Assessing Biases in Pre-Construction P50: A Historical Validation Survey (Session: Open Data Efforts in the Wind Energy Sector and Data Needs)

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Abstract

The pre-constriction energy estimate forms the foundation of the investment business case for wind plants [1]. The pre-construction energy generation of a wind farm is however difficult to estimate and evaluate. This paper presents a methodology to measure the accuracy of the p50 prediction, which we call the Historical Validation Survey (HVS), for several wind farms in the continental United States. Our results indicate that there is a significant bias between predicted and measured energy, even when controlling for factors like commission date. We also find that the results are highly dependent on the assumptions we make during analysis, which we attempt to quantify with a sensitivity analysis using bootstrapping. This method allows the estimation of uncertainty we have in our findings. Future work will focus on quantifying how other assumptions and additional data change the overall evaluation of a wind farm's estimate.

Keywords: *P50, Power production verification, Statistics, Wind resource assessment, WP3 Benchmark*

Introduction

Over estimation of the pre-construction energy production creates substantial financial loss for wind farm owners and investors. At the same time, the wind energy industry as a whole lacks a standard process for verifying pre-construction estimates [1]. We started the Historical Validation Survey (HVS), as part of the U.S. Department of Energy's Performance, Risk, Uncertainty and Finance (PRUF) project, to provide an open and transparent methodology that quantifies the average biases in the current wind resource assessment process.

Data and Methods

The P50 estimate is the most probable annual energy production value that a wind farm should be expected to produce during its lifetime [1]. We collected pre-construction p50 estimates from 59 projects in United States. Some of these projects provided an uncertainty value. Our analysis compares this single, annual value with actual net monthly energy production data provided by the Energy Information Administration (EIA) from 2003 to 2016. We define a Wind Farm Year (WFY) as any given annual data point and a Wind Farm (WF) as the aggregate of WFYs for any individual wind farm. For each WFY, we calculate the percent difference between the EIA energy production data and the p50 estimate, which illuminates bias across all WFYs. We also investigate the overall bias for any single project in our sample (i.e., each WF).

We compare the EIA data with the p50 estimate in three ways: 1) using the raw data, 2) correcting outliers in the raw data, and 3) estimating 20-year production based on a full range of MERRA2 wind data. We refer to each of these as raw, outlier-corrected, and long-term corrected respectively.

Comparing the raw EIA data with the p50 estimate is the most straightforward and unadulterated analysis. The raw EIA data is however not fully representative of the prediction paradigm of interest. Specifically the EIA includes cases of extreme curtailment and availability driven downtime, which are typically outside the scope of prediction. One way to make the EIA data more representative is to model each plant's monthly production against monthly wind data, and then correct points that are statistical outliers. We estimated the wind using NASA's MERRA2 reanalysis dataset and derived the monthly average wind speeds at 80 meters above the surface for each point closest to the EIA wind plant. This is a reasonable estimate for locations where EIA and MERRA2 are close, or where the wind plant is in a region with consistent wind (such as the middle of the country), and a poor estimate otherwise.

Our second analysis method, outlier corrected, uses a simple linear model that estimates monthly power production based on the average monthly wind speed. Points that are two standard deviations from the estimate are considered outliers and are corrected by replacing them with the model's estimate, which includes some variation based on the original data.

For some wind plants, there is also a limited amount of EIA data. Our third method, long-term corrected, estimates the wind plants' production for the last 20 years by filling in missing values with an estimate from a linear model. This method uses a combination of outlier-corrected values for the years we have data, and combines this with fabricated data from the linear model for the remaining years.

The outlier- and windiness-corrected analysis make several assumptions: the MERRA2 wind data is a close proxy for the actual monthly wind, the EIA data is a good estimate of the wind plant's production, and the linear model is a reasonable estimate of how wind and energy are related.

We address the first assumption by only including wind farms that have a stronger than 0.7 coefficient of determination (R^2) between energy production and wind speed. In other words, if there is a weak correlation between power and wind then we discard the wind farm from our results.

The other two assumptions are more difficult to address. Assessing a wind plant's performance based on a single year of data, means that we have a limited number of data points, which could have a large impact on the accuracy of the model we create. We quantify this uncertainty by bootstrapping our overall results. This involves repeated resampling of data taken from our original EIA data set. This gives us an idea of how sensitive our overall results are to the modeling assumptions.

Metric

Each wind farm year is evaluated using the percent difference from the p50 estimate. This makes it possible to compare wind farms of different magnitudes.

Results

Our results indicate that there is a significant bias when looking at all projects across the range of analysis methods we developed for HVS. There can be anywhere between a – 8.0% to -10.0% difference in the actual production and estimated p50 values, The sensitivity of our results to the underlying data is also small. We computed a standard deviation of less than 1% on our overall results using our bootstrapping method.

Comparing pre- and post-2011 wind farms is less clear. In general, post-2011 bias values are lower, but we find that there is no statistically significant difference between the two groups when looking at the raw or outlier-corrected data at either the WFY level or WF level. However, windiness corrected results reveal that the post-2011 bias is significantly different at the WFY level. In this analysis, the long-term corrected model tends to push the two groups further apart. The cause of this separation is a goal for future work.

Conclusions

We conclude that systematic negative bias of pre-construction energy production is evident in the EIA data regardless of the date of commission, the locations of wind farm, or the type of analysis used to reach the conclusion.

These benchmarking results lay the foundation for the overall PRUF project and provide a methodology for conducting an evaluation of pre-construction wind farms, which includes some uncertainty quantification of the overall results.

It is clear from this analysis that data quality and assumptions play an important role in the conclusions we draw from our analysis. Future work will utilize a more robust data set and address a larger set of assumptions to understand the sensitivity of this greater set of inputs.

References

1. Clifton, A., A. Smith and M. J. Fields, 2016: Wind Plant Preconstruction Energy Estimates: Current Practice and Opportunities. NREL Technical Report, TP-5000-64735.