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

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

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

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

**Abstract.** The financing of a wind farm directly relates to the preconstruction energy yield assessments which estimate the annual energy production for the farm. The accuracy and the precision of the preconstruction energy estimates can dictate the profitability of the wind project. Historically, the wind industry tended to overpredict the annual energy production of wind farms. Experts have been dedicated to eliminating such prediction errors in the past decade, and recently the reported average
10    energy prediction bias is declining. Herein, we present a literature review of the energy yield assessment errors across the global wind energy industry. We identify a long-term trend of reduction in the overprediction bias, whereas the uncertainty associated with the prediction error is prominent. We also summarize the recent advancements of the wind resource assessment process that justify the bias reduction, including improvements in modeling and measurement techniques. Additionally, because the energy losses and uncertainties substantially influence the prediction error, we document and examine the
15    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.
20    Finally, for this work to be as reproducible as possible, we include all of the data used in the analysis in appendices to the article.

## 1 Introduction

Determining the range of annual energy production (AEP), or the energy yield assessment (EYA), has been a key part of the wind resource assessment (WRA) process. The predicted median AEP is also known as the P50, i.e. the AEP
25    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

30   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 results in marked 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 cause observations or model predictions deviate from the truth and lead to uncertainty (Clifton et al., 2016), and uncertainty is quantified via probability (Wilks, 2011). In WRA, the P-values surrounding 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). When a sample of errors is Gaussian distributed, the standard deviation around the mean is typically used to represent the uncertainty of errors. Traditionally, the wind energy industry uses standard deviation, or $\sigma$, 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.
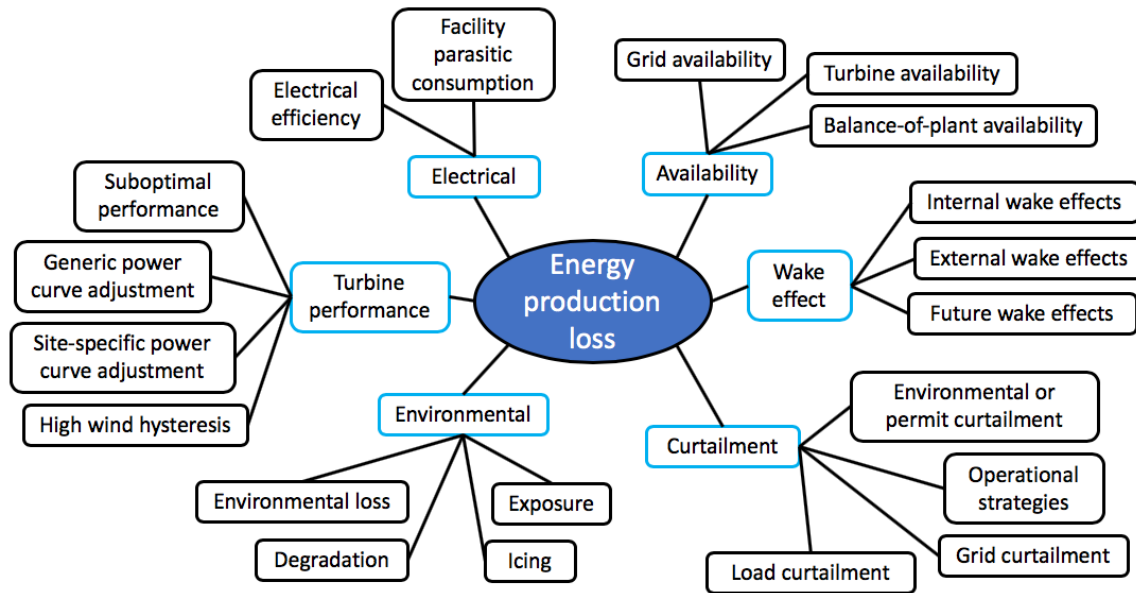
Figure 1: Mind map of energy production loss, according to the IEC 61400-15 proposed framework. The blue and black rounded rectangles represent the categorial and subcategorical losses, respectively. Details of each loss category and subcategory are discussed in Table A1.
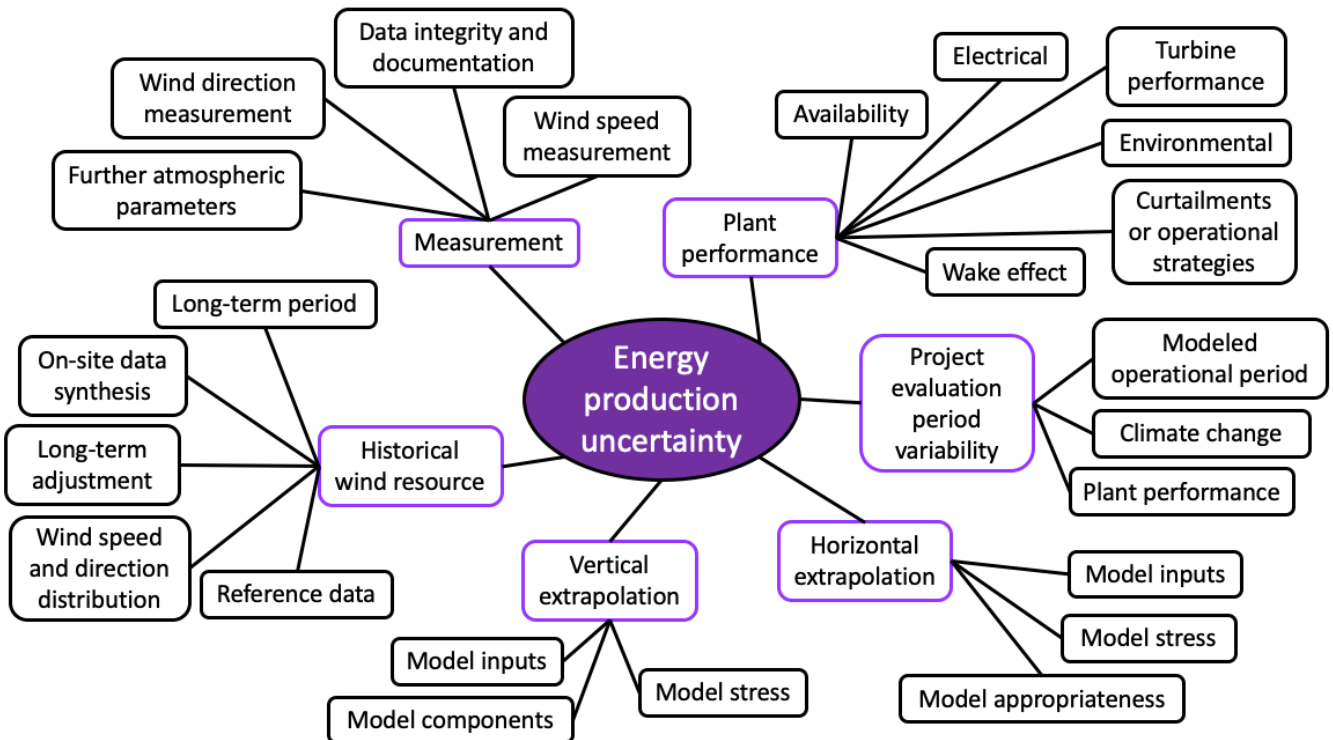
**Figure 2: Mind map of energy production uncertainty, according to the IEC 61400-15 proposed framework. The purple and black rounded rectangles represent the categorial and subcategorical uncertainties, respectively. Details of each uncertainty category and subcategory are discussed in Table A2.**

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 million of economic benefits, depending on the situation and the financial model (Brower et al., 2015; Halberg, 2017);

- a change of 1% in wind speed uncertainty can lead to a 3% to 5% change in net present value of a wind farm (Kline, 2019).

Experts in the industry have presented many studies on 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?
- 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.

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.

## 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

95  after mergers and acquisitions; hence, their presentations and publications can also represent international practices.

In most cases, we label the data source with the published year of the study, unless the author highlights a change of method at a specific time. For example, if an organization publishes a study in 2012 and reports their improvements on 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

100  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).

We also derive the trend of P50 prediction errors using polynomial regression and investigate the reasons behind such

105  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

110  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

115  regression function, whereas the prediction interval represents the uncertainty of the estimated values of the predictand (Wilks, 2011). In addition, we evaluate the regression analysis with the coefficient of determination ($R^2$), which represents the proportion of the variance of the predictand explained by the regression.

For loss and uncertainty, we have limited data samples for certain categories because these data are only sparsely available. When a source does not provide an average value, we perform a simple arithmetic mean when both the upper and

120  lower bounds are listed. For instance, when the average wake loss is between 5% and 15%, we project the average of 10% in Fig. 6, and we present all the original values in Appendix B. If only the upper bound is found, then we project the data point as a maximum: the crosses in Fig. 6 are used as an example. We also use linear regression to explore trends in loss and uncertainty estimates.

We categorize the data to the best of our knowledge to synthesize a holistic analysis. On one hand, if the type of loss

125  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.

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. 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).

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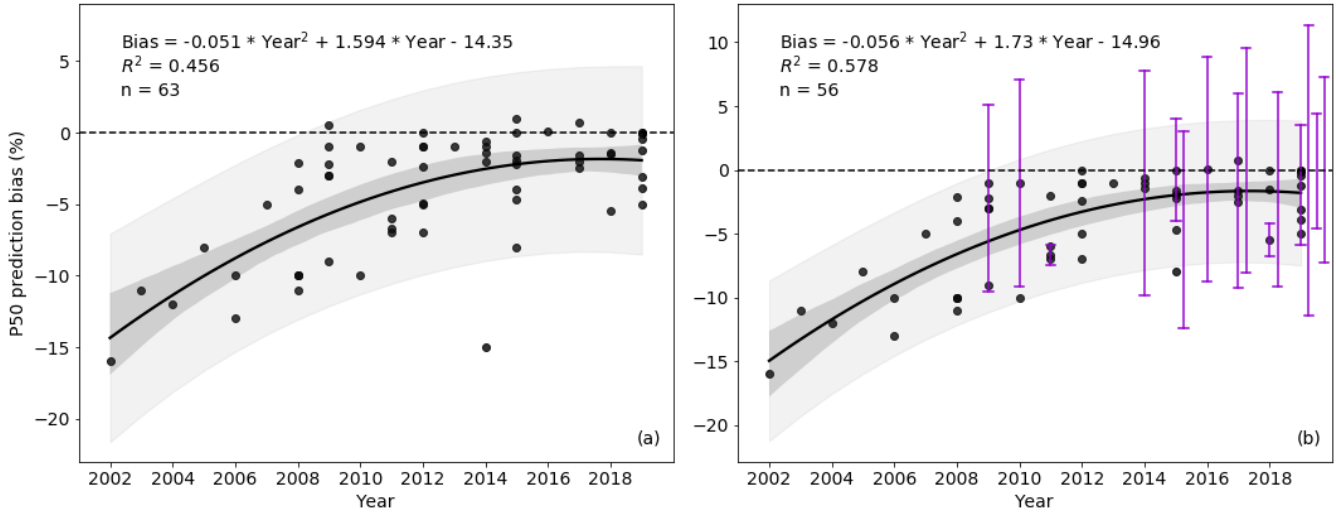
**Figure 3: The trend of P50 prediction bias: (a) scatterplot of 63 independent P50 prediction error values, where R² is the coefficient of determination and n is the sample size. Negative bias means the predicted AEP is higher than the measured AEP, and vice versa for positive bias. The black solid line represents the quadratic regression, the dark grey cone displays the 95% confidence interval of the regression line, the light grey cone depicts the 95% prediction interval, the horizontal black dashed line marks the zero P50**
165 **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
170 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.

175 **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
180 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).
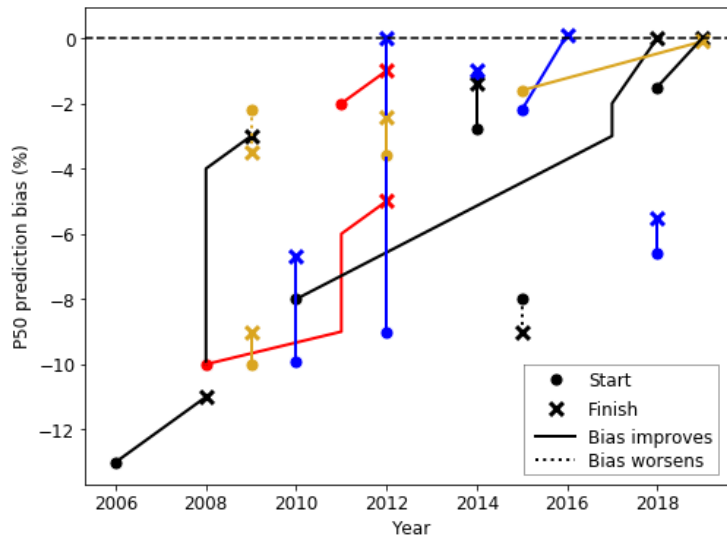
**Figure 4: Illustration of P50 bias changes over time after method modifications in 17 studies. The dot and the cross, respectively, represent the starting point and the finish point of the P50 prediction error because of method adjustments. The solid line indicates the P50 bias reduces after the method 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.**

**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., <br>• windiness or long-term correction of wind data, <br>• suboptimal operation, <br>• external wake effect, and <br>• degradation of long-term meteorological masts. | AWS Truepower, 2009; Johnson, 2012 |
| Consider meteorological effects on power production e.g., <br>• wind shear, <br>• turbulence, <br>• air inflow angle, and <br>• atmospheric stability. | AWS Truepower, 2009; Brower et al., 2012; Elkinton, 2013; Johnson, 2012; Ostridge, 2017 |

| | |
|---|---|
| Improve modeling techniques e.g.,<br><br>• turbine performance,<br>• wind flow,<br>• wake,<br>• flow over complex terrain,<br>• effects of changes in surface roughness, and<br>• 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.,<br><br>• loss assumptions, and<br>• 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

195 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

200 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

205 results in a substantial portion of energy loss, and its estimations demonstrate large variations (Fig. 6e). The magnitude of estimated wake loss is larger than that of the predicted nonwake loss, which consists of other categorical losses (Fig. 6e). The observed total curtailment loss exhibits lower variability, yet with larger magnitude than its estimation (Fig. 6f). From the eight studies that report total loss, the predictions range from 9.5% to 22.5% (Fig. 6g). We do not encounter any operational strategies loss under curtailment loss in the literature, and thus the subcategories in Fig. 6 do not cover every subcategory in Table A1.
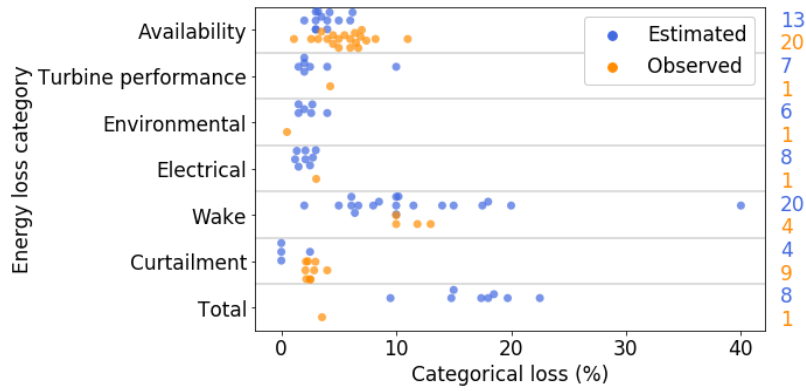
**Figure 5: Ranges of total energy-production losses in different categories, according to the proposed framework of the IEC 61400-15 standard. Each blue and orange dot, respectively, represent the mean estimated loss and mean observed loss documented in each independent reference. The losses are expressed 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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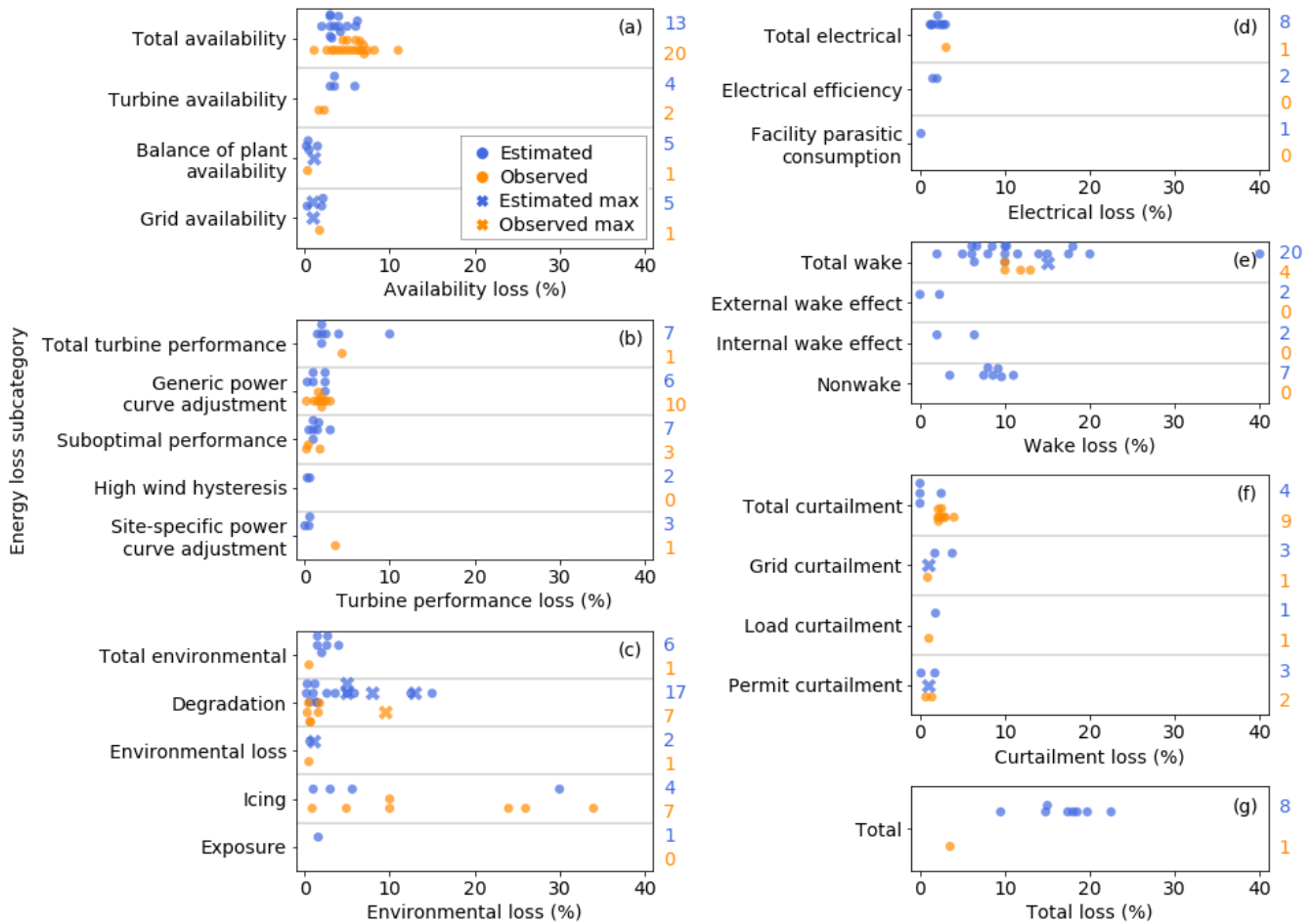

220 **Figure 6: Ranges of energy-production losses in different categories and subcategories, according to the proposed framework of the IEC 61400-15 standard, except for nonwake in (e), which is an extra subcategory summarizing other nonwake categories. Each blue and orange dot, respectively, represent 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 225 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

230 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.

235       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

240 al., 2008) and has been heavily discussed in recent years (Bleeg et al., 2018; Lee, 2019; Papadopoulos, 2019; Robinson, 2019; Spalding, 2019). Compared to some of the losses in Fig. 6, the loss magnitude of first few years of operation and blockage is relatively small, where it contributes to less than 5% of AEP reduction per year (Fig. 7).

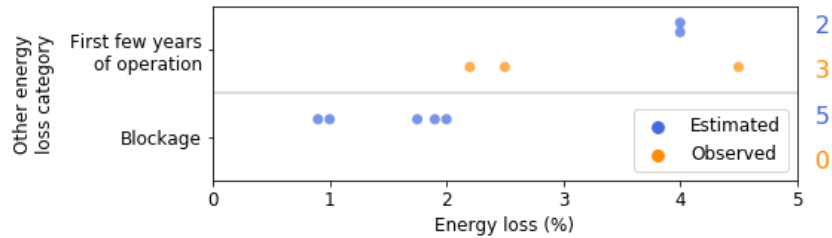
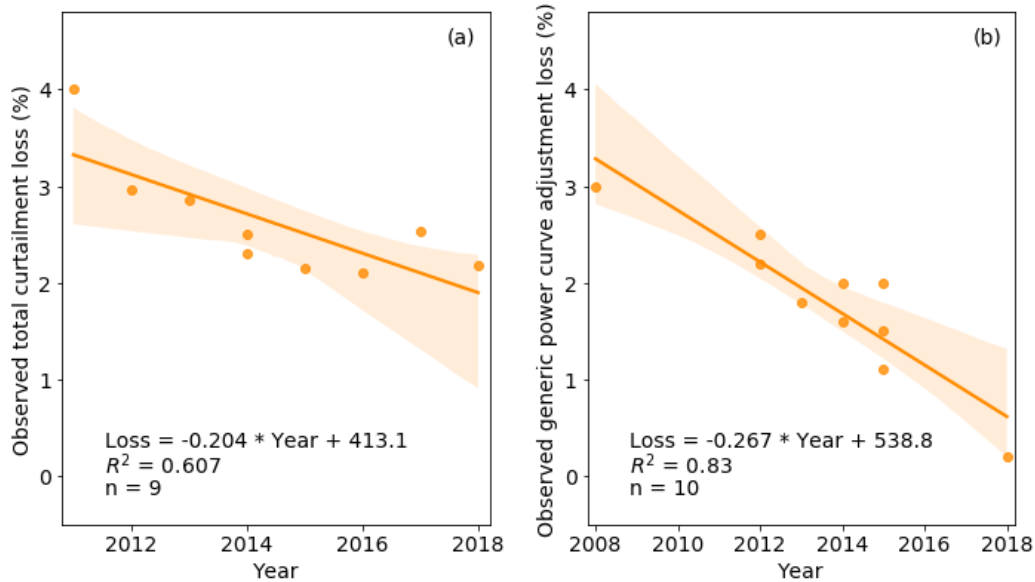
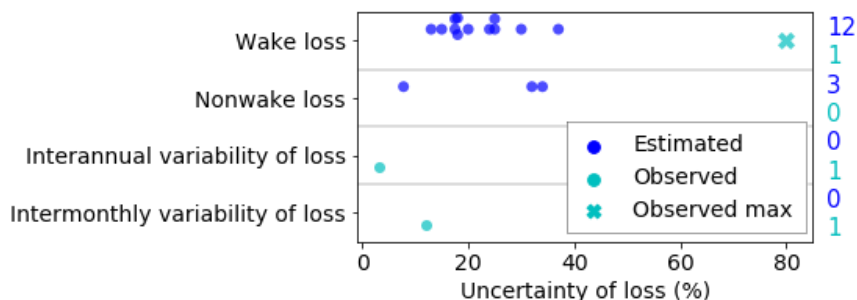



**Figure 7: As in Fig. 6, but for the loss categories outside of the proposed IEC framework, as listed in Table B4.**

245       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).

250 **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

255 tends to reveal the uncertainty of wake loss than nonwake loss according to the larger number of data sources (Fig. 9). One data source reported that depending on the location, the operational variation from month to month can alter AEP losses for more than 10% on average (Fig. 9). Note that the results in Fig. 9 represent the uncertainty of the respective production loss percentages in Fig. 6 and Table B3, rather than the AEP uncertainty.

260 **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**

265 **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

270 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

275 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).

280 In the literature, we cannot identify all the uncertainty types listed in the proposed IEC framework; hence, the following AEP uncertainty subcategories in Table A2 are omitted in Fig. 10: wind direction measurement in measurement;

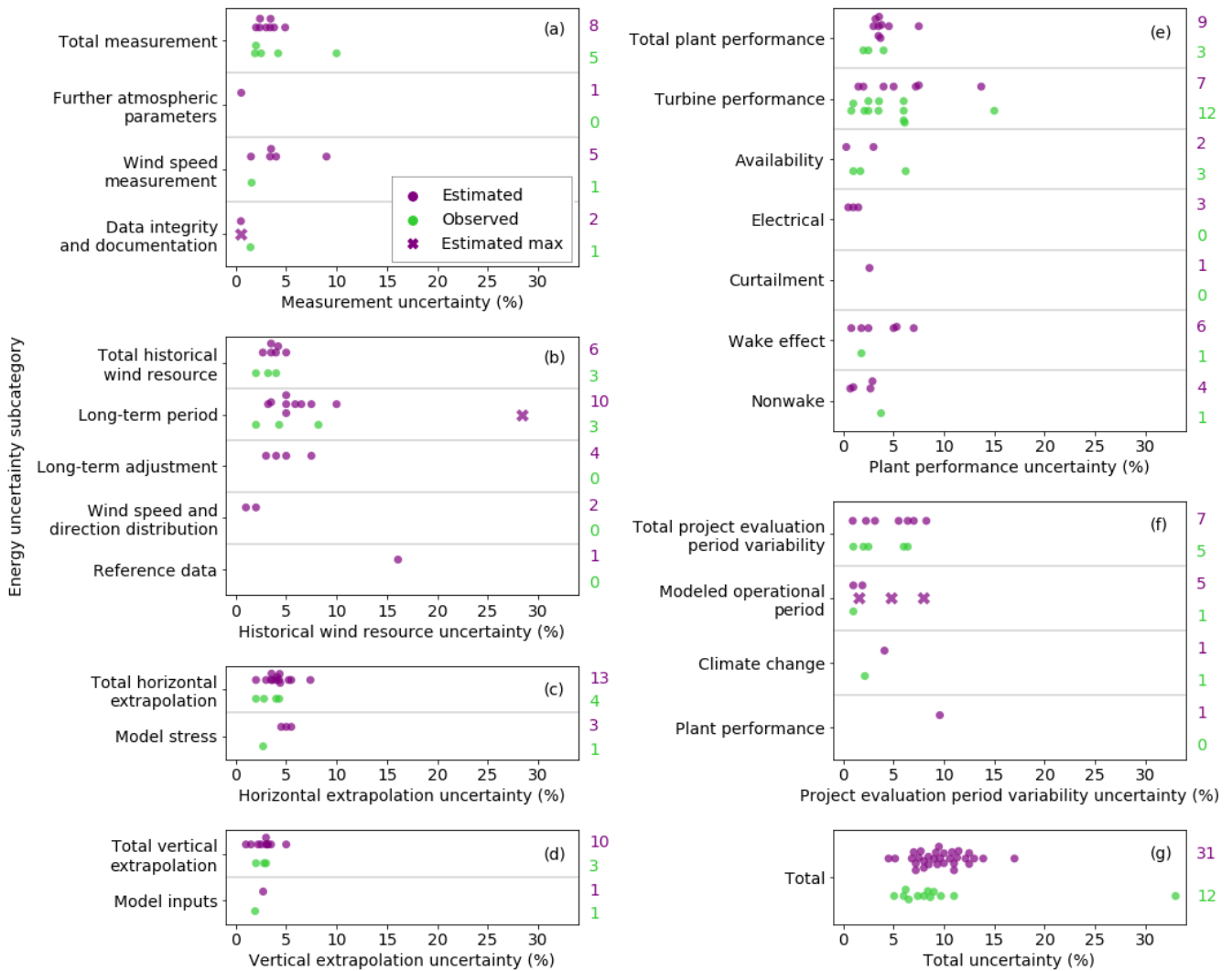
on-site data synthesis in historical wind resource; model inputs and model appropriateness in horizontal extrapolation; model components and model stress in vertical extrapolation; and environmental loss in plant performance.

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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**
290 **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.**

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.
295 11, specifically mentioned in the data sources, could be interpreted as the uncertainty from the turbine performance loss.

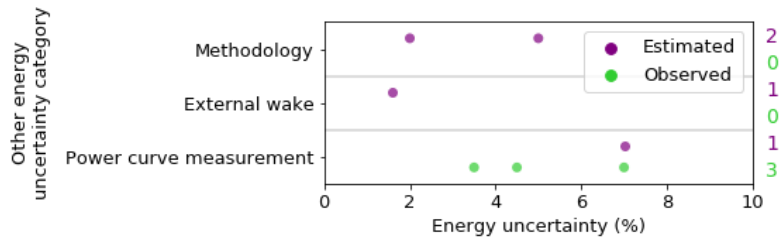



**Figure 11: As in Fig. 10, but for the uncertainty categories outside of the proposed IEC framework, as listed in Table B7.**

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**

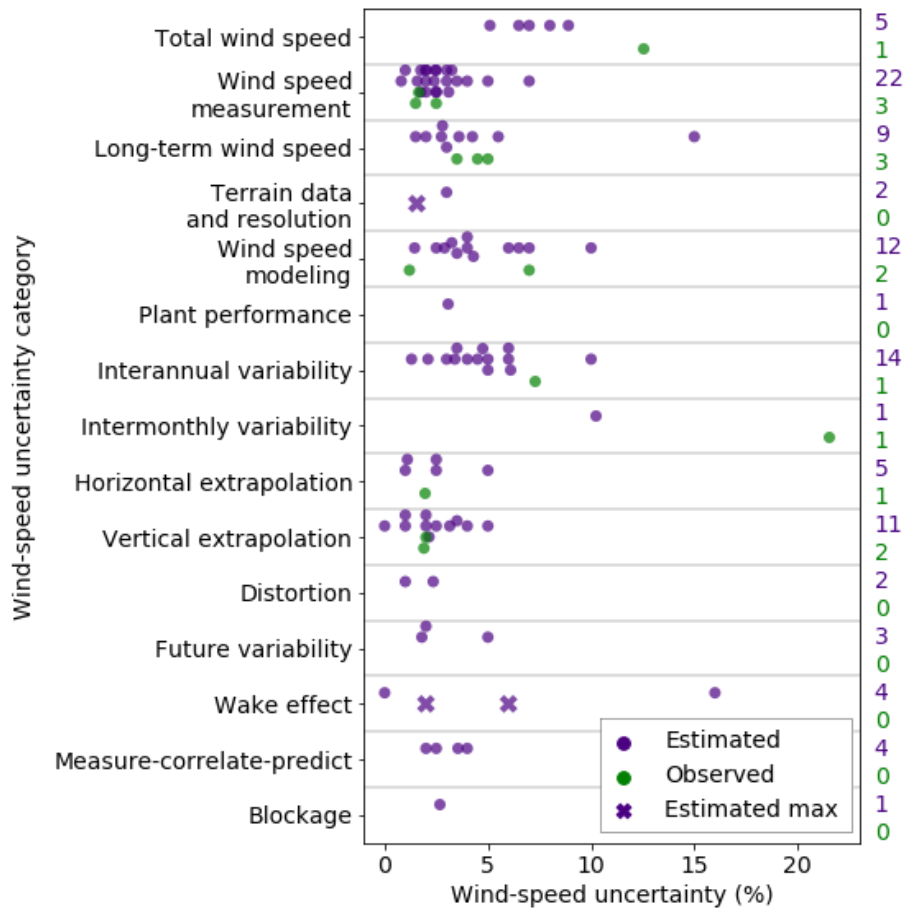
Energy production of a wind turbine is a function of wind speed to its third power. Considering wind speed, either measured, derived, or simulated, is a critical input to an energy estimation model, the uncertainty of wind speed plays an important role in the WRA process. We present various groups of 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**

320 **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

325 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

330 uncertainty from 2.68% to 2.23%, which translates to 1.2 million British pounds of equity savings for a 1-GW offshore wind farm in the United Kingdom (Crease, 2019).

# 7 Opportunities for improvements

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.

To reduce the overall AEP uncertainty, the industry should continue to assess the energy impacts of plant performance losses, especially those from wake effect and environmental events. On one hand, wake effect, as part of a grand challenge in wind energy meteorology (Veers et al., 2019), has been estimated as one of the largest energy losses (Fig. 6e). The AEP loss caused by wake effect also varies, estimated between 15% and 40% (Fig. 9), and the unpredictability of wakes contributes to the AEP uncertainty on plant performance (Fig. 10e) and the wind speed uncertainty (Fig. 12). Although the industry has been simulating and measuring energy loss caused by wake effect, its site-specific impact on AEP for the whole wind farm as well as its time-varying production impact on downwind turbines remains largely uncertain. From a macro point of view, compared to internal wake effect, external wake effect from neighboring wind farms is a bigger known unknown because of the lack of data and research. On the other hand, environmental losses display broad range of values, particularly from icing events and turbine degradation (Fig. 6c). In general, the icing problem halts energy production in the short run, and blade degradation undermines turbine performance in the long run. Diagnosing and mitigating such substantial environmental losses would reduce both loss and uncertainty on AEP. Overall, the prediction and prevention of environmental events are critical, and the production downtime during high electricity demand can lead to consequential financial losses.

Additionally, the industry recognizes the role of remote-sensing instruments in reducing the uncertainty of energy production and wind speed from extrapolation, such as profiling lidars, scanning lidars, and airborne drones (Faghani et al., 2008; Holtslag, 2013; Peyre, 2019; Rogers, 2010). The latter can also be used to inspect turbine blades (Shihavuddin et al., 2019) to reduce unexpected blade degradation loss over time. Industry-wide collaborations such as the International Energy Agency Wind Task 32 and the Consortium For Advancement of Remote Sensing, have been promoting remote-sensing implementation in WRA.

365       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

370 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

375 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

380 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

385 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

390 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

395 environmental loss predictions requires more field measurements and detailed research. Moreover, the variability of observed total availability loss is larger than its estimates. Meanwhile, the decreasing trends of measured curtailment loss and observed

generic power curve adjustment loss indicate the continuing industry effort to optimize wind energy production. Additionally, different categorical energy uncertainties and wind speed uncertainties demonstrate similar magnitude, with a majority of the data below 10%. More observations are the solution to better understand and further lower these uncertainties.

400    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.

405    **Data availability**

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

## Appendix A

410    **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 | |

**Appendix B**

420        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.

425    **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.**

| 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 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 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 |

| 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 |

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**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 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 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 |

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**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 |

| Year | | Availability | Total availability | | | | Notes | Reference |
|---|---|---|---|---|---|---|---|---|
| 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 |

| Year | o/e | Category | Type | | | | Notes | Reference |
|------|-----|----------|------|---|---|---|-------|-----------|
| 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 |

| Year | | | | | | | | |
|------|---|-----------|-------------------|------|------|------|------------------------------|------------------------------|
| 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 |

| Year | | Category | Subcategory | | | | Description | Source |
|------|---|----------|-------------|---|---|---|-------------|--------|
| 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 |

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

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

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

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

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

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

| Year | | Category | Subcategory | | | | Note | Reference |
|------|---|----------|-------------|---|---|---|------|-----------|
| 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 |

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**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 |
|---|---|---|---|---|---|---|---|

| Year | Est/Obs | Category | Subcategory | 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 |

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**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 |

| Year | | Category | Type | | | | Notes | Reference |
|---|---|---|---|---|---|---|---|---|
| 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 |

| Year | e/o | Category | Subcategory | | | | Description | Reference |
|---|---|---|---|---|---|---|---|---|
| 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 |

| Year | | Category | Subcategory | | | | Notes | Reference |
|------|---|----------|-------------|---|---|---|-------|-----------|
| 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 |

| Year | | Category | Subcategory | | | | Notes | Reference |
|------|---|----------|-------------|---|---|---|-------|-----------|
| 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 |

| Year | o/e | Category | Subcategory | | | | Notes | Reference |
|---|---|---|---|---|---|---|---|---|
| 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 |

| Year | | Project | Total project | | | | Description | Reference |
|---|---|---|---|---|---|---|---|---|
| 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 |

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

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

| Year | Type | Category | Subcategory | V1 | V2 | V3 | Notes | Reference |
|---|---|---|---|---|---|---|---|---|
| 2012 | o | Total | Total | | 9.1 | 12.9 | Range of 1-year and 10-year uncertainties | Tchou, 2012 |
| 2012 | o | Total | Total | | 6.2 | 11.1 | Range of 1-year and 10-year uncertainties | Tchou, 2012 |
| 2014 | o | Total | Total | 8.4 | 6.3 | 11.5 | | Brower, 2014 |
| 2014 | o | Total | Total | | 5.4 | 9.4 | Range of 1-year and 10-year uncertainties | Istchenko, 2014 |
| 2014 | o | Total | Total | | 4 | 8 | Nine wind farms | Redouane, 2014 |
| 2015 | o | Total | Total | | 6 | 12 | | Apple, 2015 |
| 2015 | o | Total | Total | 6.2 | | | | Istchenko, 2015 |
| 2015 | o | Total | Total | | 3.1 | 7 | | Mortensen et al., 2015a |
| 2017 | o | Total | Total | 8 | | | Post-2011 projects, 1-year standard deviation | Ostridge, 2017 |
| 2014 | e | Vertical extrapolation | Model inputs | 2.6 | 0 | 6.4 | Wind shear | AWS Truepower, 2014 |
| 2010 | o | Vertical extrapolation | Model inputs | 1.9 | | | Wind shear | Rogers, 2010 |
| 2009 | e | Vertical extrapolation | Total vertical extrapolation | 3.49 | | | Twenty-year uncertainty, 10 projects | Breakey, 2019 |
| 2011 | e | Vertical extrapolation | Total vertical extrapolation | 3.2 | 1.5 | 5 | | Comstock, 2011 |
| 2011 | e | Vertical extrapolation | Total vertical extrapolation | 3.1 | | | | Hendrickson, 2011 |
| 2013 | e | Vertical extrapolation | Total vertical extrapolation | 1 | 0 | 13 | Onshore, analyst comparison | Mortensen and Ejsing Jørgensen, 2013 |
| 2014 | e | Vertical extrapolation | Total vertical extrapolation | | 1 | 2 | | Geer, 2014 |
| 2014 | e | Vertical extrapolation | Total vertical extrapolation | | 0 | 5 | | Redouane, 2014 |

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

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**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 |

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**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 |

| Year | e/o | Type | | | | Description | Reference |
|------|-----|------|---|---|---|-------------|-----------|
| 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 |

| Year | Type | Parameter | | | | Comment | Reference |
|------|------|-----------|---|---|---|---------|-----------|
| 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 |

| 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 |

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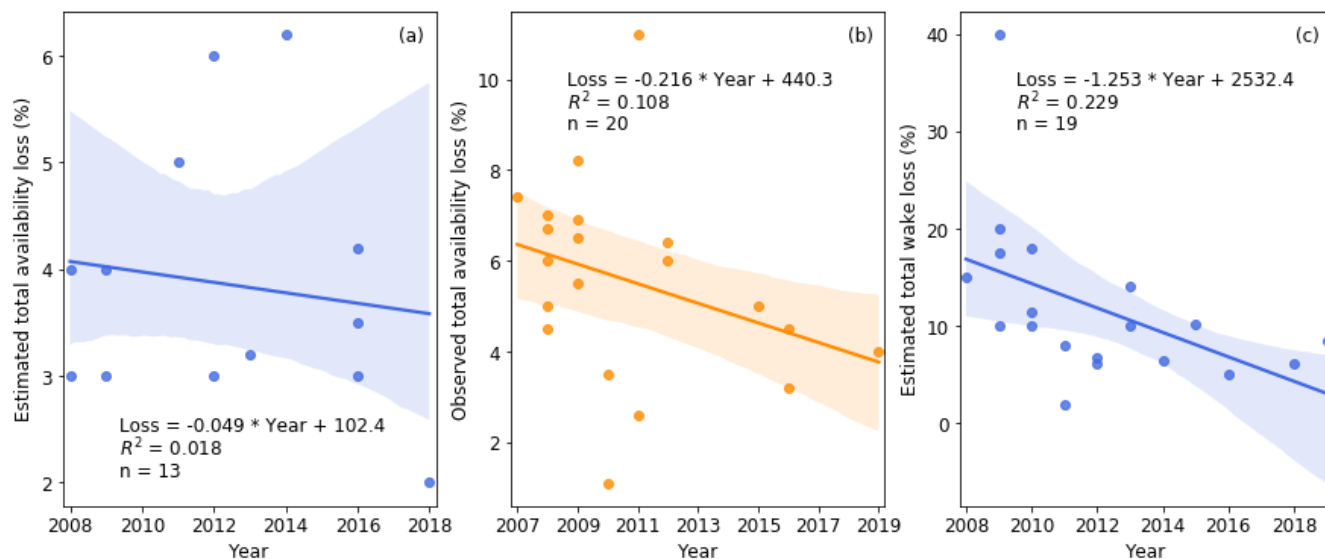
**Figure C1: As in Fig. 8, the trend in energy-production loss: (a) estimated total curtailment loss, (b) observed total availability loss, and (c) estimated total wake loss. Note that the ranges of the horizontal and vertical axes differ in each panel.**

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**Author contribution**

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

**Competing interests**

475 The authors indicate no conflict of interest.

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