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."

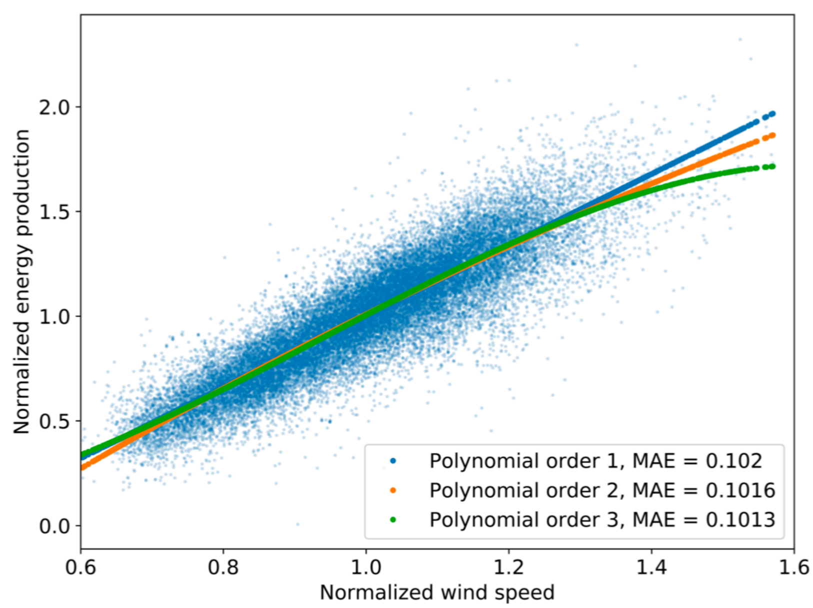

Figure 2. Scatterplot between normalized MERRA-2 monthly wind speed and monthly energy production across all 472 selected sites, and linear, quadratic and cubic best-fit lines.

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 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 of the resulting distribution (ISO and OIML, 1995; Dimitrov et al., 2018). Here, we apply this approach to derive a distribution of 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 operational AEP:

- 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 $\pm 0.5\%$ 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).
- 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.
- 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.

– Linear regression model uncertainty. This component is incorporated in the Monte Carlo method by sampling the regression slope and intercept values from normal distributions centered on their best-fit values and with standard deviations given by their 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 and e_b are used as standard deviations of the normal distribution of regression slope and intercept, respectively, from which Monte Carlo values are drawn. Slope and intercept values are strongly negatively correlated, which is captured by

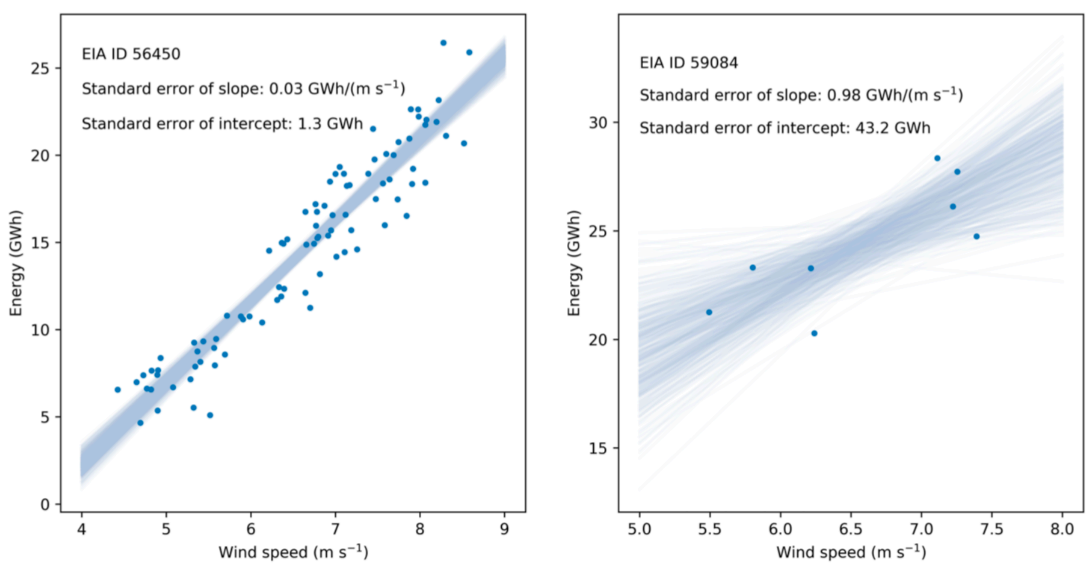

Figure 4. Sampling set of regression lines corresponding to the slope and intercept values derived from their standard errors in the Monte Carlo approach, for two stations in the EIA data set.

their covariance when performing linear regression. Therefore, to avoid sampling unrealistic combinations, we constrain the random sampling of slope and intercept values based on this covariance. 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 normal distribution centered around the best-fit parameters, and with standard deviation equal to the standard errors of slope and intercept. 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).

Each of the listed sources of uncertainty, which corresponds to a Monte Carlo sampling, 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 (related to revenue meter, reference wind speed data, wind resource IAV, linear regression,

and windiness correction), corresponding to the five considered uncertainty components, are simultaneously performed. The total uncertainty in operational AEP is then estimated as the coefficient of variation of the resulting distribution.

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 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 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

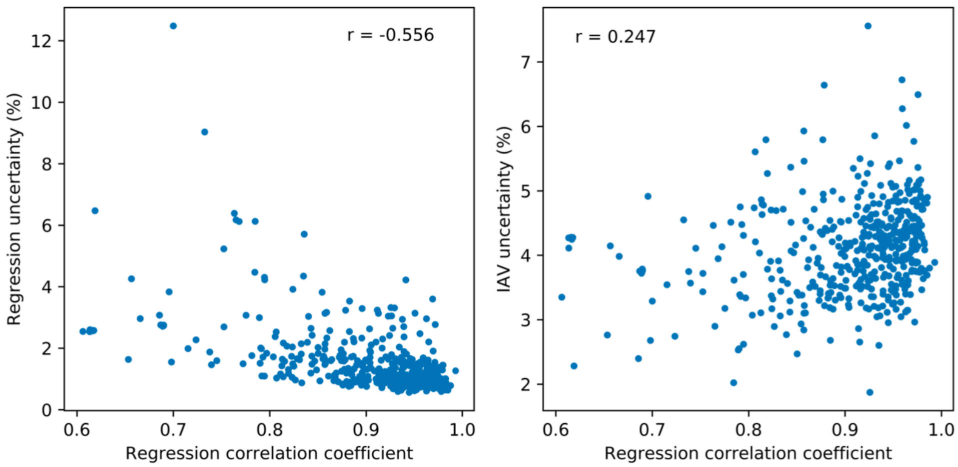

Figure 10. Dependence of linear regression uncertainty and IAV uncertainty on the R^2 of the regression between reanalysis wind speed and energy production data

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.

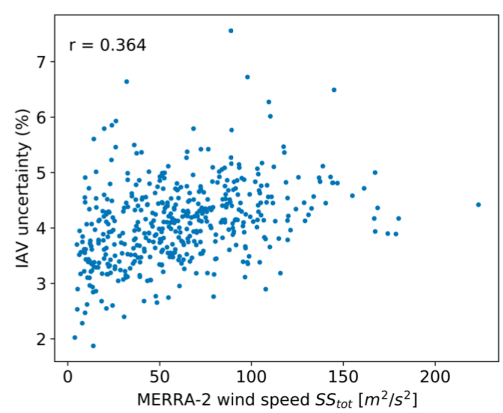

Figure 11. Dependence of IAV uncertainty on the total sum of squares $SS_{\text{tot, WS}}$ of MERRA-2 wind speed data, for the 472 projects considered.

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