Wind Energ. Sci., 6, 311–365, 2021
https://doi.org/10.5194/wes-6-311-2021
© Author(s) 2021. This work is distributed under
the Creative Commons Attribution 4.0 License.

eawe european academy of wind energy
Open Access
WIND ENERGY SCIENCE

An overview of wind-energy-production prediction bias, losses, and uncertainties

Joseph C. Y. Lee and M. Jason Fields

National Wind Technology Center, National Renewable Energy Laboratory, Golden, CO 80401, USA

Correspondence: M. Jason Fields (jason.fields@nrel.gov)

Received: 2 June 2020 – Discussion started: 10 July 2020
Revised: 11 January 2021 – Accepted: 19 January 2021 – Published: 5 March 2021

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 reported average energy prediction bias is declining. Herein, we present a literature review 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 improvements in modeling and measurement techniques. Additionally, because the energy losses and uncertainties substantially influence the prediction error, we document and 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 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 of how the wind energy industry has been quantifying and reducing prediction errors, energy losses, and production uncertainties. Finally, for this work to be as reproducible as possible, we include all of the data used in the analysis in appendices to the article.

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 P_{50}, i.e., the AEP expected to be exceeded 50 % of the time. P_{50} values are often defined with timescales such as 1, 10, and 20 years. In this study, unless stated otherwise, we primarily discuss the 20-year P_{50}, which is the typical expected lifespan of utility-scale wind turbines. For years, leaders in the field have been discussing the difference between predicted P_{50} and 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) found an average of 3.5 % to 4.5 % P_{50} overprediction bias based on a subset of wind farms in the United States and accounting for curtailment (Lunacek et al., 2018).

Such P_{50} overestimation results in marked financial implications. Healer (2018) stated that if a wind project produces a certain percentage lower than the P_{50} on a 2-year rolling basis, the energy buyer, also known as the offtaker, may have the option to terminate the contract. For a 20-year contract, if a wind farm has a 1 % chance of such underproduction over a 2-year period, the probability of such an event taking place within the 18 2-year rolling periods is 16.5 %, as $100\,\% - (100\,\% - 1\,\%)^{18} = 16.5\,\%$ (Healer, 2018), assuming each 2-year rolling period is independent. Therefore, projects with substantial energy-production uncertainty experience the financial risk from modern energy contracting.

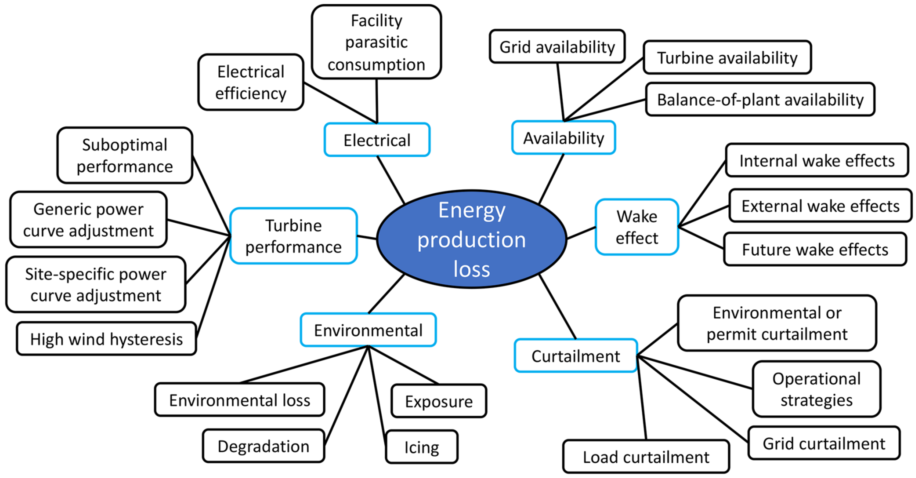

Figure 1. Mind map of energy-production loss, according to the IEC 61400-15 proposed framework. The blue and black rounded rectangles represent the categorial and subcategorical losses, respectively. Details of each loss category and subcategory are discussed in Table A1.

Random errors cause observations or model predictions to deviate from the truth and lead to uncertainty (Clifton et al., 2016), and uncertainty is quantified via probability (Wilks, 2011). In WRA, the P values surrounding P_{50} such as P_{90} and P_{95} characterize the uncertainty of the predicted AEP distribution. Such energy-estimate uncertainty depends on the cumulative certainty of the entire WRA process, from wind speed measurements to wind flow modeling (Clifton et al., 2016). When a sample of errors is Gaussian distributed, the standard deviation around the mean is typically used to represent the uncertainty of errors. Traditionally, the wind energy industry uses standard deviation, or σ, to represent uncertainty.

The WRA process governs the accuracy and precision of the P_{50}, and a key component in WRA constitutes the estimation of energy-production losses and uncertainties. Wind energy experts have been using different nomenclature 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 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 or exhaustive list of losses and uncertainties because some institution-specific practices may not fit into the proposed standard. Moreover, the proposed framework presented herein does not represent the final IEC standards, which are pending to be published.

The wind energy industry has been experiencing financial 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:

- an AEP prediction error of 1 GWh, e.g., because of the P_{50} prediction bias, translates to about EUR 50 000 to 70 000 lost (Papadopoulos, 2019);
- reducing energy uncertainty by 1 % can result in USD 0.5 to 2 million of economic benefits, depending on the situation and the financial model (Brower et al., 2015; Halberg, 2017);
- a change of 1 % in wind speed uncertainty can lead to a 3 % to 5 % change in net present value of a wind farm (Kline, 2019).

Experts in the industry have presented many studies on P_{50} prediction error, energy loss, and uncertainty for years, and the purpose of this literature review is to assemble previous findings and deliver a meaningful narrative. This article is unique and impactful because it is the first comprehensive survey and analysis of the key parameters in the WRA process across the industry. The three main research questions of this study include the following:

- Is the industry-wide P_{50} 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 review how 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.

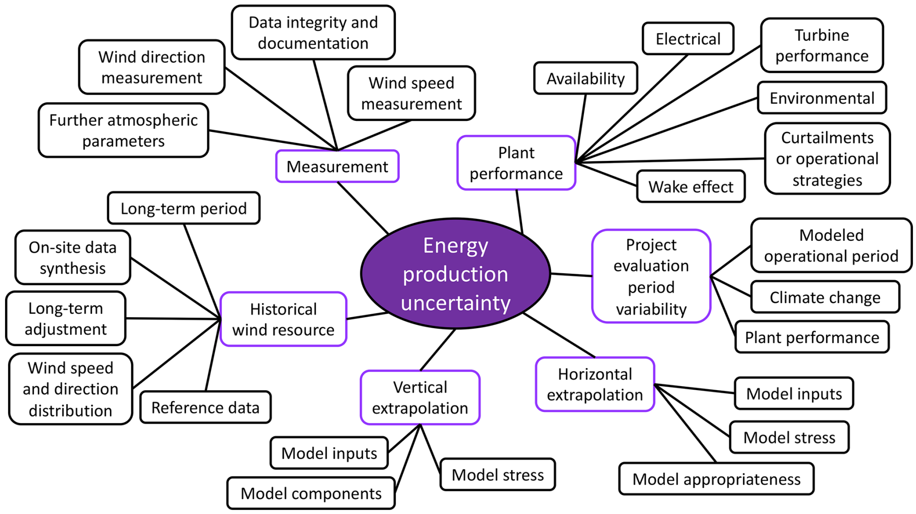

Figure 2. Mind map of energy-production uncertainty, according to the IEC 61400-15 proposed framework. The purple and black rounded rectangles represent the categorial and subcategorical uncertainties, respectively. Details of each uncertainty category and subcategory are discussed in Table A2.

We present this article with the following sections: Sect. 2 documents the data and the methodology of data filtering; Sect. 3 focuses on P_{50} prediction bias, including its trend and various reasons of bias improvement; Sects. 4 and 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 conclusions; 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 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 article have become global businesses after mergers and acquisitions; hence, their presentations and publications can also represent international practices.

In most cases, we label the data source with the published year of the study, unless the author highlights a change of method at a specific time. For example, if an organization publishes a study in 2012 and reports their improvements on P_{50} prediction bias by comparing their "current" method with their "previous set of methodology before 2012", the two P_{50} biases are recorded as 2012 and 2011, respectively. Moreover, for the same study that documents multiple P_{50} prediction errors in the same year, we select the one closest to zero, because those numbers reflect the state of the art of P_{50} validation of that year (Fig. 3). Accordingly, we use the paired P_{50} 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 P_{50} prediction errors using polynomial regression and investigate the reasons behind such trend. We use the second-degree polynomial regression (i.e., quadratic regression) to analyze the trend of the P_{50} prediction errors over time, and polynomials of higher degrees only marginally improve the fitting. We choose the polynomial regression over the simple linear regression because the P_{50} prediction errors are reducing towards zero with a diminishing rate, and we use quadratic polynomial over higher-order polynomials to avoid overfitting. Additionally, in the regressions presented in this article (Figs. 3, 8, and C1), we present an estimated 95 % confidence interval, generated via bootstrapping with replacement using the same sample size of the data, which is performed through the regplot function in the seaborn Python library (Waskom et al., 2020). The confidence interval describes the bounds of the regression coef-

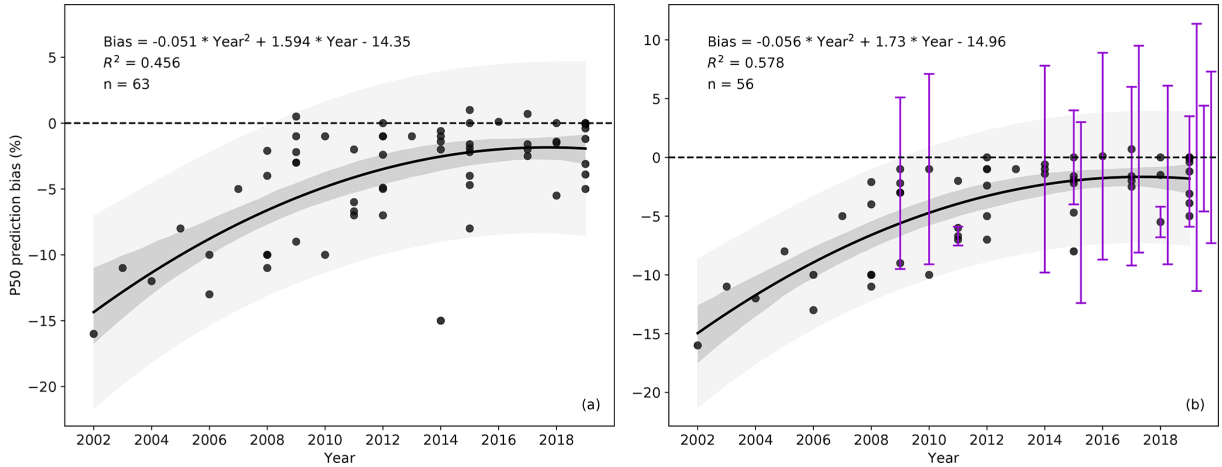

Figure 3. The trend of P_{50} prediction bias: **(a)** scatterplot of 63 independent P_{50} prediction error values, where R^2 is the coefficient of determination and n is the sample size. Negative bias means the predicted AEP is higher than the measured AEP, and vice versa for positive bias. The solid black line represents the quadratic regression, the dark grey cone displays the 95 % confidence interval of the regression line, the light grey cone depicts the 95 % prediction interval, and the horizontal dashed black line marks the zero P_{50} prediction error. **(b)** As in panel **(a)** but only for 56 studies that use more than 10 wind farms in the analyses. The vertical violet bars represent the estimated uncertainty bounds (presented as 1 standard deviation from the mean) of the mean P_{50} prediction errors in 15 of the 56 samples. Table B1 summarizes the bias data illustrated herein. For clarity, the regression uses the year 2002 as the baseline; hence, the resultant regression constant, i.e., the derived intercept, is comprehensible.

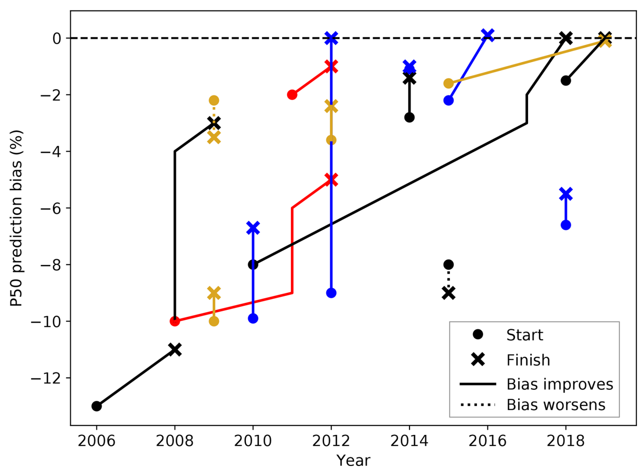

Figure 4. Illustration of P_{50} bias changes over time after method modifications in 17 studies. The dot and the cross, respectively, represent the starting point and the finish point of the P_{50} prediction error because of method adjustments. The solid line indicates the P_{50} bias reduces after 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.

ficients with 95 % confidence. Furthermore, we present the 95 % prediction interval in Fig. 3, which depicts the range of the predicted values, i.e., the P_{50} prediction bias, with 95 % confidence, given the existing data and regression model. The prediction interval is calculated using standard deviation, assuming an underlying Gaussian distribution. 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 (Wilks, 2011). 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 have limited data samples for certain categories because these data are only sparsely available. 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 also use linear regression to explore trends in loss and uncertainty estimates.

We categorize the data to the best of our knowledge to synthesize a holistic analysis. On one hand, if the type of loss 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 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" (seen in McAloon, 2010 and Walter, 2010), we label the value as both horizontal and vertical extrapolation uncertainties with a note of "extrapolation" in Tables B6 and B8. 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.

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 or 20 years. The wind speed uncertainty is stated as a percentage of wind speed in $\mathrm{m\,s^{-1}}$, and the uncertainty of an energy loss is expressed as percent of a loss percentage.

This article evaluates a compilation of averages, where each data point represents an independent number. The metadata for each study in the literature vary, in which the resultant P_{50} 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 P_{50} rather than P_{90}, which also has a strong financial implication; and the tendency in the literature to selectively report extreme losses and uncertainties caused by extraordinary events, such as availability loss and icing loss, which potentially misrepresents the reality. Our data sources are also only limited to publicly available data or those accessible at NREL. We perform a rigorous literature review from over 150 independent sources, and the results presented in this article adequately display the current state of the wind energy industry.

3 P_{50} prediction bias

3.1 Bias trend

We identify an improving trend of the mean P_{50} 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 R^2 of 0.578 in Fig. 3b implies that over half of the variance in bias can be described by the regression, and less 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, neither in wind farm sample size nor 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).

The uncertainty of the average P_{50} prediction error quantified by the studies remains large, in which the mean standard deviation is 6.6 % of the 15 data sources' reported estimated P_{50} uncertainty (violet bars in Fig. 3b). The industry started to disclose the standard deviations of their P_{50} validation studies in 2009, and it is becoming more common. With only 15 data points, we cannot identify a temporal trend of the uncertainty in P_{50} prediction bias. Even though the industry-wide mean P_{50} prediction bias is converging towards zero, the industry appears to overestimate or underpredict the AEP for many individual wind projects.

3.2 Reasons for bias changes

To correct for the historical P_{50} 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 P_{50} 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 accurately, and their P_{50} prediction errors worsen after embedding this uncertainty in their WRA process (vertical dashed lines in Fig. 4).

4 Energy-production loss

The prediction and observation of production losses are tightly related to the P_{50} prediction accuracy; hence, we contrast the estimated and measured losses in various categories and benchmark their magnitude (Figs. 5–7). 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 1 minus a categorical energy loss (Brower, 2012). Of the total categorical losses, we record the largest number of data points from availability loss, and wake loss displays 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

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 – degradation of long-term meteorological masts.	AWS Truepower (2009), Johnson (2012)
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, – flow over complex terrain, – effects of changes in 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)

one outlier, the turbine performance losses, in both predictions and observations, are about or under 5 % (Fig. 6b). Large ranges of environment losses exist, particularly for icing and degradation losses, which can drastically decrease AEP (Fig. 6c). Note that some of the icing losses indicated in the literature represent the fractional energy-generation loss from production stoppages over atypically long periods in wintertime, 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 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.

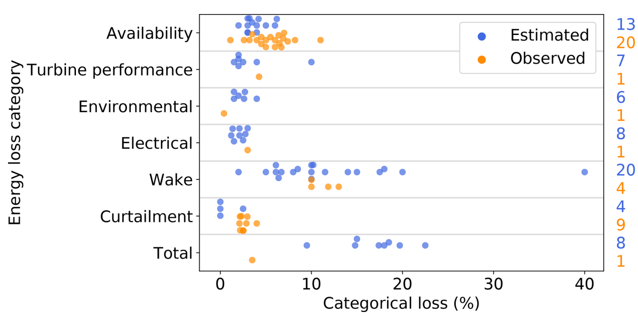

Figure 5. Ranges of total energy-production losses in different categories, according to the proposed framework of the IEC 61400-15 standard. Each blue dot and orange dot, respectively, represents the mean estimated loss and mean observed loss documented in each independent reference. The losses are expressed as percentage of AEP. The column of numbers on the right denotes the sample size in each category, where the estimated ones are in blue and the observed ones are in orange. For clarity, the horizontal grey lines separate data from each category. Table B3 catalogs the categorical losses plotted herein.

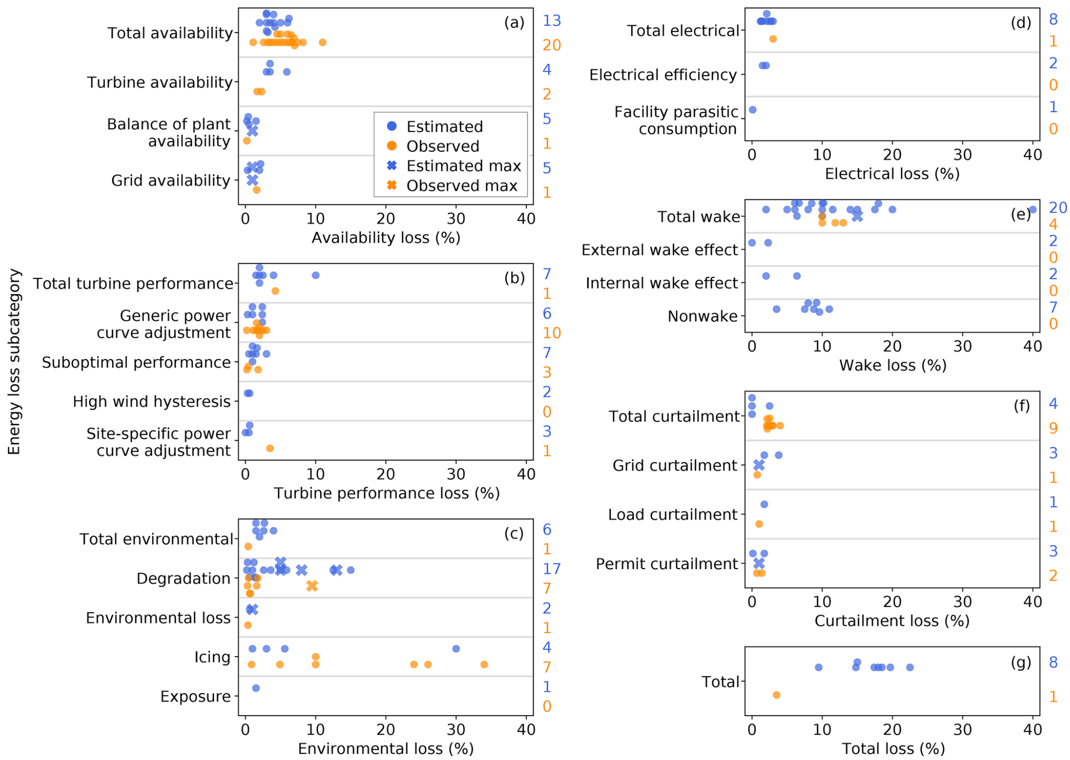

Figure 6. Ranges of energy-production losses in different categories and subcategories, according to the proposed framework of the IEC 61400-15 standard, except for nonwake in panel **(e)**, which is an extra subcategory summarizing other nonwake categories. Each blue dot and orange dot, respectively, represents the mean estimated loss and mean observed loss documented in each independent study. The 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 losses are expressed as percentage of AEP. The column of numbers on the right denotes the estimated and observed sample sizes in blue and orange, respectively, in each subcategory, and such sample size represents all the instances in that subcategory that recorded either the mean or the maximum loss values. 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 can cause considerable monetary impact. For example, blade degradation can result in a 6.8 % of AEP loss for a single turbine in the IEC Class II wind regime, where the maximum annual average wind speed is 8.5 $\mathrm{m\,s^{-1}}$; this translates to USD 43 000 per year (Wilcox et al., 2017). Generally, the typical turbine failure rate is about 6 %, where 1 % reduction in turbine failure rate can lead to around USD 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 the first few 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; 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 it contributes to less than 5 % of AEP reduction per year (Fig. 7).

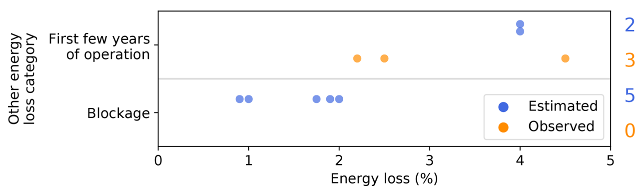

Figure 7. As in Fig. 6 but for the loss categories outside of the proposed IEC framework, as listed in Table B4.

For trend analysis, we linearly regress every subcategorical energy loss (Fig. 6 and Table B3) on time, and we only find two loss subcategories demonstrate notable and statistically confident trends (Fig. 8). The measured curtailment

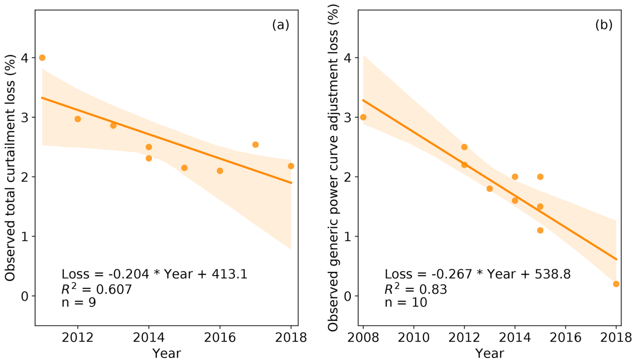

Figure 8. Trend in observed energy-production loss: **(a)** total curtailment loss and **(b)** generic power curve adjustment loss. The annotations correspond to those in Fig. 3, where the orange solid line represents simple linear regression, the light orange cone illustrates the 95 % confidence interval,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

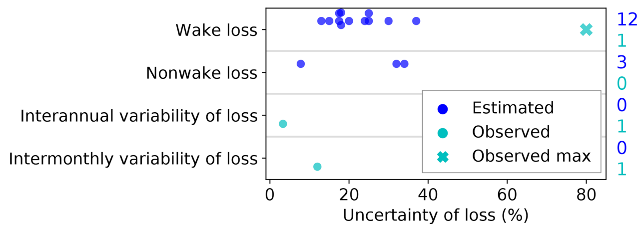

Figure 9. Uncertainty of energy-production losses, where the magnitude corresponds to the AEP loss percentages listed in Fig. 6 and Table B3. Each dark blue dot, turquoise dot, and turquoise cross represents the estimated uncertainty, the observed uncertainty, and the maximum observed uncertainty of losses, respectively. The uncertainties are expressed as percentages of uncertainty in terms of the energy-production loss percentage. The column of numbers on the right denotes the estimated and observed sample sizes in dark blue and turquoise, respectively, in each row, and such sample size represents all the instances in that row that reported either the mean or the maximum values. For clarity, the grey horizontal lines separate data from each uncertainty. Table B5 records the uncertainties displayed herein.

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).

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). The industry also tends to reveal the uncertainty of wake loss than nonwake loss according to the larger number of data sources (Fig. 9). One data source reported that depending on the location, the operational variation from month to month can alter AEP losses for more than 10 % on average (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.

5 Energy-production uncertainty

The individual energy-production uncertainties directly influence the uncertainty of P_{50} 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 is a typically consultant- and method-specific assumption (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). 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 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 components and model stress in vertical extrapolation; and environmental loss in plant performance.

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.

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

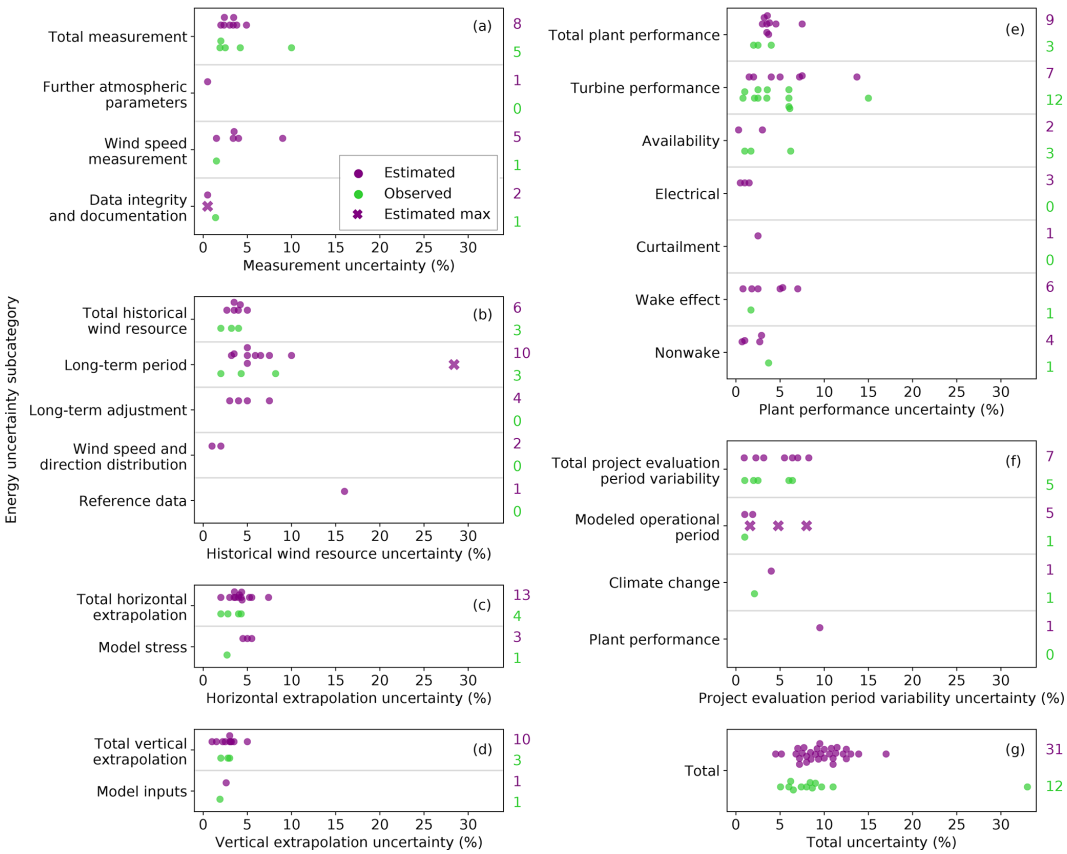

Figure 10. Ranges of energy-production uncertainties in different categories and subcategories, according to the proposed framework of the IEC 61400-15 standard. The annotations correspond to those in Fig. 6, where each purple dot, green dot, and purple cross represents the mean estimated uncertainty, the mean observed uncertainty, and the maximum of estimated uncertainty from each independent reference, respectively. The uncertainties are expressed as percentages in AEP. The column of numbers on the right denotes the estimated and observed sample sizes in purple and green, respectively, in each subcategory, and such sample size represents all the instances in that subcategory that reported either the mean or the maximum uncertainty values. For clarity, the grey horizontal lines separate data from each subcategory. Table B6 numerates the production uncertainties.

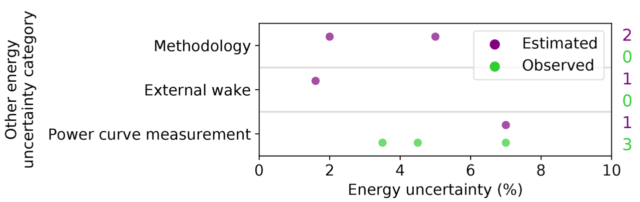

Figure 11. As in Fig. 10 but for the uncertainty categories outside of the proposed IEC framework, as listed in Table B7.

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 roughly 10 % or less of the 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.

Wind speed uncertainty greatly impacts AEP uncertainty, and the methods of translating wind speed uncertainty into AEP uncertainty also differ between organizations. For ex-

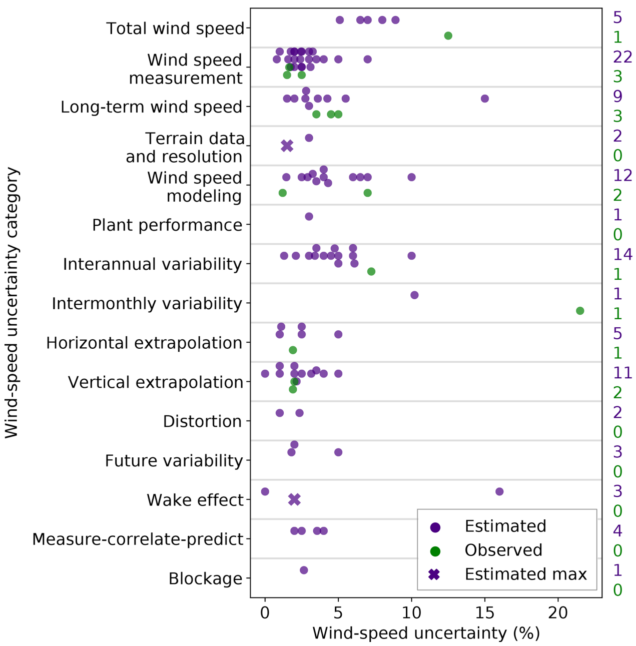

Figure 12. Ranges of wind speed uncertainties in different categories. The annotations correspond to those in Fig. 10, where each dark purple dot, dark green dot, and dark purple cross represents the mean estimated wind speed uncertainty, the mean observed wind speed uncertainty, and the maximum of estimated wind speed uncertainty from each independent study, respectively. The uncertainties are expressed as percentages of wind speed. The column of numbers on the right denotes the estimated and observed sample sizes in dark purple and dark green, respectively, in each category, and such sample size represents all the instances in that category that reported either the mean or the maximum uncertainty values. For clarity, the grey horizontal lines separate data from each category. Table B8 documents the wind speed uncertainties displayed.

ample, 1 % increase of wind speed uncertainty can lead to either a 1.6 % (AWS Truepower, 2014) or 1.8 % increase in energy-production uncertainty (Holtslag, 2013; Johnson et al., 2008; White, 2008a, b). Local wind regimes can also affect this ratio. For low wind locations, AEP uncertainty can be 3 times the wind speed uncertainty, while such a ratio drops to 1.5 at high wind sites (Nielsen et al., 2010).

Decreasing wind speed uncertainty benefits the wind energy industry. Reduction in wind speed measurement 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 GBP 1.2 million of equity savings for a 1 GW offshore wind farm in the United Kingdom (Crease, 2019).

7 Opportunities for improvements

Although the industry is reducing the mean P_{50} overprediction bias, the remarkable uncertainties inherent in the WRA process overshadow such achievement. Different organizations have been improving their techniques over time to eliminate the P_{50} bias (Table 1), and as a whole we celebrate the technological advancements; nevertheless, challenges still exist for validation and reduction of the AEP losses and uncertainties. Even though the average P_{50} prediction bias is reducing and approaches zero, the associated mean P_{50} uncertainty remains at over 6 %, even for the studies reported after 2016 (Fig. 3b). For a validation study that involves a collection of wind farms, such an uncertainty bound implies that sizable P_{50} predication errors for particular wind projects can emerge. In other words, statistically, the AEP prediction is becoming more accurate and yet is imprecise. Moreover, from an industry-wide perspective that aggregates different analyses, the variability on the mean P_{50} 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 P_{50} estimation error (Fig. 3b) suggests a considerable range of possible mean biases in future validation 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 require 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 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 energy loss 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 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 critical, and the production downtime during high electricity demand can lead to consequential 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. Industry-wide collaborations such as the International Energy Agency Wind Task 32 and the Consortium For Advancement of Remote Sensing, have been promoting remote-sensing implementation in WRA.

Leaders 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, innovators 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, different types of energy-production losses or uncertainties interact and correlate with each other, and dependent data sources can emerge in the WRA process. The resultant compound effect from two correlating sources of uncertainty can change the total uncertainty derived using 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).

More observations and publicly available data 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. Besides, challenges exist in interpreting and harmonizing results from disparate reporting of energy-production losses and uncertainties. Documentation aligned with ubiquitous reference frameworks will greatly strengthen the accuracy and repeatability of future literature reviews. Therefore, data and method transparency and standardization will continually improve insight into the WRA process, increase the AEP estimation accuracy, and drive future innovation.

8 Conclusions

In this study, we compile and present the ranges and the trends of predicted P_{50} (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. We conduct this literature review using over 150 credible sources from conference presentations to peer-reviewed journal articles.

Although the mean P_{50} bias demonstrates a decreasing trend over time because of continuous methodology adjustments, 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, 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 in this literature review according to the proposed framework by the 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, method transparency, and rigorous research, we will increasingly be able to maximize energy production and reduce its uncertainty for all project stakeholders.

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). Note that this table does not represent the final standards.

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, non-contractual 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 non-turbine 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 offtaker curtailments, grid limitations
	Environmental or 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 carve-outs

Table A2. Consensus energy-production uncertainty framework for wind resource assessment proposed by the IEC 61400-15 working group (Filippelli et al., 2018). Note that this table does not represent the final standards.

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 or 10 years) 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 or 10 years) 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 stress	Large extrapolation distance, complex terrain (measurement height relative to terrain complexity)

Table A2. Continued.

Uncertainty category	Uncertainty subcategory	Notes
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 Availability Electrical Turbine performance Environmental Curtailments or operational strategies	Refer to Table A1

Appendix B

For the P_{50} prediction error, Figs. 3 and 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. Figure 7 illustrates the losses outside of the IEC-proposed framework listed in Table B4. Figure 9 summarizes the uncertainty of production loss percentages in Table B5. Figures 10 and 11 represent the AEP uncertainty data included in Tables B6 and B7, respectively. Figure 12 displays the wind speed uncertainty data in Table B8.

Table B1. List of P_{50} biases in the literature, which is necessary to generate Fig. 3. The "Wind farm" column denotes the number of wind farms reported in the reference, and the "Wind farm year" column indicates the total number of operation years among the wind farms in that study. The "Bias (%)" column represents the average P_{50} bias, where a negative number indicates an overestimation of actual energy production. All the values in the "Uncertainty (%)" column illustrate 1 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	1		0.5	6.4	Comparison of four analysts	Derrick (2009)
2009	11	45	−2.2	7.3		White (2009)
2009	18		−3			Mönnich et al. (2016)
2010			−1	8.1	From 1806 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 from 2000 to 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 from 2005 to 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. (2015a, b)
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	7.7		Hatlee (2015)
2016	30	127	0.1	8.8		Baughman (2016)
2017		140	−2		Projects from 2011 to 2016	Elkinton (2017), Hale (2017)
2017	61		−1.6	7.6	Most projects from 2008 to 2012	Brower (2017), Hale (2017)
2017			−2.5			Hale (2017)
2017	30	127	0.7	8.8		Perry (2017)

Table B1. Continued.

Year	Wind farm	Wind farm year	Bias (%)	Uncertainty (%)	Notes	Source
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)

Table B2. List of P_{50} 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 from 2000 to 2011	Drunsic (2012)
3	2012			−5		Industry average from 2005 to 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 to 2010	Ostridge (2017)
6	2017	50		−3		Projects from 2011 to 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	2010		294	−9.9		Projects before 2011	Lunacek et al. (2018)
7	2010	56		−9.2		Projects before 2011	Lunacek et al. (2018)
7	2010			−6.7	0.8	Projects before 2011, long-term correction, R^2 filtered	Lunacek et al. (2018)
8	2011			−2		Projects from 2000 to 2011	Drunsic (2012)
8	2012			−1		Projects from 2005 to 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 years	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)

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. "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.

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 American 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 American onshore, utility grid	AWS Truepower (2014)
2016	e	Availability	Grid			1	Transmission	Clifton et al. (2016)
2019	e	Availability availability	Grid		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)

Table B3. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2013	e	Availability	Total availability	3.2			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen (2013)
2014	e	Availability	Total availability	6.2			Typical North American 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)

Table B3. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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 American onshore, combined from contractual turbine, non-contractual 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 American 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 American 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 American 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)

Table B3. Continued.

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

Table B3. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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 American 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 years	Randall (2009)
2009	e	Environmental	Degradation	1.2	0.5	1.9	20 years	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 American 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)

Table B3. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2016	o	Environmental	Degradation		1.5	2	Before blade repair	Murphy (2016)
2017	o	Environmental	Degradation	0.3			Sweden	Olauson et al. (2017)
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 American 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 American 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 to 4 times lower than this	Trudel (2016)
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)

Table B3. Continued.

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

Table B3. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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 American 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 American onshore	AWS Truepower (2014)

Table B3. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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 American 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 American onshore	AWS Truepower (2014)
2019	e	Turbine performance	Suboptimal performance		1.1	2.2	10° of yaw error	Liew et al. (2019)
2019	e	Turbine performance	Suboptimal performance	3			Yaw misalignment	Slinger et al. (2019b)
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)

Table B3. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2014	e	Turbine performance	Total turbine performance	4			Typical North American 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 American onshore	AWS Truepower (2014)
2014	e	Wake effect	Internal wake effects	6.4	0	2	Typical North American 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	9.6		Mortensen et al. (2015a)
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 offshore 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)

Table B3. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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 (2011)
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 American onshore	AWS Truepower (2014)
2015	e	Wake effect	Total wake effect		6.1	14.3	Onshore analyst comparison	Mortensen et al. (2015b)
2016	e	Wake effect	Total wake effect		0	10	Onshore analyst comparison	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)

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 (2008a)
2014	e	Availability	First few years of operation	4	2	6	Typical North American 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. (2015b)
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)

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 (2008a)
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	1-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)

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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			20-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	10-year uncertainties from three examples	Halberg (2017)
2019	e	Historical wind resource	Total historical wind resource	2.68			20-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)

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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	Non-ideal flow	Hendrickson (2009)
2009	e	Horizontal extrapolation	Total horizontal extrapolation	5.24			20-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. (2015a)
2016	e	Horizontal extrapolation	Total horizontal extrapolation		1	10		Clifton et al. (2016)
2017	e	Horizontal extrapolation	Total horizontal extrapolation		2.6	4.7	10-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			20-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)

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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			20-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	10-year uncertainties from three examples	Halberg (2017)
2019	e	Measurement	Total measurement	2.36			20-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)

Table B6. Continued.

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

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2014	o	Plant performance	Nonwake	3.7	3.2	4.5		Brower (2014)
2009	e	Plant performance	Total plant performance	3.56			20-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	10-year uncertainties from three examples	Halberg (2017)
2019	e	Plant performance	Total plant performance	4.53			20-year 10 projects; includes uncertainty, 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)

Table B6. Continued.

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

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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 (2008a)
2014	e	Project evaluation period variability	Modeled operational period	1.9				AWS Truepower (2014)
2019	e	Project evaluation period variability	Modeled operational period			8	10-year uncertainty	Dutrieux (2019)
2019	e	Project evaluation period variability	Modeled operational period			4.8	20-year uncertainty	Dutrieux (2019)
2019	e	Project evaluation period variability	Modeled operational period			1.6	30-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 1–10 met masts	Brower et al. (2015)
2009	e	Project evaluation period variability	Total project evaluation period variability	2.26			20-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)

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2012	e	Project evaluation period variability	Total project evaluation period variability		3.1	9.7	Range of 1- 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	10-year uncertainties from three examples	Halberg (2017)
2019	e	Project evaluation period variability	Total project evaluation period variability	0.94			20-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- and 10-year uncertainties	Tchou (2012)
2014	o	Project evaluation period variability	Total project evaluation period variability	6	4	9	1-year uncertainties	Istchenko (2014)
2014	o	Project evaluation period variability	Total project evaluation period variability	2	2	3	10-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			20-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)

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
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- 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- 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" 5 % to 9 % of yield assessment uncertainty	Mortensen et al. (2015b)
2015	e	Total	Total		8	11		Mortensen et al. (2015a)
2015	e	Total	Total	10.6			1-year uncertainty	Stoelinga and Hendrickson (2015)
2017	e	Total	Total		6.2	10.7	10-year uncertainties from three examples	Halberg (2017)
2017	e	Total	Total		7.9	9.1	1-year uncertainties	Perry (2017)
2017	e	Total	Total		4.1	6.2	20-year uncertainties	Perry (2017)
2017	e	Total	Total	11			Post-2011 projects, 1-year standard deviation	Ostridge (2017)

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2019	e	Total	Total	6.8			20-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)
2012	o	Total	Total		9.1	12.9	Range of 1- and 10-year uncertainties	Tchou (2012)
2012	o	Total	Total		6.2	11.1	Range of 1- 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- 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			20-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	10-year uncertainties from three examples	Halberg (2017)

Table B6. Continued.

Year	Est/ obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2019	e	Vertical extrapolation	Total vertical extrapolation	5				Žagar (2019)
2019	e	Vertical extrapolation	Total vertical extrapolation	2.21			20-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)

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)

Table B8. List of wind speed uncertainties which are used for Fig. 12. Different from other tables in Appendix B, this table records 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	Non-ideal flow; includes 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. (2015a)
2010	o	Horizontal extrapolation	1.9			Analyst comparison; "extrapolation"	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			1-year uncertainty; WindPro 2.7	Nielsen et al. (2010)
2010	e	Interannual variability	1.3			20-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)

Table B8. Continued.

Year	Est/ obs	Category	Avg (%)	Min (%)	Max (%)	Notes	Source
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 h of data	Rogers et al. (2006)
2006	o	Long-term wind speed		3	6	9000 h of data at offshore wind farms	Rogers (2011)
2006	o	Long-term wind speed		2	8	9000 h 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)

Table B8. Continued.

Year	Est/obs	Category	Avg (%)	Min (%)	Max (%)	Notes	Source
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. (2015a)
2016	e	Vertical extrapolation		2	6	Non-forested	Kelly (2016)
2017	e	Vertical extrapolation	1			Industry accepted; 1 % per 10 m	Langreder (2017)
2019	e	Vertical extrapolation		0	7	Depends on shear and terrain	Kelly et al. (2019)
2010	o	Vertical extrapolation	1.9			Analyst comparison; “extrapolation”	Walter (2010)
2019	o	Vertical extrapolation		0	4	Depends on shear and terrain	Kelly et al. (2019)
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)

Table B8. Continued.

Year	Est/ obs	Category	Avg (%)	Min (%)	Max (%)	Notes	Source
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	Non-ideal 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)

Table B8. Continued.

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

Appendix C

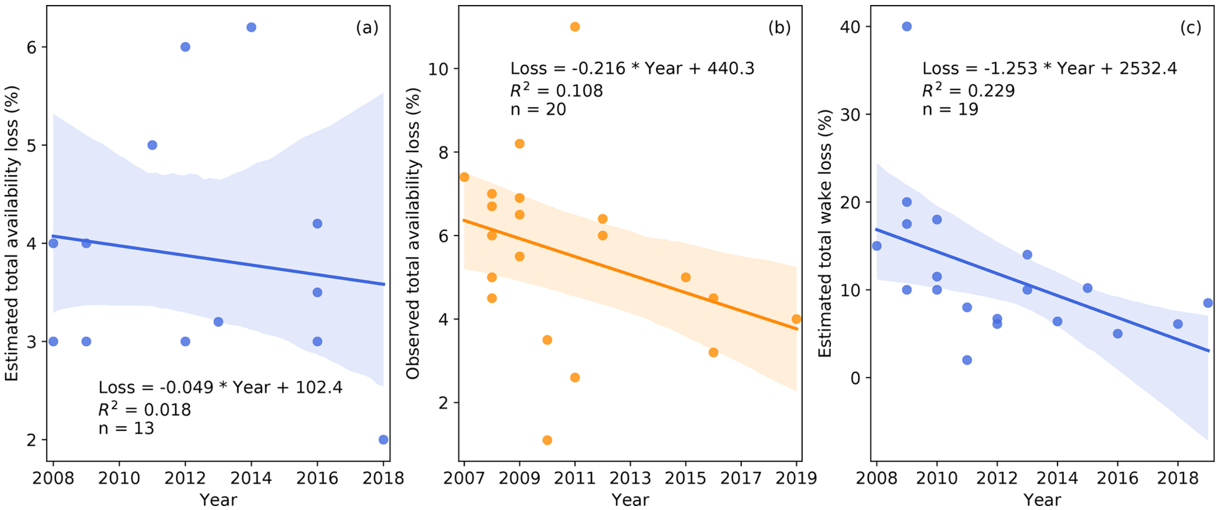

Figure C1. As in Fig. 8, the trend in energy-production loss: **(a)** estimated total curtailment loss, **(b)** observed total availability loss, and **(c)** estimated total wake loss. Note that the ranges of the horizontal and vertical axes differ in each panel.

Data availability. Appendix B includes all the data used to generate the plots in this article.

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

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This work was authored by the National Renewable Energy Laboratory (NREL), operated by the Alliance for Sustainable Energy, LLC, for the US Department of Energy (DOE), under contract no. DE-AC36-08GO28308. Funding provided by the US Department of Energy Office of Energy Efficiency and Renewable Energy Wind Energy Technologies Office. The views expressed in the article do not necessarily represent the views of the DOE or US Government. The US Government retains and the publisher, by accepting the article for publication, acknowledges that the US 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 US Government purposes.

The authors would like to thank our external collaborators including Matthew Breakey, Matthew Hendrickson, Kisha James, Cory Jog, and the American Wind Energy Association; our colleagues at NREL including Sheri Anstedt, Derek Berry, Rachel Eck, Julie Lundquist, Julian Quick, David Snowberg, Paul Veers, and the NREL library; Carlo Bottasso as our editor, Mark Kelly as our peer reviewer, and one anonymous referee.

Financial support. This research has been supported by the US Department of Energy (grant no. DE-AC36-08GO28308).

Review statement. This paper was edited by Carlo L. Bottasso and reviewed by Mark Kelly and one anonymous referee.

References

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

Albers, A., Klug, H., and Westermann, D.: Outdoor Comparison of Cup Anemometers, in: German wind energy conference, DEWEK 2000, Wilhelmshaven, Germany, p. 5, 2000.

Albers, A., Franke, K., Wagner, R., Courtney, M., and Boquet, M.: Ground-based remote sensor uncertainty – a case study for a wind lidar, available at: https://www.researchgate.net/publication/267780849_Ground-based_remote_sensor_uncertainty_-_a_case_study_for_a_wind_lidar (last access: 31 October 2020), 2013.

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

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, AWS Truepower, LLC, Albany, NY, 2009.

AWS Truepower: AWS Truepower Loss and Uncertainty Methods, Albany, NY, available at: https://www.awstruepower.com/assets/AWS-Truepower-Loss-and-Uncertainty-Memorandum-5-Jun-2014.pdf (last access: 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 electricity market, Energy Policy, 36, 1687–1696, https://doi.org/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, 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, AWS Truepower, LLC, 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.

Bird, L., Cochran, J., and Wang, X.: Wind and Solar Energy Curtailment: Experience and Practices in the United States, NREL/TP-6A20-60983, National Renewable Energy Laboratory, Golden, CO, 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, 1609, https://doi.org/10.3390/en11061609, 2018.

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, Hoboken, NJ, 2012.

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.

Brower, M. C., Robinson, N. M., and Hale, E.: Wind Flow Modeling Uncertainty: Quantification and Application to Monitoring Strategies and Project Design, AWS Truepower, LLC, 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.

Brower, M. C., Robinson, N. M., and Vila, S.: Wind Flow Modeling Uncertainty: Theory and Application to Monitoring Strategies and Project Design, AWS Truepower, LLC, 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 climate sites, in IWAIS 2015: 16th International Workshop on Atmospheric Icing of Structures, IWAIS, Uppsala, Sweden, p. 4, 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, NREL/TP-5000-64735, National Renewable Energy Laboratory, Golden, CO, 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 Considering Weibull Distribution Parameters, Energies, 7, 6856–6885, https://doi.org/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.

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, 2967–2971, https://doi.org/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 performance, J. Phys. Conf. Ser., 1037, 052021, https://doi.org/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.

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, Report no. 21858-1, Vattenfall Vindkraft AB, Stockholm, Sweden, 28 pp., 2009.

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

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, WindEurope, Bilbao, Spain, 2019.

Ehrmann, R. S., Wilcox, B., White, E. B., and Maniaci, D. C.: Effect of Surface Roughness on Wind Turbine Performance, SAND2017-10669, Sandia National Laboratories, Albuquerque, NM and Livermore, CA, 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.

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., EMD International A/S, Aalborg, Denmark, 2004.

Faghani, D.: Measurement Uncertainty of Ground-Based Remote Sensing, in: AWEA Wind Resource and Project Energy Assessment Workshop 2011, AWEA, Seattle, WA, 2011.

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.

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, report no. Risoe-R 1330(EN), Forskningscenter Risoe, Roskilde, Denmark, 2002.

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

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 wind conditions in 2000–2014?, edited by: Leahy, P., PLoS One, 14, e0211028, https://doi.org/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.

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 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.

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, 4, 1004–1020, https://doi.org/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.

Hatlee, S.: Measurement Uncertainty in Wind Resource Assessment, 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, 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.

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 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, Utrecht, the Netherlands, 2013.

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

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 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.

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.

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, No. 0121, DTU Wind Energy, Roskilde, Denmark, 2016.

Kelly, M., Kersting, G., Mazoyer, P., Yang, C., Hernández Fillols, F., Clark, S., and Matos, J. C.: Uncertainty in vertical extrapolation of measured wind speed via shear, No. E-0195, DTU Wind Energy, Roskilde, Denmark, 2019.

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.

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 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. Energ. Eng., 130, 31006–31010, https://doi.org/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, American Institute of Aeronautics and Astronautics, Kissimmee, FL, p. 13, 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, 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 Energ. Sci., 3, 845–868, https://doi.org/10.5194/wes-3-845-2018, 2018.

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., Fields, M. J., 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, 062009, https://doi.org/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 CFD Model Development of Thick Wind Turbine Airfoils with Leading Edge Erosion, J. Phys. Conf. Ser., 753, 022013, https://doi.org/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, 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.

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

Mortensen, N. G.: Planning and Development of Wind Farms: Wind Resource Assessment and Siting, report no. 0045(EN), DTU Wind Energy, Roskilde, Denmark, 2013.

Mortensen, N. G. and Ejsing Jørgensen, H.: Comparative Resource and Energy Yield Assessment Procedures (CREYAP) Pt. II, in: EWEA Technology Workshop: Resource Assessment 2013, 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), Technical Universtiy of Denmark, Copenhagen, Denmark, p. 10, 2012.

Mortensen, N. G., Nielsen, M., and Ejsing Jørgensen, H.: Comparison of Resource and Energy Yield Assessment Procedures 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, Paris, France, 2015a.

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

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

Neubert, A.: WindFarmer White Paper, DNV GL, Oldenburg, Germany, 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 Edn., Aalborg, Denmark, 2010.

Olauson, J., Edström, P., and Rydén, J.: Wind turbine performance decline in Sweden, Wind Energy, 20, 2049–2053, https://doi.org/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 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, DNV GL, Seattle, WA, 2017.

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, report no. L2C183006-UKBR-R-01, DNV GL – Energy, Bristol, England, 2019.

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

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 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, 27–38, https://doi.org/10.1002/we.178, 2006.

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.

Redouane, A.: Analysis of pre- and post construction wind farm energy yields with focus on uncertainties, Universität Kassel, 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 reproducing and predicting ice accretion, Examensarbete vid Institutionen för geovetenskaper, MS thesis, Uppsala University, Disciplinary Domain of Science and Technology, Earth Sciences, Department of Earth Sciences, LUVAL, Uppsala, Sweden, ISSN 1650-6553, 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 Wind Energy Conference 2006, Athens, Greece, 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.

Sareen, A., Sapre, C. A., and Selig, M. S.: Effects of leading edge erosion on wind turbine blade performance, Wind Energy, 17, 1531–1542, https://doi.org/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, 1420, https://doi.org/10.3390/en10091420, 2017.

Shihavuddin, A., Chen, X., Fedorov, V., Nymark Christensen, A., Andre Brogaard Riis, N., Branner, K., Bjorholm Dahl, A., and Reinhold Paulsen, R.: Wind Turbine Surface Damage Detection by Deep Learning Aided Drone Inspection Analysis, Energies, 12, 676, https://doi.org/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, Palm Springs, California, 236–243, 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.

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 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, DEWI Group, Wilhelmshaven, Germany and Lyon, France, 2008.

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

Staffell, I. and Green, R.: How does wind farm performance decline with age?, Renew. Energy, 66, 775–786, https://doi.org/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.

Stehly, T., Beiter, P., Heimiller, D., and Scott, G.: 2017 Cost of Wind Energy Review, NREL/TP-6A20-72167, National Renewable Energy Laboratory, 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, Vaisala, Seattle, WA, 2015.

Tchou, J.: Successfully Transitioning Pre-Construction Measurements to Post-Construction Operations, in: AWEA Wind 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.

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., 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, 366, 6464, https://doi.org/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 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, Zenodo, https://doi.org/10.5281/zenodo.3629446, 2020.

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 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.

Wilks, D. S.: Statistical methods in the atmospheric sciences, Academic Press, Amsterdam, the Netherlands, 2011.

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, US Department of Energy, Office of Energy Efficiency & Renewable Energy, Washington, D.C., 2019.

Wolfe, J.: Deep Array Wake Loss in Large Onshore Wind Farms (A Model Validation), in: AWEA Wind Resource and Project 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.