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A Monte Carlo-Based Approach to Assessing Annual Energy Production and Uncertainty

Mike Optis, Senior Scientist, National Renewable Energy Laboratory (NREL)

Motivation and Approach

The industry standard approach to assessing annual energy production (AEP) uncertainty can be limited because of the assumption of uncorrelated uncertainty categories and subjectivity in calculations. A Monte Carlo approach to uncertainty quantification can largely overcome these limitations and provide a more robust assessment of energy uncertainty.

Here, we demonstrate the Monte Carlo approach in the context of AEP estimation using operational data. Monthly net energy production for all reporting wind power plants in the United States was taken from the Energy Information Administration (EIA) 923 database. Atmospheric data from three reanalysis products were also considered. After filtering for wind plants that had at least 8 months of data and moderate-to-strong correlation with all three reanalysis products ($R2 > 0.6$), we assessed 472 wind power plants total.

Table 1. Uncertainty Categories Considered and Their Incorporation under a Monte Carlo Approach

Uncertainty Category	Incorporation under Monte Carlo
Revenue meter accuracy	Sample revenue meter data based on 0.5% uncertainty
Wind measurement accuracy	Consider multiple reanalysis products: • Modern-Era Retrospective analysis for Research and Applications v2 (MERRA-2) • European Reanalysis Interim (ERA-interim) • National Centers for Environmental Prediction v2 (NCEP2)
Wind interannual variability (IAV)	Sample calendar monthly wind speeds based on corresponding monthly uncertainties
Regression model	Sample slope and intercept values from their standard errors and covariance
Windiness adjustment	Sample the number of years to use in the windiness correction (between 10 and 20)

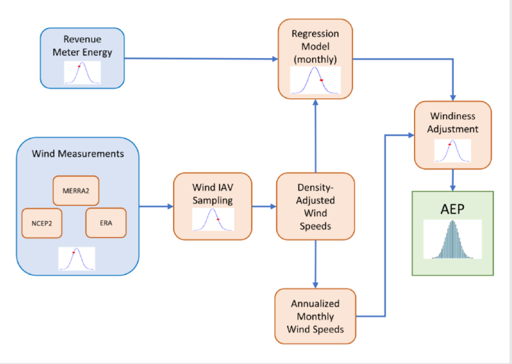

Figure 2. AEP estimation process using operational data under a Monte Carlo approach; source of uncertainty and points of Monte Carlo sampling are denoted by probability distribution images

Figure 2 outlines the process of estimating AEP using operational data under a Monte Carlo approach. Table 1 shows a summary of the uncertainty categories considered and how they are incorporated in a Monte Carlo analysis.

Uncertainty Correlations

- Wind IAV and windiness correction uncertainties are moderately correlated
- Regression and wind measurement uncertainties are weakly correlated
- Wind IAV and regression uncertainties ***appear*** weakly negatively correlated.

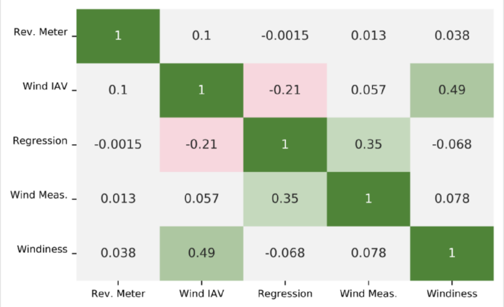

Figure 1. Correlation coefficient heat map between uncertainty categories. Note: "Rev." denotes "Revenue"

Uncertainty Contributions

- Wind resource IAV dominates the uncertainty
- Regression uncertainty is significant
- Wind resource product can be influential
- Windiness adjustment uncertainty is relatively small.

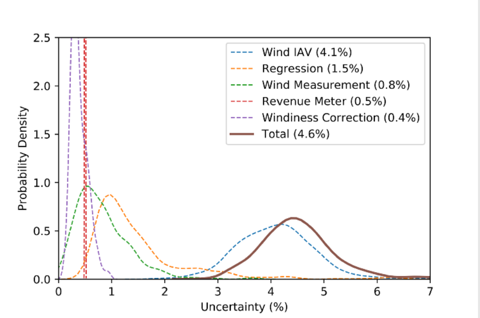

Figure 3. Uncertainty distributions across projects for the different uncertainty categories; mean values across projects are shown in the legend

Regression Uncertainty

Standard error of regression (i.e., residual)	$e_y = \sqrt{\dfrac{\sum(y_i - \hat{y}_i)^2}{n-2}}$
Standard error of slope	$e_a = \dfrac{e_y}{\sqrt{\sum(x_i - \bar{x})^2}}$
Standard error of intercept	$e_b = e_y e_a \sqrt{\dfrac{{x_i}^2}{n}}$

- Standard error of slope and intercept inversely proportional to number of data points (i.e., more data gives lower uncertainty)
- Uncertainty inversely proportional to regression strength
- Explained variance of regression uncertainty improves to 0.85 when considering both regression strength and number of data points.

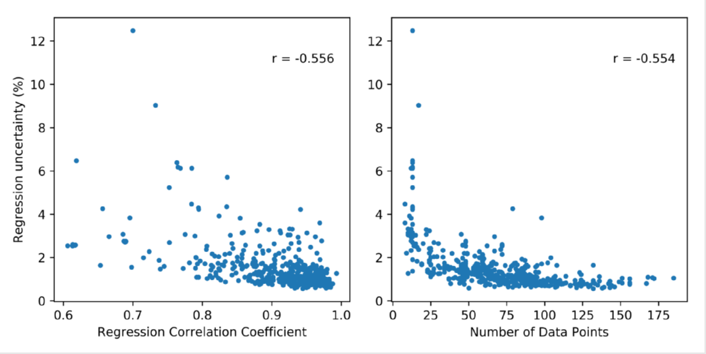

Figure 4. Dependence of regression uncertainty on both the strength of correlation between energy and wind speed and the number of data points

Conclusions

A Monte Carlo approach to assessing AEP not only directly accounts for correlations between uncertainty categories, but also provides quantitative insight into aspects of the AEP process that drive uncertainty (e.g., regression relationship and number of years in windiness correction). Furthermore, the added computational expense of running Monte Carlo relative to the industry standard AEP method is easily managed by a typical computer.

Several additional categories of uncertainty in an operational AEP were not considered because of limited reporting in the EIA-923 database. These categories include reported availability and curtailment uncertainty and various uncertainties introduced through analyst decision-making (e.g., filtering high loss months from analysis and regression outlier detection). Uncertainty in analyst decision-making in operational energy assessments is an active research area at NREL (e.g., Craig et al. [2018][1]). This aspect of uncertainty has, to our knowledge, not previously been explored in the industry.

[1] Craig, A., M. Optis, M. J. Fields, P. Moriarty. Uncertainty Quantification in the Analyses of Operational Wind Power Plant Performance *J. Phys.: Conf. Ser.* ***1037*** *(2018) 052021*

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