# EVALUATION OF PHOTOVOLTAIC SYSTEM POWER RATING METHODS FOR A CADMIUM TELLURIDE ARRAY

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## ABSTRACT

A variety of metrics are commonly used to assess whether or not a photovoltaic ("PV") system is operating as expected, but to date no standard metric has been accepted. Three commonly used metrics for assessing PV system power performance are the Power Performance Index ("PPI"), PVUSA rating as contemplated in ASTM WK22009 ("ASTM"), and Performance Energy Ratio ("PER"). This paper evaluates the suitability of each of the three metrics for use with large Cadmium Telluride (CdTe) arrays. Of particular interest is the uncertainty and stability of each result and relative differences between their magnitudes. Two different approaches for propagating measurement uncertainty to final metric uncertainty are discussed: (1) analytical and, (2) bootstrapping (similar to a Monte Carlo method). Additionally, best practices to achieve low uncertainty and high stability of a metric are addressed including choice of regression method, reference conditions and filtering range.

Iteratively reweighted least squares regression methods were found to improve the stability of metrics in cloudy climates relative to ordinary least squares methods. Choosing irradiance filtering ranges that are sufficiently large and asymmetrical about the chosen reference condition was found to bias the metrics on the order of 0.6%. Final PPI uncertainty was found to be most sensitive to irradiance and power measurement errors and ranged from +/- 3% to +/- 8% for typical ranges of sensor accuracies.

## EXPLANATION OF METRICS

Three different PV power rating metrics are examined: (1) the PPI, (2) the ASTM, and (3) the PER. All three methods use meteorological and PV system power data measured over a range of weather conditions to compare measured performance to expected performance. The PPI and ASTM methods take the approach of translating measured power to a reference meteorological condition by using a linear or multivariate regression, and then compare the measured power evaluated at the reference condition to the system nameplate power rating (typically defined at STC). The PER method takes the opposite approach, using a PV system simulation tool with measured weather data as an input to simulate expected power across a wide range of weather conditions for comparison to the non-weather-adjusted measured power data. Methods of calculating these metrics are described in the following sections.

### The PPI Rating

To calculate the PPI, measured system power, $P$ is first translated to a module reference temperature, $T_o$ (typically 25°C) using the power temperature coefficient, $\gamma$ and the measured module temperature, $T_m$:

$$P_{TC} = P / [1 + \gamma(T_m - T_o)] \quad (1)$$

The temperature corrected power, $P_{TC}$, is then expressed as a linear function of measured irradiance, $E$:

$$P_{TC} = mE + b \quad (2)$$

Substitution of the irradiance reference condition value $E_o$ into Eq. 2 with known coefficients then gives the AC or DC power, $P_o$, at the reference condition which is defined by the user depending on the application:

$$P_o = mE_o + b \quad (3)$$

The PPI is defined as the ratio of $P_o$ to the system nameplate rating, $P_{nameplate}$:

$$PPI = P_o / P_{nameplate} \quad (4)$$

### The ASTM Rating

A multivariate regression is used to fit the non-temperature corrected measured power data to measured weather data:

$$P = E(a_1 + a_2E + a_3T_a + a_4v) \quad (5)$$

$T_a$ and $v$ are ambient temperature and wind speed, respectively. Substitution of the reference condition values $E_o$, $T_o$, and $v_o$ into Eq. 5 then gives the AC or DC power, $P_o$, at the reference conditions which are defined by the user depending on the application:

$$P_o = E_o\left(a_1 + a_2E_o + a_3T_{a_o} + a_4v_o\right) \quad (6)$$

Finally, for comparison to the PPI, we compute the ratio of $P_o$ to the system nameplate rating:

$$ASTM\ Rating = {P_o}\Big/{P_{nameplate}} \quad (7)$$

**The PER Rating**

The PER is given by Eq. 8:

$$PER = {\sum P\Delta t}\Big/{\sum P_p \Delta t} \quad (8)$$

where predicted power for each time interval, $P_p$, is determined using a comprehensive system energy simulation tool such as PVSyst [1] among others, and $P$ is the measured AC or DC system power. Note that PER is largely a measure of energy production while the PPI and ASTM ratings are power/capacity-based metrics.

There is an aspect of user subjectivity to all three metrics. For example, a number of inputs specific to the PV system being evaluated such as system tilt and azimuth, loss factors and module performance coefficients are required for any comprehensive PV system simulation tool, each of which will affect the PER. In the case of the PPI and ASTM methods, the range of meteorological conditions over which the regression is fit will affect the final rating as will the chosen reference conditions. In choosing the data filtering ranges and reference conditions, there is a tradeoff between having a metric directly comparable to 100% of nameplate capacity and a metric with high stability and accuracy. For the purposes of this paper, the authors made the choice to use filtering techniques recommended in [2] to minimize bias error in the metric's value. Due to inverter clipping and a lack of high-irradiance data, this choice led to reference conditions other than STC, and consequently, the PPI and ASTM metrics reported in this paper are no longer comparable to 100% of plant capacity. In some instances, it may be mandatory to use STC as the chosen reference condition. Potential consequences of doing this without sufficient data on either side of STC for the regression fit are discussed in subsequent sections.

## METHODOLOGY

Because each metric is susceptible to user subjectivity, it is important to establish best practices for calculating each metric and a consistent method for estimating uncertainty. In this section, two different uncertainty analysis methods are first described: (1) analytical uncertainty propagation and (2) bootstrapping. This section also investigates best practices for (1) fitting regression models, (2) filtering data for fitting regression models, and (3) choosing reference conditions for metric evaluation.

**Uncertainty Analysis**

Error in power and meteorological measurements will affect each metric. Random error in measurements contributes to scatter about the regressions and is ameliorated by sufficiently large samples. Systematic measurement errors will result in biased values of metrics and are therefore of greater importance in this analysis than random measurement errors. Typical systematic uncertainties of measurements used in all three metrics are listed in Table 1.

**Table 1. Measurement accuracies**

| Measurement Device | Systematic Uncertainty (symbol) | Nominal Value | Units |
|---|---|---|---|
| Thermopile Pyranometer | +/- 3% ($b_E$) | 1000 | $W/m^2$ |
| Ambient Temperature RTD | +/- 0.13 ($b_{Ta}$) | 20 | ˚C |
| Wind Speed | +/- 2% ($b_{WS}$) | 1 | m/s |
| Module Temperature RTD | +/- 0.13 ($b_{Tm}$) | 25 | ˚C |
| Module Temperature Coefficient | +/- 0.01 ($b_\alpha$) | -0.25 | %/˚C |
| Inverter Measured DC Power | +/- 4% ($b_P$) | 600 | kW |

This uncertainty analysis does not account for factors other than measurement uncertainty that may introduce additional uncertainty into the PPI and ASTM metrics. For example, we use data from a single irradiance sensor. Use of the average of more than one irradiance sensor located within the array may significantly reduce the effect of irradiance measurement error if the sensors calibration errors are uncorrelated, and may also reduce error in the regressions. Other environmental conditions that are not considered are: spatial variations in wind speed and array and ambient temperature; spectral mismatch between the irradiance sensor (in this case, a thermopile pyranometer) and the array; differences between cell and module back surface temperature; and angle of incidence response differences between the pyranometer and the PV array.

For the PPI method, total metric uncertainty is first estimated by propagating measurement uncertainty analytically using the methods outlined in ASME PTC 19.1-2005 standard [3]. PPI uncertainty is also estimated using a bootstrap technique for comparison. Bootstrap uncertainty estimation is advantageous as it is comparatively easier to compute than the analytic method when multiple independent variables appear in the model as is the case for the ASTM metric. For this reason, only the bootstrap method was used to estimate ASTM uncertainty.

Systematic error for the PPI is estimated analytically by propagating the measurement uncertainties through Eq. 1 through Eq. 4. This propagation results in Eq. 9 which represents the total bias uncertainty in the power at reference conditions, $b_{Po}$ due to measurement error:

$$b_{Po} = \begin{bmatrix} \left[\left(1+\alpha\left(T_m - T_o\right)\right)\left(P\, b_P\right)\right]^2 + \\ \left[P\, \alpha\, b_{Tm}\right]^2 + \left[P\left(T_m - T_o\right) b_\alpha\right]^2 + \left[m b_E\right]^2 \end{bmatrix}^{1/2} \quad (9)$$

Random error $s_{Po}$ is evaluated per [3] using Eq. 10 below:

$$s_{Po} = \begin{bmatrix} \dfrac{1}{N-2}\sum_{j=1}^{N}\left(P_{TC_j} - mE_j - b\right)^2 \\ \times\left(\dfrac{1}{N} + \dfrac{\left(E_o - \bar{E}\right)^2}{\sum_{j=1}^{N}\left(E_j - \bar{E}\right)^2}\right) \end{bmatrix}^{1/2} \quad (10)$$

where $j$ indexes the observations and corresponding calculated values of $P_{Tc}$. Note that because the number of observations, $N$, appears in the denominator as the number of data points becomes larger, the random error in the rating becomes small compared to systematic error. In the analytic determination of systematic uncertainty, the average module temperature and power are calculated within a window of +/- 50 W/m$^2$ around the reference irradiance for use in Eq. 9. Coefficients for Eq. 3 are estimated by least-squares to maintain theoretical consistency with Eq. 1 and Eq. 9.

The PPI uncertainty was also estimated by a bootstrap approach. In our analysis, uncertainty in measured quantities is regarded entirely as resulting from systematic errors. Errors in irradiance, temperature, wind speed and DC power were characterized by uniform distributions with limits given in Table 1. Error in the module temperature coefficient was characterized by a normal distribution with mean and standard deviation given in Table 1; use of a normal distribution is appropriate because this parameter is estimated from a large sample of measurements. A sample of size 1,000 was generated from each error distribution, the sampled errors were applied to measured quantities to obtain an ensemble of synthetic meteorological data, the regressions were performed for each element of the ensemble and the resulting models were evaluated at chosen reference conditions to obtain a sample of size 1,000 of the performance metric. The mean and standard deviation of this sample were taken to yield the metric rating and uncertainty, respectively.

Results of using the analytical and bootstrapping techniques to estimate uncertainty for the PPI and ASTM metrics are discussed in subsequent sections.

**Best Practices for Metric Calculation**

Because there is user subjectivity present in the methods of calculating each of these metrics, it is important to discuss best practices that minimize uncertainty and improve stability of the ratings. Of primary interest are: (1) the regression method, and (2) choice of data filtering and reference conditions.

When fitting the PPI and ASTM models in cloudy climates, the regressions exhibited residuals that depended strongly on irradiance. The heteroskedasticity in the residuals likely results from measuring irradiance at a point rather than across the area of the solar plant, and from the simple form of the models used for the performance metrics. Power from a solar plant is strongly correlated with total irradiance over the plant's area, but less well-determined by irradiance measured at a single point proximal to the plant [5]. Due to spatial damping, extreme values of irradiance measured at a point are unlikely to be observed across the plant's area, particularly during cloudy conditions. Consequently, regression between power and irradiance measured at a point favor over prediction of power when irradiance is low and under prediction of power when irradiance is high. We found that performance metrics estimated by ordinary least-squares (OLS) regression were biased toward low values in the cloudy climate due to this heteroskedasticity.

Typically, a user will choose an OLS method because of its ease of application and availability for calculating both the ASTM and PPI metrics which can result in difficulty in calculating stable metrics under cloudy conditions. More robust regression methods may improve the regressions relative to OLS by eliminating the effects of outlier data points. To investigate this, PPIs were calculated on 11 consecutive weeks of data using both the OLS and a robust regression methods (specifically, an iteratively-reweighted least squares approach [4]). The OLS method yielded a mean PPI rating of 0.652 +/- 0.020 over the 11-week window while the robust method yielded a PPI of 0.655 +/- 0.013 (uncertainty intervals are 2 standard deviations calculated from the 11-week sample). This represents a 35% improvement in metric stability from week to week and an increase of 0.5% in the mean rating with the robust regression method (Fig. 1).

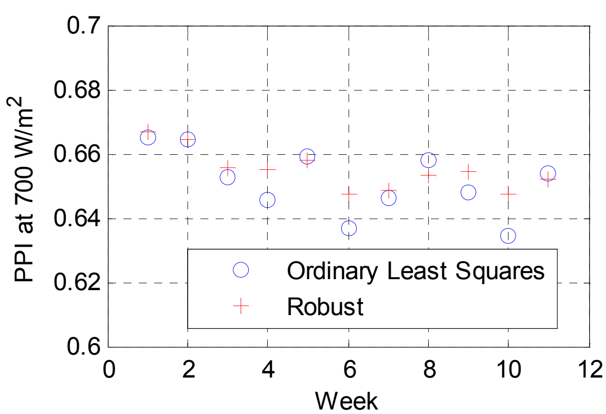


**Figure 1. Stability of PPI metrics over 11 weeks in a cloudy climate using the OLS and robust regression approaches.**

Another known preventable source of systematic error is the inclusion of overly large windows of irradiance in the regression coupled with use of asymmetric filtering intervals. Asymmetric filtering about reference conditions will result in biased ratings due to the curvature in the power versus irradiance "line". Fig. 2 depicts regression error (modeled minus measured) as a function of irradiance for the PPI regression fit using irradiance data between 400 and 1000 W/m$^2$. At 1000 W/m$^2$, the regression predicts power that is approximately 0.6% higher than the measured power. ASTM WKK2009 guidelines [2] suggest including only data that is within 20% of reference irradiance to avoid this type of error, but such filtering is not always possible if the desired reference irradiance is sufficiently high (i.e., 1000 W/m$^2$ in a low irradiance climate for comparison to published nameplate) or if inverter clipping is present at relatively low irradiances. In such cases, additional systematic error will be present in the rating due to choice of reference conditions.

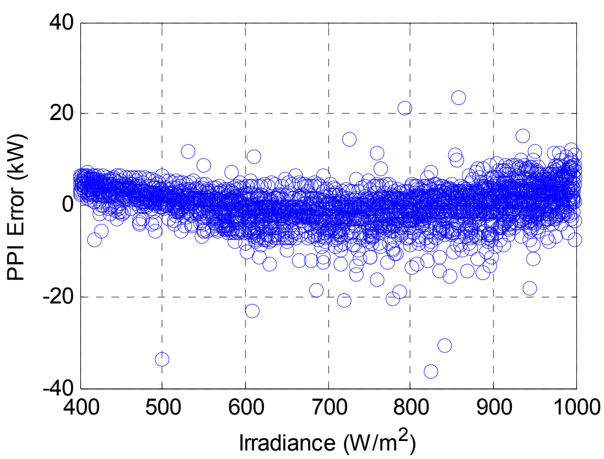


**Figure 2. PPI regression residuals for data fit using an irradiance filter of 400 to 1000 W/m$^2$.**

Based on the results described in this section, it is advised that robust regression techniques be used for calculating ASTM and PPI metrics for cloudy data sets and that symmetrical irradiance filtering be used whenever possible.

## EXAMPLE IMPLEMENTATION ON DATA FROM TWO CADMIUM TELLURIDE ARRAYS

One week of system DC power, irradiance, ambient temperature, wind speed and module temperature data is collected at 1-minute time resolution for two comparable 500 kW$_{AC}$ inverter systems in June. One system is located in a climate with variable irradiance while the other has predominantly clear skies. Each rating is calculated for both sets of data for comparison. For the ASTM method, a reference ambient temperature and wind speed of 20°C and 1 m/s are chosen, respectively. For the PPI method, the reference temperature $T_0$ is set to 25°C. In the clear climate, only data measured with irradiance between 600 and 1000 W/m$^2$ was included and a reference irradiance of 800 W/m$^2$ is used (inverter clipping was present above 1000 W/m$^2$). For the cloudy climate, data was filtered for irradiance between 500 and 900 W/m$^2$ with a chosen reference irradiance of 700 W/m$^2$.

Fig. 3 compares the DC power predicted by the PPI and ASTM regressions to the measured DC power for the clear climate; Fig. 4 shows the same results for the cloudy climate. Neither model reproduces the full scatter of the measured data, due to the regression of power to irradiance measured at a point rather than over the entire plant.

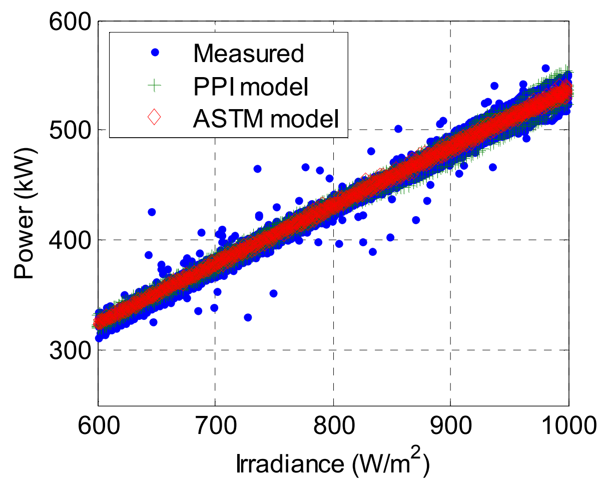


**Figure 3. Comparison of ASTM and PPI models and power in a clear climate.**

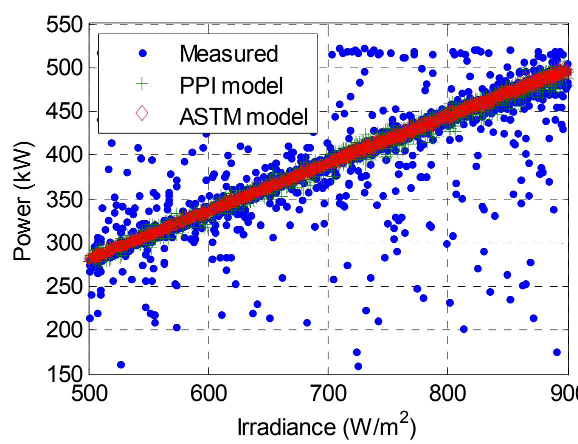


**Figure 4. Comparison of ASTM and PPI models and power in a cloudy climate.**

To calculate the PER for both the clear and cloudy data sets, measured meteorological data was input to the PVSyst energy simulation tool along with: (1) known system specifications, (2) module input parameters estimated by First Solar for First Solar modules, and (3) typical loss factors estimated by First Solar for use with PVSyst [6] to predict power production for the systems during the week of interest. The 1-minute meteorological data was reduced to hourly averages to accommodate PVSyst input requirements. Figure 5 shows the relationship between measured and modeled power at each hour, for both locations (inverter outages that occurred during this period have been disregarded in both datasets). The ratio of total weekly measured DC energy to and PVSyst modeled DC energy was taken to yield a weekly PER rating for both data sets (see Eq. 8).

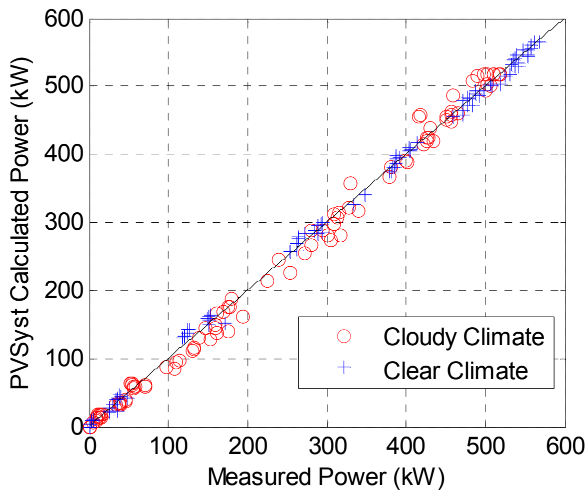


**Figure 5. Comparison of PVSyst calculated DC power to measured DC power for the inverter for both the clear (blue crosses) and cloudy (red circles) climates.**

Uncertainty in the PPI metric was quantified analytically and using the bootstrap method; uncertainty in the ASTM rating was estimated with the bootstrap only. Uncertainty in the PER was not estimated due to the labor involved in running multiple PVSYST calculations. The magnitudes of each metric with corresponding uncertainties are shown in Table 2. Nominal values for metrics computed by bootstrapping are the mean for the resulting ensemble; uncertainty values are 2 standard deviations about the nominal rating.

**Table 2. Final power metric results**

| | Clear at 800 W/m$^2$ | | Cloudy at 700 W/m$^2$ | |
|---|---|---|---|---|
| | Nominal | Uncertainty | Nominal | Uncertainty |
| PPI (a) | 0.722 | +/- 0.046 | 0.656 | +/- 0.038 |
| (b) | 0.724 | +/- 0.044 | 0.654 | +/- 0.038 |
| (c) | 0.724 | +/- 0.044 | 0.657 | +/- 0.039 |
| ASTM | 0.691 | +/- 0.039 | 0.638 | +/- 0.037 |
| PER | 0.995 | - | 1.015 | - |

(a) Robust regression; uncertainty estimated analytically
(b) Bootstrap estimate using OLS
(c) Bootstrap estimate using robust regression

## DISCUSSION OF RESULTS

The PPI and ASTM metrics are significantly lower than the PER for a number of reasons. First, they are evaluated at non-STC reference conditions but are divided by the system nameplate rating which is defined at STC. Second, losses that reduce system performance are inherently included in the measured power in the numerators of these metrics, but not in the denominators. Examples of such loss factors are: (1) mismatch, (2) soiling, (3) DC health (i.e., open-circuited strings, disconnected modules), (4) Ohmic losses, (5) diffuse shading, (6) cell to module back-surface temperature differences, and (6) angle-of-incidence losses. In contrast, the PER accounts for losses in its denominator at the level of detail of the model chosen to simulate performance. Because the PER accounts for such losses, it is a valuable metric for comparing the absolute magnitude of system performance to expected system performance when model inputs are well developed and understood. The PPI and ASTM metrics can also be used for this purpose only if they are corrected for losses and are evaluated at STC (or referenced to a manufacturer published nameplate at conditions other than STC). Because of these limitations, the PPI and ASTM methods are better suited for assessing relative system performance. They are especially useful for comparing a system to itself over long time-intervals (i.e., in degradation studies) or for comparing different PV technologies to each other (i.e., in competitive comparisons) as long as the effects of environment are similar across the systems. The ASTM metric is lower than the PPI in this case because the PPI chosen reference module temperature condition is lower than the actual operating module temperature that corresponds to the ASTM chosen reference conditions of 20˚C and 1 m/s.

Sensitivity analysis (using stepwise regression) can determine the proportion of total uncertainty attributable to each input and may guide measurement improvements that reduce uncertainty in the performance metrics. For our analysis, variance in the PPI metric is attributed to error in DC power (60%), irradiance measurement error (30%), and error in temperature (10%). Variance in the ASTM metric for our analysis is attributable to DC power error (65%) and irradiance error (35%) with very little contribution from temperature or wind speed error. The different sensitivities result from the different model formulations.

In this analysis, a relatively high-accuracy irradiance sensor (+/- 3%) was used in conjunction with a relatively low-accuracy inverter reported DC power reading (+/- 4%). However, numerous other combinations of sensor accuracies may arise which will result in different overall metric uncertainties. The analytical uncertainty analysis method was utilized to generate Fig. 6 which shows overall PPI uncertainty as a function of irradiance sensor and power measurement uncertainty.

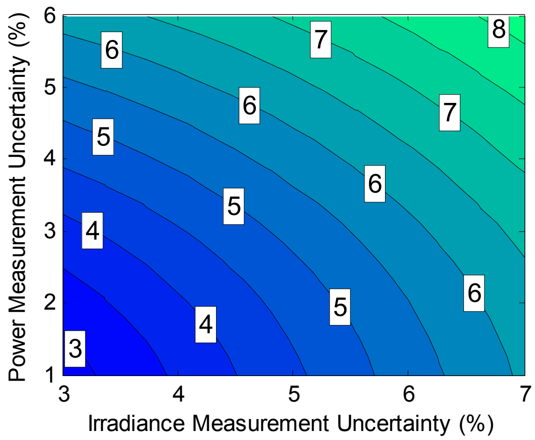


**Figure 6. Analytical PPI uncertainty (2 standard deviations) as a function of irradiance sensor and power sensor accuracy**

## CONCLUSIONS

This analysis investigated three different PV power capacity rating metrics with respect to uncertainty, stability, and magnitude of the result. Best practices for calculating each of the metrics and assessing uncertainty were investigated. Major findings are summarized below:

- The ASTM and PPI methods yield comparable results when best practices of implementation are used. Differences may arise in their magnitudes due to reference condition choice. Reference conditions should be chosen based on the intended application of calculating these metrics and additional bias error may be included in the model by choosing reference conditions that are outside of the range of actual operating conditions.

- The PER was significantly higher than both the PPI and ASTM methods due to the choice of reference irradiance and comparison to the nameplate which does not include losses in the PPI and ASTM metrics.

- Because the PER accounts for losses, it is most useful for comparing actual system performance to expected system performance for a single time period if model inputs (i.e., loss factors, module performance coefficients, etc.) are well developed and understood.

- Because the ASTM and PPI metrics do not rely on assumptions about losses and module performance, they are well-suited for relative comparisons. Specifically, they are useful for tracking the performance of a single system to itself over time to determine degradation rates or for comparing performance of multiple systems to each other over a specified time period.

- Use of a single irradiance sensor leads to biased ratings in cloudy climates when ordinary least squares regression is used. Robust regression which involves an iterative least-squares regression with outlier reweighting, improves regression stability in cloudy climates.

- The bootstrapping method of uncertainty propagation showed comparable results to the analytical approach for the PPI and offers a method of uncertainty analysis for more complicated models like the multivariate ASTM regression.

- The uncertainty of the PPI and ASTM metrics is most sensitive to irradiance and power sensor measurement accuracy. PPI uncertainties due to measurement can range between +/- 3% and +/- 8%, depending on sensor accuracy. For precise power capacity ratings, high-accuracy power and irradiance sensors should be considered.

Future work will focus on assessing the uncertainty of PV system simulation tool outputs such as PVSyst using the bootstrapping approach and developing a recommendation for the number of irradiance sensors and the best robust regression method to use to give stable ratings in cloudy climates.

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