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

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

15 observed loss and uncertainty values from the literature, according to the proposed framework in the International Electrotechnical Commission 61400-15 wind resource assessment standard. From our findings, we highlight opportunities for the industry to move forward, such as the validation and reduction of prediction uncertainty, and the prevention of energy losses caused by wake effect and environmental events. Overall, this study provides a summary on how the wind energy industry has been quantifying and reducing prediction errors, energy losses, and production uncertainties. Finally, for this work

20 to be as reproducible as possible, we include all of the data used in the analysis in appendices to the article.

1 Introduction

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Determining the range of annual energy production (AEP), or the energy yield assessment (EYA), has been a key part of the wind resource assessment (WRA) process. The predicted median AEP is also known as the P50, i.e. the AEP expected to be exceeded 50% of the time. P50 are often defined with timescales such as 1 year, 10 years, and 20 years. In this study, unless stated otherwise, we primarily discuss the 20-year P50, which is the typical expected lifespan of utility-scale wind turbines. For years, leaders in the field have been discussing the difference between predicted P50 and actual AEP, where the industry often overestimates the energy production of a wind farm (Hale, 2017; Hendrickson, 2009, 2019; Johnson et al., 2008). A recent study conducted by the researchers at the National Renewable Energy Laboratory (NREL) found an average of 3.5% to 4.5% P50 overprediction bias based on a subset of wind farms in the United States and accounting for curtailment

30 (Lunacek et al., 2018).

Such P50 overestimation causes powerful financial implications. Healer (2018) stated that if a wind project produces a certain percentage lower than the P50 on a 2-year rolling basis, the energy buyer, also known as the offtaker, may have the option to terminate the contract. For a 20-year contract, if a wind farm has a 1% chance of such underproduction over a 2-year period, the probability of such event taking place within the 18 2-year rolling periods is 16.5%, as $100\% - (100\% - 1\%)^{18} =$

35 16.5% (Healer, 2018), assuming each 2-year rolling period is independent. Therefore, projects with substantial energyproduction uncertainty experience the financial risk from modern energy contracting.

Random errors that deviate observations or model predictions from the truth lead to uncertainty (Clifton et al., 2016), and uncertainty can be expressed in probability (Wilks, 2011). In WRA, the P-values surrounding P50 such as P90 and P95 characterize the uncertainty of the predicted AEP distribution. Such energy-estimate uncertainty depends on the cumulative

40 certainty of the entire WRA process, from wind speed measurements to wind flow modeling (Clifton et al., 2016). Given a Gaussian distribution, the standard deviation around the mean represents the uncertainty of that distribution. Traditionally, the wind energy industry uses standard deviation, or σ , to represent uncertainty.

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

- 45 WRA, and inconsistent definitions and methodologies exist. To consolidate and ameliorate the assessment process, the International Electrotechnical Commission (IEC) 61400-15 working group has proposed a framework to classify various types of energy-production losses and uncertainties (Filippelli et al., 2018, adapted in Appendix A). We illustrate the categorical and subcategorical losses and uncertainties in Figs. 1 and 2. Note that the proposed framework is not an exclusive or exhaustive list of losses and uncertainties because some institution-specific practices may not fit into the proposed standard. Moreover,
- 50 the proposed framework presented herein does not represent the final IEC standards, which are pending to be published.



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



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

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

- an AEP prediction error of 1 GWh, e.g. because of the P50 prediction bias, translates to about 50,000 to 70,000 Euros lost (Papadopoulos, 2019);
- reducing energy uncertainty by 1% can result in \$0.5 to \$2 millions of economic benefits, depending on the situation and the financial model (Brower et al., 2015; Halberg, 2017);
- a change of 1% in wind speed uncertainty can lead to a 3% to 5% change in net present value of a wind farm (Kline, 2019).
- Experts in the industry have presented many studies on P50 prediction error, energy loss, and uncertainty for years, and the purpose of this literature review is to assemble previous findings and deliver a meaningful narrative. This article is unique and impactful because it is the first comprehensive survey and analysis of the key parameters in the WRA process across the industry. The three main research questions of this study include:
 - Is the industry-wide P50 prediction bias changing over time, and what are the reasons for the changes?
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- What are the ranges of different categories of energy-production losses and uncertainties?

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

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

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2 Data and methodology

We conduct our literature review over a broad spectrum of global sources. The literature includes the presentations at academic, industry, and professional conferences, particularly the Wind Resource and Project Energy Assessment workshops hosted by the American Wind Energy Association (AWEA) and the WindEurope as they are the key annual gatherings for wind resource experts. Additionally, we examine data from industry technical reports and white papers; publicly

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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.

95 In most cases, we label the data source with the published year of the study, unless the author highlights a change of

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

We also derive the trend of P50 prediction errors using polynomial regression and investigate the reasons behind such trend. We use the second-degree polynomial regression (i.e. quadratic regression) to analyze the trend of the P50 prediction 105 errors over time, and polynomials of higher degrees only marginally improve the fitting. We choose the polynomial regression

- over the simple linear regression because the P50 prediction errors are reducing towards zero with a diminishing rate, and we use quadratic polynomial over higher order polynomials to avoid overfitting. Additionally, in the regressions presented in this article (Figs. 3, 8, and C1), we present an estimated 95% confidence interval, generated via bootstrapping with replacement using the same sample size of the data, which is performed through the regplot function in the seaborn Python library (Waskom
- et al., 2020). The confidence interval describes the bounds of the regression coefficients with 95% confidence. Furthermore, 110 we present the 95% prediction interval in Fig. 3, which depicts the range of the predicted values, i.e. the P50 prediction bias, with 95% confidence, given the existing data and regression model. The prediction interval is calculated using standard deviation, assuming an underlying Gaussian distribution. In short, the confidence interval illustrates the uncertainty of the regression function, whereas the prediction interval represents the uncertainty of the estimated values of the predictand (Wilks,
- 115 2011). In addition, we evaluate the regression analysis with the coefficient of determination (\mathbb{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

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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

- 125 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
- 130 other type of energy loss, we also include nonwake loss in this study (Figs. 6 and 10). When a type of uncertainty is recorded as simply "extrapolation," we label it as both horizontal and vertical extrapolation uncertainties. We also divide the reported losses and uncertainties into two groups, the "estimated" and the "observed", where the former are based on simulations and modeling studies, and the latter are quantified via field measurements.

Unless specifically stated otherwise in Appendix B, we present a loss value as the percentage of production loss per 135 year, and we document an uncertainty number as the single standard deviation in energy percentage in the long term, usually 136 for 10 years or 20 years. The wind speed uncertainty is stated as a percentage of wind speed in m s⁻¹, and the uncertainty of an 137 energy loss is expressed as percent of a loss percentage.

This article evaluates a compilation of averages, where each data point represents an independent number. The metadata for each study in the literature vary, in which the resultant P50 prediction errors, losses, and uncertainties come from

- 140 diverse collections of wind farms with different commercial operation dates in various geographical regions and terrains. Therefore, readers should not compare a specific data point with another. In this study, we aim to discuss the WRA process from a broad perspective. Other caveats of this analysis include the potentially inaccurate classification of the data into the proposed IEC framework; the prime focus on P50 rather than P90, which also has a strong financial implication; and the tendency in the literature to selectively report extreme losses and uncertainties caused by extraordinary events, such as
- 145 availability loss and icing loss, which potentially mispresents the reality. Our data sources are also only limited to publicly available data or those accessible at NREL. We perform a rigorous literature review from over 150 independent sources, and the results presented in this article adequately display the current state of the wind energy industry.

3 P50 prediction bias

3.1 Bias trend

- We identify an improving trend of the mean P50 prediction bias, where the overprediction of energy production is gradually decreasing over time (Fig. 3), and the narrow 95% confidence interval of the regression fit justifies the long-term trend. Such an improving trend is not strictly statistically significant (Fig. 3a), even after removing the studies based on small wind farm sample sizes (Fig. 3b). However, the R² of 0.578 in Fig. 3b implies that over half of the variance in bias can be described by the regression, and less than half of the variance is caused by the inherent uncertainty between validation studies that does not change over time. The average bias magnitude also does not correlate with the size of the study, either in wind
- farm sample size or wind farm year length (not shown). Note that in some early studies, the reported biases measured in wind

farm differ from those using wind farm year from the same source; we select the error closest to zero for each independent reference because the bias units are the same (Sect. 2).



160 Figure 3: The trend of P50 prediction bias: (a) scatterplot of 63 independent P50 prediction error values, where R² is the coefficient of determination and n is the sample size. Negative bias means the predicted AEP is higher than the measured AEP, and vice versa for positive bias. The black solid line represents the quadratic regression, the dark grey cone displays the 95% confidence interval of the regression line, the light grey cone depicts the 95% prediction interval, the horizontal black dashed line marks the zero P50 prediction error. (b) as in (a), but only for 56 studies that use more than 10 wind farms in the analyses. The vertical violet bars represent the estimated uncertainty bounds (presented as one standard deviation from the mean) of the mean P50 prediction errors in 15 of the 56 samples. Table B1 summarizes the bias data illustrated herein. For clarity, the regression uses the year 2002 as the baseline, hence the resultant regression constant, i.e. the derived intercept, is comprehensible.

The uncertainty of the average P50 prediction error quantified by the studies remains large, in which the mean standard deviation is 6.6% of the 15 data sources' reported estimated P50 uncertainty (violet bars in Fig. 3b). The industry started to disclose the standard deviations of their P50 validation studies in 2009 and it is becoming more common. With only 15 data points, we cannot identify a temporal trend of the uncertainty in P50 prediction bias. Even though the industry-wide mean P50 prediction bias is converging towards zero, the industry appears to overestimate or underpredict the AEP for many individual wind projects.

3.2 Reasons for bias changes

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



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

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

Method change	Source
Account for additional factors in wind resource	AWS Truepower, 2009; Johnson, 2012
assessment and operation e.g.,	
• windiness or long-term correction of wind	
data,	
• suboptimal operation,	
• external wake effect, and	
• degradation of long-term meteorological	
masts.	
Consider meteorological effects on power production	AWS Truepower, 2009; Brower et al.,
e.g.,	2012; Elkinton, 2013; Johnson, 2012;
• wind shear,	Ostridge, 2017
• turbulence,	
• air inflow angle, and	
• atmospheric stability.	

Improve modeling techniques e.g.,	Elkinton,	2013;	Johnson,	2012;
• turbine performance,	Ostridge, 2	2017; Pap	adopoulos, 2	2019
• wind flow,				
• wake,				
• flow over complex terrain,				
• effects of changes in surface roughness, and				
• wind farm roughness.				
Improve in measurement and reduce in measurement	AWS True	power, 2	009; Johnsor	n, 2012;
bias e.g., adjust for dry friction whip of anemometers	Ostridge, 2	2017; Pap	adopoulos, 2	2019
Correct for previous methodology shortcomings e.g.,	Ostridge, 2	017; Pap	adopoulos, 2	2019
• loss assumptions, and				
shear extrapolation				

190 4 Energy-production loss

The prediction and observation of production losses are tightly related to the P50 prediction accuracy; hence, we contrast the estimated and measured losses in various categories and benchmark their magnitude (Figs. 5, 6 and 7). The total energy loss is calculated from the difference between the gross energy estimate and the product of gross energy prediction and various categorical production efficiencies, where each efficiency is one minus a categorical energy loss (Brower, 2012). Of 195 the total categorical losses, we record the largest number of data points from availability loss, and wake loss display the largest variability among studies (Fig. 5). For availability loss, the total observed loss varies more than the total estimated loss and displays a larger range (Fig. 6a). The turbine availability loss appears to be larger than the balance of plant and grid availability losses; however, more data points are needed to validate those estimates (Fig. 6a). Except for one outlier, the turbine performance losses, in both predictions and observations, are about or under 5% (Fig. 6b). Large ranges of environment losses 200 exist, particularly for icing and degradation losses, which can drastically decrease AEP (Fig. 6c). Note that some of the icing losses indicated in the literature represent the fractional energy-generation loss from production stoppages over atypically long periods in winter time, rather than a typical energy loss percentage for a calendar year. Electrical loss has been assured as a routine energy reduction with high certainty and relatively low magnitude (Fig. 6d). Of all the categories, wind turbine wake results in a substantial portion of energy loss, and its estimations demonstrate large variations (Fig. 6e). The magnitude of

205 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.



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



Figure 6: Ranges of energy-production losses in different categories and subcategories, according to the proposed framework of the 1EC 61400-15 standard, except for nonwake in (e), which is an extra subcategory summarizing other nonwake categories. Each blue and orange dot, respectively, represent the mean estimated loss and mean observed loss documented in each independent study. The blue and orange crosses, respectively, indicate the maximum of estimated loss and the maximum of observed loss reported, where the minima are not reported, and thus the averages cannot be calculated. The losses are expressed as percentage of AEP. The column of numbers on the right denotes the estimated and observed sample sizes in blue and orange, respectively, in each subcategory, and such sample size represents all the instances in that subcategory that recorded either the mean or the maximum loss values. For clarity, the grey horizontal lines separate data from each subcategory. Table B3 catalogs the categorical and subcategorical losses plotted herein.

Losses that inhibit wind farm operations can cause considerable monetary impact. For example, blade degradation can result in a 6.8% of AEP loss for a single turbine in the IEC Class II wind regime, where the maximum annual average wind speed is 8.5 m s⁻¹; this translates to \$43,000 per year (Wilcox et al., 2017). Generally, the typical turbine failure rate is about 6%, where 1% reduction in turbine failure rate can lead to around \$2 billion of global savings in operation and maintenance (Faubel, 2019). In practice, the savings may exclude the cost of preventative measures for turbine failure, such as hydraulic oil changes and turbine inspections.

We categorize two types of energy-production losses additional to the proposed IEC framework, namely first few
235 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;
240 Spalding, 2019). Compared to some of the losses in Fig. 6, the loss magnitude of first few years of operation and blockage is relatively small, where it contributes to less than 5% of AEP reduction per year (Fig. 7).



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

For trend analysis, we linearly regress every subcategorical energy loss (Fig. 6 and Table B3) on time, and we only find two loss subcategories demonstrate notable and statistically confident trends (Fig. 8). The measured curtailment loss and the observed generic power curve adjustment loss steadily decrease over time, and the reductions have reasonable R² (Fig. 8). No other reported losses with a reasonable number of data samples display remarkable trends (Fig. C1).



Figure 8: Trend in observed energy-production loss: (a) total curtailment loss and (b) generic power curve adjustment loss. The annotations correspond to those in Fig. 3, where the orange solid line represents simple linear regression, the light orange cone illustrates the 95% confidence interval, R² is the coefficient of determination, and n is sample size.

Past research further documents the uncertainties of AEP losses. Except for an outlier of measuring 80% uncertainty in wake loss, the magnitude of the uncertainty of wake loss is analogous to that of nonwake loss (Fig. 9). The industry also tends to reveal the uncertainty of wake loss than nonwake loss according to the larger number of data sources (Fig. 9). One data source reported that intermonthly variability can alter AEP losses for more than 10% (Fig. 9). Note that the results in Fig.

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



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

5 Energy-production uncertainty

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

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

uncertainty appears to record a narrower bound, after excluding an outlier (Fig. 10g).

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.



285 Figure 10: Ranges of energy-production uncertainties in different categories and subcategories, according to the proposed framework of the IEC 61400-15 standard. The annotations correspond to those in Fig. 6, where each purple dot, green dot, and purple cross represent the mean estimated uncertainty, the mean observed uncertainty, and the maximum of estimated uncertainty from each independent reference, respectively. The uncertainties is expressed as percentage in AEP. The column of numbers on the right denotes the estimated and observed sample sizes in purple and green, respectively, in each subcategory, and such sample size 290 represents all the instances in that subcategory that reported either the mean or the maximum uncertainty values. For clarity, the

grev horizontal lines separate data from each subcategory. Table B6 numerates the production uncertainties. Similar to energy losses, other types of AEP uncertainties not in the proposed IEC framework emerge. The magnitude

of the uncertainties in Fig. 11 is comparable to the uncertainties in Fig. 10. The power curve measurement uncertainty in Fig.

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



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

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

6 Wind speed uncertainty

305 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.



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

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

330 farm in the United Kingdom (Crease, 2019).

7 Opportunities for improvements

Although the industry is reducing the mean P50 overprediction bias, the remarkable uncertainties inherent in the WRA process overshadows such achievement. Different organizations have been improving their techniques over time to eliminate the P50 bias (Table 1), and as a whole we celebrate the technological advancements; nevertheless, challenges still

- exist for validation and reduction of the AEP losses and uncertainties. Even though the average P50 prediction bias is reducing and approaches zero, the associated mean P50 uncertainty remains at over 6%, even for the studies reported after 2016 (Fig. 3b). For a validation study that involves a collection of wind farms, such uncertainty bound implies that sizable P50 predication errors for particular wind projects can emerge. In other words, statistically, the AEP prediction is becoming more accurate yet is imprecise. Moreover, from an industry-wide perspective that aggregates different analyses, the variability on the mean P50
- 340 bias estimates is notable, which obscures the overall bias-reducing trend (R² below 0.5 in Fig. 3). Specifically, the magnitude of the 95% prediction interval at over 10% average P50 estimation error (Fig. 3b) suggests a considerable range of possible mean biases in future validation studies. Additionally, the uncertainties are still substantial in specific AEP losses (Fig. 9), AEP itself (Figs. 10 and 11), and wind speed (Fig. 12). Therefore, the quantification, validation, and reduction of uncertainties requires the attention of the industry collectively.
- To reduce the overall AEP uncertainty, the industry should continue to assess the energy impacts of plant performance losses, especially those from wake effect and environmental events. On one hand, wake effect, as part of a grand challenge in wind energy meteorology (Veers et al., 2019), has been estimated as one of the largest energy losses (Fig. 6e). The AEP loss caused by wake effect also varies, estimated between 15% and 40% (Fig. 9), and the unpredictability of wakes contributes to the AEP uncertainty on plant performance (Fig. 10e) and the wind speed uncertainty (Fig. 12). Although the industry has been
- 350 simulating and measuring energy loss caused by wake effect, its site-specific impact on AEP for the whole wind farm as well as its time-varying production impact on downwind turbines remains largely uncertain. From a macro point of view, compared to internal wake effect, external wake effect from neighboring wind farms is a bigger known unknown because of the lack of data and research. On the other hand, environmental losses display broad range of values, particularly from icing events and turbine degradation (Fig. 6c). In general, the icing problem halts energy production in the short run, and blade degradation undermines turbine performance in the long run. Diagnosing and mitigating such substantial environmental losses would reduce both loss and uncertainty on AEP. Overall, the prediction and prevention of environmental events are critical, and the production downtime during high electricity demand can lead to consequential financial losses.

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

Additionally, the industry recognizes the role of remote-sensing instruments in reducing the uncertainty of energy

Leaders in the field have been introducing contemporary perspectives and innovative techniques to improve the WRA

- 365 process, including time-varying and correlating losses and uncertainties. Instead of treating energy loss and uncertainty as a static property, innovators have studied time-varying AEP losses and uncertainties (Brower et al., 2012), especially when wind plants produce less energy with greater uncertainty in later operational years (Istchenko, 2015). Furthermore, different types of energy-production losses or uncertainties interact and correlate with each other, and dependent data sources can emerge in the WRA process. The resultant compound effect from two correlating sources of uncertainty can change the total uncertainty
- 370 derived using a linear (Brower, 2011) or root-sum-square approach (Istchenko, 2015). For example, an icing event can block site access and decrease turbine availability, and even lead to longer-term maintenance problems (Istchenko, 2015).

More observations and publicly available data are necessary to validate the estimates listed in this article. In this article, the ratios between the measured and predicted values are 1 to 1.9, 2.3, and 7.3, for energy loss, energy uncertainty, and wind speed uncertainty, respectively. The small number of references on measured uncertainties indicate that we need more

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

8 Conclusions 380

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

385 Although the mean P50 bias demonstrates a decreasing trend over time because of continuous methodology adjustments, the notable uncertainty of the mean prediction error reveals the imprecise prediction of annual energy production. The dominant effect of prediction uncertainty over the bias magnitude calls for further improvements on the prediction methodologies. To reduce the mean bias, industry experts have made method adjustments in recent years that minimize the energy-production prediction bias, such as the applications of remote sensing devices and the modeling advancements of 390 meteorological phenomena.

We present the wind energy production losses and uncertainties in this literature review according to the proposed framework by the International Electrotechnical Commission (IEC) 61400-15 working group. Wake effect and environmental events undermine wind plant performance and constitute the largest loss in energy production, and validating the wake and environmental loss predictions requires more field measurements and detailed research. Moreover, the variability of observed

395 total availability loss is larger than its estimates. Meanwhile, the decreasing trends of measured curtailment loss and observed generic power curve adjustment loss indicate the continuing industry effort to optimize wind energy production. Additionally, different categorical energy uncertainties and wind speed uncertainties demonstrate similar magnitude, with a majority of the data below 10%. More observations are the solution to better understand and further lower these uncertainties.

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

Data availability

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

Appendix A

Table A1: Consensus energy-production loss framework for wind resource assessment proposed by the International410Electrotechnical 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			
	Internal wake effects	Wake effects internal to the wind plant			
	External wake effects	Wake effects generated externally to the wind plant			
Wake effect		Wake effects that will impact future energy projections based on			
	Future wake effects	either confirmed or predicted new project development or			
		decommissioning			
		Including warranted availability, noncontractual availability,			
	Turbine availability	restart after grid outage, site access, downtime (or speed) to energy			
		ratio, first-year or plant start-up availability			
	Balance-of-plant	Availability of substation and collection system, other nonturbine			
Availability	availability	availability, warranted availability, site access, first-year or plant			
	avanaonny	start-up availability			
		Grid being outside the grid connection agreement operational			
	Grid availability	parameters, actual grid downtime, delays in restart after grid			
		outages			
	Electrical efficiency	Electrical losses between low- or medium-voltage side of the			
Electrical		transformer of wind turbine and the energy measurement point			
	Facility parasitic	Turbine extreme weather packages, other turbine and/or plant			
	consumption	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			
	Generic power curve	Expected deviation between advertised power curve and actual			
Turbine performance	adjustment	power performance in standard conditions ("inner range")			
r drome performance	Site-specific power curve	Accommodating for inclined flow, turbulence intensity, density,			
	adjustment	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			
	Then while hysteresis	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		
	Load curtailment	Speed and/or direction curtailments to mitigate loads		
Curtailments (or	Grid curtailment	Power-purchase-agreement or off-taker curtailments, grid limitations		
Operational strategies)	Environmental/permit	Birds, bats, marine mammals, flicker, noise (when not captured in		
Operational strategies)	curtailment	the power curve)		
	Operational strategies	Any periodic uprating, downrating, optimization, or shutdown not captured in the power curve or availability carveouts		

Table A2: Consensus energy-production uncertainty framework for wind resource assessment proposed by the IEC 61400-15415working group (Filippelli et al., 2018). Note that this table does not represent the final standards.

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

Appendix **B**

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

Table B1: List of P50 biases in the literature, which is necessary to generate Fig. 3. The "Wind Farm" column denotes the number of wind farms reported in the reference, and the "Wind Farm Year" column indicates the total number of operation years among the wind farms in that study. The "Bias (%)" column represents the average P50 bias, where a negative number indicates an overestimation of actual energy production. All the values in the "Uncertainty (%)" column illustrate one standard deviation from the mean.

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	50	112	-10			Willie, 2009
2008	36	62	-2.1			Johnson, 2012
2008			-10		Industry average	White, 2009
2008	17		-10			Mönnich et al., 2016
2009		255	-1			Horn, 2009
2009			-9			Hendrickson, 2009
2009		43	-3			Hendrickson, 2009
2009	1		0.5	6.4	Comparison of 4 analysts	Derrick, 2009

2009	11	45	-2.2	7.3		White, 2009
2009	18		-3			Mönnich et al., 2016
2010			-1	8.1	From 1,806 wind turbines	Nielsen et al., 2010
2010	11		-10			Mönnich et al., 2016
2011	1			2.4	Comparison of 15 analysts	Hendrickson, 2011
2011	89		-6		Industry average: 2000–2011	Drunsic, 2012
2011			-2			Drunsic, 2012
2011	18		-7			Mönnich et al., 2016
2011			-6.7	0.8		Lunacek et al., 2018
2012			-5		Industry average: 2005–2011	Drunsic, 2012
2012			-1			Drunsic, 2012
2012			-1			Brower et al., 2012
2012	125	382	0			Johnson, 2012
2012			-2.4			Bernadett et al., 2012
2012	11		-7			Mönnich et al., 2016
2012	6		-4.9			Pullinger et al., 2019
2013	14		-1			Mönnich et al., 2016
2014	24	106	-1	8.8		Brower, 2014
2014	31	101	-1.4			Istchenko, 2014
2014			-0.6			Geer, 2014
2014	9		-15			Redouane, 2014
2014	4		-2			Mönnich et al., 2016
2015			-1.9			Istchenko, 2015
2015	10		0	4		Sieg, 2015
2015	1		-4	3	Comparison of 20 analysts	Mortensen et al., 2015
2015	1		1			Mönnich et al., 2016
2015	25	91	-8			Cox, 2015
2015	30	127	-2.2			Stoelinga and Hendrickson,
2015	50	127				2015
2015	18	58	-1.6			Hendrickson, 2019
2015	23		-4.7	7.7		Hatlee, 2015
2016	30	127	0.1	8.8		Baughman, 2016

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

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

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

8	2012			-1		Projects from 2005–2011	Drunsic, 2012
9	2012	125	382	-9			Johnson, 2012
9	2012	125	382	0			Johnson, 2012
10	2012	24	106	-3.6	1.4		Bernadett et al., 2012
10	2012			-2.4			Bernadett et al., 2012
11	2014	31	101	-2.8		1 year	Istchenko, 2014
11	2014	31	101	-1.4		10 year	Istchenko, 2014
12	2014	24	106	-1.1	7.5		Brower, 2014
12	2014	24	106	-1	8.8	Correct for windiness	Brower, 2014
13	2015	25	91	-8			Cox, 2015
13	2015	25	91	-9		Correct for windiness	Cox, 2015
14	2015	30	127	-2.2		Adjust for windiness and	Stoelinga and Hendrickson,
						availability	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 -	Lunacek et al., 2018
-					-	filtered	.,
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. The "Avg (%)," "Min (%)," and "Max (%) indicate the average, minimum, and maximum energy loss percentages, respectively. The same column-name abbreviations apply to the following tables in Appendix B.

Year	Est/Obs	Category	Subcategory	Avg (%)	Min (%)	Max (%)	Notes	Source
2010	e	Availability	Balance of plant		1	2		Clive, 2010
2013	e	Availability	Balance of plant			1	Typical Northwest European onshore	Mortensen, 2013
2014	e	Availability	Balance of plant	0.2	0.2	0.4	Typical North America onshore, collection and substation	AWS Truepower, 2014
2016	e	Availability	Balance of plant	0.5			Substation	Clifton et al., 2016
2017	e	Availability	Balance of plant		0.3	0.5	Onshore: 0.5; Offshore: 0.3	Papadopoulos, 2019
2011	0	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	е	Availability	Grid	0.3	0.3	0.6	Typical North America onshore, utility grid	AWS Truepower, 2014
2016	e	Availability	Grid			1	Transmission	Clifton et al., 2016
2019	e	Availability	Grid availability		1	3.3		Hill et al., 2019
2008	0	Availability	Grid		0.7	2.5		Spengemann and Borget, 2008
2008	e	Availability	Total availability	3			Outside North America	Graves et al., 2008

2008	е	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	е	Availability	Total availability		3	5	United States.: southern states: 3; northern states: 5	Horn, 2009
2011	e	Availability	Total availability	5			Analyst comparison	Hendrickson, 2011
2012	e	Availability	Total availability	3				Drunsic, 2012
2012	e	Availability	Total availability	6	2	10		Brower, 2012
2013	e	Availability	Total availability	3.2			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Availability	Total availability	6.2			Typical North America onshore	AWS Truepower, 2014
2016	e	Availability	Total availability		2	5	For plants built in 2010 to 2015	Clifton et al., 2016
2016	e	Availability	Total availability	4.2				Beaucage et al., 2016
2016	e	Availability	Total availability		2	4		Bernadett et al., 2016
2018	e	Availability	Total availability	2			Onshore	Stehly et al., 2018
2007	0	Availability	Total availability	7.4				Johnson, 2011
2008	0	Availability	Total availability	4.5			North America	Graves et al., 2008
2008	0	Availability	Total availability	5				Johnson et al., 2008; White, 2008a

2008	0	Availability	Total availability	7				Johnson et al., 2008; Jones, 2008
2008	0	Availability	Total availability	6.7				Johnson, 2011
2008	0	Availability	Total availability	6				Lackner et al., 2008
2009	0	Availability	Total availability		5	6		Hendrickson, 2009
2009	0	Availability	Total availability	6.5				Randall, 2009
2009	0	Availability	Total availability	8.2			Most available in summer and fall, least in winter	Cushman, 2009
2009	0	Availability	Total availability	6.9				Johnson, 2011
2010	0	Availability	Total availability	3.5				Johnson, 2011
2010	0	Availability	Total availability	1.1	1	11	WindPro 2.7	Nielsen et al., 2010
2011	0	Availability	Total availability	11				Conroy et al., 2011
2011	0	Availability	Total availability	2.6				Johnson, 2011
2012	0	Availability	Total availability	6				Drunsic, 2012
2012	0	Availability	Total availability	6.4			Higher availability loss for higher wind speeds	Winslow, 2012
2015	0	Availability	Total availability	5			Operational issues (e.g., cables, connection, turbine)	Cox, 2015

2016	0	Availability	Total	4.5				Beaucage et al.,
			availability					2016
2016	0	Availability	Total	3.2				Bernadett et al.,
		5	availability					2016
2019	0	Availability	Total	4				Pedersen and
2017	0	Availability	availability	-				Langreder, 2019
2010	e	Availability	Turbine		2	5		Clive, 2010
2010	e	Availability	Turbine		2	5	WindPro 2.7	Nielsen et al., 2010
2013	e	Availability	Turbine	3			Typical Northwest	Mortensen 2013
2015	e	<i>T</i> valiability	T di Onic	5			European onshore	Wortensen, 2015
							Typical North	
							America onshore,	
							combined from	AWS Truepower, 2014
2014	e	Availability	Turbine	5.9	3	10.1	contractual turbine,	
							noncontractual	
							turbine, correlation,	
							restart, site access	
2011	0	Availability	Turbine	2.3				Johnson, 2011
							Combine scheduled	
2019	0	Availability	Turbine	1.67			and unscheduled	Pedersen and
							maintenance	Langreder, 2019
							Typical North	
							America onshore,	
2014	e	Curtailment	Grid		0	3.5	including power	AWS Truepower,
							purchase	2014
							agreement	
2016	e	Curtailment	Grid			1		Clifton et al., 2016
							Ireland estimate,	D 1 1
2019	e	Curtailment	Grid	3.8			based on	Papadopoulos,
							operational data	2019
		~ "			0			Ostridge and
2016	0	Curtailment	Grid		0.5	1	Interconnection cap	Rodney, 2016
								÷ .

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

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

2009	e	Environmental	Degradation	0.2	0.1	0.4	10 year	Randall, 2009
2009	e	Environmental	Degradation	1.2	0.5	1.9	20 year	Randall, 2009
2010	2	Environmental	Degradation	5		10		Standish et al.,
2010	C	Environmentar	Degradation	5		10		2010
2011	P	Environmental	Degradation	0.3				Bernadett et al.,
2011	C	Liiviioimientai	Degradation	0.5				2012
2012	P	Environmental	Degradation	0.6				Bernadett et al.,
2012	C	Liivitoimientai	Degradation	0.0				2012
2014	e	Environmental	Degradation		5	25	Wind tunnel study	Sareen et al., 2014
2014	e	Environmental	Degradation	1	0.6	13	Typical North	AWS Truepower,
2011	C	Liiviteimentui	Degradution	1	0.0	1.5	America onshore	2014
2014	e	Environmental	Degradation		5	20	Extreme cases	Redouane, 2014
2015	e	Environmental	Degradation			5		Langel et al., 2015
2016	e	Environmental	Degradation		1	2	Industry standard;	Clifton et al., 2016
							soiling and erosion	
2016	e	Environmental	Degradation			5		Maniaci et al.,
								2016
2017	e	Environmental	Degradation		0.4	2.3		Ehrmann et al.,
								2017
2017	e	Environmental	Degradation			8		Schramm et al.,
								2017
2017	e	Environmental	Degradation		4.9	6.8		Wilcox et al., 2017
2019	e	Environmental	Degradation	3.6			Normal operation	Hasager et al.,
								2019
2019	e	Environmental	Degradation	2.6			Erosion safe mode	Hasager et al.,
							operation	2019
2014	0	Environmental	Degradation		1.4	1.8	United Kingdom	Staffell and Green,
			<u> </u>					2014
2016	0	Environmental	Degradation		1.5	2	Before blade repair	Murphy, 2016
2017	0	Environmental	Degradation	0.3			Sweden	(Olauson et al.,
			Ŭ					2017)over
2018	0	Environmental	Degradation	0.44				Wiser et al., 2019

2019	0	Environmental	Degradation	0.6			Germany	Germer and Kleidon, 2019
2019	0	Environmental	Degradation			9.5	Lead edge erosion	Latoufis et al., 2019
2020	0	Environmental	Degradation		0.17	1.23	United States	Hamilton et al., 2020
2014	е	Environmental	Environmental	0.6	0	3.9	Typical North America onshore, combining temperature shutdown and lightning	AWS Truepower, 2014
2016	e	Environmental	Environmental			1	Temperature shutdown	Clifton et al., 2016
2019	0	Environmental	Environmental	0.35			Temperature shutdown	Pedersen and Langreder, 2019
2016	e	Environmental	Exposure		0	3	Exposure over time	Clifton et al., 2016
2014	e	Environmental	Icing	1	0	4.5	Typical North America onshore	AWS Truepower, 2014
2016	e	Environmental	Icing		1	5		Clifton et al., 2016
2016	e	Environmental	Icing	5.6				Beaucage et al., 2016
2019	e	Environmental	Icing	30				Abascal et al., 2019
2008	0	Environmental	Icing	26			Average of two wind farms for 4 years	Gillenwater et al., 2008
2010	0	Environmental	Icing	24			Four winters, 10% of the year	Rindeskär, 2010
2015	0	Environmental	Icing	10			Seven wind farms, 111 turbines, 272 MW in Sweden	Byrkjedal et al., 2015
2016	0	Environmental	Icing		5	15	Three consultants underestimate 1.5	Trudel, 2016
							to 4 times lower	
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							than this	
2016	0	Environmental	Loing	4.0				Beaucage et al.,
2010	0	Environmentai	ICINg	4.7				2016
2019	0	Environmental	Icing	0.87				Pedersen and
2017	0	Liiviioiiiientui	Temp	0.07				Langreder, 2019
2019	0	Environmental	Icing		33	35		Abascal et al., 2019
2011	P	Environmental	Total	2			Analyst	Hendrickson 2011
2011	c	Environmentar	environmental	2			comparison	Tienariekson, 2011
2012	e	Environmental	Total	2.6	1	6		Brower, 2012
2012	•		environmental	2.0	-	Ū		210.001, 2012
							Typical, used in	
							Wind Atlas	
							Analysis and	
2013	e	Environmental	Total		1	2	Application	Mortensen 2013
2015	C	Liiviioimentai	environmental		1	2	Program (WAsP),	Wortensen, 2015
							include blade	
							degradation, icing,	
							temp shutdown.	
							Typical Northwest	
			Total				European onshore,	
2013	e	Environmental			1	2	include blade	Mortensen, 2013
			environmentar				degradation and	
							icing.	
2014	9	Environmental	Total	27			Typical North	AWS Truepower,
2014	C	Environmentar	environmental	2.1			America onshore	2014
2016	e	Environmental	Total		1	7		Clifton et al 2016
2010	~	Environmental	environmental		1	<u> </u>		Cinton et al., 2010
2011	0	Environmental	Total	0.4				Johnson, 2011
-011	,	2	environmental					2011 2011
2010	e	Total	Total		6	13		Clive, 2010
2011	e	Total	Total	18			Analyst	Hendrickson, 2011
	-						comparison	

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

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

2014		Turbine	High wind	0.6	0	2	Typical North	AWS Truepower,
2014	C	performance	hysteresis	0.0	0	5	America onshore	2014
2009	e	Turbine performance	Site-specific power curve adjustment	0.6			Adjust for tower turbulence intensity to correct NRG Systems Max 40 anemometer overspeeding.	AWS Truepower, 2009
2014	e	Turbine performance	Site-specific power curve adjustment	0	0	1	Typical North America onshore, including inclined flow	AWS Truepower, 2014
2016	е	Turbine performance	Site-specific power curve adjustment	0.5				Papadopoulos, 2019
2014	0	Turbine performance	Site-specific power curve adjustment	2	5			Staffell and Green, 2014
2008	e	Turbine performance	Suboptimal performance	1				Johnson et al., 2008; White, 2008a
2009	е	Turbine performance	Suboptimal performance		1	2		White, 2009
2009	e	Turbine performance	Suboptimal performance	1				AWS Truepower, 2009
2013	е	Turbine performance	Suboptimal performance	0.5				Papadopoulos, 2019
2014	e	Turbine performance	Suboptimal performance	1	0	1	Typical North America onshore	AWS Truepower, 2014
2019	e	Turbine performance	Suboptimal performance		1.1	2.2	10 degrees of yaw error	Liew et al., 2019
2019	е	Turbine performance	Suboptimal performance	3			Yaw misalignment	Slinger et al., 2019b

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

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

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

2014	0	Wake effect	Total wake effect	5	15	Onshore, small (20 turbine) wind farms	Staffell and Green, 2014
2016	0	Wake effect	Total wake effect	8.4	15.3	Up to fourth row downwind	Kline, 2016
2019	0	Wake effect	Total wake effect	4	16		Stoelinga, 2019

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

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

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.

V		Catal	Avg	Min	Max	Notes	C
Y ear	Est/Obs	Category	(%)	(%)	(%)	Notes	Source

2014	0	Interannual variability of loss	3.3				Istchenko, 2014
2014	0	Intermonthly variability of loss		10	14		Istchenko, 2014
2012	e	Nonwake loss	32			Analyst comparison	Mortensen et al., 2012
2013	e	Nonwake loss	7.8			Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Nonwake loss	34			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2012	e	Wake loss	13			Analyst comparison	Mortensen et al., 2012
2013	e	Wake loss		10	20	Caused by different models and terrains	Brower and Robinson, 2013
2013	e	Wake loss		20	30	In WindFarmer	Elkinton, 2013
2013	e	Wake loss	25				McCaa, 2013
2013	e	Wake loss		15	20		Kline, 2013
2013	e	Wake loss	30				Halberg and Breakey, 2013
2013	e	Wake loss	37			Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Wake loss	18			Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Wake loss	20				AWS Truepower, 2014
2015	e	Wake loss		13	22		Mortensen et al., 2015a
2016	e	Wake loss		13	35		Clifton et al., 2016
2019	e	Wake loss	18				Stoelinga, 2019
2009	0	Wake loss			80	By second row of an offshore wind farm	Dahlberg, 2009

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

Vear	Fet/Obs	Category	Subcategory	Avg	Min	Max	Notes	Source
I cai	LSUOUS	Category	Subcategory	(%)	(%)	(%)	Notes	Source

2004	е	Historical wind resource	Long-term adjustment	5			WindPro 2.4; methods and measure- correlate-predict	EMD International A/S, 2004
2008	е	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	е	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	е	Historical wind resource	Long-term period	5			Climate variation: 1997–2007	Johnson et al., 2008; White, 2008
2010	е	Historical wind resource	Long-term period	5			WindPro 2.7; long- term wind variability	Nielsen et al., 2010
2012	е	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	е	Historical wind resource	Long-term period			28.4	One-year uncertainty	Dutrieux, 2019
2010	0	Historical wind resource	Long-term period	2				Rogers, 2010
2012	0	Historical wind resource	Long-term period	8.2			Long-term wind speed	Tchou, 2012
2012	0	Historical wind resource	Long-term period	4.3			Long-term wind speed	Tchou, 2012
2013	е	Historical wind resource	Reference data	16				Holtslag, 2013
2009	e	Historical wind resource	Total historical wind resource	3.98			Twenty-year uncertainty, 10 projects	Breakey, 2019
2011	e	Historical wind resource	Total historical wind resource	4.2	2.5	7		Comstock, 2011
2011	e	Historical wind resource	Total historical wind resource	5				Hendrickson, 2011
2016	e	Historical wind resource	Total historical wind resource		1	6		Clifton et al., 2016

2017	е	Historical wind resource	Total historical wind resource		2	5	Ten-year uncertainties from three examples	Halberg, 2017
2019	е	Historical wind resource	Total historical wind resource	2.68			Twenty-year uncertainty, 10 projects	Breakey, 2019
2012	0	Historical wind resource	Total historical wind resource		3	5		Comstock, 2012
2014	0	Historical wind resource	Total historical wind resource	3.2	1.7	5.3		Brower, 2014
2014	0	Historical wind resource	Total historical wind resource	2	2	5		Istchenko, 2014
2014	е	Historical wind resource	Wind speed and direction distribution		1.5	2.5	Interannual variability of frequency distribution	Geer, 2014
2014	е	Historical wind resource	Wind speed and direction distribution	1	0.6	1.5	Wind speed distribution	AWS Truepower, 2014
2004	e	Horizontal extrapolation	Model stress	5			WindPro 2.4; terrain description	EMD International A/S, 2004
2014	e	Horizontal extrapolation	Model stress		3	6	Complex terrain	Redouane, 2014
2016	e	Horizontal extrapolation	Model stress		1	10	For simple and complex terrain	Clifton et al., 2016
2010	0	Horizontal extrapolation	Model stress	2.7			75 North American projects; caused by topography	Rogers, 2010
2009	е	Horizontal extrapolation	Total horizontal extrapolation		1	3	Nonideal flow	Hendrickson, 2009

		II	Total				Twenty-year	
2009	e	Horizontal	horizontal	5.24			uncertainty, 10	Breakey, 2019
		extrapolation	extrapolation				projects	
			Total					
2011	e	Horizontal	horizontal	4.1	1.5	7		Comstock, 2011
		extrapolation	extrapolation					
		TT ' / 1	Total					
2011	e	Horizontal	horizontal	4.3			Flow model	Hendrickson, 2011
		extrapolation	extrapolation					
		II	Total				Oraliant	Martine 1Eister
2013	e	Horizontal	horizontal	3.5	0	9	Onsnore, analyst	Mortensen and Ejsing
		extrapolation	extrapolation				comparison	Jørgensen, 2013
		Homizontal	Total					
2014	e	Horizoniai	horizontal		2	4		Geer, 2014
		extrapolation	extrapolation					
		Horizontal	Total					AWS Truenower
2014	e	avtrapolation	horizontal	4	2.4	8	Flow model	Aws mucpower,
		extrapolation	extrapolation					2014
		Horizontal	Total					
2014	e	extrapolation	horizontal		0	14.8		Redouane, 2014
		extrapolation	extrapolation					
		Horizontal	Total					
2015	e	extrapolation	horizontal		0	8.7		Mortensen et al., 2015
		extrapolation	extrapolation					
		Horizontal	Total					
2016	e	extrapolation	horizontal		1	10		Clifton et al., 2016
		extrapolation	extrapolation					
		Horizontal	Total				Ten-year uncertainties	
2017	e	extrapolation	horizontal		2.6	4.7	from three examples	Halberg, 2017
			extrapolation					
		Horizontal	Total					
2018	e	extrapolation	horizontal		2.3	6.5	Flow model	Walls, 2018
		entrapolation	extrapolation					

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

2011	e	Measurement	Total measurement	4.9				Hendrickson, 2011
2014	e	Measurement	Total measurement		1.5	2.5		Geer, 2014
2014	e	Measurement	Total measurement	2.4	1.6	4.8		AWS Truepower, 2014
2016	e	Measurement	Total measurement		1	5	For plants built from 2010 to 2015 with anemometer-based campaign, before extrapolations	Clifton et al., 2016
2017	e	Measurement	Total measurement		2.3	4.5	Ten-year uncertainties from three examples	Halberg, 2017
2019	е	Measurement	Total measurement	2.36			Twenty-year uncertainty, 10 projects	Breakey, 2019
2002	0	Measurement	Total measurement		8	12		Friis Pedersen et al., 2002
2010	0	Measurement	Total measurement	1.9			Analyst comparison; caused by tower shadow filter and data recovery	Balfrey, 2010
2012	0	Measurement	Total measurement		2	3		Comstock, 2012
2014	0	Measurement	Total measurement	4.2	1.7	7.5		Brower, 2014
2014	0	Measurement	Total measurement	2	2	4		Istchenko, 2014
2012	e	Measurement	Wind speed measurement	3.4			Anemometer	Tchou, 2012
2013	e	Measurement	Wind speed measurement	9				Holtslag, 2013

2013	e	Measurement	Wind speed	4	1.5	10	Onshore, analyst	Mortensen and Ejsing
			measurement				comparison	Jørgensen, 2013
2015	e	Measurement	Wind speed		3	4	Anemometer and	Geer, 2015
			measurement				calibration	
2016	e	Measurement	Wind speed		1	2		Clifton et al., 2016
			measurement					
2010	0	Measurement	Wind speed	1.5	1	1.5	Tower effects on	Rogers, 2010
		DI	measurement				anemometer	
2012	e	Plant	Availability	0.3			Substation metering	Tchou, 2012
		performance						
2014	e	Plant	Availability		2	4	Interannual variability	Geer, 2014
		performance					of availability	
2009	0	Plant	Availability	6.2				Cushman, 2009
		performance						
2011	0	Plant	Availability	1				Johnson, 2011
		performance						
2012	0	Plant	Availability	1.7				Tchou, 2012
		performance						
2016		Plant	Curtailments		1	4		Clifferent 1, 2016
2016	e	performance	or Operational		1	4		Clifton et al., 2016
		Dlant	strategies				Oraham analyst	Martanan and Eising
2013	e	Plant	Electrical	0.5	0	4	Onshore, analyst	Mortensen and Ejsing
		Dlant					comparison; metering	Jørgensen, 2015
2013	e	Plant	Electrical		0	2	Metering	Mortensen, 2013
		performance						
2016	e	Plant	Electrical		1	2		Clifton et al., 2016
		performance						
2012	e	Plant	Nonwake	2.9			Analyst comparison	Mortensen et al., 2012
		performance					0.001 1.	
2013	e	Plant	Nonwake	0.7			Offshore, analyst	Mortensen and Ejsing
		performance					comparison	Jørgensen, 2013
2013	e	Plant	Nonwake	2.7			Unshore, analyst	Mortensen and Ejsing
		pertormance					comparison	Jørgensen, 2013

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

2004		Plant	Turbine	5			WindPro 2.4; power	EMD International
2004	e	performance	performance	3			curve	A/S, 2004
2012		Plant	Turbine	1.5				Tahou 2012
2012	e	performance	performance	1.5				1 chou, 2012
		Plant	Turbine				Onshore, analyst	Mortensen and Eising
2013	e	performance	performance	4	0	10	comparison; power	Jørgensen 2013
		performance	performance				curve	Jørgensen, 2015
2013	e	Plant	Turbine		5	10	Power curve	Mortensen 2013
2015	C	performance	performance		5	10		Wortensen, 2015
2014	2	Plant	Turbine		4	10.4	Dower curve	Padouana 2014
2014	C	performance	performance		4	10.4		Redouane, 2014
2016		Plant	Turbine		0	4		Clifton et al. 2016
2010	C	performance	performance		0	-		Cinton et al., 2010
2010		Plant	Turbine		86	10.0	Power curve from 10-	Vim and Shin 2010
2019	e	performance	performance		0.0	10.0	kW turbine	Killi and Silli, 2019
2002	0	Plant	Turbine		2	2	Dower curve	Friis Pedersen et al.,
2002	0	performance	performance		2	5		2002
2012	0	Plant	Turbine	0.8			Power curve	Brower et al 2012
2012	Ũ	performance	performance	0.0				Diower et ui., 2012
2012	0	Plant	Turbine	1				Tchou 2012
2012	Ũ	performance	performance	1				101100, 2012
2012	0	Plant	Turbine	6.1			Power curve	Drees and Weiss,
2012	0	performance	performance	0.1				2012
2012	0	Plant	Turbine	15			From air density of	Winslow 2012
2012	0	performance	performance	15			power curve	winsiow, 2012
2012	0	Plant	Turbine		4	8	Power curve	Jaynes 2012
2012	0	performance	performance		-	0		Jaynes, 2012
2013	0	Plant	Turbine		0.5	6.5	Power curve	Kassebaum 2013
2015	0	performance	performance		0.5	0.5		Kassebaum, 2015
2014	0	Plant	Turbine	6			Dower curve	Ostridge 2014
2014	0	performance	performance	0				Osuluge, 2014
2015	0	Plant	Turbine	6			Power curve	Ostridge 2015
2015	0	performance	performance	0				Osuluge, 2013
		1	1		1	1		

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

2014	e	Project evaluation period variability	Modeled operational period	1.9				AWS Truepower, 2014
2019	e	Project evaluation period variability	Modeled operational period			8	Ten-year uncertainty	Dutrieux, 2019
2019	e	Project evaluation period variability	Modeled operational period			4.8	Twenty-year uncertainty	Dutrieux, 2019
2019	e	Project evaluation period variability	Modeled operational period			1.6	Thirty-year uncertainty	Dutrieux, 2019
2010	0	Project evaluation period variability	Modeled operational period	1			Changes in long-term wind speed	Rogers, 2010
2015	e	Project evaluation period variability	Plant performance		7	12	With 1 to 10 met masts	Brower et al., 2015
2009	e	Project evaluation period variability	Total project evaluation period variability	2.26			Twenty-year future variability	Breakey, 2019
2011	e	Project evaluation period variability	Total project evaluation period variability		6	10.5		Comstock, 2011

$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			Project	Total project					
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	2011		evaluation	evaluation	-				H 1 1 0011
$ \begin{array}{ c c c c c c } \hline & & variability & vari$	2011	e	period	period	/				Hendrickson, 2011
2012eProject evaluation period variabilityTotal project evaluation period variability3.19.7Range of 1-year and 10-year uncertaintiesTchou, 20122016eProject evaluation period variabilityTotal project evaluation period variability110Clifton et al., 2016			variability	variability					
2012eevaluation period variabilityevaluation period variabilityevaluation period variability3.19.7Range of 1-year and 10-year uncertaintiesTchou, 20122016eProject evaluation period variabilityTotal project evaluation period variability110Clifton et al., 2016			Project	Total project					
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variabilityvariability2016eProjectTotal projectevaluationevaluation1periodperiod1variabilityvariability1	2012	e	period	period		3.1	9.7	10-year uncertainties	1 chou, 2012
2016eProjectTotal project2016eProjectevaluationperiodperiod1variabilityvariability1			variability	variability					
2016eevaluation period variabilityevaluation period variability110Clifton et al., 2016			Project	Total project					
period period variability variability la	2016	2	evaluation	evaluation		1	10		Clifton at al. 2016
variability variability	2010	e	period	period		1	10		Clinton et al., 2010
			variability	variability					
Project Total project			Project	Total project					
evaluation evaluation 2.8 2.5 Ten-year uncertainties	2017	_	evaluation	evaluation		20	2.5	Ten-year uncertainties	Halbang 2017
2017 e period period 2.8 5.5 from three examples Halberg, 2017	2017	e	period	period		2.8	3.3	from three examples	Halberg, 2017
variability variability			variability	variability					
Project Total project			Project	Total project					
evaluation evaluation Twenty-year future	2010	_	evaluation	evaluation	0.04			Twenty-year future	D
2019 e beriod period 0.94 variability Breakey, 2019	2019	e	period	period	0.94			variability	Breakey, 2019
variability variability			variability	variability					
Project Total project			Project	Total project					
evaluation evaluation 1	2010	0	evaluation	evaluation	1				Pagers 2010
period period reference period	2010	0	period	period	1				Kogers, 2010
variability variability			variability	variability					
Project Total project			Project	Total project					
evaluation evaluation 2 3 Comstock 2012	2012	0	evaluation	evaluation		2	3		Comstock 2012
period period period constock, 2012	2012	0	period	period		2	5		Comstock, 2012
variability variability			variability	variability					
Project Total project			Project	Total project					
evaluation evaluation Range of 1-year and Tahon 2012	2012	0	evaluation	evaluation		3.1	07	Range of 1-year and	Tchou 2012
period period [3.1] 5.7 10-year uncertainties [10100, 2012]	2012	0	period	period		5.1	7.1	10-year uncertainties	10100, 2012
variability variability			variability	variability					

2014	0	Project evaluation period variability	Total project evaluation period variability	6	4	9	One-year uncertainties	Istchenko, 2014
2014	0	Project evaluation period variability	Total project evaluation period variability	2	2	3	Ten-year uncertainties	Istchenko, 2014
2000	e	Total	Total		3	6	For flat and complex terrains	Albers et al., 2000
2004	e	Total	Total	10			WindPro 2.4	EMD International A/S, 2004
2007	е	Total	Total	9.6			Twenty-year uncertainty, 10 projects	Breakey, 2019
2008	e	Total	Total		9.9	12.7	Range of 1-year and lifetime uncertainties	AWS Truepower, 2009
2009	e	Total	Total		7.9	10.5	Range of 1-year and lifetime uncertainties	AWS Truepower, 2009
2010	e	Total	Total	8		10	WindPro 2.7	Nielsen et al., 2010
2011	e	Total	Total	13	10	18		Hendrickson, 2011
2011	e	Total	Total	7.2				Bernadett et al., 2012
2012	e	Total	Total		7	11		Comstock, 2012
2012	e	Total	Total		10.4	13.9	Range of 1-year and 10-year uncertainties	Tchou, 2012
2012	e	Total	Total	7.7				Bernadett et al., 2012
2012	e	Total	Total	11	6	21	Analyst comparison	Mortensen et al., 2012
2013	e	Total	Total	17				Holtslag, 2013
2013	e	Total	Total	10.8				Holtslag, 2013
2013	e	Total	Total	10	6.2	21	Offshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2013	e	Total	Total	8	3.6	12	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013

2013	e	Total	Total		10	15		Mortensen, 2013
2014	e	Total	Total		7.9	10.8	Range of 1-year and 10-year uncertainties	Istchenko, 2014
2014	e	Total	Total	7.5	5.2	13.5		AWS Truepower, 2014
2014	e	Total	Total		11.1	16.7	Nine wind farms, 1- year uncertainties	Redouane, 2014
2014	e	Total	Total		8.4	14.5	Nine wind farms, 10- year uncertainties	Redouane, 2014
2015	e	Total	Total		10	15		Apple, 2015
2015	e	Total	Total	7.2				Istchenko, 2015
2015	e	Total	Total		5	9	"Minimum"	Mortensen et al., 2015
2015	e	Total	Total		8	11		Mortensen et al., 2015a
2015	e	Total	Total	10.6			One-year uncertainty	Stoelinga and Hendrickson, 2015
2017	e	Total	Total		6.2	10.7	Ten-year uncertainties from three examples	Halberg, 2017
2017	e	Total	Total		7.9	9.1	One-year uncertainties	Perry, 2017
2017	e	Total	Total		4.1	6.2	Twenty-year uncertainties	Perry, 2017
2017	е	Total	Total	11			Post-2011 projects, 1- year standard deviation	Ostridge, 2017
2019	e	Total	Total	6.8			Twenty-year uncertainty, 10 projects	Breakey, 2019
2009	0	Total	Total	9.7		9.7		Derrick, 2009
2009	0	Total	Total	33			One offshore wind farm	Dahlberg, 2009
2012	0	Total	Total		5	8		Comstock, 2012

2012	0	Total	Total		9.1	12.9	Range of 1-year and 10-year uncertainties	Tchou, 2012
2012	0	Total	Total		6.2	11.1	Range of 1-year and 10-year uncertainties	Tchou, 2012
2014	0	Total	Total	8.4	6.3	11.5		Brower, 2014
2014	0	Total	Total		5.4	9.4	Range of 1-year and 10-year uncertainties	Istchenko, 2014
2014	0	Total	Total		4	8	Nine wind farms	Redouane, 2014
2015	0	Total	Total		6	12		Apple, 2015
2015	0	Total	Total	6.2				Istchenko, 2015
2015	0	Total	Total		3.1	7		Mortensen et al.,
2013	0	Total	Total		5.1	/		2015a
2017	0	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	0	Vertical extrapolation	Model inputs	1.9			Wind shear	Rogers, 2010
2009	e	Vertical extrapolation	Total vertical extrapolation	3.49			Twenty-year uncertainty, 10 projects	Breakey, 2019
2011	e	Vertical extrapolation	Total vertical extrapolation	3.2	1.5	5		Comstock, 2011
2011	e	Vertical extrapolation	Total vertical extrapolation	3.1				Hendrickson, 2011
2013	e	Vertical extrapolation	Total vertical extrapolation	1	0	13	Onshore, analyst comparison	Mortensen and Ejsing Jørgensen, 2013
2014	e	Vertical extrapolation	Total vertical extrapolation		1	2		Geer, 2014
2014	e	Vertical extrapolation	Total vertical extrapolation		0	5		Redouane, 2014

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

455 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	0	Power-curve measurement		6	8		Friis Pedersen et al., 2002
2013	0	Power-curve measurement	3.5			Power curve test	Kassebaum, 2013
2015	0	Power-curve measurement	4.5				Kassebaum, 2015

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

Veen	E-t/Ol-	Catagoria	Avg	Min	Max	Natar	S
Year	Est/Obs	Category	(%)	(%)	(%)	INOLES	Source
2018	e	Blockage		1.9	3.4		Bleeg et al., 2018
						Nonideal flow; include	
2011	e	Distortion		0	2	tower, boom, other	Hatlee, 2011
						equipment	
2014		Distortion		1 1	2.6	Include distortion of terrain	
2014	e	Distortion		1.1	5.0	and mounting.	Redouane, 2014
2010	0	Future variability		1	3	Future climate; WindPro	Nielsen et al. 2010
2010	C	Tuture variability		1	5	2.7	Thersen 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		1	4		Comstock 2011
2011	C	extrapolation		1			Combrook, 2011
2013	e	Horizontal	5			Reference data	Holtslag 2013
2015	· ·	extrapolation	5				110101010, 2010
2013	e	Horizontal	1			Lidar	Holtslag 2013
2013	C	extrapolation	1				1101010102, 2015
2013	e	Horizontal		0	5		Mortensen, 2013
2010	-	extrapolation		Ŭ	U		
2015	e	Horizontal		0	2.2	Long-term extrapolation	Mortensen et al 2015
2010	· ·	extrapolation		Ŭ	2.2	Long torm entruperation	
2010	0	Horizontal	19			Analyst comparison	Walter 2010
2010	Ũ	extrapolation	1.9			7 maryst comparison	Walter, 2010
1991	e	Interannual	61				Simon 1991
1771	č	variability	0.1				
2006	e	Interannual		8	12	Northern Europe	Prvor et al 2006
2000	č	variability		0	12	Normeni Europe	11yor et al., 2000
2008	e	Interannual		2	7	Windiness	Johnson et al. 2008
2000		variability		-	,		501115011 et u 1., 2000

2009	e	Interannual	6			Recommend in	Garrad Hassan and Partners
2007	č	variability	0			WindFarmer	Ltd, 2009
2010		Interannual	2.5				Handrickson 2010
2010	e	variability	5.5				Hendrickson, 2010
2010		Interannual	6			One-year uncertainty;	Nielsen et al. 2010
2010	e	variability	0			WindPro 2.7	Niciscii et al., 2010
2010	e	Interannual	13			Twenty-year uncertainty;	Nielsen et al. 2010
2010	č	variability	1.5			WindPro 2.7	11015011 et ul., 2010
2011	e	Interannual		4	6	United States	Rogers 2011
2011	· ·	variability			Ŭ		1005010, 2011
2013	e	Interannual		2	6	Variability	Mortensen 2013
2015	· ·	variability		-	Ũ	, and only	11010013011, 2013
2014	e	Interannual		2	4		Brower, 2014
		variability					
2014	e	Interannual		3.5	6		Geer. 2014
	_	variability			Ĩ		
2017	e	Interannual	5				Perry, 2017
	_	variability					
2018	e	Interannual	2.1			37 years in contiguous	Lee et al., 2018
		variability				United States	,
2019	e	Interannual		1.4	5.4		Gkarakis and Orfanaki,
	_	variability					2019
2014	0	Interannual		5.7	8.8		Istchenko, 2014
		variability					
2018	e	Intermonthly	10.2			37 years in contiguous	Lee et al., 2018
		variability				United States	,
2014	0	Intermonthly		19	24		Istchenko, 2014
		variability					
2010	e	Long-term wind	3	2	4		Clive, 2010
		speed					
		Long-term wind				Combine nearby weather	
2011	e	speed		3.7	4.8	station, airport, modeled	Rogers, 2011
						data	

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	0	Long-term wind speed	3.5		20	1000 hours of data	Rogers et al., 2006
2006	0	Long-term wind speed		3	6	9000 hours of data at offshore wind farms	Rogers, 2011
2006	0	Long-term wind speed		2	8	9000 hours of data at offshore wind farms	Rogers, 2011
2010	e	Measure-correlate- predict		1	3	WindPro 2.7	Nielsen et al., 2010
2012	e	Measure-correlate- predict	2.5	1	3	Long-term wind speed and correction	Mortensen et al., 2012
2013	e	Measure-correlate- predict	4			Lidar; long-term representation and correlation	Holtslag, 2013
2014	e	Measure-correlate- predict		0.7	6.4		Redouane, 2014
2010	e	Plant performance	3	1	4	Energy loss model	Clive, 2010
2010	e	Terrain data and resolution	3		4		Clive, 2010

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

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

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

2010	e	Wind speed modeling		3	10		Brower et al., 2010
2011	e	Wind speed modeling		2	5		Faghani, 2011
2012	e	Wind speed modeling		1	5.5		Brown, 2012
2012	e	Wind speed modeling		2	10	Flow model	Brower, 2012
2013	e	Wind speed modeling		1.7	6.9		Abiven et al., 2013
2015	e	Wind speed modeling	10		12		Brower et al., 2015
2017	e	Wind speed modeling		3	5	WAsP	Jog, 2017
2017	e	Wind speed modeling		0.9	2	Ensemble model	Jog, 2017
2017	e	Wind speed modeling	2.9	1.4	7.6		Poulos, 2017
2019	e	Wind speed modeling	2.5			2.5% per km of extrapolation distance in WAsP; industry- recommended assumption	Zhang et al., 2019
2015	0	Wind speed modeling		4	10		Brower et al., 2015
2016	0	Wind speed modeling	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.

470 Author contribution

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

Competing interests

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