Total availability	5				Johnson et al., 2008; White, 2008a

2008	o	Availability	Total availability	7				Johnson et al., 2008; Jones, 2008
2008	o	Availability	Total availability	6.7				Johnson, 2011
2008	o	Availability	Total availability	6				Lackner et al., 2008
2009	o	Availability	Total availability		5	6		Hendrickson, 2009
2009	o	Availability	Total availability	6.5				Randall, 2009
2009	o	Availability	Total availability	8.2			Most available in summer and fall, least in winter	Cushman, 2009
2009	o	Availability	Total availability	6.9				Johnson, 2011
2010	o	Availability	Total availability	3.5				Johnson, 2011
2010	o	Availability	Total availability	1.1	1	11	WindPro 2.7	Nielsen et al., 2010
2011	o	Availability	Total availability	11				Conroy et al., 2011
2011	o	Availability	Total availability	2.6				Johnson, 2011
2012	o	Availability	Total availability	6				Drunsic, 2012
2012	o	Availability	Total availability	6.4			Higher availability loss for higher wind speeds	Winslow, 2012
2015	o	Availability	Total availability	5			Operational issues (e.g., cables, connection, turbine)	Cox, 2015

2016	o	Availability	Total availability	4.5				Beaucage et al., 2016
2016	o	Availability	Total availability	3.2				Bernadett et al., 2016
2019	o	Availability	Total availability	4				Pedersen and Langreder, 2019
2010	e	Availability	Turbine		2	5		Clive, 2010
2010	e	Availability	Turbine		2	5	WindPro 2.7	Nielsen et al., 2010
2013	e	Availability	Turbine	3			Typical Northwest European onshore	Mortensen, 2013
2014	e	Availability	Turbine	5.9	3	10.1	Typical North America onshore, combined from contractual turbine, noncontractual turbine, correlation, restart, site access	AWS Truepower, 2014
2011	o	Availability	Turbine	2.3				Johnson, 2011
2019	o	Availability	Turbine	1.67			Combine scheduled and unscheduled maintenance	Pedersen and Langreder, 2019
2014	e	Curtailment	Grid		0	3.5	Typical North America onshore, including power purchase agreement	AWS Truepower, 2014
2016	e	Curtailment	Grid			1		Clifton et al., 2016
2019	e	Curtailment	Grid	3.8			Ireland estimate, based on operational data	Papadopoulos, 2019
2016	o	Curtailment	Grid		0.5	1	Interconnection cap	Ostridge and Rodney, 2016

2014	e	Curtailment	Load		0	3.5	Typical North America onshore, directional	AWS Truepower, 2014
2019	o	Curtailment	Load	1.02			Load shutdown	Pedersen and Langreder, 2019
2014	e	Curtailment	Permit		0	3.5	Typical North America onshore	AWS Truepower, 2014
2016	e	Curtailment	Permit			1		Clifton et al., 2016
2018	e	Curtailment	Permit		0.05	0.2	Shadow flicker	Mibus, 2018
2016	o	Curtailment	Permit		0.4	2.4	Bat	Ostridge and Rodney, 2016
2019	o	Curtailment	Permit		0.67	0.71	Bat and shadow flicker	Pedersen and Langreder, 2019
2011	e	Curtailment	Total curtailment	0			Analyst comparison	Hendrickson, 2011
2012	e	Curtailment	Total curtailment	0	0	5		Brower, 2012
2014	e	Curtailment	Total curtailment	0			Typical North America onshore	AWS Truepower, 2014
2016	e	Curtailment	Total curtailment		1	4		Clifton et al., 2016
2011	o	Curtailment	Total curtailment	4				Johnson, 2011
2012	o	Curtailment	Total curtailment	2.97				Wiser et al., 2019
2013	o	Curtailment	Total curtailment	2.86				Wiser et al., 2019
2014	o	Curtailment	Total curtailment		1	4	Varies geographically	Bird et al., 2014
2014	o	Curtailment	Total curtailment	2.31				Wiser et al., 2019
2015	o	Curtailment	Total curtailment	2.15				Wiser et al., 2019

2016	o	Curtailment	Total curtailment	2.1				Wiser et al., 2019
2017	o	Curtailment	Total curtailment	2.54				Wiser et al., 2019
2018	o	Curtailment	Total curtailment	2.18				Wiser et al., 2019
2014	e	Electrical	Electrical efficiency	2	1	3	Typical North America onshore	AWS Truepower, 2014
2016	e	Electrical	Electrical efficiency		1	2	Collector system	Clifton et al., 2016
2014	e	Electrical	Facility parasitic consumption	0.1	0	0.1	Typical North America onshore, weather package	AWS Truepower, 2014
2010	e	Electrical	Total electrical		2	3		Clive, 2010
2011	e	Electrical	Total electrical	3			Analyst comparison	Hendrickson, 2011
2012	e	Electrical	Total electrical	2.1	2	3		Brower, 2012
2013	e	Electrical	Total electrical	1.2			Typical Northwest European onshore	Mortensen, 2013
2013	e	Electrical	Total electrical		1	2	Typical Northwest European onshore	Mortensen, 2013
2014	e	Electrical	Total electrical		0.7	2		Colmenar-Santos et al., 2014
2014	e	Electrical	Total electrical	2.1			Typical North America onshore	AWS Truepower, 2014
2016	e	Electrical	Total electrical		2	3.5		Clifton et al., 2016
2008	o	Electrical	Total electrical	3				Spengemann and Borget, 2008
2006	e	Environmental	Degradation			13		Spruce and Turner, 2006

2009	e	Environmental	Degradation	0.2	0.1	0.4	10 year	Randall, 2009
2009	e	Environmental	Degradation	1.2	0.5	1.9	20 year	Randall, 2009
2010	e	Environmental	Degradation	5		10		Standish et al., 2010
2011	e	Environmental	Degradation	0.3				Bernadett et al., 2012
2012	e	Environmental	Degradation	0.6				Bernadett et al., 2012
2014	e	Environmental	Degradation		5	25	Wind tunnel study	Sareen et al., 2014
2014	e	Environmental	Degradation	1	0.6	1.3	Typical North America onshore	AWS Truepower, 2014
2014	e	Environmental	Degradation		5	20	Extreme cases	Redouane, 2014
2015	e	Environmental	Degradation			5		Langel et al., 2015
2016	e	Environmental	Degradation		1	2	Industry standard; soiling and erosion	Clifton et al., 2016
2016	e	Environmental	Degradation			5		Maniaci et al., 2016
2017	e	Environmental	Degradation		0.4	2.3		Ehrmann et al., 2017
2017	e	Environmental	Degradation			8		Schramm et al., 2017
2017	e	Environmental	Degradation		4.9	6.8		Wilcox et al., 2017
2019	e	Environmental	Degradation	3.6			Normal operation	Hasager et al., 2019
2019	e	Environmental	Degradation	2.6			Erosion safe mode operation	Hasager et al., 2019
2014	o	Environmental	Degradation		1.4	1.8	United Kingdom	Staffell and Green, 2014
2016	o	Environmental	Degradation		1.5	2	Before blade repair	Murphy, 2016
2017	o	Environmental	Degradation	0.3			Sweden	(Olauson et al., 2017)over
2018	o	Environmental	Degradation	0.44				Wiser et al., 2019

2019	o	Environmental	Degradation	0.6			Germany	Germer and Kleidon, 2019
2019	o	Environmental	Degradation			9.5	Lead edge erosion	Latoufis et al., 2019
2020	o	Environmental	Degradation		0.17	1.23	United States	Hamilton et al., 2020
2014	e	Environmental	Environmental	0.6	0	3.9	Typical North America onshore, combining temperature shutdown and lightning	AWS Truepower, 2014
2016	e	Environmental	Environmental			1	Temperature shutdown	Clifton et al., 2016
2019	o	Environmental	Environmental	0.35			Temperature shutdown	Pedersen and Langreder, 2019
2016	e	Environmental	Exposure		0	3	Exposure over time	Clifton et al., 2016
2014	e	Environmental	Icing	1	0	4.5	Typical North America onshore	AWS Truepower, 2014
2016	e	Environmental	Icing		1	5		Clifton et al., 2016
2016	e	Environmental	Icing	5.6				Beaucage et al., 2016
2019	e	Environmental	Icing	30				Abascal et al., 2019
2008	o	Environmental	Icing	26			Average of two wind farms for 4 years	Gillenwater et al., 2008
2010	o	Environmental	Icing	24			Four winters, 10% of the year	Rindeskär, 2010
2015	o	Environmental	Icing	10			Seven wind farms, 111 turbines, 272 MW in Sweden	Byrkjedal et al., 2015
2016	o	Environmental	Icing		5	15	Three consultants underestimate 1.5	Trudel, 2016

							to 4 times lower than this	
2016	o	Environmental	Icing	4.9				Beaucage et al., 2016
2019	o	Environmental	Icing	0.87				Pedersen and Langreder, 2019
2019	o	Environmental	Icing		33	35		Abascal et al., 2019
2011	e	Environmental	Total environmental	2			Analyst comparison	Hendrickson, 2011
2012	e	Environmental	Total environmental	2.6	1	6		Brower, 2012
2013	e	Environmental	Total environmental		1	2	Typical, used in Wind Atlas Analysis and Application Program (WAsP), include blade degradation, icing, temp shutdown.	Mortensen, 2013
2013	e	Environmental	Total environmental		1	2	Typical Northwest European onshore, include blade degradation and icing.	Mortensen, 2013
2014	e	Environmental	Total environmental	2.7			Typical North America onshore	AWS Truepower, 2014
2016	e	Environmental	Total environmental		1	7		Clifton et al., 2016
2011	o	Environmental	Total environmental	0.4				Johnson, 2011
2010	e	Total	Total		6	13		Clive, 2010
2011	e	Total	Total	18			Analyst comparison	Hendrickson, 2011

2012	e	Total	Total	18.5	7.8	37		Brower, 2012
2012	e	Total	Total	14.8			Analyst comparison	Mortensen et al., 2012
2013	e	Total	Total	22.5			Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Total	Total	17.4			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Total	Total	19.7	8.5	32.2	Typical North America onshore	AWS Truepower, 2014
2018	e	Total	Total	15			Onshore	Stehly et al., 2018
2008	o	Total	Total		2	5		Johnson et al., 2008
2008	e	Turbine performance	Generic power curve adjustment	1				Johnson et al., 2008
2009	e	Turbine performance	Generic power curve adjustment	0.3			Turbulence-intensity-dependent power curves	AWS Truepower, 2009
2012	e	Turbine performance	Generic power curve adjustment	2.4	1	4		Brower et al., 2012
2014	e	Turbine performance	Generic power curve adjustment	2.4	0	2.4	Typical North America onshore	AWS Truepower, 2014
2016	e	Turbine performance	Generic power curve adjustment	2.4				Bernadett et al., 2016
2019	e	Turbine performance	Generic power curve adjustment	1				Lee, 2019

2008	o	Turbine performance	Generic power curve adjustment	2	4			Johnson et al., 2008; Jones, 2008
2012	o	Turbine performance	Generic power curve adjustment	2.2		3.2		Drees and Weiss, 2012
2012	o	Turbine performance	Generic power curve adjustment	2.5				Johnson, 2012
2013	o	Turbine performance	Generic power curve adjustment	1.8			Without yaw error correction	Osler, 2013
2014	o	Turbine performance	Generic power curve adjustment	2				Staffell and Green, 2014
2014	o	Turbine performance	Generic power curve adjustment	1.6	1	3		Ostridge, 2014
2015	o	Turbine performance	Generic power curve adjustment	2	0	4		Geer, 2015
2015	o	Turbine performance	Generic power curve adjustment	1.5				Ostridge, 2015
2015	o	Turbine performance	Generic power curve adjustment	1.1				Kassebaum, 2015
2018	o	Turbine performance	Generic power curve adjustment	0.2				Pram, 2018
2010	e	Turbine performance	High wind hysteresis	0.3			WindPro 2.7	Nielsen et al., 2010

2014	e	Turbine performance	High wind hysteresis	0.6	0	3	Typical North America onshore	AWS Truepower, 2014
2009	e	Turbine performance	Site-specific power curve adjustment	0.6			Adjust for tower turbulence intensity to correct NRG Systems Max 40 anemometer overspeeding.	AWS Truepower, 2009
2014	e	Turbine performance	Site-specific power curve adjustment	0	0	1	Typical North America onshore, including inclined flow	AWS Truepower, 2014
2016	e	Turbine performance	Site-specific power curve adjustment	0.5				Papadopoulos, 2019
2014	o	Turbine performance	Site-specific power curve adjustment	2	5			Staffell and Green, 2014
2008	e	Turbine performance	Suboptimal performance	1				Johnson et al., 2008; White, 2008a
2009	e	Turbine performance	Suboptimal performance		1	2		White, 2009
2009	e	Turbine performance	Suboptimal performance	1				AWS Truepower, 2009
2013	e	Turbine performance	Suboptimal performance	0.5				Papadopoulos, 2019
2014	e	Turbine performance	Suboptimal performance	1	0	1	Typical North America onshore	AWS Truepower, 2014
2019	e	Turbine performance	Suboptimal performance		1.1	2.2	10 degrees of yaw error	Liew et al., 2019
2019	e	Turbine performance	Suboptimal performance	3			Yaw misalignment	Slinger et al., 2019b

Year	o/e	Category	Subcategory				Notes	Reference
2012	o	Turbine performance	Suboptimal performance		0	3.6		Johnson, 2012
2019	o	Turbine performance	Suboptimal performance	0.41				Pedersen and Langreder, 2019
2019	o	Turbine performance	Suboptimal performance	0.21			Yaw	Pedersen and Langreder, 2019
2010	e	Turbine performance	Total turbine performance		1	3		Clive, 2010
2010	e	Turbine performance	Total turbine performance	10		19		Clive, 2010
2011	e	Turbine performance	Total turbine performance	2			Analyst comparison	Hendrickson, 2011
2012	e	Turbine performance	Total turbine performance	2.5	0	5		Brower, 2012
2013	e	Turbine performance	Total turbine performance		1	2	Typical Northwest European onshore	Mortensen, 2013
2014	e	Turbine performance	Total turbine performance	4			Typical North America onshore	AWS Truepower, 2014
2016	e	Turbine performance	Total turbine performance		1	3		Clifton et al., 2016
2019	o	Turbine performance	Total turbine performance		2	6.5	Rotor aerodynamic imbalance, yaw static misalignment	Rezzoug, 2019
2013	e	Wake effect	External wake effects	2.3			Offshore, analyst comparison, including neighboring wind farm wake	Mortensen and Ejsing Jørgensen, 2013
2014	e	Wake effect	External wake effects	0			Typical North America onshore	AWS Truepower, 2014
2014	e	Wake effect	Internal wake effects	6.4	0	2	Typical North America onshore	AWS Truepower, 2014

2018	e	Wake effect	Internal wake effects	2	0	4	Turbine interaction	Bleeg, 2018
2011	e	Wake effect	Nonwake		3	4		Comstock, 2011
2011	e	Wake effect	Nonwake	11	6	15	Analyst comparison	Hendrickson, 2011
2012	e	Wake effect	Nonwake	9.2	5	20	Analyst comparison	Mortensen et al., 2012
2013	e	Wake effect	Nonwake	9.6	7.5	13	Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Wake effect	Nonwake	8	4.4	20	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Wake effect	Nonwake		5	10	Typical Northwest European onshore	Mortensen, 2013
2015	e	Wake effect	Nonwake		8	9.2		Mortensen et al., 2015b
2008	e	Wake effect	Total wake effect		10	20		Barthelmie et al., 2008
2009	e	Wake effect	Total wake effect	20			After 20 rows of turbines	White, 2009
2009	e	Wake effect	Total wake effect	40			After 70 rows of offshore turbines	Tindal, 2009
2009	e	Wake effect	Total wake effect		15	20	After 15 rows of onshore turbines	Tindal, 2009
2009	e	Wake effect	Total wake effect	10				Nielsen et al., 2010
2010	e	Wake effect	Total wake effect	18				Wolfe, 2010
2010	e	Wake effect	Total wake effect		5	15	WindPro 2.7	Nielsen et al., 2010

2010	e	Wake effect	Total wake effect	11.5			Account for deep-array loss and turbulence intensity	Nielsen et al., 2010
2011	e	Wake effect	Total wake effect		1	3		Comstock, 201
2011	e	Wake effect	Total wake effect	8	6	10	Analyst comparison	Hendrickson, 2011
2012	e	Wake effect	Total wake effect	6.7	3	15		Brower, 2012
2012	e	Wake effect	Total wake effect	6.1	4.5	8.1	Analyst comparison	Mortensen et al., 2012
2013	e	Wake effect	Total wake effect	14	6.9	37	Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Wake effect	Total wake effect	10	3.9	17	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Wake effect	Total wake effect	6.4	1.1	18.1	Typical North America onshore	AWS Truepower, 2014
2015	e	Wake effect	Total wake effect		6.1	14.3		Mortensen et al., 2015b
2016	e	Wake effect	Total wake effect		0	10		Clifton et al., 2016
2018	e	Wake effect	Total wake effect		4.5	7.7		Walls, 2018
2019	e	Wake effect	Total wake effect			15		Slinger et al., 2019a
2019	e	Wake effect	Total wake effect		3	14		Stoelinga, 2019
2010	o	Wake effect	Total wake effect	13			By the fifth row	Wolfe, 2010

2014	o	Wake effect	Total wake effect		5	15	Onshore, small (20 turbine) wind farms	Staffell and Green, 2014
2016	o	Wake effect	Total wake effect		8.4	15.3	Up to fourth row downwind	Kline, 2016
2019	o	Wake effect	Total wake effect		4	16		Stoelinga, 2019

410

Table B4: List of other categorical losses outside the IEC proposed framework (Table A1), which are used to generate Fig. 7.

Year	Est/Obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2008	e	Availability	First few years of operation		3	5	Include first-year operation; also stated in Table B3	Johnson et al., 2008; White, 2008b
2014	e	Availability	First few years of operation	4	2	6	Typical North America onshore, first year	AWS Truepower, 2014
2010	o	Availability	First few years of operation		4	5	First year of operation	Johnson, 2011
2011	o	Availability	First few years of operation		2	3	First year of operation	Johnson, 2011
2019	o	Availability	First few years of operation	2.2			First 2 years of operation	Pullinger et al., 2019
2018	e	Turbine performance	Blockage	1				Bleeg, 2018
2019	e	Turbine performance	Blockage		0.3	1.5		Spalding, 2019
2019	e	Turbine performance	Blockage	1.75				Robinson, 2019
2019	e	Turbine performance	Blockage	1.9	0	6		Lee, 2019
2019	e	Turbine performance	Blockage	2	1	5		Papadopoulos, 2019

Table B5: List of uncertainties of energy losses, as projected in Fig. 9. Note that a value herein represents the percent of energy percentage loss.

Year	Est/Obs	Category	Avg (%)	Min (%)	Max (%)	Notes	Source

2014	o	Interannual variability of loss	3.3				Istchenko, 2014
2014	o	Intermonthly variability of loss		10	14		Istchenko, 2014
2012	e	Nonwake loss	32			Analyst comparison	Mortensen et al., 2012
2013	e	Nonwake loss	7.8			Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Nonwake loss	34			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2012	e	Wake loss	13			Analyst comparison	Mortensen et al., 2012
2013	e	Wake loss		10	20	Caused by different models and terrains	Brower and Robinson, 2013
2013	e	Wake loss		20	30	In WindFarmer	Elkinton, 2013
2013	e	Wake loss	25				McCaa, 2013
2013	e	Wake loss		15	20		Kline, 2013
2013	e	Wake loss	30				Halberg and Breakey, 2013
2013	e	Wake loss	37			Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Wake loss	18			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Wake loss	20				AWS Truepower, 2014
2015	e	Wake loss		13	22		Mortensen et al., 2015a
2016	e	Wake loss		13	35		Clifton et al., 2016
2019	e	Wake loss	18				Stoelinga, 2019
2009	o	Wake loss			80	By second row of an offshore wind farm	Dahlberg, 2009

415

Table B6: List of energy uncertainties, according to the categories and subcategories in Table A2. These values correspond to Fig. 10.

Year	Est/Obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source

2004	e	Historical wind resource	Long-term adjustment	5			WindPro 2.4; methods and measure-correlate-predict	EMD International A/S, 2004
2008	e	Historical wind resource	Long-term adjustment		5	10	Measure-correlate-predict process	Anderson, 2008
2010	e	Historical wind resource	Long-term adjustment	3		10	WindPro 2.7; long-term correction	Nielsen et al., 2010
2013	e	Historical wind resource	Long-term adjustment	4	0	11	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
1991	e	Historical wind resource	Long-term period	10				Simon, 1991
2004	e	Historical wind resource	Long-term period	5			WindPro 2.4; wind statistics	EMD International A/S, 2004
2008	e	Historical wind resource	Long-term period	5			Climate variation: 1997–2007	Johnson et al., 2008; White, 2008
2010	e	Historical wind resource	Long-term period	5			WindPro 2.7; long-term wind variability	Nielsen et al., 2010
2012	e	Historical wind resource	Long-term period	5.9			Long-term wind speed	Tchou, 2012
2013	e	Historical wind resource	Long-term period	3.5	0	12	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Historical wind resource	Long-term period		2	11	Long-term wind speed and its interannual variability	Geer, 2014

2014	e	Historical wind resource	Long-term period	3.2	2.1	4.8		AWS Truepower, 2014
2015	e	Historical wind resource	Long-term period		5.5	9.5		Breakey, 2019
2019	e	Historical wind resource	Long-term period			28.4	One-year uncertainty	Dutrieux, 2019
2010	o	Historical wind resource	Long-term period	2				Rogers, 2010
2012	o	Historical wind resource	Long-term period	8.2			Long-term wind speed	Tchou, 2012
2012	o	Historical wind resource	Long-term period	4.3			Long-term wind speed	Tchou, 2012
2013	e	Historical wind resource	Reference data	16				Holtslag, 2013
2009	e	Historical wind resource	Total historical wind resource	3.98			Twenty-year uncertainty, 10 projects	Breakey, 2019
2011	e	Historical wind resource	Total historical wind resource	4.2	2.5	7		Comstock, 2011
2011	e	Historical wind resource	Total historical wind resource	5				Hendrickson, 2011
2016	e	Historical wind resource	Total historical wind resource		1	6		Clifton et al., 2016

2017	e	Historical wind resource	Total historical wind resource		2	5	Ten-year uncertainties from three examples	Halberg, 2017
2019	e	Historical wind resource	Total historical wind resource	2.68			Twenty-year uncertainty, 10 projects	Breakey, 2019
2012	o	Historical wind resource	Total historical wind resource		3	5		Comstock, 2012
2014	o	Historical wind resource	Total historical wind resource	3.2	1.7	5.3		Brower, 2014
2014	o	Historical wind resource	Total historical wind resource	2	2	5		Istchenko, 2014
2014	e	Historical wind resource	Wind speed and direction distribution		1.5	2.5	Interannual variability of frequency distribution	Geer, 2014
2014	e	Historical wind resource	Wind speed and direction distribution	1	0.6	1.5	Wind speed distribution	AWS Truepower, 2014
2004	e	Horizontal extrapolation	Model stress	5			WindPro 2.4; terrain description	EMD International A/S, 2004
2014	e	Horizontal extrapolation	Model stress		3	6	Complex terrain	Redouane, 2014
2016	e	Horizontal extrapolation	Model stress		1	10	For simple and complex terrain	Clifton et al., 2016
2010	o	Horizontal extrapolation	Model stress	2.7			75 North American projects; caused by topography	Rogers, 2010
2009	e	Horizontal extrapolation	Total horizontal extrapolation		1	3	Nonideal flow	Hendrickson, 2009

2009	e	Horizontal extrapolation	Total horizontal extrapolation	5.24			Twenty-year uncertainty, 10 projects	Breakey, 2019
2011	e	Horizontal extrapolation	Total horizontal extrapolation	4.1	1.5	7		Comstock, 2011
2011	e	Horizontal extrapolation	Total horizontal extrapolation	4.3			Flow model	Hendrickson, 2011
2013	e	Horizontal extrapolation	Total horizontal extrapolation	3.5	0	9	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Horizontal extrapolation	Total horizontal extrapolation		2	4		Geer, 2014
2014	e	Horizontal extrapolation	Total horizontal extrapolation	4	2.4	8	Flow model	AWS Truepower, 2014
2014	e	Horizontal extrapolation	Total horizontal extrapolation		0	14.8		Redouane, 2014
2015	e	Horizontal extrapolation	Total horizontal extrapolation		0	8.7		Mortensen et al., 2015
2016	e	Horizontal extrapolation	Total horizontal extrapolation		1	10		Clifton et al., 2016
2017	e	Horizontal extrapolation	Total horizontal extrapolation		2.6	4.7	Ten-year uncertainties from three examples	Halberg, 2017
2018	e	Horizontal extrapolation	Total horizontal extrapolation		2.3	6.5	Flow model	Walls, 2018

2019	e	Horizontal extrapolation	Total horizontal extrapolation	3.54			Twenty-year uncertainty, 10 projects	Breakey, 2019
2010	o	Horizontal extrapolation	Total horizontal extrapolation		2.3	3.3	Analyst comparison; "Extrapolation"	Walter, 2010
2010	o	Horizontal extrapolation	Total horizontal extrapolation	2			Analyst comparison; "Extrapolation"	McAloon, 2010
2014	o	Horizontal extrapolation	Total horizontal extrapolation	4.3	1.7	8.5	Flow model	Brower, 2014
2014	o	Horizontal extrapolation	Total horizontal extrapolation	4	1	8		Istchenko, 2014
2014	e	Measurement	Data integrity and documentation	0.5	0.2	1		AWS Truepower, 2014
2016	e	Measurement	Data integrity and documentation			0.5		Clifton et al., 2016
2010	o	Measurement	Data integrity and documentation	1.4			Data recovery and validation	Rogers, 2010
2013	e	Measurement	Further atmospheric parameters	0.5	0	5	Onshore, analyst comparison; Air density	Mortensen and Ejsing Jørgensen, 2013
2009	e	Measurement	Total measurement	3.45			Twenty-year uncertainty, 10 projects	Breakey, 2019
2011	e	Measurement	Total measurement	3.8	2.5	6		Comstock, 2011

2011	e	Measurement	Total measurement	4.9				Hendrickson, 2011
2014	e	Measurement	Total measurement		1.5	2.5		Geer, 2014
2014	e	Measurement	Total measurement	2.4	1.6	4.8		AWS Truepower, 2014
2016	e	Measurement	Total measurement		1	5	For plants built from 2010 to 2015 with anemometer-based campaign, before extrapolations	Clifton et al., 2016
2017	e	Measurement	Total measurement		2.3	4.5	Ten-year uncertainties from three examples	Halberg, 2017
2019	e	Measurement	Total measurement	2.36			Twenty-year uncertainty, 10 projects	Breakey, 2019
2002	o	Measurement	Total measurement		8	12		Friis Pedersen et al., 2002
2010	o	Measurement	Total measurement	1.9			Analyst comparison; caused by tower shadow filter and data recovery	Balfrey, 2010
2012	o	Measurement	Total measurement		2	3		Comstock, 2012
2014	o	Measurement	Total measurement	4.2	1.7	7.5		Brower, 2014
2014	o	Measurement	Total measurement	2	2	4		Istchenko, 2014
2012	e	Measurement	Wind speed measurement	3.4			Anemometer	Tchou, 2012
2013	e	Measurement	Wind speed measurement	9				Holtslag, 2013

2013	e	Measurement	Wind speed measurement	4	1.5	10	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2015	e	Measurement	Wind speed measurement		3	4	Anemometer and calibration	Geer, 2015
2016	e	Measurement	Wind speed measurement		1	2		Clifton et al., 2016
2010	o	Measurement	Wind speed measurement	1.5	1	1.5	Tower effects on anemometer	Rogers, 2010
2012	e	Plant performance	Availability	0.3			Substation metering	Tchou, 2012
2014	e	Plant performance	Availability		2	4	Interannual variability of availability	Geer, 2014
2009	o	Plant performance	Availability	6.2				Cushman, 2009
2011	o	Plant performance	Availability	1				Johnson, 2011
2012	o	Plant performance	Availability	1.7				Tchou, 2012
2016	e	Plant performance	Curtailments or Operational strategies		1	4		Clifton et al., 2016
2013	e	Plant performance	Electrical	0.5	0	4	Onshore, analyst comparison; metering	Mortensen and Ejsing Jørgensen, 2013
2013	e	Plant performance	Electrical		0	2	Metering	Mortensen, 2013
2016	e	Plant performance	Electrical		1	2		Clifton et al., 2016
2012	e	Plant performance	Nonwake	2.9			Analyst comparison	Mortensen et al., 2012
2013	e	Plant performance	Nonwake	0.7			Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Plant performance	Nonwake	2.7			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013

2013	e	Plant performance	Nonwake	1	0	10	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	o	Plant performance	Nonwake	3.7	3.2	4.5		Brower, 2014
2009	e	Plant performance	Total plant performance	3.56			Twenty-year uncertainty, 10 projects	Breakey, 2019
2011	e	Plant performance	Total plant performance	3.2	1	5		Comstock, 2011
2011	e	Plant performance	Total plant performance	3.8				Hendrickson, 2011
2013	e	Plant performance	Total plant performance	3				Holtslag, 2013
2014	e	Plant performance	Total plant performance		2	5		Geer, 2014
2014	e	Plant performance	Total plant performance	3.5	3.2	4.8		AWS Truepower, 2014
2016	e	Plant performance	Total plant performance		0	15		Clifton et al., 2016
2017	e	Plant performance	Total plant performance		3	4.4	Ten-year uncertainties from three examples	Halberg, 2017
2019	e	Plant performance	Total plant performance	4.53			Twenty-year uncertainty, 10 projects; include interannual variability of turbine performance	Breakey, 2019
2010	o	Plant performance	Total plant performance	2				Rogers, 2010
2012	o	Plant performance	Total plant performance		2	3		Comstock, 2012
2014	o	Plant performance	Total plant performance	4	3	5		Istchenko, 2014

2004	e	Plant performance	Turbine performance	5			WindPro 2.4; power curve	EMD International A/S, 2004
2012	e	Plant performance	Turbine performance	1.5				Tchou, 2012
2013	e	Plant performance	Turbine performance	4	0	10	Onshore, analyst comparison; power curve	Mortensen and Ejsing Jørgensen, 2013
2013	e	Plant performance	Turbine performance		5	10	Power curve	Mortensen, 2013
2014	e	Plant performance	Turbine performance		4	10.4	Power curve	Redouane, 2014
2016	e	Plant performance	Turbine performance		0	4		Clifton et al., 2016
2019	e	Plant performance	Turbine performance		8.6	18.8	Power curve from 10-kW turbine	Kim and Shin, 2019
2002	o	Plant performance	Turbine performance		2	3	Power curve	Friis Pedersen et al., 2002
2012	o	Plant performance	Turbine performance	0.8			Power curve	Brower et al., 2012
2012	o	Plant performance	Turbine performance	1				Tchou, 2012
2012	o	Plant performance	Turbine performance	6.1			Power curve	Drees and Weiss, 2012
2012	o	Plant performance	Turbine performance	15			From air density of power curve	Winslow, 2012
2012	o	Plant performance	Turbine performance		4	8	Power curve	Jaynes, 2012
2013	o	Plant performance	Turbine performance		0.5	6.5	Power curve	Kassebaum, 2013
2014	o	Plant performance	Turbine performance	6			Power curve	Ostridge, 2014
2015	o	Plant performance	Turbine performance	6			Power curve	Ostridge, 2015

2015	o	Plant performance	Turbine performance	2.1			Power curve	Kassebaum, 2015
2017	o	Plant performance	Turbine performance		3.1	4	Power curve	Filippelli et al., 2017
2018	o	Plant performance	Turbine performance	2.5			Power curve	Pram, 2018
2012	e	Plant performance	Wake effect	7				Tchou, 2012
2012	e	Plant performance	Wake effect	0.8			Analyst comparison	Mortensen et al., 2012
2013	e	Plant performance	Wake effect	5.3			Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Plant performance	Wake effect	1.8	0	13	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Plant performance	Wake effect		0	5		Mortensen, 2013
2014	e	Plant performance	Wake effect		0	10		Redouane, 2014
2014	o	Plant performance	Wake effect	1.7	0.7	3.1		Brower, 2014
2019	e	Project evaluation period variability	Climate change	4				Wilkinson et al., 2019
2014	o	Project evaluation period variability	Climate change	2.1	1.4	2.8	Future climate	Brower, 2014
2008	e	Project evaluation period variability	Modeled operational period	1			Short-term climatology	Johnson et al., 2008; White, 2008

2014	e	Project evaluation period variability	Modeled operational period	1.9				AWS Truepower, 2014
2019	e	Project evaluation period variability	Modeled operational period			8	Ten-year uncertainty	Dutrieux, 2019
2019	e	Project evaluation period variability	Modeled operational period			4.8	Twenty-year uncertainty	Dutrieux, 2019
2019	e	Project evaluation period variability	Modeled operational period			1.6	Thirty-year uncertainty	Dutrieux, 2019
2010	o	Project evaluation period variability	Modeled operational period	1			Changes in long-term wind speed	Rogers, 2010
2015	e	Project evaluation period variability	Plant performance		7	12	With 1 to 10 met masts	Brower et al., 2015
2009	e	Project evaluation period variability	Total project evaluation period variability	2.26			Twenty-year future variability	Breakey, 2019
2011	e	Project evaluation period variability	Total project evaluation period variability		6	10.5		Comstock, 2011

2011	e	Project evaluation period variability	Total project evaluation period variability	7				Hendrickson, 2011
2012	e	Project evaluation period variability	Total project evaluation period variability		3.1	9.7	Range of 1-year and 10-year uncertainties	Tchou, 2012
2016	e	Project evaluation period variability	Total project evaluation period variability		1	10		Clifton et al., 2016
2017	e	Project evaluation period variability	Total project evaluation period variability		2.8	3.5	Ten-year uncertainties from three examples	Halberg, 2017
2019	e	Project evaluation period variability	Total project evaluation period variability	0.94			Twenty-year future variability	Breakey, 2019
2010	o	Project evaluation period variability	Total project evaluation period variability	1				Rogers, 2010
2012	o	Project evaluation period variability	Total project evaluation period variability		2	3		Comstock, 2012
2012	o	Project evaluation period variability	Total project evaluation period variability		3.1	9.7	Range of 1-year and 10-year uncertainties	Tchou, 2012

2014	o	Project evaluation period variability	Total project evaluation period variability	6	4	9	One-year uncertainties	Istchenko, 2014
2014	o	Project evaluation period variability	Total project evaluation period variability	2	2	3	Ten-year uncertainties	Istchenko, 2014
2000	e	Total	Total		3	6	For flat and complex terrains	Albers et al., 2000
2004	e	Total	Total	10			WindPro 2.4	EMD International A/S, 2004
2007	e	Total	Total	9.6			Twenty-year uncertainty, 10 projects	Breakey, 2019
2008	e	Total	Total		9.9	12.7	Range of 1-year and lifetime uncertainties	AWS Truepower, 2009
2009	e	Total	Total		7.9	10.5	Range of 1-year and lifetime uncertainties	AWS Truepower, 2009
2010	e	Total	Total	8		10	WindPro 2.7	Nielsen et al., 2010
2011	e	Total	Total	13	10	18		Hendrickson, 2011
2011	e	Total	Total	7.2				Bernadett et al., 2012
2012	e	Total	Total		7	11		Comstock, 2012
2012	e	Total	Total		10.4	13.9	Range of 1-year and 10-year uncertainties	Tchou, 2012
2012	e	Total	Total	7.7				Bernadett et al., 2012
2012	e	Total	Total	11	6	21	Analyst comparison	Mortensen et al., 2012
2013	e	Total	Total	17				Holtslag, 2013
2013	e	Total	Total	10.8				Holtslag, 2013
2013	e	Total	Total	10	6.2	21	Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Total	Total	8	3.6	12	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013

2013	e	Total	Total		10	15		Mortensen, 2013
2014	e	Total	Total		7.9	10.8	Range of 1-year and 10-year uncertainties	Istchenko, 2014
2014	e	Total	Total	7.5	5.2	13.5		AWS Truepower, 2014
2014	e	Total	Total		11.1	16.7	Nine wind farms, 1-year uncertainties	Redouane, 2014
2014	e	Total	Total		8.4	14.5	Nine wind farms, 10-year uncertainties	Redouane, 2014
2015	e	Total	Total		10	15		Apple, 2015
2015	e	Total	Total	7.2				Istchenko, 2015
2015	e	Total	Total		5	9	"Minimum"	Mortensen et al., 2015
2015	e	Total	Total		8	11		Mortensen et al., 2015a
2015	e	Total	Total	10.6			One-year uncertainty	Stoelinga and Hendrickson, 2015
2017	e	Total	Total		6.2	10.7	Ten-year uncertainties from three examples	Halberg, 2017
2017	e	Total	Total		7.9	9.1	One-year uncertainties	Perry, 2017
2017	e	Total	Total		4.1	6.2	Twenty-year uncertainties	Perry, 2017
2017	e	Total	Total	11			Post-2011 projects, 1-year standard deviation	Ostridge, 2017
2019	e	Total	Total	6.8			Twenty-year uncertainty, 10 projects	Breakey, 2019
2009	o	Total	Total	9.7		9.7		Derrick, 2009
2009	o	Total	Total	33			One offshore wind farm	Dahlberg, 2009
2012	o	Total	Total		5	8		Comstock, 2012

Year		Category	Subcategory				Notes	Reference
2012	o	Total	Total		9.1	12.9	Range of 1-year and 10-year uncertainties	Tchou, 2012
2012	o	Total	Total		6.2	11.1	Range of 1-year and 10-year uncertainties	Tchou, 2012
2014	o	Total	Total	8.4	6.3	11.5		Brower, 2014
2014	o	Total	Total		5.4	9.4	Range of 1-year and 10-year uncertainties	Istchenko, 2014
2014	o	Total	Total		4	8	Nine wind farms	Redouane, 2014
2015	o	Total	Total		6	12		Apple, 2015
2015	o	Total	Total	6.2				Istchenko, 2015
2015	o	Total	Total		3.1	7		Mortensen et al., 2015a
2017	o	Total	Total	8			Post-2011 projects, 1-year standard deviation	Ostridge, 2017
2014	e	Vertical extrapolation	Model inputs	2.6	0	6.4	Wind shear	AWS Truepower, 2014
2010	o	Vertical extrapolation	Model inputs	1.9			Wind shear	Rogers, 2010
2009	e	Vertical extrapolation	Total vertical extrapolation	3.49			Twenty-year uncertainty, 10 projects	Breakey, 2019
2011	e	Vertical extrapolation	Total vertical extrapolation	3.2	1.5	5		Comstock, 2011
2011	e	Vertical extrapolation	Total vertical extrapolation	3.1				Hendrickson, 2011
2013	e	Vertical extrapolation	Total vertical extrapolation	1	0	13	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Vertical extrapolation	Total vertical extrapolation		1	2		Geer, 2014
2014	e	Vertical extrapolation	Total vertical extrapolation		0	5		Redouane, 2014

2016	e	Vertical extrapolation	Total vertical extrapolation		0	6		Clifton et al., 2016
2017	e	Vertical extrapolation	Total vertical extrapolation		2.1	3.9	Ten-year uncertainties from three examples	Halberg, 2017
2019	e	Vertical extrapolation	Total vertical extrapolation	5				Žagar, 2019
2019	e	Vertical extrapolation	Total vertical extrapolation	2.21			Twenty-year uncertainty, 10 projects	Breakey, 2019
2010	o	Vertical extrapolation	Total vertical extrapolation		2.3	3.3	Analyst comparison; "Extrapolation"	Walter, 2010
2010	o	Vertical extrapolation	Total vertical extrapolation	2			Analyst comparison; "Extrapolation"	McAloon, 2010
2014	o	Vertical extrapolation	Total vertical extrapolation	3	0	5		Istchenko, 2014

420

Table B7: List of other energy uncertainties outside of the IEC proposed framework (Table A2), and the values herein are necessary to generate Fig. 11.

Year	Est/Obs	Category	Avg (%)	Min (%)	Max (%)	Notes	Source
2013	e	External wake	1.6			Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Methodology	5			Energy calculation	Holtslag, 2013
2018	e	Methodology		1	3	Analyst uncertainty	Craig et al., 2018
2014	e	Power-curve measurement		4	10		Redouane, 2014
2002	o	Power-curve measurement		6	8		Friis Pedersen et al., 2002
2013	o	Power-curve measurement	3.5			Power curve test	Kassebaum, 2013
2015	o	Power-curve measurement	4.5				Kassebaum, 2015

425

Table B8: List of wind speed uncertainties, which are used for Fig. 12. Differ from other tables in Appendix B, this table record values in percentage of wind speed.

Year	Est/Obs	Category	Avg (%)	Min (%)	Max (%)	Notes	Source
2018	e	Blockage		1.9	3.4		Bleeg et al., 2018
2011	e	Distortion		0	2	Nonideal flow; include tower, boom, other equipment	Hatlee, 2011
2014	e	Distortion		1.1	3.6	Include distortion of terrain and mounting.	Redouane, 2014
2010	e	Future variability		1	3	Future climate; WindPro 2.7	Nielsen et al., 2010
2011	e	Future variability		4	6		Comstock, 2011
2012	e	Future variability		1.4	2.2	Future wind resource	Brower, 2012
2011	e	Horizontal extrapolation		1	4		Comstock, 2011
2013	e	Horizontal extrapolation	5			Reference data	Holtslag, 2013
2013	e	Horizontal extrapolation	1			Lidar	Holtslag, 2013
2013	e	Horizontal extrapolation		0	5		Mortensen, 2013
2015	e	Horizontal extrapolation		0	2.2	Long-term extrapolation	Mortensen et al., 2015
2010	o	Horizontal extrapolation	1.9			Analyst comparison	Walter, 2010
1991	e	Interannual variability	6.1				Simon, 1991
2006	e	Interannual variability		8	12	Northern Europe	Pryor et al., 2006
2008	e	Interannual variability		2	7	Windiness	Johnson et al., 2008

2009	e	Interannual variability	6			Recommend in WindFarmer	Garrad Hassan and Partners Ltd, 2009
2010	e	Interannual variability	3.5				Hendrickson, 2010
2010	e	Interannual variability	6			One-year uncertainty; WindPro 2.7	Nielsen et al., 2010
2010	e	Interannual variability	1.3			Twenty-year uncertainty; WindPro 2.7	Nielsen et al., 2010
2011	e	Interannual variability		4	6	United States	Rogers, 2011
2013	e	Interannual variability		2	6	Variability	Mortensen, 2013
2014	e	Interannual variability		2	4		Brower, 2014
2014	e	Interannual variability		3.5	6		Geer, 2014
2017	e	Interannual variability	5				Perry, 2017
2018	e	Interannual variability	2.1			37 years in contiguous United States	Lee et al., 2018
2019	e	Interannual variability		1.4	5.4		Gkarakis and Orfanaki, 2019
2014	o	Interannual variability		5.7	8.8		Istchenko, 2014
2018	e	Intermonthly variability	10.2			37 years in contiguous United States	Lee et al., 2018
2014	o	Intermonthly variability		19	24		Istchenko, 2014
2010	e	Long-term wind speed	3	2	4		Clive, 2010
2011	e	Long-term wind speed		3.7	4.8	Combine nearby weather station, airport, modeled data	Rogers, 2011

2011	e	Long-term wind speed		1.5	4		Comstock, 2011
2012	e	Long-term wind speed		1	2		Brown, 2012
2012	e	Long-term wind speed		1.6	4		Brower, 2012
2013	e	Long-term wind speed	2			Reference data; long-term representation	Holtslag, 2013
2014	e	Long-term wind speed		0	11	Uncertainty is smaller with longer years	Hamel, 2014
2014	e	Long-term wind speed	15				Hendrickson, 2014
2014	e	Long-term wind speed		1.1	6.1	From data analysis and measure-correlate-predict	Redouane, 2014
2006	o	Long-term wind speed	3.5		20	1000 hours of data	Rogers et al., 2006
2006	o	Long-term wind speed		3	6	9000 hours of data at offshore wind farms	Rogers, 2011
2006	o	Long-term wind speed		2	8	9000 hours of data at offshore wind farms	Rogers, 2011
2010	e	Measure-correlate-predict		1	3	WindPro 2.7	Nielsen et al., 2010
2012	e	Measure-correlate-predict	2.5	1	3	Long-term wind speed and correction	Mortensen et al., 2012
2013	e	Measure-correlate-predict	4			Lidar; long-term representation and correlation	Holtslag, 2013
2014	e	Measure-correlate-predict		0.7	6.4		Redouane, 2014
2010	e	Plant performance	3	1	4	Energy loss model	Clive, 2010
2010	e	Terrain data and resolution	3		4		Clive, 2010

2012	e	Terrain data and resolution			1.5		Brown, 2012
2010	e	Total wind speed	7	3	10		Clive, 2010
2012	e	Total wind speed		3	13		Brower, 2012
2013	e	Total wind speed	8.9			Reference data	Holtslag, 2013
2013	e	Total wind speed	5.1			Lidar	Holtslag, 2013
2015	e	Total wind speed		3	10		Brower et al., 2015
2014	o	Total wind speed		9	16	Nine locations	Redouane, 2014
2011	e	Vertical extrapolation		1	3		Comstock, 2011
2011	e	Vertical extrapolation		0	4		Faghani, 2011
2012	e	Vertical extrapolation		0	6.3		Brower, 2012
2013	e	Vertical extrapolation	5			Reference data	Holtslag, 2013
2013	e	Vertical extrapolation	0			Lidar	Holtslag, 2013
2013	e	Vertical extrapolation		0	5		Mortensen, 2013
2014	e	Vertical extrapolation		0	2		Redouane, 2014
2015	e	Vertical extrapolation		0.7	3.6		Mortensen et al., 2015
2016	e	Vertical extrapolation		2	6	Nonforested	Kelly, 2016
2017	e	Vertical extrapolation	1			Industry accepted; 1% per 10 m	Langreder, 2017
2010	o	Vertical extrapolation	1.9			Analyst comparison	Walter, 2010
2012	e	Wake effect			2		Brown, 2012

2014	e	Wake effect	16			Actuator disk and computational fluid dynamics models	Abiven et al., 2014
2014	e	Wake effect	0			Park and Ainslie models	Abiven et al., 2014
2019	e	Wake effect		6			Slinger et al., 2019
2007	e	Wind speed measurement	2.4				Breakey, 2019
2010	e	Wind speed measurement	3	1	4		Clive, 2010
2010	e	Wind speed measurement	2			WindPro 2.7	Nielsen et al., 2010
2011	e	Wind speed measurement		1	2.5	Ideal flow; calibration	Hatlee, 2011
2011	e	Wind speed measurement		1.5	5	Nonideal flow; total measurement	Hatlee, 2011
2011	e	Wind speed measurement	3.1				Rogers, 2011
2011	e	Wind speed measurement		1.5	3.5		Comstock, 2011
2011	e	Wind speed measurement		2	3		Faghani, 2011
2012	e	Wind speed measurement		0.5	1.5		Brown, 2012
2012	e	Wind speed measurement		1	2.5	Single anemometer	Brower, 2012
2013	e	Wind speed measurement	5			Reference data; wind statistics	Holtslag, 2013
2013	e	Wind speed measurement	3			Lidar; wind statistics	Holtslag, 2013
2013	e	Wind speed measurement		2	5	Wind measurement	Mortensen, 2013
2014	e	Wind speed measurement		0	5	Measurement campaign	Redouane, 2014

2015	e	Wind speed measurement	2			Anemometer and calibration	Geer, 2015
2015	e	Wind speed measurement	2			Two met masts	Brower et al., 2015
2016	e	Wind speed measurement	2				Kelly, 2016
2017	e	Wind speed measurement	0.8				Breakey, 2019
2019	e	Wind speed measurement	1.58	1.54	1.86	Range of standard, recommended, and lidar methods	Medley and Smith, 2019
2019	e	Wind speed measurement	4			Lidar calibration	Slater, 2019
2019	e	Wind speed measurement		2.23	2.68	Range from using computational fluid dynamics models or not	Crease, 2019
2019	e	Wind speed measurement		6	8		Keck et al., 2019
2013	o	Wind speed measurement		2	3	Lidar on flat terrain	Albers et al., 2013
2015	o	Wind speed measurement		1.1	2.2	Anemometer	Clark, 2015
2016	o	Wind speed measurement		1	2	Anemometer; industry accepted	Smith et al., 2016
2009	e	Wind speed modeling	7				VanLuvanee et al., 2009
2010	e	Wind speed modeling	4	2	6	Flow model accuracy	Clive, 2010
2010	e	Wind speed modeling		3	10		Brower et al., 2010
2011	e	Wind speed modeling		2	5		Faghani, 2011

2012	e	Wind speed modeling		1	5.5		Brown, 2012
2012	e	Wind speed modeling		2	10	Flow model	Brower, 2012
2013	e	Wind speed modeling		1.7	6.9		Abiven et al., 2013
2015	e	Wind speed modeling	10		12		Brower et al., 2015
2017	e	Wind speed modeling		3	5	WAsP	Jog, 2017
2017	e	Wind speed modeling		0.9	2	Ensemble model	Jog, 2017
2017	e	Wind speed modeling	2.9	1.4	7.6		Poulos, 2017
2019	e	Wind speed modeling	2.5			2.5% per km of extrapolation distance in WAsP; industry-recommended assumption	Zhang et al., 2019
2015	o	Wind speed modeling		4	10		Brower et al., 2015
2016	o	Wind speed modeling	1.2		4.3	Weighted absolute total error in WindFarmer	Neubert, 2016

430

Appendix C

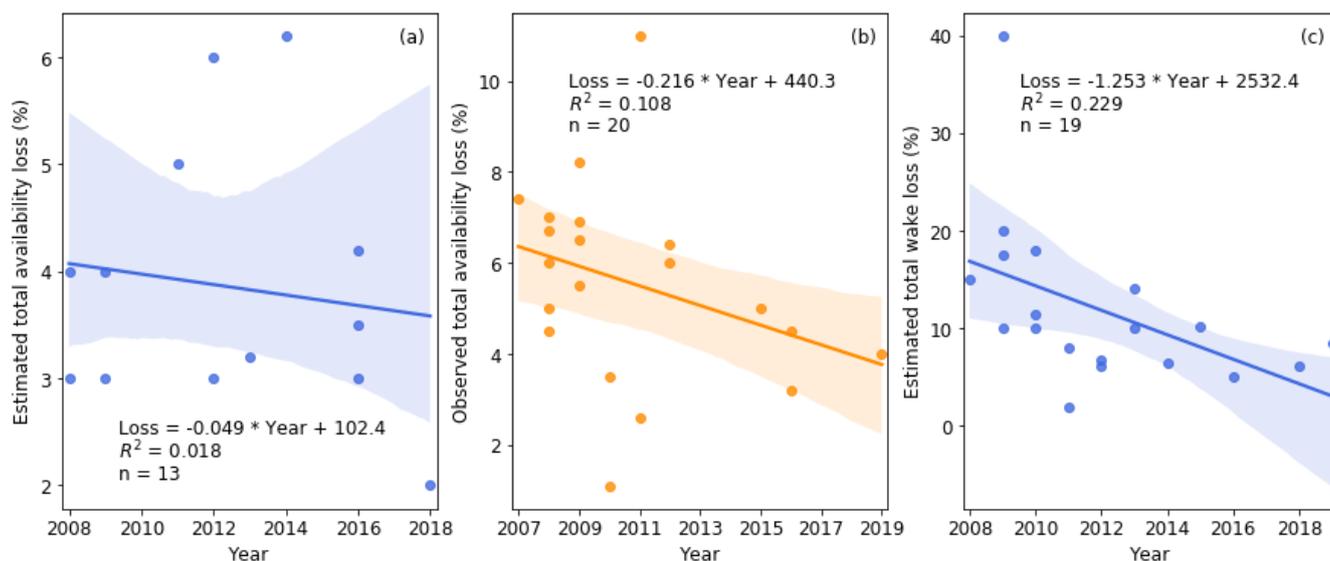



Figure C1: As in Fig. 8, the trend in energy-production loss: (a) estimated total curtailment loss, (b) observed total availability loss, and (c) estimated total wake loss. Note that the ranges of the horizontal and vertical axes differ in each panel.

435

Author contribution

JCYL performed the literature search, conducted the data analysis, and prepared the manuscript. MJF provided guidance and reviewed the manuscript.

Competing interests

440   The authors indicate no conflict of interest.

Acknowledgments

This work was authored by the National Renewable Energy Laboratory (NREL), operated by the Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE), under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies

445   Office. The views expressed in the article do not necessarily represent the views of the DOE or U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

The authors would like to thank our external collaborators including Matthew Breakey, Matthew Hendrickson, Kisha

450   James, Cory Jog, and the American Wind Energy Association, as well as our colleagues at NREL including Sheri Anstedt, Derek Berry, Rachel Eck, Julie Lundquist, Julian Quick, David Snowberg, Paul Veers and the NREL library.

References

Abascal, A., Herrero, M., Torrijos, M., Dumont, J., Álvarez, M. and Casso, P.: An approach for estimating energy losses due

455   to ice in pre-construction energy assessments, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Abiven, C., Brady, O. and Triki, I.: Mesoscale and CFD Coupling for Wind Resource Assessment, in AWEA Wind Resource and Project Energy Assessment Workshop 2013, AWEA, Las Vegas, NV., 2013.

Abiven, C., Parisse, A., Watson, G. and Brady, O.: CFD Wake Modeling: Where Do We Stand?, in AWEA Wind Resource and Project Energy Assessment Workshop 2014, AWEA, Orlando, FL., 2014.

460   Albers, A., Klug, H. and Westermann, D.: Outdoor Comparison of Cup Anemometers., 2000.

Albers, A., Franke, K., Wagner, R., Courtney, M. and Boquet, M.: Ground-based remote sensor uncertainty – a case study for a wind lidar., 2013.

Anderson, M.: Seasonality, Stability and MCP, in AWEA Wind Resource and Project Energy Assessment Workshop 2008, AWEA, Portland, OR., 2008.

465   Apple, J.: Wind Farm Power Curves: Guidelines for New Applications, in AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

AWS Truepower: Closing The Gap On Plant Underperformance: A Review and Calibration of AWS Truepower's Energy Estimation Methods., 2009.

AWS Truepower: AWS Truepower Loss and Uncertainty Methods, Albany, NY. [online] Available from:

470   https://www.awstruepower.com/assets/AWS-Truepower-Loss-and-Uncertainty-Memorandum-5-Jun-2014.pdf (Accessed 29 August 2017), 2014.

Balfrey, D.: Data Processing, in AWEA Wind Resource and Project Energy Assessment Workshop 2010, AWEA, Oklahoma City, OK., 2010.

Barthelmie, R. J., Murray, F. and Pryor, S. C.: The economic benefit of short-term forecasting for wind energy in the UK

475   electricity market, Energy Policy, 36(5), 1687–1696, doi:10.1016/J.ENPOL.2008.01.027, 2008.

Baughman, E.: Error Distributions, Tails, and Outliers, in AWEA Wind Resource and Project Energy Assessment Workshop 2016, AWEA, Minneapolis, MN., 2016.

Beaucage, P., Kramak, B., Robinson, N. and Brower, M. C.: Modeling the dynamic behavior of wind farm power generation: Building upon SCADA system analysis, in AWEA Wind Resource and Project Energy Assessment Workshop 2016, AWEA,

480   Minneapolis, MN., 2016.

Bernadett, D., Brower, M., Van Kempen, S., Wilson, W. and Kramak, B.: 2012 Backcast Study: Verifying AWS Truepower's Energy and Uncertainty Estimates, Albany, NY., 2012.

Bernadett, D., Brower, M. and Ziesler, C.: Loss Adjustment Refinement, in AWEA Wind Resource and Project Energy Assessment Workshop 2016, AWEA, Minneapolis, MN., 2016.

485   Bird, L., Cochran, J. and Wang, X.: Wind and Solar Energy Curtailment: Experience and Practices in the United States., 2014.

Bleeg, J.: Accounting for Blockage Effects in Energy Production Assessments, in AWEA Wind Resource and Project Energy Assessment Workshop 2018, AWEA, Austin, TX., 2018.

Bleeg, J., Purcell, M., Ruisi, R. and Traiger, E.: Wind Farm Blockage and the Consequences of Neglecting Its Impact on Energy Production, Energies, 11(6), 1609, doi:10.3390/en11061609, 2018.

490   Breakey, M.: An Armchair Meteorological Campaign Manager: A Retrospective Analysis, in AWEA Wind Resource and Project Energy Assessment Workshop 2019, AWEA, Renton, WA., 2019.

Brower, M.: What do you mean you're not sure? Concepts in uncertainty and risk management, in AWEA Wind Resource and Project Energy Assessment Workshop 2011, AWEA, Seattle, WA., 2011.

Brower, M. C.: Wind resource assessment : a practical guide to developing a wind project, Wiley., 2012.

495   Brower, M. C.: Measuring and Managing Uncertainty, in AWEA Wind Resource and Project Energy Assessment Workshop 2014, AWEA, Orlando, FL., 2014.

Brower, M. C.: State of the P50, in AWEA WINDPOWER 2017, AWEA, Anaheim, CA., 2017.

Brower, M. C. and Robinson, N. M.: Validation of the openWind Deep Array Wake Model (DAWM), in AWEA Wind Resource and Project Energy Assessment Workshop 2013, AWEA, Las Vegas, NV., 2013.

500   Brower, M. C., Robinson, N. M. and Hale, E.: Wind Flow Modeling Uncertainty: Quantification and Application to Monitoring Strategies and Project Design, Albany, NY., 2010.

Brower, M. C., Bernadett, D., Van Kempen, S., Wilson, W. and Kramak, B.: Actual vs. Predicted Plant Production: The Role of Turbine Performance, in AWEA Wind Resource and Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

505   Brower, M. C., Robinson, N. M. and Vila, S.: Wind Flow Modeling Uncertainty: Theory and Application to Monitoring Strategies and Project Design, Albany, NY., 2015.

Brown, G.: Wakes: Ten Rows and Beyond, a Cautionary Tale!, in AWEA Wind Resource and Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

Byrkjedal, Ø., Hansson, J. and van der Velde, H.: Development of operational forecasting for icing and wind power at cold
510   climate sites, in IWAIS 2015: 16th International Workshop on Atmospheric Icing of Structures, p. 4, IWAIS, Uppsala, Sweden., 2015.

Clark, S.: Wind Tunnel Comparison of Anemometer Calibration, in AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

Clifton, A., Smith, A. and Fields, M.: Wind Plant Preconstruction Energy Estimates: Current Practice and Opportunities.
515   [online] Available from: http://www.nrel.gov/docs/fy16osti/64735.pdf (Accessed 19 July 2017), 2016.

Clive, P.: Wind Farm Performance, in AWEA Wind Resource and Project Energy Assessment Workshop 2010, AWEA, Oklahoma City, OK., 2010.

Colmenar-Santos, A., Campíez-Romero, S., Enríquez-Garcia, L., Pérez-Molina, C., Colmenar-Santos, A., Campíez-Romero, S., Enríquez-Garcia, L. A. and Pérez-Molina, C.: Simplified Analysis of the Electric Power Losses for On-Shore Wind Farms

520   Considering Weibull Distribution Parameters, Energies, 7(11), 6856–6885, doi:10.3390/en7116856, 2014.

Comstock, K.: Uncertainty and Risk Management in Wind Resource Assessment, in AWEA Wind Resource and Project Energy Assessment Workshop 2011, AWEA, Seattle, WA., 2011.

Comstock, K.: Identifying Pitfalls and Quantifying Uncertainties in Operating Project Re-Evaluation, in AWEA Wind Resource and Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

525   Conroy, N., Deane, J. P. and Ó Gallachóir, B. P.: Wind turbine availability: Should it be time or energy based? – A case study in Ireland, Renew. Energy, 36(11), 2967–2971, doi:10.1016/J.RENENE.2011.03.044, 2011.

Cox, S.: Validation of 25 offshore pre-construction energy forecasts against real operational wind farm data, in AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

Craig, A., Optis, M., Fields, M. J. and Moriarty, P.: Uncertainty quantification in the analyses of operational wind power plant

530   performance, J. Phys. Conf. Ser., 1037(5), 052021, doi:10.1088/1742-6596/1037/5/052021, 2018.

Crease, J.: CFD Modelling of Mast Effects on Anemometer Readings, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Crescenti, G. H., Poulos, G. S. and Bosche, J.: Valuable Lessons From Outliers In A Wind Energy Resource Assessment Benchmark Study, in AWEA Wind Resource and Project Energy Assessment Workshop 2019, AWEA, Renton, WA., 2019.

535   Cushman, A.: Industry Survey of Wind Farm Availability, in AWEA Wind Resource and Project Energy Assessment Workshop 2009, AWEA, Minneapolis, MN., 2009.

Dahlberg, J.-Å.: Assessment of the Lillgrund Windfarm., 2009.

Derrick, A.: Uncertainty: The Classical Approach, in AWEA Wind Resource and Project Energy Assessment Workshop 2009, AWEA, Minneapolis, MN., 2009.

540   Drees, H. M. and Weiss, D. J.: Compilation of Power Performance Test Results, in AWEA Wind Resource and Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

Drunsic, M. W.: Actual vs. Predicted Wind Project Performance: Is the Industry Closing the Gap?, in AWEA Wind Resource and Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

Dutrieux, A.: How long should be long term to reduce uncertainty on annual wind energy assessment, in WindEurope 2019,

545   WindEurope, Bilbao, Spain., 2019.

Ehrmann, R. S., Wilcox, B., White, E. B. and Maniaci, D. C.: Effect of Surface Roughness on Wind Turbine Performance, Albuquerque, NM., 2017.

Elkinton, M.: Strengthening Wake Models: DNV GL Validations & Advancements, in AWEA Wind Resource and Project Energy Assessment Workshop 2013, AWEA, Las Vegas, NV., 2013.

550   Elkinton, M.: Current view of P50 estimate accuracy based on validation efforts, in AWEA WINDPOWER 2017, AWEA, Anaheim, CA., 2017.

EMD International A/S: WindPRO 2.4., 2004.

Faghani, D.: Measurement Uncertainty of Ground-Based Remote Sensing, in AWEA Wind Resource and Project Energy

Assessment Workshop 2011, AWEA, Seattle, WA., 2011.

555   Faghani, D., Desrosiers, E., Aït-Driss, B. and Poulin, M.: Use of Remote Sensing in Addressing Bias & Uncertainty in Wind Measurements, in AWEA Wind Resource and Project Energy Assessment Workshop 2008, AWEA, Portland, OR., 2008.

Faubel, A.: Digitalisation: Creating Value in O&M, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Filippelli, M., Bernadett, D., Sloka, L., Mazoyer, P. and Fleming, A.: Concurrent Power Performance Measurements, in AWEA Wind Resource and Project Energy Assessment Workshop 2017, AWEA, Snowbird, UT., 2017.

560   Filippelli, M., Sherwin, B. and Fields, J.: IEC 61400-15 Working Group Update, in AWEA Wind Resource and Project Energy Assessment Workshop 2018, AWEA, Austin, TX., 2018.

Friis Pedersen, T., Gjerding, S., Enevoldsen, P., Hansen, J. K. and Jørgensen, H. K.: Wind turbine power performance verification in complex terrain and wind farms, Denmark. [online] Available from: 1330(EN), 2002.

Garrad Hassan and Partners Ltd: GH WindFarmer Theory Manual, Bristol, England., 2009.

565   Geer, T.: Towards a more realistic uncertainty model, in AWEA Wind Resource and Project Energy Assessment Workshop 2014, AWEA, Orlando, FL., 2014.

Geer, T.: Identifying production risk in preconstruction assessments: Can we do it?, in AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

Germer, S. and Kleidon, A.: Have wind turbines in Germany generated electricity as would be expected from the prevailing

570   wind conditions in 2000-2014?, edited by P. Leahy, PLoS One, 14(2), e0211028, doi:10.1371/journal.pone.0211028, 2019.

Gillenwater, D., Masson, C. and Perron, J.: Wind Turbine Performance During Icing Events, in 46th AIAA Aerospace Sciences Meeting and Exhibit, American Institute of Aeronautics and Astronautics, Reston, Virigina., 2008.

Gkarakis, K. and Orfanaki, G.: Historical wind speed trends and impact on long-term adjustment and interannual variability in Cyprus, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

575   Graves, A., Harman, K., Wilkinson, M. and Walker, R.: Understanding Availiability Trends of Operating Wind Farms, in AWEA WINDPOWER 2008, AWEA, Houston, TX., 2008.

Halberg, E.: A Monetary Comparison of Remote Sensing and Tall Towers, in AWEA Wind Resource and Project Energy Assessment Workshop 2017, AWEA, Snowbird, UT., 2017.

Halberg, E. and Breakey, M.: On-Shore Wake Validation Study: Wake Analysis Based on Production Data, in AWEA Wind

580   Resource and Project Energy Assessment Workshop 2013, AWEA, Las Vegas, NV., 2013.

Hale, E.: External Perspectives: Estimate Accuracy and Plant Operations, in AWEA Wind Resource and Project Energy Assessment Workshop 2017, AWEA, Snowbird, UT., 2017.

Hamel, M.: Estimating 50-yr Extreme Wind Speeds from Short Datasets, in AWEA Wind Resource and Project Energy Assessment Workshop 2014, AWEA, Orlando, FL., 2014.

585   Hamilton, S. D., Millstein, D., Bolinger, M., Wiser, R. and Jeong, S.: How Does Wind Project Performance Change with Age in the United States?, Joule, doi:10.1016/j.joule.2020.04.005, 2020.

Hasager, C., Bech, J. I., Bak, C., Vejen, F., Madsen, M. B., Bayar, M., Skrzypinski, W. R., Kusano, Y., Saldern, M., Tilg, A.-

M., Fæster, S. and Johansen, N. F.-J.: Solution to minimize leading edge erosion on turbine blades, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

590 Hatlee, S.: Measurement Uncertainty in Wind Resource Asessment, in AWEA Wind Resource and Project Energy Assessment Workshop 2011, AWEA, Seattle, WA., 2011.

Hatlee, S.: Operational Performance vs. Precon Estimate, in AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

Healer, B.: Liquid Power Markets 201, in AWEA Wind Resource and Project Energy Assessment Workshop 2018, AWEA,

595 Austin, TX., 2018.

Hendrickson, M.: 2009 AWEA Wind Resource & Project Energy Assessment Workshop - Introduction, in AWEA Wind Resource and Project Energy Assessment Workshop 2009, AWEA, Minneapolis, MN., 2009.

Hendrickson, M.: Extending Data – by whatever means necessary, in AWEA Wind Resource and Project Energy Assessment Workshop 2010, AWEA, Oklahoma City, OK., 2010.

600 Hendrickson, M.: Industry Survey of Wind Energy Assessment Techniques, in AWEA Wind Resource and Project Energy Assessment Workshop 2011, AWEA, Seattle, WA., 2011.

Hendrickson, M.: Extreme Winds in the Suitability Context: Should we be Concerned?, in AWEA Wind Resource and Project Energy Assessment Workshop 2014, AWEA, Orlando, FL., 2014.

Hendrickson, M.: P50 Bias Update: Are we there yet??, in AWEA Wind Resource and Project Energy Assessment Workshop

605 2019, AWEA, Renton, WA., 2019.

Hill, N., Pullinger, D., Zhang, M. and Crutchley, T.: Validation of windfarm downtime modelling and impact on grid-constrained projects, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Holtslag, E.: Improved Bankability: The Ecofys position on LiDAR use., 2013.

Horn, B.: Achieving Measurable Financial Results in Operational Assessments, in AWEA Wind Resource and Project Energy

610 Assessment Workshop 2009, AWEA, Minneapolis, MN., 2009.

Istchenko, R.: WRA Uncertainty Validation, in AWEA Wind Resource and Project Energy Assessment Workshop 2014, AWEA, Orlando, FL., 2014.

Istchenko, R.: Re-examining Uncertainty and Bias, in AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

615 Jaynes, D.: The Vestas Operating Fleet: Real-World Experience in Wind Turbine Siting and Power Curve Verification, in AWEA Wind Resource and Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

Jog, C.: Benchmark: Wind flow, in AWEA Wind Resource and Project Energy Assessment Workshop 2017, AWEA, Snowbird, UT., 2017.

Johnson, C.: Actual vs. Predicted performance – Validating pre construction energy estimates, in AWEA Wind Resource and

620 Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

Johnson, C., White, E. and Jones, S.: Summary of Actual vs. Predicted Wind Farm Performance: Recap of WINDPOWER

2008, in AWEA Wind Resource and Project Energy Assessment Workshop 2008, AWEA, Portland, OR., 2008.

Johnson, J.: Typical Availability Losses and Categorization: Observations from an Operating Project Portfolio, in AWEA Wind Resource and Project Energy Assessment Workshop 2011, AWEA, Seattle, WA., 2011.

625 Jones, S.: Project Underperformance: 2008 Update, in AWEA WINDPOWER 2008, AWEA, Houston, TX., 2008.

Kassebaum, J.: Power Curve Testing with Remote Sensing Devices, in AWEA Wind Resource and Project Energy Assessment Workshop 2013, AWEA, Las Vegas, NV., 2013.

Kassebaum, J. L.: What p-level is your p-ower curve?, in AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

630 Keck, R.-E., Sondell, N. and Håkansson, M.: Validation of a fully numerical approach for early stage wind resource assessment in absence of on-site measurements, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Kelly, M.: Uncertainty in vertical extrapolation of wind statistics: shear-exponent and WAsP/EWA methods., 2016.

Kim, K. and Shin, P.: Analysis on the Parameters Under the Power Measurement Uncertainty for a Small Wind Turbine, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

635 Kline, J.: Wind Farm Wake Analysis: Summary of Past & Current Work, in AWEA Wind Resource and Project Energy Assessment Workshop 2013, AWEA, Las Vegas, NV., 2013.

Kline, J.: Wake Model Validation Test, in AWEA Wind Resource and Project Energy Assessment Workshop 2016, AWEA, Minneapolis, MN., 2016.

Kline, J.: Detecting and Correcting for Bias in Long-Term Wind Speed Estimates, in AWEA Wind Resource and Project
640 Energy Assessment Workshop 2019, AWEA, Renton, WA., 2019.

Lackner, M. A., Rogers, A. L. and Manwell, J. F.: Uncertainty Analysis in MCP-Based Wind Resource Assessment and Energy Production Estimation, J. Sol. Energy Eng., 130(3), 31006–31010, doi:10.1115/1.2931499, 2008.

Langel, C. M., Chow, R., Hurley, O. F., van Dam, C. P., Ehrmann, R. S., White, E. B. and Maniaci, D.: Analysis of the Impact of Leading Edge Surface Degradation on Wind Turbine Performance, in AIAA SciTech 33rd Wind Energy Symposium, p. 13,
645 American Institute of Aeronautics and Astronautics, Kissimmee, FL., 2015.

Langreder, W.: Uncertainty of Vertical Wind Speed Extrapolation, in AWEA Wind Resource and Project Energy Assessment Workshop 2017, AWEA, Snowbird, UT., 2017.

Latoufis, K., Riziotis, V., Voutsinas, S. and Hatziargyriou, N.: Effects of leading edge erosion on the power performance and acoustic noise emissions of locally manufactured small wind turbines blades, in WindEurope 2019, WindEurope, Bilbao,
650 Spain., 2019.

Lee, J.: Banter on Blockage, in AWEA Wind Resource and Project Energy Assessment Workshop 2019, AWEA, Renton, WA., 2019.

Lee, J. C. Y., Fields, M. J. and Lundquist, J. K.: Assessing variability of wind speed: comparison and validation of 27 methodologies, Wind Energy Sci., 3(2), 845–868, doi:10.5194/wes-3-845-2018, 2018.

655 Liew, J., Urbán, A. M., Dellwick, E. and Larsen, G. C.: The effect of wake position and yaw misalignment on power loss in

wind turbines, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Lunacek, M., Jason Fields, M., Craig, A., Lee, J. C. Y., Meissner, J., Philips, C., Sheng, S. and King, R.: Understanding Biases in Pre-Construction Estimates, J. Phys. Conf. Ser., 1037(6), 062009, doi:10.1088/1742-6596/1037/6/062009, 2018.

Maniaci, D. C., White, E. B., Wilcox, B., Langel, C. M., van Dam, C. P. and Paquette, J. A.: Experimental Measurement and
660 CFD Model Development of Thick Wind Turbine Airfoils with Leading Edge Erosion, J. Phys. Conf. Ser., 753(2), 022013, doi:10.1088/1742-6596/753/2/022013, 2016.

McAloon, C.: Wind Assessment: Raw Data to Hub Height Winds, in AWEA Wind Resource and Project Energy Assessment Workshop 2010, AWEA, Oklahoma City, OK., 2010.

McCaa, J.: Wake modeling at 3TIER, in AWEA Wind Resource and Project Energy Assessment Workshop 2013, AWEA,
665 Las Vegas, NV., 2013.

Medley, J. and Smith, M.: The "Why?", "What?" and "How?" of lidar type classification, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Mibus, M.: Conservatism in Shadow Flicker Assessment and Wind Farm Design, in AWEA Wind Resource and Project Energy Assessment Workshop 2018, AWEA, Austin, TX., 2018.

670 Mönnich, K., Horodyvskyy, S. and Krüger, F.: Comparison of Pre-Construction Energy Yield Assessments and Operating Wind Farm's Energy Yields, Oldenburg, Germany., 2016.

Mortensen, N. G.: Planning and Development of Wind Farms: Wind Resource Assessment and Siting, Roskilde, Denmark., 2013.

Mortensen, N. G. and Ejsing Jørgensen, H.: Comparative Resource and Energy Yield Assessment Procedures (CREYAP) Pt.
675 II, in EWEA Technology Workshop: Resource Assessment 2013, Technical Universtiy of Denmark, Dublin, Ireland., 2013.

Mortensen, N. G., Ejsing Jørgensen, H., Anderson, M. and Hutton, K.-A.: Comparison of resource and energy yield assessment procedures, in Proceedings of EWEA 2012 - European Wind Energy Conference & Exhibition European Wind Energy Association (EWEA), p. 10, Technical Universtiy of Denmark., 2012.

Mortensen, N. G., Nielsen, M. and Ejsing Jørgensen, H.: Comparison of Resource and Energy Yield Assessment Procedures
680 2011-2015: What have we learned and what needs to be done?, in Proceedings of the European Wind Energy Association Annual Event and Exhibition 2015, European Wind Energy Association., 2015a.

Mortensen, N. G., Nielsen, M. and Ejsing Jørgensen, H.: EWEA CREYAP benchmark exercises: summary for offshore wind farm cases, Technical Universtiy of Denmark., 2015b.

Murphy, O.: Blade Erosion Performance Impact, in 21st Meeting of the Power Curve Working Group, PCWG, Glasgow,
685 Scotland., 2016.

Neubert, A.: WindFarmer White Paper., 2016.

Nielsen, P., Villadsen, J., Kobberup, J., Madsen, P., Jacobsen, T., Thøgersen, M. L., Sørensen, M. V., Sørensen, T., Svenningsen, L., Motta, M., Bredelle, K., Funk, R., Chun, S. and Ritter, P.: WindPRO 2.7 User Guide, 3rd Edition, Aalborg, Denmark., 2010.

690   Olauson, J., Edström, P. and Rydén, J.: Wind turbine performance decline in Sweden, Wind Energy, 20(12), 2049–2053, doi:10.1002/we.2132, 2017.

Osler, E.: Yaw Error Detection and Mitigation with Nacelle Mounted Lidar, in AWEA Wind Resource and Project Energy Assessment Workshop 2013, AWEA, Las Vegas, NV., 2013.

Ostridge, C.: Understanding & Predicting Turbine Performance, in AWEA Wind Resource and Project Energy Assessment
695   Workshop 2014, AWEA, Orlando, FL., 2014.

Ostridge, C.: Using Pattern of Production to Validate Wind Flow, Wakes, and Uncertainty: Using Pattern of Production to Validate Wind Flow, Wakes, and Uncertainty, in AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

Ostridge, C.: Wind Power Project Performance White Paper 2017 Update, Seattle, WA., 2017.

700   Ostridge, C. and Rodney, M.: Modeling Wind Farm Energy, Revenue and Uncertainty on a Time Series Basis, in AWEA Wind Resource and Project Energy Assessment Workshop 2016, AWEA, Minneapolis, MN., 2016.

Papadopoulos, I.: DNV GL Energy Production Assessment Validation 2019, Bristol, England., 2019.

Pedersen, H. S. and Langreder, W.: Hack the Error Codes of a Wind Turbine, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

705   Perry, A.: Cross Validation of Operational Energy Assessments, in AWEA Wind Resource and Project Energy Assessment Workshop 2017, AWEA, Snowbird, UT., 2017.

Peyre, N.: How can drones improve topography inspections, terrain modelling and energy yield assessment?, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Poulos, G. S.: Complex Terrain Mesoscale Wind Flow Modeling: Successes, Failures and Practical Advice, in AWEA Wind
710   Resource and Project Energy Assessment Workshop 2017, AWEA, Snowbird, UT., 2017.

Pram, M.: Analysis of Vestas Turbine Performance, in AWEA Wind Resource and Project Energy Assessment Workshop 2018, AWEA, Austin, TX., 2018.

Pryor, S. C., Barthelmie, R. J. and Schoof, J. T.: Inter-annual variability of wind indices across Europe, Wind Energy, 9(1–2), 27–38, doi:10.1002/we.178, 2006.

715   Pullinger, D., Ali, A., Zhang, M., Hill, M. and Crutchley, T.: Improving accuracy of wind resource assessment through feedback loops of operational performance data: a South African case study, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Randall, G.: Energy Assessment Uncertainty Analysis, in AWEA Wind Resource and Project Energy Assessment Workshop 2009, AWEA, Minneapolis, MN., 2009.

720   Redouane, A.: Analysis of pre- and post construction wind farm energy yields with focus on uncertainties, Universität Kassel., 2014.

Rezzoug, M.: Innovative system for performance optimization: Independent data to increase AEP and preserve turbine lifetime, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Rindeskär, E.: Modelling of icing for wind farms in cold climate: A comparison between measured and modelled data for
725   reproducing and predicting ice accretion, Examensarbete vid Institutionen för geovetenskaper. [online] Available from:
urn:nbn:se:uu:diva-133381 (Accessed 5 December 2019), 2010.

Robinson, N.: Blockage Effect Update, in AWEA Wind Resource and Project Energy Assessment Workshop 2019, AWEA,
Renton, WA., 2019.

Rogers, A. L., Rogers, J. W. and Manwell, J. F.: Uncertainties in Results of Measure-Correlate-Predict Analyses, in European
730   Wind Energy Conference 2006, p. 10., 2006.

Rogers, T.: Effective Utilization of Remote Sensing, in AWEA Wind Resource and Project Energy Assessment Workshop
2010, AWEA, Oklahoma City, OK., 2010.

Rogers, T.: Estimating Long-Term Wind Speeds, in AWEA Wind Resource and Project Energy Assessment Workshop 2011,
AWEA, Seattle, WA., 2011.

735   Sareen, A., Sapre, C. A. and Selig, M. S.: Effects of leading edge erosion on wind turbine blade performance, Wind Energy,
17(10), 1531–1542, doi:10.1002/we.1649, 2014.

Schramm, M., Rahimi, H., Stoevesandt, B. and Tangager, K.: The Influence of Eroded Blades on Wind Turbine Performance
Using Numerical Simulations, Energies, 10(9), 1420, doi:10.3390/en10091420, 2017.

Shihavuddin, A., Chen, X., Fedorov, V., Nymark Christensen, A., Andre Brogaard Riis, N., Branner, K., Bjorholm Dahl, A.
740   and Reinhold Paulsen, R.: Wind Turbine Surface Damage Detection by Deep Learning Aided Drone Inspection Analysis,
Energies, 12(4), 676, doi:10.3390/en12040676, 2019.

Sieg, C.: Validation Through Variation: Using Pattern of Production to Validate Wind Flow, Wakes, and Uncertainty, in
AWEA Wind Resource and Project Energy Assessment Workshop 2015, AWEA, New Orleans, LA., 2015.

Simon, R. L.: Long-term Inter-annual Resource Variations in California, in Wind Power, pp. 236–243, Palm Springs,
745   California., 1991.

Slater, J.: Floating lidar uncertainty reduction for use on operational wind farms, in WindEurope 2019, WindEurope, Bilbao,
Spain., 2019.

Slinger, C. W., Harris, M., Ratti, C., Sivamani, G. and Smith, M.: Nacelle lidars for wake detection and waked inflow energy
loss estimation, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019a.

750   Slinger, C. W., Sivamani, G., Harris, M., Ratti, C. and Smith, M.: Wind yaw misalignment measurements and energy loss
projections from a multi-lidar instrumented wind farm, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019b.

Smith, M., Wylie, S., Woodward, A. and Harris, M.: Turning the Tides on Wind Measurements: The Use of Lidar to Verify
the Performance of A Meteorological Mast, in WindEurope 2016, WindEurope., 2016.

Spalding, T.: Wind Farm Blockage Modeling Summary, in AWEA Wind Resource and Project Energy Assessment Workshop
755   2019, AWEA, Renton, WA., 2019.

Spengemann, P. and Borget, V.: Review and analysis of wind farm operational data validation of the predicted energy yield
of wind farms based on real energy production data., 2008.

Spruce, C. J. and Turner, J. K.: Pitch Control for Eliminating Tower Vibration Events on Active Stall Wind Turbines, Surrey, United Kingdom., 2006.

760 Staffell, I. and Green, R.: How does wind farm performance decline with age?, Renew. Energy, 66, 775–786, doi:10.1016/j.renene.2013.10.041, 2014.

Standish, K., Rimmington, P., Laursen, J., Paulsen, H. and Nielsen, D.: Computational Predictions of Airfoil Roughness Sensitivity, in 48th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition, American Institute of Aeronautics and Astronautics, Reston, Virigina., 2010.

765 Stehly, T., Beiter, P., Heimiller, D. and Scott, G.: 2017 Cost of Wind Energy Review, Golden, CO., 2018.

Stoelinga, M.: A Multi-Project Validation Study of a Time Series-Based Wake Model, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Stoelinga, M. and Hendrickson, M.: A Validation Study of Vaisala's Wind Energy Assessment Methods., 2015.

Tchou, J.: Successfully Transitioning Pre-Construction Measurements to Post-Construction Operations, in AWEA Wind
770 Resource and Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

Tindal, A.: Wake modelling and validation, in AWEA Wind Resource and Project Energy Assessment Workshop 2009, AWEA, Minneapolis, MN., 2009.

Trudel, S.: Icing Losses Estimate Vadliation: From Development To Operation, in AWEA Wind Resource and Project Energy Assessment Workshop 2016, AWEA, Minneapolis, MN., 2016.

775 VanLuvanee, D., Rogers, T., Randall, G., Williamson, A. and Miller, T.: Comparison of WAsP, MS-Micro/3, CFD, NWP, and Analytical Methods for Estimating Site-Wide Wind Speeds, in AWEA Wind Resource and Project Energy Assessment Workshop 2009, AWEA, Minneapolis, MN., 2009.

Veers, P., Dykes, K., Lantz, E., Barth, S., Bottasso, C. L., Carlson, O., Clifton, A., Green, J., Green, P., Holttinen, H., Laird, D., Lehtomäki, V., Lundquist, J. K., Manwell, J., Marquis, M., Meneveau, C., Moriarty, P., Munduate, X., Muskulus, M.,
780 Naughton, J., Pao, L., Paquette, J., Peinke, J., Robertson, A., Sanz Rodrigo, J., Sempreviva, A. M., Smith, J. C., Tuohy, A. and Wiser, R.: Grand challenges in the science of wind energy, Science (80-.)., 366(6464), doi:10.1126/science.aau2027, 2019.

Walls, L.: A New Method to Assess Wind Farm Performance and Quantify Model Uncertainty, in AWEA Wind Resource and Project Energy Assessment Workshop 2018, AWEA, Austin, TX., 2018.

Walter, K.: Wind Assessment: Raw Data to Hub Height Winds, in AWEA Wind Resource and Project Energy Assessment
785 Workshop 2010, AWEA, Oklahoma City, OK., 2010.

Waskom, M., Botvinnik, O., Ostblom, J., Lukauskas, S., Hobson, P., MaozGelbart, Gemperline, D. C., Augspurger, T., Halchenko, Y., Cole, J. B., Warmenhoven, J., Ruiter, J. de, Pye, C., Hoyer, S., Vanderplas, J., Villalba, S., Kunter, G., Quintero, E., Bachant, P., Martin, M., Meyer, K., Swain, C., Miles, A., Brunner, T., O'Kane, D., Yarkoni, T., Williams, M. L. and Evans, C.: mwaskom/seaborn: v0.10.0, , doi:10.5281/zenodo.3629446, 2020.

790 White, E.: Continuing Work on Improving Plant Performance Estimates, in AWEA Wind Resource and Project Energy Assessment Workshop 2008, AWEA, Portland, OR., 2008a.

White, E.: Understanding and Closing the Gap on Plant Performance, in AWEA WINDPOWER 2008, AWEA, Houston, TX., 2008b.

White, E.: Operational Performance: Closing the Loop on Pre-Construction Estimates, in AWEA Wind Resource and Project
795 Energy Assessment Workshop 2009, AWEA, Minneapolis, MN., 2009.

Wilcox, B. J., White, E. B. and Maniaci, D. C.: Roughness Sensitivity Comparisons of Wind Turbine Blade Sections, Albuquerque, NM., 2017.

Wilkinson, L., Kay, E. and Lawless, M.: Braced for the Storm? Startling Insights into the Impact of Climate Change on Offshore Wind Operations, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

800 Winslow, G.: Secondary Losses: Using Operational Data to Evaluate Losses and Revisit Estimates, in AWEA Wind Resource and Project Energy Assessment Workshop 2012, AWEA, Pittsburgh, PA., 2012.

Wiser, R., Bolinger, M., Barbose, G., Barghouth, N., Hoen, B., Mills, A., Rand, J., Millstein, D., Jeong, S., Porter, K., Disanti, N. and Oteri, F.: 2018 Wind Technologies Market Report., 2019.

Wolfe, J.: Deep Array Wake Loss in Large Onshore Wind Farms (A Model Validation), in AWEA Wind Resource and Project
805 Energy Assessment Workshop 2010, AWEA, Oklahoma City, OK., 2010.

Žagar, M.: Wind Resource from an OEM perspective, in WindEurope 2019, WindEurope, Bilbao, Spain., 2019.

Zhang, M., Pullinger, D., Hill, N. and Crutchley, T.: Validating wind flow model uncertainty using operational data, in WindEurope 2019, AWEA, Renton, WA., 2019.