

# A STANDARDIZED APPROACH TO PV SYSTEM PERFORMANCE MODEL VALIDATION

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## ABSTRACT

PV performance models are used to predict how much energy a PV system will produce at a given location and subject to prescribed weather conditions. These models are commonly used by project developers to choose between module technologies and array designs (e.g., fixed tilt vs. tracking) for a given site or to choose between different geographic locations, and are used by the financial community to establish project viability. Available models can differ significantly in their underlying mathematical formulations and assumptions and in the options available to the analyst for setting up a simulation. Some models lack complete documentation and transparency, which can result in confusion on how to properly set up, run, and document a simulation. Furthermore, the quality and associated uncertainty of the available data upon which these models rely (e.g., irradiance, module parameters, etc.) is often quite variable and frequently undefined. For these reasons, many project developers and other industry users of these simulation tools have expressed concerns related to the confidence they place in PV performance model results. To address this problem, we propose a standardized method for the validation of PV system-level performance models and a set of guidelines for setting up these models and reporting results. This paper describes the basic elements for a standardized model validation process adapted especially for PV performance models, suggests a framework to implement the process, and presents an example of its application to a number of available PV performance models.

## INTRODUCTION

There exist numerous commercial and academic computer models and algorithms for simulating the performance of PV systems. Klise and Stein [1] present a description and summary of many existing models. These models differ in their conceptual approach and the amount of data required for simulation but each essentially predicts the energy (DC and/or AC power over a time step) produced for a given global horizontal, and direct normal irradiance, and the resultant plane-of-array (POA) irradiance and module (or cell) temperature. The validity of a given modeling approach rests in the ability of the model to match observed power (and energy) produced by

the system taking into account measurement and other system uncertainties. A standard method for validating these models has not yet emerged. Furthermore, the validation efforts that have been well documented (e.g., [2]) are performed for a single model and a unique set of arrays and locations and are not designed for comparing the performance of different performance models. Thus, models are rarely tested against a common set of weather and performance data and it is therefore very difficult to know how one model may perform relative to another for a given site. This paper suggests a validation methodology that can be applied to models to increase the confidence in their results when applied to proposed PV systems. The procedure presented here is intended to be applied to the full range of module technologies and a representative set of locations chosen to represent different climates.

## A STANDARD MODEL VALIDATION PROCEDURE

A standard model validation procedure is beneficial because it provides a common approach to test the ability of various models to predict PV performance for different system designs and technologies in varied climates. In addition, the use of a standard approach allows the results of different validation studies to be compared, which leads to a better understanding of the various strengths and weaknesses of available models. Finally, the approach discussed here is intended to provide information that can be used to improve existing models by identifying specific relationships or sub models that lead to the models deviating from measured performance. For example, performance models typically rely on a radiation sub model to estimate plane of array irradiance. This standard approach can be used to assess the accuracy of the radiation model separately from the accuracy of the performance model. The major elements of the model validation process include:

1. Develop data sets for model validation including system description, weather data and performance data for multiple technologies, applications, and climates.
2. Provide the system description and weather data to modelers, who will model the system and provide results.
3. Apply a unified mathematical/statistical approach for comparing measured and modeled quantities and

document comparisons in a standardized reporting format.

4. Identify opportunities for model improvement, when possible.

### **PV Array Description**

To test the effectiveness of our approach under this initial model validation, arrays that will be considered need to be as close to ideal design conditions as possible. For example, arrays with partial shading should be avoided. More complex arrays, for example with row-to-row shading, will be included as validation efforts advance to features such as shading algorithms. Heavy soiling environments should be avoided, and arrangements should be made to regularly clean both the array and adjacent irradiance sensors. The period of assessment should ideally last a complete year but, at the least, from solstice to solstice to ensure that the full range of solar elevation angles is represented. The system design (tilt, wiring diagram, wire lengths) must be fully characterized and documented, and performance data on major components must be available.

### **Measured Weather Data**

All PV performance models rely on solar radiation and ambient air temperature data, which is either measured directly at the site or derived from measurements made in the region. The accuracy of the cell temperature sub model may be improved with a wind speed measurement as well. In order to isolate the quality of the model from the quality of the input data it is desirable to measure solar radiation with as much accuracy as possible and to evaluate the magnitude of the measurement uncertainties. An ideal data set for model validation would include total horizontal, horizontal diffuse, direct beam, and plane-of-array irradiance (ideally characterized by pyranometer and matched reference cell).

Another issue is that measurement errors for high quality irradiance sensors can be between +2.5% to -10% for pyranometers and +/- 2.5% for pyrhemometers [3]. Lower quality instruments such as photodiodes can have larger measurement errors. Given this reality and the wide variation between instrument maintenance and calibration procedures at different sites, it is challenging to compare irradiance data collected at two different sites at a sufficient accuracy for performance model validation purposes.

### **Measured Performance Data**

At a minimum, the AC power output of the array must be measured, but if possible, measurements of DC current and voltage should also be made as they are useful for identifying problems with the array, such as short circuits or blown fuses as well as evaluations of inverter efficiency and DC side line losses. If problems occur, data collected during these periods should be filtered out of the final data

set (performance and weather data) so the models are only tested under normal operating conditions. Additionally, if module back-side temperatures can be monitored, the cell temperature sub models can be evaluated.

Similar to irradiance measurements, there are accuracy issues with electrical performance measurements. Cumulative AC power should be measured with a revenue grade meter that has an accuracy of between 0.5 and 1%. Power measurements directly from the inverter should be treated with suspicion, unless independently calibrated. The accuracy of DC current and voltage is typically less than AC power from a revenue grade meter unless high quality, calibrated power analyzers are used. Variations in data quality between different systems limit the accuracy of model comparisons across different systems.

### **Additional Challenges**

One of the primary challenges to selecting appropriate array performance datasets for model validation turns out to be a lack of consistency in quality and data collection procedures between different sites. The use of different weather instruments and/or calibration schedules at different sites can result in a several percent variation between irradiance measurement accuracy. Similar problems exist for electrical measurement accuracy. In an effort to solve this problem, the U.S. Department of Energy (DOE) is currently pursuing a program that will define a standard set of monitoring equipment and procedures for measuring system performance and weather conditions at a site. These standards will be applied to a number of federally-funded photovoltaic generation projects across the country with the goal of collecting consistently accurate data from these systems. This program should provide high quality and consistent performance and weather data which will be valuable for determining appropriate system derate factors and for testing various models.

### **Mathematical/Statistical Approach**

A popular method for comparing model predictions with measurements is based on regression techniques and is often limited to reporting the  $R^2$  value from a linear regression between measured and simulated quantities (e.g. DC or AC power). Comparisons may also report random and systematic errors (e.g., root mean square error (RMSE) and mean bias error (MBE)). While these metrics are valuable, they do little to increase our understanding of why and where the model deviates from the measurements. The more interesting questions are under what conditions errors arise and which sub models or components result in modeling errors? The method of residual analysis we propose here provides information needed to begin to answer these questions.

Residual analysis is based on examining the distribution and sensitivity of model residuals (difference between

modeled and measured values) with respect to other time-varying variables in the analysis. The relationship between predictions of a "perfectly valid" model and measured performance should be "statistical" rather than deterministic. This is because models are based on mathematical functions and model parameters derived to match mean behavior, not point-by-point behavior of the system. Furthermore, all measurements (weather and performance) are characterized by uncertainties, meaning that any particular measured value is a sample from some underlying uncertainty distribution, which is often poorly defined. For these reasons, a completely valid model is one which results in residuals that are randomly distributed with respect to all variables in the analysis.

We propose the following analysis steps to quantify the degree to which this relationship is random. The first step is to identify the quantities of interest and calculate residuals. In the case of PV performance models, these quantities can include: annual, monthly, daily, hourly, and/or sub-hourly energy produced by the system. Intermediate quantities of interest include plane of array irradiance and module/cell temperatures, among others. There are several ways to determine the degree of randomness in the residuals.

First the residuals are plotted as a function of time (run plot) to ensure that there are no significant trends with time. A general sudden shift in the residual values indicates that there may have been a change in the system, such as a component failure, soiling (or cleaning) event, etc. A gradual monotonic trend in the residuals might indicate instrument drift or system or component degradation. These features, if they exist, indicate that the measured performance data is not as controlled as thought and the data may need to be filtered to exclude these changes. If the trend follows a periodic or seasonal trend it could indicate an error in the model related to temperature or sun elevation angle or a measurement or calibration error related to these seasonal sensitive parameters. In addition, outliers can also be identified and excluded from the run plot and other statistical calculations. Outliers can occur due to a number of reasons, such as occasional shading of sensors, severe soiling, electrical noise, etc., but identification after the data has been collected is usually very difficult if not impossible. Therefore, it is usually justified to simply remove outliers from the validation analysis.

Second, the residuals are plotted as a histogram, a cumulative distribution function, and/or on a probability plot to examine the distribution. A perfectly valid model should result in normally distributed residuals. However, normally distributed residuals do not guarantee a valid model because the periodic (diurnal) nature of PV performance data can result in systematic residuals that when combined over a year behave normally. We will discuss this later.

Third, the residuals are analyzed using a stepwise regression and graphical residuals analysis techniques. A stepwise linear regression of the residuals identifies and ranks input variables in order of their contribution to residual variance, assuming a linear model form. Variables with a relatively high contribution to residual variance help to identify specific sub models or parameters that are contributing to modeling error.

Stepwise regression is based on performing a series of linear regressions of the form:

$$Y = b_o + \sum_{j=1}^P b_j X_j, \quad (1)$$

where  $Y$  is a vector of dependent variables and  $X$  is a set of  $P$  vectors of independent variables included in the stepwise model. The  $b$  coefficients in (1) can be used to develop a prediction model, if desired. In the first step, the method tests the linear regression between  $Y$  (in our case, model residuals) and a set of independent variables (time-varying variables in the analysis) to see which variable results in the best linear fit (highest  $R^2$ ). For the second and subsequent steps, additional independent variables are added to the regression in order of which variable provides the highest  $R^2$  value for each step. This process continues until the probability ( $p$ ) that an effect is due to chance is exceeded. For our application we are interested in the order of the  $X$  variables that are selected for the model and the resulting  $R^2$  values. This method is limited in that it can only identify linear trends, but if applied judiciously, it can shed light on which variables are most correlated with model residuals and help to quantify the validity of a PV performance model.

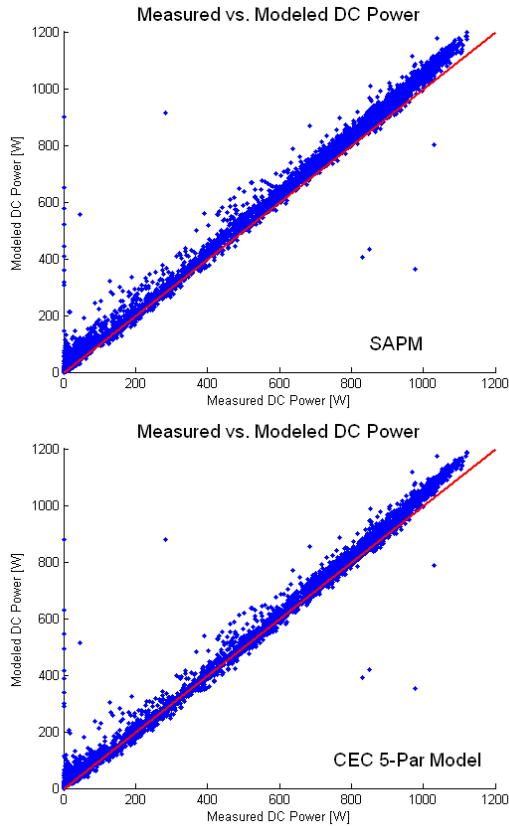
Graphical residual analysis examines the relationship between residuals and input variables and is useful for identifying both linear and non linear patterns. An illustration of this can be made by plotting mean residuals calculated in bins defined by time-varying variables against the bin midpoints. If these mean residual plots show systematic trends (monotonic or periodic) this suggests a non-random effect. One simple metric is to compare the standard deviation of the bin means divided by the standard deviation of the entire residual population. Higher values indicate that the variable is affecting the residuals.

### EXAMPLE APPLICATION OF THE VALIDATION APPROACH

To illustrate the approach we examined performance data from a small (1 kW) c-Si grid-tied PV system at Sandia National Laboratories in Albuquerque, NM between April 1 2007 and March 31 2008. As model input, we measured irradiance (direct normal, diffuse horizontal, and global horizontal), air temperature, and wind speed. We also monitored electrical performance on the DC (current and voltage) and AC (power) sides of the inverter. We ran two PV performance models included in the Solar Advisor

Model (SAM) [4]: The Sandia Array Performance Model (SAPM) [5] and the CEC 5-parameter model [6]. No derate factors were included for these runs.

Figure 1 shows scatter plots of modeled and measured DC power for both models. Except for a slight difference in the annual energy bias, which could be compensated by including an appropriate derate factor, the models appear to perform quite similarly. It is not until the methods of residual analysis are applied do differences between the models begin to appear.



**Figure 1 Scatter plots of modeled DC Power against measured DC power for two models.**

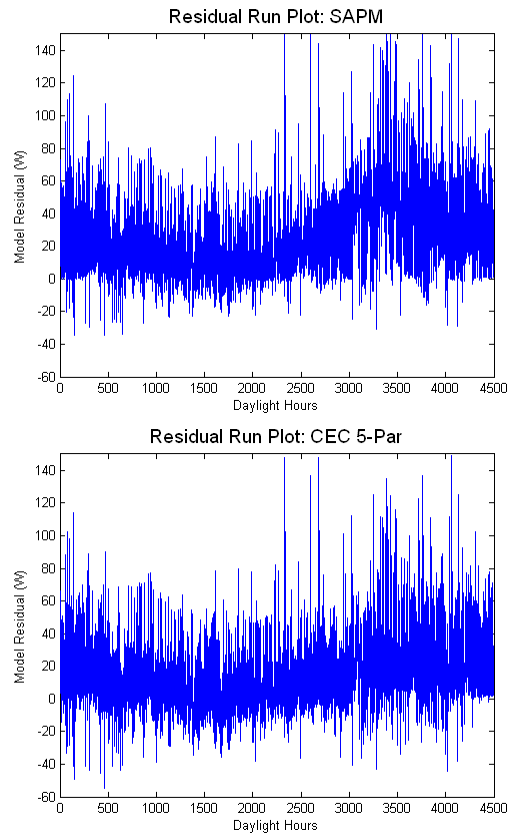
Several outliers are evident in the data. Outliers below the 1:1 red line are likely due to occasional shading of the irradiance sensors for brief periods of time (cleaning, birds perching, etc.). Outliers above the 1:1 red line might indicate occasional shading of the array by field workers, birds, or electrical noise from the power sensors. Before proceeding, we have filtered out residuals that are greater than 150 W and less than -150. When a residual value is filtered for one model, we filter out the same records from the other model to ensure that annual comparisons are valid between models.

From this filtered data we next calculate annual percent bias error, root mean square error (RMSE) of residuals with bias removed and mean bias error (MBE). The

annual bias error is the percent difference between modeled DC energy (sum of hourly DC power values) and measured DC energy. RMSE is the square root of the mean of the squared residuals (bias removed) in units of Watts. Mean bias error is the difference between the mean of the modeled power and the mean of the measured power in units of Watts. Table 1 displays these statistics for both models. Quantities are calculated after outliers and zero values have been removed.

	SAPM	CEC 5 Par
<b>Annual Bias</b>	5.6%	3.3%
<b>RMSE (bias removed)</b>	26 W	23 W
<b>MBE</b>	27 W	16 W

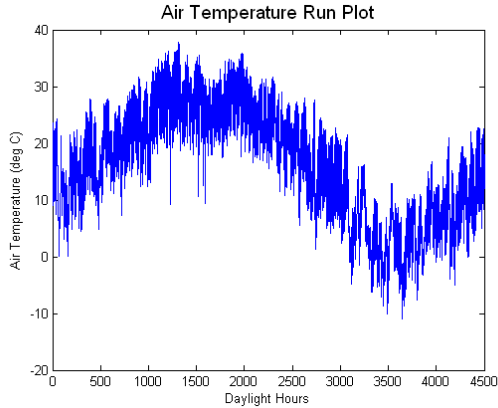
**Table 1. Summary of Annual Model Results**



**Figure 2. Residual run plots for SAPM (top) and CEC 5-Parameter model. X-axis runs from April 2007 to March 2008.**

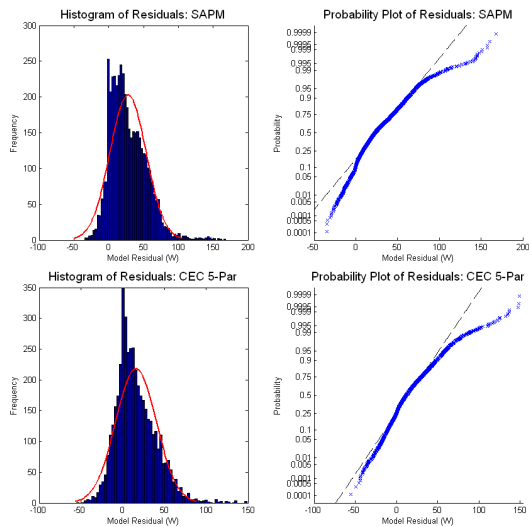
Figure 2 compares run plots for both simulations with nighttime periods excluded from the dataset. Both models appear to show some seasonal pattern to the residuals with a dip in the summer period and a spike (more prominent in the SAPM residuals) at the coldest period of the year (see Figure 3 for a similar plot of air temperature). This pattern suggests that the SAPM model results might

be improved by lowering the magnitude of the module temperature coefficients as the model appears to be over compensating for temperature.



**Figure 3. Daytime air temperature run plot. X-axis runs from April 2007 to March 2008.**

The next step is to analyze the distribution of residuals. Figure 4 shows histograms and probability plots of the residuals for each model. The residuals from both models share normally distributed characteristics except for a slight skewness towards the left, which comes from a high frequency of residuals close to zero. This pattern is expected since two periods each day have low irradiance (morning and evening) and therefore will be characterized by residuals with a low absolute magnitude.



**Figure 4. Comparison of the distribution of the residuals: Histograms are shown on the left and probability plots are shown on the right.**

The final step in the model validation process is to identify if there are any other input variables that are affecting the residuals in a systematic way. Stepwise regression is a useful technique for this purpose. We ran a stepwise regression on the residuals from each model (outliers removed). The independent variables that were included

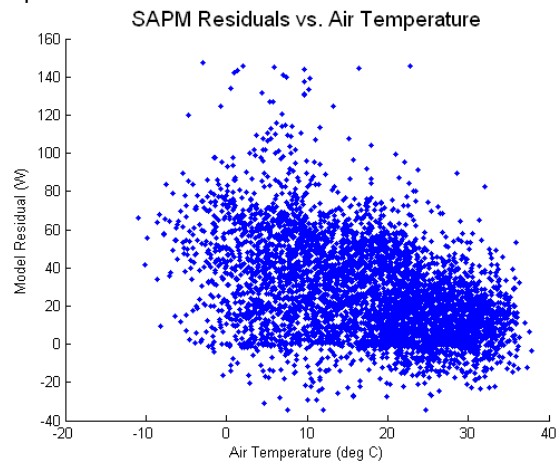
were irradiance (incident beam, diffuse, and total), temperature, wind speed, sun zenith and azimuth angles, angle of incidence, and air mass. The results of the stepwise regression are summarized in Table 2.

SAPM			
Order	Variable	R <sup>2</sup>	Incremental R <sup>2</sup>
1	Temp	0.18	0.18
2	Incident Tot	0.35	0.17
3	Azimuth	0.37	0.02
4	Zenith	0.39	0.02
CEC 5-Par			
Order	Variable	R <sup>2</sup>	Incremental R <sup>2</sup>
1	Incident beam	0.12	0.12
2	Temp	0.22	0.10
3	WS	0.27	0.05
4	Azimuth	0.28	0.01

**Table 2. Stepwise Regression Results.**

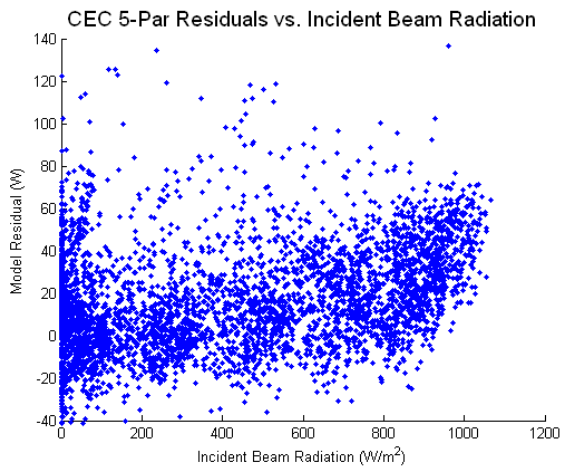
These results are interpreted as follows. The incremental R<sup>2</sup> value is the fraction of the variance in the residuals explained by the variable. Therefore, about 35% of the variance in the SAPM residuals is explained by a linear trend with air temperature and total incident radiation. In a similar pattern, 22% of the variance in the CEC 5-Par residuals can be explained by linear trends with incident beam radiation and air temperature. The variable in the third and fourth steps account for such small fractions of the variance they can be ignored.

Figure 5 shows a scatter plot of SAPM residuals vs. air temperature.



**Figure 5. SAPM model residuals vs. air temperature.** Figure 6 shows a scatter plot of CDC 5-Par model residuals vs. incident beam radiation. These plots visually

demonstrate the correlations identified in the stepwise regression.



**Figure 6. CEC 5-Par model residuals vs. incident beam radiation.**

### SUMMARY AND CONCLUSIONS

A standard approach for PV performance model validation has been presented along with a short example of its application to two performance models that were run for one year of data collected from a PV system in Albuquerque, NM. The methodology is based on applying residual analysis, which aims to quantify the magnitude of the residuals as well as check the degree to which model residuals are randomly distributed and not correlated with other variables in the analysis. Models are typically run without derates in order to understand how bias errors differ between models. Initial model validation efforts suggest that different models require different derate factors, which means that derate is a function of both system design *and* choice of model. A better understanding of this relationship will lead to greater confidence in performance model results.

A model validation report should include the following:

1. A detailed description of the PV system that is being used for the validation, including information on sensor accuracy and precision.
2. An accurate description of how the model was run including all parameter values
3. Annual and monthly summary statistics of model residuals (both random and systematic errors)
4. Residual analysis results following the example set forward in this paper
5. Estimate of data and model uncertainties

The method assumes that quality data (weather and electrical performance) have been collected and that uncertainties in this data are understood. However, in practice, this is rarely the case. In fact, the application of residual analysis frequently aids in identifying data quality problems.

As an example, the residual analysis method was demonstrated with two performance models on a dataset from Albuquerque, NM. Both models were shown to have similar patterns in their residuals, with the highest correlations attributed to air temperature and irradiance levels, respectively. Correlation with air temperature suggests that the model predictions could be improved by adjusting the module temperature coefficients or the cell temperature model. If module backside temperatures are measured, the application of residual analysis to the modeled cell temperature would determine whether the source of the correlation with temperature arises from the module temperature coefficients or the cell temperature model and coefficients.

Future work will focus on applying these analysis techniques to different datasets. There is a great need to examine how commonly used models perform in different climates, with different module technologies (e.g., thin films, concentrator technology), and with different performance and weather instrumentation. The application of a standard approach to validating performance models will help improve understanding of how these models perform, provide model developers with information allowing them to make model improvements, and lead to greater confidence in the results.

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