

Abstract

The capacity test is a widely accepted method for evaluating whether a system, during or after its commissioning phase, is capable of delivering the energy it was designed to produce.

It involves comparing the system's **measured production**—as a function of plane of array (POA) irradiance, air temperature, and wind speed—with the **target production**, which is also modeled based on those same inputs. The calculation uses a linear regression with four coefficients (a1–a4) and is referenced to a set of *reporting conditions* for POA irradiance, air temperature, and wind speed.

However, both the measured and target capacity values are estimates of system capacity under *reporting conditions*. Because these are estimates, there is always some level of uncertainty involved.

According to the ASTM E2848-13 standard, the typical uncertainty of a capacity test ranges between **3.5% and 7.5%**, though this can vary depending on the test conditions—particularly the POA irradiance levels.

In general, **higher irradiance and more stable weather conditions** during the test, along with having sufficient data points under such conditions, result in **lower uncertainty**. Conversely, **low irradiance and/or unstable conditions** in the test dataset will lead to **higher uncertainty** in the estimated capacity.

In our experience, we have observed uncertainty values ranging from **approximately 1% to 30%**. Capacity test results with high or out-of-range uncertainty values are not recommended for assessing system performance.

Uncertainty:

Since capacity test results are based on an **estimation of system capacity under reporting conditions**, there is inherent uncertainty in the calculation.

The **main contributors** to this uncertainty are:

- Variability in POA irradiance, air temperature, and wind speed across the site** – affects the measured dataset.
- Uncertainty in the linear regression model** – affects both the measured and target capacity estimates.

Uncertainty is typically categorized into **Type A** and **Type B**:

- Type A uncertainty** is evaluated through statistical analysis of repeated observations.
- Type B uncertainty** is evaluated by other means, such as instrument specifications, calibration certificates, or prior knowledge.
- Standard Uncertainty:**
The result of evaluating uncertainty from either **Type A** (statistical analysis) and/or **Type B** (non-statistical sources), expressed as a standard deviation.
- Combined Standard Uncertainty:**
The overall uncertainty obtained by combining **all individual Type A and Type B standard uncertainties** using the root-sum-square method. It represents the total uncertainty associated with a measurement result before applying any coverage factor.
- Expanded Uncertainty:** Expanded uncertainty is the quantity that defines an interval around a measurement result, within which a large portion of the distribution of values reasonably attributable to the measurand is expected to lie.

Error vs. Uncertainty

These are **distinct concepts** and should not be used interchangeably:

- Error** is the difference between a measured value and the true value.
- Uncertainty** represents the **doubt** about how close a measurement or an estimate is to the true value.

Uncertainty Estimation Methods

Uncertainty in an estimated value can be evaluated using one of the following methods:

- GUM Framework (Guide to the Expression of Uncertainty in Measurement):** Provides an **approximate** combined uncertainty using sensitivity coefficients and standard uncertainties.
- Analytical Method:** Provides **exact** expressions for uncertainty when the mathematical model allows it.
- Monte Carlo Method:** Uses random sampling to simulate uncertainty with a **controllable level of numerical accuracy**.

In this poster, the GUM uncertainty framework has been applied.

Types of Errors

- Random Error:**
Caused by unpredictable changes over time or location. These errors lead to variations in repeated measurements but tend to cancel out when averaged over many observations.
- Systematic Error:**
Caused by consistent, repeatable influences that bias the result in a particular direction. If known, these effects can be corrected using appropriate correction factors. After correction, the remaining systematic error is assumed to have zero mean.
- Classification of Uncertainty Components:**
Uncertainty components are sometimes labeled as "random" or "systematic," based on the type of error they originate from. However, this labeling can be ambiguous. A component considered "random" in one context may behave as a "systematic" component in another—for example, when a previous measurement is reused as an input in another calculation.

Uncertainty – Target Dataset

Main Contributor:

- Uncertainty from linear regression:**
Since the target capacity is derived using regression coefficients and a defined set of reporting conditions, the primary uncertainty arises from the uncertainty of the regression model itself.

Note:
There is **no measurement uncertainty** in the target dataset, as it is generated by an energy model rather than physical measurements. Additionally, the input conditions (POA irradiance, air temperature, and wind speed) are **assumed uniform across the site**, so no spatial variability is introduced.

Uncertainty – Measured Dataset

Main Contributors:

- Measurement uncertainty:**
Arises from instrument accuracy, calibration, and environmental factors affecting the sensors (e.g., POA irradiance, air temperature, and wind speed).
- Variability between multiple measurements:**
If multiple sensors are used (e.g., multiple irradiance sensors or weather stations), their differences introduce additional uncertainty due to spatial variation across the site.
- Uncertainty from linear regression:**
The process of fitting the measured data to the regression model introduces uncertainty in the estimated capacity under reporting conditions.

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Target Capacity

Combined Standard Uncertainty:

Step 1: define 'Measurement function':
 $P = E(a_1 + a_2E + a_3T + a_4WS)$

Step 2: calculate estimate $x_1, \dots, x_n$:
 $E_{RC} = T_{RC} - WS_{RC}$
 $a_1 = a_2 = a_3 = a_4$

Step 3: Not Applicable

Step 4-5: Not Applicable

Step 6: calculate the standard uncertainty:
 $u(y) = u_{\text{regression}} \text{ (Standard Error)}$

$$RSS = \sum_{i=1}^n (y_i - \hat{y}_i)^2$$
$$u_{\text{regression}} = s = \sqrt{\frac{RSS}{n - m}}$$

n: Number of Data Points
m: 4 (Number of fitted parameters)

Step 7: estimate y: estimate **Target Capacity** at reporting condition

Step 8: Not Applicable

Step 9: determine coverage probability:
 $p_{95}: \alpha = 0.05$

Step 10: determine the effective degrees of freedom:
 $\nu_{eff} = n - m$
n: Number of Data Points
m: 4 (Number of fitted parameters)

Step 11: determine coverage factor k:
 $k = t_{1-\frac{\alpha}{2}, \nu_{eff}} = t_{0.975, \nu_{eff}}$

Step 12: calculate the expanded uncertainty:
 $U_{95} = k \times u(y)$

Step 13: calculate the coverage interval:
Estimated **Target Capacity** $\pm U_{95}$

Measured Capacity

Combined Standard Uncertainty:

Step 1: define 'Measurement function':
 $P = E(a_1 + a_2E + a_3T + a_4WS)$

Step 2: calculate estimate $x_1, \dots, x_n$:
 $E_{RC} = T_{RC} - WS_{RC}$
 $a_1 = a_2 = a_3 = a_4$

Step 3: calculate standard uncertainties:
 $Rel_i = \frac{\text{std dev across sensors}}{\text{mean across sensors}} \text{ (QTY > 1)}$

$Rel_i = \frac{\text{Standard deviation over time}}{\sqrt{n}} \text{ QTY = 1}$

$u(x_i) = \text{mean } Rel_i \times x_{i,RC}$
 $u(P) = \text{Measured Capacity} \times \text{Revenue Meter Uncertainty}$

Step 4-5: generate partial derivatives of model:

$$c_E = \frac{dP}{dE} = a_1 + 2a_2E + a_3T + a_4WS$$
$$c_T = \frac{dP}{dT} = a_3E$$
$$c_{WS} = \frac{dP}{dWS} = a_4E$$
$$c_P = \frac{dP}{dP} = 1$$
$$\bar{c}_{E,T,WS} = \frac{1}{n} \sum_{i=1}^n \bar{c}_{E,T,WS}(i)$$

Step 6: calculate the standard uncertainty:
 $u(y) = \sqrt{(c_E \times u(E))^2 + (c_T \times u(T))^2 + (c_{WS} \times u(WS))^2 + (u(P))^2}$

Step 7: estimate y: estimate **Measured Capacity** at reporting condition

Step 8: determine degrees of freedom $\nu_1, \dots, \nu_N$:
 $\nu_i = \text{Number of Data Points} - 1 \text{ (i: POA, WS, T)}$
 $\nu_P = \infty$

Step 9: determine coverage probability:
 $p_{95}: \alpha = 0.05$

Step 10: determine the effective degrees of freedom:
Welch-Satterthwaite
 $\frac{u(y)^4}{\sum \frac{(c_i \times u(x_i))^4}{\nu_i}}$

Step 11: determine coverage factor k:
 $k = t_{1-\frac{\alpha}{2}, \nu_{eff}} = t_{0.975, \nu_{eff}}$

Step 12: calculate the expanded uncertainty:
 $U_{95} = k \times u(y)$

Step 13: calculate the coverage interval:
Estimated **Measured Capacity** $\pm U_{95}$

Total Combined Standard Uncertainty

$$u_n(y) = \sqrt{(\text{Target_Uncertainty})^2 + (\text{Measured_Uncertainty})^2}$$

Expanded Uncertainty

$$U_{95} = \frac{\text{Measured_Capacity}}{\text{Target_Capacity}} \pm u_n(y)$$

Conclusion

- Evaluating the uncertainty in capacity calculations offers a robust method to validate result accuracy. Relying solely on the POA vs. P graph can be deceptive.
- The primary driver of test uncertainty is weather—especially plane-of-array (POA) irradiance.
- Since it isn't always possible to run tests under perfectly stable conditions, quantifying uncertainty provides a reliable way to ensure results remain within an acceptable uncertainty range.
- While uncertainties below 3.5% are ideal, a maximum measured uncertainty of up to 7.5% can still be used to confirm that a test was performed under acceptable conditions.

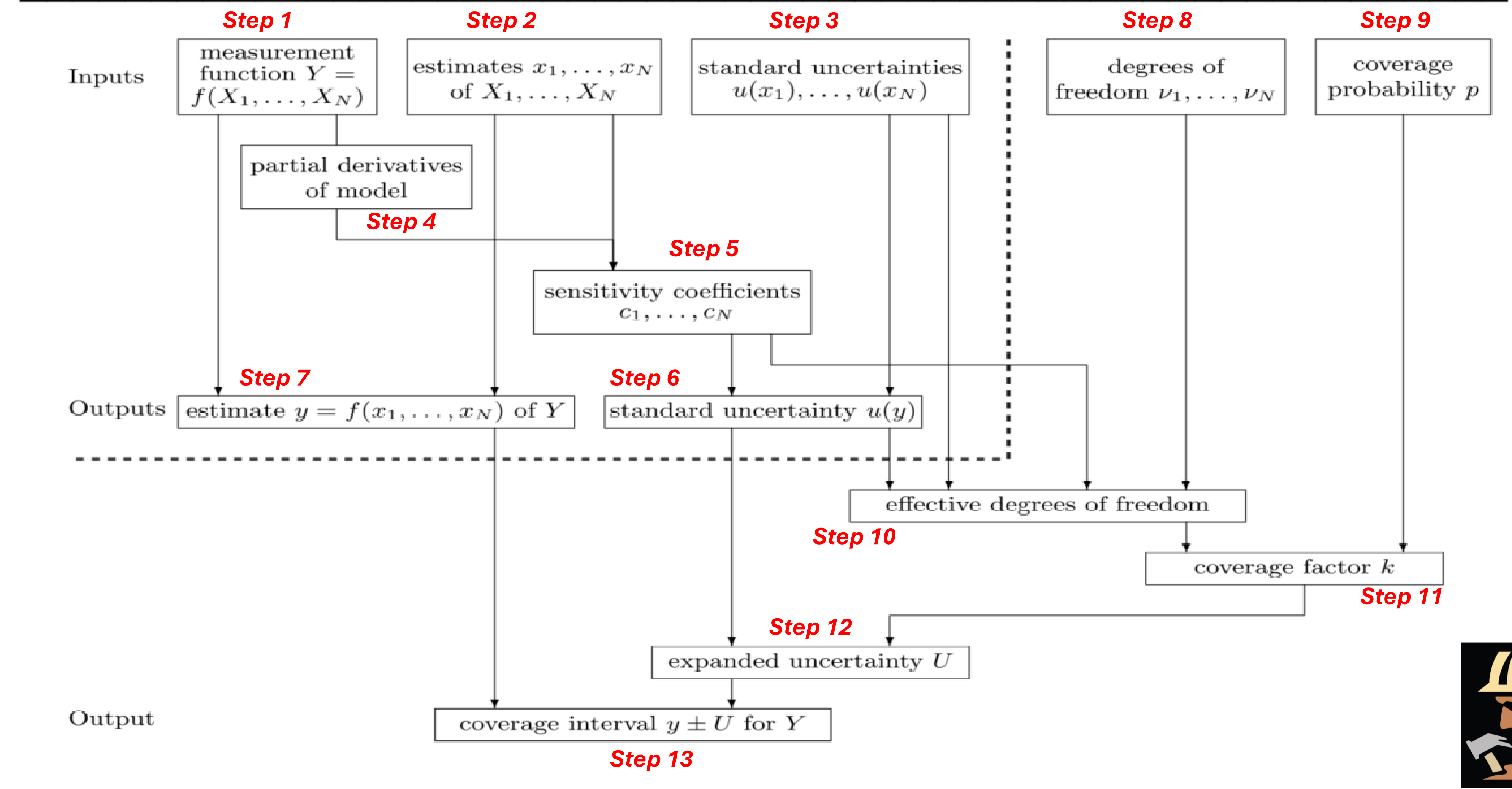
Recommendations

- The best way to run the capacity test is to follow ASTM E2848-13.
- Additional filtering—such as a minimum irradiance threshold or the *optional* filters outlined in the standard—can make testing more challenging, especially for systems with high DC:AC ratios.
- Report the Expanded Uncertainty per the ASTM E2848 in the Capacity Test Report.
- We recommend applying these additional filters only if testing per the standard without them results in an uncertainty above 7.5%.

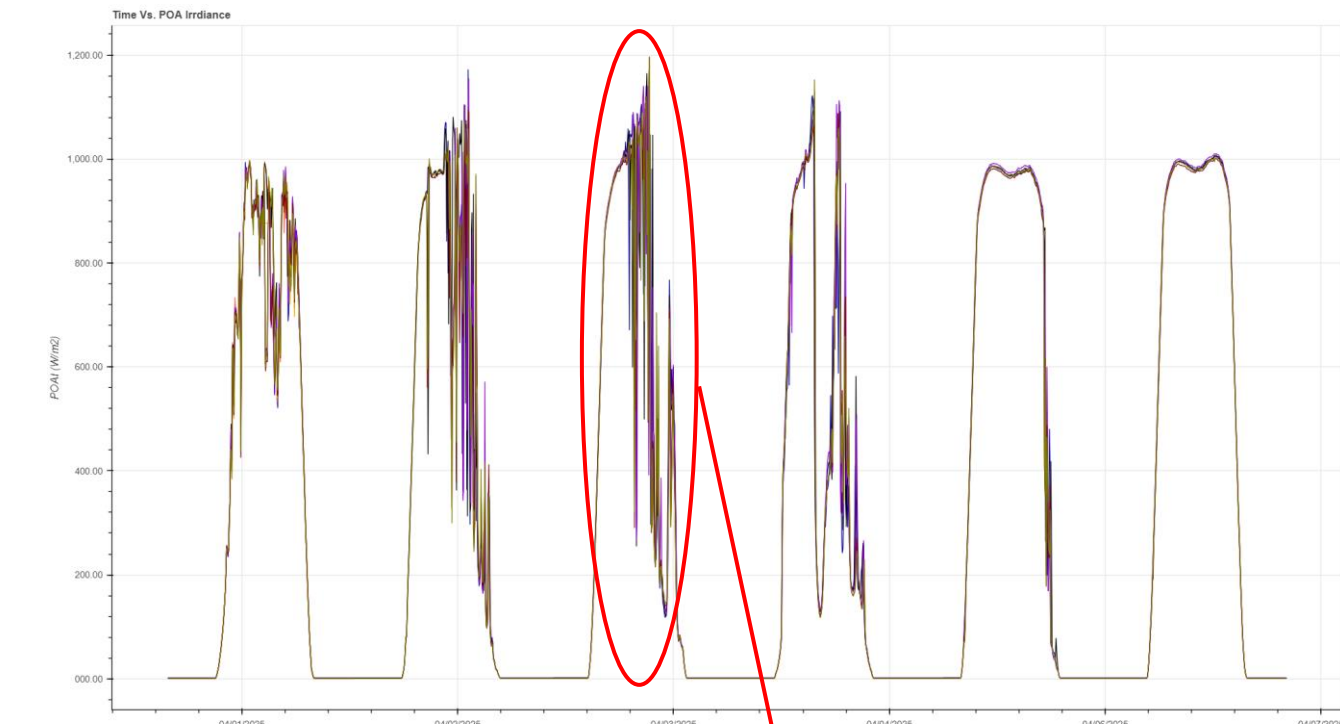
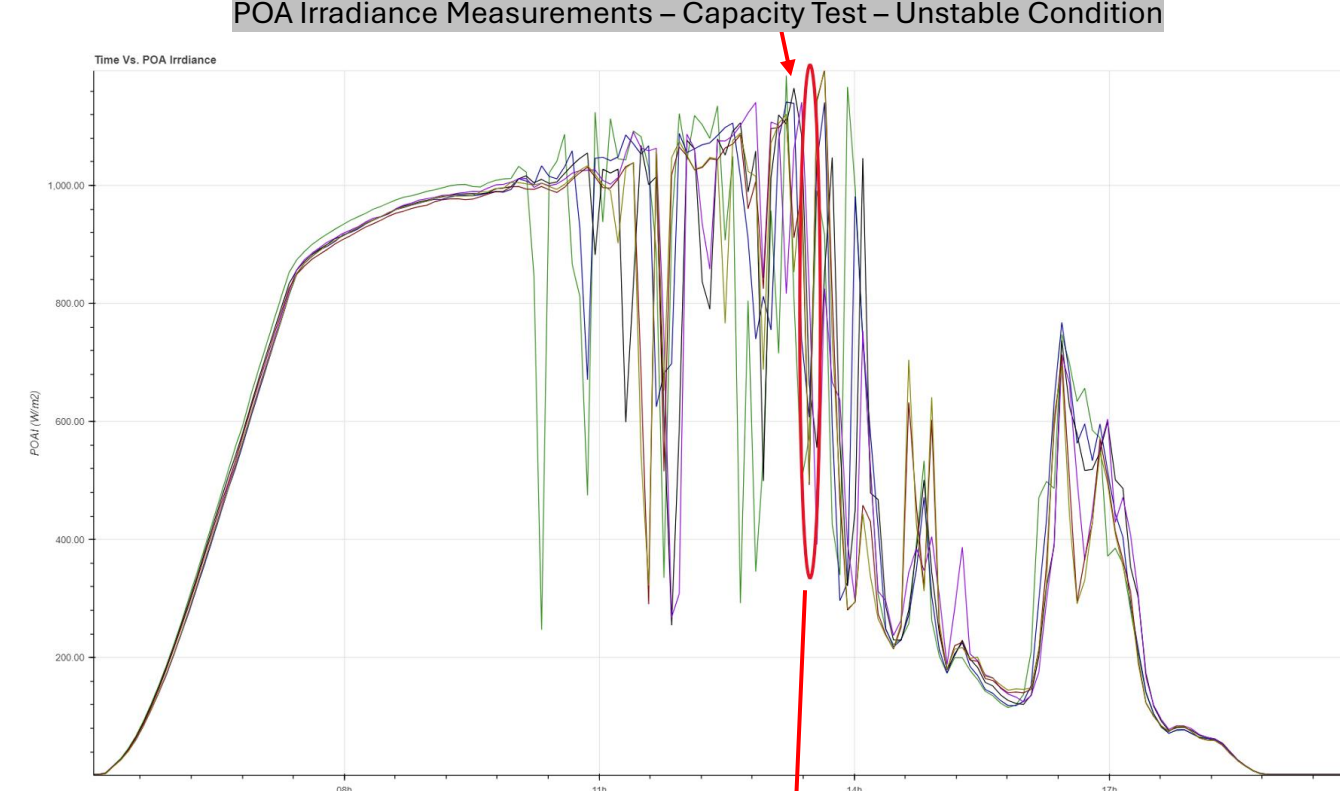
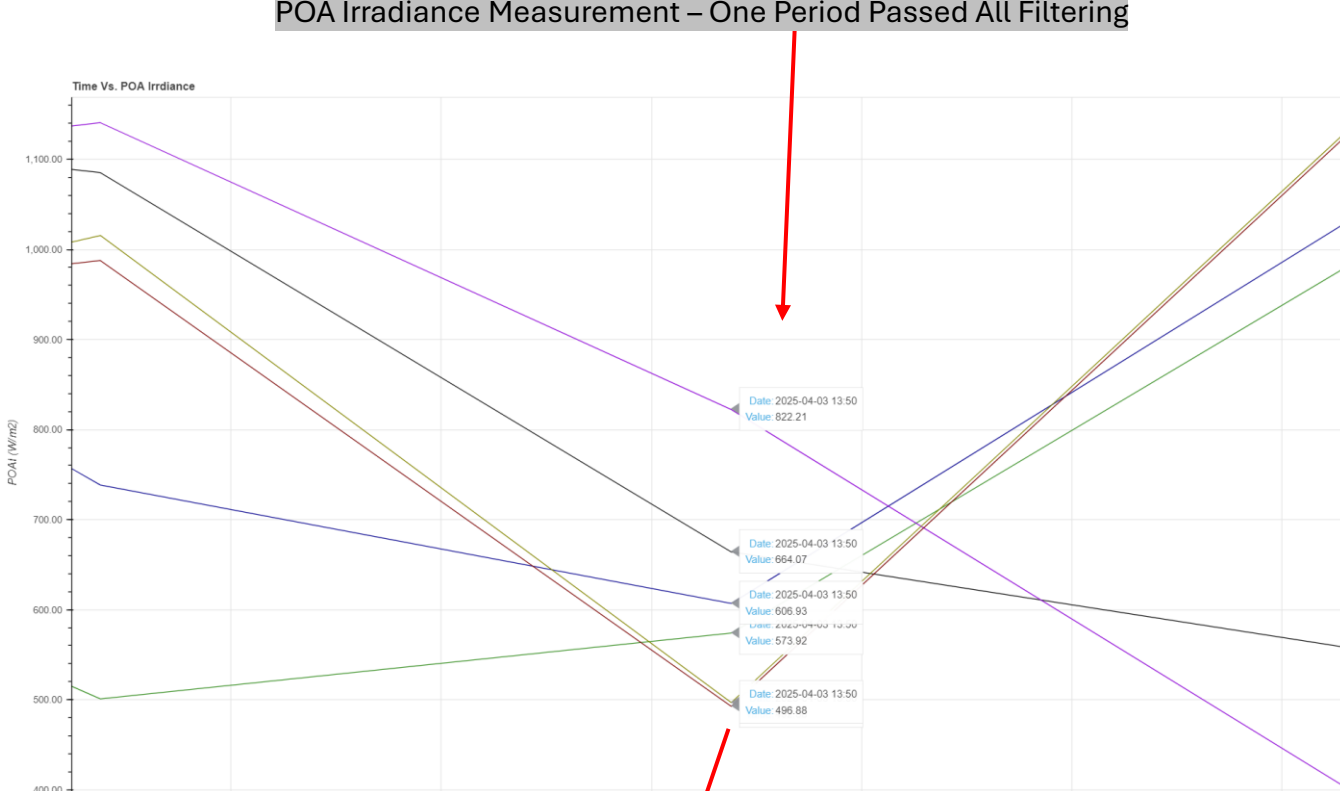
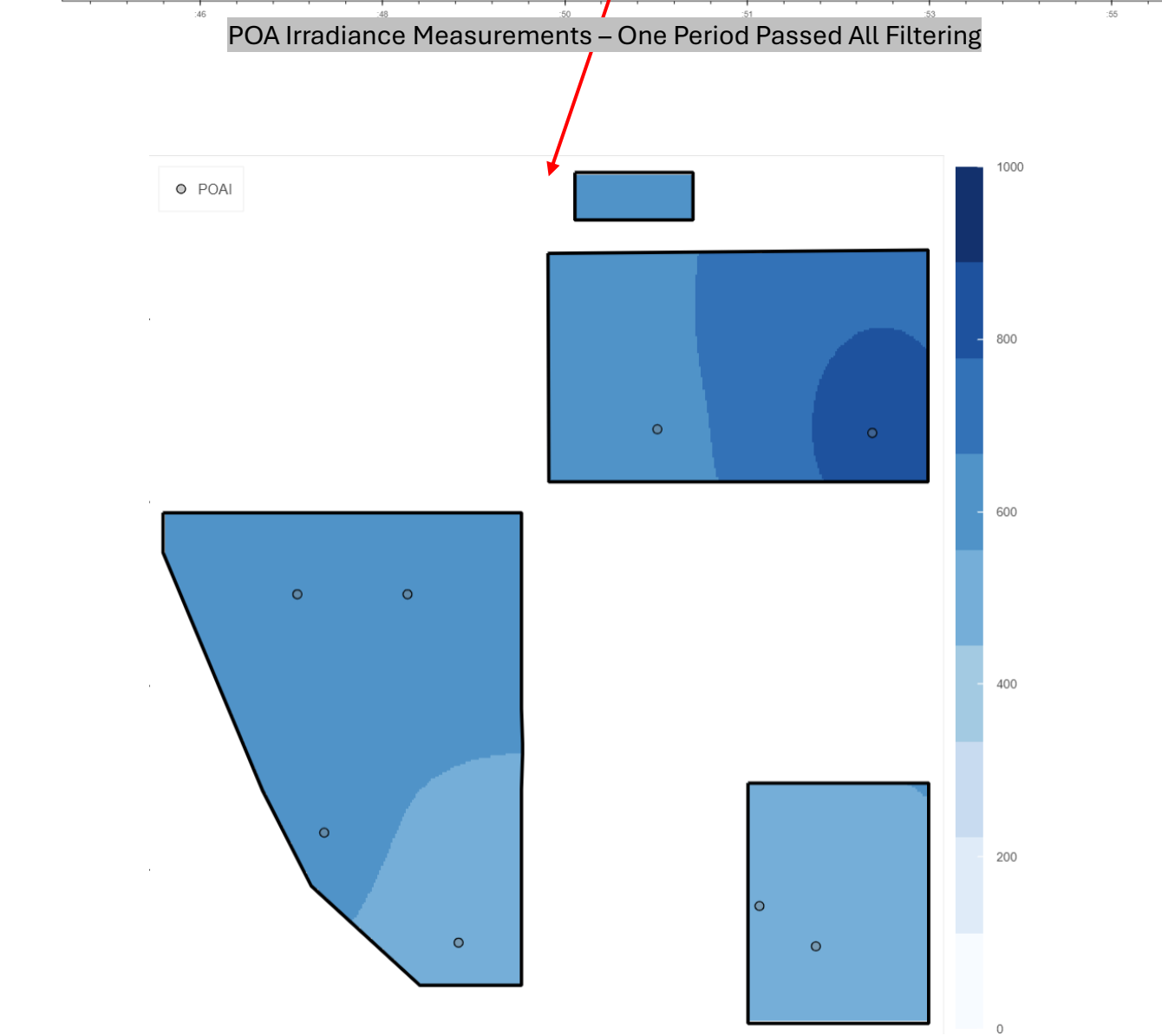
Citations

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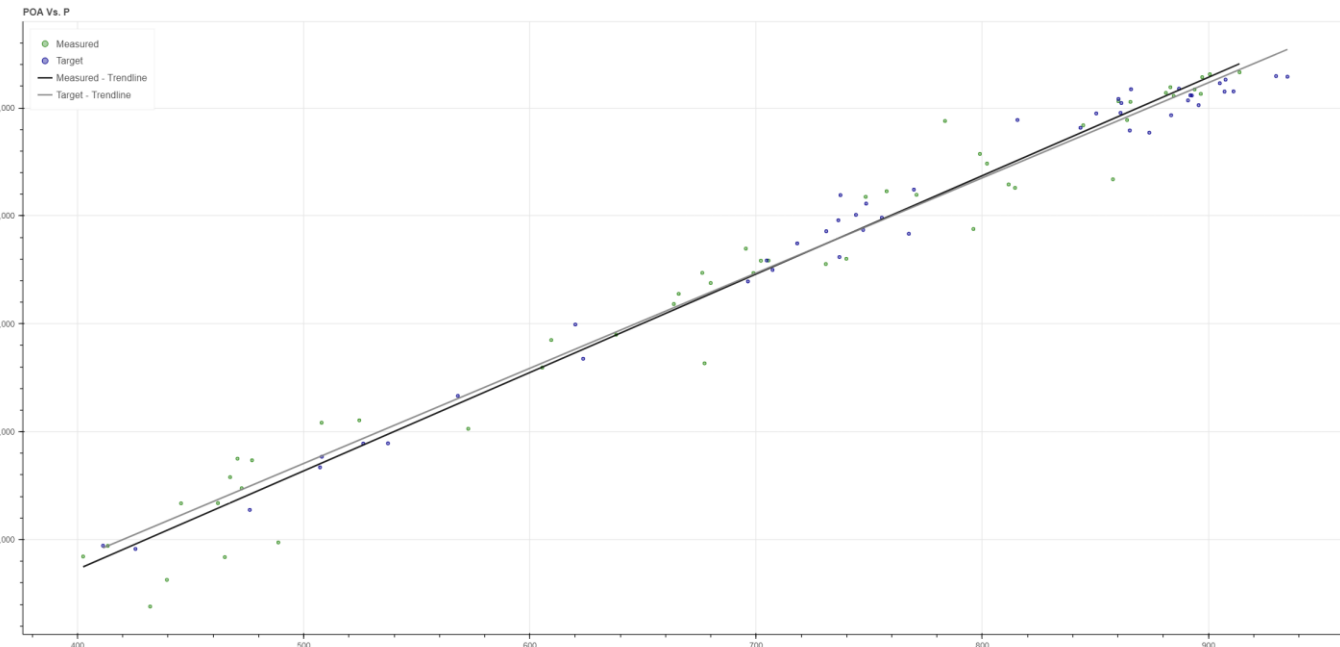
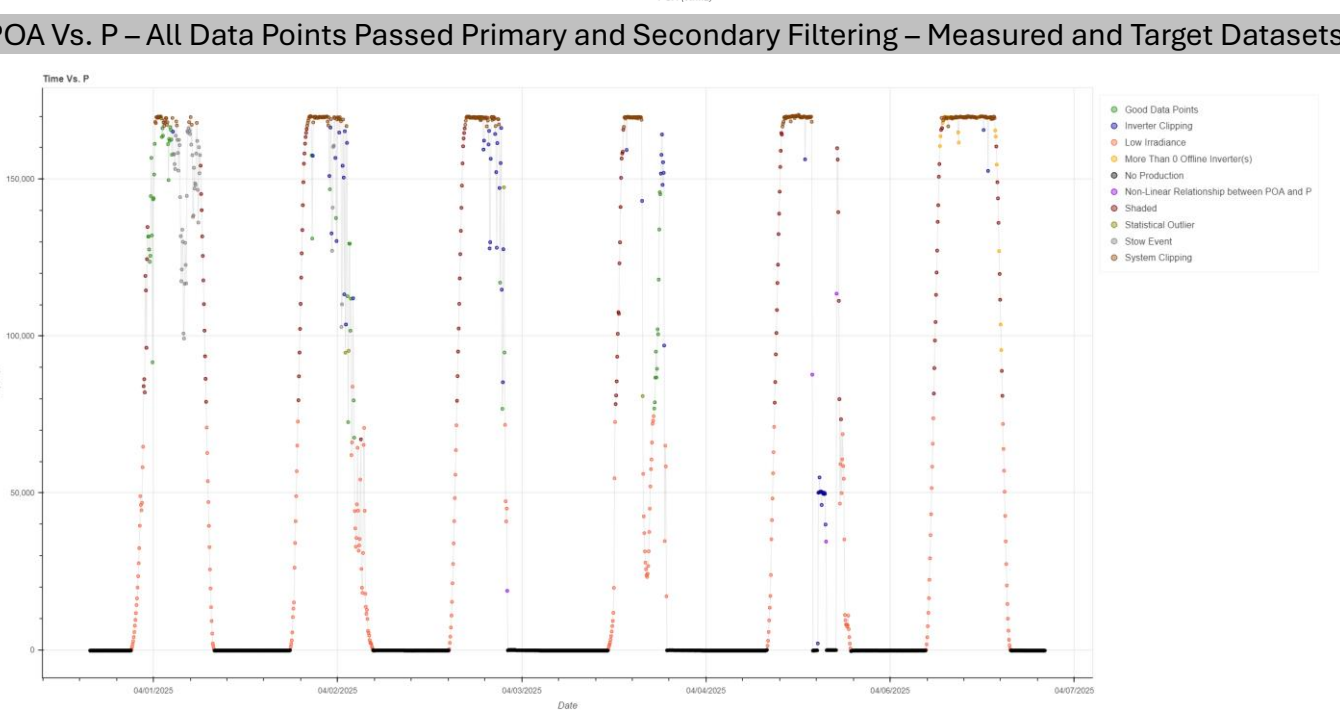
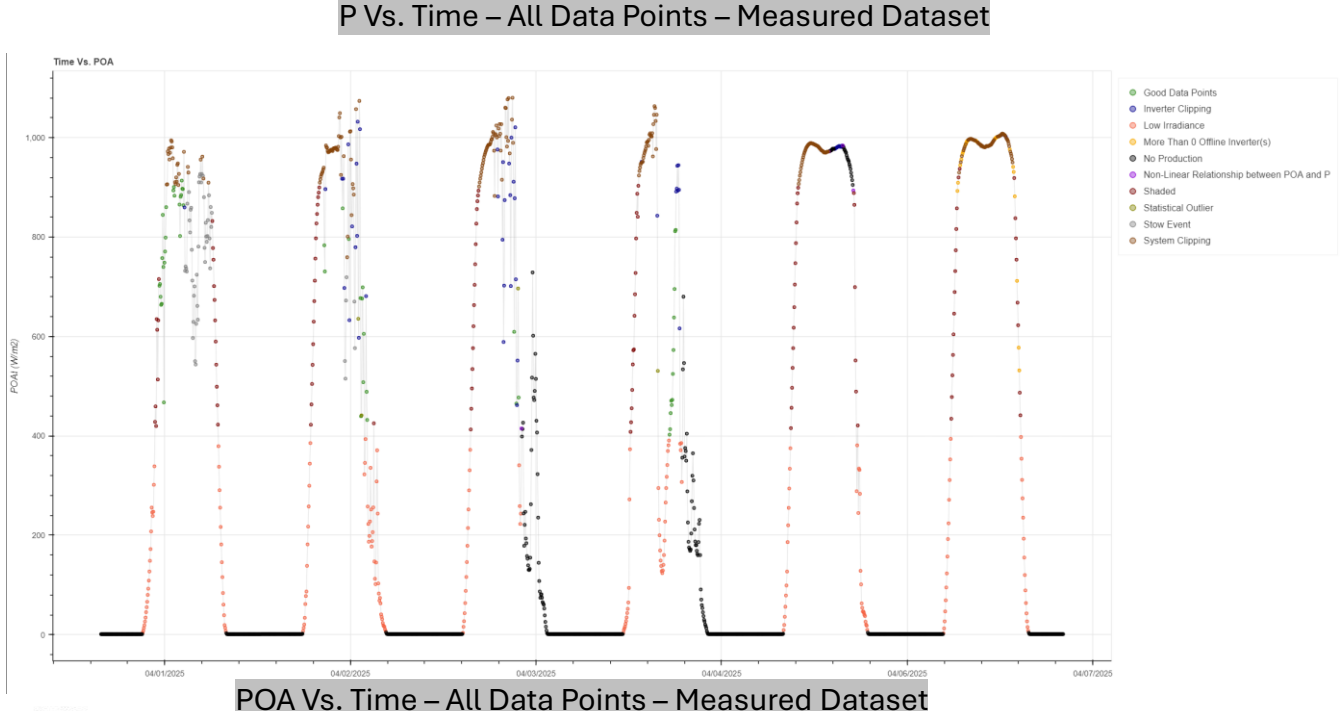
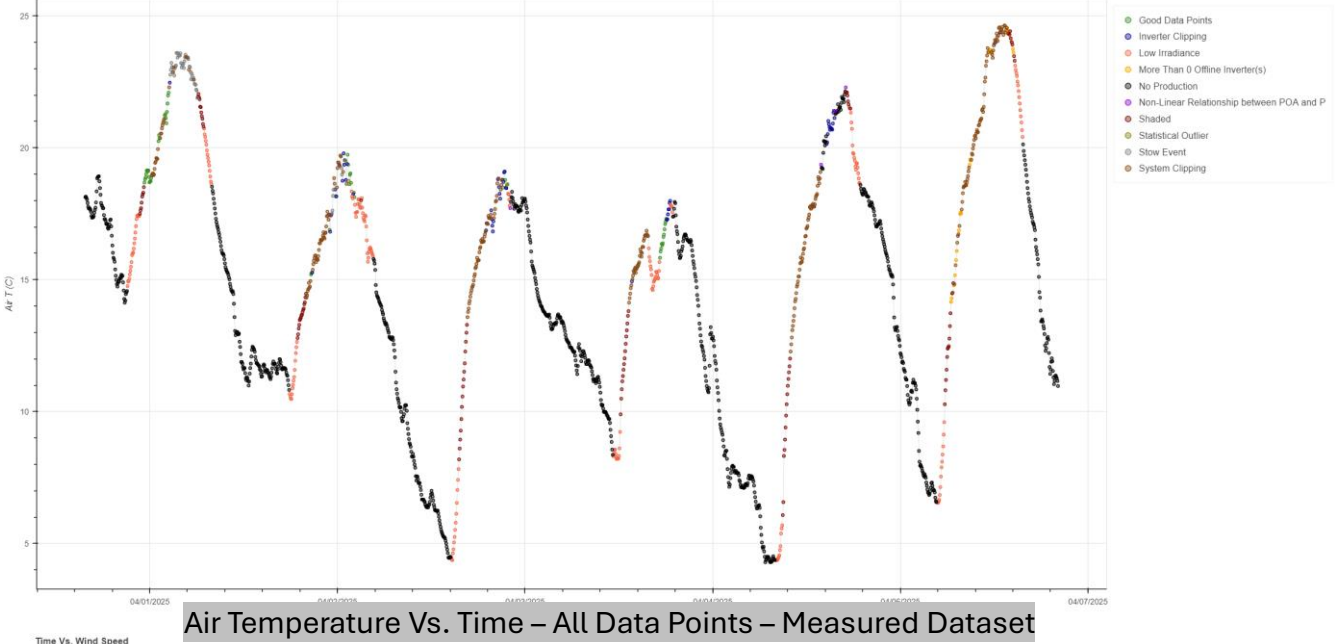
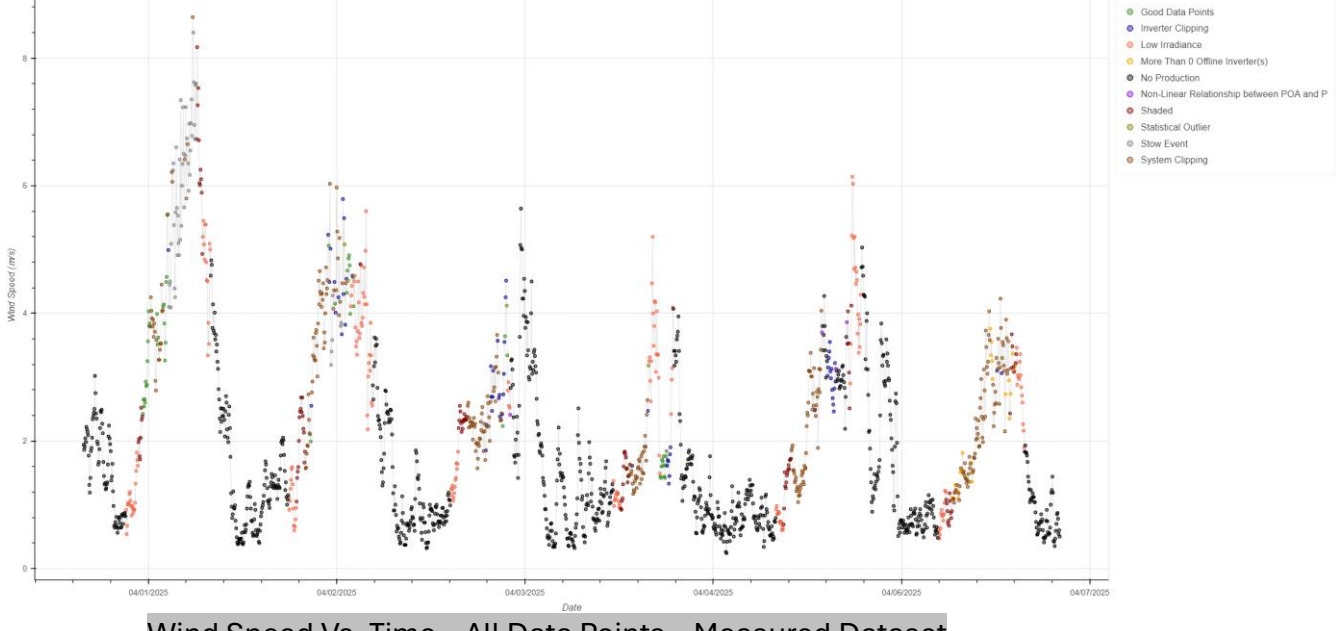
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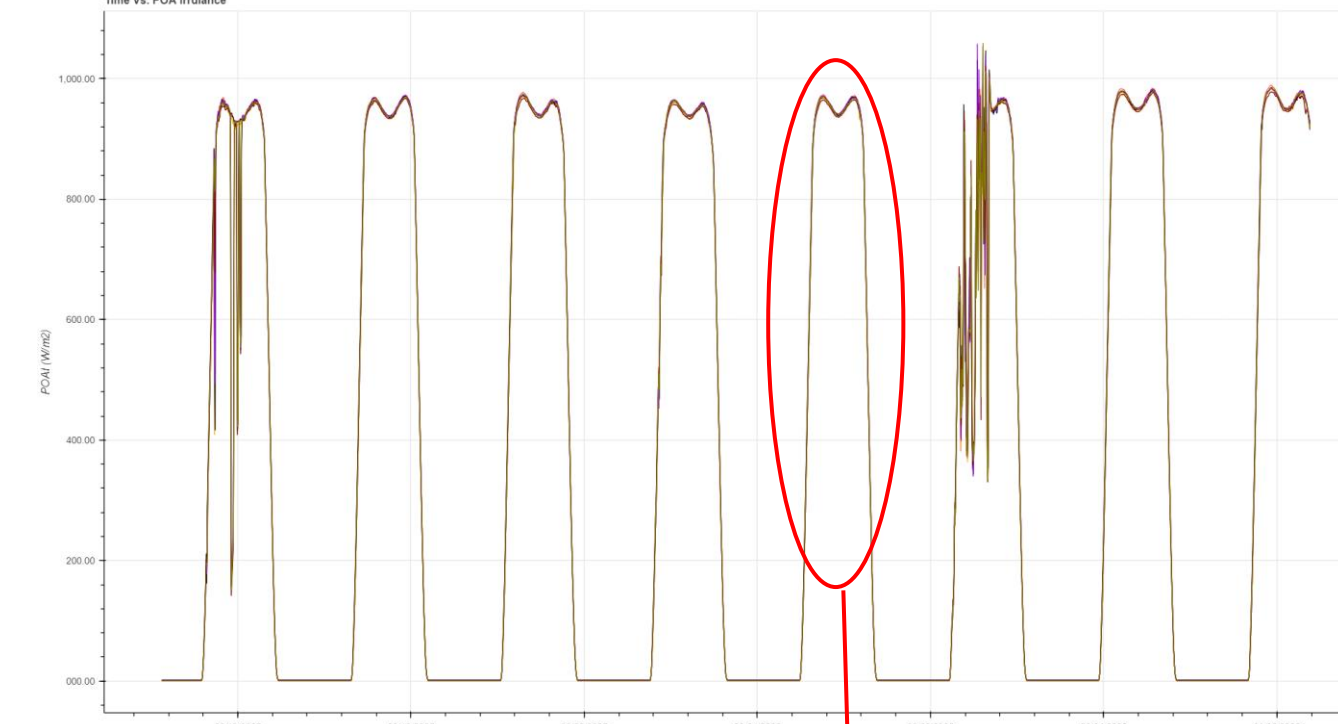
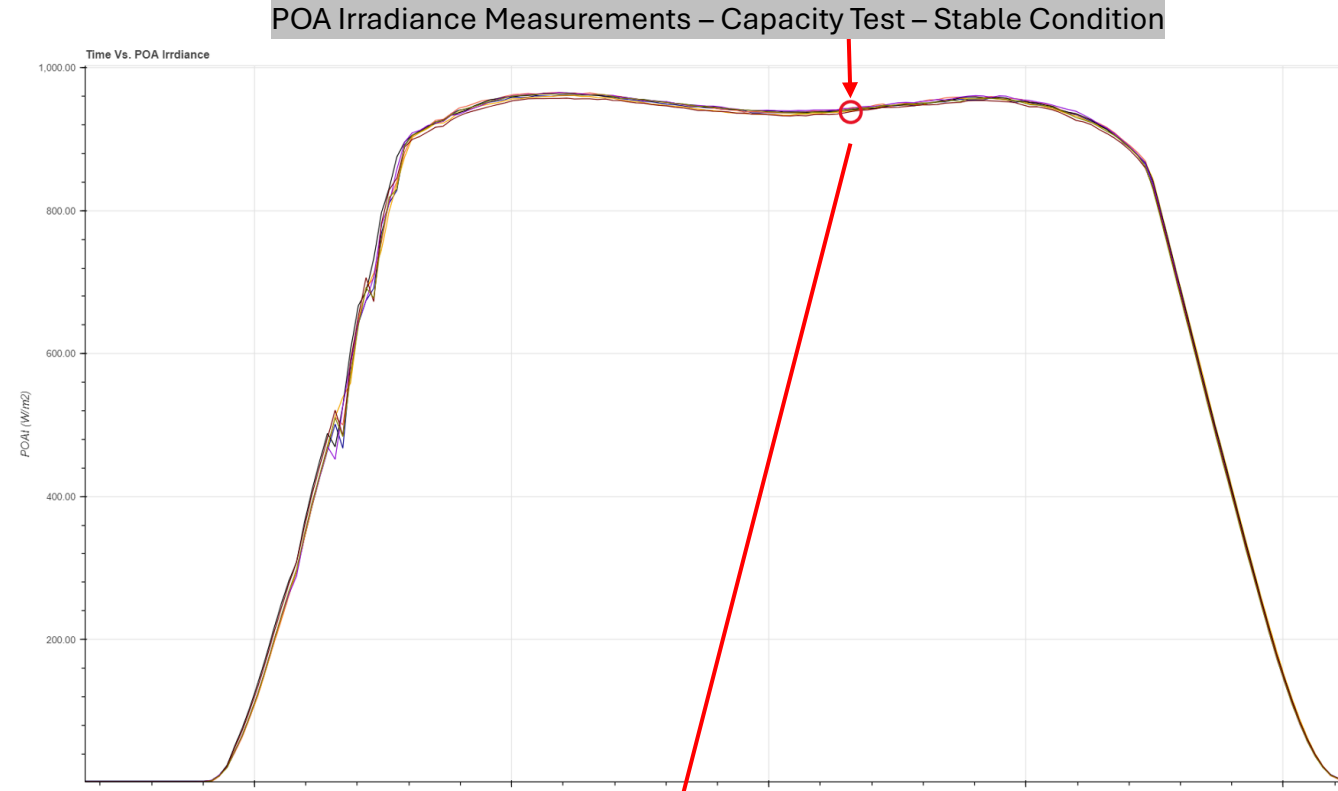
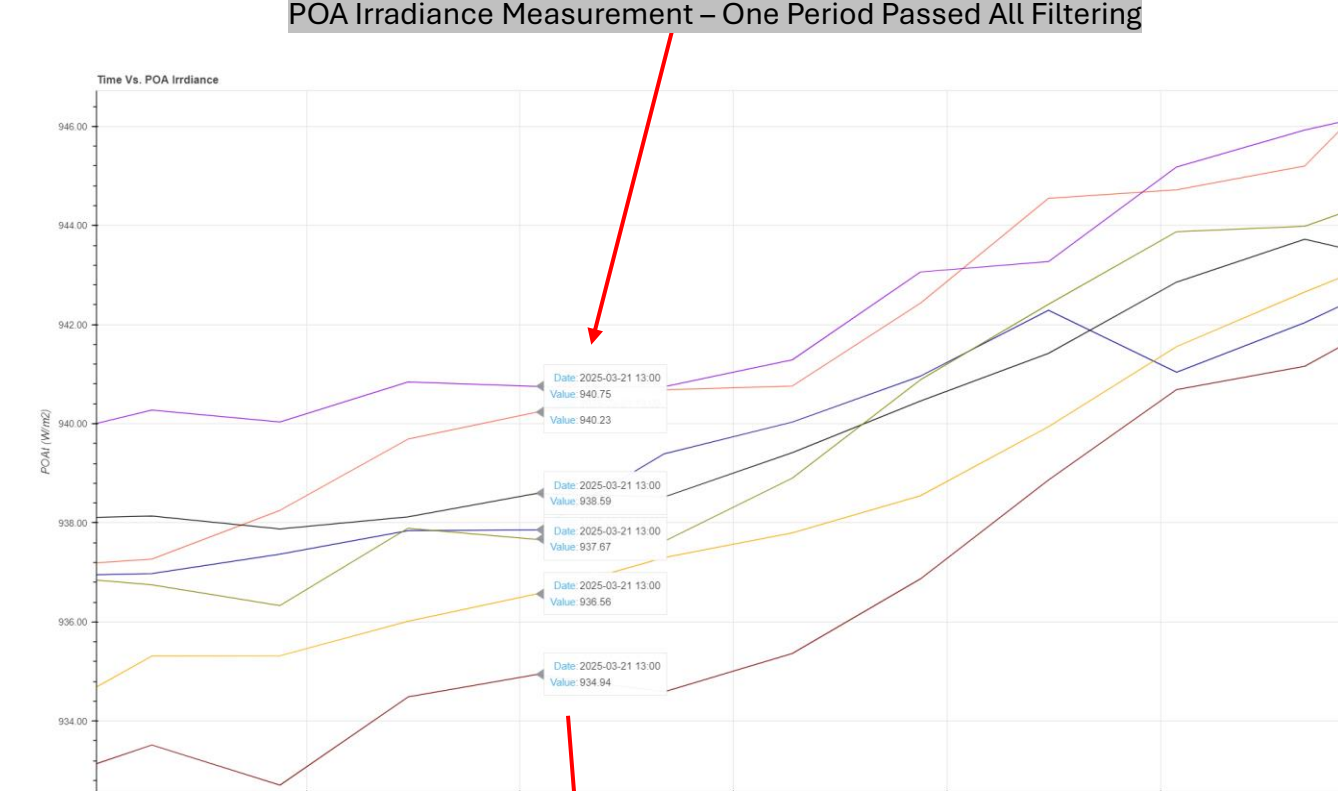
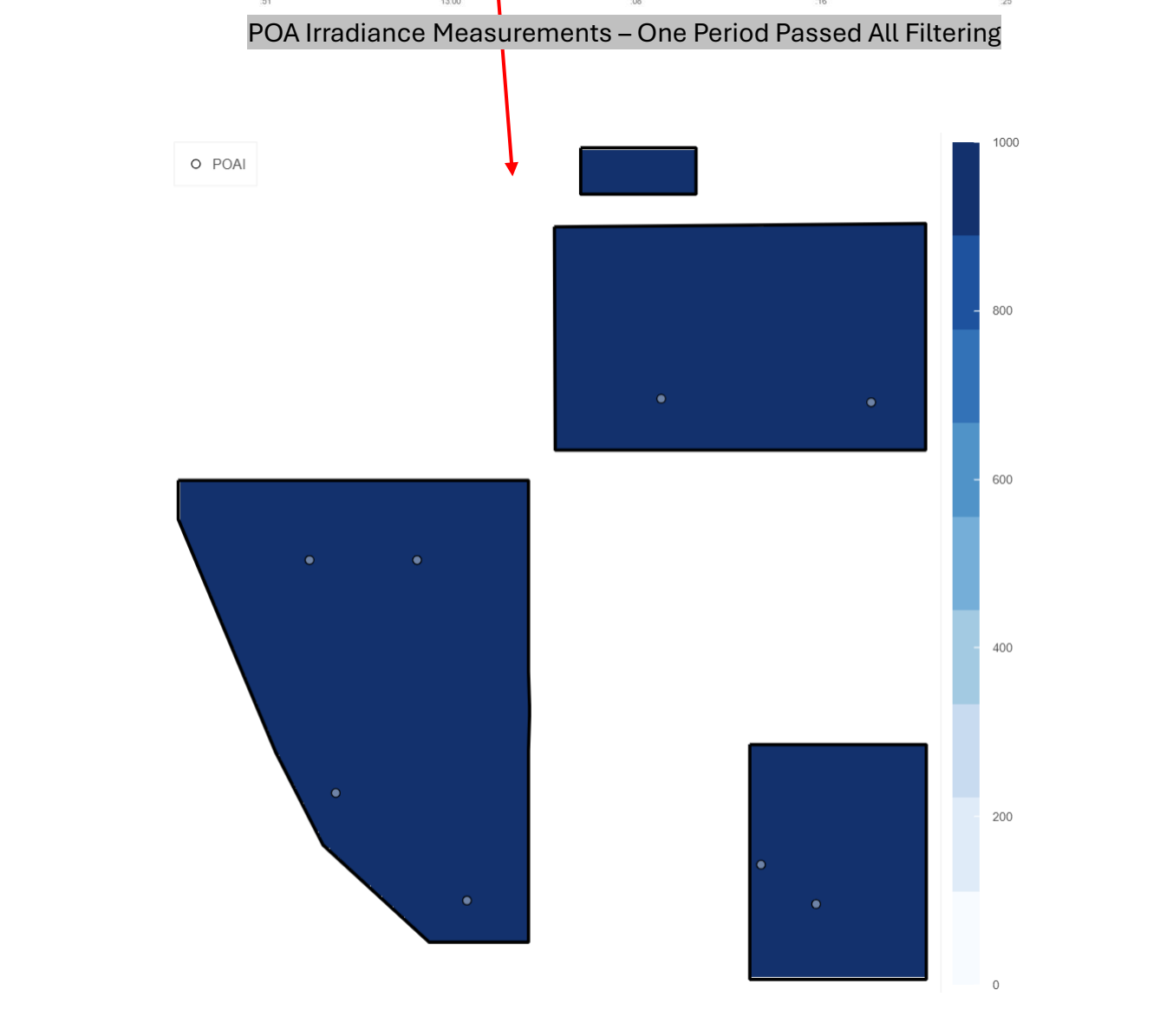
High Uncertainty Capacity Test
Unstable Conditions



Measured Capacity Estimate Uncertainty (%)	19.62
Target Capacity Estimate Uncertainty (%)	3.23
Test Uncertainty (%)	19.88



Low Uncertainty Capacity Test
Stable Conditions



Measured Capacity Estimate Uncertainty (%)	2.33
Target Capacity Estimate Uncertainty (%)	2.36
Test Uncertainty (%)	3.32

