In this document, the reviewer's comments are in black, the authors' responses are in red.

The authors thank the reviewer for their thoughtful and productive comments.

General comments

This work examines the combination of 5 uncertainty components inherent in operational-based windfarm AEP uncertainty estimation, where the estimation is based on production data and a particular type of long-term correction (linear regression on monthly means).
There is some relevant stuff here, and information from production data of > 400 wind farms which can be of use. However, unfortunately the draft does not (yet) appear to be sufficiently clear, rigorous, or complete; it offers a somewhat *qualitative* (incomplete) description of *quantitative* methods/analysis/results and subsequent conclusions. Hopefully with some thought and revision, it can become useful to a number of readers.
Thank you for acknowledging the significant amount of data we used in our analysis. We think that all the modifications we have included in the revised manuscript have greatly improved its scientific and presentation quality.

The title is not honestly representative (nor scientifically accurate), as it connotes/implies consideration of all (or even typical) uncertainty components in production estimates—i.e., it overstates the scope and results of the work. But this draft only considers the LTC and observed/reference data aspects, i.e. operational AEP. The emerging IEC 61400-15 standard includes a much longer list of uncertainty components (and subcomponents), including different modelling uncertainties and plant- performance aspects, among others (as you mention in the final sentence of the conclusion). Further, the emerging standard does allow for correlated uncertainty components. An appropriate title would be something more like "*Operational-based AEP uncertainty: are its components actually uncorrelated?*". Or it could resemble "*correlations between uncertainties in operational-based* (or alternately *long-term correction of) wind farm annual energy estimates*".
We agree with the reviewer that our analysis is focused on the operational-based AEP uncertainty, as we stated multiple times in the introduction of our manuscript. To make the title of the manuscript consistent with the purpose of our study, we have changed it in: *"Operational-Based Annual Energy Production Uncertainty: Are its Components Actually Uncorrelated?"*. We have also replaced "*AEP*" with "*operational AEP*" or similar wordings in many places throughout the manuscript.

The terminology is a bit problematic, in a number of ways: e.g. the definition of *'windiness correction'* is unclear (is direction involved as well?); its relationship with the 'regression' uncertainty component is unclear; the classification 'regression' refers to only certain type of long-term correction (linear).
We have expanded Section 2.2 to add details about the operational AEP methodology applied in our analysis (see later comment on this), and the make clear how the linear regression is applied:
"A linear regression between monthly gross energy production and concurrent monthly average wind speeds is performed."
We have also clarified what we intend for 'windiness correction' in Section 2.2:

"Slope and intercept values from the regression relationship are then applied to the long-term monthly average wind speed data, with the long-term or so-called windiness correction. A long-term data set of monthly (January, February, ...) gross energy production is obtained."
Therefore, the long-term windiness correction only focuses on the uncertainty driven by how different historical periods represent the 'long-term' wind resource at a site.
To make this more explicit, we have also used the term "*long-term windiness correction*" in many places throughout the manuscript to make this concept easier to understand and remember.

To justify our choice of using a linear regression, we have added the following analysis and comment in Section 2.1:
"The fundamental step in an AEP calculation involves a regression between wind speed and energy production. To investigate whether a simple linear function can be assumed to express the relationship between wind speed and wind farm energy pro- duction when considering monthly data, we show a scatterplot between MERRA-2 monthly wind speed and monthly energy production across all 472 sites in Figure 2. For each site, data have been normalized by the respective site mean. We show best-fits using a linear, quadratic, and cubic function, and calculate the mean absolute error of each fit. We find that the difference between the normalized MAE values from the considered functions is less than 0.7%. Therefore, the uncertainty connected with the choice of using a linear regression in the operational AEP methodology at monthly time resolution appears minimal. Moreover, through conversations with wind industry professionals, we found that a linear regression based on monthly data is the standard industry approach when performing bankable operational AEP analyses."

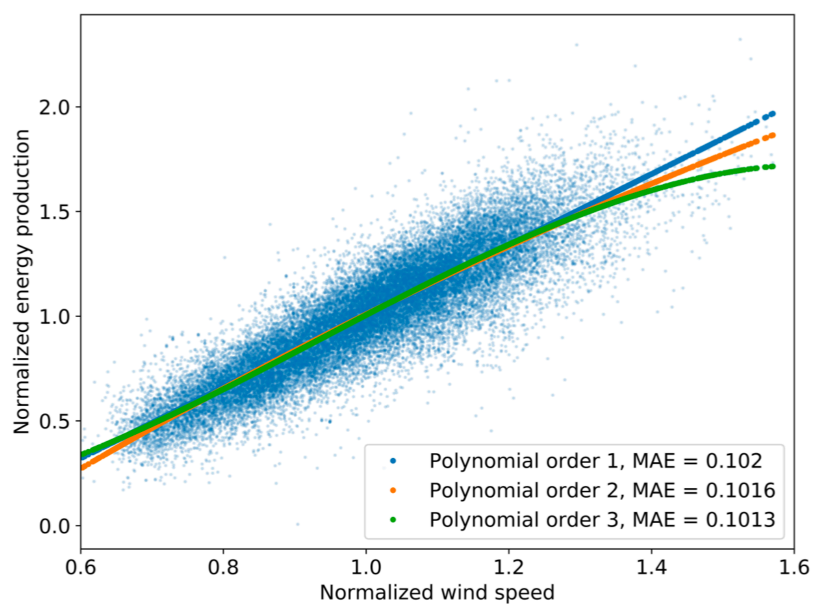

Figure 2. Scatterplot between normalized MERRA-2 monthly wind speed and monthly energy production across all 472 selected sites, and linear, quadratic and cubic best-fit lines.

We have also changed "*regression*" with "*linear regression*" in many places throughout the manuscript.

Yet more problematic is the lack of mathematical or specific definitions for the individual calculations/processes, to which the 5 uncertainty components are ascribed.
The total uncertainty calculation is missing, or rather mathematical description of the model for total operationally-based uncertainty estimation—along with mathematical description of all components; e.g. per the latter, the IAV 'incorporation' is not clear.
We have greatly improved the Methodology part of our manuscript (Sections 2.2 and 2.3), to add details and clarity to it. We have included the revised version of Section 2.2 in response to the reviewer's specific comment #7. We include here the revised version of Section 2.3:

2.3 Monte Carlo Analysis

To quantify the uncertainty of the long-term operational AEP estimate obtained using the methodology described in the previous section, we implement a Monte Carlo approach. In general, a Monte Carlo method involves the randomized sampling of inputs to or calculations within a method which, when repeated many times, results in a distribution of possible outcomes from which uncertainty can be deduced, usually calculated as the standard deviation or the coefficient of variation of the resulting distribution (ISO and OIML, 1995; Dimitrov et al., 2018). Here, we apply this approach to derive a distribution of long-term operational AEP values, from which its uncertainty can be calculated. To do so, we consider and include in the Monte Carlo approach five operational-based uncertainty components, so that five different samplings are performed at each Monte Carlo iteration. The following uncertainty components are included in our proposed Monte Carlo methodology for long-term operational AEP:

- Revenue meter measurement error. We incorporate this uncertainty component in the Monte Carlo simulation by sampling monthly revenue meter data from a normal distribution centered on the reported value, and 0.5% standard deviation. In fact, a value of 0.5% is coherent with what is typically assumed in the wind energy community as revenue meter uncertainty (IEC 60688:2012; ANSI C12.1-2014).

- Reference wind speed data modeling error. Quantifying the uncertainty of the long-term wind resource data used in the operational AEP assessment is challenging, as it can vary based on the location, long-term wind speed product used, or instrument from which reference observations are taken. To include this uncertainty component in a systematic way across the 472 locations considered in our analysis, we incorporate it in the Monte Carlo simulation by randomly selecting, at each iteration at each site, wind resource data from one of the three considered reanalysis products.

- Linear regression model uncertainty. This component is incorporated in the Monte Carlo method by sampling the regression slope and intercept values from a multivariate normal distribution centered on their best-fit values and covariance matrix equal to the one of the best-fit parameters. The diagonal terms in the covariance matrix are given by the square of the slope and intercept standard errors. For a regression model between an independent variable x and a dependent variable y the standard error of the regression is defined as

$$e_y = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n-2}}, \quad (4)$$

where $\hat{y}_i$ is the regression-predicted value for y_i, and n is the number of data points used in the regression. The standard error of the regression slope:

$$e_a = \frac{e_y}{\sum \left(x_i - \overline{x_i}\right)^2}, \tag{5}$$

and the standard error of the intercept:

$$e_b = e_y \, e_a \sqrt{\frac{\sum x_i^2}{n}}. \tag{6}$$

e_a^2 and e_b^2 are the diagonal terms in the covariance matrix of the multivariate normal distribution of regression slope and intercept, from which Monte Carlo values are drawn. Slope and intercept values are strongly negatively correlated, which is captured by their covariance when performing the linear regression. The off-diagonal terms in the covariance matrix of the multivariate normal distribution constrain the random sampling of slope and intercept values, to avoid sampling unrealistic combinations. An example of this sampling is shown in Figure 4 for two projects of different regression strengths. We sample 500 slope and intercept values from a multivariate normal distribution centered around the best-fit parameters, and with covariance matrix derived from the standard errors of slope and intercept and their covariance. As shown in the Figure, the low standard errors found for the leftmost regression relationship constrain the possible slope and intercept values that can be sampled while the high standard errors in the rightmost regression relationship allow for a much wider sampling.

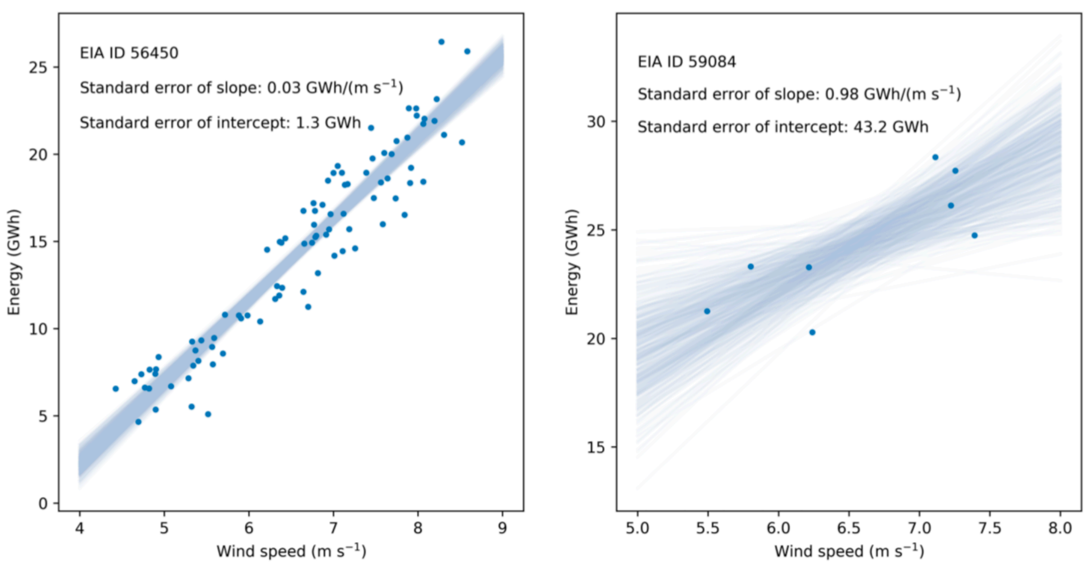

Figure 4. Sampling set of regression lines corresponding to the slope and intercept values derived from their standard errors in the Monte Carlo approach, for two stations in the EIA data set.

- Long-term (windiness) correction uncertainty. We incorporate this component by sampling the number of years (between 10 and 20) to use as the long-term wind resource data to which the regression coefficients are applied to derive long-term energy production data (the so-called windiness correction).
- Wind resource inter-annual variability (IAV) uncertainty. We incorporate this uncertainty component in the Monte Carlo method by sampling the long-term (reanalysis) average calendar monthly wind speeds (i.e., average January, average February) used to calculate long-term monthly energy production data. The sampling distribution is normal, centered on the calculated long-term average calendar monthly wind speed, and with a standard deviation equal to the 20-year standard deviation of the long-term average monthly wind speed for each calendar month.

Each of the listed sources of uncertainty corresponds to a Monte Carlo sampling, and is highlighted by a probability distribution in the flowchart in Figure 3. Note that uncertainty components related to availability and curtailment losses are not considered in our approach because the EIA 923 database does not include measurements of these losses.

For each wind farm, we estimate the total operational AEP uncertainty by running a Monte Carlo simulation 10,000 times. At each iteration, all five samplings, corresponding to the five considered uncertainty components (revenue meter, reference wind speed data, wind resource IAV, linear regression, and windiness correction), are simultaneously performed. The total uncertainty in long-term operational AEP is then estimated as the coefficient of variation of its resulting distribution. Convergence of the AEP distribution within 0.5% of the true mean after the 10,000 Monte Carlo runs was verified for all projects, with a 95% confidence.

To understand the impact of the single uncertainty components and study their correlation, we also run, at each site, the Monte Carlo simulation with only a single sampling performed (i.e. either revenue meter, reference wind speed data, IAV, linear regression, or windiness correction). At each wind farm, we run the Monte Carlo simulation 10,000 time for each of the five single operational uncertainty components considered. We quantify the impact of each single uncertainty component on the long-term operational AEP in terms of the coefficient of variation of the distribution of operational AEP resulting from the Monte Carlo simulation run when sampling only that single uncertainty component.

The code used to perform the AEP calculations is published and documented in NREL's open-source operational assessment software, OpenOA.[2] Calculations were performed on Eagle, NREL's high-performance computing cluster. Specifically, each wind farm was assigned a different processor and run in parallel. Given the general simplicity of the AEP method used here, computational requirements were moderate despite the 60,000 simulations (10,000 runs x 6 uncertainty setups) required for each wind farm.

The paper first shows the correlations between uncertainty components in § 3.2. But these correlations are used to describe the uncertainty contributions in section 3.1, and presumably these correlations have already been used to prescribe/run the Monte Carlo simulations which were described in section 2.3. But there is no description of the use of the covariance matrix in the MC calculations, or how these correlations were incorporated in the MC analysis.

The correlations between different operational AEP uncertainty components are not assigned/prescribed at all in the Monte Carlo approach; rather, they reveal themselves from the results of the Monte Carlo runs across the 472 wind farms considered in our analysis. And this is one of the main results of our analysis. We understand this was not clear enough in our original draft. Therefore, we have refined and improved the discussion of the Results, to make sure this essential step is made clear to the reader. As an example, we have rephrased the first part of Section 3.2 as follows:

"Because operational AEP uncertainty calculated by assuming a lack of correlation among its different components can greatly differ from the uncertainty values obtained when allowing for

potential correlations, it is worth exploring the correlation between uncertainty components which are responsible for this difference. We leverage the results of the Monte Carlo analysis at the 472 wind farms considered to reveal the correlation between the single operational AEP uncertainty components, in terms of their Pearson correlation coefficient. As a result, we obtain the average correlation matrix in Figure 6.".

We have also rephrased the caption on Figure 6 (the correlation matrix) as *"Correlation coefficient heat map between operational AEP uncertainty components, as calculated from the results of the Monte Carlo approach applied at the 472 wind farms considered in the analysis.".*

We have also rephrased and improved many parts of Section 3.1, to emphasize that the results described in that section are indeed a consequence of the comparison between the two considered methods for operational AEP uncertainty assessment (Monte Carlo, which allows for correlations to be revealed, *vs* sum of squares, which instead assumes uncorrelated uncertainty components), but can be understood without the need of having read the detailed analysis of the specific correlations given later in Section 3.2:

"[…] The proposed Monte Carlo approach does not require any assumption on the correlation between the different uncertainty components; on the other hand, the conventional sum of squares approach assumes the uncertainty components are all uncorrelated. Therefore, we compare the total operational AEP uncertainty from the Monte Carlo method with all the five simultaneous samplings (σ_MonteCarlo) with the total uncertainty σ_uncorrelated calculated using the conventional sum of squares approach. For the latter approach, we quantify each of the five uncertainty components as the coefficient of variation of the corresponding operational AEP distribution obtained by running the Monte Carlo simulation with a single sampling performed. We then combine the five uncertainty components into the overall AEP uncertainty using Eq. 1. Figure 5 shows the results of this comparison for the 472 wind farms considered, […]

In other words, if correlations between the different uncertainty components are allowed and taken into account in the calculation method, the whole AEP uncertainty is then, on average, slightly reduced. […]

Moreover, assuming that all the uncertainty components are uncorrelated can introduce significant errors in the assessment of the AEP uncertainty for the single projects, with about 47% (16%) of the considered wind farms showing a ±5% (10%) uncertainty difference compared to the values from the Monte-Carlo-based approach."

The idea (and Fig.11a) about 'spread' and variance can be stated succinctly mathematically, and in a less confusing manner—instead of with only semi-qualitative demonstration.

We have eliminated Figure 11, and changed the explanation of the correlation between linear regression uncertainty and IAV uncertainty as follows:

Finally, the (weak) negative correlation between linear regression and wind resource IAV uncertainties is linked to the fact they respond differently to the R^2 coefficient between the reanalysis wind speed and the energy production data (Figure 10). Predictably, the linear regression uncertainty is inversely proportional to the coefficient of determination because a stronger

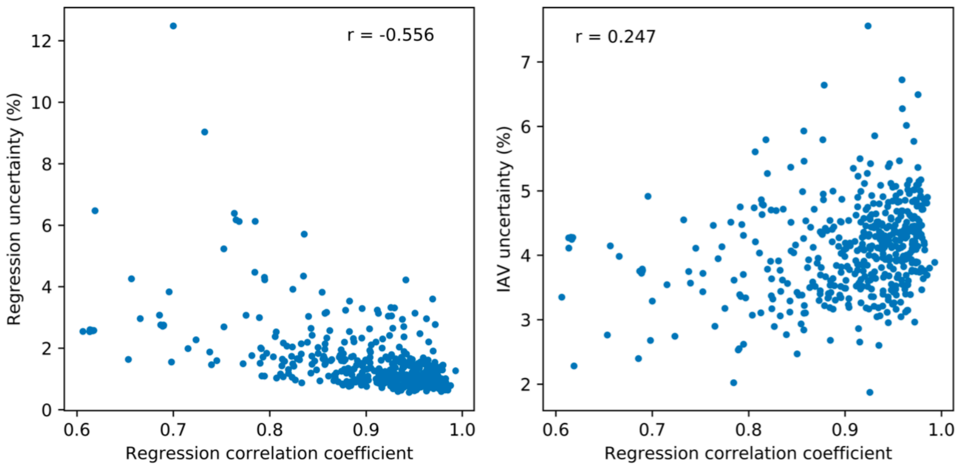

Figure 10. Dependence of linear regression uncertainty and IAV uncertainty on the R^2 of the regression between reanalysis wind speed and energy production data

correlation between winds and energy production will lead to a reduced uncertainty of the regression between the two variables. On the other hand, wind resource IAV uncertainty shows a direct correlation with the regression R^2 coefficient. This dependency can be explained as both quantities are directly correlated with the total variance of wind speed or, equivalently, produced energy. Figure 11 shows the relationship between IAV uncertainty and the total sum of squares $SS_{\text{tot, WS}}$ of reanalysis wind speed (here, using MERRA-2 monthly data), which is proportional to the variance of the data:

$$SS_{\text{tot, WS}} = \sum_i (WS_i - \overline{WS})^2 \tag{8}$$

A direct correlation between IAV uncertainty and $SS_{\text{tot, WS}}$ emerges. At the same time, the linear regression R^2 coefficient also depends on the variance of the produced energy (and, equivalently, of wind speed) as it is defined as

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}} \tag{9}$$

where SS_{res} is the total sum of the residuals from the linear regression. Equation 9 shows that when the total sum of squares SS_{tot} increases, so does R^2, thus confirming the direct correlation between R^2 and the variance in the data.

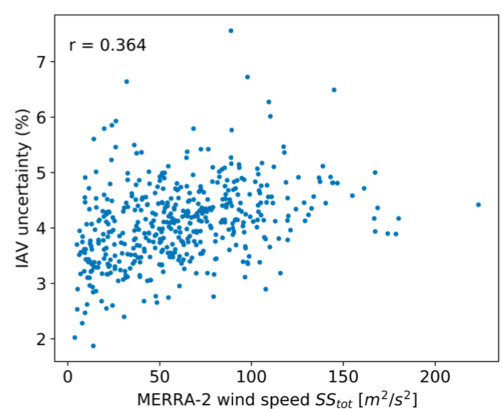

Figure 11. Dependence of IAV uncertainty on the total sum of squares $SS_{\text{tot, WS}}$ of MERRA-2 wind speed data, for the 472 projects considered.

Again, as mentioned just above, the MC method itself does not show correlations between components; rather, you _assign_ these from having calculated the correlation matrix.
See the detailed comment above on the topic. Crucially – the MC method does not assign correlations between uncertainty categories. Rather, these correlations (or lack thereof) reveal themselves when comparing uncertainty categories across the 472 wind farms.

The conclusions also include some overstatement, e.g. labelling Monte Carlo simulations as "our technique". MC methods have become more commonly used in UQ within the wind industry (e.g. from Williams et al 2008 for economic analysis, to Takeshi+Yamaguchi 2015 for extremes with MCP, to Müller+Cheng 2018 for probabilistic design), and also in some standard references (e.g. GUM); this should have been mentioned and referenced.
We have rephrased the conclusions, to avoid any unwanted overstatements of the results of our analysis.
We have also added the following sentence to the Introduction of the paper: "*Monte Carlo methods have been used in different applications for uncertainty quantification within the wind industry, ranging from the prediction of extreme wind speed events (Ishihara and Yamaguchi, 2015), to offshore fatigue design (Müller and Cheng, 2018), to economic analysis of the benefits of wind energy projects (Williams et al., 2008).*"

Specific comments

1. Abstract/l.3: replace 'standard' with 'a popular', since the uncorrelated assumption is not necessarily standard.
   Changed.

2. l.4 and many places: replace 'categories' with 'components'; one does not add up categories, but calculates using component uncertainties.
   Changed throughout the manuscript.

3. l.97: include a reference on complex terrain/challenging for RA products.
   We have added a reference to Shravan Kumar et Anandan, GRL 2009.

4. l.106 [point 2]: regarding *'between monthly energy production and average wind speeds'* — be explicit: a linear relationship is assumed for a presumably nonlinear P(U) dependence? Or derived wind to long-term wind data? Which "average wind speeds"?
   See answer to comment 7.

5. l.108 [point 3]: perhaps this step should be noted differently because you don't perform it in your analysis. Or, you could indicate clearly the steps that you do calculate.
   See answer to comment 7.

6. l.111–113 [point 5]: how the values are applied needs to be made explicit/clear to the reader (without assumptions or ambiguity): which "long-term resource data" is operated upon (i.e.

scaled and shifted)? One could assume e.g. that measured or production-derived monthly speeds are corrected...
See answer to comment 7.

7. l.114 [point 6]: how are the gross energies 'denormalized', and what is meant by 'normal' number of days?
Thank you for pointing out that this list, which is an essential description of the methodology we applied, was not clear and detailed enough. We have significantly improved it following all your comments/suggestions, to make our analysis replicable to the interested reader:

2.2 Operational AEP Methodology

Given the lack of existing guidelines for a standard approach for operational AEP calculations, we instead base our methodology on conversations with several wind energy consultants. These conversations overwhelmingly revealed the following characteristics of an industry standard and bankable[1] operational AEP analysis:

1. Wind speed data (measured or modeled) are density-corrected at their native time resolution, using equation 2.
2. Monthly revenue meter data, monthly average availability and curtailment losses, and monthly average wind speeds from a long-term wind resource product are calculated.

[1] Results are accepted by banks, investors, and so on for use in financing, buying/selling, and acquiring wind farms.

3. Monthly revenue meter data are normalized to 30-day months (e.g. for January, the revenue meter values are multiplied by 30/31).
4. Monthly revenue meter data are corrected for monthly availability and curtailment (i.e., monthly gross energy data are calculated).
5. A linear regression between monthly gross energy production and concurrent monthly average wind speeds is performed
6. Long-term monthly average wind speed is then calculated for each calendar month (i.e., average January wind speed, average February wind speed, and so forth), using 10–20 years of the available long-term reference monthly wind resource data (reanalysis products, long-term reference measurements, ...).
7. Slope and intercept values from the regression relationship are then applied to the long-term monthly average wind speed data, with the long-term or so-called windiness correction. A long-term data set of monthly (January, February, ...) gross energy production is obtained.
8. The resulting long-term monthly gross energy estimates, which are based on 30-day months, are then denormalized to the actual number of days in each calendar month (e.g. for January, the obtained value is multiplied by 31/30).
9. Long-term estimates of availability and curtailment losses are finally applied to the denormalized long-term monthly gross energy data, leading to a long-term calculation of operational AEP.

In the EIA-923 database, availability and curtailment data are not available. Therefore, in our analysis we omit steps 4 and 9 of the list, and only perform calculations on net energy data. A diagram outlining the resulting general process of the operational AEP analysis adopted in our study is shown in Figure 3.

8. l.119–122: include references for Monte-Carlo approach; e.g. GUM has some guidance, others (e.g. Dimitrov *et al.*, 2018 WES) outline use in our field.
Besides the references to Monte Carlo methods added to the introduction as described above, we have also included the suggested references here.

9. Table 2 [p.7]: There is no description explaining/defending your choices of 'incorporation in Monte Carlo approach.
   a. How did you arrive at 0.5% for meter accuracy?
   We have rephrased this part as follows and added references:
   "Revenue meter accuracy. We incorporate this uncertainty component in the Monte Carlo simulation by sampling monthly revenue meter data from a uniform distribution centered on the reported value, and with boundaries at ±0.5% from it. In fact, a value of 0.5% is coherent with what is typically assumed in the wind energy community as revenue meter uncertainty (IEC 60688:2012; ANSI C12.1-2014)."

   b. How can one justify that a random choice from 3 RA products is equivalent to the uncertainty in that long-term reference dataset or 'wind measurement accuracy'? For example, there are places where all 3 have a similar bias; further, the uncertainty in each (as being representative of speeds at a place) can be similar for a number of locations, but the variability amongst the 3 sources can then be significantly smaller.
   We agree with the reviewer that representing the uncertainty in long-term reference wind speed data is challenging. To justify and provide context to our choice, we have rephrased this part of the paper as follows:
   "Reference wind speed data accuracy. Quantifying the uncertainty of the long-term wind resource data used in the operational AEP assessment is challenging, as it can vary based on the location, long-term wind speed product used, or instrument from which reference observations are taken. To include this uncertainty component in a systematic way across the 472 locations considered in our analysis, we incorporate it in the Monte Carlo simulation by randomly selecting, at each iteration at each site, wind resource data from one of the three considered reanalysis products."

   c. How is sampling the number of years for the 'windiness correction' accounting for the uncertainty in using a linear adjustment? The latter may likely dominate this uncertainty component.
   Please see the extensive answer we have given on this topic to the third general comment.

10. Fig.5 / p.10: caption should refer to eqn.7, so the reader knows that these are % differences of uncertainties (which are also in %, Fig.5a).
    We have added a reference to Eq. 7 in the caption of Figure 5.

11. l.186: need reference and short mention/description of p-test.
    We have rephrased and expanded the paragraph, which now reads: *"To assess which correlations have statistical significance, we calculate the p−value (Westfall and Young, 1993) associated with the ten obtained correlation coefficients. The test reveals that for three pairs of uncertainty components the probability of finding the observed not-zero correlation coefficients if the actual correlation coefficient were in fact zero (p−value) is less than 10−5. Therefore, the following three correlations have strong statistical significance:"*.

12. Fig.9/l.210-212: is this randomly-sampled months, or an increasing sample size building consecutively/sequentially from some given time?
    As stated in the caption of the figure, the data used are "periods of record of different lengths (all ending in December 2017)".

Technical corrections

There are many English usage/grammatical corrections and suggestions, which are included in the attached annotated PDF-file. I thus only include a sample of them here in this list.

Thank you for the careful review of the manuscript also from a linguistic point of view. We have incorporated the changes listed here and those included in the supplement attached by the reviewer.

- l.4: need comma after 'uncorrelated'; replace 'through a sum of squares approach' with 'as the sum of their squares'.
- l.5: remove 'In this analysis'; replace 'rigor' with 'practical validity', add 'for operationally-based uncertainty, which is comprised of components associated with long-term correction and measurements,' after 'assumption'.
- l.6: replace 'standard uncertainty assumption' with 'uncorrelated sum-of-squares method'; replace 'to uncertainty quantification' with a comma.
- l.7: replace first instance of 'categories' with 'components'; replaces second instance with 'component pairs.
- l.8: replace 'do, in fact, show' with 'exhibit'; remove *', namely'*; replace 'windiness' with a more accepted term like *'linearized long-term correction'*.
- l.9: replace comma after '(positive correlation)' with a semicolon; delete *'wind resource'*; replace comma after 'negative)' with a semicolon.
- l.12: replace 'industry standard approach' with 'simple approach which neglects correlations between uncertainty components'.
- l.34/p.2: is there not a DNV-GL report on this? Not to our knowledge. We have rephrased the sentence as "*There are to our knowledge, however, …*"
- l.58–59: rewrite 'the more simple AEP calculation relative to the preconstruction method' as 'that the operationally-driven calculation is much simpler than the calculation needed for preconstruction estimates'.
- l.60: replace 'equally' with 'also'
- l.75,77: need 'dataset' after 'interim)' and 'NCEP-2)'.
- l.104/p.5 [point 1]: remove 'Analysis is performed on a monthly timescale (i.e.,'; replace end parens with 'are calculated'.
- l.130–136: cite GUM / textbook(s).
- l.165–166: remove 'uncertainty calculated with the current usual industry standard, which assumes uncorrelated components and calculates the'.
- l.167: replace 'with' with 'using'.
- l.169: replace *'472 considered wind farms, both in terms of a scatterplot and'* with *'472 wind farms considered, as a scatterplot and also as'*.
- l.170: remove ', Δ_σ,'; change ', calculated as' to a colon.
- l.172: add comma after 'observed'.

Please also note the supplement to this comment: https://www.wind-energ-sci-discuss.net/wes-2019-82/wes-2019-82-RC1- supplement.pdf

In this document, the reviewer's comments are in black, the authors' responses are in red.

The authors thank the reviewer for their thoughtful and productive comments.

General comments

The authors have worked to propose a more statistically accurate method for operational AEP wind farm estimates through correlations with various sources of uncertainty. The topic is certainly worthwhile, as large projects involve huge financial contributions and associated risk. Overall the paper is well laid and out and written. As per the comments, there are a number of places where wording and figure captions need improvement for clarity. Similarly, some specific details of the method and metric equations need better definition.
Thank you for finding our manuscript interesting and well written. We have addressed your specific comments to add clarity to our paper.

My main challenge with the paper is the use of the word 'uncertainty' in a non-precise manner. Uncertainty accrues from various sources including measurement errors (epistemic) and underlying stochastic processes (aleatoric). Moreover, the statistical quantification of that uncertainty has to be careful, whether it's a uniform, normal, or other distribution that describes the range of uncertain values (PDF of values). The paper is a bit too loose in using the term uncertainty, and also in the numerical MC sampling of those variables assumed uncertain. Tightening up the presentation in this respect would really help statistical validity and understanding of the method and results.
We have addressed your specific comments on the theme, to add more rigor to the description of our analysis.

Specific Comments

1. ln 25; I wonder given the emphasis of the paper on AEP if better figures to quote would be GWh produced vs. (or in addition to) GW installed capacity?
   We have added the following sentence to the paragraph: "In the United States, wind farms generated over 300,000 GWh in 2019, about 7.5 % of the total US electricity generation from utility-scale facilities that year, with a 50% increase over a 6-year period (Energy Information Administration, 2020).".

2. Around Table 1: Need to define windiness correction factor (formula, etc). The word 'accuracy' used throughout table; is that true? or is it really combination of epistemic and aleatoric uncertainties? Really need to discuss more on sources of uncertainty in terms of measurement errors and underlying stochastic processes involved.
   We have aligned the terminology used in Table 1:

Uncertainty component	Description
On-site measurements	Measurement error in met mast wind speeds (pre-construction) or power at the revenue meter (operational)
Reference wind speed data	Measurement or modeling error in long-term reference measured or modeled wind speed data
Losses	Error in estimated or reported availability and curtailment losses
Regression	Sensitivity in the regression relationship between on-site measurements and reference wind speeds
Long-term (windiness) correction	Sensitivity in the long-term correction applied to the regression relationship between on-site measurements and reference wind speeds
Inter-annual variability of resource	Sensitivity in future energy production because of resource variability

Table 1. Main Sources of Uncertainty in a Long-Term Operational AEP Estimate.

3. In the intro discussion on operational AEP estimates, the wording seems a little counterintuitive, in that AEP can be calculated exactly (in terms of delivered energy) given the data (and just whatever error in the power meter itself). I think a little rewording here talking more about the purpose of operational AEP for e.g. future year operations, etc. would help reveal the intent and importance of the work.
   We have now referred to operational AEP as "long-term operational AEP" in many places throughout the introduction. Moreover, we think the following sentence in the introduction will clarify the point to the reader: "operational estimates of long-term AEP are required for important wind farm transactions, such as refinancing, purchasing/selling, and mergers/acquisitions."

4. Would be nice to explicitly relate eqn 2 back to CP equation for readers to understand exponential weighting.
   We have rephrased this part as:

   The wind speed data are density-corrected at their native time resolutions to correlate more strongly with wind farm power production (i.e., higher density air in winter produces more power than lower density air in summer, wind speed being the same):

   $$U_{\text{dens,corr}} = U\left(\frac{\rho}{\rho_{\text{mean}}}\right)^{1/3} \quad (2)$$

   where $U_{\text{dens,corr}}$ is the density-corrected wind speed, U is the wind speed, ρ is air density (calculated at the same height as wind speed), ρ_{mean} is the mean density over the entire period of record of the reanalysis product, and the exponent $1/3$ is derived from the basic relationship between wind power and wind speed cubed (Manwell et al., 2010). To calculate air density at the

5. ln 95; the data exclusions that end up being geographically driven suggest the need for some more discussion here (or later) on the ramifications for the correlations uncovered; i.e. are there physical reasons the correlations would be different for more complex terrain locations?
   We have added the following sentence at the end of Section 3.2: "Finally, we note that although the sites selected for this analysis are primarily in simple terrain (Figure 1), we do not expect more complex topography to impact the correlations revealed from the Monte

Carlo analysis, as all the underlying relationships would also be applicable to more complex sites.”.

6. list in lns 105-115; not clear what ’regression’ in item 5. Also 10-20 years of hindcast (vs. forward prediction) right?
   We have rephrased this part to make more explicit which regression is performed: “A linear regression between monthly gross energy production and concurrent monthly average wind speeds is performed.”
   We have also added details to the description of the long-term data used to clarify that these are past data, i.e. a hindcast approach: “Long-term monthly average wind speed is then calculated for each calendar month (i.e., average January wind speed, average February wind speed, and so forth) with a hindcast approach, using 10--20 years of the available long-term reference monthly wind resource data (reanalysis products, long-term reference measurements, ...).”

7. Fig 2 ‘Wind IAV’ not defined.
   The caption of the Figure now states: “Note: IAV denotes inter-annual variability.”

8. Did you consider more efficient Monte Carlo sampling methods, and/or convergence of statistics at 10000 samples?
   We have tested the convergence of the Monte Carlo AEP distribution at 10,000 samples, and added the following sentence to the paragraph: “Convergence of the AEP distribution within 0.5% of the true mean after the 10,000 Monte Carlo runs was verified for all projects, with a 95% confidence.”

9. Table 2; need to define pdf type for each uncertain variable (uniform, normal, etc.) Would also be nice to see more justification for e.g. 0.5% uncertainty values assumed.
   We have greatly improved the description of the single uncertainty components considered in our analysis. We have added information on the pdf type used, and justified the choice of 0.5% for the revenue meter uncertainty. The paragraphs now read:

2.3 Monte Carlo Analysis

To quantify the uncertainty of the long-term operational AEP estimate obtained using the methodology described in the previous section, we implement a Monte Carlo approach. In general, a Monte Carlo method involves the randomized sampling of inputs to or calculations within a method which, when repeated many times, results in a distribution of possible outcomes from which uncertainty can be deduced, usually calculated as the standard deviation or the coefficient of variation of the resulting distribution (ISO and OIML, 1995; Dimitrov et al., 2018). Here, we apply this approach to derive a distribution of long-term operational AEP values, from which its uncertainty can be calculated. To do so, we consider and include in the Monte Carlo approach five operational-based uncertainty components, so that five different samplings are performed at each Monte Carlo iteration. The following uncertainty components are included in our proposed Monte Carlo methodology for long-term operational AEP:

– Revenue meter measurement error. We incorporate this uncertainty component in the Monte Carlo simulation by sampling monthly revenue meter data from a normal distribution centered on the reported value, and 0.5% standard deviation. In fact, a value of 0.5% is coherent with what is typically assumed in the wind energy community as revenue meter uncertainty (IEC 60688:2012; ANSI C12.1-2014).

– Reference wind speed data modeling error. Quantifying the uncertainty of the long-term wind resource data used in the operational AEP assessment is challenging, as it can vary based on the location, long-term wind speed product used, or instrument from which reference observations are taken. To include this uncertainty component in a systematic way across the 472 locations considered in our analysis, we incorporate it in the Monte Carlo simulation by randomly selecting, at each iteration at each site, wind resource data from one of the three considered reanalysis products.

– Linear regression model uncertainty. This component is incorporated in the Monte Carlo method by sampling the regression slope and intercept values from a multivariate normal distribution centered on their best-fit values and covariance matrix equal to the one of the best-fit parameters. The diagonal terms in the covariance matrix are given by the square of the slope and intercept standard errors. For a regression model between an independent variable x and a dependent variable y the standard error of the regression is defined as

$$e_y = \sqrt{\frac{\sum (y_i - \hat{y_i})^2}{n-2}}, \tag{4}$$

where $\hat{y_i}$ is the regression-predicted value for y_i, and n is the number of data points used in the regression. The standard error of the regression slope:

$$e_a = \frac{e_y}{\sum (x_i - \overline{x_i})^2}, \tag{5}$$

and the standard error of the intercept:

$$e_b = e_y \, e_a \sqrt{\frac{\sum x_i^2}{n}}. \tag{6}$$

e_a^2 and e_b^2 are the diagonal terms in the covariance matrix of the multivariate normal distribution of regression slope and intercept, from which Monte Carlo values are drawn. Slope and intercept values are strongly negatively correlated, which is captured by their covariance when performing the linear regression. The off-diagonal terms in the covariance matrix of the multivariate normal distribution constrain the random sampling of slope and intercept values, to avoid sampling unrealistic combinations. An example of this sampling is shown in Figure 4 for two projects of different regression strengths. We sample 500 slope and intercept values from a multivariate normal distribution centered around the best-fit parameters, and with covariance matrix derived from the standard errors of slope and intercept and their covariance. As shown in the Figure, the low standard errors found for the leftmost regression relationship constrain the possible slope and intercept values that can be sampled while the high standard errors in the rightmost regression relationship allow for a much wider sampling.

– Long-term (windiness) correction uncertainty. We incorporate this component by sampling the number of years (between 10 and 20) to use as the long-term wind resource data to which the regression coefficients are applied to derive long-term energy production data (the so-called windiness correction).

– Wind resource inter-annual variability (IAV) uncertainty. We incorporate this uncertainty component in the Monte Carlo method by sampling the long-term (reanalysis) average calendar monthly wind speeds (i.e., average January, average February) used to calculate long-term monthly energy production data. The sampling distribution is normal, centered on the calculated long-term average calendar monthly wind speed, and with a standard deviation equal to the 20-year standard deviation of the long-term average monthly wind speed for each calendar month.

Each of the listed sources of uncertainty corresponds to a Monte Carlo sampling, and is highlighted by a probability distribution in the flowchart in Figure 3. Note that uncertainty components related to availability and curtailment losses are not considered in our approach because the EIA 923 database does not include measurements of these losses.

10. Fully linking Table 2 variables explicitly in Fig 2 would help to understand the method.
The last part of the paragraph copied above connects the detailed explanation of the uncertainty components with what shown in Figure 2. We have also changed the diagram to have it better match the description in the test:

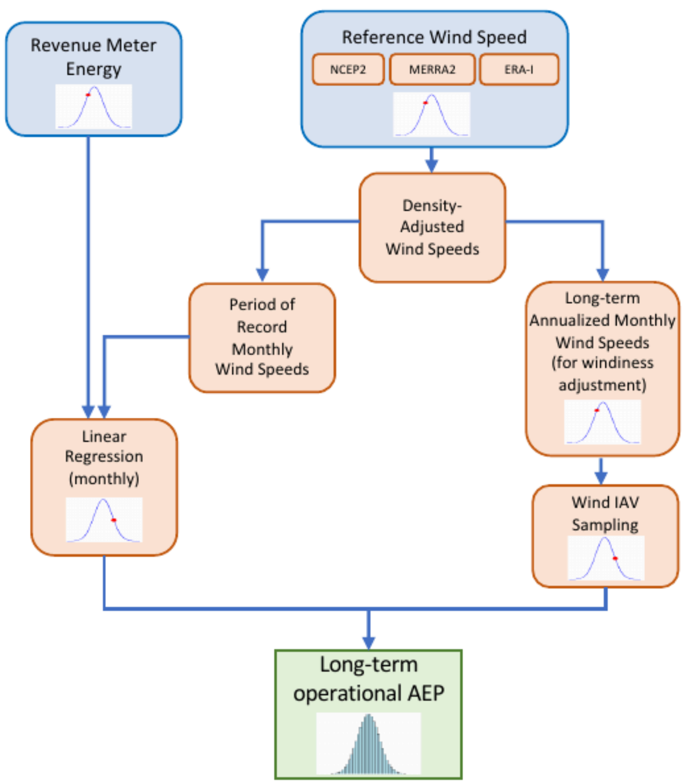

Figure 3. Long-term annual energy production (AEP) estimation process using operational data under a Monte Carlo approach; sources of uncertainty and points of Monte Carlo sampling are denoted by probability distribution images. Note: IAV denotes inter-annual variability.

11. Around ln 140; define how covariance defined, and numerical procedure in MC for ensuring the covariance is respected.
    We have added more details to the description of the technique used, as can be seen in the linear regression model uncertainty paragraph shown in the answer to specific comment #9.

12. Throughout the word uncertainty is used; I think you're always meaning standard deviation, but need to explicitly define as numerical results are presented
    We have clarified in many parts throughout the manuscript that we quantify uncertainty in terms of the coefficient of variation of the AEP distribution.
    In Section 2.3, we have added the following sentences to make clear how we calculate the total AEP uncertainty and its components: "The total uncertainty in operational AEP is then estimated as the coefficient of variation of the resulting distribution." And also "We quantify the impact of each single uncertainty component on the operational AEP in terms of the coefficient of variation of the distribution of operational AEP resulting from the Monte Carlo simulation run when sampling only that single uncertainty component."
    In Section 3.1 we now have: "The application of the different setups of the Monte Carlo approach first allows for an assessment of the distributions of the total operational-based AEP uncertainty and of its single components across the 472 wind farms, expressed as percent coefficient of variation (Figure 5)."
    Caption of Figure 5 now includes: "Uncertainty values are quantified as the percent coefficient of variation of the AEP distribution."
    Caption of Figure 6 now explicitly states: "Uncertainty is quantified as the percent coefficient of variation of the resulting AEP distribution."
    We have also decided to use CoV instead of σ in equation 7.

13. It's not clear to me what's been plotted in Fig 4? How is uncertainty defined in % terms? How is computed across your results sets? Is that eqn 7?
    We have clarified this point - see our answer to previous comment.

14. Define which data used to make Fig 7.
    We have rephrased the paragraph as "The correlation between linear regression and reference wind speed data uncertainties can be justified given the dependence of both these uncertainty components on the number of data points used in the regression between energy production data and concurrent wind speed data (Figure 8)".
    We have also changed the caption as "Dependence of linear regression uncertainty and reference wind speed data uncertainty on the number of data points in the period of record, for the 471 projects considered in the analysis."

15. In conclusions, towards a universal method, should explore MC sampling convergence requirement. Also, the assumed distribution type (as defined presumably by the 'uncertainty') is undefined, so not clear how to implement and assumptions there.
    We have added the following sentence: "For all the projects considered in this study, the Monte Carlo simulation reached convergence within 10,000 runs." Regarding the distribution type of the various uncertainty components, since each component involves

different ways to be incorporated in the Monte Carlo approach, we have the details of the methods in Section 2.3.

~~Are Uncertainty Categories in a Wind Farm~~ Operational-Based Annual Energy Production ~~Estimate~~ Uncertainty: Are its Components Actually Uncorrelated?

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Abstract. Calculations of annual energy production (AEP) from a wind farm—whether based on ~~preconstruction~~ pre-construction or operational data—are critical for wind farm financial transactions. The uncertainty in the AEP calculation is especially important in quantifying risk and is a key factor in determining financing terms. ~~Standard industry practice assumes~~ A popular industry practice is to assume that different uncertainty ~~categories~~ components within an AEP calculation are uncorrelated, and can therefore be combined ~~through a sum of squares approach. In this analysis, we assess the rigor~~ as the sum of their squares. We assess the practical validity of this assumption for operational-based uncertainty, which is comprised of components associated with long-term correction and measurements, by performing operational AEP estimates for over 470 wind farms in the United States. We contrast the ~~standard uncertainty assumption~~ uncorrelated sum-of-squares method with a Monte Carlo approach~~to uncertainty quantification~~, in which no assumptions of correlation between uncertainty ~~categories~~ components are made. Results show that several ~~uncertainty categories do, in fact, show~~ component pairs exhibit weak to moderate correlations~~, namely: wind resource interannual~~: inter-annual variability and the ~~windiness~~ linearized long-term correction (positive correlation)~~, wind resource interannual variability and~~; wind resource inter-annual variability and linear regression (negative)~~, and wind speed measurement uncertainty and~~; and reference wind speed uncertainty and linear regression (positive). The sources of these correlations are described and illustrated in detail in this paper, and the effect on the total AEP uncertainty calculation is investigated. Based on these results, we conclude that a Monte Carlo approach to operational AEP uncertainty quantification is more robust and accurate than the ~~industry standard approach~~ simple approach which neglects correlations between uncertainty components.

1 Introduction

Calculations of wind farm annual energy production (AEP)—whether based on ~~preconstruction~~ pre-construction data before a wind power plant is built or on operational data after a wind farm has started its operations—are vital for wind farm financial transactions. ~~Preconstruction~~ Pre-construction estimates of AEP are needed to secure and set the terms for new project financing, whereas operational estimates of long-term AEP are required for important wind farm transactions, such as refinancing, purchasing/selling, and mergers/acquisitions. The need for AEP analyses of wind farms is increasing, as global wind capacity increased to 539 GW in 2017, representing 11% and 91% increases over 1-year and 5-year periods, respectively; and capacity is expected to increase by another 56% to 841 GW by 2022 (Global Wind Energy Council, 2018). In the United States, wind farms generated over 300,000 GWh in 2019, about 7.5% of the total US electricity generation from utility-scale facilities that year, with a 50% increase over a 6-year period (Energy Information Administration, 2020).

This rapid growth of the wind energy industry is putting an increased spotlight on the accuracy and consistency of AEP calculations. For ~~preconstruction~~ pre-construction AEP estimates, there has been considerable movement towards standardization. The International Energy Commission (IEC) is currently developing a standard (IEC 61400-15:draft), and there have long been guidance and best practices available (Brower, 2012). By contrast, long-term operational AEP estimates do not have such extensive guidance or standards. Only limited standards covering ~~some~~ operational analyses exist~~:~~; IEC 61400-12-1:2017 addresses turbine power curve testing, and IEC 61400-26-3:2016 addresses the derivation and categorization of availability loss metrics. There are to our knowledge, however, no standards and very limited published guidance on calculating long-term AEP from operational data. Rather, documentation seems to be limited to a consultant report (Lindvall et al., 2016), an academic thesis (Khatab, 2017), and limited conference proceedings (Cameron, 2012; Lunacek et al., 2018).

Documentation and standards for ~~preconstruction~~ pre-construction AEP methods are of limited use for operational-based AEP methods, given the many differences between the two approaches. In general, operational AEP calculations are ~~much simpler than preconstruction~~ simpler than pre-construction estimates because actual measurements of wind farm power production at the revenue meter replace the complicated ~~preconstruction~~ pre-construction estimate process (e.g., meteorological measurements, wind and wake-flow modeling, turbine performance, estimates of wind farm losses). However, the two methods do share several similarities, including regression relationships between on-site measurements and a long-term wind speed reference, the associated ~~windiness correction~~long-term (windiness) correction applied to the on-site measurements, and estimates of uncertainty in the resulting AEP calculation. The uncertainty ~~categories~~ components for operational AEP calculations are simplified relative to those in a ~~preconstruction~~ pre-construction estimate (IEC 61400-15:draft); shared ~~categories~~ components between the two methods are listed in Table 1.

The uncertainty values from each ~~category~~ component listed in Table 1 must be combined to produce a total estimate of AEP uncertainty. We found no guidance in the literature for combining uncertainty ~~categories~~ components in an operational AEP estimate. However, considerable guidance exists for combining ~~preconstruction~~ pre-construction uncertainties (Lackner et al., 2007; Brower, 2012; Vaisala, 2014; Kalkan, 2015; Clifton et al., 2016). In every case, recommended best practices assume that

~~Category~~ Uncertainty component	Description
On-site measurements	~~Accuracy in measured~~ Measurement error in met mast wind speeds (~~preconstruction~~pre-construction) or power at the revenue meter (operational)
~~Long-term reference measurements~~Reference wind speed data	~~Accuracy~~ Measurement or modeling error in long-term reference measured or modeled wind speed data
Losses	~~Accuracy~~ Error in estimated or reported availability and curtailment losses
Regression	~~Confidence~~ Sensitivity in the regression relationship between on-site measurements and ~~long-term~~ reference wind speeds
~~Windiness correction~~ Long-term (windiness) correction	~~Confidence~~ Sensitivity in the long-term correction applied to the regression relationship between on-site measurements and reference wind speeds
~~Interannual~~ Inter-annual variability of resource	~~Uncertainty~~ Sensitivity in future energy production because of resource variability

Table 1. Main Sources of Uncertainty in ~~an~~ a Long-Term Operational AEP Estimate.

all uncertainties, σ_i, are uncorrelated and can therefore be combined using a sum of squares approach to give the total AEP uncertainty, $\sigma_{\text{tot,uncorr}}$:

$$\sigma_{\text{tot,uncorr}} = \sqrt{\sum_i \sigma_{\text{i}}^2} \tag{1}$$

To better understand how uncertainties are combined in long-term operational AEP calculations, we reached out to several wind energy consultants who regularly perform these analyses. These conversations revealed that uncertainties in ~~an~~ a long-term operational AEP calculation are also assumed uncorrelated and combined using Equation 1.

1.1 Goal of Study

The purpose of this study is to examine the extent to which the assumption of uncorrelated uncertainties—and therefore the combination of those uncertainties through a sum of squares approach—is accurate and appropriate for operational AEP calculations. Specifically, this study aims to identify potential correlations between AEP uncertainty ~~categories~~ components and propose a Monte Carlo approach to capture such correlations when combining individual uncertainty ~~categories. The focus~~

~~here~~ components. Monte Carlo methods have been used in different applications for uncertainty quantification within the wind energy industry, ranging from the prediction of extreme wind speed events (Ishihara and Yamaguchi, 2015), to offshore fatigue design (Müller and Cheng, 2018), to economic analysis of the benefits of wind energy projects (Williams et al., 2008). Here, the focus is on operational AEP uncertainty, ~~given~~ using publicly available wind farm operational data~~and the more simple AEP calculationrelative to the preconstruction method. However,~~ . While in the analysis we focus on operational AEP calculation, we expect that the results from this analysis—namely the potential identification of correlated uncertainty ~~categories—are~~ components—can be equally relevant for informing and improving ~~preconstruction~~ pre-construction AEP methods.

In Section 2, we first describe the data sources used in this analysis—namely wind farm operational data and reanalysis products—as well as the Monte Carlo approach to calculate ~~AEP~~operational AEP and quantify its uncertainty. Section 3 presents the main results of our analysis, in terms of uncertainty contributions and correlation among the different ~~categories~~components. We conclude and suggest future work in Section 4.

2 Data and Methods

2.1 Wind Farm Operational Data and Reanalysis Products

~~Wind~~ Operational wind farm energy production data for this analysis ~~were~~ are obtained from the publicly available Energy Information Administration (EIA) 923 database (EIA, 2018). This database provides reporting of monthly net energy production from all power plants in the United States, including wind farms. A total of over 670 unique wind farms ~~were~~ are available from this data set.

~~Map of the 472 wind farms that were considered in this study~~

Long-term wind speed data (needed to perform the ~~"windiness correction "~~ long-term or windiness correction in an AEP estimate) are used from three reanalysis products over the period of January 1997 through December 2017:

- The Modern-Era Retrospective analysis for Research and Applications v2 (MERRA-2) (Gelaro et al., 2017). We specifically use the M2T1NXSLV data product, which provides diagnostic wind speed at 50 m above ground level (AGL), interpolated from the lowest model level output (on average about 32 m AGL), using Monin Obukhov similarity theory. Data are provided at an hourly time resolution.

- The European Reanalysis Interim (ERA-interim) data set (Dee et al., 2011). We specifically use output at the 58th model level, which on average corresponds to a height of about 72 m AGL. Data are provided at 6-hourly time resolution.

- The National Centers for Environmental Prediction v2 (NCEP-2) data set (Saha et al., 2014). We specifically use diagnostic wind speed data at 10 m AGL. Data are provided at a 6-hourly time resolution.

The wind speed data are density-corrected at their native time resolutions to correlate more strongly with wind farm power production (i.e., higher density air in winter produces more power than lower density air in summer, wind speed being the

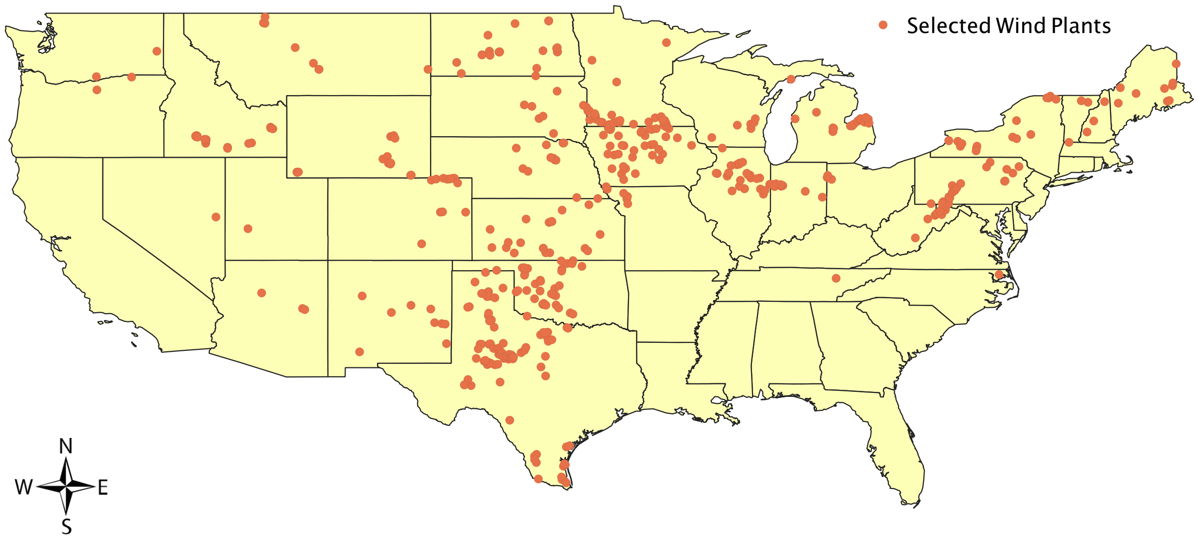


Figure 1. Map of the 472 wind farms that were considered in this study.

same):

$$U_{\text{dens,corr}} = U\left(\frac{\rho}{\rho_{\text{mean}}}\right)^{1/3} \tag{2}$$

where $U_{\text{dens,corr}}$ is the density-corrected wind speed, U is the wind speed, ρ is air density (calculated at the same height as wind speed), ~~and~~ ρ_{mean} is the mean density over the entire period of record of the reanalysis product~~.~~ , and the exponent $1/3$ is derived from the basic relationship between wind power and wind speed cubed (Manwell et al., 2010) . To calculate air density at the same height as wind speed, we first extrapolate the reported surface pressure to the wind speed measurement height, assuming hydrostatic equilibrium:

$$p = p_{\text{surf}} \exp\left[\frac{gz}{RT_{\text{avg}}}\right] \tag{3}$$

where p is the pressure at the wind speed measurement height, p_{surf} is the surface pressure, g is the acceleration caused by gravity, z is the wind speed measurement height, R is the gas constant, and T_{avg} is the average temperature between the reported value at 2 m AGL and at the wind speed measurement height. ~~To compute air density at the wind speed measurement height, the ideal gas law assumption is used.~~

To lessen the impact of limited and/or ~~poor quality~~ poor-quality data on the results of our analysis, we filter for wind farms with at least 8 months of data and with a moderate-to-strong correlation with all three reanalysis products ($R^2 > 0.6$). A threshold of 8 months is selected in order to investigate uncertainty as it relates to a low number of data points but not so low as to make the use of a regression relationship questionable. A total of 472 wind farms ~~were~~ are kept for the final analysis, and their locations are shown in Figure 1. Because obtaining an accurate representation of wind data in complex terrain by

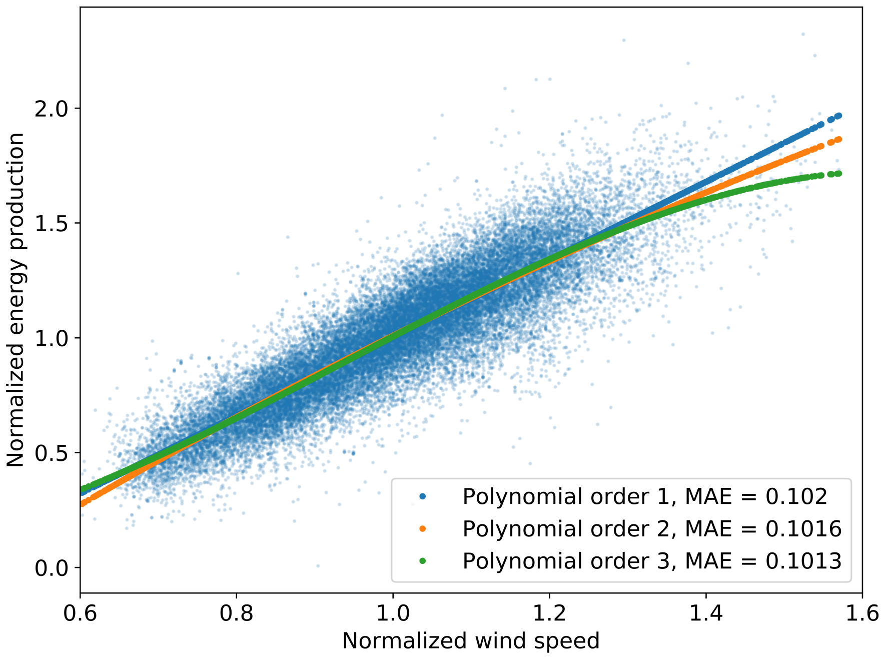


Figure 2. Scatterplot between normalized MERRA-2 monthly wind speed and monthly energy production across all 472 selected sites, and linear, quadratic and cubic best-fit lines.

reanalysis products is challenging (Shravan Kumar and Anandan, 2009), most of the selected wind plants are located in the Midwest and Southern Plains. Notably, no wind farms in California pass the filtering criteria, because they are predominately located in areas with thermally driven wind regimes such as Tehachapi Pass, where coarse-resolution reanalysis products are poor predictors of wind energy production.

The fundamental step in an AEP calculation involves a regression between wind speed (here, from the reanalysis products) and energy production (here, from the EIA 923 database). To investigate whether a simple linear function can be assumed to express the relationship between wind speed and wind farm energy production when considering monthly data, we show a scatterplot between MERRA-2 monthly wind speed and monthly energy production across all 472 sites in Figure 2. For each site, data have been normalized by the respective site mean. We show best-fits using a linear, quadratic, and cubic function, and calculate the mean absolute error of each fit. We find that the difference between the normalized MAE values from the considered functions is less than 0.7%. Therefore, the uncertainty connected with the choice of using a linear regression in the operational AEP methodology at monthly time resolution appears minimal. Moreover, through conversations with wind industry professionals, we found that a linear regression based on monthly data is the standard industry approach when performing bankable[1] operational AEP analyses.

[1] Results are accepted by banks, investors, and so on for use in financing, buying/selling, and acquiring wind farms.

2.2 Operational AEP Methodology

Given the ~~current~~ lack of existing guidelines ~~that offer~~ for a standard approach for operational AEP calculations, we instead base our methodology ~~from~~ on conversations with several wind energy consultants. These conversations overwhelmingly revealed the following characteristics of an industry standard and bankable [2] operational AEP analysis:

1. ~~Analysis is performed on a monthly timescale (i.e., monthly energy production~~ Wind speed data (measured or modeled) are density-corrected at their native time resolution, using equation 2.

2. Monthly revenue meter data, monthly average availability and curtailment losses, and monthly average wind speeds from a long-term wind resource product ~~)~~are calculated.

3. ~~Linear regression between monthly energy production and average wind speeds is used to perform the windiness correction~~Monthly revenue meter data are normalized to 30-day months (e.g. for January, the revenue meter values are multiplied by 30/31).

4. Monthly revenue meter data are corrected for monthly availability and curtailment (i.e., ~~to calculate gross energy) to improve the linear regression relationship~~[2]monthly gross energy data are calculated).

5. ~~Monthly energy production is normalized to 30-day months to improve the accuracy of the regression relationship.~~A linear regression between monthly gross energy production and concurrent monthly average wind speeds is performed.

6. Long-term monthly average wind speed is then calculated for each calendar month (i.e., average January wind speed, average February wind speed, and so forth) with a hindcast approach, using 10–20 years of the available long-term reference monthly wind resource data (reanalysis products, long-term reference measurements, ...).

7. Slope and intercept values from the regression relationship are then applied to ~~10–20 years of~~ the long-term ~~wind resource datato perform the~~ monthly average wind speed data, with the long-term or so-called windiness correction. ~~Long-term monthly gross energy production (i.e., average Januarywind speed, average Februarywind speed, and so forth) is then calculated~~A long-term data set of monthly (January, February, ...) gross energy production is obtained.

8. The resulting long-term monthly gross energy estimates~~are then "denormalized " to the normal~~ , which are based on 30-day months, are then denormalized to the actual number of days ~~per month , and long-term~~ in each calendar month (e.g. for January, the obtained value is multiplied by 31/30).

9. Long-term estimates of availability and curtailment losses are finally applied to ~~arrive at an~~ the denormalized long-term monthly gross energy data, leading to a long-term calculation of operational AEP.

[2]~~Results are accepted by banks, investors, and so on for use in financing, buying/selling, and acquiring wind farms.~~

[2]~~These loss data are not available in the EIA-923 database and therefore are not considered in this analysis.~~

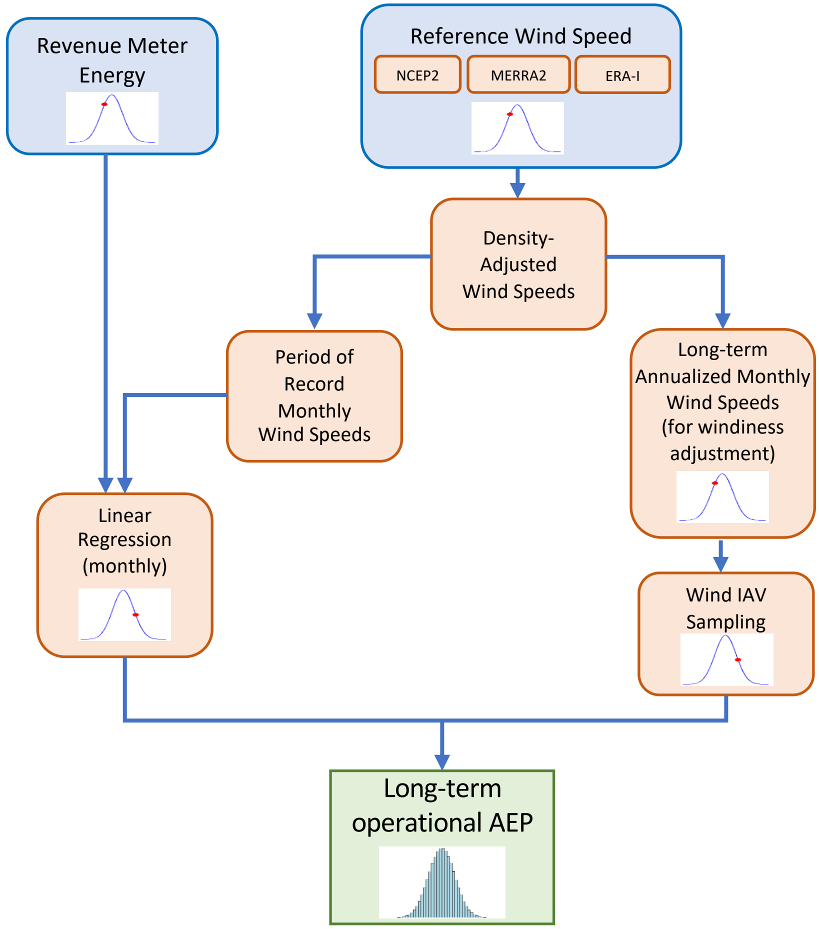


Figure 3. ~~Annual~~ Long-term annual energy production (AEP) estimation process using operational data under a Monte Carlo approach; ~~source~~ sources of uncertainty and points of Monte Carlo sampling are denoted by probability distribution images. Note: IAV ~~for~~ denotes inter-annual variability.

In the EIA-923 database, availability and curtailment data are not available. Therefore, in our analysis we omit steps 4 and 9 of the list, and only perform calculations on net energy data. A diagram outlining ~~this general process~~ the resulting general process of the operational AEP analysis adopted in our study is shown in Figure 3.

2.3 Monte Carlo Analysis

To quantify ~~uncertainty from the AEP calculation~~ the uncertainty of the long-term operational AEP estimate obtained using the methodology described in the previous section, we implement a Monte Carlo approach. In general, a Monte Carlo ~~approach~~ method involves the randomized sampling of inputs to or calculations within a method which, when repeated many times, results in a distribution of possible outcomes from which uncertainty can be deduced~~(~~, usually calculated as the standard deviation ~~of the distribution). We~~ or the coefficient of variation of the resulting distribution (ISO and OIML, 1995; Dimitrov et al., 2018) . Here, we apply this approach to ~~the operational AEP calculation to quantify the key sources of uncertainty. The procedure is repeated 10,000 times under random sampling of the key uncertainty sources to produce~~ derive a distribution of ~~AEP values from which total~~ long-term operational AEP values, from which its uncertainty can be ~~quantified. In this process~~calculated. To do so, we consider ~~five uncertainty categories and ways to incorporate them~~ and include in the Monte Carlo approach ~~, as listed in Table ??. Note that uncertainty categories related to availability and curtailment losses are not considered because the EIA 923 database does not include measurements of these losses.~~

~~Category Incorporation in Monte Carlo approachRevenue meter accuracy Sampling~~ five operational-based uncertainty components, so that five different samplings are performed at each Monte Carlo iteration. The following uncertainty components are included in our proposed Monte Carlo methodology for long-term operational AEP:

- Revenue meter measurement error. We incorporate this uncertainty component in the Monte Carlo simulation by sampling monthly revenue meter data from a ~~distribution with an imposed~~ normal distribution centered on the reported value, and 0.5% standard deviation. In fact, a value of 0.5% ~~uncertainty.Wind measurement accuracy Randomly selecting one of the three reanalysis products for each Monte Carlo iteration. Wind interannual variability (IAV) Sampling the~~ is coherent with what is typically assumed in the wind energy community as revenue meter uncertainty (IEC 60688:2012; ANSI C12.1-2014) .

- Reference wind speed data modeling error. Quantifying the uncertainty of the long-term ~~average calendar monthly wind speeds (i.e., average January, average February) based on corresponding~~ wind resource data used in the operational AEP assessment is challenging, as it can vary based on the location, long-term ~~uncertainties for each calendar month (calculated from 20-year long reanalysis data). Regression model Sampling~~ wind speed product used, or instrument from which reference observations are taken. To include this uncertainty component in a systematic way across the 472 locations considered in our analysis, we incorporate it in the Monte Carlo simulation by randomly selecting, at each iteration at each site, wind resource data from one of the three considered reanalysis products.

- Linear regression model uncertainty. This component is incorporated in the Monte Carlo method by sampling the regression slope and intercept values from ~~the distribution derived from their standard errors. Windiness adjustment Sampling the number of years to use in the windiness correction (between 10 and 20). Sources of Uncertainty and their incorporation in the Monte Carlo approach for Operational AEP Estimate~~

  ~~Sampling set of regression lines corresponding to the slope and intercept values derived from their standard errors in the Monte Carlo approach, for two stations in the EIA dataset.~~

  ~~Given the approach to calculating regression uncertainty described in Table ??, we describe it in more detail here.~~ a multivariate normal distribution centered on their best-fit values and covariance matrix equal to the one of the best-fit parameters. The diagonal terms in the covariance matrix are given by the square of the slope and intercept standard errors. For a regression model between an independent variable ~~,~~ x ~~,~~ and a dependent variable ~~,~~ y ~~, we can define~~ the standard error of the regression ~~:~~ is defined as

$$e_y = \sqrt{\frac{\sum\left(y_i - \hat{y_i}\right)^2}{n-2}}, \tag{4}$$

where $\hat{y}_i$ is the regression-predicted value for y_i, and n is the number of data points used in the regression. ~~We can then introduce the~~ The standard error of the regression slope:

$$e_a = \frac{e_y}{\sum\left(x_i - \overline{x_i}\right)^2}, \tag{5}$$

and the standard error of the intercept:

$$e_b = e_y\, e_a \sqrt{\frac{\sum x_i^2}{n}}. \tag{6}$$

e_a^2 and e_b^2 are the diagonal terms in the covariance matrix of the multivariate normal distribution of regression slope and intercept, from which Monte Carlo values are drawn. Slope and intercept values are strongly negatively correlated, which is captured by ~~the covariance result when performing~~ their covariance when performing the linear regression. ~~Therefore, to avoid sampling unrealistic combinations, we~~ The off-diagonal terms in the covariance matrix of the multivariate normal distribution constrain the random sampling of slope and intercept values~~based on this covariance.~~ , to avoid sampling unrealistic combinations. An example of this sampling is shown in Figure 4 for two projects of different regression strengths. We sample 500 slope and intercept values from a multivariate normal distribution centered around the best-fit parameters, and with ~~standard deviation equal to~~ covariance matrix derived from the standard errors of slope and intercept and their covariance. As shown in the Figure, the low standard errors found for the leftmost regression relationship constrain the possible slope and intercept values that can be sampled while the high standard errors in the rightmost regression relationship allow for a much wider sampling.

– Long-term (windiness) correction uncertainty. We incorporate this component by sampling the number of years (between 10 and 20) to use as the long-term wind resource data to which the regression coefficients are applied to derive long-term energy production data (the so-called windiness correction).

– Wind resource inter-annual variability (IAV) uncertainty. We incorporate this uncertainty component in the Monte Carlo method by sampling the long-term (reanalysis) average calendar monthly wind speeds (i.e., average January, average February) used to calculate long-term monthly energy production data. The sampling distribution is normal, centered on the calculated long-term average calendar monthly wind speed, and with a standard deviation equal to the 20-year standard deviation of the long-term average monthly wind speed for each calendar month.

Each of the ~~previously mentioned~~ listed sources of uncertainty ~~, which~~ corresponds to a Monte Carlo sampling, and is highlighted by a probability distribution in the flowchart in Figure 3. Note that uncertainty components related to availability and

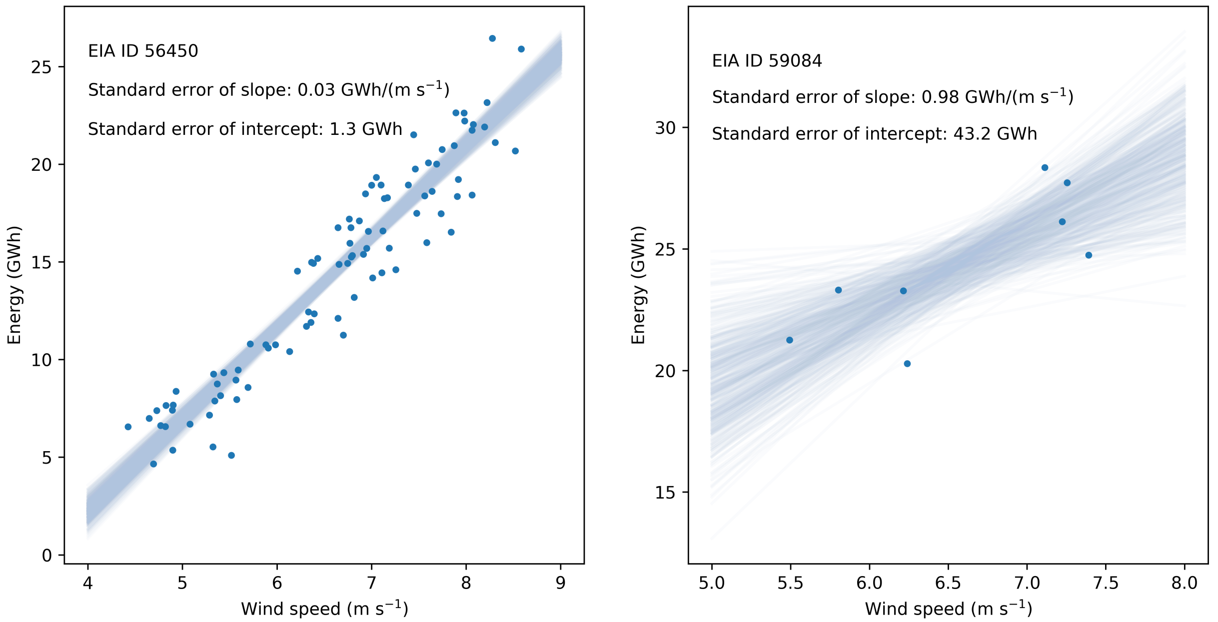


Figure 4. Sampling set of regression lines corresponding to the slope and intercept values derived from their standard errors in the Monte Carlo approach, for two stations in the EIA data set.

curtailment losses are not considered in our approach because the EIA 923 database does not include measurements of these losses.

For each wind farm, we estimate ~~both the total AEP uncertainty and its single components from each uncertainty category considered . Each uncertainty contribution is quantified from~~ the total operational AEP uncertainty by running a Monte Carlo simulation 10,000 times. At each iteration, all five samplings, corresponding to the five considered uncertainty components (revenue meter, reference wind speed data, wind resource IAV, linear regression, and windiness correction), are simultaneously performed. The total uncertainty in long-term operational AEP is then estimated as the coefficient of variation of its resulting distribution. Convergence of the AEP distribution ~~obtained by running the Monte Carlo simulation with a single category of sampling (~~within 0.5% of the true mean after the 10,000 Monte Carlo runs was verified for all projects, with a 95% confidence.

To understand the impact of the single uncertainty components and study their correlation, we also run, at each site, the Monte Carlo simulation with only a single sampling performed (i.e. either revenue meter, ~~wind measurement~~reference wind speed data, IAV, linear regression, or windiness ~~) only. Finally, the total uncertainty is determined by running the~~ correction). At each wind farm, we run the Monte Carlo simulation 10,000 time for each of the five single operational uncertainty components considered. We quantify the impact of each single uncertainty component on the long-term operational AEP in terms of the coefficient of variation of the distribution of operational AEP resulting from the Monte Carlo simulation ~~with all five samplings performed simultaneously~~run when sampling only that single uncertainty component.

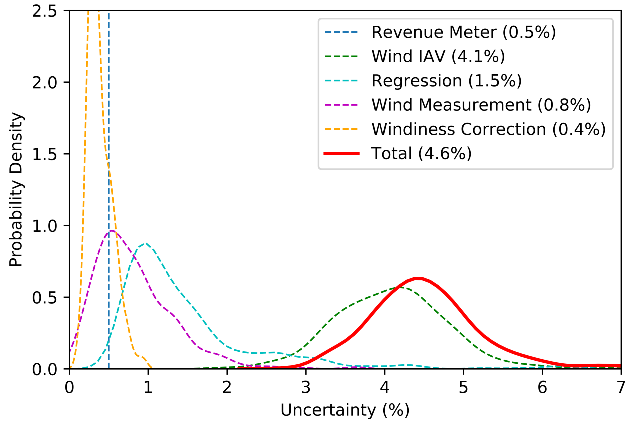


Figure 5. ~~Uncertainty~~ Operational-based AEP uncertainty distributions across projects for the different uncertainty ~~categories~~components; mean values across projects are shown in the legend. Uncertainty values are quantified as the percent coefficient of variation of the long-term operational AEP distribution. Note that the sum of squares of the average values of the single components does not add up to the average of the total uncertainty.

The code used to perform the AEP calculations is published and documented in NREL's open-source operational assessment software, OpenOA.[2] Calculations were performed on Eagle, NREL's high-performance computing cluster. Specifically, each wind farm was assigned a different processor and run in parallel. Given the general simplicity of the AEP method used here, computational requirements were moderate despite the 60,000 simulations (10,000 runs x 6 uncertainty setups) required for each wind farm.

~~Code used to perform the AEP calculations is published and documented in NREL's open-source operational assessment software, OpenOA.~~[3]

3 Results

3.1 Operational-Based AEP Uncertainty Contributions

The application of the different setups of the Monte Carlo approach first allows for an assessment of the distributions of the ~~different components of the AEP uncertainty~~ total operational-based AEP uncertainty and of its single components across the 472 wind farms, expressed in terms of the percent coefficient of variation of the resulting AEP distributions (Figure 5). Uncertainty connected to wind resource IAV is found to contribute the most (average 4.1% across all wind farms). The uncertainty in the linear regression model has the second largest contribution (1.5%), followed by the uncertainty of the ~~wind measurements~~ reference wind speed data (0.8%; here, of the reanalysis products), and revenue meter data (here, imposed at 0.5%~~, see Table ??~~). The long-term windiness correction has the smallest uncertainty component (0.4%). Therefore, the number of years used

[2] https://github.com/NREL/OpenOA
[3] ~~https://github.com/NREL/OpenOA~~

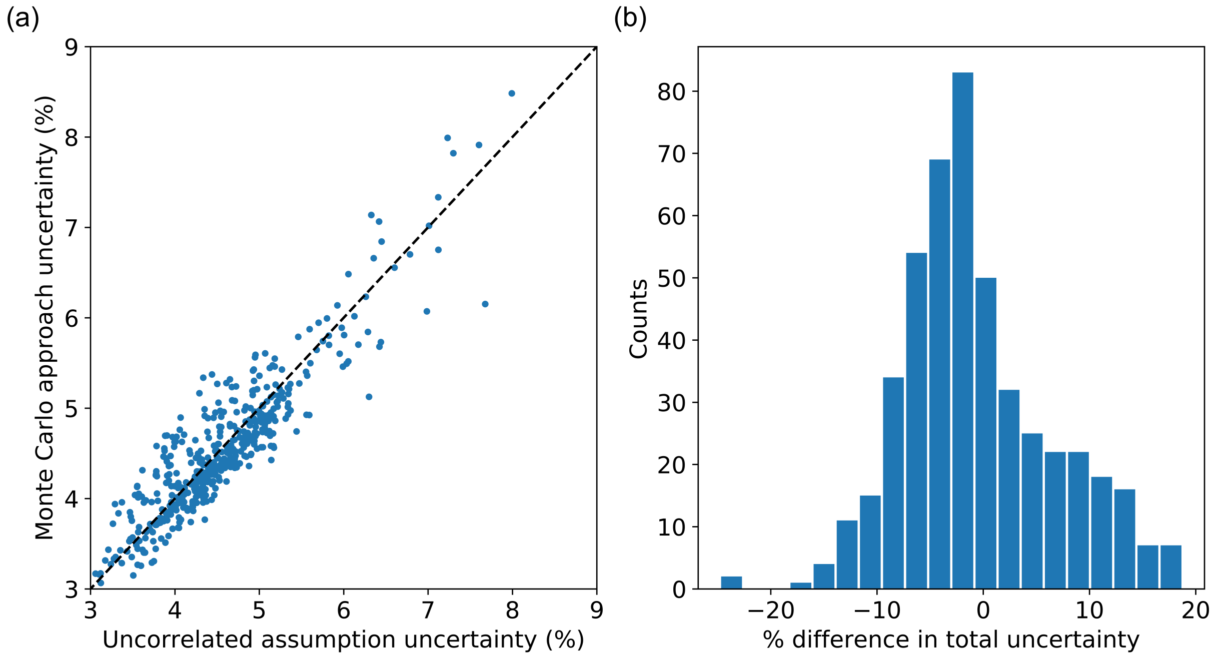


Figure 6. (a) Scatterplot of total operational AEP ~~uncertainties~~ uncertainty values calculated with the proposed Monte Carlo approach and assuming uncorrelated uncertainty components for the 472 ~~considered~~ wind farms considered. Uncertainty is quantified as the percent coefficient of variation of the resulting long-term AEP distribution. (b) Histogram of percentage differences (Eq. 7) between the AEP uncertainties calculated using the two different approaches.

for the long-term windiness correction does not have a large impact on the overall uncertainty in operational AEP, at least for the sampled range of 10–20 years. Using as few as 10 years seems sufficient to give stability to the long-term AEP estimate, and adding additional years does not provide a significant reduction in ~~uncertainty~~the uncertainty connected with the long-term estimate.

The ~~total AEP uncertainty calculated with the~~ proposed Monte Carlo approach ~~($\sigma_{\text{Monte Carlo}}$) can be compared with the uncertainty calculated with the current usual industry standard, which assumes uncorrelated components and calculates the total uncertainty ($\sigma_{\text{uncorrelated}}$) with a~~ does not require any assumption on the correlation between the different uncertainty components; on the other hand, the conventional sum of squares approach assumes the uncertainty components are all uncorrelated. Therefore, we compare the total operational AEP uncertainty from the Monte Carlo method with all the five simultaneous samplings ($\text{CoV}_{\text{Monte Carlo}}$) with the total uncertainty calculated using the conventional sum of squares approach ($\text{CoV}_{\text{uncorrelated}}$). For the ~~sum of squares approach, each uncertainty contribution is quantified from~~ latter approach, we quantify each of the five uncertainty components as the coefficient of variation of the corresponding operational AEP distribution obtained by running the Monte Carlo simulation with a single ~~category of sampling .~~ sampling performed. We then combine the five uncertainty components into the overall AEP uncertainty using Eq. 1. Figure 6 shows the results of this comparison ~~from~~ for the 472

~~considered wind farms , both in terms of~~ wind farms considered, as a scatterplot and also as a histogram of the percentage difference ~~, Δ_σ,~~ between the two versions of the total ~~uncertainty, calculated as~~ AEP uncertainty:

$$\Delta_{\cancel{\sigma}\mathrm{CoV}} = \cancel{\frac{\sigma_{\text{Monte Carlo}} - \sigma_{\text{uncorrelated}}}{0.5 \cdot (\sigma_{\text{Monte Carlo}} + \sigma_{\text{uncorrelated}})}} \frac{\mathrm{CoV}_{\text{Monte Carlo}} - \mathrm{CoV}_{\text{uncorrelated}}}{0.5 \cdot (\mathrm{CoV}_{\text{Monte Carlo}} + \mathrm{CoV}_{\text{uncorrelated}})} \cdot 100 \tag{7}$$

A weak bias can be observed, with a median value of ~~-2%~~ -2% in uncertainty percentage difference (which corresponds to a ~~-0.25%~~ -0.25% median difference in the actual total uncertainty value). In other words, if ~~the~~ correlations between the different uncertainty components are allowed and taken into account in the calculation method, the whole AEP uncertainty is then, on average, slightly reduced. This difference can be explained by considering that the two biggest sources of uncertainty (linear regression and IAV) are slightly negatively correlated (as will be shown in detail in the next section), thus making the Monte-Carlo-based total uncertainty lower, on average, than the one derived with the uncorrelated assumption. Moreover, ~~ignoring the existing correlation between the uncertainty components~~ assuming that all the uncertainty components are uncorrelated can introduce significant errors in the assessment of the AEP uncertainty for the single projects, with about 47% (16%) of the considered wind farms showing a $\pm 5\%$ (10%) uncertainty difference compared to the values from the Monte-Carlo-based approach. The mean absolute error of the distribution of uncertainty percentage differences is approximately 6% (Figure shown in the Supplement).

3.2 Correlation Between Operational-Based AEP Uncertainty ~~Correlations~~Components

Because operational AEP uncertainty calculated by ~~ignoring the~~ assuming a lack of correlation among its different components can greatly differ from the uncertainty values obtained when ~~considering these~~ allowing for potential correlations, it is worth exploring ~~which contributions~~ the correlation between uncertainty components which are responsible for this difference. ~~By calculating the Pearson correlation coefficients between the different uncertainty components from~~ We leverage the results of the Monte Carlo analysis at the 472 wind farms ~~, we derived~~ considered to reveal the correlation between the single operational AEP uncertainty components, in terms of their Pearson correlation coefficient. As a result, we obtain the average correlation matrix in Figure 7. ~~Out of the 10 possible assessments of correlation between uncertainty categories, three pairs are correlated with a~~ To assess which of the obtained correlations have statistical significance, we calculate the $p-$value (Westfall and Young, 1993) associated with the ten correlation coefficients. The test reveals that for three pairs of uncertainty components the probability of finding the *observed* not-zero correlation coefficients if the *actual* correlation coefficient were in fact zero ($p-$value) is less than 10^{-5} ~~and therefore of~~. Therefore, the following three correlations have strong statistical significance:

– The wind resource IAV and the long-term windiness correction uncertainties are moderately correlated ($R = 0.49$, $p = 1.9 \cdot 10^{-29}$).

– The ~~regression and wind measurement~~ linear regression and reference wind speed data uncertainties are weakly correlated ($R = 0.35$, $p = 2.5 \cdot 10^{-15}$).

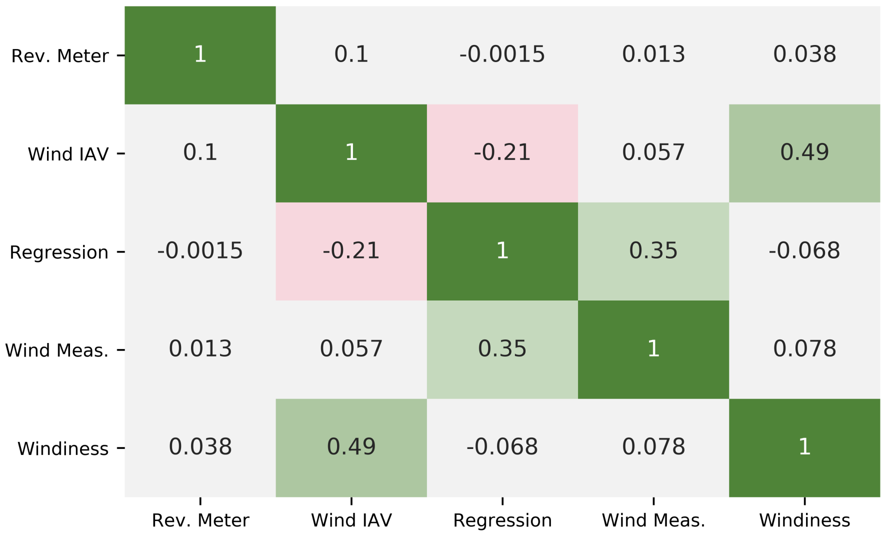


Figure 7. Correlation coefficient heat map between operational AEP uncertainty ~~categories~~components, as calculated from the results of the Monte Carlo approach applied at the 472 wind farms considered in the analysis. Note: “Rev.” denotes “Revenue".~~”~~

– The wind resource IAV and the linear regression uncertainties appear weakly negatively correlated ($R = -0.21$, $p = 2.6 \cdot 10^{-6}$).

The first correlation noted earlier (wind resource IAV and ~~windiness~~long-term windiness correction) is explained simply by the fact that both ~~uncertainties~~ uncertainty components are driven by wind resource variability. At a site with large wind variability, IAV will be large by definition, and so will the uncertainty introduced by different lengths of time series used for the long-term AEP calculation.

The correlation between ~~regression and measurement~~ linear regression and reference wind speed data uncertainties can be justified ~~,~~ given the dependence of both these uncertainty components on the number of data points used in the regression between energy production data and concurrent wind speed data (Figure 8).

Both the slope and intercept ~~error~~ errors (Equations 5 and 6), from which the linear regression uncertainty depends (as described in Section 2.3), are inversely proportional to the number of data points, so that when a regression is performed on few data points, its uncertainty increases. This ~~relationship~~ dependence is exemplified in Figure 4, where we ~~compare~~ have compared the sampling sets of regression lines for two stations in the EIA data set: for ~~this case~~these two cases, the standard errors of regression slope and intercept for the station with 8 data points (on the right) are 30-50 times larger than what is found for the station with 90 data points (on the left).

~~For measurement uncertainty~~The number of data points used for the regression has also an impact on the reference wind speed data uncertainty. In fact, short periods of wind plant operation record can lead to different interpretations from the

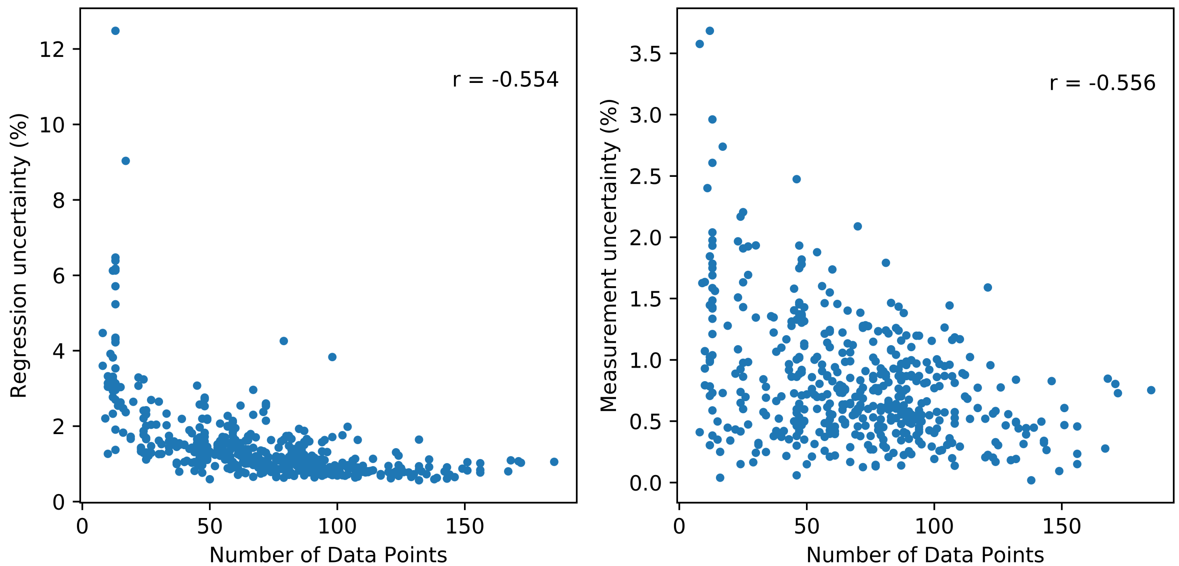


Figure 8. Dependence of linear regression uncertainty and ~~measurement~~ reference wind speed data uncertainty on the number of data points in the period of record, for the 471 projects considered in the analysis.

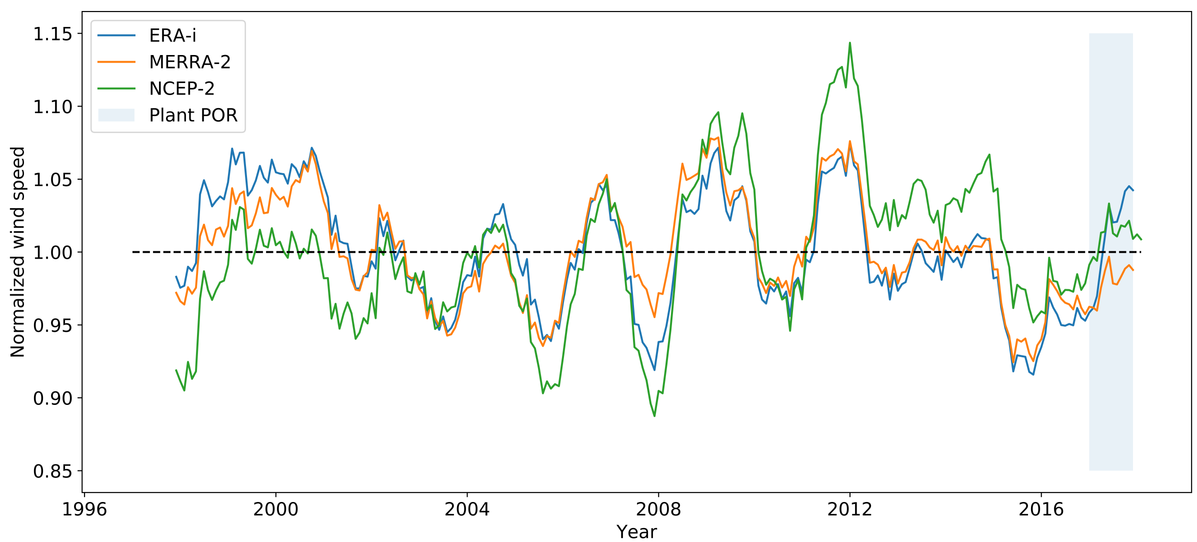


Figure 9. Long-term time series of normalized wind speed for EIA station ID 60502 from the three reanalysis products used in the study. The period of record (POR) for the wind farm is highlighted in light blue.

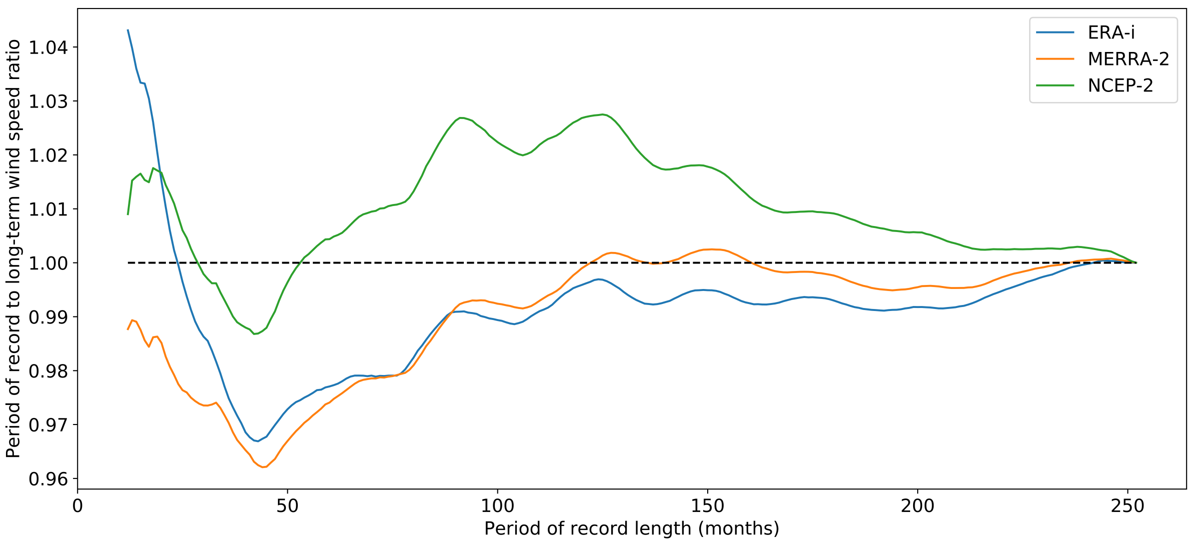


Figure 10. Ratio of wind speed to the long-term, 20-year average for periods of record of different lengths (all ending in December 2017), for EIA station ID 60502 using data from the three reanalysis products in the study.

~~reanalysis products~~ reference wind resource data sets used as to whether that short period of record was above, equal to, or below the long-term average resource. Over a longer period of record, these potential discrepancies between ~~reanalysis products~~ different wind resource data sets (in our case, reanalysis products) tend to average out, therefore leading to a reduced ~~measurement~~ uncertainty. We illustrate this phenomenon by exploring the long-term trend of the reanalysis products for the wind farm with one of the highest reported ~~measurement~~ reference wind speed data uncertainties (EIA ID 60502, reported 3.7% ~~wind speed measurement~~ reference wind speed data uncertainty). Figure 9 shows the result. The period of record for wind farm operation (shown ~~as shaded blue~~ by a shaded blue area in Figure 9) was only 12 months. As shown in the figure, the various reanalysis products have very different interpretations of the wind resource in the short period of record~~wind resource~~, relative to the long-term (ERA-i: 4% above average, MERRA-2: 1% below average; NCEP-2: 1% above average). Consequently, the use of each reanalysis product will ~~make different magnitude~~ lead to different magnitudes (both positive and negative) in the long-term windiness corrections, leading to high uncertainty in the resulting operational AEP calculation.

By increasing the period of record (i.e., increasing the number of data points used in the regression), such discrepancies tend to average out. This is illustrated in Figure 10, where we show how the period of record to long-term wind speed ratio varies as we extend the period of record by increasing the number of months while keeping December 2017 as ~~the constant~~ fixed ending time. For short periods of record, there is considerable deviation of this ratio ~~between~~ among the different reanalysis products (i.e., ~~high wind speed measurement uncertainty~~ the reference wind speed data uncertainty is high). As the length of the period of record increases, this ratio tends to converge to 1.0, and the spread between the three reanalysis products decreases (i.e., ~~low~~

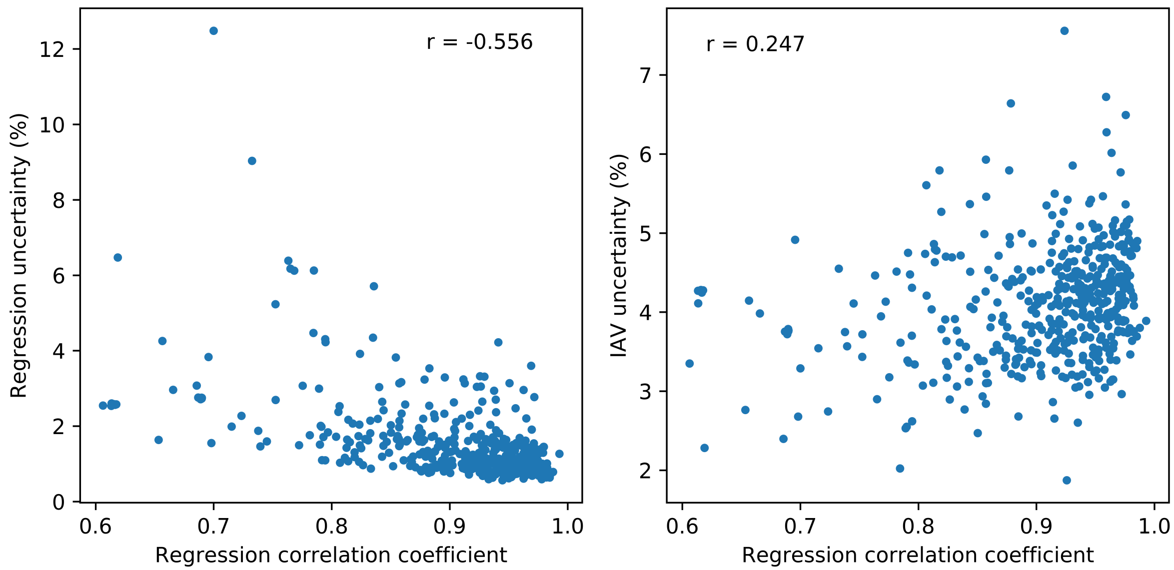


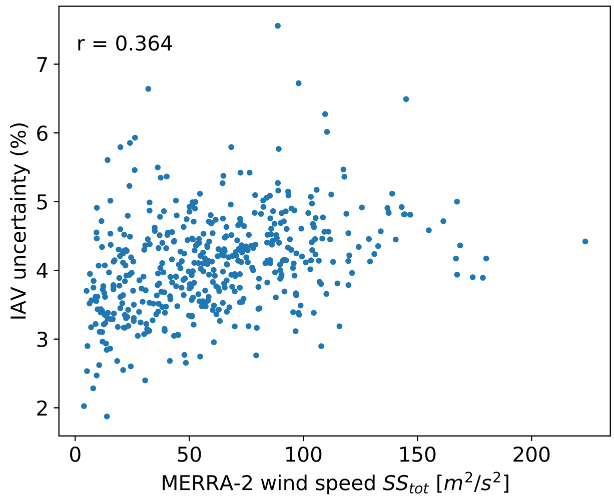
Figure 11. Dependence of linear regression uncertainty and IAV uncertainty on the R^2 of the regression between reanalysis wind speed and energy production data

~~wind speed measurement uncertainty~~ the reference wind speed data uncertainty is low).

Finally, the (weak) negative correlation between ~~regression and~~ linear regression and wind resource IAV uncertainties is linked to the fact they respond differently to the R^2 coefficient between the reanalysis wind speed and the energy production data (Figure 11). Predictably, the linear regression uncertainty is inversely proportional to the coefficient of determination because a stronger correlation between winds and energy production will lead to a reduced uncertainty of the regression between the two variables. On the other hand, wind resource IAV uncertainty shows a direct correlation with the regression R^2 ~~. We hypothesize that higher IAV leads to large ranges~~ coefficient. This dependency can be explained as both quantities are directly correlated with the total variance of wind speed ~~in the regression relationship , which acts to "stabilize" regression and increase the regression strength. This phenomenon is illustrated in Figure **??**(a). Here,~~ or, equivalently, produced energy. Figure 12 shows the relationship between IAV uncertainty and the ~~data set in blue has an equal spread in the regression relationship than the dataset in orange but over a large range of wind speeds. As shown in the figure, this longer range (quantified by the coefficient of variation of the wind speeds) leads to a higher R^2 in the regression.~~ total sum of squares $SS_{\text{tot, WS}}$ of reanalysis wind speed (here, using MERRA-2 monthly data), which is proportional to the variance of the data:

$$SS_{\text{tot, WS}} = \sum_i (WS_i - \overline{WS})^2 \tag{8}$$

~~(a) Scatterplot of two ideal variables with equal spread, but different data ranges, and impact on the correspondent R^2 and coefficient of variation. (b) Dependence of the coefficient of variation of MERRA-2 wind speeds on the R^2 of the regression between reanalysis wind speed and energy production data. We test this hypothesis in Figure **??**(b) where this coefficient of variation in a period of record wind speeds is calculated for each wind farm and compared to the regression correlation coefficient. As expected, a moderate correlation is observed. Therefore, we conclude that sites that experience a more variable wind resource tend to have a broader distribution of monthly wind speeds over their period of record. This broadness augments the range of the linear regression, which stabilizes the regression itself,~~



~~and lowers its uncertainty~~

Figure 12. Dependence of IAV uncertainty on the total sum of squares $SS_{\text{tot, WS}}$ of MERRA-2 wind speed data, for the 472 projects considered.

A direct correlation between IAV uncertainty and $SS_{\text{tot, WS}}$ emerges. At the same time, the linear regression R^2 coefficient also depends on the variance of the produced energy (and, equivalently, of wind speed) as it is defined as

$$R^2 = 1 - \frac{SS_{\text{res}}}{SS_{\text{tot}}} \tag{9}$$

where SS_{res} is the total sum of the residuals from the linear regression. Equation 9 shows that when the total sum of squares SS_{tot} increases, so does R^2, thus confirming the direct correlation between R^2 and the variance in the data.

Finally, we note that although the sites selected for this analysis are primarily in simple terrain (Figure 1), we do not expect more complex topography to impact the correlations revealed from the Monte Carlo analysis, as all the underlying relationships would also be applicable to more complex sites.

4 Conclusions

Financial operations related to wind farms require accurate calculations of the annual energy production (AEP) and its uncertainty ~~, both~~ prior to the construction of the plant and, often, in the context of its operational analysis. As ~~the~~ wind energy penetration ~~keeps increasing~~ increases globally, the need for ~~accurate techniques to~~ techniques to accurately assess AEP uncertainty is a priority for the wind energy industry. Typically, ~~the current industry standard assumes that the~~ current industry practice assumes that uncertainty components in AEP estimates are uncorrelated~~, and it combines them with a sum of squares approach~~. However, we have shown that this assumption is not valid ~~on the~~ for the six components which comprise an operational-based uncertainty, using the EIA data set.

In this study ~~, we investigated the assumption of uncorrelated uncertainty components by proposing~~ we used a Monte Carlo approach to assess annual energy production~~. Our technique not only directly~~ ; this not only accounts for correlations between uncertainty ~~categories~~components, but also provides quantitative insight into aspects of the AEP ~~process that drive this~~ calculation that drive its uncertainty. We have applied this approach using operational data from 472 wind farms across the United States in the EIA-923 database.

Our results show that ~~assuming uncorrelated uncertainties determines~~ ignoring correlations between uncertainty components causes a mean absolute ~~percentage~~ difference of 6% compared to the uncertainty calculated with the Monte-Carlo-based approach, with larger deviations (up to 20%) for specific sites. Moreover, three pairs of uncertainty components reveal a statistically significant correlation~~, which is neglected in the current industry standard: wind IAV and windiness~~ : wind resource inter-annual variability (IAV) and long-term windiness correction (positive correlation)~~, wind IAV and~~ ; wind resource IAV and linear regression (negative)~~, and wind measurement and~~ ; and reference wind speed data and linear regression (positive). Wind ~~IAV and windiness~~ resource IAV and long-term windiness correction uncertainties are correlated because they both depend on wind resource variability. Wind resource IAV uncertainty is correlated with linear regression uncertainty because they are both inversely proportional to the number of data points in the period of record. Finally, ~~measurement (reanalysis) uncertainty and~~ reference wind speed data uncertainty and linear regression uncertainty show a negative correlation because they respond oppositely to the R^2 coefficient between the ~~reanalysis~~ (reanalysis) wind speed and energy production data. Therefore, our results suggest that a Monte Carlo approach should be preferred to take into account these correlations between uncertainty components to lead to more accurate results, compared to the current industry standard approach. For all the projects considered in this study, the Monte Carlo simulation reached convergence within 10,000 runs. To facilitate the transition towards this proposed new industry standard, NREL's open-source OpenOA software[3] already supports the recommended Monte Carlo approach to assess AEP. In addition, the benefit of this technique will be further described in a guideline document in preparation for publication by the AWEA TR-1 working group.

Additional ~~categories~~ components of uncertainty in an operational AEP were not considered in our study because of limited reporting in the EIA-923 database. These ~~categories~~ components include reported availability, curtailment uncertainty, and various uncertainties introduced through analyst decision-making (e.g., filtering high-loss months from analysis and regression outlier detection). Future studies could include the impact of these additional sources of uncertainty on the operational AEP assessment. Finally, this study focused on correlations between operational AEP uncertainty ~~categories~~components. Future work could explore correlations between ~~preconstruction AEP categories~~pre-construction AEP uncertainty components. Given

[3] https://github.com/NREL/OpenOA

the numerous ~~categories~~ components (e.g., wake loss, wind speed extrapolation, wind flow model) and their intercomplexities, a Monte Carlo approach could reveal correlations that are at present not considered.

Code and data availability. EIA data used in this study are accessible from https://www.eia.gov/electricity/data/eia923/. Geographical data of the EIA wind farms are available at https://www.eia.gov/maps/layer_info-m.php. Software used to assess operational AEP is available from https://github.com/NREL/OpenOA.

Author contributions. NB and MO are equal contributors to this work. MO performed the AEP estimates on the wind farms considered in the study. NB and MO analyzed the processed data. NB wrote the manuscript, with significant contributions by MO.

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

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