Tackling uncertainty in energy yield forecasts

Forecast uncertainty | The uncertainty in energy yield forecasts is frequently underestimated. Keith McIntosh of PV Lighthouse describes the reasons why, the ramifications, and the steps that the PV industry is taking to improve forecasts

Credit: Tilt Renewables

PV yield forecasts are widely considered to be inaccurate, partly because they underestimate uncertainty

Yield forecasts are an integral part of the PV industry. They inform decision makers at many stages of a solar project, from prospecting to design, financing, commissioning and operations.

Trustworthy forecasts convey many advantages. They allow a developer to better optimise the design of their plant, like sizing the inverters or deciding what land to grade. They give lenders and investors more confidence in future revenues, leading to better financial terms like a lower interest rate or a larger loan. They reassure project builders (EPCs) that a well-constructed plant will pass its commissioning tests. And they help operators assess whether a plant is behaving to expectation and how maintenance schedules might be optimised. Thus, small improvements to yield forecasting have significant financial benefits, particularly in relation to the enormous solar projects of the modern day.

The importance of yield forecasts is evident in the scale of the forecasting industry. There are scores of engineering firms with forecasting specialists, there are about ten software providers that make ever-more sophisticated programs to predict yield, there are a half-dozen meteorology companies predicting the weather for solar applications, and there are many metrology companies making instruments to monitor weather and PV modules. Moreover, most solar conferences now contain sessions solely focused on yield forecasting; in fact, an annual workshop, the PVPMC, is devoted entirely to this field of research.

And yet, despite their importance, and despite the huge resources dedicated to them, yield forecasts are widely considered to be inaccurate.

Forecast uncertainty

A yield forecast constitutes a prediction of the sunlight that will fall upon a solar power plant (the input energy) and a prediction of how much of that sunlight will be converted into electricity (the plant efficiency). Combined, these predictions provide a forecast of the electricity sold to the grid (the energy yield).

This is not an easy task. Consider the solar irradiance: an exact energy forecast for a solar plant requires a perfect prediction of the future sunlight at any point in time for, say, 30 years of operation. That's clearly impossible. By itself, the year-to-year variability in annual irradiance lies between about ±4% and ±8% at most sites (±two sigma); then there is the day-to-day variability, where the irradiance during one overcast day might be 80% less than during the previous sunny day; and there is the minute-to-minute variability, where the solar irradiance might suddenly halve when the sun ducks behind a cloud.

This high variability poses several complications for forecasters, such as how many years of historical data are required to estimate the future. And how will climate change affect irradiance? And, relevant to this article, how should the uncertainty in the solar irradiance be incorporated into a yield forecast?

Predicting irradiance is hard enough, but that is just one of a plethora of uncertainties. Other major sources include module degradation, shading, the amount of dirt falling on the modules (soiling), the energy that cannot be sold when a plant is disconnected from the grid (curtailment) and the fraction of power lost due to malfunctioning inverters and other components (availability). Moreover, the equations inherent to forecasters' models are approximations of the real world that introduce yet more uncertainties (model error).

Thus, a yield forecast is not credible without a rigorous analysis of its uncertainty.

Probability distributions

Since forecasters cannot predict yield exactly, they instead provide yield probabilities, where the forecast is almost always represented as a Gaussian distribution—also called a normal distribution—as illustrated in Figure 1.

These probability distributions are often distilled in terms of P-values, which quantify the likelihood that a certain yield will be exceeded. For example, if a forecaster assigns a P95 of 200MWh, the forecaster is saying that they are 95% confident that the plant will produce at least 200MWh. (Mathematically speaking—and