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

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

1 Introduction

Determining the range of annual energy production (AEP), or the energy yield assessment (EYA), has been a key part of the wind resource assessment (WRA) process. The predicted median AEP is also known as the $P_{50}$, i.e., the AEP expected to be exceeded 50 % of the time. $P_{50}$ values are often defined with timescales such as 1, 10, and 20 years. In this study, unless stated otherwise, we primarily discuss the 20-year $P_{50}$, which is the typical expected lifespan of utility-scale wind turbines. For years, leaders in the field have been discussing the difference between predicted $P_{50}$ and actual AEP, where the industry often overestimates the energy production of a wind farm (Hale, 2017; Hendrickson, 2009, 2019; Johnson et al., 2008). A recent study conducted by the researchers at the National Renewable Energy Laboratory (NREL) found an average of 3.5 % to 4.5 % $P_{50}$ overprediction bias based on a subset of wind farms in the United States and accounting for curtailment (Lunacek et al., 2018).

Such $P_{50}$ overestimation results in marked financial implications. Healer (2018) stated that if a wind project produces a certain percentage lower than the $P_{50}$ on a 2-year rolling basis, the energy buyer, also known as the offtaker, may have the option to terminate the contract. For a 20-year contract, if a wind farm has a 1 % chance of such underproduction over a 2-year period, the probability of such an event taking place within the 18 2-year rolling periods is 16.5 %, as $100 \% - (100 \% - 1 \%)^{18} = 16.5 \%$ (Healer, 2018), assuming each 2-year rolling period is independent. Therefore, projects with substantial energy-production uncertainty experience the financial risk from modern energy contracting.
Random errors cause observations or model predictions to deviate from the truth and lead to uncertainty (Clifton et al., 2016), and uncertainty is quantified via probability (Wilks, 2011). In WRA, the $P$ values surrounding $P_{50}$ such as $P_{90}$ and $P_{95}$ characterize the uncertainty of the predicted AEP distribution. Such energy-estimate uncertainty depends on the cumulative certainty of the entire WRA process, from wind speed measurements to wind flow modeling (Clifton et al., 2016). When a sample of errors is Gaussian distributed, the standard deviation around the mean is typically used to represent the uncertainty of errors. Traditionally, the wind energy industry uses standard deviation, or $\sigma$, to represent uncertainty.

The WRA process governs the accuracy and precision of the $P_{50}$, and a key component in WRA constitutes the estimation of energy-production losses and uncertainties. Wind energy experts have been using different nomenclature in WRA, and inconsistent definitions and methodologies exist. To consolidate and ameliorate the assessment process, the International Electrotechnical Commission (IEC) 61400-15 working group has proposed a framework to classify various types of energy-production losses and uncertainties (Filibelli et al., 2018, adapted in Appendix A). We illustrate the categorical and subcategorical losses and uncertainties in Figs. 1 and 2. Note that the proposed framework is not an exclusive or exhaustive list of losses and uncertainties because some institution-specific practices may not fit into the proposed standard. Moreover, the proposed framework presented herein does not represent the final IEC standards, which are pending to be published.

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

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

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

- Is the industry-wide $P_{50}$ prediction bias changing over time, and what are the reasons for the changes?
- What are the ranges of different categories of energy-production losses and uncertainties?
- Given our understanding on losses and uncertainties, what are the opportunities for improvements in the industry?

From past research, in addition to the energy-production uncertainties, we review how the industry has been quantifying various wind speed uncertainties, particularly from wind measurements, extrapolation methods, and modeling. We also compile and present the wind speed results herein.
We present this article with the following sections: Sect. 2 documents the data and the methodology of data filtering; Sect. 3 focuses on $P_{50}$ prediction bias, including its trend and various reasons of bias improvement; Sects. 4 and 5, respectively, illustrate the energy-production loss and uncertainty, according to the IEC-proposed framework; Sect. 6 describes the numerical ranges of various wind speed uncertainties; Sect. 7 discusses the implications and future outlook based on our findings; Sect. 8 provides conclusions; Appendix A outlines the energy loss and uncertainty frameworks proposed by the IEC 61400-15 working group; Appendix B compiles the data used in this analysis.

2 Data and methodology

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

In most cases, we label the data source with the published year of the study, unless the author highlights a change of method at a specific time. For example, if an organization publishes a study in 2012 and reports their improvements on $P_{50}$ prediction bias by comparing their “current” method with their “previous set of methodology before 2012”, the two $P_{50}$ biases are recorded as 2012 and 2011, respectively. Moreover, for the same study that documents multiple $P_{50}$ prediction errors in the same year, we select the one closest to zero, because those numbers reflect the state of the art of $P_{50}$ validation of that year (Fig. 3). Accordingly, we use the paired $P_{50}$ errors to indicate the effects from method adjustments (Fig. 4). To track the bias impact of technique changes from different organizations, we combine the closely related, ongoing series of studies from a single organization, usually by the same authors from the same institutions (each line in Fig. 4).

We also derive the trend of $P_{50}$ prediction errors using polynomial regression and investigate the reasons behind such trend. We use the second-degree polynomial regression (i.e., quadratic regression) to analyze the trend of the $P_{50}$ prediction errors over time, and polynomials of higher degrees only marginally improve the fitting. We choose the polynomial regression over the simple linear regression because the $P_{50}$ prediction errors are reducing towards zero with a diminishing rate, and we use quadratic polynomial over higher-order polynomials to avoid overfitting. Additionally, in the regressions presented in this article (Figs. 3, 8, and C1), we present an estimated 95% confidence interval, generated via bootstrapping with replacement using the same sample size of the data, which is performed through the regplot function in the seaborn Python library (Waskom et al., 2020). The confidence interval describes the bounds of the regression coef-
The trend of $P_{50}$ prediction bias: (a) scatterplot of 63 independent $P_{50}$ prediction error values, where $R^2$ is the coefficient of determination and $n$ is the sample size. Negative bias means the predicted AEP is higher than the measured AEP, and vice versa for positive bias. The solid black line represents the quadratic regression, the dark grey cone displays the 95 % confidence interval of the regression line, the light grey cone depicts the 95 % prediction interval, and the horizontal dashed black line marks the zero $P_{50}$ prediction error. (b) As in panel (a) but only for 56 studies that use more than 10 wind farms in the analyses. The vertical violet bars represent the estimated uncertainty bounds (presented as 1 standard deviation from the mean) of the mean $P_{50}$ prediction errors in 15 of the 56 samples. Table B1 summarizes the bias data illustrated herein. For clarity, the regression uses the year 2002 as the baseline; hence, the resultant regression constant, i.e., the derived intercept, is comprehensible.

Illustration of $P_{50}$ bias changes over time after method modifications in 17 studies. The dot and the cross, respectively, represent the starting point and the finish point of the $P_{50}$ prediction error because of method adjustments. The solid line indicates the $P_{50}$ bias reduces after the method change, and the dotted line displays the opposite. The different colors are solely used to differentiate the lines and represent no meaning. The paired data are presented in Table B2.

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

For loss and uncertainty, we have limited data samples for certain categories because these data are only sparsely available. When a source does not provide an average value, we perform a simple arithmetic mean when both the upper and lower bounds are listed. For instance, when the average wake loss is between 5 % and 15 %, we project the average of 10 % in Fig. 6, and we present all the original values in Appendix B. If only the upper bound is found, then we project the data point as a maximum: the crosses in Fig. 6 are used as an example. We also use linear regression to explore trends in loss and uncertainty estimates.

We categorize the data to the best of our knowledge to synthesize a holistic analysis. On one hand, if the type of loss and uncertainty from a source uses marginally different terminology from the IEC-proposed framework, we first attempt to classify it within the IEC framework, we gather other values in the same category or subcategory from the same data source, and we select the minimum and the maximum. As an illustration, if the total electrical losses from the substation and the transmission line are, respectively, 1 % and 2 %, we then label the total electrical loss with the range of 1 % to 2 %. On the other hand, when the type of loss and uncertainty illustrated in the literature largely differ from the
IEC framework, we label them separately (Figs. 7 and 11). Because a few studies contrast wake loss and nonwake loss, where nonwake loss represents every other type of energy loss, we also include nonwake loss in this study (Figs. 6 and 10). When a type of uncertainty is recorded as simply “extrapolation” (seen in McAloon, 2010 and Walter, 2010), we label the value as both horizontal and vertical extrapolation uncertainties with a note of “extrapolation” in Tables B6 and B8. We also divide the reported losses and uncertainties into two groups, the “estimated” and the “observed”, where the former are based on simulations and modeling studies, and the latter are quantified via field measurements.

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

This article evaluates a compilation of averages, where each data point represents an independent number. The metadata for each study in the literature vary, in which the resultant $P_{50}$ prediction errors, losses, and uncertainties come from diverse collections of wind farms with different commercial operation dates in various geographical regions and terrains. Therefore, readers should not compare a specific data point with another. In this study, we aim to discuss the WRA process from a broad perspective. Other caveats of this analysis include the potentially inaccurate classification of the data into the proposed IEC framework; the prime focus on $P_{50}$ rather than $P_{90}$, which also has a strong financial implication; and the tendency in the literature to selectively report extreme losses and uncertainties caused by extraordinary events, such as availability loss and icing loss, which potentially misrepresents the reality. Our data sources are also only limited to publicly available data or those accessible at NREL. We perform a rigorous literature review from over 150 independent sources, and the results presented in this article adequately display the current state of the wind energy industry.

3 $P_{50}$ prediction bias

3.1 Bias trend

We identify an improving trend of the mean $P_{50}$ prediction bias, where the overprediction of energy production is gradually decreasing over time (Fig. 3), and the narrow 95% confidence interval of the regression fit justifies the long-term trend. Such an improving trend is not strictly statistically significant (Fig. 3a), even after removing the studies based on small wind farm sample sizes (Fig. 3b). However, the $R^2$ of 0.578 in Fig. 3b implies that over half of the variance in bias can be described by the regression, and less than half of the variance is caused by the inherent uncertainty between validation studies that does not change over time. The average bias magnitude also does not correlate with the size of the study, neither in wind farm sample size nor wind farm year length (not shown). Note that in some early studies, the reported biases measured in wind farm differ from those using wind farm year from the same source; we select the error closest to zero for each independent reference because the bias units are the same (Sect. 2).

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

3.2 Reasons for bias changes

To correct for the historical $P_{50}$ prediction errors, some organizations publicize the research and the adjustments they have been conducting for their WRA processes. We summarize the major modifications of the WRA procedure in Table 1. Most studies demonstrate mean $P_{50}$ bias improvement over time (Fig. 4), and the magnitude of such bias reduction varies. In two studies, the authors examine the impact of accounting for windiness, which is the quantification of long-term wind speed variability, in their WRA methodologies. They acknowledge the difficulty in quantifying interannual wind speed variability accurately, and their $P_{50}$ prediction errors worsen after embedding this uncertainty in their WRA process (vertical dashed lines in Fig. 4).

4 Energy-production loss

The prediction and observation of production losses are tightly related to the $P_{50}$ prediction accuracy; hence, we contrast the estimated and measured losses in various categories and benchmark their magnitude (Figs. 5–7). The total energy loss is calculated from the difference between the gross energy estimate and the product of gross energy prediction and benchmark their magnitude (Figs. 5–7). The total energy loss is calculated from the difference between the gross energy estimate and the product of gross energy prediction and benchmark their magnitude (Figs. 5–7). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 5).
one outlier, the turbine performance losses, in both predictions and observations, are about or under 5\% (Fig. 6b). Large ranges of environment losses exist, particularly for icing and degradation losses, which can drastically decrease AEP (Fig. 6c). Note that some of the icing losses indicated in the literature represent the fractional energy-generation loss from production stoppages over atypically long periods in wintertime, rather than a typical energy loss percentage for a calendar year. Electrical loss has been assured as a routine energy reduction with high certainty and relatively low magnitude (Fig. 6d). Of all the categories, wind turbine wake results in a substantial portion of energy loss, and its estimations demonstrate large variations (Fig. 6e). The magnitude of estimated wake loss is larger than that of the predicted nonwake loss, which consists of other categorical losses (Fig. 6e). The observed total curtailment loss exhibits lower variability, yet with larger magnitude than its estimation (Fig. 6f). From the eight studies that report total loss, the predictions range from 9.5\% to 22.5\% (Fig. 6g). We do not encounter any operational strategies loss under curtailment loss in the literature, and thus the subcategories in Fig. 6 do not cover every subcategory in Table A1.
Losses that inhibit wind farm operations can cause considerable monetary impact. For example, blade degradation can result in a 6.8% of AEP loss for a single turbine in the IEC Class II wind regime, where the maximum annual average wind speed is 8.5 m s\(^{-1}\); this translates to USD 43,000 per year (Wilcox et al., 2017). Generally, the typical turbine failure rate is about 6%, where 1% reduction in turbine failure rate can lead to around USD 2 billion of global savings in operation and maintenance (Faubel, 2019). In practice, the savings may exclude the cost of preventative measures for turbine failure, such as hydraulic oil changes and turbine inspections.

We categorize two types of energy-production losses additional to the proposed IEC framework, namely the first few years of operation and blockage effect (Fig. 7). For the former loss, a newly constructed wind farm typically does not produce to its full capacity for the first few months or even for the first 2 years. The loss from the first few years of operation captures this time-specific and availability-related production loss. Regarding the later loss, the blockage effect describes the wind speed slowdown upwind of a wind farm (Bleeg et al., 2018). Wind farm blockage is not a new topic (mentioned in Johnson et al., 2008) and has been heavily discussed in recent years (Bleeg et al., 2018; Lee, 2019; Papadopoulos, 2019; Robinson, 2019; Spalding, 2019). Compared to some of the losses in Fig. 6, the loss magnitude of first few years of operation and blockage is relatively small, where it contributes to less than 5% of AEP reduction per year (Fig. 7).

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).

Past research further documents the uncertainties of AEP losses. Except for an outlier of measuring 80% uncertainty in wake loss, the magnitude of the uncertainty of wake loss is analogous to that of nonwake loss (Fig. 9). The industry also tends to reveal the uncertainty of wake loss than nonwake loss according to the larger number of data sources (Fig. 9). One data source reported that depending on the location, the operational variation from month to month can alter AEP losses for more than 10% on average (Fig. 9). Note that the results in Fig. 9 represent the uncertainty of the respective production loss percentages in Fig. 6 and Table B3, rather than the AEP uncertainty.

5 Energy-production uncertainty

The individual energy-production uncertainties directly influence the uncertainty of $P_{50}$ prediction. Total uncertainty is the root sum square of the categorical uncertainties; the assumption of correlation between categories can reduce the overall uncertainty, and this is a typically consultant- and method-specific assumption (Brower, 2012). Except for a few outliers, the magnitude of the individual energy-production uncertainties across categories and subcategories is about or below 10% (Fig. 10). The energy uncertainties from wind measurements range below 5%, after omitting two extreme data points (Fig. 10a). The estimated long-term period uncertainty varies the most in historical wind resource (Fig. 10b), which indicates the representativeness of historical reference data (Table A2). Horizontal extrapolation generally yields higher energy-production uncertainty than vertical extrapolation (Fig. 10c and d). For plant performance, each subcategorical uncertainty corresponds to the respective AEP loss (Fig. 6 and Table A1). The range of the predicted energy uncertainty caused by wake effect is about 6% (Fig. 10c). The estimated uncertainty of turbine performance loss and total project evaluation period match with those observed (Fig. 10e and f). Overall, the average estimated total uncertainty varies by about 10%, whereas the observed total uncertainty appears to record a narrower bound, after excluding an outlier (Fig. 10g).

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

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

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

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

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

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

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

10 m of vertical extrapolation, which could overestimate the uncertainty, except for forested locations (Langreder, 2017).
7 Opportunities for improvements

Although the industry is reducing the mean $P_{50}$ overprediction bias, the remarkable uncertainties inherent in the WRA process overshadow such achievement. Different organizations have been improving their techniques over time to eliminate the $P_{50}$ bias (Table 1), and as a whole we celebrate the technological advancements; nevertheless, challenges still exist for validation and reduction of the AEP losses and uncertainties. Even though the average $P_{50}$ prediction bias is reducing and approaches zero, the associated mean $P_{50}$ uncertainty remains at over 6%, even for the studies reported after 2016 (Fig. 3b). For a validation study that involves a collection of wind farms, such an uncertainty bound implies that sizable $P_{50}$ prediction errors for particular wind projects can emerge. In other words, statistically, the AEP prediction is becoming more accurate and yet is imprecise. Moreover, from an industry-wide perspective that aggregates different analyses, the variability on the mean $P_{50}$ bias estimates is notable, which obscures the overall bias-reducing trend ($R^2$ below 0.5 in Fig. 3). Specifically, the magnitude of the 95% prediction interval at over 10% average $P_{50}$ estimation error (Fig. 3b) suggests a considerable range of possible mean biases in future validation studies. Additionally, the uncertainties are still substantial in specific AEP losses (Fig. 9), AEP itself (Figs. 10 and 11), and wind speed (Fig. 12). Therefore, the quantification, validation, and reduction of uncertainties require the attention of the industry collectively.

To reduce the overall AEP uncertainty, the industry should continue to assess the energy impacts of plant performance losses, especially those from wake effect and environmental events. On one hand, wake effect, as part of a grand challenge in wind energy meteorology (Veers et al., 2019), has been estimated as one of the largest energy losses (Fig. 6e). The AEP loss caused by wake effect also varies, estimated between 15% and 40% (Fig. 9), and the unpredictability of wakes contributes to the AEP uncertainty on plant performance (Fig. 10e) and the wind speed uncertainty (Fig. 12). Although the industry has been simulating and measuring energy loss caused by wake effect, its site-specific impact on AEP for the whole wind farm as well as its time-varying production impact on downwind turbines remains largely uncertain. From a macro point of view, compared to internal wake effect, external wake effect from neighboring wind farms is a bigger known unknown because of the lack of data and research. On the other hand, environmental losses display a 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.
In this study, we compile and present the ranges and the
8 Conclusions
AEP estimation accuracy, and drive future innovation.
continually improve insight into the WRA process, increase the
data and method transparency and standardization will con-
tinuous reference frameworks will greatly strengthen the accu-
losses and uncertainties. Documentation aligned with ubiqui-
ticable when wind plants produce less energy with greater
energy uncertainties and wind speed uncertainties demon-
resultant compound effect from two correlating sources of un-
certainty can change the total uncertainty derived using a lin-
er (Brower, 2011) or root-sum-square approach (Istchenko,
For example, an icing event can block site access and
depending on the weather and environmental conditions. The
leading to longer-term maintenance problems (Istchenko,
More observations and publicly available data are neces-
small number of references on measured uncertainties indicate that we
estimates. Besides, challenges exist in interpreting and harmo-
result from disparate reporting of energy-production
changes of energy-production predictions, the notable uncertainty of the mean prediction error
highlights the potential future progress, including the importance of accurately predicting and vali-
dating energy-production uncertainty, the impact of wake ef-
factors that contribute to the uncertainty of the mean prediction error. The mean $P_{50}$ bias and the deci-
sion error at $P_{50}$ values demonstrate an increasing trend over time because of continuous methodology adjustments, the notable uncertainty of the mean prediction error reveals the imprecise prediction of annual energy produc-
similar magnitude, with a majority of the data below
10%. More observations are the solution to better understand and further lower these uncertainties.
In our findings, we highlight the potential future progress, including the importance of accurately predicting and vali-
dating energy-production uncertainty, the impact of wake ef-
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 rigor-
ous research, we will increasingly be able to maximize energy production and reduce its uncertainty for all project stakeholders.

8 Conclusions
In this study, we compile and present the ranges and the
trends of predicted $P_{50}$ (i.e., median annual energy produc-
tion) errors, as well as the estimated and observed energy
losses, energy uncertainties, and wind speed uncertainties embedded in the wind resource assessment process. We con-
duct this literature review using over 150 credible sources from conference presentations to peer-reviewed journal arti-
cles.
### Table A1. Consensus energy-production loss framework for wind resource assessment proposed by the International Electrotechnical Commission (IEC) 61400-15 working group (Filippelli et al., 2018). Note that this table does not represent the final standards.

| Loss category       | Loss subcategory                        | Notes                                                                                                                                                                                                 |
|---------------------|-----------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| **Wake effect**     | Internal wake effects                   | Wake effects internal to the wind plant                                                                                                                                                               |
|                     | External wake effects                   | Wake effects generated externally to the wind plant                                                                                                                                                    |
|                     | Future wake effects                     | Wake effects that will impact future energy projections based on either confirmed or predicted new project development or decommissioning                                                              |
| **Availability**    | Turbine availability                    | Including warranted availability, non-contractual availability, restart after grid outage, site access, downtime (or speed) to energy ratio, first-year or plant start-up availability |
|                     | Balance-of-plant availability           | Availability of substation and collection system, other non-turbine availability, warranted availability, site access, first-year or plant start-up availability                                                  |
|                     | Grid availability                       | Grid being outside the grid connection agreement operational parameters, actual grid downtime, delays in restart after grid outages                                                                    |
| **Electrical**      | Electrical efficiency                   | Electrical losses between low- or medium-voltage side of the transformer of wind turbine and the energy measurement point                                                                             |
|                     | Facility parasitic consumption          | Turbine extreme weather packages, other turbine and/or plant parasitic electrical losses (while operating or not operating)                                                                             |
|                     | Suboptimal performance                  | Performance deviations from the optimal wind plant performance caused by software, instrumentation, and control setting issue                                                                       |
| **Turbine performance** | Generic power curve adjustment          | Expected deviation between advertised power curve and actual power performance in standard conditions (“inner range”)                                                                                     |
|                     | Site-specific power curve adjustment    | Accommodating for inclined flow, turbulence intensity, density, shear, and other site- or project-specific adjustments (“outer range”)                                                           |
|                     | High wind hysteresis                    | Energy lost in hysteresis loop between high-wind-speed cut out and recut in                                                                                                                             |
| **Environmental**   | Icing                                   | Performance degradation and shutdown caused by icing                                                                                                                                                     |
|                     | Degradation                             | Blade fouling, efficiency losses, and other environmentally driven performance degradation                                                                                                              |
|                     | Environmental loss                      | High- or low-temperature shutdown or derate, lightning, hail, and other environmental shutdowns                                                                                                            |
|                     | Exposure                                | Tree growth or logging, other building development                                                                                                                                                      |
| **Curtailments (or operational strategies)** | Load curtailment                        | Speed and/or direction curtailments to mitigate loads                                                                                                                                                   |
|                     | Grid curtailment                        | Power purchase agreement or offtaker curtailments, grid limitations                                                                                                                                  |
|                     | Environmental or permit curtailment     | Birds, bats, marine mammals, flicker, noise (when not captured in the power curve)                                                                                                                                 |
|                     | Operational strategies                  | Any periodic uprating, downrating, optimization, or shutdown not captured in the power curve or availability carve-outs                                                                               |
### Table A2. Consensus energy-production uncertainty framework for wind resource assessment proposed by the IEC 61400-15 working group (Filippelli et al., 2018). Note that this table does not represent the final standards.

| Uncertainty category | Uncertainty subcategory | Notes |
|----------------------|-------------------------|-------|
| Long-term period     | Reference data          | 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. |
|                      | Historical wind resource| How accurate or reliable is the chosen reference data source? In other words, historical data consistency (e.g., are there possible underlying trends in the data?) |
|                      | Long-term adjustment    | What is the uncertainty associated with the prediction process? Statistical or empirical uncertainty in establishing a correlation or carrying out a prediction, which may be conditioned upon the correlation method and span or the quantity of concurrent data period. |
|                      | Wind speed and direction distribution | Mean wind speed aside, how representative is the measured or predicted distribution and wind rose or energy rose shape of the long term? |
|                      | On-site data synthesis   | Uncertainty associated with gap-filling missing data periods. Usually done using directional correlations or the measure–correlate–predict process, and hence long-term and reference data categories may apply. |
| Project evaluation period variability | Modeled operational period | The statistical uncertainty associated with how closely the wind resource over the modeled operational period (i.e., 1 or 10 years) may match the long-term site average. |
|                      | Climate change          | When an impact of climate change can be assessed, then this may be considered as an uncertainty. |
|                      | Plant performance       | The statistical uncertainty associated with how closely the plant performance over the modeled operational period (i.e., 1 or 10 years) may match the long-term site average. |
| Measurement          | Wind speed measurement  | Including effects for wind speed sensor characteristics (cup or sonic), wind speed sensor mounting or deployment (cup or sonic), wind speed sensor data handling and processing characteristics (e.g., tower shadow, icing, and degradation), system motion, consistency and exposure, data acquisition, and data handling. Additionally, the reduction in uncertainty caused by sensor combination is considered. |
|                      | Data integrity and documentation | Documentation, verification, and traceability of the data. |
|                      | Wind direction measurement | Sensor type or quality, operational characteristics, mounting effects, alignment, acquisition, long-term representativeness. |
|                      | Further atmospheric parameters | Air temperature, pressure, relative humidity, and other atmospheric parameters. |
| Vertical extrapolation | Model inputs            | Terrain surface characterization, wind data measurement heights, wind statistics or shear, measurement uncertainty. |
|                      | Model components        | Representativeness per height or terrain, profile fit. |
|                      | Model stress            | Large extrapolation distance, complex terrain (measurement height relative to terrain complexity). |
| Uncertainty category | Uncertainty subcategory | Notes |
|----------------------|-------------------------|-------|
| Horizontal extrapolation | Model inputs | Fidelity and appropriateness, given sensitivity of model to terrain data, roughness, forestry information, atmospheric conditions |
|                      | Model stress | Representativeness of initiation points relative to turbine locations in terms of complicating factors (e.g., forestry, stability, steep slopes, distance, elevation, veer); the intensity of and sensitivity to complicating factors |
|                      | Model appropriateness | Physical scientific plausibility of model to capture complicating factors; validation of implementation of model: published validation of specific implementation and relevance to complicating factors present on site; on-site model verification: site to site (untuned, blind); consider the quality of any shear verification |
| Plant performance | Wake effect | Refer to Table A1 |
|                      | Availability | |
|                      | Electrical | |
|                      | Turbine performance | |
|                      | Environmental | |
|                      | Curtailments or operational strategies | |
Appendix B

For the $P_{50}$ prediction error, Figs. 3 and 4 use the data from Table B1 and Table B2, respectively. For the various categories and subcategories of losses, Figs. 5, 6, 8, and C1 portray the values in Table B3. Figure 7 illustrates the losses outside of the IEC-proposed framework listed in Table B4. Figure 9 summarizes the uncertainty of production loss percentages in Table B5. Figures 10 and 11 represent the AEP uncertainty data included in Tables B6 and B7, respectively. Figure 12 displays the wind speed uncertainty data in Table B8.
Table B1. List of $P_{50}$ biases in the literature, which is necessary to generate Fig. 3. The “Wind farm” column denotes the number of wind farms reported in the reference, and the “Wind farm year” column indicates the total number of operation years among the wind farms in that study. The “Bias (%)” column represents the average $P_{50}$ bias, where a negative number indicates an overestimation of actual energy production. All the values in the “Uncertainty (% )” column illustrate 1 standard deviation from the mean.

| Year  | Wind farm | Wind farm year | Bias (%) | Uncertainty (%) | Notes | Source |
|-------|-----------|----------------|----------|-----------------|-------|--------|
| 2002  | 12        |                | $-16$    |                 |       | Mönnich et al. (2016) |
| 2003  | 10        |                | $-11$    |                 |       | Mönnich et al. (2016) |
| 2004  | 19        |                | $-12$    |                 |       | Mönnich et al. (2016) |
| 2005  | 37        |                | $-8$     |                 |       | Mönnich et al. (2016) |
| 2006  |           |                | $-13$    |                 |       | Johnson et al. (2008) |
| 2006  | 21        |                | $-10$    |                 |       | Mönnich et al. (2016) |
| 2007  | 23        |                | $-5$     |                 |       | Mönnich et al. (2016) |
| 2008  | 59        | 243            | $-11$    |                 |       | Johnson et al. (2008), Jones (2008) |
| 2008  | 41        | 113            | $-4$     |                 |       | Johnson et al. (2008) |
| 2008  | 56        | 112            | $-10$    |                 |       | White (2009) |
| 2008  | 36        | 62             | $-2.1$   |                 |       | Johnson (2012) |
| 2008  |           |                | $-10$    | Industry average |       | White (2009) |
| 2008  | 17        |                | $-10$    |                 |       | Mönnich et al. (2016) |
| 2009  | 255       |                | $-1$     |                 | Horn (2009) |
| 2009  |           |                | $-9$     |                 | Hendrickson (2009) |
| 2009  | 43        |                | $-3$     |                 | Hendrickson (2009) |
| 2009  | 1         |                | 0.5      | 6.4             | Comparison of four analysts | Derrick (2009) |
| 2009  | 11        | 45             | $-2.2$   | 7.3             | White (2009) |
| 2009  | 18        |                | $-3$     |                 | Mönnich et al. (2016) |
| 2010  |           |                | $-1$     | 8.1             | From 1806 wind turbines | Nielsen et al. (2010) |
| 2010  | 11        |                | $-10$    |                 | Mönnich et al. (2016) |
| 2011  | 1         |                | 1        | 2.4             | Comparison of 15 analysts | Hendrickson (2011) |
| 2011  | 89        |                | $-6$     | Industry average from 2000 to 2011 | Drunsic (2012) |
| 2011  |           |                | $-2$     |                 | Drunsic (2012) |
| 2011  | 18        |                | $-7$     |                 | Mönnich et al. (2016) |
| 2011  |           |                | $-6.7$   | 0.8             | Lunacek et al. (2018) |
| 2012  |           |                | $-5$     | Industry average from 2005 to 2011 | Drunsic (2012) |
| 2012  |           |                | $-1$     |                 | Drunsic (2012) |
| 2012  | 125       | 382            | 0        |                 | Johnson (2012) |
| 2012  |           |                | $-2.4$   |                 | Bermadett et al. (2012) |
| 2012  | 11        |                | $-7$     |                 | Mönnich et al. (2016) |
| 2012  | 6         |                | $-4.9$   |                 | Pullinger et al. (2019) |
| 2013  | 14        |                | $-1$     |                 | Mönnich et al. (2016) |
| 2014  | 24        | 106            | $-1$     | 8.8             | Brower (2014) |
| 2014  | 31        | 101            | $-1.4$   |                 | Istchenko (2014) |
| 2014  |           |                | $-0.6$   |                 | Geer (2014) |
| 2014  | 9         |                | $-15$    |                 | Redouane (2014) |
| 2014  | 4         |                | $-2$     |                 | Mönnich et al. (2016) |
| 2015  |           |                | $-1.9$   |                 | Istchenko (2015) |
| 2015  | 10        |                | 0        | 4               | Sieg (2015) |
| 2015  | 1         |                | $-4$     | 3               | Comparison of 20 analysts | Mortensen et al. (2015a, b) |
| 2015  |           |                | 1        |                 | Mönnich et al. (2016) |
| 2015  | 25        | 91             | $-8$     |                 | Cox (2015) |
| 2015  | 30        | 127            | $-2.2$   |                 | Stoeblinga and Hendrickson (2015) |
| 2015  | 18        | 58             | $-1.6$   |                 | Hendrickson (2019) |
| 2015  | 23        |                | $-4.7$   | 7.7             | Hatlee (2015) |
| 2016  | 30        | 127            | 0.1      | 8.8             | Baughman (2016) |
| 2017  | 140       |                | $-2$     | Projects from 2011 to 2016 | Elkinton (2017), Hale (2017) |
| 2017  | 61        |                | $-1.6$   | 7.6             | Most projects from 2008 to 2012 | Brower (2017), Hale (2017) |
| 2017  |           |                | $-2.5$   |                 | Hale (2017) |
| 2017  | 30        | 127            | 0.7      | 8.8             | Perry (2017) |
Table B1. Continued.

| Year | Wind farm | Wind farm year | Bias (%) | Uncertainty (%) | Notes | Source |
|------|-----------|----------------|----------|-----------------|-------|--------|
| 2018 | 56        | 294            | −5.5     | 1.3             |       | Lunacek et al. (2018) |
| 2018 | 50        | 0              | 0        |                 |       | Hendrickson (2019)   |
| 2018 | 6         | −1.5           | 7.6      |                 |       | Hendrickson (2019)   |
| 2018 | 6         | −1.4           | 0        |                 |       | 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 | 30        | 7              | 0        | 7.3             |       | Hendrickson (2019)   |
| 2019 | 87        | 570            | −3.1     |                 |       | Papadopoulos (2019)  |
| 2019 | 25        | 146            | −5       |                 |       | Papadopoulos (2019)  |
| 2019 | 11        | 59             | −0.4     |                 |       | Papadopoulos (2019)  |
| 2019 | 11        | 24             | −3.9     |                 |       | Papadopoulos (2019)  |
Table B2. List of $P_{50}$ bias groups for Fig. 4, expanding from Table B1. Different groups (the “Group” column) are represented by different line colors in Fig. 4.

| Group | Year | Wind farm year | Bias (%) | Uncertainty (%) | Notes | Source |
|-------|------|----------------|----------|-----------------|-------|--------|
| 1     | 2006 |                | −13      |                 |       |        |
| 1     | 2008 | 59            | 41       | 11              |       |        |
| 2     | 2008 | 41            | 41       | 4               | Adjust for windiness and availability | Johnson et al. (2008) |
| 2     | 2009 | 43            | 43       | 3               |       | Hendrickson (2009) |
| 3     | 2008 |               | −10      |                 | Industry average | White (2009) |
| 3     | 2011 | 476           | −9       |                 | Industry average | Drunsic (2012) |
| 3     | 2011 | 89            | −6       |                 | Industry average from 2000 to 2011 | Drunsic (2012) |
| 4     | 2012 |               | −5       |                 | Industry average from 2005 to 2011 | Drunsic (2012) |
| 4     | 2009 |               | −10      |                 | Exclude Texas projects | Hendrickson (2009) |
| 4     | 2009 | 11            | 45       | −2.2            | 7.3   | White (2009) |
| 5     | 2009 | 11            | 45       | −3.5            | Accounting for windiness | White (2009) |
| 6     | 2010 |               | −8       |                 | Projects from 2000 to 2010 | Ostridge (2017) |
| 6     | 2017 | 50            | −3       |                 | Projects from 2011 to 2016 | Elkinton (2017), Hale (2017) |
| 6     | 2017 | 140           | −2       |                 | Adjusted for curtailment and windiness, and so on. | Elkinton (2017), Hale (2017) |
| 6     | 2018 | 50            | 0        |                 | Projects before 2011 | Hendrickson (2019) |
| 7     | 2010 | 294           | −9.9     |                 | Projects before 2011 | Lunacek et al. (2018) |
| 7     | 2010 | 56            | −9.2     |                 | Projects before 2011 | Lunacek et al. (2018) |
| 7     | 2010 |               | −6.7     | 0.8             | Projects before 2011, long-term correction, $R^2$ filtered | Lunacek et al. (2018) |
| 8     | 2011 |               | −2       |                 | Projects from 2000 to 2011 | Drunsic (2012) |
| 8     | 2012 |               | −1       |                 | Projects from 2005 to 2011 | Drunsic (2012) |
| 9     | 2012 | 125           | 382      | −9              |       |        |
| 9     | 2012 | 125           | 382      | 0               |       | Johnson (2012) |
| 10    | 2012 | 24            | 106      | −3.6            | 1.4   | Bernardet al. (2012) |
| 10    | 2012 |               | −2.4     |                 |       | Bernardet al. (2012) |
| 11    | 2014 | 31            | 101      | −2.8            | 1 year | Istchenko (2014) |
| 11    | 2014 | 31            | 101      | −1.4            | 10 years | Istchenko (2014) |
| 12    | 2014 | 24            | 106      | −1.1            | 7.5   | Brower (2014) |
| 12    | 2014 | 24            | 106      | −1              | 8.8   | Correct for windiness | Brower (2014) |
| 13    | 2014 | 25            | 91       | −9              |       | Cox (2015) |
| 14    | 2015 | 25            | 91       | −9              | Correct for windiness | Cox (2015) |
| 14    | 2015 | 30            | 127      | −2.2            | Adjust for windiness and availability | Stoeinga and Hendrickson (2015) |
| 14    | 2016 | 30            | 127      | 0.1             | 8.8   | Baughman (2016) |
| 15    | 2015 | 18            | 58       | −1.6            | 4.4   | Hendrickson (2019) |
| 15    | 2019 | 30            | 111      | −0.1            | 4.5   | Hendrickson (2019) |
| 16    | 2018 | 65            | −6.6     |                 | Projects after 2011 | Lunacek et al. (2018) |
| 16    | 2018 | 23            | −6.4     |                 | Projects after 2011 | Lunacek et al. (2018) |
| 16    | 2018 |               | −5.5     | 1.28            | Long-term correction, $R^2$ filtered | Lunacek et al. (2018) |
| 17    | 2018 |               | −1.5     | 7.6             |       | Hendrickson (2019) |
| 17    | 2019 |               | 0        | 7.3             |       | Hendrickson (2019) |
Table B3. List of energy losses, corresponding to Figs. 6 and 8. The “e” and “o” in the “Est/obs” column represent estimated and observed values, respectively. The energy loss categories and subcategories align with those in Table A1. “Avg (%),” “Min (%),” and “Max (%),” indicate the average, minimum, and maximum energy loss percentages, respectively. The same column-name abbreviations apply to the following tables in Appendix B.

| Year | Est/obs | Category       | Subcategory                  | Avg (%)| Min (%)| Max (%)| Notes                                      | Source                          |
|------|---------|----------------|------------------------------|--------|--------|--------|--------------------------------------------|---------------------------------|
| 2010 | e       | Availability   | Balance of plant             | 1      | 2      |        |                                             | Clive (2010)                    |
| 2013 | e       | Availability   | Balance of plant             | 1      |        |        | Typical northwest European onshore         | Mortensen (2013)                |
| 2014 | e       | Availability   | Balance of plant             | 0.2    | 0.2    | 0.4    | Typical North American onshore, collection, and substation | AWS Truepower (2014) |
| 2016 | e       | Availability   | Balance of plant             | 0.5    |        |        | Substation                                 | Clifton et al. (2016)           |
| 2017 | e       | Availability   | Balance of plant             | 0.3    | 0.5    |        | Onshore: 0.5; Offshore: 0.3                 | Papadopoulos (2019)             |
| 2011 | o       | Availability   | Balance of plant             | 0.2    |        |        |                                             | Johnson (2011)                  |
| 2010 | e       | Availability   | Grid                         | 2      | 1      | 3      | WindPro 2.7                                 | Nielsen et al. (2010)          |
| 2013 | e       | Availability   | Grid                         | 1      |        |        | Typical northwest European onshore         | Mortensen (2013)                |
| 2014 | e       | Availability   | Grid                         | 0.3    | 0.3    | 0.6    | Typical North American onshore, utility grid | AWS Truepower (2014)           |
| 2016 | e       | Availability   | Grid                         | 1      |        |        | Transmission                                | Clifton et al. (2016)           |
| 2019 | e       | Availability   | Grid                         | 1      | 3.3    |        |                                             | Hill et al. (2019)              |
| 2008 | o       | Availability   | Grid                         | 0.7    | 2.5    |        |                                             | Spengemann and Borget (2008)    |
| 2008 | e       | Availability   | Total availability           | 3      |        |        | Outside North America                       | Graves et al. (2008)           |
| 2008 | e       | Availability   | Total availability           | 3      | 5      |        | Include first-year operation, also stated in Table B4 | Johnson et al. (2008), White (2008a) |
| 2009 | e       | Availability   | Total availability           | 3      | 2      | 3      |                                             | Randall (2009)                 |
| 2009 | e       | Availability   | Total availability           | 3      | 5      |        | United States: southern states: 3; northern states: 5 | Horn (2009)                    |
| 2011 | e       | Availability   | Total availability           | 5      |        |        | Analyst comparison                          | Hendrickson (2011)             |
| 2012 | e       | Availability   | Total availability           | 3      |        |        |                                             | Drunsic (2012)                 |
| 2012 | e       | Availability   | Total availability           | 6      | 2      | 10     |                                             | Brower (2012)                  |

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Table B3. Continued.

| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2013 | e       | Availability | Total availability | 3.2     |         |         | Onshore, analyst comparison | Mortensen and Ejisng Jørgensen (2013) |
| 2014 | e       | Availability | Total availability | 6.2     |         |         | Typical North American onshore | AWS Truepower (2014) |
| 2016 | e       | Availability | Total availability | 2       | 5       |         | For plants built in 2010 to 2015 | Clifton et al. (2016) |
| 2016 | e       | Availability | Total availability | 4.2     |         |         | | Beaucage et al. (2016) |
| 2016 | e       | Availability | Total availability | 2       | 4       |         | | Bernadett et al. (2016) |
| 2018 | e       | Availability | Total availability | 2       |         |         | Onshore | Stehly et al. (2018) |
| 2007 | o       | Availability | Total availability | 7.4     |         |         | | Johnson (2011) |
| 2008 | o       | Availability | Total availability | 4.5     |         |         | North America | Graves et al. (2008) |
| 2008 | o       | Availability | Total availability | 5       |         |         | | Johnson et al. (2008), White (2008a) |
| 2008 | o       | Availability | Total availability | 7       |         |         | | Johnson et al. (2008), Jones (2008) |
| 2008 | o       | Availability | Total availability | 6.7     |         |         | | Johnson (2011) |
| 2008 | o       | Availability | Total availability | 6       |         |         | | Lackner et al. (2008) |
| 2009 | o       | Availability | Total availability | 5       | 6       |         | Most available in summer and fall, least in winter | Cushman (2009) |
| 2009 | o       | Availability | Total availability | 6.5     |         |         | | Randall (2009) |
| 2009 | o       | Availability | Total availability | 8.2     |         |         | Most available in summer and fall, least in winter | Cushman (2009) |
| 2009 | o       | Availability | Total availability | 6.9     |         |         | | Johnson (2011) |
| 2010 | o       | Availability | Total availability | 3.5     |         |         | | Johnson (2011) |
| 2010 | o       | Availability | Total availability | 1.1     | 1       | 11      | WindPro 2.7 | Nielsen et al. (2010) |
| 2011 | o       | Availability | Total availability | 11      |         |         | | Conroy et al. (2011) |
| 2011 | o       | Availability | Total availability | 2.6     |         |         | | Johnson (2011) |
| 2012 | o       | Availability | Total availability | 6       |         |         | | Drunsic (2012) |
| 2012 | o       | Availability | Total availability | 6.4     |         |         | Higher availability loss for higher wind speeds | Winslow (2012) |
Table B3. Continued.

| Year | Est. | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|------|----------|-------------|---------|---------|---------|-------|--------|
| 2015 | o    | Availability | Total availability | 5       |         |         | Operational issues (e.g., cables, connection, turbine) | Cox (2015) |
| 2016 | o    | Availability | Total availability | 4.5     |         |         | Beaucage et al. (2016) |
| 2016 | o    | Availability | Total availability | 3.2     |         |         | Bernadett et al. (2016) |
| 2019 | o    | Availability | Total availability | 4       |         |         | Pederssen 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       |         |         | Mortensen (2013) |
| 2014 | e    | Availability | Turbine | 5.9      | 3       | 10.1    | Typical North American onshore, combined from contractual turbine, non-contractual turbine, correlation, restart, site access | AWS Truepower (2014) |
| 2011 | o    | Availability | Turbine | 2.3     |         |         | Johnson (2011) |
| 2019 | o    | Availability | Turbine | 1.67    |         |         | Pederssen and Langreder (2019) |
| 2014 | e    | Curtailment | Grid    | 0       | 3.5     |         | Typical North American onshore, including power purchase agreement | AWS Truepower (2014) |
| 2016 | e    | Curtailment | Grid    | 1       |         |         | Clifton et al. (2016) |
| 2019 | e    | Curtailment | Grid    | 3.8     |         |         | Papadopoulos (2019) |
| 2016 | o    | Curtailment | Grid    | 0.5     | 1       |         | Ostridge and Rodney (2016) |
| 2014 | e    | Curtailment | Load    | 0       | 3.5     |         | Typical North American onshore, directional | AWS Truepower (2014) |
| 2019 | o    | Curtailment | Load    | 1.02    |         |         | Pederssen and Langreder (2019) |
| 2014 | e    | Curtailment | Permit  | 0       | 3.5     |         | Typical North American onshore | AWS Truepower (2014) |
| 2016 | e    | Curtailment | Permit  | 1       |         |         | Clifton et al. (2016) |
| 2018 | e    | Curtailment | Permit  | 0.05    | 0.2     |         | Mibus (2018) |
Table B3. Continued.

| Year | Est/obs | Category  | Subcategory         | Avg (%) | Min (%) | Max (%) | Notes                  | Source                        |
|------|---------|-----------|---------------------|---------|---------|---------|------------------------|-------------------------------|
| 2016 | o       | Curtailment| Permit              | 0.4     | 0.3     | 0.6     | Bat                   | Ostridge and Rodney (2016)   |
| 2019 | o       | Curtailment| Permit              | 0.67    | 0.61    | 0.71    | Bat and shadow flicker| Pedersen and Langreder (2019) |
| 2011 | e       | Curtailment| Total curtailment   | 0       | 0       | 5       | Analyst comparison    | Hendrickson (2011)           |
| 2012 | e       | Curtailment| Total curtailment   | 0       | 0       | 5       | Brower (2012)         |                               |
| 2014 | e       | Curtailment| Total curtailment   | 0       | 0       | 5       | Typical North American onshore | AWS Truepower (2014) |
| 2016 | e       | Curtailment| Total curtailment   | 1       | 4       | 5       | Clifton et al. (2016)  |                               |
| 2011 | o       | Curtailment| Total curtailment   | 4       | 4       | 4       | Johnson (2011)         |                               |
| 2012 | o       | Curtailment| Total curtailment   | 2.97    | 2.97    | 2.97    | Wiser et al. (2019)    |                               |
| 2013 | o       | Curtailment| Total curtailment   | 2.86    | 2.86    | 2.86    | Wiser et al. (2019)    |                               |
| 2014 | o       | Curtailment| Total curtailment   | 2.31    | 2.31    | 2.31    | Bird et al. (2014)     |                               |
| 2014 | o       | Curtailment| Total curtailment   | 2.15    | 2.15    | 2.15    | Wiser et al. (2019)    |                               |
| 2015 | o       | Curtailment| Total curtailment   | 2.15    | 2.15    | 2.15    | Wiser et al. (2019)    |                               |
| 2016 | o       | Curtailment| Total curtailment   | 2.15    | 2.15    | 2.15    | Wiser et al. (2019)    |                               |
| 2017 | o       | Curtailment| Total curtailment   | 2.54    | 2.54    | 2.54    | Wiser et al. (2019)    |                               |
| 2018 | o       | Curtailment| Total curtailment   | 2.18    | 2.18    | 2.18    | Wiser et al. (2019)    |                               |
| 2014 | e       | Electrical| Electrical efficiency| 2       | 1       | 3       | Typical North American onshore | AWS Truepower (2014) |
| 2016 | e       | Electrical| Electrical efficiency| 1       | 2       | 2       | Collector system       | Clifton et al. (2016)         |
| 2014 | e       | Electrical| Facility parasitic consumption | 0.1 | 0   | 0.1 | Typical North American onshore, weather package | AWS Truepower (2014) |
| 2010 | e       | Electrical| Total electrical     | 2       | 2       | 3       | Clive (2010)           |                               |
| 2011 | e       | Electrical| Total electrical     | 3       | 3       | 3       | Analyst comparison    | Hendrickson (2011)           |
| 2012 | e       | Electrical| Total electrical     | 2.1     | 2       | 3       | Brower (2012)         |                               |
Table B3. Continued.

| Year | Est/obs | Category     | Subcategory                     | Avg (%) | Min (%) | Max (%) | Notes                      | Source                       |
|------|---------|--------------|---------------------------------|---------|---------|---------|---------------------------|------------------------------|
| 2013 | e       | Electrical   | Total electrical                | 1.2     |         |         | Typical northwest European onshore | Mortensen (2013)             |
| 2013 | e       | Electrical   | Total electrical                | 1       | 2       |         | Typical northwest European onshore | Mortensen (2013)             |
| 2014 | e       | Electrical   | Total electrical                | 0.7     |         | 2       | Colmenar-Santos et al. (2014)  | AWS Truepower (2014)         |
| 2014 | e       | Electrical   | Total electrical                | 2.1     |         |         | Typical North American onshore | AWS Truepower (2014)         |
| 2016 | e       | Electrical   | Total electrical                | 2       |         | 3.5     | Clifton et al. (2016)        | Ambrose et al. (2016)        |
| 2008 | o       | Electrical   | Total electrical                | 3       |         |         | Spengemann and Borget (2008)  | AWS Truepower (2014)         |
| 2006 | e       | Environmental Degradation | 13       |         |         | Spruce and Turner (2006)      | AWS Truepower (2014)         |
| 2009 | e       | Environmental Degradation | 0.2 | 0.1 | 0.4 | 10 years | Randall (2009) | AWS Truepower (2014)         |
| 2009 | e       | Environmental Degradation | 1.2 | 0.5 | 1.9 | 20 years | Randall (2009) | AWS Truepower (2014)         |
| 2010 | e       | Environmental Degradation | 5       |         | 10     | Standish et al. (2010)        | AWS Truepower (2014)         |
| 2011 | e       | Environmental Degradation | 0.3     |         |         | Bernadett et al. (2012)       | AWS Truepower (2014)         |
| 2012 | e       | Environmental Degradation | 0.6     |         |         | Bernadett et al. (2012)       | AWS Truepower (2014)         |
| 2014 | e       | Environmental Degradation | 5       |         | 25     | Wind tunnel study | Sareen et al. (2014) | AWS Truepower (2014)         |
| 2014 | e       | Environmental Degradation | 1       | 0.6 | 1.3 | Typical North American onshore | AWS Truepower (2014)         |
| 2014 | e       | Environmental Degradation | 5       |         | 20     | Extreme cases | Redouane (2014) | AWS Truepower (2014)         |
| 2015 | e       | Environmental Degradation | 5       |         |         | Langel et al. (2015)          | AWS Truepower (2014)         |
| 2016 | e       | Environmental Degradation | 1       |         | 2      | Industry standard; soiling and erosion | Clifton et al. (2016) | AWS Truepower (2014)         |
| 2016 | e       | Environmental Degradation | 5       |         |         | Maniaci et al. (2016)         | AWS Truepower (2014)         |
| 2017 | e       | Environmental Degradation | 0.4 | 2.3 |         | Ehrmann et al. (2017)          | AWS Truepower (2014)         |
| 2017 | e       | Environmental Degradation | 8       |         |         | Schramm et al. (2017)          | AWS Truepower (2014)         |
| 2017 | e       | Environmental Degradation | 4.9 | 6.8 |         | Wilcox et al. (2017)           | AWS Truepower (2014)         |
| 2019 | e       | Environmental Degradation | 3.6 |     | Normal operation | Hasager et al. (2019) | AWS Truepower (2014)         |
| 2019 | e       | Environmental Degradation | 2.6 |     | Erosion safe mode operation | Hasager et al. (2019) | AWS Truepower (2014)         |
| 2014 | o       | Environmental Degradation | 1.4 | 1.8 | United Kingdom | Staffell and Green (2014) | AWS Truepower (2014)         |
Table B3. Continued.

| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2016 | o       | Environmental | Degradation | 1.5     | 2       |         | Before blade repair | Murphy (2016) |
| 2017 | o       | Environmental | Degradation | 0.3     |         | Sweden  |       | Olauson et al. (2017) |
| 2018 | o       | Environmental | Degradation | 0.44    |         |         |       | Wiser et al. (2019) |
| 2019 | o       | Environmental | Degradation | 0.6     |         | Germany |       | Germer and Kleidon (2019) |
| 2019 | o       | Environmental | Degradation | 9.5     |         |         | Lead edge erosion | Latoufis et al. (2019) |
| 2020 | o       | Environmental | Degradation | 0.17    | 1.23    |         | United States | Hamilton et al. (2020) |
| 2014 | e       | Environmental | Environmental | 0.6     | 0       | 3.9     | Typical North American onshore, combining temperature shutdown and lightning | AWS Truepower (2014) |
| 2016 | e       | Environmental | Environmental | 1       |         |         | Temperature shutdown | Clifton et al. (2016) |
| 2019 | o       | Environmental | Environmental | 0.35    |         |         | Temperature shutdown | Pedersen and Langreder (2019) |
| 2016 | e       | Environmental | Exposure | 0       | 3       |         | Exposure over time | Clifton et al. (2016) |
| 2014 | e       | Environmental | Icing | 1       | 0       | 4.5     | Typical North American onshore | AWS Truepower (2014) |
| 2016 | e       | Environmental | Icing | 1       |         | 5       |         | Clifton et al. (2016) |
| 2016 | e       | Environmental | Icing | 5.6     |         |         |         | Beaucage et al. (2016) |
| 2019 | e       | Environmental | Icing | 30      |         |         |         | Abascal et al. (2019) |
| 2008 | o       | Environmental | Icing | 26      |         |         | Average of two wind farms for 4 years | Gillenwater et al. (2008) |
| 2010 | o       | Environmental | Icing | 24      |         |         | Four winters, 10% of the year | Rindeskär (2010) |
| 2015 | o       | Environmental | Icing | 10      |         |         | Seven wind farms, 111 turbines, 272 MW in Sweden | Byrkjedal et al. (2015) |
| 2016 | o       | Environmental | Icing | 5       | 15      |         | Three consultants underestimate 1.5 to 4 times lower than this | Trudel (2016) |
| 2016 | o       | Environmental | Icing | 4.9     |         |         |         | Beaucage et al. (2016) |
| 2019 | o       | Environmental | Icing | 0.87    |         |         |         | Pedersen and Langreder (2019) |
| 2019 | o       | Environmental | Icing | 33      | 35      |         |         | Abascal et al. (2019) |
| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2011 | e       | Environmental | Total environmental | 2       | Analyst | Hendrickson (2011) |
| 2012 | e       | Environmental | Total environmental | 2.6     | 1       | 6       | Brower (2012) |
| 2013 | e       | Environmental | Total environmental | 1       | 2       | Mortensen (2013) |
| 2014 | e       | Environmental | Total environmental | 2.7     | Typical North American onshore | AWS Truepower (2014) |
| 2016 | e       | Environmental | Total environmental | 1       | 7       | Clifton et al. (2016) |
| 2011 | o       | Environmental | Total environmental | 0.4     | Johnson (2011) |
| 2010 | e       | Total | Total | 6       | 13      | Clive (2010) |
| 2011 | e       | Total | Total | 18      | Analyst comparison | Hendrickson (2011) |
| 2012 | e       | Total | Total | 18.5    | 7.8     | 37      | Brower (2012) |
| 2012 | e       | Total | Total | 14.8    | Analyst comparison | Mortensen et al. (2012) |
| 2013 | e       | Total | Total | 22.5    | Offshore, analyst comparison | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e       | Total | Total | 17.4    | Onshore, analyst comparison | Mortensen and Ejsing Jørgensen (2013) |
| 2014 | e       | Total | Total | 19.7    | 8.5     | 32.2    | Typical North American onshore | AWS Truepower (2014) |
| 2018 | e       | Total | Total | 15      | Onshore | Stehly et al. (2018) |
| 2008 | o       | Total | Total | 2       | 5       | Johnson et al. (2008) |
| 2008 | e       | Turbine performance | Generic power curve adjustment | 1       |       |       | Johnson et al. (2008) |
| 2009 | e       | Turbine performance | Generic power curve adjustment | 0.3     | Turbulence-intensity-dependent power curves | AWS Truepower (2009) |
Table B3. Continued.

| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2012 | e       | Turbine  | Generic power curve adjustment | 2.4     | 1       | 4       |       | Brower et al. (2012) |
| 2014 | e       | Turbine  | Generic power curve adjustment | 2.4     | 0       | 2.4     | Typical North American onshore | AWS Truepower (2014) |
| 2016 | e       | Turbine  | Generic power curve adjustment | 2.4     |         |         |       | Bernadett et al. (2016) |
| 2019 | e       | Turbine  | Generic power curve adjustment | 1       |         |         |       | Lee (2019) |
| 2008 | o       | Turbine  | Generic power curve adjustment | 2       | 4       |         |       | Johnson et al. (2008), Jones (2008) |
| 2012 | o       | Turbine  | Generic power curve adjustment | 2.2     | 3.2     |         |       | Drees and Weiss (2012) |
| 2012 | o       | Turbine  | Generic power curve adjustment | 2.5     |         |         |       | Johnson (2012) |
| 2013 | o       | Turbine  | Generic power curve adjustment | 1.8     |         |         | Without yaw error correction | Osler (2013) |
| 2014 | o       | Turbine  | Generic power curve adjustment | 2       |         |         |       | Staffell and Green (2014) |
| 2014 | o       | Turbine  | Generic power curve adjustment | 1.6     | 1       | 3       |       | Ostridge (2014) |
| 2015 | o       | Turbine  | Generic power curve adjustment | 2       | 0       | 4       |       | Geer (2015) |
| 2015 | o       | Turbine  | Generic power curve adjustment | 1.5     |         |         |       | Ostridge (2015) |
| 2015 | o       | Turbine  | Generic power curve adjustment | 1.1     |         |         |       | Kassebaum (2015) |
| 2018 | o       | Turbine  | Generic power curve adjustment | 0.2     |         |         |       | Pram (2018) |
| 2010 | e       | Turbine  | High wind hysteresis | 0.3     |         |         |       | Nielsen et al. (2010) |
| 2014 | e       | Turbine  | High wind hysteresis | 0.6     | 0       | 3       | Typical North American onshore | AWS Truepower (2014) |
### Table B3. Continued.

| Year | Est/obs | Category Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------------------|---------|---------|---------|-------|--------|
| 2009 | e       | Turbine performance  | 0.6     |         |         | Adjust for tower turbulence intensity to correct NRG Systems Max 40 anemometer overspeeding | AWS Truepower (2009) |
| 2014 | e       | Turbine performance  | 0       | 0       | 1       | Typical North American onshore, including inclined flow | AWS Truepower (2014) |
| 2016 | e       | Turbine performance  | 0.5     |         |         |        | Papadopoulos (2019) |
| 2014 | o       | Turbine performance  | 2       | 5       |         |        | Staffell and Green (2014) |
| 2008 | e       | Turbine performance  | 1       |         |         |        | Johnson et al. (2008), White (2008a) |
| 2009 | e       | Turbine performance  | 1       | 2       |         |        | White (2009) |
| 2009 | e       | Turbine performance  | 1       |         |         |        | AWS Truepower (2009) |
| 2013 | e       | Turbine performance  | 0.5     |         |         |        | Papadopoulos (2019) |
| 2014 | e       | Turbine performance  | 1       | 0       | 1       | Typical North American onshore | AWS Truepower (2014) |
| 2019 | e       | Turbine performance  | 1.1     | 2.2     | 10° of yaw error | Liew et al. (2019) |
| 2019 | e       | Turbine performance  | 3       |         |         | Yaw misalignment | Slinger et al. (2019b) |
| 2012 | o       | Turbine performance  | 0       | 3.6     |         |        | Johnson (2012) |
| 2019 | o       | Turbine performance  | 0.41    |         |         |        | Pedersen and Langreder (2019) |
| 2019 | o       | Turbine performance  | 0.21    |         |         | Yaw | Pedersen and Langreder (2019) |
| 2010 | e       | Turbine performance  | 1       | 3       |         |        | Clive (2010) |
| 2010 | e       | Turbine performance  | 10      | 19      |         |        | Clive (2010) |
| 2011 | e       | Turbine performance  | 2       |         |         | Analyst comparison | Hendrickson (2011) |
| 2012 | e       | Turbine performance  | 2.5     | 0       | 5       |        | Brower (2012) |
| 2013 | e       | Turbine performance  | 1       | 2       |         | Typical northwest European onshore | Mortensen (2013) |
| Year | Est/obs | Category     | Subcategory      | Avg (%) | Min (%) | Max (%) | Notes                                                                 | Source                          |
|------|---------|--------------|------------------|---------|---------|---------|----------------------------------------------------------------------|---------------------------------|
| 2014 | e       | Turbine      | Total turbine    | 4       |         |         | Typical North American onshore                                        | AWS Truepower (2014)            |
| 2016 | e       | Turbine      | Total turbine    | 1       | 3       |         | Clifton et al. (2016)                                                 |                                 |
| 2019 | o       | Turbine      | Total turbine    | 2       | 6.5     |         | Rotor aerodynamic imbalance, yaw static misalignment                 | Rezzoug (2019)                  |
| 2013 | e       | Wake effect  | External wake    | 2.3     |         |         | Offshore, analyst comparison, including neighboring wind farm wake   | Mortensen and Ejsing Jørgensen (2013) |
| 2014 | e       | Wake effect  | External wake    | 0       |         |         | Typical North American onshore                                        | AWS Truepower (2014)            |
| 2014 | e       | Wake effect  | Internal wake     | 6.4     | 0       | 2       | Typical North American onshore                                        | AWS Truepower (2014)            |
| 2018 | e       | Wake effect  | Internal wake     | 2       | 0       | 4       | Turbine interaction                                                  | Bleege (2018)                   |
| 2011 | e       | Wake effect  | Nonwake           | 3       | 4       |         | Comstock (2011)                                                       |                                 |
| 2011 | e       | Wake effect  | Nonwake           | 11      | 6       | 15      | Analyst comparison                                                  | Hendrickson (2011)              |
| 2012 | e       | Wake effect  | Nonwake           | 9.2     | 5       | 20      | Analyst comparison                                                  | Mortensen et al. (2012)         |
| 2013 | e       | Wake effect  | Nonwake           | 9.6     | 7.5     | 13      | Offshore, analyst comparison                                          | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e       | Wake effect  | Nonwake           | 8       | 4.4     | 20      | Onshore, analyst comparison                                           | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e       | Wake effect  | Nonwake           | 5       | 10      |         | Typical northwest European onshore                                   | Mortensen (2013)                |
| 2015 | e       | Wake effect  | Nonwake           | 8       | 9.6     |         | Mortensen et al. (2015a)                                             |                                 |
| 2008 | e       | Wake effect  | Total wake        | 10      | 20      |         | Barthelmie et al. (2008)                                             |                                 |
| 2009 | e       | Wake effect  | Total wake        | 20      |         |         | After 20 rows of turbines                                            | White (2009)                    |
| 2009 | e       | Wake effect  | Total wake        | 40      |         |         | After 70 rows of offshore turbines                                   | Tindal (2009)                   |
| 2009 | e       | Wake effect  | Total wake        | 15      | 20      |         | After 15 rows of offshore turbines                                   | Tindal (2009)                   |
| 2009 | e       | Wake effect  | Total wake        | 10      |         |         | Nielsen et al. (2010)                                               |                                 |
| 2010 | e       | Wake effect  | Total wake        | 18      |         |         | Wolfe (2010)                                                         |                                 |
| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2010 | e       | Wake effect | Total wake effect | 5       | 15      | WindPro 2.7                  | Nielsen et al. (2010) |
| 2010 | e       | Wake effect | Total wake effect | 11.5    |         | Account for deep-array loss and turbulence intensity | Nielsen et al. (2010) |
| 2011 | e       | Wake effect | Total wake effect | 1       | 3       |         | Comstock (2011) |
| 2011 | e       | Wake effect | Total wake effect | 8       | 6       | 10      | Analyst comparison | Hendrickson (2011) |
| 2012 | e       | Wake effect | Total wake effect | 6.7     | 3       | 15      |         | Brower (2012) |
| 2012 | e       | Wake effect | Total wake effect | 6.1     | 4.5     | 8.1     | Analyst comparison | Mortensen et al. (2012) |
| 2013 | e       | Wake effect | Total wake effect | 14      | 6.9     | 37      | Offshore, analyst comparison | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e       | Wake effect | Total wake effect | 10      | 3.9     | 17      | Onshore, analyst comparison | Mortensen and Ejsing Jørgensen (2013) |
| 2014 | e       | Wake effect | Total wake effect | 6.4     | 1.1     | 18.1    | Typical North American onshore | AWS Truepower (2014) |
| 2015 | e       | Wake effect | Total wake effect | 6.1     | 14.3    |         | Onshore analyst comparison | Mortensen et al. (2015b) |
| 2016 | e       | Wake effect | Total wake effect | 0       | 10      |         | Onshore analyst comparison | Clifton et al. (2016) |
| 2018 | e       | Wake effect | Total wake effect | 4.5     | 7.7     |         | Walls (2018) |
| 2019 | e       | Wake effect | Total wake effect | 15      |         |         | Slinger et al. (2019a) |
| 2019 | e       | Wake effect | Total wake effect | 3       | 14      |         | Stoelinga (2019) |
| 2010 | o       | Wake effect | Total wake effect | 13      |         | By the fifth row | Wolfe (2010) |
| 2014 | o       | Wake effect | Total wake effect | 5       | 15      |         | Onshore, small (20-turbine) wind farms | Staffell and Green (2014) |
| 2016 | o       | Wake effect | Total wake effect | 8.4     | 15.3    |         | Up to fourth row downwind | Kline (2016) |
| 2019 | o       | Wake effect | Total wake effect | 4       | 16      |         | Stoelinga (2019) |
Table B4. List of other categorical losses outside the IEC-proposed framework (Table A1), which are used to generate Fig. 7.

| Year | Est/obs | Category     | Subcategory                              | Avg (%) | Min (%) | Max (%) | Notes                                                   | Source                                      |
|------|---------|--------------|------------------------------------------|---------|---------|---------|---------------------------------------------------------|---------------------------------------------|
| 2008 | e       | Availability | First few years of operation             | 3       | 5       |         | Include first-year operation; also stated in Table B3  | Johnson et al. (2008), White (2008a)       |
| 2014 | e       | Availability | First few years of operation             | 4       | 2       | 6       | Typical North American onshore, first year              | AWS Truepower (2014)                        |
| 2010 | o       | Availability | First few years of operation             | 4       | 5       |         | First year of operation                                | Johnson (2011)                              |
| 2011 | o       | Availability | First few years of operation             | 2       | 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       |         |         |                                                        | Bleg (2018)                                |
| 2019 | e       | Turbine performance | Blockage                      | 0.3     | 1.5     |         |                                                        | Spalding (2019)                            |
| 2019 | e       | Turbine performance | Blockage                      | 1.75    |         |         |                                                        | Robinson (2019)                            |
| 2019 | e       | Turbine performance | Blockage                      | 1.9     | 0       | 6       |                                                        | Lee (2019)                                 |
| 2019 | e       | Turbine performance | Blockage                      | 2       | 1       | 5       |                                                        | Papadopoulos (2019)                         |
Table B5. List of uncertainties of energy losses, as projected in Fig. 9. Note that a value herein represents the percent of energy percentage loss.

| Year | Est/obs | Category                  | Avg (%) | Min (%) | Max (%) | Notes                                                      | Source                                      |
|------|---------|---------------------------|---------|---------|---------|------------------------------------------------------------|---------------------------------------------|
| 2014 | o       | Interannual variability of loss | 3.3     |         |         |                                                             | Istchenko (2014)                           |
| 2014 | o       | Intermonthly variability of loss | 10      | 14      |         |                                                             | Istchenko (2014)                           |
| 2012 | e       | Nonwake loss              | 32      |         |         | Analyst comparison                                         | Mortensen et al. (2012)                    |
| 2013 | e       | Nonwake loss              | 7.8     |         |         | Offshore, analyst comparison                               | Mortensen and Ejsing Jørgensen (2013)     |
| 2013 | e       | Nonwake loss              | 34      |         |         | Onshore, analyst comparison                               | Mortensen and Ejsing Jørgensen (2013)     |
| 2012 | e       | Wake loss                 | 13      |         |         | Analyst comparison                                         | Mortensen et al. (2012)                    |
| 2013 | e       | Wake loss                 | 10      | 20      |         | Caused by different models and terrains                    | Brower and Robinson (2013)                |
| 2013 | e       | Wake loss                 | 20      | 30      |         | In WindFarmer                                              | Elkinton (2013)                            |
| 2013 | e       | Wake loss                 | 25      |         |         |                                                            | McCaa (2013)                               |
| 2013 | e       | Wake loss                 | 15      | 20      |         |                                                            | Kline (2013)                               |
| 2013 | e       | Wake loss                 | 30      |         |         |                                                            | Halberg and Breakey (2013)                |
| 2013 | e       | Wake loss                 | 37      |         |         | Offshore, analyst comparison                               | Mortensen and Ejsing Jørgensen (2013)     |
| 2013 | e       | Wake loss                 | 18      |         |         | Onshore, analyst comparison                               | Mortensen and Ejsing Jørgensen (2013)     |
| 2014 | e       | Wake loss                 | 20      |         |         |                                                            | AWS Truepower (2014)                      |
| 2015 | e       | Wake loss                 | 13      | 22      |         |                                                            | Mortensen et al. (2015b)                  |
| 2016 | e       | Wake loss                 | 13      | 35      |         |                                                            | Clifton et al. (2016)                     |
| 2019 | e       | Wake loss                 | 18      |         |         |                                                            | Stoelinga (2019)                          |
| 2009 | o       | Wake loss                 | 80      |         |         | By second row of an offshore wind farm                    | Dahlberg (2009)                            |
Table B6. List of energy uncertainties, according to the categories and subcategories in Table A2. These values correspond to Fig. 10.

| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2004 | e       | Historical wind resource | Long-term adjustment | 5       |         |         | WindPro 2.4; methods and measure–correlate–predict | EMD International A/S (2004) |
| 2008 | e       | Historical wind resource | Long-term adjustment | 5       | 10      |         | Measure–correlate–predict process | Anderson (2008) |
| 2010 | e       | Historical wind resource | Long-term adjustment | 3       | 10      |         | WindPro 2.7; long-term correction | Nielsen et al. (2010) |
| 2013 | e       | Historical wind resource | Long-term adjustment | 4       | 0       | 11      | Onshore, analyst comparison | Mortensen and Ejsing Jørgensen (2013) |
| 1991 | e       | Historical wind resource | Long-term period | 10      |         |         |        | Simon (1991) |
| 2004 | e       | Historical wind resource | Long-term period | 5       |         |         | WindPro 2.4; wind statistics | EMD International A/S (2004) |
| 2008 | e       | Historical wind resource | Long-term period | 5       |         |         | Climate variation: 1997–2007 | Johnson et al. (2008), White (2008a) |
| 2010 | e       | Historical wind resource | Long-term period | 5       |         |         | WindPro 2.7; long-term wind variability | Nielsen et al. (2010) |
| 2012 | e       | Historical wind resource | Long-term period | 5.9     |         |         | Long-term wind speed | Tchou (2012) |
| 2013 | e       | Historical wind resource | Long-term period | 3.5     | 0       | 12      | Onshore, analyst comparison | Mortensen and Ejsing Jørgensen (2013) |
| 2014 | e       | Historical wind resource | Long-term period | 2       | 11      |         | Long-term wind speed and its interannual variability | Geer (2014) |
| 2014 | e       | Historical wind resource | Long-term period | 3.2     | 2.1     | 4.8     |         | AWS Truepower (2014) |
| 2015 | e       | Historical wind resource | Long-term period | 5.5     | 9.5     |         | Breakey (2019) |
| 2019 | e       | Historical wind resource | Long-term period | 28.4    |         |         | 1-year uncertainty | Dutrieux (2019) |
| 2010 | o       | Historical wind resource | Long-term period | 2       |         |         | Rogers (2010) |
| 2012 | o       | Historical wind resource | Long-term period | 8.2     |         |         | Long-term wind speed | Tchou (2012) |
Table B6. Continued.

| Year | Est/obs | Category                  | Subcategory                          | Avg (%) | Min (%) | Max (%) | Notes                                      | Source               |
|------|---------|---------------------------|--------------------------------------|---------|---------|---------|--------------------------------------------|----------------------|
| 2012 | o       | Historical wind resource  | Long-term period                     | 4.3     |         |         | Long-term wind speed                       | Tchou (2012)         |
| 2013 | e       | Historical wind resource  | Reference data                       | 16      |         |         |                                            | Holtslag (2013)      |
| 2009 | e       | Historical wind resource  | Total historical wind resource       | 3.98    | 2.5     | 7       | 20-year uncertainty, 10 projects          | Breakey (2019)       |
| 2011 | e       | Historical wind resource  | Total historical wind resource       | 4.2     | 2.5     | 7       |                                            | Comstock (2011)      |
| 2011 | e       | Historical wind resource  | Total historical wind resource       | 5       |         |         |                                            | Hendrickson (2011)   |
| 2016 | e       | Historical wind resource  | Total historical wind resource       | 1       | 6       |         |                                            | Clifton et al. (2016) |
| 2017 | e       | Historical wind resource  | Total historical wind resource       | 2       | 5       |         | 10-year uncertainties from three examples  | Halberg (2017)       |
| 2019 | e       | Historical wind resource  | Total historical wind resource       | 2.68    | 2       | 5       | 20-year uncertainty, 10 projects          | Breakey (2019)       |
| 2012 | o       | Historical wind resource  | Total historical wind resource       | 3       | 5       |         |                                            | Comstock (2012)      |
| 2014 | o       | Historical wind resource  | Total historical wind resource       | 3.2     | 1.7     | 5.3    |                                            | Brower (2014)        |
| 2014 | o       | Historical wind resource  | Total historical wind resource       | 2       | 2       | 5      |                                            | Istchenko (2014)     |
| 2014 | e       | Historical wind resource  | Wind speed and direction distribution | 1.5     | 0.6     | 1.5    | Interannual variability of frequency       | Geer (2014)          |
|       |         |                           | Wind speed and direction distribution |         |         |        | distribution                                |                      |
| 2004 | e       | Horizontal extrapolation  | Model stress                         | 5       |         |         | WindPro 2.4; terrain description           | EMD International A/S (2004) |
| 2014 | e       | Horizontal extrapolation  | Model stress                         | 3       | 6       |         | Complex terrain                            | Redouane (2014)      |
| 2016 | e       | Horizontal extrapolation  | Model stress                         | 1       | 10      |         | For simple and complex terrain             | Clifton et al. (2016) |
Table B6. Continued.

| Year | Est/obs | Category       | Subcategory               | Avg (%) | Min (%) | Max (%) | Notes | Source                    |
|------|---------|----------------|---------------------------|---------|---------|---------|-------|---------------------------|
| 2010 | o       | Horizontal     | Model stress              | 2.7     | 75      | 100     | 75 North American projects; caused by topography | Rogers (2010) |
|      |         | extrapolation   | Total horizontal          | 1       | 3       |         | Non-ideal flow             | Hendrickson (2009) |
| 2010 | o       | Horizontal     | Total horizontal          | 4.1     | 1.5     | 7       | Onshore, analyst comparison | Mortensen and Jørgensen (2013) |
|      |         | extrapolation   | Total horizontal          | 4.3     | 2       | 8       | Flow model                  | AWS Truepower (2014) |
|      |         | Total horizontal | Total horizontal          | 2.6     | 4.7     |         | 10-year uncertainties from three examples | Halberg (2017) |
|      |         | Total horizontal | Total horizontal          | 2.3     | 6.5     |         | Flow model                  | Walls (2018) |
|      |         | Total horizontal | Total horizontal          | 3.5     | 2.4     | 8       | Flow model                  | Breakey (2019) |
|      |         | Total horizontal | Total horizontal          | 2.3     | 3.3     |         | Analyst comparison; “extrapolation” | Walter (2010) |
|      |         | Total horizontal | Total horizontal          | 2       |         |         | Analyst comparison; “extrapolation” | McAloon (2010) |
Table B6. Continued.

| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2014 | o       | Horizontal extrapolation | Total horizontal extrapolation | 4.3     | 1.7     | 8.5     | Flow model | Brower (2014) |
| 2014 | o       | Horizontal extrapolation | Total horizontal extrapolation | 4       | 1       | 8       | Istchenko (2014) |
| 2014 | e       | Measurement | Data integrity and documentation | 0.5     | 0.2     | 1       | AWS Truepower (2014) |
| 2016 | e       | Measurement | Data integrity and documentation | 0.5     |         |         | Clifton et al. (2016) |
| 2010 | o       | Measurement | Data integrity and documentation | 1.4     |         |         | Rogers (2010) |
| 2013 | e       | Measurement | Further atmospheric parameters | 0.5     | 0       | 5       | Onshore, analyst comparison; air density | Mortensen and Jørgensen (2013) |
| 2009 | e       | Measurement | Total measurement | 3.45    |         |         | 20-year uncertainty, 10 projects | Breakey (2019) |
| 2011 | e       | Measurement | Total measurement | 3.8     | 2.5     | 6       | Comstock (2011) |
| 2011 | e       | Measurement | Total measurement | 4.9     |         |         | Hendrickson (2011) |
| 2014 | e       | Measurement | Total measurement | 1.5     | 2.5     |         | Geer (2014) |
| 2014 | e       | Measurement | Total measurement | 2.4     | 1.6     | 4.8     | AWS Truepower (2014) |
| 2016 | e       | Measurement | Total measurement | 1       | 5       |         | For plants built from 2010 to 2015 with anemometer-based campaign, before extrapolations | Clifton et al. (2016) |
| 2017 | e       | Measurement | Total measurement | 2.3     | 4.5     |         | 10-year uncertainties from three examples | Halberg (2017) |
| 2019 | e       | Measurement | Total measurement | 2.36    |         |         | 20-year uncertainty, 10 projects | Breakey (2019) |
| 2002 | o       | Measurement | Total measurement | 8       | 12      |         | Friis Pedersen et al. (2002) |
| 2010 | o       | Measurement | Total measurement | 1.9     |         |         | Analyst comparison; caused by tower shadow filter and data recovery | Balfrey (2010) |
| 2012 | o       | Measurement | Total measurement | 2       | 3       |         | Comstock (2012) |
### Table B6. Continued.

| Year | Est/obs | Category     | Subcategory          | Avg (%) | Min (%) | Max (%) | Notes                                | Source                          |
|------|---------|--------------|----------------------|---------|---------|---------|--------------------------------------|--------------------------------|
| 2014 | o       | Measurement  | Total measurement    | 4.2     | 1.7     | 7.5     |                                     | Brower (2014)                   |
| 2014 | o       | Measurement  | Total measurement    | 2       | 2       | 4       |                                     | Istchenko (2014)                |
| 2012 | e       | Measurement  | Wind speed           | 3.4     |         |         | Anemometer                          | Tchou (2012)                    |
| 2013 | e       | Measurement  | Wind speed           | 9       |         |         |                                     | Holtslag (2013)                 |
| 2013 | e       | Measurement  | Wind speed           | 4       | 1.5     | 10      | Onshore, analyst comparison         | Mortensen and Ejsing Jørgensen (2013) |
| 2015 | e       | Measurement  | Wind speed           | 3       | 4       |         | Anemometer and calibration          | Geer (2015)                     |
| 2016 | e       | Measurement  | Wind speed           | 1       | 2       |         |                                     | Clifton et al. (2016)           |
| 2010 | o       | Measurement  | Wind speed           | 1.5     | 1       | 1.5     | Tower effects on anemometer         | Rogers (2010)                   |
| 2012 | e       | Plant        | Availability         | 0.3     |         |         | Substation metering                 | Tchou (2012)                    |
| 2014 | e       | Plant        | Availability         | 2       | 4       |         | Interannual variability of availability | Geer (2014)                    |
| 2009 | o       | Plant        | Availability         | 6.2     |         |         |                                     | Cushman (2009)                  |
| 2011 | o       | Plant        | Availability         | 1       |         |         |                                     | Johnson (2011)                  |
| 2012 | o       | Plant        | Availability         | 1.7     |         |         |                                     | Tchou (2012)                    |
| 2016 | e       | Plant        | Curtailments or operational strategies | 1 | 4 | | | Clifton et al. (2016) |
| 2013 | e       | Plant        | Electrical           | 0.5     | 0       | 4       | Onshore, analyst comparison; metering | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e       | Plant        | Electrical           | 0       | 2       |         | Metering                            | Mortensen (2013)                |
| 2016 | e       | Plant        | Electrical           | 1       | 2       |         |                                     | Clifton et al. (2016)           |
| 2012 | e       | Plant        | Nonwake              | 2.9     |         |         | Analyst comparison                  | Mortensen et al. (2012)         |
| 2013 | e       | Plant        | Nonwake              | 0.7     |         |         | Offshore, analyst comparison        | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e       | Plant        | Nonwake              | 2.7     |         |         | Onshore, analyst comparison          | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e       | Plant        | Nonwake              | 1       | 0       | 10      | Onshore, analyst comparison          | Mortensen and Ejsing Jørgensen (2013) |
| Year | Est/obs | Category   | Subcategory       | Avg (%) | Min (%) | Max (%) | Notes                                                                 | Source                      |
|------|---------|------------|-------------------|---------|---------|---------|----------------------------------------------------------------------|-----------------------------|
| 2014 | o       | Plant      | Nonwake           | 3.7     | 3.2     | 4.5     | Brower (2014)                                                          |                             |
| 2009 | e       | Plant      | Total plant       | 3.56    | 20-year |         | Breakey (2019)                                                        |                             |
| 2011 | e       | Plant      | Total plant       | 3.2     | 1       | 5       | Comstock (2011)                                                       |                             |
| 2011 | e       | Plant      | Total plant       | 3.8     |         |         | Hendrickson (2011)                                                    |                             |
| 2013 | e       | Plant      | Total plant       | 3       |         |         | Holtslag (2013)                                                       |                             |
| 2014 | e       | Plant      | Total plant       | 3.5     | 3.2     | 4.8     | AWS Truepower (2014)                                                  |                             |
| 2016 | e       | Plant      | Total plant       | 0       | 15      |         | Clifton et al. (2016)                                                 |                             |
| 2017 | e       | Plant      | Total plant       | 3       | 4.4     |         | Halberg (2017)                                                        |                             |
| 2019 | e       | Plant      | Total plant       | 4.53    | 20-year |         | Breakey (2019)                                                        |                             |
| 2010 | o       | Plant      | Total plant       | 2       |         |         | Rogers (2010)                                                         |                             |
| 2012 | o       | Plant      | Total plant       | 2       | 3       |         | Comstock (2012)                                                       |                             |
| 2014 | o       | Plant      | Total plant       | 4       | 3       | 5       | Istchenko (2014)                                                      |                             |
| 2004 | e       | Plant      | Turbine           | 5       |         |         | WindPro 2.4; power curve                                              | EMD International A/S (2004) |
| 2012 | e       | Plant      | Turbine           | 1.5     |         |         | Tchou (2012)                                                          |                             |
| 2013 | e       | Plant      | Turbine           | 4       | 0       | 10      | Onshore, analyst comparison; power curve                               | Mortensen and Jørgensen (2013) |
| 2013 | e       | Plant      | Turbine           | 5       | 10      | Power curve                                                          | Mortensen (2013)            |
| 2014 | e       | Plant      | Turbine           | 4       | 10.4    | Power curve                                                          | Redouane (2014)             |
| 2016 | e       | Plant      | Turbine           | 0       | 4       |         | Clifton et al. (2016)                                                 |                             |
| 2019 | e       | Plant      | Turbine           | 8.6     | 18.8    |         | Power curve from 10 kW turbine                                         | Kim and Shin (2019)         |

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Table B6. Continued.

| Year | Est/obs | Category         | Subcategory       | Avg (%) | Min (%) | Max (%) | Notes                          | Source                          |
|------|---------|------------------|-------------------|---------|---------|---------|--------------------------------|--------------------------------|
| 2002 | o       | Plant performance| Turbine           | 2       | 3       |         | Power curve                    | Friis Pedersen et al. (2002)   |
| 2012 | o       | Plant performance| Turbine           | 0.8     |         |         | Power curve                    | Brower et al. (2012)           |
| 2012 | o       | Plant performance| Turbine           | 1       |         |         | Tchou (2012)                   |                                |
| 2012 | o       | Plant performance| Turbine           | 6.1     |         |         | Power curve                    | Drees and Weiss (2012)         |
| 2012 | o       | Plant performance| Turbine           | 15      |         |         | From air density of power curve| Winslow (2012)                 |
| 2012 | o       | Plant performance| Turbine           | 4       | 8       |         | Power curve                    | Jaynes (2012)                  |
| 2013 | o       | Plant performance| Turbine           | 0.5     | 6.5     |         | Power curve                    | Kassebaum (2013)               |
| 2014 | o       | Plant performance| Turbine           | 6       |         |         | Power curve                    | Ostridge (2014)                |
| 2015 | o       | Plant performance| Turbine           | 6       |         |         | Power curve                    | Ostridge (2015)                |
| 2015 | o       | Plant performance| Turbine           | 2.1     |         |         | Power curve                    | Kassebaum (2015)               |
| 2017 | o       | Plant performance| Turbine           | 3.1     | 4       |         | Power curve                    | Filippelli et al. (2017)       |
| 2018 | o       | Plant performance| Turbine           | 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 Jørgensen (2013) |
| 2013 | e       | Plant performance| Wake effect       | 1.8     | 0       | 13      | Onshore, analyst comparison    | Mortensen and 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)                  |                                |
| Year | Est/obs | Category       | Subcategory     | Avg (%) | Min (%) | Max (%) | Notes              | Source                                |
|------|---------|----------------|-----------------|---------|---------|---------|--------------------|---------------------------------------|
| 2019 | e       | Project evaluation period | Climate change | 4       |         |         | Wilkinson et al. (2019) |
| 2014 | o       | Project evaluation period | Climate change | 2.1     | 1.4     | 2.8     | Future climate     | Brower (2014)                         |
| 2008 | e       | Project evaluation period | Modeled operational period | 1       |         |         | Short-term climatology | Johnson et al. (2008), White (2008a) |
| 2014 | e       | Project evaluation period | Modeled operational period | 1.9     |         |         | AWS Truepower (2014) |
| 2019 | e       | Project evaluation period | Modeled operational period | 8       |         |         | 10-year uncertainty  | Dutrieux (2019)                       |
| 2019 | e       | Project evaluation period | Modeled operational period | 4.8     |         |         | 20-year uncertainty  | Dutrieux (2019)                       |
| 2019 | e       | Project evaluation period | Modeled operational period | 1.6     |         |         | 30-year uncertainty  | Dutrieux (2019)                       |
| 2010 | o       | Project evaluation period | Modeled operational period | 1       |         |         | Changes in long-term wind speed | Rogers (2010)                         |
| 2015 | e       | Project evaluation period | Plant performance | 7       | 12      |         | With 1–10 met masts  | Brower et al. (2015)                  |
| 2009 | e       | Project evaluation period | Total project evaluation period variability | 2.26    |         |         | 20-year future variability | Breakey (2019)                       |
| 2011 | e       | Project evaluation period | Total project evaluation period variability | 6       | 10.5    |         |                     | Comstock (2011)                       |
| 2011 | e       | Project evaluation period | Total project evaluation period variability | 7       |         |         |                     | Hendrickson (2011)                   |
| Year | Est/obs | Category             | Subcategory                               | Avg (%) | Min (%) | Max (%) | Notes                                          | Source                  |
|------|---------|----------------------|-------------------------------------------|---------|---------|---------|------------------------------------------------|-------------------------|
| 2012 | e       | Project evaluation   | Project Total project                    | 3.1     | 9.7     | Range of 1- and 10-year uncertainties           | Tchou (2012)            |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2016 | e       | Project evaluation   | Total project Total                      | 1       | 10      |                                                   | Clifton et al. (2016)   |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2017 | e       | Project evaluation   | Project Total project                    | 2.8     | 3.5     | 10-year uncertainties from three examples       | Halberg (2017)          |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2019 | e       | Project evaluation   | Total project Total                      | 0.94    |         | 20-year future variability                      | Breakey (2019)          |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2010 | o       | Project evaluation   | Project Total project                    | 1       |         |                                                   | Rogers (2010)           |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2012 | o       | Project evaluation   | Project Total project                    | 2       | 3       |                                                   | Comstock (2012)         |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2012 | o       | Project evaluation   | Project Total project                    | 3.1     | 9.7     | Range of 1- and 10-year uncertainties           | Tchou (2012)            |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2014 | o       | Project evaluation   | Project Total project                    | 6       | 4       | 1-year uncertainties                             | Istchenko (2014)        |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2014 | o       | Project evaluation   | Project Total project                    | 2       | 2       | 10-year uncertainties                            | Istchenko (2014)        |
|      |         | period variability   | Total project evaluation period           |         |         |                                                   |                         |
| 2000 | e       | Total                | Total                                     | 3       | 6       | For flat and complex terrains                   | Albers et al. (2000)    |
| 2004 | e       | Total                | Total                                     | 10      |         | WindPro 2.4                                      | EMD International A/S (2004) |
| 2007 | e       | Total                | Total                                     | 9.6     |         | 20-year uncertainty, 10 projects                 | Breakey (2019)          |
| 2008 | e       | Total                | Total                                     | 9.9     | 12.7    | Range of 1-year and lifetime uncertainties      | AWS Truepower (2009)    |
| 2009 | e       | Total                | Total                                     | 7.9     | 10.5    | Range of 1-year and lifetime uncertainties      | AWS Truepower (2009)    |
| 2010 | e       | Total                | Total                                     | 8       | 10      | WindPro 2.7                                      | Nielsen et al. (2010)   |

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| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2011 | e Total | Total    | Total       | 13      | 10      | 18      |       | Hendrickson (2011) |
| 2011 | e Total | Total    | Total       | 7.2     |         |         |       | Bernadett et al. (2012) |
| 2012 | e Total | Total    | Total       | 7       | 11      |         |       | Comstock (2012) |
| 2012 | e Total | Total    | Total       | 10.4    | 13.9    |         | Range of 1- and 10-year uncertainties | Tchou (2012) |
| 2012 | e Total | Total    | Total       | 7.7     |         |         |       | Bernadett et al. (2012) |
| 2012 | e Total | Total    | Total       | 11      | 6       | 21      | Analyst comparison | Mortensen et al. (2012) |
| 2013 | e Total | Total    | Total       | 17      |         |         |       | Holtslag (2013) |
| 2013 | e Total | Total    | Total       | 10.8    |         |         |       | Holtslag (2013) |
| 2013 | e Total | Total    | Total       | 10      | 6.2     | 21      | Offshore, analyst comparison | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e Total | Total    | Total       | 8       | 3.6     | 12      | Onshore, analyst comparison | Mortensen and Ejsing Jørgensen (2013) |
| 2013 | e Total | Total    | Total       | 10      | 15      |         |       | Mortensen (2013) |
| 2014 | e Total | Total    | Total       | 7.9     | 10.8    |         | Range of 1- and 10-year uncertainties | Istchenko (2014) |
| 2014 | e Total | Total    | Total       | 7.5     | 5.2     | 13.5    |       | AWS Truepower (2014) |
| 2014 | e Total | Total    | Total       | 11.1    | 16.7    |         | Nine wind farms, 1-year uncertainties | Redouane (2014) |
| 2014 | e Total | Total    | Total       | 8.4     | 14.5    |         | Nine wind farms, 10-year uncertainties | Redouane (2014) |
| 2015 | e Total | Total    | Total       | 10      | 15      |         |       | Apple (2015) |
| 2015 | e Total | Total    | Total       | 7.2     |         |         |       | Istchenko (2015) |
| 2015 | e Total | Total    | Total       | 5       | 9       |         | “Minimum” 5 % to 9 % of yield assessment uncertainty | Mortensen et al. (2015b) |
| 2015 | e Total | Total    | Total       | 8       | 11      |         |       | Mortensen et al. (2015a) |
| 2015 | e Total | Total    | Total       | 10.6    |         | 1-year uncertainty |       | Stoelinga and Hendrickson (2015) |
| 2017 | e Total | Total    | Total       | 6.2     | 10.7    |         | 10-year uncertainties from three examples | Halberg (2017) |
| 2017 | e Total | Total    | Total       | 7.9     | 9.1     | 1-year uncertainties |       | Perry (2017) |
| 2017 | e Total | Total    | Total       | 4.1     | 6.2     | 20-year uncertainties |       | Perry (2017) |
| 2017 | e Total | Total    | Total       | 11      |         | Post-2011 projects, 1-year standard deviation | Ostridge (2017) |
| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|-------------|---------|---------|---------|-------|--------|
| 2019 | e       | Total    | Total       | 6.8     |         |         | 20-year uncertainty, 10 projects | Breakey (2019) |
| 2009 | o       | Total    | Total       | 9.7     | 9.7     |         | Derrick (2009) |
| 2009 | o       | Total    | Total       | 33      |         |         | One offshore wind farm | Dahlberg (2009) |
| 2012 | o       | Total    | Total       | 5       | 8       |         | Comstock (2012) |
| 2012 | o       | Total    | Total       | 9.1     | 12.9    |         | Range of 1- and 10-year uncertainties | Tchou (2012) |
| 2012 | o       | Total    | Total       | 6.2     | 11.1    |         | Range of 1- and 10-year uncertainties | Tchou (2012) |
| 2014 | o       | Total    | Total       | 8.4     | 6.3     | 11.5    | Brower (2014) |
| 2014 | o       | Total    | Total       | 5.4     | 9.4     |         | Istchenko (2014) |
| 2014 | o       | Total    | Total       | 4       | 8       |         | Nine wind farms | Redouane (2014) |
| 2015 | o       | Total    | Total       | 6.2     |         |         | Apple (2015) |
| 2015 | o       | Total    | Total       | 3.1     | 7       |         | Istchenko (2015) |
| 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    |         |         | 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      | Mortensen and Jørgensen (2013) |
| 2014 | e       | Vertical extrapolation | Total vertical extrapolation | 1       | 2       |         | Geer (2014) |
| 2014 | e       | Vertical extrapolation | Total vertical extrapolation | 0       | 5       |         | Redouane (2014) |
| 2016 | e       | Vertical extrapolation | Total vertical extrapolation | 0       | 6       |         | Clifton et al. (2016) |
| 2017 | e       | Vertical extrapolation | Total vertical extrapolation | 2.1     | 3.9     |         | 10-year uncertainties from three examples | Halberg (2017) |
Table B6. Continued.

| Year | Est/obs | Category | Subcategory | Avg (%) | Min (%) | Max (%) | Notes                                      | Source                  |
|------|---------|----------|-------------|---------|---------|---------|--------------------------------------------|-------------------------|
| 2019 | e       | Vertical | Total vertical extrapolation | 5       |         |         | Zagar (2019)                              |                         |
| 2019 | e       | Vertical | Total vertical extrapolation | 2.21    |         |         | Breakey (2019); 20-year uncertainty, 10 projects |                         |
| 2010 | o       | Vertical | Total vertical extrapolation | 2.3     | 3.3     |         | Walter (2010); Analyst comparison; "extrapolation" |                         |
| 2010 | o       | Vertical | Total vertical extrapolation | 2       |         |         | McAloon (2010); Analyst comparison; "extrapolation" |                         |
| 2014 | o       | Vertical | Total vertical extrapolation | 3       | 0       | 5       | Istchenko (2014)                           |                         |

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

| Year | Est/obs | Category       | Avg (%) | Min (%) | Max (%) | Notes                                      | Source |                      |
|------|---------|----------------|---------|---------|---------|--------------------------------------------|--------|----------------------|
| 2013 | e       | External wake  | 1.6     |         |         | Offshore, analyst comparison               | Mortensen and Ejsing Jørgensen (2013) |         |
| 2013 | e       | Methodology    | 5       |         |         | Energy calculation                         | Holtslag (2013)                    |         |
| 2018 | e       | Methodology    | 1       | 3       |         | Analyst uncertainty                       | Craig et al. (2018)                |         |
| 2014 | e       | Power curve measurement | 4 | 10 | | Redouane (2014) |                         |         |
| 2002 | o       | Power curve measurement | 6 | 8 | | Friis Pedersen et al. (2002) |                         |         |
| 2013 | o       | Power curve measurement | 3.5 |     |         | Power curve test                           | Kassebaum (2013)                  |         |
| 2015 | o       | Power curve measurement | 4.5 | | | Kassebaum (2015) |                         |         |
Table B8. List of wind speed uncertainties which are used for Fig. 12. Different from other tables in Appendix B, this table records values in percentage of wind speed.

| Year | Est/obs | Category                | Avg (%) | Min (%) | Max (%) | Notes                                                                 | Source                        |
|------|---------|-------------------------|---------|---------|---------|----------------------------------------------------------------------|-------------------------------|
| 2018 | e       | Blockage                | 1.9     | 3.4     |         |                                                                      | Blee et al. (2018)           |
| 2011 | e       | Distortion              | 0       | 2       |         | Non-ideal flow; includes tower, boom, other equipment                | Hatle (2011)                 |
| 2014 | e       | Distortion              | 1.1     | 3.6     |         | Include distortion of terrain and mounting                          | Redouane (2014)              |
| 2010 | e       | Future variability      | 1       | 3       |         | Future climate; WindPro 2.7                                          | Nielsen et al. (2010)        |
| 2011 | e       | Future variability      | 4       | 6       |         |                                                                      | Comstock (2011)              |
| 2012 | e       | Future variability      | 1.4     | 2.2     |         | Future wind resource                                                | Brower (2012)                |
| 2011 | e       | Horizontal extrapolation| 1       | 4       |         |                                                                      | Comstock (2011)              |
| 2013 | e       | Horizontal extrapolation| 5       |         |         | Reference data                                                       | Holtslag (2013)              |
| 2013 | e       | Horizontal extrapolation| 1       |         |         | Lidar                                                               | Holtslag (2013)              |
| 2013 | e       | Horizontal extrapolation| 0       | 5       |         |                                                                      | Mortensen (2013)             |
| 2015 | e       | Horizontal extrapolation| 0       | 2.2     |         | Long-term extrapolation                                              | Mortensen et al. (2015a)     |
| 2010 | o       | Horizontal extrapolation| 1.9     |         |         | Analyst comparison; “extrapolation”                                  | Walter (2010)                |
| 1991 | e       | Interannual variability | 6.1     |         |         |                                                                      | Simon (1991)                 |
| 2006 | e       | Interannual variability | 8       | 12      |         | Northern Europe                                                      | Pryor et al. (2006)         |
| 2008 | e       | Interannual variability | 2       | 7       |         | Windiness                                                            | Johnson et al. (2008)       |
| 2009 | e       | Interannual variability | 6       |         |         | Recommend in WindFarmer                                              | Garrad Hassan and Partners Ltd (2009) |
| 2010 | e       | Interannual variability | 3.5     |         |         |                                                                      | Hendrickson (2010)           |
| 2010 | e       | Interannual variability | 6       |         |         | 1-year uncertainty; WindPro 2.7                                      | Nielsen et al. (2010)       |
| 2010 | e       | Interannual variability | 1.3     |         |         | 20-year uncertainty; WindPro 2.7                                     | Nielsen et al. (2010)       |
| 2011 | e       | Interannual variability | 4       | 6       |         | United States                                                        | Rogers (2011)                |
| 2013 | e       | Interannual variability | 2       | 6       |         | Variability                                                          | Mortensen (2013)             |
| 2014 | e       | Interannual variability | 2       | 4       |         |                                                                      | Brower (2014)                |
| 2014 | e       | Interannual variability | 3.5     | 6       |         |                                                                      | Geer (2014)                  |
| Year | Est/obs | Category | Avg (%) | Min (%) | Max (%) | Notes | Source |
|------|---------|----------|---------|---------|---------|-------|--------|
| 2017 | e       | Interannual variability | 5       |         |         | Perry (2017) |
| 2017 | e       | Interannual variability | 2.1     |         | 37 years in contiguous United States | Lee et al. (2018) |
| 2019 | e       | Interannual variability | 1.4     | 5.4     |         | Gkarakis and Orfanaki (2019) |
| 2014 | o       | Interannual variability | 5.7     | 8.8     |         | Istchenko (2014) |
| 2018 | e       | Intermonthly variability | 10.2    |         | 37 years in contiguous United States | Lee et al. (2018) |
| 2014 | o       | Intermonthly variability | 19      | 24      |         | Istchenko (2014) |
| 2010 | e       | Long-term wind speed | 3       | 2       | 4       | Clive (2010) |
| 2011 | e       | Long-term wind speed | 3.7     | 4.8     | Combine nearby weather station, airport, modeled data | Rogers (2011) |
| 2011 | e       | Long-term wind speed | 1.5     | 4       |         | Comstock (2011) |
| 2012 | e       | Long-term wind speed | 1       | 2       |         | Brown (2012) |
| 2012 | e       | Long-term wind speed | 1.6     | 4       |         | Brower (2012) |
| 2013 | e       | Long-term wind speed | 2       |         | Reference data; long-term representation | Holtslag (2013) |
| 2014 | e       | Long-term wind speed | 0       | 11      | Uncertainty is smaller with longer years | Hamel (2014) |
| 2014 | e       | Long-term wind speed | 15      |         |         | Hendrickson (2014) |
| 2014 | e       | Long-term wind speed | 1.1     | 6.1     | From data analysis and measure–correlate–predict | Redouane (2014) |
| 2006 | o       | Long-term wind speed | 3.5     | 20      | 1000 h of data | Rogers et al. (2006) |
| 2006 | o       | Long-term wind speed | 3       | 6       | 9000 h of data at offshore wind farms | Rogers (2011) |
| 2006 | o       | Long-term wind speed | 2       | 8       | 9000 h of data at offshore wind farms | Rogers (2011) |
| 2010 | e       | Measure–correlate–predict | 1       | 3       | WindPro 2.7 | Nielsen et al. (2010) |
| 2012 | e       | Measure–correlate–predict | 2.5     | 1       | 3       | Long-term wind speed and correction | Mortensen et al. (2012) |
| 2013 | e       | Measure–correlate–predict | 4       |         | Lidar; long-term representation and correlation | Holtslag (2013) |
| 2014 | e       | Measure–correlate–predict | 0.7     | 6.4     | Redouane (2014) |
Table B8. Continued.

| Year | Est/obs | Category                        | Avg (%) | Min (%) | Max (%) | Notes                              | Source                  |
|------|---------|---------------------------------|---------|---------|---------|------------------------------------|-------------------------|
| 2010 | e       | Plant performance               | 3       | 1       | 4       | Energy loss model                  | Clive (2010)            |
| 2010 | e       | Terrain data and resolution     | 3       | 4       |         |                                     | Clive (2010)            |
| 2012 | e       | Terrain data and resolution     | 1.5     |         |         |                                     | Brown (2012)            |
| 2010 | e       | Total wind speed                | 7       | 3       | 10      | Clive (2010)                        |
| 2012 | e       | Total wind speed                | 8.9     |         | Reference data                      | Brower (2012)           |
| 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                                           | Mortensened (2013)      |
| 2014 | e       | Vertical extrapolation          | 0       | 2       |         | Redouane (2014)                     |                         |
| 2015 | e       | Vertical extrapolation          | 0.7     | 3.6     |         | Mortensened et al. (2015a)          |                         |
| 2016 | e       | Vertical extrapolation          | 2       | 6       |         | Non-forested                         | Kelly (2016)            |
| 2017 | e       | Vertical extrapolation          | 1       |         |         | Industry accepted; 1 % per 10 m    | Langreder (2017)        |
| 2019 | e       | Vertical extrapolation          | 0       | 7       |         | Depends on shear and terrain        | Kelly et al. (2019)     |
| 2010 | o       | Vertical extrapolation          | 1.9     |         |         | Analyst comparison; “extrapolation” | Walter (2010)           |
| 2019 | o       | Vertical extrapolation          | 0       | 4       |         | Depends on shear and terrain        | Kelly et al. (2019)     |
| 2012 | e       | Wake effect                     | 2       |         |         | Brown (2012)                        |                         |
| 2014 | e       | Wake effect                     | 16      |         |         | Actuator disk and computational fluid dynamics models | Abiven et al. (2014)    |
| 2014 | e       | Wake effect                     | 0       |         |         | Park and Ainslie models             | Abiven et al. (2014)    |
Table B8. Continued.

| Year | Est/obs | Category               | Avg (%) | Min (%) | Max (%) | Notes                                                   | Source                           |
|------|---------|------------------------|---------|---------|---------|---------------------------------------------------------|----------------------------------|
| 2007 | e       | Wind speed measurement | 2.4     |         |         |                                                         | Breakey (2019)                   |
| 2010 | e       | Wind speed measurement | 3       | 1       | 4       |                                                         | Clive (2010)                     |
| 2010 | e       | Wind speed measurement | 2       |         |         | WindPro 2.7                                             | Nielsen et al. (2010)            |
| 2011 | e       | Wind speed measurement | 1       | 2.5     |         | Ideal flow; calibration                                 | Hatlee (2011)                    |
| 2011 | e       | Wind speed measurement | 1.5     | 5       |         | Non-ideal flow; total measurement                       | Hatlee (2011)                    |
| 2011 | e       | Wind speed measurement | 3.1     |         |         |                                                         | Rogers (2011)                    |
| 2011 | e       | Wind speed measurement | 1.5     | 3.5     |         |                                                         | Comstock (2011)                  |
| 2011 | e       | Wind speed measurement | 2       | 3       |         |                                                         | Faghani (2011)                   |
| 2012 | e       | Wind speed measurement | 0.5     | 1.5     |         |                                                         | Brown (2012)                     |
| 2012 | e       | Wind speed measurement | 1       | 2.5     |         | Single anemometer                                       | Brower (2012)                    |
| 2013 | e       | Wind speed measurement | 5       |         |         | Reference data; wind statistics                         | Holtslag (2013)                  |
| 2013 | e       | Wind speed measurement | 3       |         |         | Lidar; wind statistics                                  | Holtslag (2013)                  |
| 2013 | e       | Wind speed measurement | 2       | 5       |         | Wind measurement                                        | Mortensen (2013)                 |
| 2014 | e       | Wind speed measurement | 0       | 5       |         | Measurement campaign                                    | Redouane (2014)                  |
| 2015 | e       | Wind speed measurement | 2       |         |         | Anemometer and calibration                              | Geer (2015)                      |
| 2015 | e       | Wind speed measurement | 2       |         |         | Two met masts                                           | Brower et al. (2015)             |
| 2016 | e       | Wind speed measurement | 2       |         |         |                                                         | Kelly (2016)                     |
| 2017 | e       | Wind speed measurement | 0.8     |         |         |                                                         | Breakey (2019)                   |
| 2019 | e       | Wind speed measurement | 1.58    | 1.54    | 1.86    | Range of standard, recommended, and lidar methods       | Medley and Smith (2019)          |
| 2019 | e       | Wind speed measurement | 4       |         |         | Lidar calibration                                       | Slater (2019)                    |
| 2019 | e       | Wind speed measurement | 2.23    | 2.68    |         | Range from using computational fluid dynamics models or not | Crease (2019)                    |
| Year | Est/obs | Category               | Avg (%) | Min (%) | Max (%) | Notes                                                                 | Source                        |
|------|---------|------------------------|---------|---------|---------|                                                                     |                               |
| 2019 | e       | Wind speed measurement | 6       | 8       |         |                                                                      | Keck et al. (2019)           |
| 2013 | o       | Wind speed measurement | 2       | 3       |         | Lidar on flat terrain                                               | Albers et al. (2013)         |
| 2015 | o       | Wind speed measurement | 1.1     | 2.2     |         | Anemometer                                                           | Clark (2015)                 |
| 2016 | o       | Wind speed measurement | 1       | 2       |         | Anemometer; industry accepted                                       | Smith et al. (2016)          |
| 2009 | e       | Wind speed modelining   | 7       |         |         |                                                                      | VanLuvanee et al. (2009)     |
| 2010 | e       | Wind speed modelining   | 4       | 2       | 6       | Flow model accuracy                                                  | Clive (2010)                 |
| 2010 | e       | Wind speed modelining   | 3       | 10      |         |                                                                      | Brower et al. (2010)         |
| 2011 | e       | Wind speed modelining   | 2       | 5       |         |                                                                      | Faghani (2011)               |
| 2012 | e       | Wind speed modelining   | 1       | 5.5     |         |                                                                      | Brown (2012)                 |
| 2012 | e       | Wind speed modelining   | 2       | 10      |         | Flow model                                                           | Brower (2012)                |
| 2013 | e       | Wind speed modelining   | 1.7     | 6.9     |         |                                                                      | Abiven et al. (2013)         |
| 2015 | e       | Wind speed modelining   | 10      | 12      |         |                                                                      | Brower et al. (2015)         |
| 2017 | e       | Wind speed modelining   | 3       | 5       |         | WAsP                                                                  | Jog (2017)                   |
| 2017 | e       | Wind speed modelining   | 0.9     | 2       |         | Ensemble model                                                       | Jog (2017)                   |
| 2017 | e       | Wind speed modelining   | 2.9     | 1.4     | 7.6     |                                                                      | Poulos (2017)                |
| 2019 | e       | Wind speed modelining   | 2.5     |         | 2.5     | 2.5 % per km of extrapolation distance in WAsP; industry-recommended assumption | Zhang et al. (2019)          |
| 2015 | o       | Wind speed modelining   | 4       | 10      |         |                                                                      | Brower et al. (2015)         |
| 2016 | o       | Wind speed modelining   | 1.2     | 4.3     |         | Weighted absolute total error in WindFarmer                         | Neubert (2016)               |
Figure C1. As in Fig. 8, the trend in energy-production loss: (a) estimated total curtailment loss, (b) observed total availability loss, and (c) estimated total wake loss. Note that the ranges of the horizontal and vertical axes differ in each panel.
Data availability. Appendix B includes all the data used to generate the plots in this article.

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

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

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