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An independent analysis of bias sources and variability in wind plant pre-construction energy yield estimation methods

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Abstract

The wind resource assessment community has long had the goal of reducing the bias between wind plant pre-construction energy yield assessment (EYA) and the observed annual energy production (AEP). This comparison is typically made between the 50% probability of exceedance (P50) value of the EYA and the long-term corrected operational AEP (hereafter OA AEP) and is known as the P50 bias. The industry has critically lacked an independent analysis of bias investigated across multiple consultants to identify the greatest sources of uncertainty and variance in the EYA process and the best opportunities for uncertainty reduction. The present study addresses this gap by benchmarking consultant methodologies against each other and against operational data at a scale not seen before in industry collaborations. We consider data from 10 wind plants in North America and evaluate discrepancies between eight consultancies in the steps taken from estimates of gross to net energy. Consultants tend to overestimate the gross energy produced at the turbines and then compensate by further overestimating downstream losses, leading to a mean P50 bias near zero, still with significant variability among the individual wind plants. Within our data sample, we find that consultant estimates of all loss categories, except environmental losses, tend to reduce the project-to-project variability of the P50 bias. The disagreement between consultants, however, remains flat throughout the addition of losses. Finally, we find that differences in consultants' estimates of project performance can lead to differences up to \$10/MWh in the levelized cost of energy for a wind plant.

KEYWORDS
annual energy production, benchmark, energy yield assessment, open-source code, operational analysis, P50 bias, pre-construction estimates, pre–post-construction reconciliation, wind energy

1 | INTRODUCTION

Power generation from wind plants is one of the dominant and most rapidly increasing sources of renewable power generation worldwide, with global wind capacity expected to increase by about 100 GW every year this decade.[1] However, profit margins in the wind energy sector are sensitive to the terms of financing for a potential wind plant, which are largely determined by pre-construction estimates of the annual energy production (AEP) and associated prediction uncertainty (estimated as the standard deviation of the AEP distribution). A recent study showed that pre-construction estimates of AEP have historically overpredicted the potential energy production by 3% to 5% on average, even when predictions account for grid curtailment.[2]

Consultancies performing pre-construction energy estimates claim that their mean prediction bias in the central estimate of AEP, or P50, is converging toward 0.[3–6] However, the variability in P50 bias across projects can exceed 10% in some regions.[3] What remains unknown is whether this variability is driven by site-specific prediction challenges (e.g., icing events, complex terrain, and unexpected curtailments) or by differing methodologies used by individual consultants or consultant groups. Because evaluations of these pre-construction estimates are conducted internally by wind energy consultants using their own data and methods, they may be subject to various confirmation and selection biases. An independent analysis of bias reduction investigated across multiple wind energy consultants would help identify the greatest sources of uncertainty and variance in the pre-construction energy yield assessment (EYA) process and thereby identify the best opportunities for uncertainty reduction.

The EYA process includes several components: data collection, data analysis and quality control, resource modeling, estimates of gross energy production at a proposed site, estimates of expected losses (from curtailment, availability, electrical issues, environmental conditions, turbine blade degradation, and wake effects), and quantified uncertainties in the steps taken to arrive at the associated predictions. While it is reasonable to expect significant variations in estimates of gross energy production and certain loss categories due to the geographical location, wind plant layout, and general size of a proposed plant, the methodologies used by different consultancies may also play a significant role in the large spread of the resulting P50 bias. Identifying the sources of variability in AEP estimates and understanding which components of the EYA process introduce the largest sources of variability are therefore critical steps toward improving methods for reducing the spread in P50 bias.

This study provides a unique and independent evaluation of the state of the EYA process across 8 different consultancies and 10 wind plants. As part of the Wind Plant Performance Prediction (WP3) Benchmarking[7] initiative's goal to better understand how consultants arrive at existing P50 estimates and where further improvements are possible, this project provides an independent analysis that addresses issues with proprietary self-validations such as confirmation bias and method transparency. The WP3 project showcases a major collaborative effort between over 20 industry stakeholders, including plant owner/operators, consultant groups, original equipment manufacturers, and academic and government institutions. While the data collection effort for the benchmarking initiative considers over 100 projects representing over 25 GW of installed capacity, this phase of the benchmark presents a detailed analysis of consultant predictions for 10 operating wind plants, and it provides an evaluation of trends in overall P50 bias, losses, and uncertainties relative to the operational data.

The paper is outlined as follows: In Section 2, we describe the data used in the WP3 benchmarking initiative. Section 3 follows with a discussion of our methodology for comparing EYA and operational data. In Section 4, we present the various consultant estimates of gross energy, loss categories, and resulting P50 bias, along with our understanding of where consultants agree on methodologies. In this context, we also quantify the difference between consultant loss estimates and those calculated from observed data and explain the sources of deviation for the EYA-based and operational data-based AEP estimates. We discuss in Section 4.2 how the lack of agreement in uncertainty quantification between consultants translates to potential financial risks. Finally, we conclude with recommendations on where the wind industry may focus efforts to reduce the spread in P50 bias, increase confidence, and thereby increase investment returns.

2 | DATA

This study considered data from 10 operating wind power plants across North America. These plants were chosen due to their relatively simple terrain and to encompass a range of plant properties and locations across central North America from Texas to Canada. Figure 1 displays key project parameters such as nameplate capacities, number of turbines, rotor diameters, and commercial operating dates. In an effort to protect the identities of individual participants and projects, the names and descriptions of each project and participant are anonymized herein, and absolute scales are not provided in the figures throughout the rest of the paper. Further information on the WP3 benchmarking project selection and data collection processes can be found in Fields et al.[7]

2.1 | Operational data

Owner/operators of the 10 considered wind plants have provided the following operational data:

- turbine-level supervisory control and data acquisition (SCADA) data and
- plant-level data
  - net energy production data from revenue meter and
  - availability and curtailment losses.

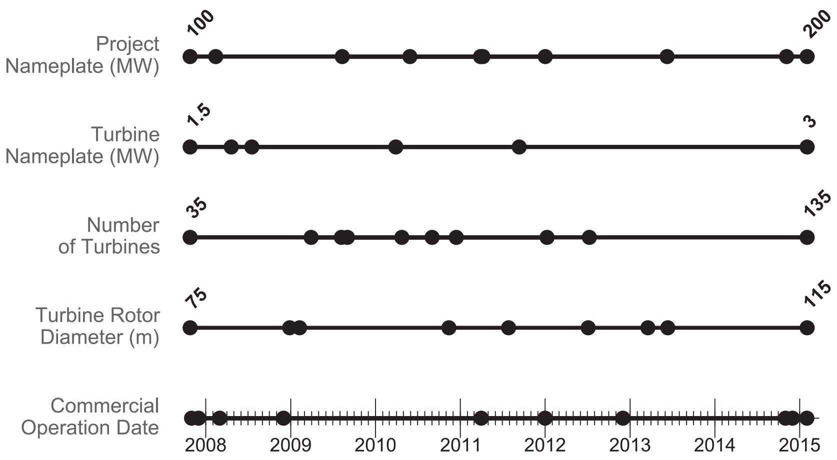

FIGURE 1 WP3 Phase 1 project metadata summary. For each axis, each dot represents one wind plant studied in the WP3 benchmarking initiative.

The period of record of operational data provided for a given plant is between 1 and 5 years. Quality control was performed for each wind plant, including checking for outlier data, checking for gaps in the data, and aligning the time stamps of the ingested data.

2.2 | EYA data

Pre-construction EYAs for the 10 wind plants are provided by eight participating consultancies, each of which were provided the same pre-construction data package for each wind plant.

Each consultant was given an identical data package that simulated the industry process as closely as possible. The data package consisted of wind plant information (details on the turbine model, power curve, wind plant layout, roads, and electrical infrastructure), raw meteorological data, and site and environmental characteristics (details on terrain, land cover, and any other relevant consideration). Each consultant was also given a project overview document, which presented and summarized what included in the data package, provided a map of the wind plant, and spelled out any explicit modeling considerations as relayed by the plant owners. The consultants started with this set of raw data inputs and performed their own quality control, shear modeling, long-term correction (with no constraints on the choice of the long-term reference data), spatial modeling, wake modeling, energy yield, and uncertainty quantification.

The EYA data provided by the consultants contain the following metrics:

- the predicted annual gross energy production;
- losses, disaggregated by loss type (according to IEC 61400-15[8]) into
  - wake effect (for internal, external, and future wake effects),
  - turbine level (sub-optimal performance, high wind hysteresis, and generic and site-specific power curve adjustments),
  - electrical (electrical efficiency and facility parasitic consumption),
  - availability (turbine, grid, and balance of plant availability),
  - curtailment (load, grid, environmental/permit curtailment, and operational strategies), and
  - environmental (icing, degradation, exposure, and other environmental factors such as high/low-temperature shutdown or derate, lightning, hail, and other environmental shutdowns); and
- the predicted annual net energy production.

Consultants also provide their estimates of the following uncertainty components (according to IEC 61400-15[8]):

- uncertainty due to the historical wind resource,
- uncertainty due to horizontal extrapolation of wind speed,
- uncertainty of the on-site wind resource measurements,
- plant performance uncertainty,
- project lifetime variability uncertainty,

- uncertainty due to vertical extrapolation, and
- total project uncertainty.

While consultants may reflect time-dependent changes in metrics such as availability losses and wind resource variability by providing different estimates of AEP, losses, and uncertainties for 1-, 10-, and 20-year timeframes, the results presented in this study use only the 10-year estimates, as this is the most common timeframe for commercial products per discussion with the WP3 industry partners. Finally, we note that the pre-construction wind measurements used for wind resource assessment in this study had some flaws (e.g., incomplete documentation) and do not necessarily represent current best practices in the wind industry, but they do represent best practice datasets at the time of their deployment.

The wind plants for which each consultant completed EYAs are shown in Table 1. While not all eight consultants completed EYAs for all 10 wind plants, we decided to not discard any consultants/wind plants in an effort to maximize the amount of data used in the analysis.

3 | METHODS

An ideal analysis of the gaps between EYA-predicted P50 and operational AEP (which we will simply refer to as a "gap analysis" in the remainder of the paper) would compare the predicted gross energy, loss values, and net energy from the EYAs to the corresponding values based on operational data. However, pure gross energy cannot be obtained from operational data because wake losses, turbine performance losses, and blade degradation losses are inherently present in the reported SCADA data from each wind turbine. Therefore, we begin our gap analysis by calculating the turbine ideal energy[9] (TIE), which we define as the gross energy with the abovementioned losses included, from both the EYA and operational data. Next, we continue the gap analysis by progressively adding electrical losses, availability losses, and any remaining losses to the EYA-derived and operational TIE values, finally leading to a comparison in terms of net energy. Table 1 summarizes the quantities of interest, which will be used to present the gap analysis results in Section 4.

We incorporate uncertainty quantification in the methods of calculating the long-term corrected operational AEP, TIE, and electrical losses by using a Monte Carlo approach. We run the Monte Carlo simulations 10,000 times to obtain a distribution of long-term corrected operational AEP and electrical losses (monthly data) and 500 times to obtain a distribution of long-term corrected operational TIE (daily data, computationally more expensive). For each metric, we calculate uncertainty in terms of the standard deviation of the resulting Monte Carlo distribution. In the following paragraphs, for each metric, we will detail which parameters are Monte Carlo sampled to provide uncertainty quantification. When possible, we base the choices of the uncertainty values on existing literature (e.g., the choice of a revenue meter uncertainty of 0.5% is consistent with what is typically assumed by wind energy consultants for revenue meter uncertainty based on IEC 60688:2012[10] and ANSI C12.1-2014[11]). Where published guidance is not available, we base our choices on discussions with consultants and pick values as could be done by a "reasonable analyst" (introduced by Craig[12] in the context of uncertainty quantification for wind plant energy estimates).

To analyze the wind plant operational data, we use an open-source package for operational analysis (OpenOA,[9] v2.0.1). The OpenOA functionality implemented for the operational data in this study includes data quality control, calculation of operational energy production estimates, estimation of losses from SCADA data, and gap analysis routines. All these quantities are long-term corrected to ensure the relatively short

TABLE 1 Completion matrix of EYAs from each consultant for each wind plant

	Project										
Participant	A	B	C	D	E	F	G	H	I	J	TOTAL
0	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	5
1	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	5
2	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	8
3	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
4	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
5	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
6	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
7	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	10
TOTAL	8	8	8	8	7	7	6	6	5	5	68

Note: Green check marks indicate that an EYA was completed. Red "X" marks indicate that an EYA was not completed. Five out of eight consultants completed all 10 projects.

periods of record of each wind plant are rescaled to reflect potential long-term variability in the wind resource and match the long-term period considered in the EYA data.

The remainder of this section provides an overview of the methods used for calculating the quantities listed in Table 2, along with the methods used to calculate the uncertainty of the operational quantities.

3.1 | Turbine ideal energy

The TIE from EYA data is calculated by taking gross energy estimates and applying wake effect losses, turbine performance losses, and blade degradation losses (the latter comes from the environmental loss macro-category).

To calculate the long-term corrected operational TIE, we first calculate TIE values during the period of record from turbine SCADA data, and then we perform a regression between period of record TIE values and concurrent atmospheric variables taken from reanalysis products. The regression results are then applied to long-term atmospheric reanalysis data to obtain a time series of long-term corrected operational TIE values.

More in detail, the TIE calculation involves the following steps (and ways to incorporate uncertainty quantification):

- First, we apply a set of filtering algorithms to each turbine SCADA data. We flag data based on a range filter (we discard time stamps with a SCADA-reported wind speed below 0 m/s or above 40 m/s, or a turbine energy below zero or above the turbine nominal capacity) and a window filter (we discard data points where the wind speed is between 5 and 50 m/s and the reported power is lower than 2% or greater than the turbine nominal capacity). Next, we apply a bin-filtering algorithm to each turbine's operational power curve (i.e., the scatterplot of each turbine's produced power and concurrent reanalysis wind speed). Data points in the turbine power curve are binned based on power, up to a percentage of the turbine rated power. Within this filtering process, we Monte Carlo sample two imposed thresholds. The first is the percentage of turbine rated power that corresponds to the upper boundary of the last bin used in the filter. We sample this threshold from a uniform distribution between 80% and 90% of the turbine rated power. The second is the threshold from the wind speed median value in each bin. We sample this value from a uniform distribution between 1 and 3 standard deviations from the wind speed median value in each bin, in either direction. Data points not within these thresholds from the median wind speed value in each bin are filtered out. This filter design acts to remove periods of underperformance or downtime, along with extraneous data points that fall outside normal operating conditions. An example of a filtered turbine operational power curve is shown in Figure 2.
- We then gather the unflagged (from the step above) SCADA energy data into daily sums. Days with a percentage of unflagged SCADA data below a Monte Carlo sampled threshold (between 85% and 95%) are discarded from the TIE calculation. Finally, missing data for each turbine are imputed based on reported energy data from other highly correlated turbines within the wind plant.
- Next, we process reanalysis data (wind speed, wind direction, and air density) to daily means. Assessing the uncertainty connected with the choice of the reference atmospheric variables to use is a challenging task, especially when considering spatial variations. As a proxy for this complex uncertainty component, we randomly selected atmospheric data from one of three reanalysis products (MERRA-2,[13] NCEP-2,[14] and ERA-I[15]) at each Monte Carlo iteration.
- We then perform, for each turbine, a regression (using a generalized additive model[16]) between daily sums of SCADA energy data and concurrent daily mean wind speed, wind direction, and air density from one of the three reanalysis products. In this step, we incorporate the uncertainty in the SCADA data by sampling them from a normal distribution centered on the filtered, imputed values and with a standard deviation equal to 0.5% of the filtered, imputed values.
- The best-fit generalized additive model is then applied to long-term atmospheric variables (daily mean wind speed, wind direction, and air density) from the reanalysis products to calculate long-term TIE for each turbine within the wind plant.
- The sum of the long-term TIE values for all the wind turbines gives the total long-term TIE for each wind plant.

The code to calculate TIE can be found in the OpenOA GitHub repository.*

TABLE 2 Summary of the quantities used in the gap analysis, for both EYAs and operational data

Quantity	EYA	Operational data
Gross energy	Reported by consultants	Cannot be derived
TIE	Calculated (Section 3.1)	Calculated (Section 3.1)
Electrical losses	Reported by consultants	Calculated (Section 3.2)
Availability losses	Reported by consultants	Reported by owner/operator
Other environmental/unexplained losses	Calculated (Section 3.4)	Calculated (Section 3.4)
AEP	Reported by consultants	Calculated (Section 3.3)

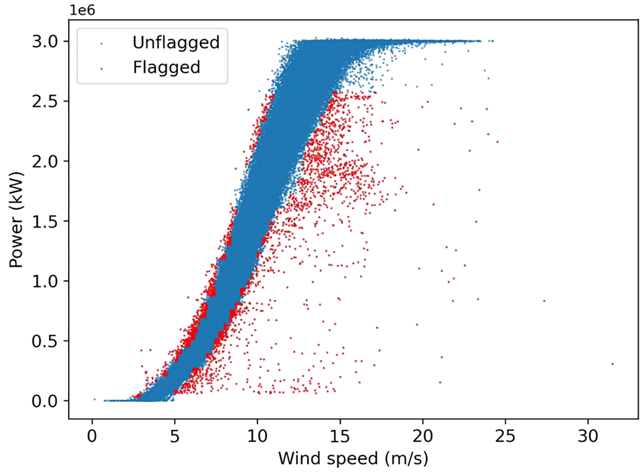

FIGURE 2 Example of a filtered turbine operational power curve, from one of the 10 wind plants considered in the analysis. For this case, thresholds of 85% and 2 standard deviations (see details in the text) are used in the bin filter.

3.2 | Electrical losses from operational data

Electrical losses from operational data were calculated in OpenOA by comparing energy production measured by the turbine SCADA data with the plant-level energy recorded at the revenue meter:

$$\text{Electrical Losses} = 1 - \frac{\text{Plant Revenue Meter Energy}}{\text{Turbine SCADA Energy}}$$

For both SCADA and revenue meter data, we incorporate uncertainty by sampling values from a normal distribution centered on the reported value and with a standard deviation equal to 0.5% of the reported value.

More in detail, for those wind plants that report data at daily or sub-daily time resolution, we calculate daily sums of energy production from the turbine SCADA and from the revenue meter data, only for days when all turbines within the wind plant are reporting at all time steps. We then calculate the average electrical losses, using the sum of the selected daily total energy from the revenue meter and turbine SCADA data over the period of record.

When revenue meter data are only available at a monthly time resolution (two wind plants in the set of 10 considered in our analysis), we filter out months in which there were less than an imposed percentage of time stamps with all turbines within the wind plant running (the filter threshold is sampled from a uniform distribution between 90% and 97%). The sum of filtered monthly revenue meter and turbine SCADA data over the period of record for each wind plant is then calculated and used to compute the average electrical loss.

3.3 | AEP from operational data

OA AEP is calculated in OpenOA using an industry-standard approach whereby energy production during the period of record is related to wind resource data via a linear regression model at monthly resolution. The regression model is then applied to long-term wind resource data to estimate the long-term corrected AEP. Recently, Bodini et al.[17] showed how more sophisticated regression algorithms and finer temporal resolution would improve the calculation of AEP from operational data by allowing to capture the nonlinearity and multivariate nature of the relationship between produced power and atmospheric state. Still, given the main goal of this analysis, here, we follow the industry-standard approach of a univariate linear regression at monthly resolution.

More specifically:

- The monthly available energy during the period of record is calculated by adding reported availability and curtailment losses to the revenue meter energy production. As done in the calculation of electrical losses, we sample revenue meter data from a normal distribution centered on the reported value and with a standard deviation equal to 0.5% of the reported value.
- We normalize the monthly available energy to 30-day months (e.g., for January, the values are multiplied by 30/31).

- A linear regression is then performed between monthly available energy and concurrent density-adjusted monthly wind speeds from an atmospheric reanalysis product (Monte Carlo sampled between MERRA-2, NCEP-2, and ERA-I as a way to account for long-term reference data uncertainty, as detailed above). The uncertainty in the regression relationship is assessed using a bootstrapping approach, where for each Monte Carlo iteration, all data are randomly sampled with replacement. An example of such regression is shown in Figure 3.
- The best-fit slope and intercept from the regression model are applied to long-term density-adjusted monthly wind speeds from MERRA-2, NCEP-2, and ERA-I (Monte Carlo sampled) to determine the long-term corrected available energy. To assess the uncertainty in the long-term correction, we randomly sampled between 10 and 20 years of reanalysis data to perform the long-term correction at each Monte Carlo iteration.
- The long-term monthly available energy (all based on 30-day months) is denormalized to the actual number length of each month (e.g., for January, the value is multiplied by 31/30).
- Finally, the long-term corrected operational AEP is estimated by subtracting long-term availability and curtailment losses from the calculated long-term available energy. We note how, because we did not calculate plant-level availability losses (provided by plant owners), we applied a constant 0.5% uncertainty to these losses, which is consistent with what is typically assumed by wind energy consultants.

We note how some consultants might have used different reanalysis products (e.g., ERA-5) in their EYA estimates, which could introduce an additional source of error between the EYA and OA estimates of AEP.

3.4 | Other environmental/unexplained losses

The last quantity in the gap analysis is connected to any remaining energy losses that were not included in the variables defined in the previous sections.

For EYA data, we calculate this quantity as the sum of all the EYA-reported environmental losses except for blade degradation, which is instead accounted for in the TIE.

On the other hand, for operational data, we calculate this quantity as the difference between the sum of operational TIE, electrical losses, and availability losses minus the wind plant long-term corrected operational AEP. We note that for operational data, this is a more nuanced quantity, which includes a combination of environmental losses (except for blade degradation) and any remaining unexplained losses that are not perfectly quantified in the methods used to quantify operational TIE, electrical losses, and AEP (e.g., because of imperfect filtering of underperforming data points in the calculation of TIE).

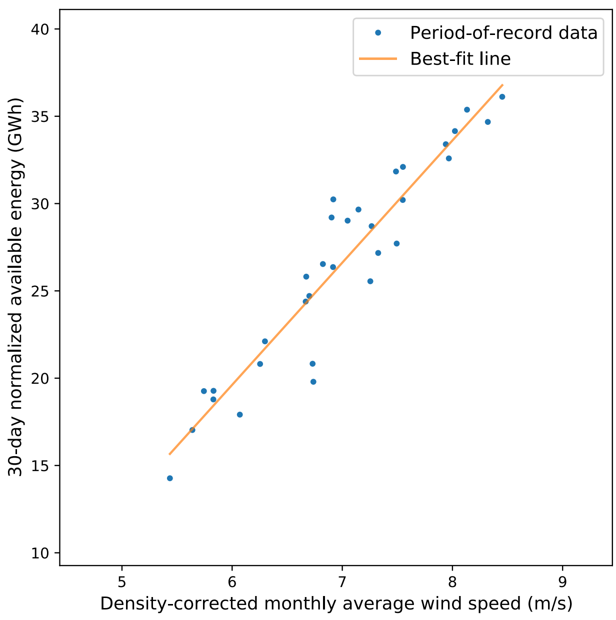

FIGURE 3 Example of a linear regression between density-corrected monthly average wind speed and 30-day normalized available energy, from one of the 10 wind plants considered in the analysis

4 | RESULTS

We begin this section by looking at the bias of EYA-estimated P50 compared to the OA AEP, which we will call P50 bias. As shown in Figure 4, the average P50 bias across our sample of 10 wind plants and 68 individual EYA submissions is -1.2% with a standard deviation of 4.8%. So, while the mean bias for our sample of projects is lower than those indicated by the $+3.5\%$ found in Lunacek et al.[2] (and even slightly negative), there remains significant variability in P50 bias between different EYA estimates and wind plants. We note that, for the relatively small sample size of projects and consultants considered here, the variability observed here is lower than the total uncertainty estimated by the consultants (described later in Section 4.2), which could suggest that the EYA uncertainty may be overestimated.

Next, we assessed how the agreement between consultants varies when moving from the EYA-estimated gross energy to net energy through the addition of the various EYA-estimated losses. We first explored how the consultant estimates, aggregated at the project level, converged toward the OA AEP value as loss categories were added in Figure 5. In the left panel of Figure 5, we first considered the project-to-project variability as the average consultant estimate converges toward the OA AEP by plotting each project's mean bias from the OA AEP. We found a large variability among project means of the EYA gross energy estimates (6.9% interquartile range [IQR] relative to OA AEP). On the other hand, we saw a reduction in the variability among projects when EYA estimates of the energy losses were added, as shown by the reducing IQR of bias when wake effect, turbine performance, and blade degradation losses (all accounted for in the TIE), and the electrical and availability losses are considered. This held true for all losses except for other environmental/unexplained losses, which increased the project-to-project variability of the resulting EYA P50 values (from 4.8% IQR to 5.6% IQR, rightmost quantity in the left panel of Figure 5). The right panel of Figure 5 shows the standard deviation of the consultants' EYA estimates for each project. This helps quantify the consultant disagreement in estimating a given quantity for the 10 wind plants. We found that, on average, the disagreement between consultants does not show any strong change when moving from their EYA estimates of gross to net energy.

In Figure 6, we compare the EYA-estimated TIE, downstream losses, and AEP to the corresponding metrics from the operational analysis. This helps to show by how much consultants tend to overpredict/underpredict each step of the EYA process. We see a significant overestimation of the energy at the turbine, with EYA estimates of the TIE overpredicting the TIE operational values by $+3.9\%$ on average. This overestimation of TIE is followed by overestimation of electrical losses ($+0.5\%$ on average), availability losses ($+2.1\%$ on average), and other environmental/unexplained losses ($+2.4\%$ on average), which results in the negative mean bias in P50 estimates seen for our sample of submissions. While there is initially a large spread in bias of TIE estimates from the observed TIE (standard deviation of 4.9%), the remaining downstream losses exhibit much less spread (maximum standard deviation of 1.6%).

The same pattern of overprediction in TIE followed by overprediction of energy losses is observed on a project-to-project basis, where EYA submissions that initially overestimate the TIE result in P50 values near or below the OA AEP (Figure 7). Similarly, those EYA submissions that initially underpredict TIE result in strong negative P50 bias estimates. For example, Participant 2 (shown by the green dots in Figure 7) initially overpredicts the TIE in Project G by more than 7%, but further overprediction of electrical ($+0.7\%$), availability ($+4.5\%$), and other environmental losses ($+2.7\%$) results in a P50 that is underestimated by 1.2%. Also, we note how projects with a large initial spread in EYA estimates of TIE (e.g., Projects B and F) have a correspondingly large spread in the additional steps of the EYA process.

Finally, we note how, for some wind plants, the sum of operational TIE, electrical losses, and availability losses is lower than the OA AEP (e.g., for Projects A, D, and F). This inconsistency is due to the fact that operational availability losses and net energy production values are provided by owners/operators as plant-level metrics at timescales different from the turbine-level SCADA data from which the TIE is calculated;

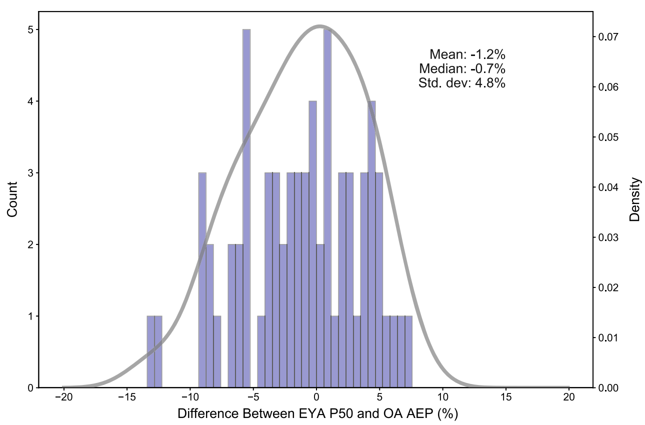

FIGURE 4 Histogram of estimated EYA P50 values compared with OA AEP values. P50 bias is calculated as EYA P50-OA AEP. The solid line shows a kernel density estimate of the probability density function obtained using Gaussian kernels.

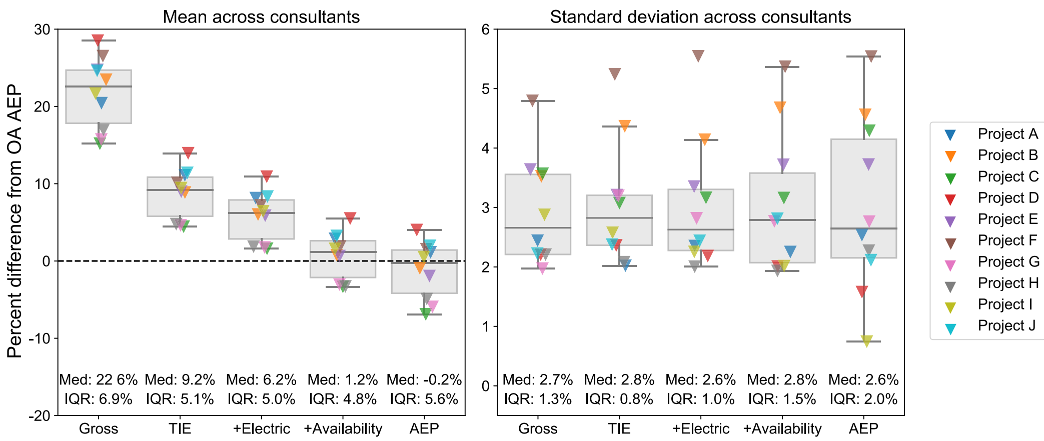

FIGURE 5 Mean and standard deviation of project bias from the OA AEP. Each triangle represents a project. The leftmost quantity (Gross) is the gross energy estimate as reported by the consultant. The rightmost quantity (AEP) is the gross energy with all downstream losses subtracted (i.e., the EYA-estimated P50). Each box extends from the first quartile (Q1) to the third quartile (Q3) of the data. The horizontal line shows the median of the data. The whiskers extend from the box by 1.5× the interquartile range (IQR). We can see that the mean of the consultant estimates approaches the OA AEP as losses are added in. The standard deviation of the consultant estimates remains flat.

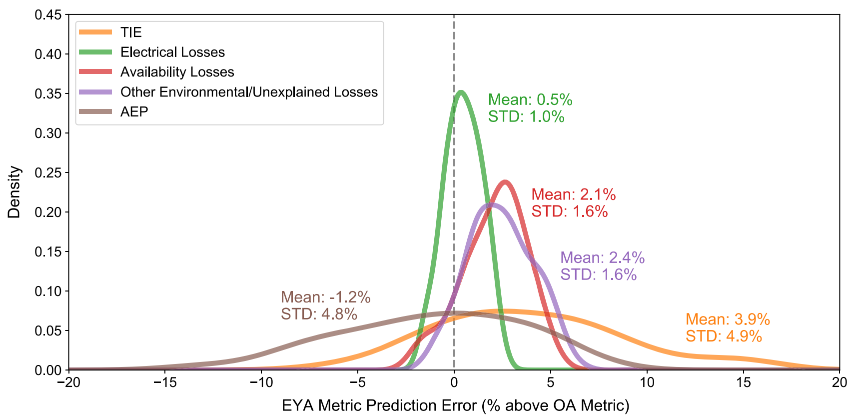

FIGURE 6 Distribution (obtained using Gaussian kernels) of prediction errors for each step of the EYA process based on the 68 submissions in this analysis. Colored numbers in the labels next to each line indicate the mean and standard deviation of the prediction bias relative to the corresponding metric calculated from the operational data.

therefore, it is possible that some time-based discrepancies exist when comparing operational TIE and electrical losses to the availability losses and P50.

4.1 | Sources of variability among EYA submissions

While our gap analysis provides a useful understanding of the average bias in consultant EYAs, it is important to understand whether the bias and variability arise from project-specific considerations or from different methodologies used by the consultant groups. Figure 8 shows the consultant estimates of P50 bias (bottom panel—normalized by the project OA AEP) organized by project and by participant. There is clearly more variability in P50 bias between projects than between participants, even so some projects exhibit a spread in consultant estimates as large as 16%.

Consultant loss estimates exhibit a similar amount of variability between projects and between participants (Figure 8). Some participants consistently estimate higher (e.g., Participant 3) or lower (e.g., Participants 2 and 6) losses compared to their counterparts. However, there are some projects where consultants collectively predict lower (e.g., Project A) or higher (e.g., Project E) losses compared to the portfolio of projects, because of consultants' consistent estimates of high or low wake losses for those specific wind plants.

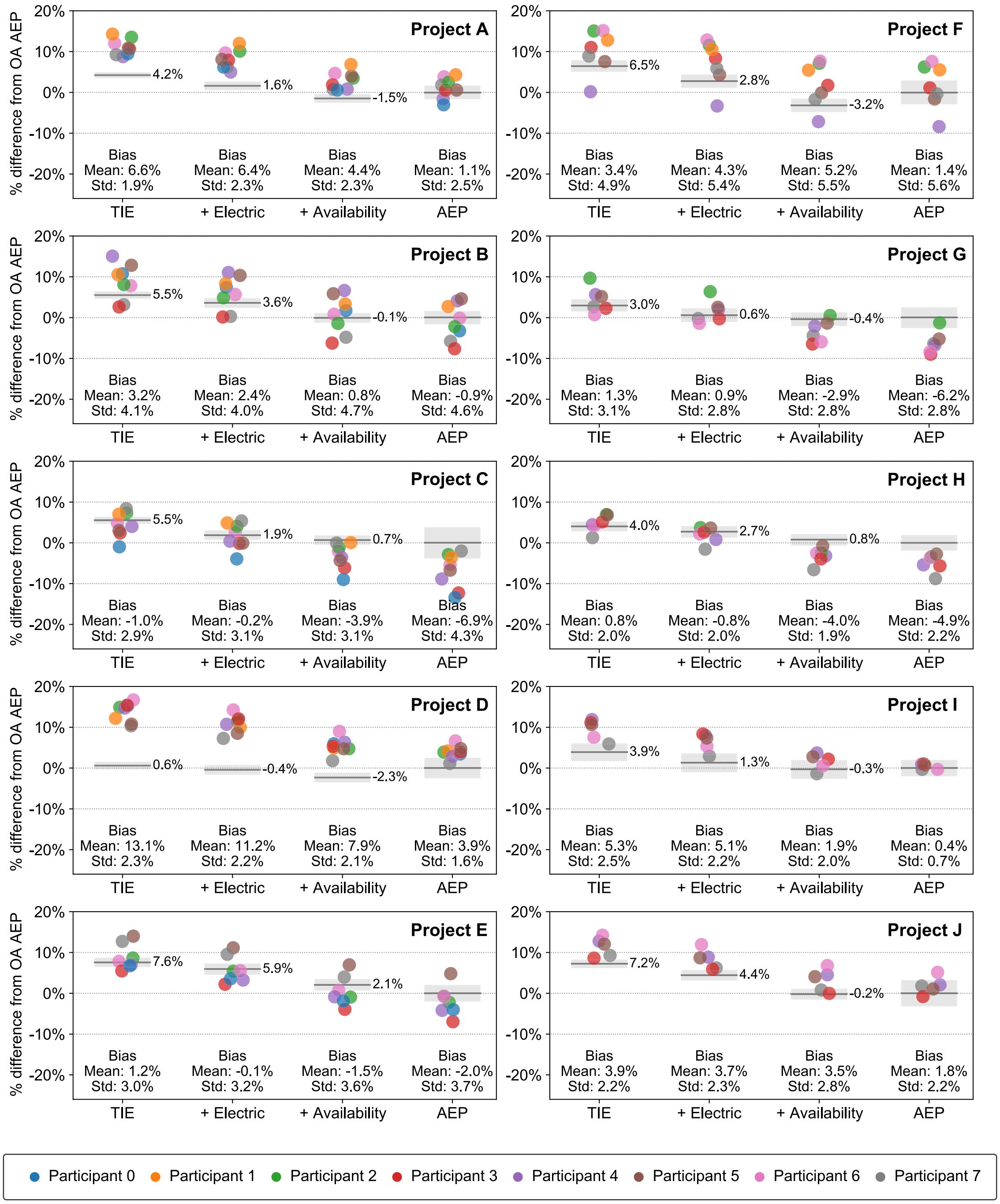

FIGURE 7 EYA estimates of TIE, plus the addition of electrical, availability, and environmental losses, for the 10 wind plants considered in the analysis. Operational values of these metrics for each project are indicated by the gray bar (magnitude of the EYA quantities above the OA AEP is indicated by the three annotations) with uncertainty (calculated as detailed in Section 3) indicated by the light gray bands on either side of the lines. Mean and standard deviation of the bias in consultant estimates for each metric are annotated at the bottom of the figure. Project names are ordered by their degree of submission completion.

We quantify whether the largest variability occurs between projects or between participants by calculating the intersection over union (IOU, also known as the Jaccard index[18]) of distribution pairs formed by the submissions for a project or participant. The IOU value (or Jaccard index) J can be defined as follows:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

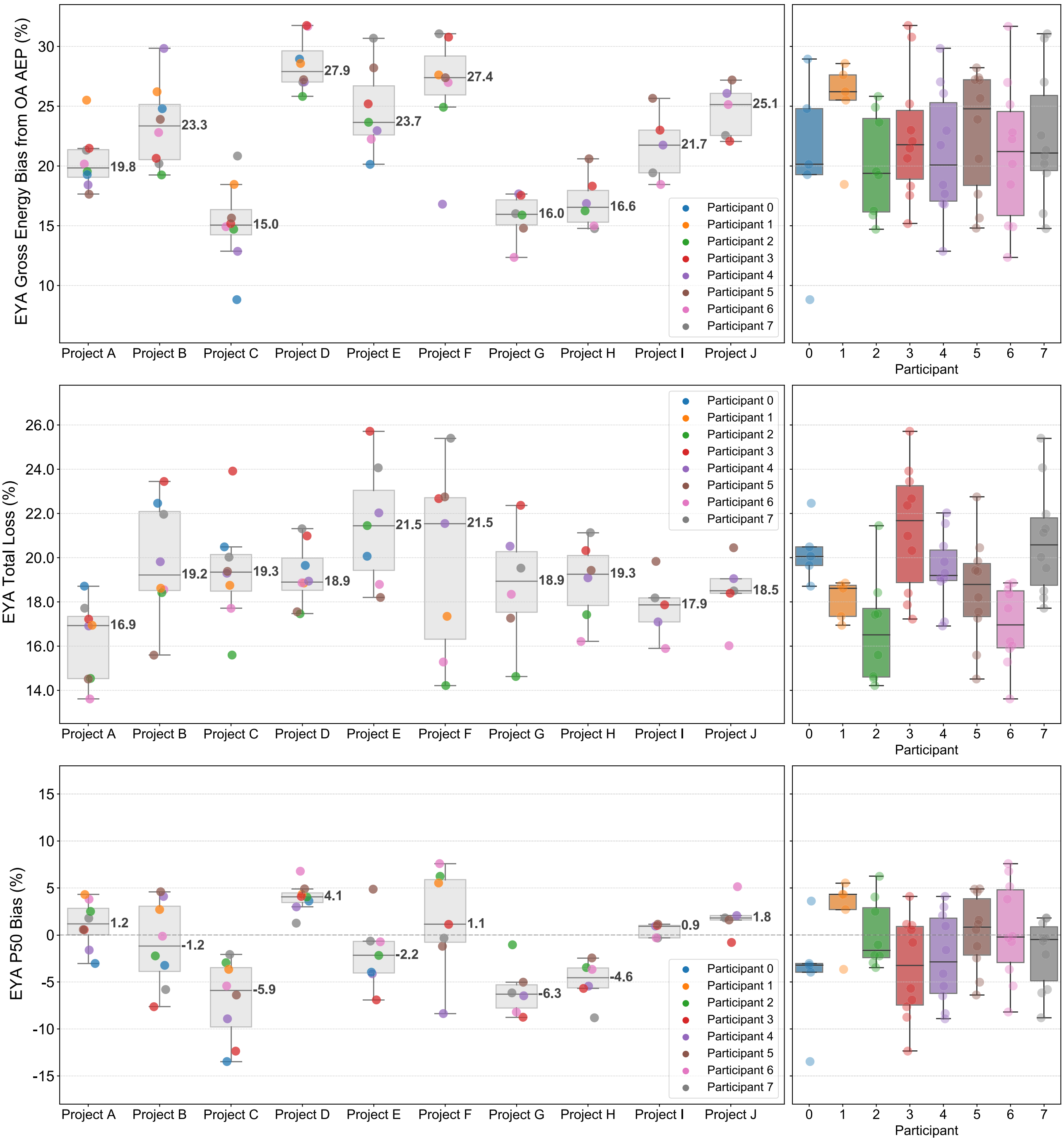

FIGURE 8 EYA gross energy bias from OA AEP (top), EYA total losses (middle), and EYA P50 bias from OA AEP (bottom) by project (left) and by participant (right)

where *A* and *B* represent two Gaussian distributions. The IOU is therefore an indication of the similarity of any two distributions where a value of 1 indicates 100% overlap and 0 indicates no overlap. We first group submissions by project and fit a Gaussian distribution to all the consultant's submissions for each single project. We calculate the IOU value for all the possible pairs of projects (e.g., A vs. B, A vs. C, B vs. C, etc.) and then take the mean IOU of all the pairs. We then compare the values with the IOU obtained by grouping submission by consultant, where we fit a Gaussian distribution to each consultant's submissions for all wind plants. We calculate the IOU value for all the possible pairs of consultants (e.g., 1 vs. 2, 1 vs. 3, 2 vs. 3, etc.) and then take the mean IOU of all the pairs. By taking the mean of all IOU values by project and by participant, we can therefore determine if there is more similarity between projects or between participants.

The qualitative argument that there is greater P50 bias variability between projects is supported by the IOU metrics in Table 3, along with the similar variability of total loss estimates between projects and between participants. Furthermore, there exists far less gross energy bias

TABLE 3 Mean IOU for categorical energy, loss, and uncertainty categories

	IOU mean (projects)	IOU mean (participants)
Gross energy bias[a]	0.26	0.86
P50 bias	0.23	0.64
Total loss	0.43	0.45
Total uncertainty	0.37	0.18
Availability loss	0.74	0.02
Electrical loss	0.90	0.00
Environmental loss	0.54	0.58
Turbine loss	0.65	0.20
Wake effect loss	0.34	0.51
Historical uncertainty	0.50	0.24
Horizontal uncertainty	0.37	0.40
Measurement uncertainty	0.52	0.26
Plant uncertainty	0.73	0.07
Project uncertainty	0.65	0.13
Vertical uncertainty	0.44	0.12

Note: Values range from 0 to 1 and indicate the mean of all pairwise IOU values, calculated from Gaussian fits to the group of submissions (whether by project or by participant). A value of 0 indicates no overlap between the intersection and union distributions, and a value of 1 indicates a full overlap. For each row, we highlight in green the case (either between projects or between participants) where we find more similarity. In cases where there is no clear difference, we highlight both cases in yellow.

[a]Gross energy bias estimates have been scaled relative to the project OA AEP.

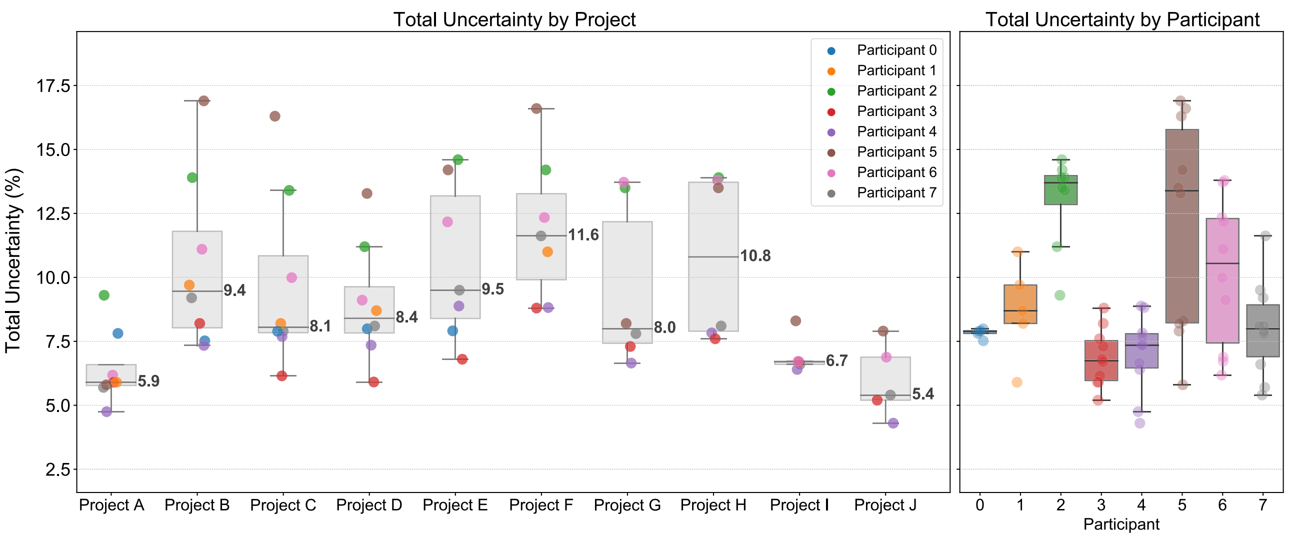

FIGURE 9 Total estimated project uncertainty, organized by project (left) and by participant (right). Numeric values plotted on the left panel indicate the project median uncertainty (in percentage).

(bias from the project's OA AEP) variability on average within a project than between projects. Each project location will inherently have differing wind resource availability, even when considering plants with similar turbine layout and terrain variability. However, there remains a large amount of spread in the gross energy bias within each project (Figure 8), with spreads up to 15% of the project net energy production.

The mean of IOU values of individual loss categories indicates that the only category in which the project-to-project variability is significantly larger is for wake effect losses. This is likely because the layout and distribution of wind directions for each wind plant are different, and therefore, it can be expected that the wake effect losses will inherently have more variability between projects. The striking similarity of consultant estimates of availability, electrical, and turbine performance losses from one project to the next indicates less consideration for project-level variability for these types of losses and potentially a lack of benchmarking against data that could challenge agreed-upon estimates. Environmental losses exhibit a similar amount of variability between projects and between participants. The reason is likely a result of project-level considerations such as icing at northern wind plants combined with biases from individual consultant methodologies.

4.2 | Uncertainty and finance

Every uncertainty category except horizontal extrapolation (directly linked to the wind resource assessment and projects' turbine layouts) shows more variability between consultants than between projects (Table 3). With this regard, we note how the International Electrotechnical Commission (IEC) is currently developing a standard (IEC 61400-15[8]) to gain more consensus and try to reduce this disagreement. Furthermore, each consultant tends to have a high or a low uncertainty across all projects compared with the mean across all consultants (Figure 9). Total uncertainty estimates can range over 10% within a given project, with the average range of over 6%. The total uncertainty affects the width of the predicted AEP curve, which represents the likelihood of the mean annual energy generation over the project lifetime and, by extension, revenue scenarios.

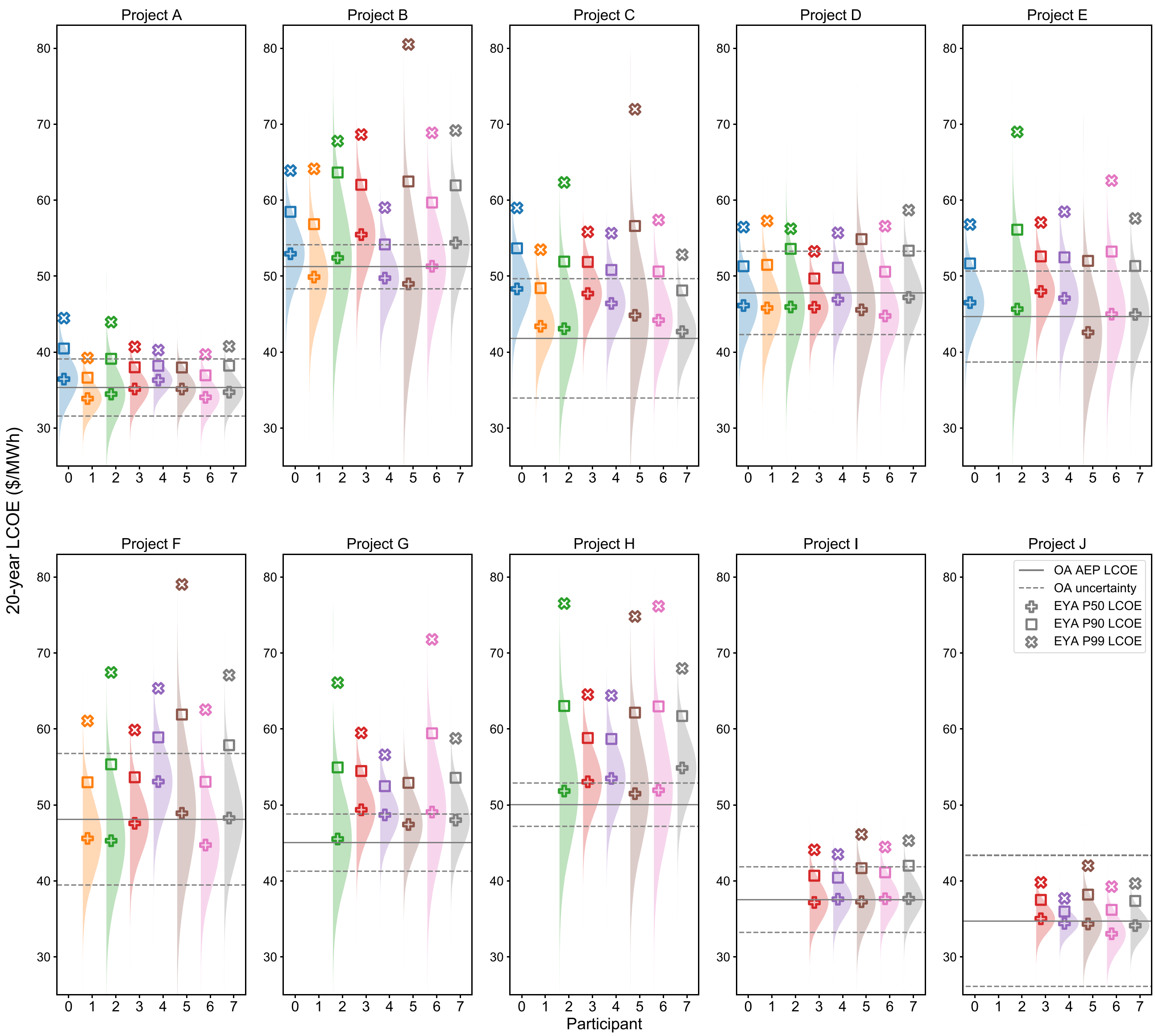

FIGURE 10 EYA-based LCOE distributions per project by participant and corresponding OA LCOE. OA LCOE uncertainty is calculated from the uncertainty (expressed as standard deviation) in OA AEP. The LCOE is calculated by dividing the total operating cost per year by the estimated annual energy production.

Therefore, uncertainty in estimated P50 has crucial financial implications, because larger uncertainties indicate a higher risk of not meeting the expected revenue to cover wind plant capital and operational costs.

To better understand how the EYA P50 and its associated uncertainty may affect the expected revenue, we calculated the estimated levelized cost of energy (LCOE):

$$\mathrm{LCOE} = \frac{(\text{Capital cost} \times \text{Fixed charge rate}) + \text{Annual operational cost}}{\text{Net average annual energy production}}$$

with units of LCOE in \$/MWh. To derive the LCOE for each project from each consultant, we scale the capital and operational costs (given in \$/kW) of a land-based reference project in Stehly and Beiter[19] by the plant capacity and divide by the EYA-predicted P50 (Figure 10). We also include in Figure 10 a measure of the uncertainty in EYA LCOE by calculating it from EYA-predicted P90 and P99 values. While perceived financial risk at the P50 level and the P90 level is more nuanced than substituting the P50 for P90 in this equation, the LCOEs of P90 and P99 are used here to demonstrate a simplified view of the financial implications based on the predicted project uncertainty.

The results in Figure 10 are notable in that for projects for which the estimated uncertainty was low across all consultancies (Projects A, I, and J), both the estimated LCOE and the bias between consultant-predicted LCOE and the LCOE derived from operational data are much lower. Furthermore, these projects exhibit far less spread between consultant groups. For a project that yields more uncertain energy production (Project F), the P50 differences between consultants could translate to about \$10/MWh differences in LCOE.

5 | CONCLUSIONS

Independent analyses of pre-construction estimates from multiple consultancies and over multiple projects are rare in the wind industry.[2,20] The results presented in this paper provide a unique look at the state of modern EYA techniques over a sample of 10 wind plants in North America. Furthermore, we have demonstrated methods for comparing EYA-predicted loss metrics with estimates of those losses from wind plant operational data. Our results indicate that the near-zero mean P50 bias between EYA and operational data is a result of initial EYA overestimation of energy at the turbines combined with an overestimation of downstream losses—a result that is not necessarily due to industry convergence of methodologies for wind resource assessment and loss estimation. Furthermore, large initial disagreement in EYA-estimated gross energy is propagated through to the resulting large spread in EYA estimates of AEP, with up to a 16% range in some of the resulting P50 bias estimates.

While pre-construction estimates have shown improvement in terms of P50 bias from the levels demonstrated by Lunacek et al.,[2] our study indicates where some further improvements could take place. In particular, improvements could be made in reducing the overall spread in EYA gross energy estimates and in the TIE. Gross energy estimates are a direct result of the long-term wind resource assessments, which yield inherently different results depending on, for example, the anticipated interannual variability (suggested by Bodini et al.[21] and Lee et al.[22] to be the largest source of uncertainty). However, modern meteorological campaigns, including the more pervasive use of increased measurement density and remote sensing instruments, may help reduce uncertainty and narrow the spread in consultants' gross energy estimates. Future work may be able to further break down the TIE and loss estimates to quantify wake losses and turbine losses from operational data. Because wake effect losses and turbine performance losses are two of the largest sources of loss in consultants' EYA estimates, estimating operational wake losses and turbine performance losses would help to better determine whether the EYA overestimation of TIE is due to overestimation of the long-term wind resource or to an underestimation of specific energy losses.

After TIE (which includes wake losses and turbine losses), the EYA estimates of the other environmental/unexplained losses are the largest source of variability, when taking the average over all EYAs in our sample, in the relative P50 bias. Because the resulting variability around this loss category increases the spread in P50 bias by 0.8% in our data, improved environmental loss EYA estimation may help to narrow the variability seen in P50 bias. These types of losses may also benefit from improved meteorological campaigns and advanced operational techniques.

Finally, we find a striking lack of agreement in how consultants estimate uncertainty in their predictions, which could have a significant impact on the resulting financing of certain projects. The source of this disagreement is not yet clear, but addressing uncertainty related to the wind resource assessment process and the environmental losses would likely help reduce both spread in P50 bias and the total project uncertainty. For example, projects that exhibit smaller spreads of operational and estimated LCOEs (e.g., Projects A, I, and J) share a common trait of being located in the South Central United States, indicating that uncertainties related to environmental loss estimates (e.g., icing) may play a large role in total project uncertainty. Regardless, the industry would benefit from an agreement on uncertainty quantification methods, as certain consultancies consistently provide a similar magnitude of uncertainty across all projects.

The work presented here suggests that pre-construction estimates may well be converging on P50 biases near zero, but at the expense of overpredicting both the gross energy and downstream losses. While these results provide an in-depth analysis of the gaps between consultant estimates, we were not able to investigate the details of the first step in an EYA—the estimate of the long-term wind resource. We anticipate that future work to estimate observed wake effect losses will help to further understand the sources of error in the pre-construction overestimation of the TIE, but a true analysis of the WRA process, focused on meteorological data[23] (similar to that of Mortensen et al.[20,24,25]), will be required to understand bias and uncertainty in the long-term wind resource estimates. Also, a more detailed look into project-level uncertainty and its effect on financing of wind plants will provide a better understanding of how the large range in consultant estimates can affect the financial risk of developing a site for wind energy production. We anticipate that future work will continue to further understand the sources of bias and variability in pre-construction estimates and how the wind industry can advance methodologies to better estimate energy production for future wind plants. Finally, we note how additional data-sharing initiatives could help reduce the selection bias which might impact limited validation analyses.

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CONFLICTS OF INTEREST

The authors declare no potential conflicts of interest.

AUTHOR CONTRIBUTIONS

Mike Optis and Michael Jason Fields envisioned the analysis. Austin C. Todd ran the analysis for the 10 wind power plants, in close consultation with Mike Optis and Nicola Bodini. All co-authors helped refine the analysis. Austin C. Todd wrote the manuscript, with significant contributions by Mike Optis and Nicola Bodini. All authors reviewed the manuscript.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

The wind power plant data used in this work are proprietary and cannot be shared with the public. The open-source software used to perform wind plant operational analysis is publicly available at https://github.com/NREL/OpenOA.

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ENDNOTE

* OpenOA: https://github.com/NREL/OpenOA.

REFERENCES

1. Global Wind Energy Council. Global wind report 2022, tech. rep., Global Wind Energy Council; 2022.
2. Lunacek M, Fields MJ, Craig A, et al. Understanding biases in pre-construction estimates. *J Phys Conf Ser*. 2018;1037:062009.
3. DNV GL. Wind power project performance white paper. Brazil Wind Power Conference 2020; 2020.
4. Stoelinga M, Hendrickson M. A validation study of Vaisala's wind energy assessment methods. Vaisala White Paper; 2015.
5. AWS Truepower. Closing the gap on plant underperformance: a review and calibration of AWS Truepower's energy estimation methods. White Paper; 2012.
6. UL. 2018 BACKCAST STUDY AND METHODS UPDATE—verifying and updating UL AWS Truepower's methods for performing pre-construction wind energy production estimates. White Paper; 2018.
7. Fields MJ, Optis M, Perr-Sauer J, et al. Wind plant performance prediction benchmark phase 1 technical report. Golden, CO: National Renewable Energy Laboratory; 2021. NREL/TP-5000-78715. https://www.nrel.gov/docs/fy22osti/78715.pdf
8. IEC 61400-15:draft: assessment of site specific wind conditions for wind power stations, standard. International Electrotechnical Commission, in Review; 2020.
9. Perr-Sauer J, Optis M, Fields MJ, et al. OpenOA: an open-source codebase for operational analysis of wind farms. *J Open Source Softw*. 2021;6(58):2171. doi:10.21105/joss.02171

10. IEC 60688:2012: electrical measuring transducers for converting A.C. and D.C. electrical quantities to analogue or digital signals, Standard, International Electrotechnical Commission; 2012.
11. ANSI C12.1-2014: electric meters—code for electricity metering, Standard, National Electrical Manufacturers Association, Virginia; 2014. https://webstore.ansi.org/preview-pages/NEMA/preview_ANSI+C12.1-2014.pdf
12. Craig A. Uncertainty quantification in wind plant energy estimation. AIAA Scitech 2019 Forum; 2019.
13. Gelaro R, McCarty W, Suárez MJ, et al. The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). *J Climate*. 2017; 30(14):5419-5454. doi:10.1175/JCLI-D-16-0758.1
14. Saha S, Moorthi S, Wu X, et al. The NCEP Climate Forecast System version 2. *J Climate*. 2014;27(6):2185-2208. doi:10.1175/JCLI-D-12-00823.1
15. Dee DP, Uppala SM, Simmons AJ, et al. The ERA-Interim reanalysis: configuration and performance of the data assimilation system. *Q J Roy Meteorol Soc*. 2011;137(656):553-597. doi:10.1002/qj.828
16. Hastie TJ, Tibshirani RJ. *Generalized Additive Models*. Routledge; 2017. doi:10.1201/9780203753781
17. Bodini N, Optis M, Perr-Sauer J, Simley E, Fields MJ. Lowering post-construction yield assessment uncertainty through better wind plant power curves. *Wind Energy*. 2022;25(1):5-22. doi:10.1002/we.2645
18. Jaccard P. Nouvelles recherches sur la distribution florale. *Bull Soc Vaud Sci Nat*. 1908;44:223-270.
19. Stehly T, Beiter P. 2018 cost of wind energy review. Golden, CO: National Renewable Energy Laboratory; 2020. NREL/TP-5000-74598. https://www.nrel.gov/docs/fy20osti/74598.pdf
20. Mortensen NG, Nielsen M, Jørgensen HE. Comparison of resource and energy yield assessment procedures 2011-2015: what have we learned and what needs to be done? Proceedings of the EWEA Annual Event and Exhibition 2015 European Wind Energy Association (EWEA); 2015.
21. Bodini N, Lundquist JK, Zardi D, Handschy M. Year-to-year correlation, record length, and overconfidence in wind resource assessment. *Wind Energy Sci*. 2016;1(2):115-128. doi:10.5194/wes-1-115-2016
22. Lee JCY, Fields MJ, Lundquist JK. Assessing variability of wind speed: comparison and validation of 27 methodologies. *Wind Energ Sci*. 2018;3(2): 845-868. doi:10.5194/wes-3-845-2018
23. Clifton A, Smith A, Fields M. Wind plant preconstruction energy estimates. Current practice and opportunities. No. NREL/TP-5000-64735. National Renewable Energy Lab. (NREL), Golden, CO (United States); 2016.
24. Mortensen NG, Ejsing Jørgensen H, Anderson M, Hutton K-A. Comparison of resource and energy yield assessment procedures. Proceedings of EWEA 2012—European Wind Energy Conference & Exhibition European Wind Energy Association (EWEA), Technical University of Denmark, Copenhagen, Denmark; 2012.
25. Mortensen NG, Nielsen M, Ejsing Jørgensen H. *EWEA CREYAP Benchmark Exercises: Summary for Offshore Wind Farm Cases*. Roskilde, Denmark: Technical University of Denmark; 2015.

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