Solar Capacity Test Case Study – Uncertainty Calculation

Jeffery Newmiller, Principal Engineer - DNV
Kyle LaBrosse, Senior Project Engineer – Invenergy

Introduction

Solar capacity tests are a critical tool for validating plant performance. However, inherent uncertainties in capacity testing – stemming from sensor accuracy, irradiance variability, temperature effects, and differences in methods – can significantly impact the reliability of solar capacity test results. This uncertainty is the reason why many solar capacity tests have a passing threshold of 97% or 98%, rather than 100%. Despite this, most projects do not perform a project-specific capacity test uncertainty analysis. Invenergy and DNV present a case study of a utility-scale solar capacity test uncertainty calculation, the major sensitivities, and lessons learned. This was the first calculation of its kind for DNV and Invenergy.

Method

The studied Solar Capacity test utilizes linear regression of observed data to form a best-fit line relating temperature-adjusted power to irradiance and then uses the obtained equation to estimate temperature-adjusted AC output power at a plane-of-array irradiance of $1000\ \mathrm{W/m^2}$ and 25 °C cell temperature. This procedure works with field measurements subject to typical measurement errors characterized by real-world probability distributions (uncertainty and variability) and arrives at an estimate of capacity that will in general be different from an ideal result. The uncertainty of the capacity test estimate is defined as the statistical probability distribution of possible answers that may be obtained using the procedure. In this case we identify the spread of this probability distribution that encompasses the central 95% probability range of possible answers, where the spread is expressed as a percentage relative to the mean of possible answers.

DNV used a Monte-Carlo simulation to characterize the impact of the measurement uncertainties. A PVsyst-derived typical-year dataset accounting for linear and non-linear energy conversion mechanisms is treated as "true parameter values" from a window of time considered similar to a day of the year. A randomly-sampled set of error values from a defined distribution for each key measurement is added to the "true" data to simulate imperfect measurement. The capacity test procedure is then run using this "imperfect" data. The weather and measurement randomization and regression-based capacity prediction steps are repeated with larger iteration counts until the results appear to stabilize. The impact of choosing subsets of that data with different errors and at different times of year (ranges of input data) can be observed in the obtained results.

Uncertainty Sources

Instrumentation
- Pyranometers
- Temperature Sensors
- Plant Revenue Meter

Installation Impacts
- Soiling - Temporal
- Soiling - Calibration
- Soiling - Spatial
- Non-uniform Irradiance

Other
- Module Temperature Coefficient
- Tracking
- Backtracking

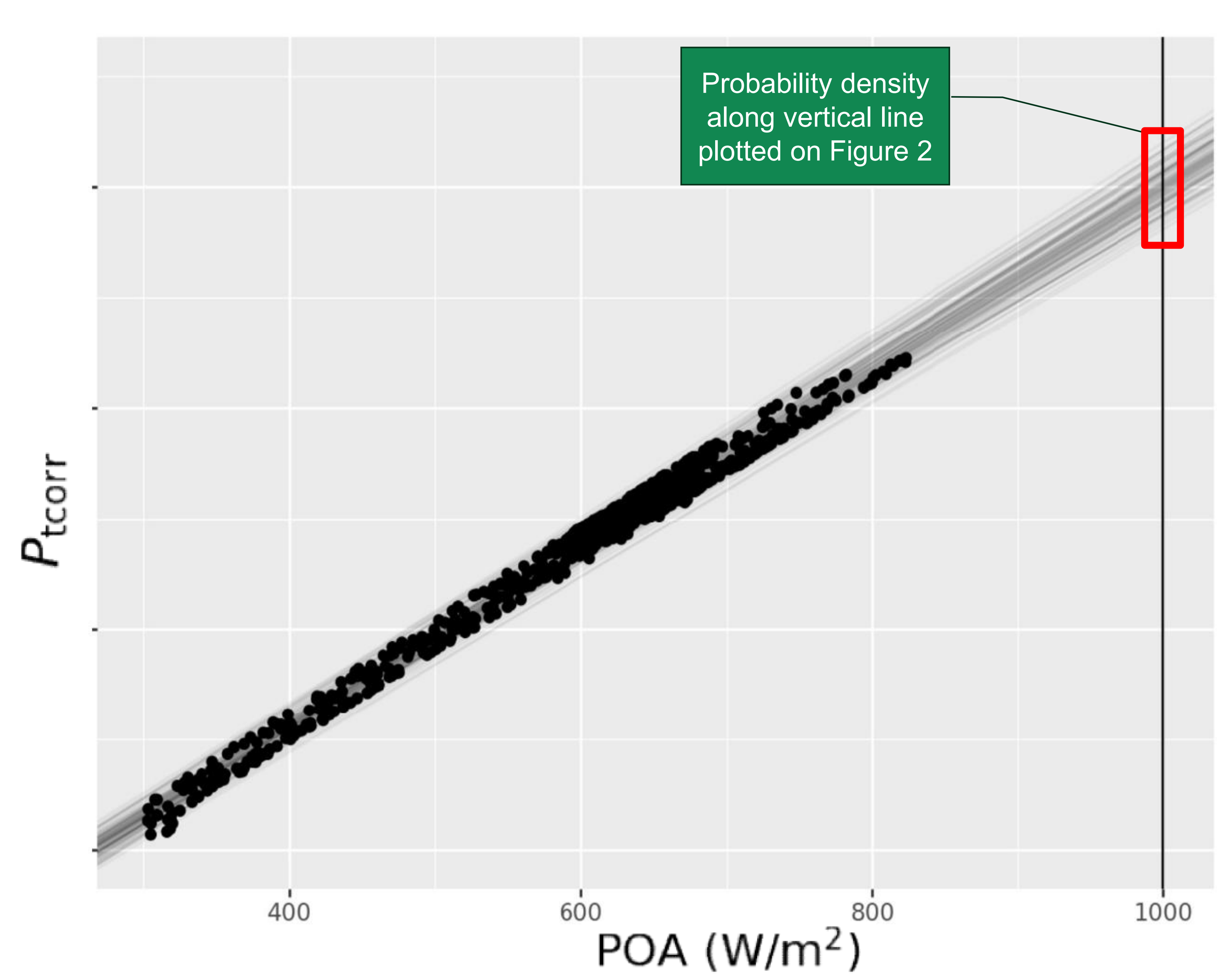
The factors listed above are combined as sum-of-variance among similar sensor/error type categories to reduce the number of MC inputs, and the square root is taken to obtain effective input P95 spread values by category, where Table 1 specifies the P95 input spreads used for the shown simulation. This site involved a single-axis tracker and required a module temperature-based extrapolation to STC.

Input	Back-tracking	Tracking	Multiplier	Offset
GlobInc	2.0°	2.0°	0.023	15.0 W/m²
T_m				0.3 °C
C_t				0.0003 1/°C

*GlobInc = POA irradiance, T_m = measured temperature, C_t = temperature coefficient

Table 1. Two-sided P95 Uncertainties of calibration terms used in Monte Carlo simulations

Simulation Results



*P_{tcorr} = Plant Output Temperature-Corrected AC Power

Figure 1. Sample lines of best fit for various measurement error combinations

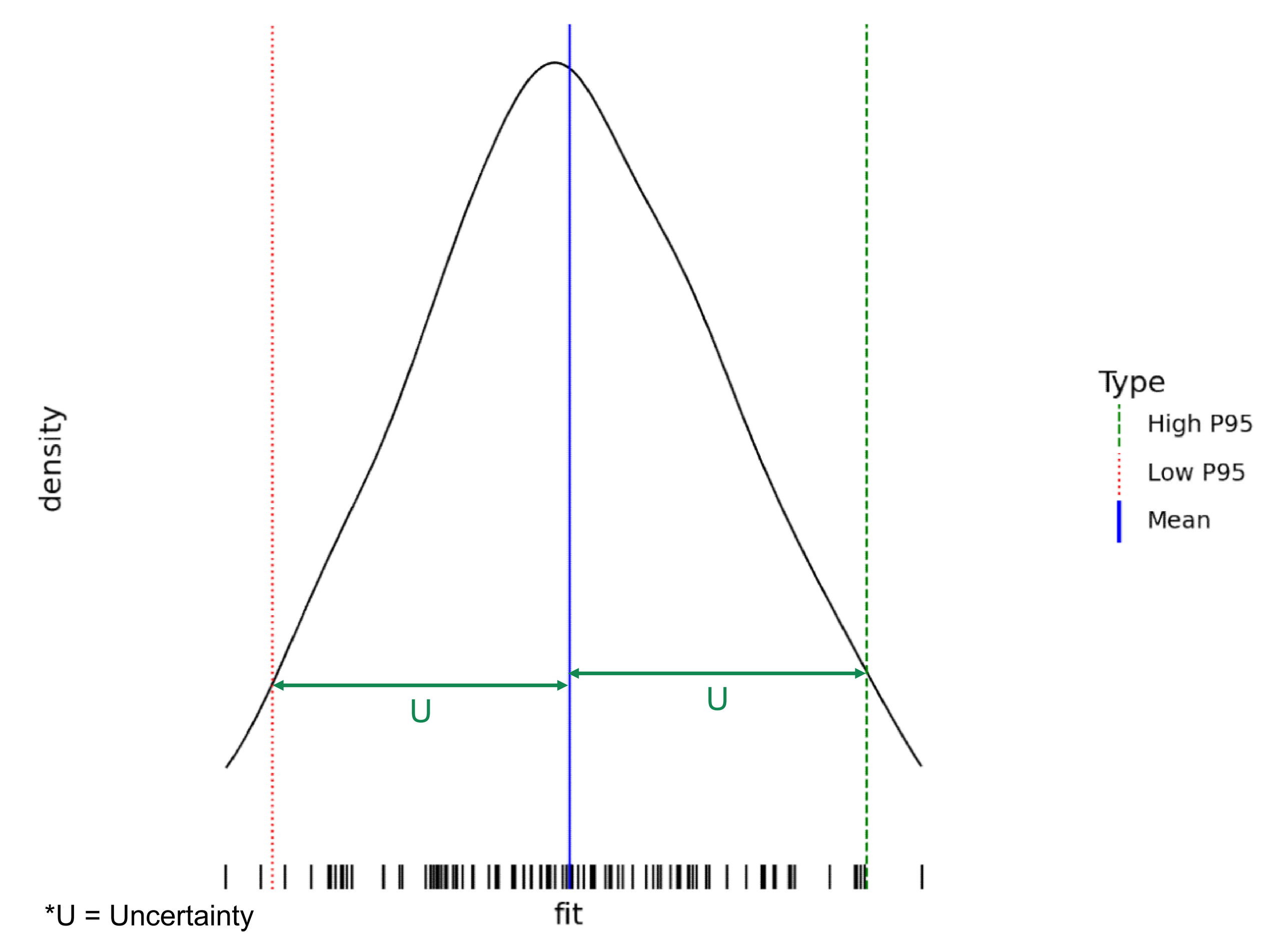


Figure 2. Probability density plot of sample of simulated capacity result for various measurement error combinations

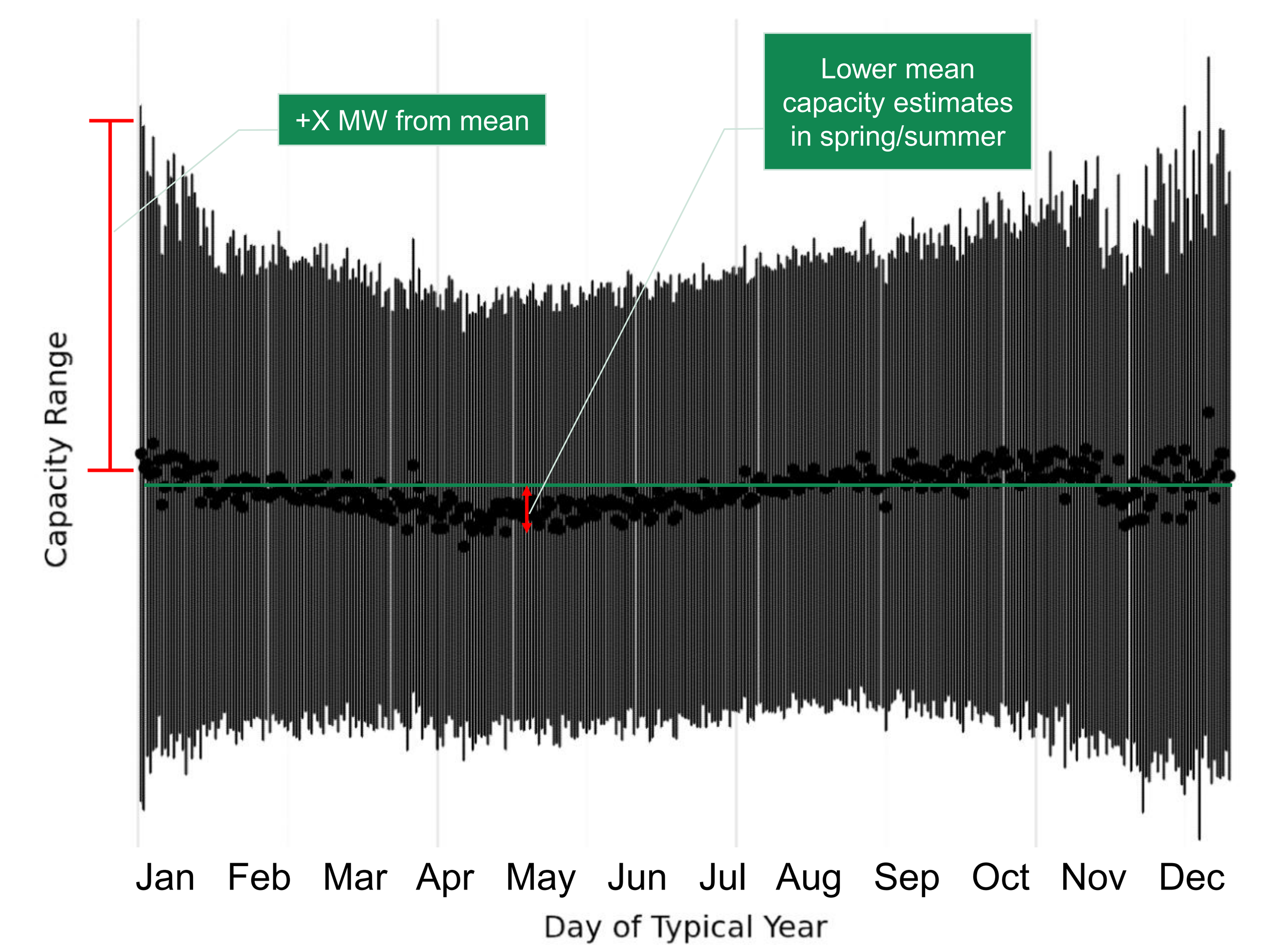


Figure 3. Extrapolated capacity test uncertainty due to measurement uncertainty and weather variability

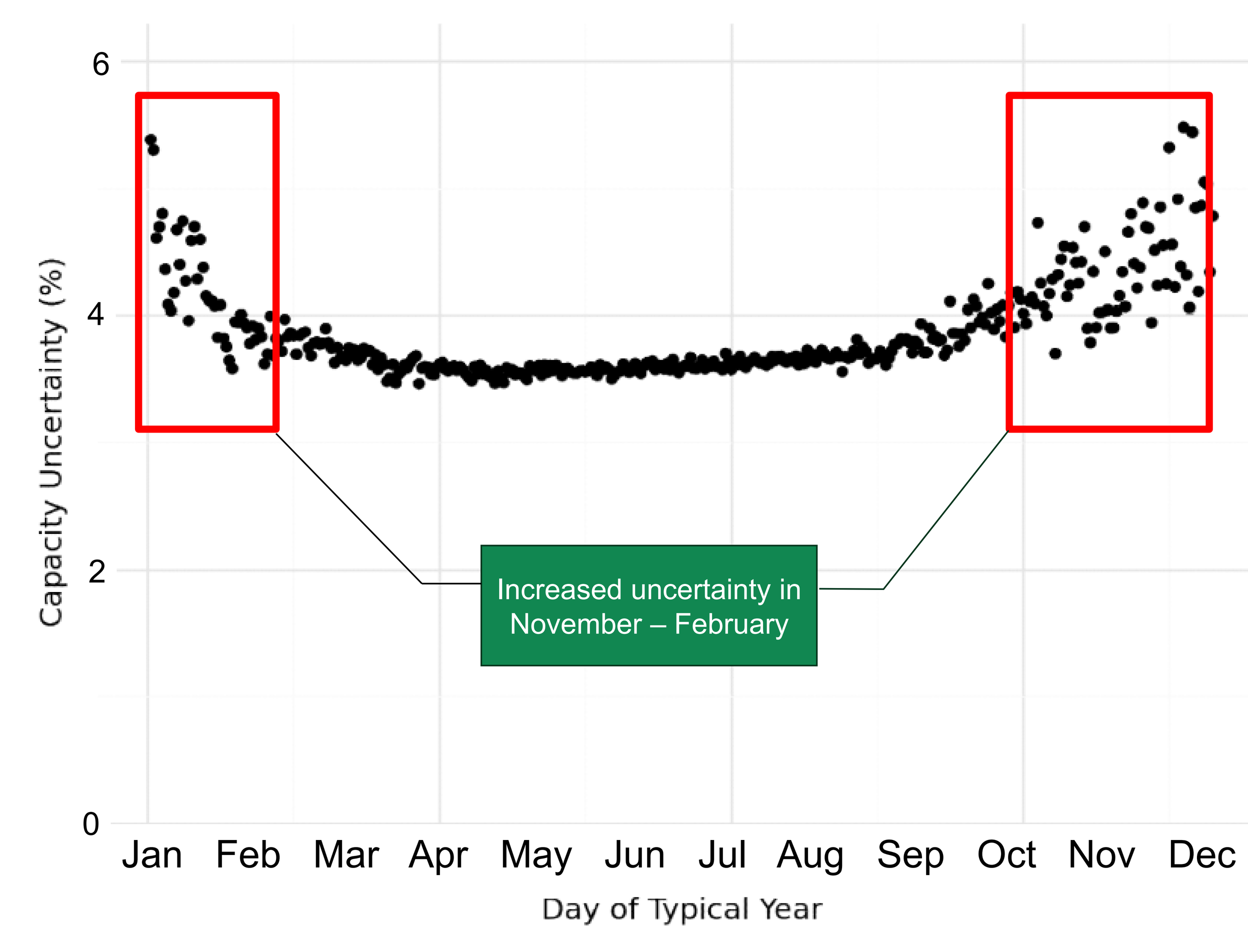


Figure 4. Extrapolated capacity test relative uncertainty due to measurement uncertainty and weather variability

Discussion

Figure 1 shows an example set of 150 points overlaid with the regressions of temperature-corrected power versus plane-of-array irradiance along with 100 regression lines obtained by adding 100 sets of errors to the sample data. The regressions show that some of the spread of capacity estimates is due to extrapolation error as the STC reference conditions are rather different than the "measured" conditions, but there is visible spread in regression-line-predicted power throughout the irradiance data range as well.

Figure 2 shows the distribution of the 100 results shown in Figure 1 along the $1000\ \mathrm{W/m^2}$ vertical line with a kernel-based probability density estimate ("smoothed histogram"). Since only 100 simulations are represented here, the distribution is lumpy.

There is a seasonal component to the uncertainty of a capacity test result. One mechanism driving this is the fact that pyranometer misalignment with the array has a small impact when the direct sunlight incidence angle is small (nearly perpendicular to the array surface) but an increasingly large impact as the incidence angle increases such that the uncertainty results vary seasonally as the average daily sun elevation changes. In addition, wintertime irradiance values tend to be reduced by comparison with summertime, so the capacity estimate distribution is subject to more extrapolation spread along the perturbed regression lines from the measured data points to the STC irradiance reference conditions in winter than in summer.

Figure 3 shows the estimated mean of all capacity estimates and P95 spread for each center day of the year. Accuracy is noticeably improved in the summer. Note that there is a bias in winter toward higher estimates, likely due to extrapolation to high irradiance from lower power outputs where tare losses cause the power to droop below a straight line from the origin.

Figure 4 presents the uncertainty from Figure 3 expressed as a percent of the mean estimate. The increased spread in the winter is due to increased extrapolation from smaller power values, higher sensitivity to orientation errors, and the fact that some of the sources of error do not decrease in proportion to the power/irradiance, so the relative errors even at low power increase.

Conclusion

While uncertainty results will vary based on factors including sensor selection, location, and test method, the range of uncertainty demonstrated in this case study highlights the value of executing project-specific uncertainty analyses, particularly when accounting for seasonal variations in test conditions or estimating risk in contractual minimum thresholds.

DNV

Invenergy