

IMPROVED TEST METHOD TO VERIFY THE POWER RATING OF A PHOTOVOLTAIC (PV) PROJECT

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ABSTRACT

This paper reviews the PVUSA power rating method [1-6] and presents two additional methods that seek to improve this method in terms of model precision and increased seasonal applicability. It presents the results of an evaluation of each method based upon regression analysis of over 12 MW of operating photovoltaic (PV) systems located in a wide variety of climates. These systems include a variety of PV technologies, mounting configurations, and array sizes to ensure the conclusions are applicable to a wide range of PV designs and technologies. The work presented in this paper will be submitted to ASTM for use in the development of a standard test method for certifying the power rating of PV projects.

BACKGROUND AND PURPOSE

Two metrics critical to the initial and on-going evaluation of PV system performance include power ratings and total energy production. While total energy production is the most important factor in determining the economic value of a system, a flat-plate PV project's power rating remains a critical metric in contracting for, and acceptance of, PV projects. Typically, energy production is evaluated over long periods, such as a year, while power rating tests can be conducted in relatively short periods – even as short as a few days.

The motivation for this work is the need to develop a system power rating protocol for use in PV plant acceptance testing. Of particular interest is a test that can be executed in a short period of time at any time of year that will give reasonable assurance that the delivered system is capable of producing the amount of energy expected in the contract. At present, there is no recognized industry standard for testing and rating the AC electrical power capacity of PV systems. The lack of a clear standard has resulted in confusion for system providers, customers, and investors as well as costly complications to the contracting process. In order to advance the industry, it is important to standardize on a single, industry-accepted best practice to verify the power capacity of a PV project.

One important consideration for a standard is ease of use. It is important that the method chosen be transparent and relatively easy to understand and implement by a variety of stakeholders. The PVUSA method does a good job of meeting these needs through its simple, fast analysis method and use of standard meteorological equipment. The new methods presented attempt to retain these benefits while reducing model uncertainty and increasing seasonal applicability.

Since some PV projects are completed during the winter months, expanding the months of the year in which the test can be performed is important. The original PVUSA equation required collecting enough empirical data to satisfy a minimum of 10 hours of solar irradiance above 1,000 W/m². In practice, this meant winter ratings were not possible, and ratings at other times of the year could take up to 30 days to collect a satisfactorily large data set. In some locations it is not possible to obtain 10 hours of data above 1000 W/m² at any time of year.

RELATED STANDARDS

Several existing standards are related to this proposed method, and should be acknowledged here. ASTM E2527 is a standard that employs the PVUSA System Rating described above for the purpose of rating concentrating PV plants [7]. IEC 61829 outlines procedures for PV array IV testing, and cites IEC 60891 as a method for translating measured results to the reference condition. The IEC standards address measurements of the DC system, excluding the inverter, transformer, or other power conditioning equipment.

We have made efforts to harmonize our proposed method with existing international norms, however, our recommendations may differ from these norms to the extent that our purposes are different. In particular, we are interested in an AC system rating. Current standards for flat-plate PV only addresses projects where an IV curve of the entire DC array is possible, which is not practical for large PV projects such as the ones described in this paper. The method under development here requires only an AC power measurement and can be applied to any PV Project whether it is 1kW or a large multi-Megawatt utility project.

PVUSA AC SYSTEM RATING

The PVUSA AC rating method was developed by engineers working on the PVUSA project initiated by Pacific Gas & Electric Company in the late 1980s [1-5]. One of their primary goals was to assess in a side-by-side setting the relative AC-level performance of the plethora of available PV technologies. They recognized that extrapolation to the Standard Test Condition (STC) from field data would be a problem and unfairly benefit technologies with high temperature coefficients or operating temperature [8, 9]. They chose to address this issue by choosing a set of conditions closer to expected actual operating conditions in a majority of locations, resulting in the PVUSA Test Conditions (PTC) of 1000W/m², 20 degrees C air temperature, and a wind speed of 1 m/s.

The original PVUSA regression method is presented in Equation 1, below.

$$P = I \cdot (A + B \cdot I + C \cdot T_a + D \cdot WS) \quad (1)$$

Where:

P = AC power in kW at the specific test condition

I = Plane of array irradiance (W/m²)

T_a = Ambient temperature (C)

WS = Wind speed (m/s)

A - D = Regression constants derived from operational data

ALTERNATIVE RATING METHODS

Both of the alternative rating methods explored for this work involve characterizing the relationship of module temperature to irradiance, ambient temperature, and wind speed using a thermal model that is separate from the main form of the AC power rating regression.

For improved accuracy, this thermal model should be constrained to relatively stable operating conditions, nominally clear days, particularly when the measured variables are average values over several minutes (5 to 60). Module heat capacitance, thermal transients, temperature gradients across the module, and radiative heat transfer are not easily addressed, particularly during rapidly varying weather conditions, without adding significant complexity. However, experience has shown that the following simple model does a reasonable job [10,12] for a variety of PV technologies and mounting configurations, providing module temperature during stable conditions within about ±5°C [4]. This equation provides an explicitly determined module temperature associated with the PTC rating condition.

$$T_m = I_e \cdot e^{(a+b \cdot WS)} + T_a \quad (2)$$

Where:

I_e = Effective Irradiance (dimensionless, discussed below)

a, b = regression coefficients derived from operational data

T_m = Measured module temperature (°C)

T_a, WS as defined above

Method 1 – BEW Method

This method was developed by assuming photovoltaic conversion efficiency varies with both temperature and irradiance. The original PVUSA equation substituted an expression for module temperature which is a linear function of irradiance, air temperature, and wind speed, which suggests that module temperature will drop linearly with increasing wind speed. However, as the wind speed increases this cooling effect is muted. The BEW method begins by finding the regression coefficients defined in Eqn.2 so that this effect can be modeled in the power rating.

The original PVUSA model also assumed that the inverter efficiency is constant. A more accurate assumption is to model the major loss mechanisms in an inverter as tare losses or fixed and to model the ohmic losses as proportional to current squared. The current can be modeled as approximately proportional to irradiance in a maximum-power-tracking PV system. Equations 3 and 4 represent these more detailed assumptions. Eqn. 4 is a linearized form of Eqn. 3.

$$P = (C_1 + C_2 \cdot T_a + C_3 \cdot I \cdot e^{(a+b \cdot WS)}) \times (I + C_4 + C_5 \cdot I^2) \quad (3)$$

$$P = C_{1L} + C_{2L} \cdot I + C_{3L} \cdot I^2 + C_{4L} \cdot T_a + C_{5L} \cdot I \cdot T_a + C_{6L} \cdot I^2 \cdot T_a + C_{7L} \cdot I \cdot e^{(a+b \cdot WS)} + C_{8L} \cdot I^2 \cdot e^{(a+b \cdot WS)} + C_{9L} \cdot I^3 \cdot e^{(a+b \cdot WS)} \quad (4)$$

Where:

P, T_a, I, WS are as defined above

C₁ – C₅ = regression constants for the nonlinear form

C_{1L} – C_{9L} = regression constants for the linear form

Eqn. 3 is the preferred form, however, regression using a non-linear form is relatively complex and results are dependent on both the loss function used to minimize residuals and on initial “guesses” for the coefficients. Eqn. 4, though simpler to evaluate, utilizes nine coefficients. This makes it less constrained than a regression with four coefficients as in the PVUSA method, but can introduce more scatter in the model and instability in the regression coefficients.

Method 2 – King 3-Part Method

Method 2 was developed by integrating different aspects from the PV array performance model and the inverter performance model developed by Sandia National Laboratories [10-12]. This model quantifies PV system performance in three separate steps or parts by defining parametric relationships for the effective solar irradiance, the electrical performance of array and inverter, and the operating temperature as related to weather conditions.

The first part of this method involves measuring the solar irradiance while addressing the factors unique to PV technologies, all of which can significantly influence the accuracy of PV system power ratings. For instance, solar

irradiance measurements, as well as PV array performance, are influenced by solar spectral variation, solar angle-of-incidence (AOI), ratio of diffuse to direct components of solar irradiance, temperature, calibration and accuracy of irradiance sensors, soiling, and other factors. Measuring an appropriate solar irradiance value is perhaps the most important, the most difficult, and often the most neglected aspect of PV system performance measurements. The concept of 'effective' solar irradiance, E_e , as discussed elsewhere [10], provides a means for minimizing the influence of these factors and results in a system power rating more closely related to the established performance standards for PV cells and modules. There are multiple methods for determining the effective irradiance; the simplest, and the one employed for these analyses, is to use a 'matched' and 'clean' reference cell accurately oriented in the plane-of-array.

The second part of this method characterizes system performance in a manner similar to the other methods, by using periodic measurements of system AC-power, effective irradiance, and module temperature, followed by regression analysis using the model described by Eqn. 5. The intent of this model formulation was to retain some physical significance in each of the four terms, resulting in regression coefficients that provide meaningful information. For instance, the 'a' coefficient has units of kW and is an estimate of the array STC power as diminished by inverter efficiency, the 'd' coefficient has units of kW/°C and is an estimate of the AC-power temperature coefficient, the second term in the equation mimics the logarithmic relationship between PV module voltage and irradiance, and the third term attempts to account for any further non-linear behavior of the array and/or inverter at low or high irradiance levels.

$$P = A_1 * I_e + A_2 * I_e * (T_m + 273) * \ln(I_e) + A_3 * I_e * [(T_m + 273) * \ln(I_e)]^2 + A_4 * I_e * (T_m - T_o) \quad (5)$$

Where:

I_e , T_m as defined above

$A_1 - A_4$ = regression coefficients

T_o = Reference module temperature, typically 25°C

The third part of this method provides an empirical relationship for module temperature as a function of irradiance, ambient temperature, and wind speed, as previously described by Eqn. (2).

PROJECTS EVALUATED

Operational data from several PV systems were utilized to validate the different test methods. These projects include a 10MW PV Project located in Germany, 2MW of PV Projects located in San Francisco, four small PV Projects located at NREL's Outdoor Test Facility in Golden, CO, and a small mc-Si array located at Sandia National Laboratories in Albuquerque, NM.

The intent was to include operational data from a wide variety of climates, PV technologies, mounting types, and array sizes to compare methods and ensure that the recommended method is applicable to a wide variety of PV designs and technologies. Table 1 provides a design summary of these projects. The number in parenthesis is the number of data sets evaluated with this feature.

Table 1. Summary of the type and number of projects evaluated

Climate	Module Technology	Mounting Type	System Size
Clear (5) Diffuse (7)	c/mc- Si (11) Thin film (2)	BIPV (6) Horizontal (7) 1-axis Track (1) Latitude Tilt (4)	Under 5 kW (5) Over 5 kW (9)

Data Filtering

In evaluating the AC rating, measured data with the following operational issues were removed because they are not relevant to understanding the power rating.

- Inverter outages
- Periods with snow
- Excessive soiling
- Shading

However, it should be noted that these factors must be addressed in determining the overall system energy production [15, 16]. Development of a system energy rating procedure compatible with this power rating method is important future work, but is outside the scope of this paper.

OTHER CONSIDERATIONS

There are several influences that are independent of the form of regression model used. For instance: soiling (modules and irradiance sensor); degradation (permanent or seasonal annealing); spectral effects (modules relative to pyranometers or reference cells) [8,9]; calibration of thermopile pyranometers as a function of AOI, as well as accuracy of mounting in the plane of the array; location of wind sensor as it impacts the module operating temperature, inverter performance characteristics (MPPT, input voltage and temperature influence on efficiency); accuracy of ac-power meter, as well as all other instrumentation [13]. Each of these influences can have significant impact on the precision of the result, and must be considered. The future standard should provide guidance on test uncertainty, but leave the final decision up to the parties conducting the specific acceptance test.

While an in-depth discussion of an uncertainty analysis is outside the scope of this paper, we will briefly address the issue of irradiance sensor choice: pyranometer vs. reference cell.

Relative to irradiance measured with a thermal pyranometer, solar irradiance determined with a properly calibrated and packaged reference cell results in less scatter in regression analyses because spectral, AOI, and diffuse irradiance effects are implicitly compensated. If a matched reference

cell is used to collect irradiance data, the measured data is taken with respect to a predefined reference spectrum. In principle there should be no seasonal or air mass related spectral effects in the data. Data collected with a properly calibrated and packaged reference cell should have less scatter than a thermal detector (pyranometer) because scatter from varying outdoor spectral irradiance is eliminated and the time constant of the reference cell is matched to the PV array eliminating scatter when the light is rapidly varying. If a thermal detector (pyranometer) is used to measure the total irradiance; then the data is measured with respect to the prevailing site and seasonal conditions. This may be the goal for side by side comparisons of various technologies or for locations where it is considered a loss if they cannot fully utilize the solar spectrum.

RESULTS AND DISCUSSION

The two primary improvements sought through this work are increased seasonal applicability and reduced uncertainty of the result. Figure 1 below illustrates the PTC ratings obtained from a 670 kW segment of the 10 MW Project located in Germany during three different months using each of the three methods. The methods were applied to several subsets of the available data:

1. All data above 100 W/m² with pyranometer
2. All data above 100 W/m² with reference cell
3. Clear-day data above 100 W/m² with pyranometer
4. Clear-day data above 100 W/m² with reference cell

Note that while the 3-Part method addresses the concept of reference cells and “effective irradiance” explicitly, use of this concept is not specific to the 3-Part method. Using irradiance data obtained through a reference cell will implicitly introduce this concept into any of the methods evaluated here, and this is demonstrated in Figure 1 and Table 2.

The error bars in Figure 1 represent the standard error of the regression model result. Note that the model error is only one component of the total uncertainty associated with the power rating. (Additional discussion of uncertainty is found in subsequent sections.) Table 2 details the results shown in Figure 1.

For the 10 MW Project described above, the model error/uncertainty for each case was similar for all three models, with the BEW linear model tending to have the smallest model uncertainty for April and June. There was variance in system rating from month to month in all of the models, and was anywhere from 2-6%. The King 3-Part model had the smallest seasonal variation. This analysis also illustrated that both model uncertainty and seasonal variation are reduced for all three models when a reference cell is used for irradiance sensing compared to a pyranometer. Limiting the data set to clear days had the effect of further reducing model error.

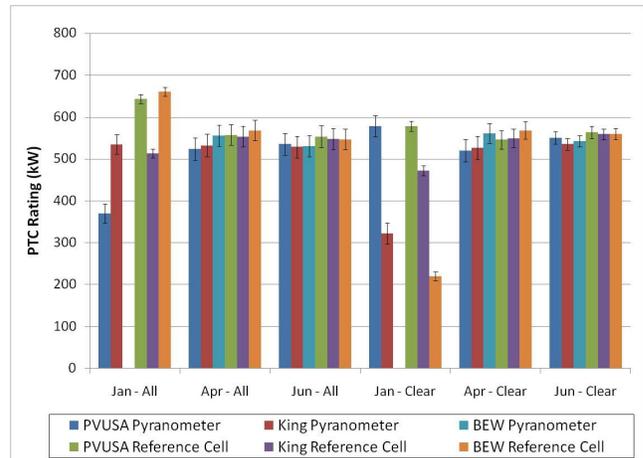


Figure 1. PTC Plant ratings for a 670 kWp segment of a 10MW PV project located in Germany

Table 2. PTC plant ratings and standard error for a 670 kWp segment of a 10MW PV project located in Germany

Irradiance:		Pyranometer		Reference Cell		Reference Cell	
Conditions	Month	PVUSA		BEW Linear		King 3-Part	
		P(ptc)	% Error	P(ptc)	% Error	P(ptc)	% Error
All Days	January	370	6.1%			535	4.3%
All Days	April	524	5.1%	556	4.6%	532	5.1%
All Days	June	535	4.8%	531	4.7%	529	4.9%
Clear days	January	579	4.3%			322	7.7%
Clear days	April	520	5.2%	561	4.2%	527	5.3%
Clear days	June	550	2.7%	543	2.5%	536	2.6%
Irradiance:		Reference Cell		Reference Cell		Reference Cell	
Conditions	Month	PVUSA		BEW Linear		King 3-Part	
		P(ptc)	% Error	P(ptc)	% Error	P(ptc)	% Error
All Days	January	643	1.7%	661	1.5%	513	2.0%
All Days	April	558	4.4%	568	4.2%	553	4.4%
All Days	June	554	4.6%	547	4.6%	548	4.6%
Clear days	January	579	2.1%	220	4.8%	472	2.5%
Clear days	April	546	4.0%	568	3.7%	550	4.1%
Clear days	June	564	2.5%	560	2.4%	559	2.2%

Figure 1 shows that none of the methods were robust enough to handle the January dataset well. While the ratings for April and June are all in good agreement (model errors are overlapping in all cases for these months), the January ratings were hugely varied. The original PVUSA method restricted to clear days seems to be the best option for January rating of this system.

While neither of the new models suggests a clear winter-rating improvement for the Bavaria system, which has relatively extreme winter conditions, the authors evaluated multiple systems in fairer climates. These results do suggest that the proposed alternatives to the PVUSA method offer a reduction in model uncertainty during winter months. Table 3 shows the system power rating and standard error of the model for the King 3-part and the original PVUSA method for each of five different systems, each using a different module technology. For five of the six technologies, the King 3-Part method resulted in a reduced uncertainty compared to the original PVUSA method; for the mc-Si system, the uncertainty is unchanged. Data sets used in this analysis all included irradiance data measured above 400 W/m² using a reference cell.

Table 3. Ratings and model error, 3-Part and PVUSA for NREL and Sandia systems (each 1-2 kWp). All regressions performed against irradiance data measured by a reference cell on clear days only

System	PVUSA					
	P(ptc)			% Standard Error		
	January	April	June	January	April	June
HIT Si	0.856	0.843	0.814	1.8%	1.2%	1.1%
EFG Si	1.069	1.010	1.013	1.2%	2.0%	2.2%
CIGSS thin-film	0.923	0.906	0.915	1.7%	1.6%	1.1%
a-Si thin-film	0.889	0.933	0.926	3.2%	1.8%	1.8%
mc-Si	1.792	1.801	1.817	1.0%	1.0%	0.8%
System	King 3-Part					
	P(ptc)			% Standard Error		
	January	April	June	January	April	June
HIT Si	0.857	0.849	0.805	1.6%	0.9%	0.5%
EFG Si	1.058	1.014	0.991	0.9%	1.2%	0.8%
CIGSS thin-film	0.897	0.914	0.907	1.2%	0.8%	0.5%
a-Si thin-film	0.883	0.924	0.947	2.7%	1.8%	1.6%
mc-Si	1.783	1.802	1.788	1.0%	0.9%	0.7%

The standard errors for the regressions shown in Table 3 are smaller than those calculated for the Germany Project. The average standard error for April and June for the NREL and Sandia systems is between 1% for the 3-part method and 1.5% for the PVUSA method, while the April and June standard error for the Germany Project is on the order of 2.5-4% depending on the method. The Germany Project uncertainty is probably more representative of the uncertainty we would expect for large plants in general, since it covers a large area (nearly 4,000 modules for the segment illustrated in Fig. 1 and Table 1) and will be subject to much larger variation in the temperature model due to non-uniform temperatures throughout the array. The small projects fielded at NREL and Sandia are much smaller (1-2 kW). The measured data collected for these projects are more controlled and homogenous.

Table 4 details a similar comparison of model error between the original PVUSA method and both the linear and non-linear versions of the BEW method for the same systems that were evaluated in Table 3. Table 4 evaluates model uncertainty using the mean bias error and root mean square error obtained from curve fits derived with various combinations of power models and time periods. This analysis included a “stress-test” of the models by using them to evaluate data from only one and two weeks in January.

All three models predicted PTC Power well in April, but in January the one-week data set showed large MBE for the mc-Si data that was cut by at least a factor of four for the two week data set. Both the nonlinear and linearized models were able to work with the low irradiance data in January, but the PVUSA model was not usable due to the lack of data near the rating conditions. The linearized model performed very similar to the nonlinear model suggesting that the additional computational complexity of the nonlinear model may not be required in order to obtain PV system ratings in the winter months.

Table 4. Ratings and model error, BEW and PVUSA for NREL and Sandia systems (each 1-2 kWp). All regressions performed against irradiance data measured by a pyranometer for all days

Estimated PTC Rating		0.914kW		0.838kW		1.014kW	
Data Set		a-Si thin film		HIT Si		EFG Si	
Period	Model	MBE	RMSE	MBE	RMSE	MBE	RMSE
April	PVUSA	-2.1%	2.4%	-5.0%	4.3%	-1.1%	1.4%
April	Nonlinear	0.7%	2.9%	-7.3%	3.0%	-0.7%	2.6%
April	Linearized	0.8%	2.9%	-3.4%	2.9%	-1.0%	2.6%
Jan - 1wk	PVUSA	-1.4%	1.9%	-1.7%	2.4%	2.5%	0.6%
Jan - 1wk	Nonlinear	-0.4%	3.4%	0.1%	3.1%	2.9%	0.9%
Jan - 1wk	Linearized	-2.6%	3.4%	4.0%	3.1%	2.1%	0.7%
Jan - 2wk	PVUSA	-2.6%	2.8%	1.8%	1.9%	5.8%	2.0%
Jan - 2wk	Nonlinear	-2.0%	3.7%	-0.3%	2.6%	5.8%	1.5%
Jan - 2wk	Linearized	-2.5%	3.7%	3.4%	2.5%	5.2%	1.5%
Estimated PTC Rating		0.911kW		1.763kW			
Data Set		CIGSS thin film		mc-Si			
Period	Model	MBE	RMSE	MBE	RMSE		
April	PVUSA	-0.4%	1.3%	-0.3%	3.6%		
April	Nonlinear	-0.2%	2.0%	-1.0%	3.7%		
April	Linearized	-0.1%	2.0%	-0.5%	3.7%		
Jan - 1wk	PVUSA	-7.8%	2.5%	9.3%	5.5%		
Jan - 1wk	Nonlinear	-5.8%	2.2%	11.3%	6.1%		
Jan - 1wk	Linearized	-9.7%	2.2%	10.3%	6.0%		
Jan - 2wk	PVUSA	-0.3%	2.4%	1.5%	6.0%		
Jan - 2wk	Nonlinear	-1.4%	2.0%	2.3%	6.1%		
Jan - 2wk	Linearized	-0.5%	2.0%	1.0%	6.0%		

REGRESSION DIAGNOSTICS

In understanding the uncertainty of the analysis it is helpful to look at the regression statistics. High p values (>0.05) indicate that the particular regression coefficient is unstable and may lead to erroneous conclusions. For example, p values for our January regressions for the Germany Project are high, explaining the large variation in results between models. In practice, high p values are an indication that the data collected for the given predictor variable is insufficient for system rating. The standard error and 95% confidence interval of the estimate provides an indication of the accuracy of the regression analysis and can be used in uncertainty analysis.

CONCLUSIONS

Our analysis results to date suggest that both the BEW and the King 3-Part methods offer moderate improvements in model uncertainty and seasonal applicability. Apart from the regression methods themselves, our analyses illustrate how variations in data collection and test procedure affect results. In particular, selecting a matched reference cell rather than a pyranometer for irradiance measurement will reduce model uncertainty and seasonal variability in the result. Limiting the analysis to only clear days further reduces uncertainty and variability in the model. These procedural choices seem to be more important than the particular form of regression equation chosen. Because reduced uncertainty in the regression result was a key criterion in this work, we will recommend to the ASTM committee that reference cells be listed as the preferred sensor for this type of testing. Pyranometers can of course be used, but increased scatter about the model function (and resulting rating) will occur.

The issue of clear days vs. all days during a time period is also of interest. **The original PVUSA method recommended the collection of at least 30 days of data, but our analysis shows that similar results can be obtained with much smaller data sets when the data is limited to clear days.** If several clear days occur shortly after the commencement of the test period, then using just a few clear days would shorten the test period, however, a long string of cloudy days could delay testing beyond the period required if all data is considered.

Finally, based on the analyses performed for this work, we can help to inform one of the most problematic issues of project acceptance from a commercial perspective – that of the appropriate level of uncertainty to attach to a system rating result. While a full uncertainty analysis is outside the scope of this paper, we can point out the largest sources of uncertainty in this type of test. They include:

- Model uncertainty, which we estimate at 2-8%
- Solar Irradiance measurement uncertainty, which ranges between 2-5%
- Module temperature measurement uncertainty, which ranges between 2-4%
- AC power measurement uncertainty, which ranges between 0.4-1%.

Therefore, we estimate that total overall uncertainty of power ratings using these methods will be on the order of 3.5 – 7.5%. All uncertainties discussed in this paper are at a 95% confidence interval.

If uncertainty is important, a formal analysis should be conducted [14]. Before system testing, it is recommended that all parties to the test agree to the uncertainty analysis methods and how the uncertainty analysis results can be applied to the performance test results in the form of a tolerance.

FUTURE WORK

The analyses completed in support of this effort help to illuminate a number of the intricacies and considerations discussed above. This paper represents the first step in developing a power rating standard, and has identified several key areas in which further work is needed. These areas include: 1) a full uncertainty analysis for each of the methods using various sensor types and data limitations. 2) Resolution on recommendations for key test procedures including: the length of test period, the minimum irradiance required, the choice of the rating condition (e.g. include reference spectrum or not), as well module temperature measurements and their role in ratings, and 3) development of a companion standard for system energy ratings.

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