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

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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 reducing. 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 on 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.

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1 Introduction

Determining the range of annual energy production (AEP), or the energy yield assessment (EYA), has been a key part of the wind resource assessment (WRA) process. The predicted median AEP is also known as the P50, i.e. the AEP expected to be exceeded 50% of the time. P50 are often defined with timescales such as 1 year, 10 years, and 20 years. In this study, unless stated otherwise, we primarily discuss the 20-year P50, which is the typical expected lifespan of utility-scale wind turbines. For years, leaders in the field have been discussing the difference between predicted P50 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

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of 3.5% to 4.5% P50 overprediction bias based on a subset of wind farms in the United States and accounting for curtailment (Lunacek et al., 2018).

Such P50 overestimation causes powerful financial implications. Healer (2018) stated that if a wind project produces a certain percentage lower than the P50 on a 2-year rolling basis, the energy buyer, also known as the offtaker, 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 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.

Random errors that deviate observations or model predictions from the truth lead to uncertainty (Clifton et al., 2016), and uncertainty can be expressed in probability (Wilks, 2011). In WRA, the P-values surrounding P50 such as P90 and P95 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). Given a Gaussian distribution, the standard deviation around the mean represents the uncertainty of that distribution. Traditionally, the wind energy industry uses standard deviation, or σ, to represent uncertainty.

The WRA process governs the accuracy and precision of the P50, and a key component in WRA constitutes the estimation of energy-production losses and uncertainties. Wind energy experts have been using different nomenclature 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.

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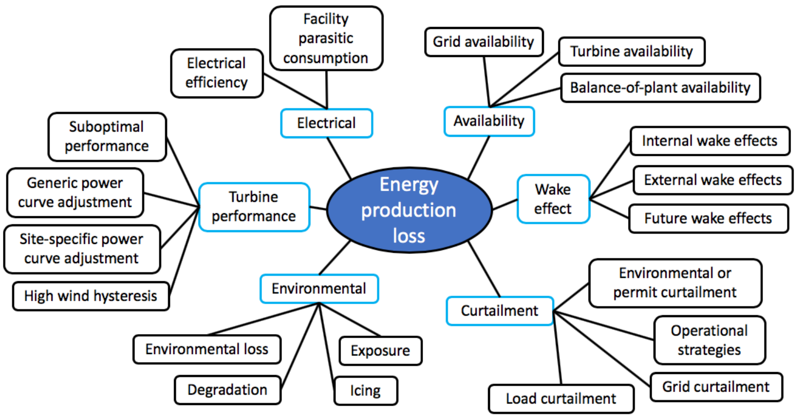


Figure 1: Mind map of energy production loss, according to the IEC 61400-15 proposed framework. The blue and black rounded rectangles represent the categorial and subcategorical losses, respectively. Details of each loss category and subcategory are
80 **discussed in Table A1.**

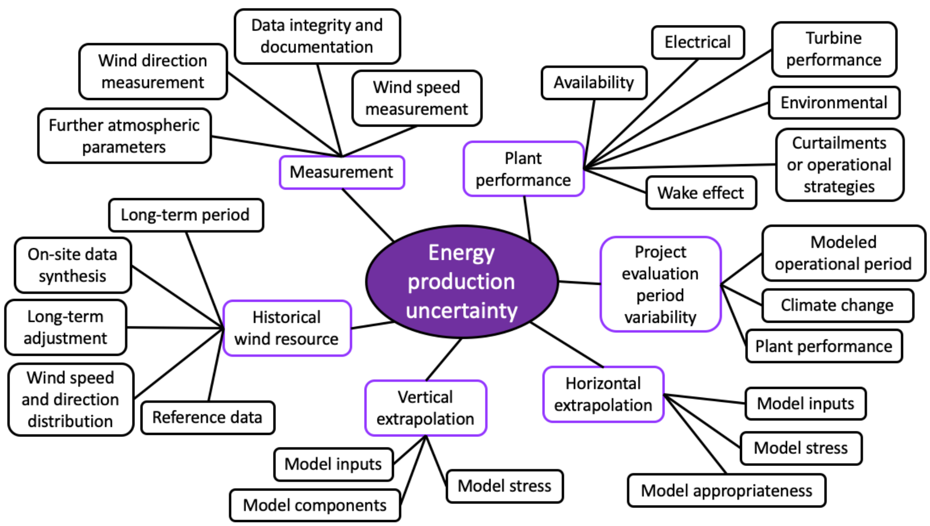


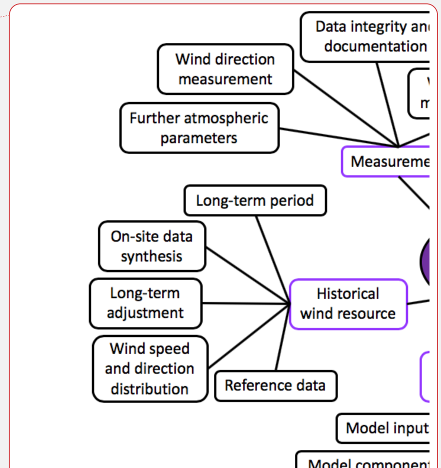
Figure 2: Mind map of energy production uncertainty, according to the IEC 61400-15 proposed framework. The purple and black rounded rectangles represent the categorial and subcategorical uncertainties, respectively. Details of each uncertainty category and subcategory are discussed in Table A2.

The wind energy industry has been experiencing 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 P50 prediction bias, translates to about 50,000 to 70,000 Euros lost (Papadopoulos, 2019);
- reducing energy uncertainty by 1% can result in \$0.5 to \$2 millions of economic benefits, depending on the situation and the financial model (Brower et al., 2015; Halberg, 2017);
- 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 P50 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:

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



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- 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.

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We present this article with the following sections: Sect. 2 documents the data and the methodology of data filtering; Sect. 3 focuses on P50 prediction bias, including its trend and various reasons of bias improvement; Sect. 4 and Sect. 5, respectively, illustrate the energy-production loss and uncertainty, according to the IEC proposed framework; Sect. 6 describes the numerical ranges of various wind speed uncertainties; Sect. 7 discusses the implications and future outlook based on our findings; Sect. 8 provides 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.

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2 Data and methodology

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

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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 P50 prediction bias by comparing their "current" method with their "previous set of methodology before 2012", the two P50 biases are recorded as 2012 and 2011, respectively. Moreover, for the same study that documents multiple P50 prediction errors in the same year, we select the one closest to zero, because those numbers reflect the state of the art of P50 validation of that year (Fig. 3). Accordingly, we use the paired P50 errors to indicate the effects from method adjustments (Fig. 4). To track the bias impact of technique changes from different organizations, we combine the closely related, ongoing series of studies from a single organization, usually by the same authors from the same institutions (each line in Fig. 4).

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We also derive the trend of P50 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 P50 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 P50 prediction errors are reducing towards zero with a diminishing rate, and we

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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 coefficients with 95% confidence. Furthermore, we present the 95% prediction interval in Fig. 3, which depicts the range of the predicted values, i.e. the P50 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.

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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.

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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," we label it as both horizontal and vertical extrapolation uncertainties. We also divide the reported losses and uncertainties into two groups, the "estimated" and the "observed", where the former are based on simulations and modeling studies, and the latter are quantified via field measurements.

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

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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 P50 prediction errors, losses, and uncertainties come from diverse collections of wind farms with different commercial operation dates in various geographical regions and terrains.

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Therefore, readers should not compare a specific data point with another. In this study, we aim to discuss the WRA process from a broad perspective. Other caveats of this analysis include the potentially inaccurate classification of the data into the proposed IEC framework; the prime focus on P50 rather than P90, which also has a strong financial implication; and the tendency in the literature to selectively report extreme losses and uncertainties caused by extraordinary events, such as availability loss and icing loss, which potentially mispresents 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 P50 prediction bias

3.1 Bias trend

We identify an improving trend of the mean P50 prediction bias, where the overprediction of energy production is gradually decreasing over time (Fig. 3), and the narrow 95% confidence interval of the regression fit justifies the long-term trend. Such an improving trend is not strictly statistically significant (Fig. 3a), even after removing the studies based on small wind farm sample sizes (Fig. 3b). However, the 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, either in wind farm sample size or wind farm year length (not shown). Note that in some early studies, the reported biases measured in wind farm differ from those using wind farm year from the same source; we select the error closest to zero for each independent reference because the bias units are the same (Sect. 2).

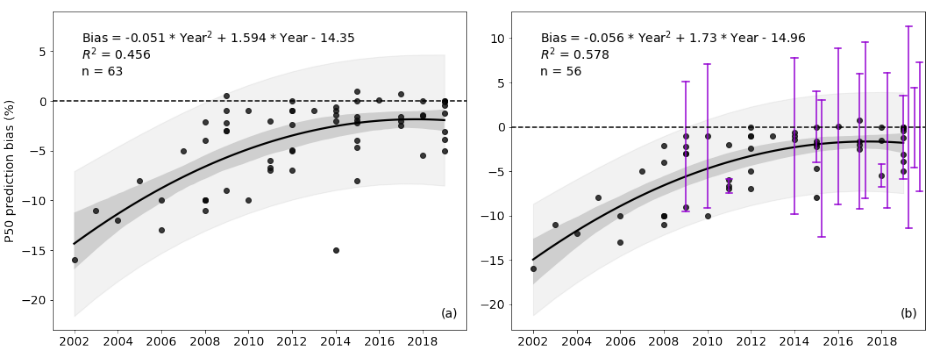

Figure 3: The trend of P50 prediction bias: (a) scatterplot of 63 independent P50 prediction error values, where R^2 is the coefficient of determination and n is the sample size. Negative bias means the predicted AEP is higher than the measured AEP, and vice versa for positive bias. The black solid line represents the quadratic regression, the dark grey cone displays the 95% confidence interval

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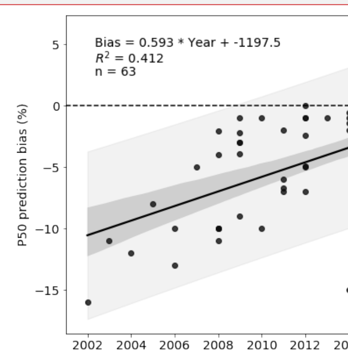

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of the regression line, the light grey cone depicts the 95% prediction interval, the horizontal black dashed line marks the zero P50 prediction error. (b) as in (a), but only for 56 studies that use more than 10 wind farms in the analyses. The vertical violet bars represent the estimated uncertainty bounds (presented as one standard deviation from the mean) of the mean P50 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.

The uncertainty of the average P50 prediction error quantified by the studies remains large, in which the mean standard deviation is 6.6% of the 15 data sources' reported estimated P50 uncertainty (violet bars in Fig. 3b). The industry started to disclose the standard deviations of their P50 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 P50 prediction bias. Even though the industry-wide mean P50 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 P50 prediction errors, some organizations publicize the research and the adjustments they have been conducting for their WRA processes. We summarize the major modifications of the WRA procedure in Table 1. Most studies demonstrate mean P50 bias improvement over time (Fig. 4), and the magnitude of such bias reduction varies. In two studies, the authors examine the impact of accounting for windiness, which is the quantification of long-term wind speed variability, in their WRA methodologies. They acknowledge the difficulty in quantifying interannual wind speed variability accurately, and their P50 prediction errors worsen after embedded this uncertainty in their WRA process (vertical dash lines in Fig. 4).

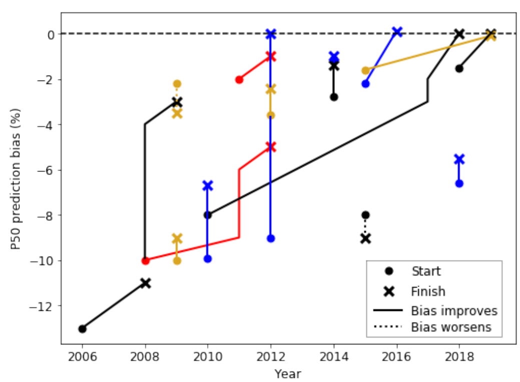

Figure 4: Illustration of P50 bias changes over time after method modifications in 17 studies. The dot and the cross, respectively, represent the starting point and the finish point of the P50 prediction error because of method adjustments. The solid line indicates the P50 bias reduces after the method change, and the dotted line displays the opposite. The different colors are solely used to differentiate the lines and represent no meaning. The paired data are presented in Table B2.

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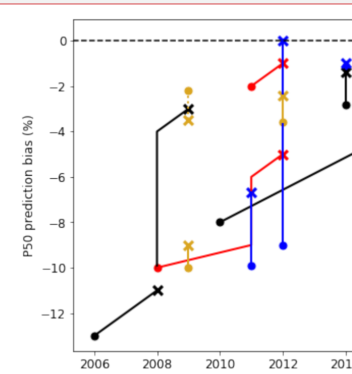

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Table 1: Categories of method adjustments to improve the wind resource assessment process and the respective data sources.

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

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4 Energy-production loss

The prediction and observation of production losses are tightly related to the P50 prediction accuracy; hence, we contrast the estimated and measured losses in various categories and benchmark their magnitude (Figs. 5, 6 and 7). The total energy loss is calculated from the difference between the gross energy estimate and the product of gross energy prediction and various categorical production efficiencies, where each efficiency is one minus a categorical energy loss (Brower, 2012). Of the total categorical losses, we record the largest number of data points from availability loss, and wake loss display the largest variability among studies (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 6a). The turbine availability loss appears to be larger than the balance of plant and grid availability losses; however, more data points are needed to validate those estimates (Fig. 6a). Except for one outlier, the turbine performance losses, in both predictions and observations, are about or under 5% (Fig. 6b). Large ranges of environment losses 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 winter time, 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.

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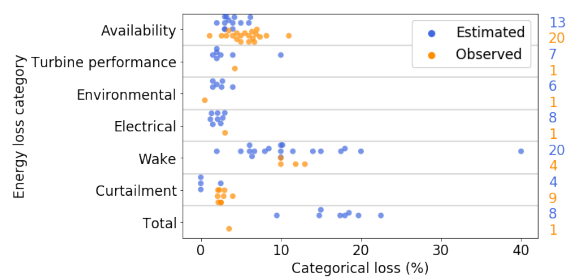
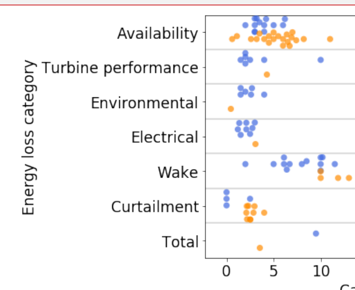


Figure 5: Ranges of total energy-production losses in different categories, according to the proposed framework of the IEC 61400-15 standard. Each blue and orange dot, respectively, represent the mean estimated loss and mean observed loss documented in each independent reference. The losses are expressed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



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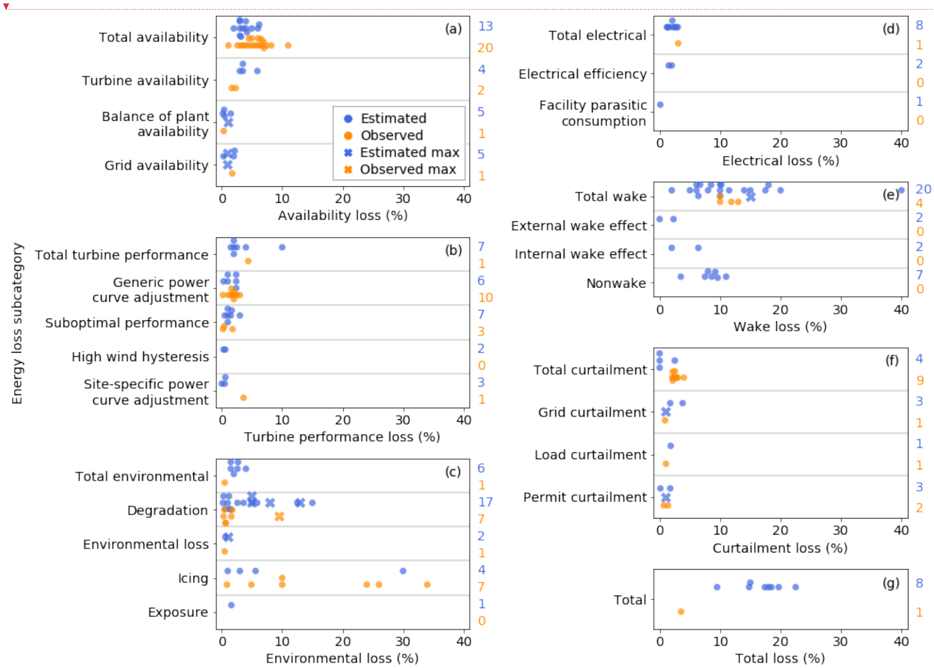
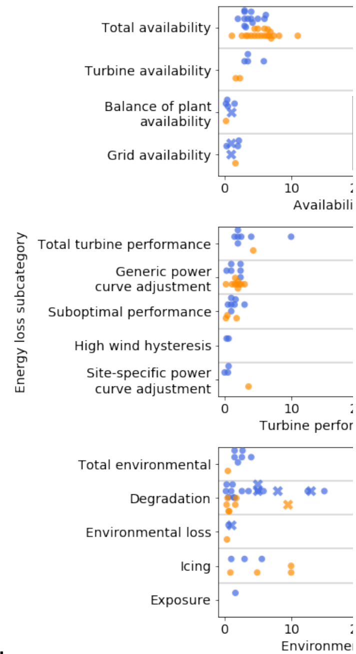


Figure 6: Ranges of energy-production losses in different categories and subcategories, according to the proposed framework of the IEC 61400-15 standard, except for nonwake in (e), which is an extra subcategory summarizing other nonwake categories. Each blue and orange dot, respectively, represent the mean estimated loss and mean observed loss documented in each independent study. The 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 m s^{-1}; this translates to $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 $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.



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We categorize two types of energy-production losses additional to the proposed IEC framework, namely 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).

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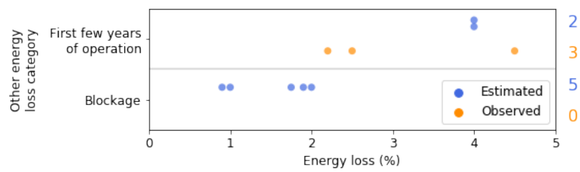

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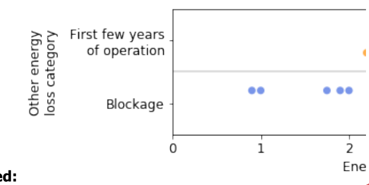

Figure 7: As in Fig. 6, but for the loss categories outside of the proposed IEC framework, as listed in Table B4.

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 loss and the observed generic power curve adjustment loss steadily decrease over time, and the reductions have reasonable R^2 (Fig. 8). No other reported losses with a reasonable number of data samples display remarkable trends (Fig. C1).

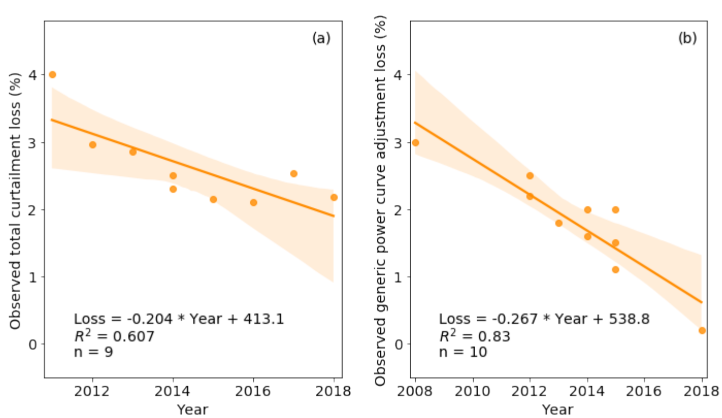

Figure 8: Trend in observed energy-production loss: (a) total curtailment loss and (b) generic power curve adjustment loss. The annotations correspond to those in Fig. 3, where the orange solid line represents simple linear regression, the light orange cone illustrates the 95% confidence interval, R^2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

Past research further documents the uncertainties of AEP losses. Except for an outlier of measuring 80% uncertainty in wake loss, the magnitude of the uncertainty of wake loss is analogous to that of nonwake loss (Fig. 9). 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 intermonthly variability can alter AEP losses for more than 10% (Fig. 9). Note that the results in Fig. 9 represent the uncertainty of the respective production loss percentages in Fig. 6 and Table B3, rather than the AEP uncertainty.

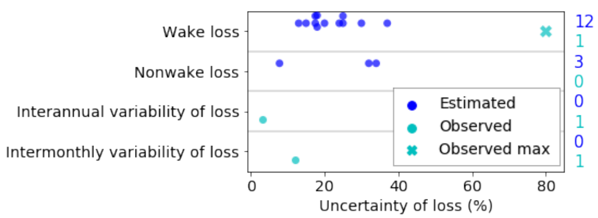

Figure 9: Uncertainty of energy-production losses, where the magnitude corresponds to the AEP loss percentages listed in Fig. 6 and Table B3. Each dark blue dot, turquoise dot, and turquoise cross represents the estimated uncertainty, the observed uncertainty, and the maximum observed uncertainty of losses, respectively. The uncertainties is expressed as percentage 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.

5 Energy-production uncertainty

The individual energy-production uncertainties directly influence the uncertainty of P50 prediction. Total uncertainty is the root-sum-square of the categorical uncertainties; the assumption of correlation between categories can reduce the overall uncertainty, and this assumption is typically consultant- and method-specific (Brower, 2012). Except for a few outliers, the magnitude of the individual energy-production uncertainties across categories and subcategories is about or below 10% (Fig. 10). The energy uncertainties from wind measurements range below 5%, after omitting two extreme data points (Fig. 10a). 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;

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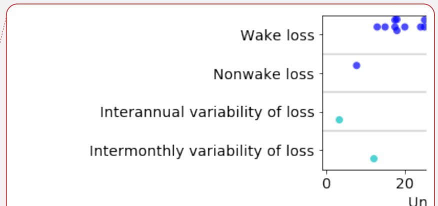

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on-site data synthesis in historical wind resource; model inputs and model appropriateness in horizontal extrapolation; model components and model stress in vertical extrapolation; and environmental loss in plant performance.

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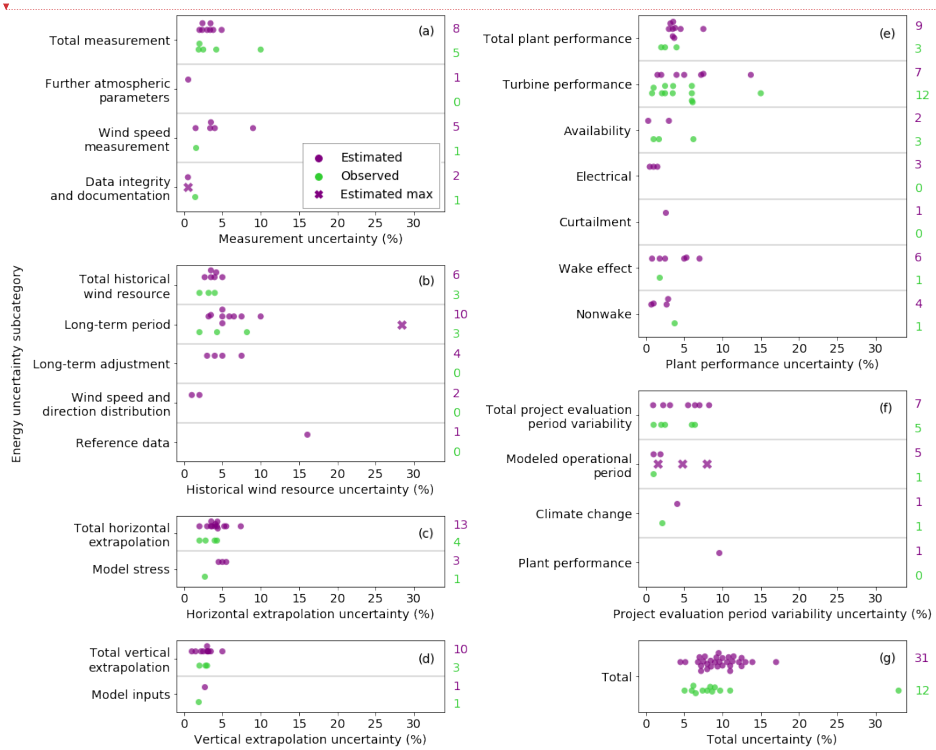

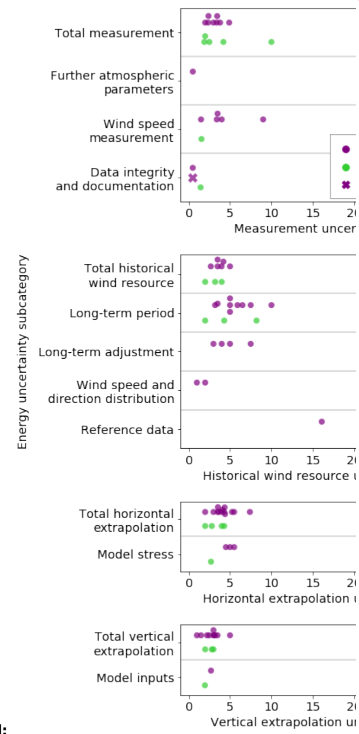

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Figure 10: Ranges of energy-production uncertainties in different categories and subcategories, according to the proposed framework of the IEC 61400-15 standard. The annotations correspond to those in Fig. 6, where each purple dot, green dot, and purple cross represent the mean estimated uncertainty, the mean observed uncertainty, and the maximum of estimated uncertainty from each independent reference, respectively. The uncertainties is expressed as percentage 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.

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

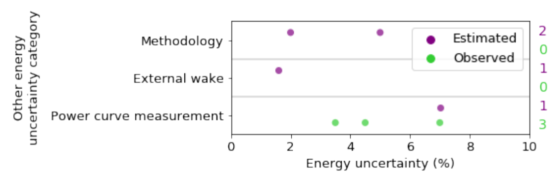
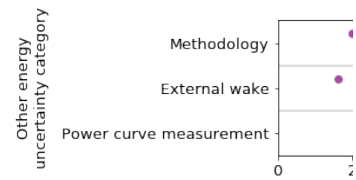


Figure 11: As in Fig. 10, but for the uncertainty categories outside of the proposed IEC framework, as listed in Table B7.

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

6 Wind speed uncertainty

Energy production of a wind turbine is a function of wind speed to its third power. Considering wind speed, either measured, derived, or simulated, is a critical input to an energy estimation model, the uncertainty of wind speed plays an important role in the WRA process. We present various groups of wind speed uncertainties in the literature herein (Fig. 12). The bulk of the wind speed uncertainties are 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.



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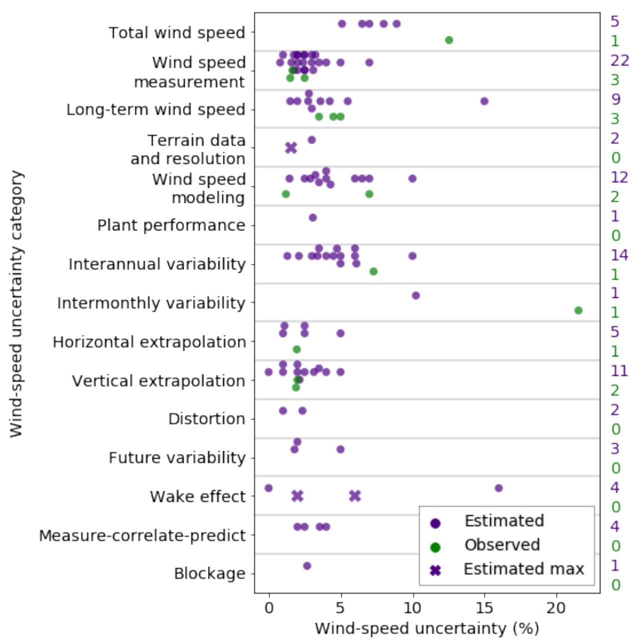
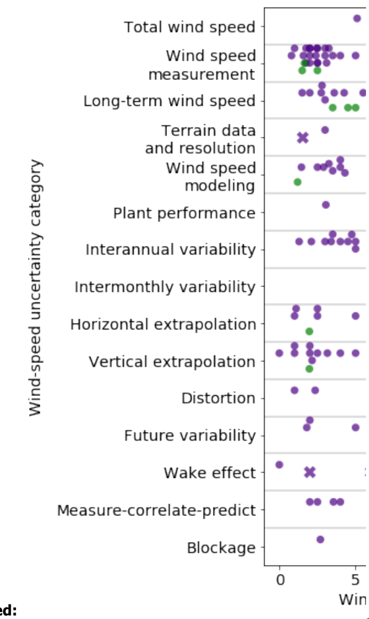


Figure 12: Ranges of wind speed uncertainties in different categories. The annotations correspond to those in Fig. 10, where each dark purple dot, dark green dot, and dark purple cross represent the mean estimated wind speed uncertainty, the mean observed wind speed uncertainty, and the maximum of estimated wind speed uncertainty from each independent study respectively. The uncertainties is expressed as percentage 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.

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



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7 Opportunities for improvements

Although the industry is reducing the mean P50 overprediction bias, the remarkable uncertainties inherent in the WRA process overshadows such achievement. Different organizations have been improving their techniques over time to eliminate the P50 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 P50 prediction bias is reducing and approaches zero, the associated mean P50 uncertainty remains at over 6%, even for the studies reported after 2016 (Fig. 3b). For a validation study that involves a collection of wind farms, such uncertainty bound implies that sizable P50 predication errors for particular wind projects can emerge. In other words, statistically, the AEP prediction is becoming more accurate yet is imprecise. Moreover, from an industry-wide perspective that aggregates different analyses, the variability on the mean P50 bias estimates is notable, which obscures the overall bias-reducing trend (R^2 below 0.5 in Fig. 3). Specifically, the magnitude of the 95% prediction interval at over 10% average P50 estimation error (Fig. 3b) suggests a considerable range of possible mean biases in future validation studies. Additionally, the uncertainties are still substantial in specific AEP losses (Fig. 9), AEP itself (Figs. 10 and 11), and wind speed (Fig. 12). Therefore, the quantification, validation, and reduction of uncertainties requires the attention of the industry collectively.

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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.

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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 P50 (i.e. median annual energy production) errors, as well as the estimated and observed energy losses, energy uncertainties, and wind speed uncertainties embedded in the wind resource assessment process. We conduct this literature review using over 150 credible sources from conference presentations to peer-reviewed journal articles.

Although the mean P50 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 International Electrotechnical Commission (IEC) 61400-15 working group. Wake effect and environmental events undermine wind plant performance and constitute the largest loss in energy production, and validating the wake and environmental loss predictions requires more field measurements and detailed research. Moreover, the variability of observed total availability loss is larger than its estimates. Meanwhile, the decreasing trends of measured curtailment loss and observed

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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.

Data availability

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

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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, noncontractual availability, restart after grid outage, site access, downtime (or speed) to energy ratio, first-year or plant start-up availability
	Balance-of-plant availability	Availability of substation and collection system, other nonturbine availability, warranted availability, site access, first-year or plant start-up availability
	Grid availability	Grid being outside the grid connection agreement operational parameters, actual grid downtime, delays in restart after grid outages
Electrical	Electrical efficiency	Electrical losses between low- or medium-voltage side of the transformer of wind turbine and the energy measurement point
	Facility parasitic consumption	Turbine extreme weather packages, other turbine and/or plant parasitic electrical losses (while operating or not operating)
Turbine performance	Suboptimal performance	Performance deviations from the optimal wind plant performance caused by software, instrumentation, and control setting issue
	Generic power curve adjustment	Expected deviation between advertised power curve and actual power performance in standard conditions ("inner range")
	Site-specific power curve adjustment	Accommodating for inclined flow, turbulence intensity, density, shear, and other site or project-specific adjustments ("outer range")
	High wind hysteresis	Energy lost in hysteresis loop between high wind speed cut-out and recut-in
Environmental	Icing	Performance degradation and shutdown caused by icing

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

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 year or 10 year) may match the long-term site average
	Climate change	When an impact of climate change can be assessed, then this may be considered as an uncertainty.
	Plant performance	The statistical uncertainty associated with how closely the plant performance over the modeled operational period (i.e., 1 year or 10 year) may match the long-term site average.
Measurement	Wind speed measurement	Including effects for wind speed sensor characteristics (cup or sonic), wind speed sensor mounting or deployment (cup or sonic), wind speed sensor data handling and processing characteristics (e.g., tower shadow, icing, and degradation), system motion, consistency and exposure, data acquisition, and data handling. Additionally, the reduction in uncertainty caused by sensor combination is considered.

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

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Appendix B

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

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

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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 4 analysts	Derrick, 2009

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2009	11	45	-2.2	7.3		White, 2009
2009	18		-3			Mönnich et al., 2016
2010			-1	8.1	From 1,806 wind turbines	Nielsen et al., 2010
2010	11		-10			Mönnich et al., 2016
2011	1			2.4	Comparison of 15 analysts	Hendrickson, 2011
2011	89		-6		Industry average: 2000–2011	Drunsic, 2012
2011			-2			Drunsic, 2012
2011	18		-7			Mönnich et al., 2016
2011			-6.7	0.8		Lunacek et al., 2018
2012			-5		Industry average: 2005–2011	Drunsic, 2012
2012			-1			Drunsic, 2012
2012			-1			Brower et al., 2012
2012	125	382	0			Johnson, 2012
2012			-2.4			Bernadett et al., 2012
2012	11		-7			Mönnich et al., 2016
2012	6		-4.9			Pullinger et al., 2019
2013	14		-1			Mönnich et al., 2016
2014	24	106	-1	8.8		Brower, 2014
2014	31	101	-1.4			Istchenko, 2014
2014			-0.6			Geer, 2014
2014	9		-15			Redouane, 2014
2014	4		-2			Mönnich et al., 2016
2015			-1.9			Istchenko, 2015
2015	10		0	4		Sieg, 2015
2015	1		-4	3	Comparison of 20 analysts	Mortensen et al., 2015
2015	1		1			Mönnich et al., 2016
2015	25	91	-8			Cox, 2015
2015	30	127	-2.2			Stoelinga and Hendrickson, 2015
2015	18	58	-1.6			Hendrickson, 2019
2015	23		-4.7	7.7		Hatlee, 2015
2016	30	127	0.1	8.8		Baughman, 2016

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2017		140	-2		Projects from 2011–2016	Elkinton, 2017; Hale, 2017
2017	61		-1.6	7.6	Most projects from 2008–2012	Brower, 2017; Hale, 2017
2017			-2.5			Hale, 2017
2017	30	127	0.7	8.8		Perry, 2017
2018	56	294	-5.5	1.3		Lunacek et al., 2018
2018	50		0			Hendrickson, 2019
2018			-1.5	7.6		Hendrickson, 2019
2018	6		-1.4			Pullinger et al., 2019
2019	31	212	-1.2	4.7		Crescenti et al., 2019
2019	30	144	0	11.37		Hendrickson, 2019
2019	30	111	-0.1	4.5		Hendrickson, 2019
2019			0	7.3		Hendrickson, 2019
2019	87	570	-3.1			Papadopoulos, 2019
2019	25	146	-5			Papadopoulos, 2019
2019	11	59	-0.4			Papadopoulos, 2019
2019	11	24	-3.9			Papadopoulos, 2019

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

640 **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

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

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

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

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

2012	e	Terrain data and resolution			1.5		Brown, 2012
2010	e	Total wind speed	7	3	10		Clive, 2010
2012	e	Total wind speed		3	13		Brower, 2012
2013	e	Total wind speed	8.9			Reference data	Holtslag, 2013
2013	e	Total wind speed	5.1			Lidar	Holtslag, 2013
2015	e	Total wind speed		3	10		Brower et al., 2015
2014	o	Total wind speed		9	16	Nine locations	Redouane, 2014
2011	e	Vertical extrapolation		1	3		Comstock, 2011
2011	e	Vertical extrapolation		0	4		Faghani, 2011
2012	e	Vertical extrapolation		0	6.3		Brower, 2012
2013	e	Vertical extrapolation	5			Reference data	Holtslag, 2013
2013	e	Vertical extrapolation	0			Lidar	Holtslag, 2013
2013	e	Vertical extrapolation		0	5		Mortensen, 2013
2014	e	Vertical extrapolation		0	2		Redouane, 2014
2015	e	Vertical extrapolation		0.7	3.6		Mortensen et al., 2015
2016	e	Vertical extrapolation		2	6	Nonforested	Kelly, 2016
2017	e	Vertical extrapolation	1			Industry accepted; 1% per 10 m	Langreder, 2017
2019	e	Vertical extrapolation		0	7	Depends on shear and terrain	Kelly et al., 2019
2010	o	Vertical extrapolation	1.9			Analyst comparison	Walter, 2010

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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
2019	e	Wake effect			6		Slinger et al., 2019
2007	e	Wind speed measurement	2.4				Breakey, 2019
2010	e	Wind speed measurement	3	1	4		Clive, 2010
2010	e	Wind speed measurement	2			WindPro 2.7	Nielsen et al., 2010
2011	e	Wind speed measurement		1	2.5	Ideal flow; calibration	Hatlee, 2011
2011	e	Wind speed measurement		1.5	5	Nonideal flow; total measurement	Hatlee, 2011
2011	e	Wind speed measurement	3.1				Rogers, 2011
2011	e	Wind speed measurement		1.5	3.5		Comstock, 2011
2011	e	Wind speed measurement		2	3		Faghani, 2011
2012	e	Wind speed measurement		0.5	1.5		Brown, 2012
2012	e	Wind speed measurement		1	2.5	Single anemometer	Brower, 2012
2013	e	Wind speed measurement	5			Reference data; wind statistics	Holtslag, 2013
2013	e	Wind speed measurement	3			Lidar; wind statistics	Holtslag, 2013

2013	e	Wind speed measurement		2	5	Wind measurement	Mortensen, 2013
2014	e	Wind speed measurement		0	5	Measurement campaign	Redouane, 2014
2015	e	Wind speed measurement	2			Anemometer and calibration	Geer, 2015
2015	e	Wind speed measurement	2			Two met masts	Brower et al., 2015
2016	e	Wind speed measurement	2				Kelly, 2016
2017	e	Wind speed measurement	0.8				Breakey, 2019
2019	e	Wind speed measurement	1.58	1.54	1.86	Range of standard, recommended, and lidar methods	Medley and Smith, 2019
2019	e	Wind speed measurement	4			Lidar calibration	Slater, 2019
2019	e	Wind speed measurement		2.23	2.68	Range from using computational fluid dynamics models or not	Crease, 2019
2019	e	Wind speed measurement		6	8		Keck et al., 2019
2013	o	Wind speed measurement		2	3	Lidar on flat terrain	Albers et al., 2013
2015	o	Wind speed measurement		1.1	2.2	Anemometer	Clark, 2015
2016	o	Wind speed measurement		1	2	Anemometer; industry accepted	Smith et al., 2016
2009	e	Wind speed modeling	7				VanLuvanee et al., 2009
2010	e	Wind speed modeling	4	2	6	Flow model accuracy	Clive, 2010

2010	e	Wind speed modeling		3	10		Brower et al., 2010
2011	e	Wind speed modeling		2	5		Faghani, 2011
2012	e	Wind speed modeling		1	5.5		Brown, 2012
2012	e	Wind speed modeling		2	10	Flow model	Brower, 2012
2013	e	Wind speed modeling		1.7	6.9		Abiven et al., 2013
2015	e	Wind speed modeling	10		12		Brower et al., 2015
2017	e	Wind speed modeling		3	5	WAsP	Jog, 2017
2017	e	Wind speed modeling		0.9	2	Ensemble model	Jog, 2017
2017	e	Wind speed modeling	2.9	1.4	7.6		Poulos, 2017
2019	e	Wind speed modeling	2.5			2.5% per km of extrapolation distance in WAsP; industry-recommended assumption	Zhang et al., 2019
2015	o	Wind speed modeling		4	10		Brower et al., 2015
2016	o	Wind speed modeling	1.2		4.3	Weighted absolute total error in WindFarmer	Neubert, 2016

Appendix C

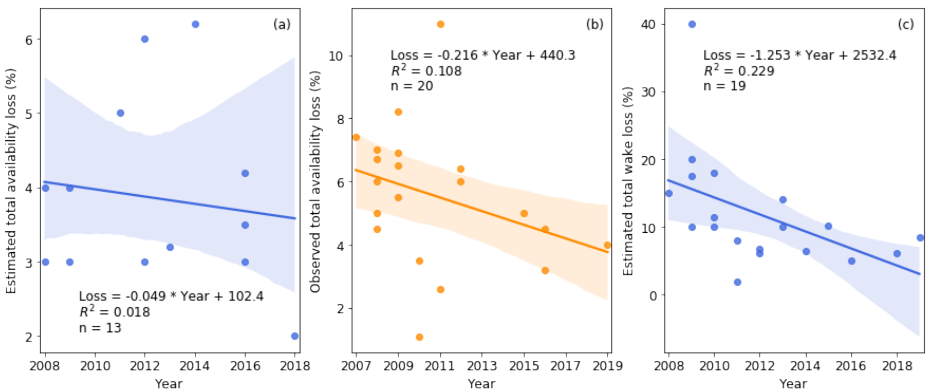

Figure C1: As in Fig. 8, the trend in energy-production loss: (a) estimated total curtailment loss, (b) observed total availability loss, and (c) estimated total wake loss. Note that the ranges of the horizontal and vertical axes differ in each panel.

Author contribution

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

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Competing interests

The authors indicate no conflict of interest.

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Response to Referee 1

We thank the reviewer for conducting a deliberate review to improve our manuscript, we greatly appreciate it.

Regarding your comment on the length of the tables, we will discuss with copy editors about the options to shrink them. Moreover, we want to keep the tables in Appendix A because the definitions presented in Appendix A are fundamental in categorizing different losses and uncertainties in the wind resource assessment process. We understand the final standards are in the works, that is why the text and tables refer it as a "proposed framework". We edited the text in Sect. 1 (lines 58 to 63) and Appendix A (line 593) to make this clear.

Our responses to your specific comments below begin with "Response:".

l.10: the expression "near-zero" is qualitative (how much has the bias been reduced?), and contrary to the notion of uncertainty quantification–which is a primary subject of this work.

Response: The sentence is changed to "… recently the reported average energy prediction bias is reducing."

l.28 to what average are you referring? Do you mean that your subset of US wind farms gave a bias of 3.5 to 4.5%, or do you mean that there is a distribution of biases over e.g. 2-year rolling periods?

Response: The former interpretation is correct. For clarity, the sentence is changed to "A recent study conducted by the researchers at the National Renewable Energy Laboratory (NREL) found an average of 3.5% to 4.5% P50 overprediction bias based on a subset of wind farms in the United States and accounting for curtailment (Lunacek et al., 2018)."

l.30–34: are you defining P50 in terms of a 2-year basis? If so, you should have done that in l.24–25. Then for the long-term (e.g. 20-year lifetime), you are considering the distribution of overlapping 2-year "P50" values. It is the width of this distribution (e.g. its 'sigma' if symmetric, or associated P25 or P10) which determines moreso the odds of underproduction. I.e., the "1%" on line 32 is crucial to such.

Response: We refer to the P50 in 20-year time frame for this manuscript. The reference we discuss here uses a specific P50 definition, which is the 1-year P50 within a 2-year rolling period. We are citing this reference here to explain why P50 overprediction has implications. To clarify the P50 definition used in this manuscript, lines 24 to 26 now read, "P50 are often defined with timescales such as 1 year, 10 years, and 20 years. In this study, unless stated otherwise, we primarily discuss the 20-year P50, which is the typical expected lifespan of utility-scale wind turbines."

l.30–35 and Section 1 generally: if using a statistic such as P50 with a particular (e.g. 2-year) definition, would it not make sense to show a distribution of this?

Response: As mentioned above, we focus on the 20-year P50 in this manuscript. By definition, P50 is the predicted median annual energy production, which does not have an underlying distribution.

l.35–36: You mention uncertainty in a vague sense, but it would be helpful to explicitly state what is/can be quantified; this again relates to the comments above.

Response: Per your suggestion, we added a discussion on uncertainty. Lines 50 to 55 now read, "Random errors that deviate observations or model predictions from the truth lead to uncertainty (Clifton et al., 2016), and uncertainty can be expressed in probability (Wilks, 2011). In WRA, the P-values surrounding P50 such as P90 and P95 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). Given a Gaussian distribution, the standard deviation around the mean represents the uncertainty of that distribution. Traditionally, the wind energy industry uses standard deviation, or σ, to represent uncertainty."

Fig.2: There is no depiction of the combination of uncertainties; this itself is a nontrivial aspect. Also, "stressor" under Vertical Extrapolation should be "stress" to be consistent with horizontal extrapolation.

Response: The discussion of combined uncertainties (in terms of total uncertainty) is listed in the beginning of Sect. 5. Besides, we used "stressor" under vertical extrapolation in Filippelli et al. (2018). We are following your suggestion and change this and subsequent instances to "stress" instead.

l.55: "financial impact" is also found in the other 2 bullet points (see annotated PDF).

Response: Lines 88 to 96 have been edited accordingly, thank you.

l.96–97: What distribution (PDF) are you assuming, to estimate 95l.97–98: Do you mean boot-strap resampling from the entire sample? How much of the sample, and is re-sampling allowed, conditional or otherwise?

Response: The construction of the bootstrapped confidence intervals is based on a Gaussian distribution, according to the central limit theorem; we do not presume any specific parametric distribution for the data. The bootstrapped sample size is the same as the original data (e.g. 63 in Fig. 3). By definition, resampling is allowed in bootstrapping, and the resampling with replacement is random. These details are included in Waskom et al. (2020), which is cited here. We also edited the text to make this clearer, and lines 151 to 170 now read, "We also derive the trend of P50 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 P50 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 P50 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 coefficients with 95% confidence. Furthermore, we present the 95% prediction interval in Fig. 3, which depicts the range of the predicted values, i.e. the P50 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."

l.101: is the prediction interval assuming a Gaussian distribution, or what?

Response: That is correct. Please see our response above for the edits in the text.

l.101–3: Why do you evaluate the R^2 of the linear fit? What does this tell you? More importantly: *why would you use a linear fit for a quantity that is unlikely to continue to rise linearly? The bias is decreasing, towards zero, and will likely not increase beyond that at the same rate.*

Response: The reviewer raised an excellent point. We now switched to the second-degree polynomial regression for Fig. 3. We also expanded the methodology description from lines 151 to 173. The R^2 is a commonly used metric to evaluate statistical fitting, and it describes the variance of the predictand explained by the regression.

l.104: do you "need to interpret a small subset", or are your forced to to so?

Response: We only have limited data for a specific category or subcategory of loss and uncertainty. Lines 174 to 175 now read "For loss and uncertainty, we have limited data samples for certain categories because these data are only sparsely available."

l.156–7: you argued in the previous paragraph that the low R^2 of the linear fit means most of the variability in bias is not described by the regression. Thus how can you say the bias is approaching zero? Statistically, you can say that its magnitude is decreasing; again, perhaps a linear trend is not appropriate (though this is difficult also to prove statistically, given the limited data).

Response: Thank you. Because we changed from linear regression to quadratic regression, the R^2 has improved in Fig. 3b, where the studies based on fewer than 10 wind farms are removed.

l.151: why is 'typically' included? Isn't it just one standard deviation?

Response: We checked that the uncertainty values presented in Fig. 3 and Table B1 all represent one standard deviation from the mean. The relevant sentences here and throughout the manuscript are modified.

Fig.5: In the caption, indicate how many observations/cases/references were used.

Response: This is a great suggestion, and we added the sample size as part of this plot and all the similar plots in the manuscript (Figs. 5, 6, 7, 9, 10, 11, and 12). We edited the captions accordingly as well.

Fig.6: there appears to be no "observed max" in any subcategories, except degradation. Perhaps explain why there are relatively few yellow dots.

Response: We display the references we can gather in this study, and the sample size of observed numbers usually trails that of the estimated values. The lack of observations is discussed in the last paragraph of Sect. 7. Regarding your comment that only degradation has "Observed max" values, this is what the data show.

Fig.12 (also 9): the intermonthly variability appears to be much too large; is this taken out of context? E.g., is this a just a higher percentage of a smaller number than the other losses?

Response: For Fig. 9, we only have 1 data point for the observed uncertainty of energy production loss from month to month. That study explicitly cited that the intermonthly variability contributes to 10% to 14% of energy production loss, depending on the location. The study did not specify which types of categorical energy production loss it refers to, so we cannot answer on your last question with evidence. We understand that the value is nontrivial in magnitude while this is what was reported in that study.

Regarding Fig. 12, the green dot of intermonthly variability you refer to is also from the same study above. They observed 19% to 24% of wind speed variability from month to month, depending on the region.

l.305–306: This sentence is confusing. It appears that you are trying to say that the uncertainty in WRA is larger than the industry-wide mean bias; i.e. the ensemble mean error is smaller than the variability.

Response: The sentence now reads "Although the industry is reducing the mean P50 overprediction bias, the remarkable uncertainties inherent in the WRA process overshadows such achievement."

l.341–2: "the resultant compound effect can become larger than the total value from a linear approach" is not mathematically correct. Here you are conflating two things: significant higher-order moments involving correlated values, and simple 2nd-order quantities that have significant correlation. Explicitly, the former causes extra terms which appear to give a 'sum' greater than the linear combination of two correlated component uncertainties; I remind that the latter is equal to the result for two perfectly correlated quantities.

Response: Thank you. Lines 528 to 531 now read "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)."

l.355: I'd suggest "being reduced" over time, not "approaching zero", because the un- certainty will not disappear—but rather decrease, as practices and reporting improve.

Response: Thank you. The instances of "is approaching zero" in the manuscript are changed to "is reducing".

Table B1: The caption denotes "usually illustrates one standard deviation"—you should note where it does not, e.g. with an asterisk (not just text, but in the table).

Response: Please see the comment above regarding line 151.

Table B1–headers: the values for 'Wind Farm' and 'Wind Farm Year' are not defined here in Appendix B.

Response: Thank you. The definition has been added, and lines 611 to 613 now read “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.”

Technical corrections

There are a number of English usage errors; in the first pages I make a number of corrections and suggestions via the attached annotated PDF, to help get the authors started with this aspect of revision.

Response: Thank you. The copy-editing team of Wind Energy Science will also review the manuscript too.

l.73–4: disallow line-break between “Sect.” and “5”.

Response: We do not think the line-break here is against the rules of Wind Energy Science. Because the final form of the manuscript will have a different format, we are not editing the line-break here in this version.

Table 1/p.8: under ’improve modeling techniques’, it should be “flow over complex terrain”; and “effects of changes in” needs to be prepended to ’surface roughness’.

Response: Thank you.

l.159: “of” should be “for”

Response: Thank you.

Fig.5 caption: English corrected to “losses are expressed as percentage of AEP”

Response: Thank you. Subsequent captions are also edited accordingly.

l.305: “immersed” should be “inherent”.

Response: Thank you, this is a better word here.

Table B2: in Group 16, shouldn't the first Lunacek et al (2018) line be for projects before (not after) 2011? Also, should similar distinctions be included for the Lunacek [et al 2018] data shown on the first two lines of group 7?

Response: You raised a great point. The three entries of group 7 are now labeled as "2010" with "Projects before 2011" in the notes. We also updated Fig. 4 accordingly.

references: many are to presentations at workshops/conferences, but lack any link or specific designations (e.g. session/talk numbers, etc.) within proceedings.

Response: Many of the presentations at AWEA and WindEurope conferences are only available for attendees or their members, and they often lack specific session details. We cannot provide the links to the presentations on our end because we do not possess the copyright. We are doing our best to document the references in this manuscript.

l.608: reference incomplete

Response: The technical report does not indicate any report number. We added the location of Ecofys, the company that published the report, in the citation.

l.632: update to 2019 report; also reference is incomplete (e.g. DTU report ...).

Response: We edited the citation and we included the 2019 DTU report in the analysis.

l.657: "M.J" should come after "Fields", without 'Jason'; otherwise should be listed as e.g. "Fields, M. Jason"

Response: Thank you, the citation is fixed now.

l.675: reference is garbled (Denmark, in Ireland?)

Response: The conference location was Dublin, Ireland.

Please also note the supplement to this comment:
https://wes.copernicus.org/preprints/wes-2020-85/wes-2020-85-RC1-supplement.pdf

Response: We accepted a lot of your proposed changes. For those of your suggestions that require further discussions, please see our comments below.

Line 156-157: “but you argued above that the "uncertainty between validation studies" is large enough that this is not necessarily true”

Response: With the improved quadratic regression, the reducing trend of the P50 bias is more reliable. We also edited the sentence, it now reads, “Even though the industry-wide mean P50 prediction bias is converging towards zero, the industry appears to overestimate or underpredict the AEP for many individual wind projects.”

Table 1: “remove windiness”

Response: We are keeping the term “windiness”, which is useful here because it is a commonly used term in the industry.

Response to Referee 2

We thank the reviewer for the comments. We hope the industry can carry on producing similar literature reviews every few years as well. Our responses to your specific comments below begin with “Response:”.

Having all this written, however, I have doubts if the manuscript qualifies as a scientific paper in Wind Energy Science. Apart from the very relevant data basis, I represent the opinion that the study lacks substantial new concepts, ideas or methods. Trends are identified and to some extent explained but no actual concept is deduced from this. In that sense, my recommendation to the authors would be either to revise the approach of the manuscript and add more scientific methods and contents, or find a better way of publishing this indeed very relevant and valuable study.

Response: This is a literature review article, and Wind Energy Science accepts literature review submissions. To make it clear that this is a review article, we have added the phrase “literature review” explicitly throughout the manuscript, including the Abstract, Introduction, Data and methodology, and Conclusions.

In addition to the materials we report from the literature, we also discuss new insights based on our literature survey, including the discussion in Sect. 7 on the dominant role of uncertainty in the P50 bias trend and the sources of substantial plant performance loss. As stated in lines 98 to 100, “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.”

Minor remark: (e.g. Figure 3) I would recommend not to use years on the x-axis and for the application of a regression analysis – this gives rather non-intuitive values for the derived intercepts.

Response: We changed the regression from linear to quadratic, per the request from another reviewer. We also changed the baseline of the variable “Year” to the year 2002, which leads to a more comprehensible intercept. We updated Fig.3 and lines 251 to 252 now read, “For clarity, the regression uses the year 2002 as the baseline, hence the resultant regression constant, i.e. the derived intercept, is comprehensible.”