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PV Performance Modeling Workshop Summary Report

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Prepared by
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Abstract

A number of PV system performance models have been developed and are in use, but little has been published on validation of these models or the accuracy and uncertainty of their output. With support from the U.S. Department of Energy's Solar Energy Technologies Program, Sandia National Laboratories organized a PV Performance Modeling Workshop in Albuquerque, New Mexico, September 22-23, 2010. The workshop was intended to address the current state of PV system models, develop a path forward for establishing best practices on PV system performance modeling, and set the stage for standardization of testing and validation procedures for models and input parameters. This report summarizes discussions and presentations from the workshop, as well as examines opportunities for collaborative efforts to develop objective comparisons between models and across sites and applications.

ACKNOWLEDGMENTS

The authors would like to express appreciation to Ben Bourne of SunPower for sharing his extensive notes from the workshop and to Geoff Klise of Sandia for capturing the workshop discussion on flip charts.

The authors also wish to thank the workshop participants and presenters for their contributions to the workshop.

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NOMENCLATURE

AC or ac	Alternating current
AOI	Angle of incidence
a-Si	Amorphous silicon
BIPV	Building-integrated photovoltaics
CdTe	Cadmium telluride
CEC	California Energy Commission
CECPV	California Energy Commission Photovoltaic (calculator)
CIS	Copper indium diselenide
c-Si	Crystalline silicon
DC or dc	Direct current
DMPPT	distributed maximum power point tracking
DOE	U.S. Department of Energy
HIT	Heterojunction with intrinsic thin layer
IEC	International Electrotechnical Commission
I-V curve	Current-voltage curve
kW	Kilowatt
kWh	Kilowatt hour
kWp	Kilowatt peak
mc-Si	Multicrystalline silicon
MPP	Maximum power point
MPPT	Maximum power point tracking
MW	Megawatt
NOCT	Nominal cell operating temperature
MWp	Megawatt-peak
NREL	National Renewable Energy Laboratory
PV	Photovoltaic or photovoltaics
SAM	System Advisor Model
SAPM	Sandia PV Array Performance Model
SNL	Sandia National Laboratories
TMY	Typical meteorological year

1. OVERVIEW

1.1 Background

During the development of a solar photovoltaic (PV) energy project, predicting expected energy production from a system is a key part of understanding system value. System energy production is a function of the system design and location, the mounting configuration, the power conversion system, and the module technology, as well as the solar resource. Even if all other variables are held constant, annual energy yield (kWh/kWp) will vary among module technologies because of differences in response to low-light levels and temperature.

> PV Systems Modeling Development and Evaluation is performed within the Systems Integration sub-program area of the U.S. DOE Solar Energy Technologies Program.
>
> The missions of the modeling team are:
>
> - to provide manufacturers, system integrators, project developers, and the financial community with validated tools to calculate key metrics, such as expected system performance and Levelized Cost of Energy, including the contributions of component and system lifetime, durability, and availability, and, as a result,
> - to help reduce cost and hasten market development by reducing uncertainty in expected performance and Levelized Cost of Energy, thereby reducing risk and the cost associated with that risk (cost of and time to obtain financing, cost of warranties and service agreements, etc.)
>
> Sandia's role is to evaluate and validate PV performance models, including DOE and non-DOE models, by characterize accuracy and uncertainty. A key supporting activity is collecting high-quality sets of weather, solar resource, and system performance data for use in model evaluation.
>
> One outcome of model evaluation is to identify and implement opportunities for model improvement. Assessment is not limited to public models; it can also be performed for proprietary models run by others.

A number of system performance models have been developed and are in use, but little has been published on validation of these models and on the accuracy and uncertainty of their output.

With support from the U.S. Department of Energy's (DOE's) Solar Energy Technologies Program, Sandia National Laboratories (Sandia) organized a PV Performance Modeling Workshop in Albuquerque, New Mexico, September 22-23, 2010. The workshop had the following primary objectives:

- Understanding the current state of PV system models and modeling tools
- Developing a path forward for establishing best practices on PV system performance modeling
- Working toward standardization of testing and validation procedures for 1) documenting the accuracy and uncertainty of model input parameters, and 2) evaluating and improving the accuracy of models and tools.

There may be no single model that can suit all modeling purposes. Rather, there are trade-offs among model attributes including accuracy, availability and cost of solar resource and component performance data, ease of use, and integration with related tools such as financial models and shade analysis tools such as Solmetric's SunEye. This workshop was an opportunity for modelers and model users to discuss the attributes and importance of such trade-offs.

In an effort to optimize the collaborative nature of the meeting and focus participation on modeling experts, the meeting was by invitation only. Participants included model developers, modelers from PV module manufacturers and systems integrators, and independent engineers who perform due diligence for project developers and the financial community. Appendix A contains the meeting agenda and the list of participants is in Appendix B.

The workshop was a significant step towards establishing a Sandia-led PV Performance Modeling Collaborative, which will provide a framework for partnering to conduct objective comparisons between models and across different sites and applications. The collaborative will also research opportunities to improve models through evaluations of modeling algorithms and enhancements in accuracy and availability of model input data.

1.2 Meeting Structure

The meeting was structured to encourage interaction and discussion of industry needs, combined with presentations from modeling experts.

Key topic areas of the meeting were as follows:

- Overview and Needs Assessment from Integrators, Manufacturers, and Independent Engineers
- Analysis of Model Accuracy
    - Recent studies of PV performance models
    - A proposed approach to model validation
    - Results of model intercomparison
- Modeling the Module
    - Module models
    - Modeling module temperature
    - Discussion of needs, priorities, and paths forward
    - Industry perspectives: Review of system performance models and needs and issues in performance modeling
- Beyond the Module – Systems Modeling
    - Modeling system losses
    - Shading, mismatch, and modeling distributed maximum power point tracking
    - Modeling large systems
- Impact of uncertainty
- Discussion on ensuring quality, need for standards, model validation
- Action items and next steps

A unique aspect of the meeting was the assignment of pre-work. Participants were sent design descriptions of three PV systems along with measured solar resource and weather data. They were asked to model system performance using the model or models of their choice and then return the results to Sandia for analysis before the meeting. This activity provided a basis for discussion of model accuracy and inter-comparison.

This report provides an overview and highlights of the workshop contents and summarizes the key discussion and outputs. Presentation titles are linked to downloads of the presentation files.

2. PRESENTATION SUMMARIES / WORKSHOP CONTENT

2.1 Day 1: Wednesday, September 22

2.1.1 Overview and Needs Assessment from Integrators, Manufacturers, and Independent Engineers

Review of System Performance Models (Bradley Hibberd and Tarn Yates, Borrego Solar)

Borrego Solar is an integrated project developer specializing in grid-connected commercial and public sector turnkey solar systems. The company was invited to present an overview of system performance modeling from the perspective of a systems integrator. Borrego was represented by Bradley Hibberd, Director of Technology, and Tarn Yates, an applications engineer. The two co-published, "Production Modeling for Grid-Tied PV Systems" (SolarPro, April/May 2010)[1].

Borrego emphasized several important aspects of accurate production modeling:

- Predicted energy production drives project design and potential revenue
- Even differences of 1% in predicted production can have significant impact on financing and investor confidence
- Proposals far outweigh executed projects, so modeling needs to be efficient and reliable in order to help select projects with the best revenue potential and opportunity for success

In addition, Borrego emphasized that energy production estimates need to be consistent and reproducible in order to satisfy investors and meet requirements of independent engineering reviews. Modeling tools must be able to accurately and efficiently model numerous project complexities such as multiple arrays, inverters, and mounting structures; shading; soiling; weather; and various technologies. Simple rectangular configurations do not represent the reality in PV project design and models must account for this.

The company seeks several specific attributes when selecting modeling tools, including:

- Accurate and site-specific weather data that includes typical meteorological year (TMY) TMY2 and TMY3 data as well as data for locations far from existing ground stations, i.e., satellite data
- Verified models for calculating incident irradiance, module temperature, and energy production
- Databases based on independently tested, frequently updated information about all commercially-available components
- Detailed control of system loss factors, e.g. dynamically-calculated wiring losses and option to enter monthly soiling losses
- Ability to handle various shading effects in both beam and diffuse components, and, preferably, the ability to interface with AutoCAD site drawings

[1] SolarPro Magazine, April/May 2010, http://solarprofessional.com/article/?file=SP3_3_pg6_TOC.

- Ability to handle a variety of advanced system configurations, including single-axis and back-trackers, multiple arrays and inverters, and heterogeneous arrays, as shown in Figure 1.
- Reports documenting model inputs and system losses, including loss diagrams and hourly output reports
- Parametric and optimization tools as well as options for time-of-use and time-of-day rates and various forms of financial analysis

Models currently being used by Borrego include PVWatts™ [2], PV-DesignPro[3], PV*SOL[4], the System Advisor Model (SAM)[5], and PVsyst[6]. The company mostly uses PVsyst for its performance modeling, primarily because of the model's flexibility and extensive features.

Figure 1. The Reality of Solar Projects.

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[2] National Renewable Energy Laboratory, http://www.nrel.gov/rredc/pvwatts/.
[3] Maui Solar Software, http://www.mauisolarsoftware.com/.
[4] Valentin Software, http://valentin-software.com/xcartgold/PV-SOL.html.
[5] National Renewable Energy Laboratory: https://www.nrel.gov/analysis/sam/.
[6] University of Geneva, Switzerland: http://www.pvsyst.com/.

Needs and Issues in System Performance Modeling (Ben Bourne, SunPower)

SunPower created its own proprietary simulation tool, called PVSim. The model is generally built from publicly available algorithms, such as irradiance translation algorithms and the Sandia module and inverter performance models. Some algorithms, such as those for shading and tracking, were developed by SunPower and are specific to the company's products. SunPower has instrumented more than 650 systems and has used these data to validate and improve the accuracy of PVSim. This allows SunPower to provide customers with accurate estimates of power and energy production and gives SunPower the information they need to price their systems. As shown in Figure 2, on average, annual delivery is 1.2% greater than predicted.

SunPower cited soiling as the greatest source of uncertainty. While simple soiling models work well most of the time, some climates and regions are more difficult because of soiling composition, variable rainfall, ambient conditions, the surrounding environment, and avian migration patterns.

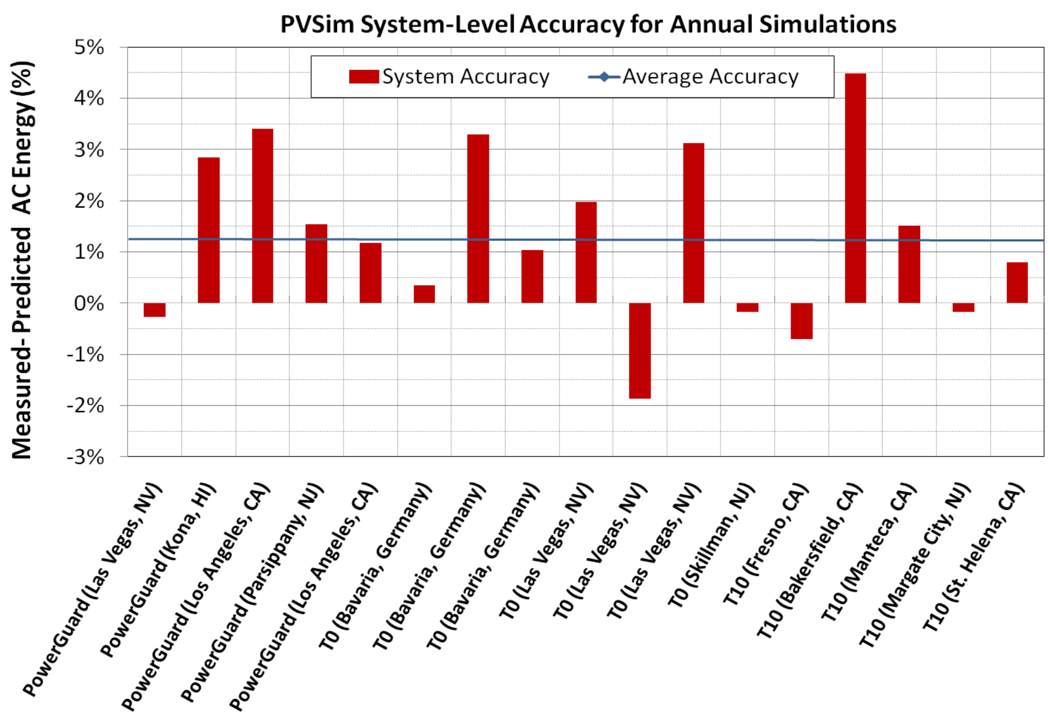


Figure 2. Sample of SunPower's PVSim Output.

SunPower highlighted the need for evaluation and validation of performance models, including reconciliation of the models and third-party field test data. Testing standards supported by quality requirements and audits are needed and must account for baseline and evolving module ratings. Also, there needs to be a clear definition and understanding of metrics including delivered AC power, annual energy, yield (in kilowatt hours/kilowatt-peak [kWh/kWp], noting the importance of the watt-peak [Wp] rating), and Levelized Cost of Energy.

Needs and Issues in System Performance Modeling – Manufacturer/Integrator (Adie Kimber, First Solar)

First Solar's team of analysts, engineers, and field technicians in the United States and Germany monitor more than 50 systems totaling 150 megawatts (MW). The collected data are then fed into development and validation of system performance models. First Solar primarily uses PVsyst for modeling, but develops its own *.PAN (module performance coefficient) files and system loss parameters based on measured data. The company also utilizes its own alternating current (AC) model to account for losses and employs weather prospecting to evaluate prospective projects.

First Solar agrees with other participants that meteorological data, and irradiance in particular, are the largest source of model uncertainty. First Solar suggests several improvements for modeling software to help alleviate irradiance errors:

- Taking advantage of advanced processing power to model multiple years (~30) of data when available instead of using only TMY data
- Finding a means to allow comparisons among multiple source inputs
- Allowing sub-hourly time-steps of input data to address energy prediction and help characterize variability and to estimating inverter clipping losses. This would include development of a tool that could produce stochastic sub-hourly estimates from hourly data inputs.

First Solar identified model inputs as a more significant issue than the models themselves, with the caveat that thin-films are difficult to model using a single-diode model and may require empirical models. Improvements to model inputs include the addition of manufacturing tolerances and distributions so that mismatch can be explicitly included in modeling array output. Third-party measurements of model input parameters, especially temperature coefficients, are also needed and performance coefficients should be derived from testing of multiple modules.

First Solar notes that module operating temperature can differ by 10 °C or more between the edge and the center of a large array. Current models assume uniform temperature and irradiance across the array and during each hourly modeling interval. Since modeling spatial and temporal variations of temperature and insolation in a large system would likely be extremely intricate and difficult to validate, First Solar cites the need to understand whether the additional complexity would be warranted relative to the inherent uncertainty of model outputs.

First Solar indicated the need for more advanced modeling of inverters and inverter-grid interactions and included a suggestion that model developers could help address uncertainty by providing an option to enter values for input uncertainty. Because the end user controls the input parameters, the use of "uncertainty parameters" could enhance modeling.

A final key issue noted by First Solar pertains to ownership of models. First Solar raised pros and cons of several approaches but did not recommend one over another.

Needs and Issues in System Performance Modeling – Independent Engineer (Jeff Newmiller, BEW Engineering) *no presentation materials*

As an independent engineering firm, BEW Engineering performs modeling during due diligence review of proposed or actual solar projects. BEW presented an oral overview of its modeling needs, but did not use presentation materials.

For firms like BEW and the customers they serve, it is essential that modeling capture performance risks and the related impact on energy production. Ideally, modeling would capture all uncertainties in future simulations. As real world operation does not have a normal distribution, there is a better chance of getting lower output than higher output from a PV system. Meeting this goal would require comprehensive uncertainty and production variability analysis.

Weather uncertainty is of particular concern to engineers trying to predict and verify performance. BEW stresses that all weather data sources should be examined, including 30 individual years rather than just typical years, i.e., TMY data. Effects from soiling and cleaning the modules should also be considered.

BEW raised two key points that were later addressed in greater detail during the meeting: first, not all sources of uncertainty are mutually exclusive (independent). Uncertainty in one attribute can drive uncertainty in a second; therefore, correlations need to be identified and understood wherever possible. Second, *variability* is different from *uncertainty* and easier to evaluate, although many PV performance models do not consider variability as carefully as uncertainty.

2.1.2 Analysis of Model Accuracy

Recent Studies of PV Performance Models (Steve Ransome, SRCL Consulting)

Independent consultant Steve Ransome performed measurements and modeling at BP Solar for 19 years before leaving in 2008 to be an independent PV consultant. Recently, clients have increasingly inquired about modeling issues, expressing concern about two primary issues:

- Companies have evaluated expected energy yield of their modules and those of competitors through indoor and outdoor testing and are finding that simulation programs give estimates of relative kWh/kWp that are not consistent with internal test results.
- Customers are designing solar plants using simulation programs and guaranteeing predicted kWh/kWp production to banks/financiers.

In his introduction, Ransome noted that some PV manufacturers claim up to 33% higher kWh/kWp than (crystalline silicon) competitors due to “thermal, spectral, low light and angle of incidence (AOI) improvements.” However, as module efficiency is improving, c-Si and thin-film modules have a more constant efficiency across different weather conditions and less variation in kWh/kWp may be expected now than earlier measurements may have suggested. Ransome reported that many recent independent tests show variation in annual yield from modules is less than ±5% kWh/kWp, and the dominant uncertainty is actual module output power compared to nameplate rating.

Some models also predict >5% kWh/kWp differences (usually better for thin-film). One of the reasons this can occur is that hourly averaging of irradiance causes the simulation to be performed with more energy at low light levels, where efficiency is higher, than actually occurs during operation (Figure 3).

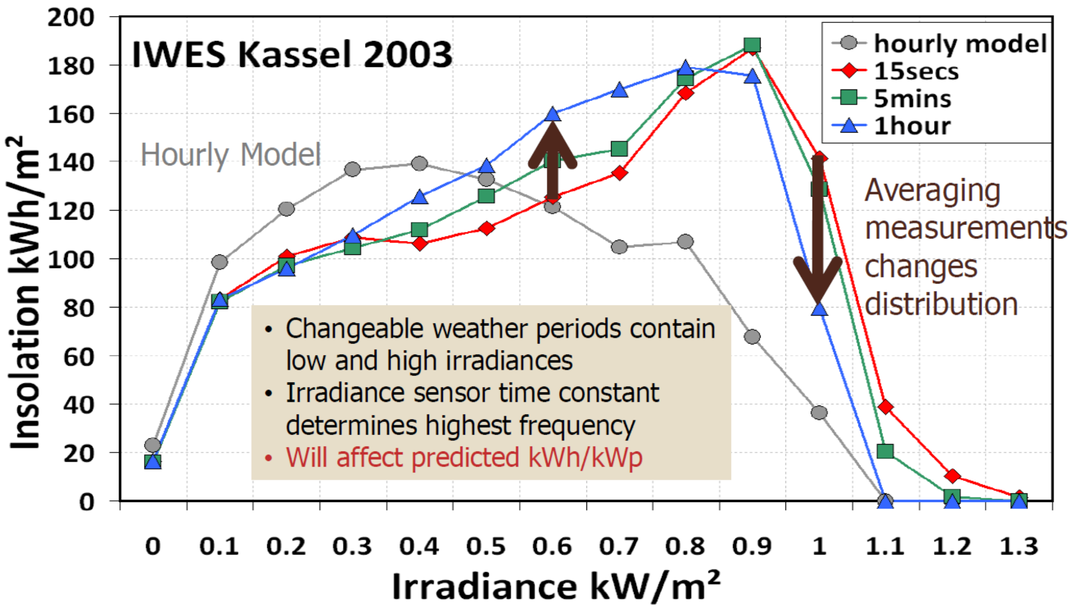


Figure 3. Hourly Averaging of Insolation Over-predicts Insolation at Low Light Levels.

Ransome identified a number of factors that contribute to kWh/kWp modeling uncertainty, including:

Table 1. Factors that Contribute to Uncertainty in Model Output.

Factor	Uncertainty
Reference module calibration	±2.5%
Flash tester repeatability	1% ?
Nameplate allowance	-1 to -3%
Light Induced Degradation/Degradation	-10 to 35%
Module Pmax bin width	±2.5%
Insolation sensor calibration	
Pyranometer calibration, deterioration	±2-3%
Reference cell calibration, deterioration	±1.7-7%
Satellite data, tilted plane algorithms	???
Yearly insolation variability	±4%/yr
Dirt loss	?
kWh/kWp (lowest uncertainty possible)	$(2.5\%)^2 + (1\%)^2 + (2.5\%)^2 + (2\%)^2 =$ 4.2%

Ransome presented a number of examples of the sensitivity of models to various parameters. Two key examples highlight the fact that models often use different values for low-light efficiency change and gamma than found on manufacturer's data sheets:

- An error in gamma, the maximum power point (MPP) temperature coefficient, of ±0.05%/°C, as seen in some models, leads to a predicted change in energy yield of ±0.5% in a dull climate (Helsinki, Finland) and ±1% in a bright climate (Albuquerque, New Mexico) *see slide 18*
- An error in LLEC (the low light efficiency change relative to STC conditions) of 30%, as seen in some models, leads to a predicted change in energy yield of 15% in a dull climate (Helsinki, Finland) and 6% in a bright climate (Albuquerque, New Mexico) *see slide 19*

Ransome explained that models should be validated against current technology modules, not older modules, and that every stage of performance modeling needs to be evaluated. Hourly or daily outputs should be evaluated, since annual output may conceal self-canceling errors. Also, one site is not sufficient for model validation.

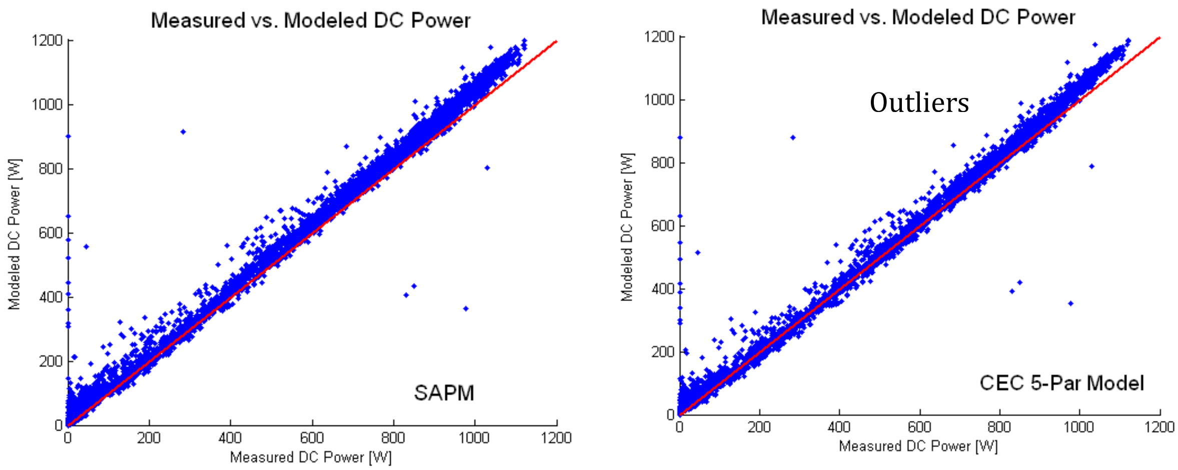
A Proposed Approach to PV Performance Model Validation (Joshua Stein, Sandia National Laboratories)

Joshua Stein, Principal Member of Technical Staff at Sandia National Laboratories, reviewed a model validation approach that was first presented at IEEE's Photovoltaic Specialists Conference in June 2010[7]. This method inputs measured weather data and system design information into a model and then compares the modeled output to measured output using residual analysis in a MATLAB platform. This approach is preferably done as a blind test where the modeler does not have access to the measured results, as was done for the pre-work exercise for this workshop (results follow later in this report).

Stein et al.'s validation approach looks not only at annual output of AC energy, but hourly predictions of AC output as well as intermediate model outputs, such as plane-of-array irradiance, module temperature, and direct current (DC) power. Residual values are then calculated (*residual = modeled value – measured value*) and are analyzed to evaluate model validity. Residuals from a valid model will be as small as possible and randomly distributed.

To illustrate this technique, one year's operation of a 1-kW c-Si system located at Sandia's campus in Albuquerque, New Mexico was modeled using two models within the System Advisor Model: the Sandia PV Array Performance Model (SAPM) and the California Energy Commission (CEC) 5-parameter model. The results, shown in Figure 4, demonstrate that modeled vs. measured results look identical. When the models were run, the system loss (derate) factors were set to zero, so it is expected that the models would over-predict array output. There is a slight difference in the bias errors of the two models.

[7] J. S. Stein et al., "A Standardized Approach to PV Systems Performance Model Validation," Proceedings of the 35th IEEE Photovoltaics Specialists Conference, Honolulu, Hawaii, June, 2010.



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

Figure 4. Measured vs. Modeled Results for SAPM and CEC 5-parameter Models.

If residuals are plotted vs. time, differences between the two modules begin to appear, as shown in Figure 5.

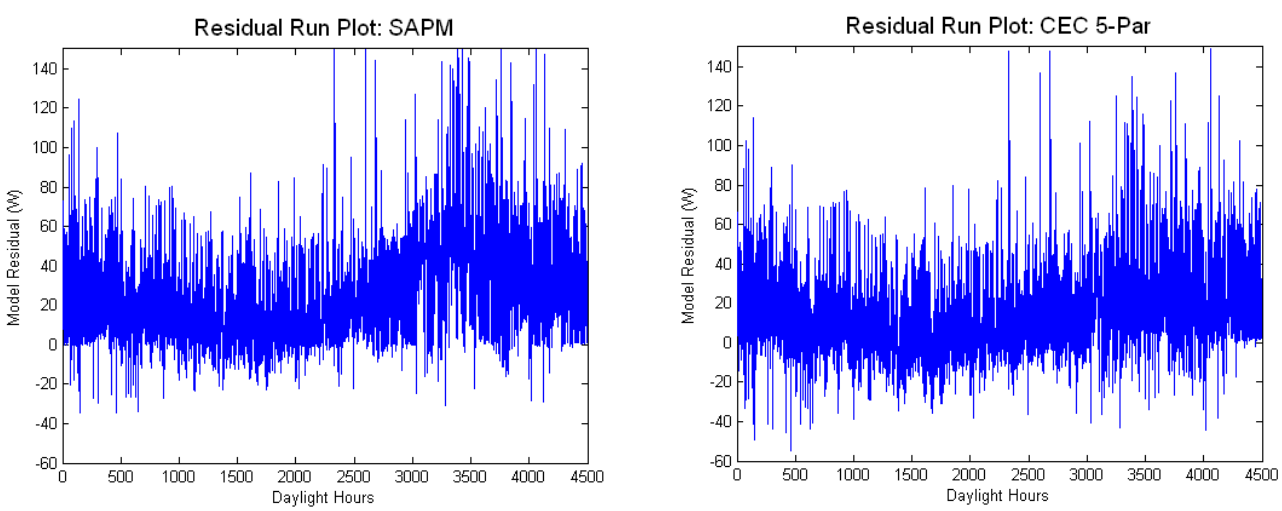


Figure 5. Residual Run Plots, SAPM vs. CEC 5-parameter Models.

The next step in the analysis is to perform stepwise regression, which allows the variables that contribute to the residuals to be identified and ranked:

$$Y = b_0 + \sum_{j=1}^{P} b_j X_j$$

Y = dependent variables
X = P vectors of independent variables
b = linear regression coefficients

Table 2. Results of Residual Analysis.

SAPM			
Order	**Variable**	R^2	**Incremental** R^2
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^2	**Incremental** R^2
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**

In this example, the residual analysis shows that SAPM residuals are most correlated with air temperature while the CEC model residuals are most correlated with incident beam radiation.

Results of Model Inter-Comparison (Joshua Stein, Sandia National Laboratories)

As a pre-workshop exercise, participants were sent design descriptions of three systems along with recorded solar resource and weather data. They were asked to model system performance using the model or models of their choice and return the results to Sandia for analysis before the meeting. Since recorded performance data was available for the same time period, this exercise provided a basis for discussion of model accuracy and inter-comparison.

The three systems that were analyzed were a 1.4kW multicrystalline silicon (mc-Si) and a 1.1kW copper-indium-diselenide (CIS) system, both located in Golden, Colorado; and a 1kW c-Si system located in Albuquerque, New Mexico. All were simple south-facing, rack-mount systems with no significant shading. For each system, participants were provided with a design description, including azimuth, tilt, inverter model information, module model and data sheet; and a TMY-2 format solar resource and weather file. The measured performance data were not provided to the modelers, so this was a blind study.

Seventeen individuals submitted results on one or more of the systems. Some individuals ran more than one model, so 25 total contributions each representing one individual and one model[8]

[8] Each model run was a contribution. Some individuals ran more than one model.

were received, each including information for one to three systems. Responses came from integrators, consultants, academia, national labs, and state government; none of the module manufacturers participated.

A variety of models was used and implemented through various tools. For example, users of the System Advisor Model can use the CEC 5-parameter model, SAPM, or PVWatts from within the SAM platform, as shown in Table 3.

Table 3. Model Combinations Currently Available.

Model Forms

Implementation	5-Par	5-Par Modifed Temp	SAPM	PVSyst	PVWatts	Internal	Other
SAM	***		*		*		
PVWatts					*		
PVForm							*
PVSyst				*******			
EES		***					
CECPV	*	*					
Internal			*			**	
Other			*				*

Total = 24

Participants encountered a number of issues when running models. Some had difficulty reading in the TMY-format weather files provided by Sandia. In an attempt to remedy this, one participant used the TMY file for a nearby location; those results are not included in the analysis. Another common problem was that either the modules or the inverter were not in the databases provided with the modeling platforms. Also, no guidance was given with respect to derate factors; modelers were left to set those based on their experience and the provided design data (Appendix C). Some modelers did not include derate factors.

The results of the comparisons for the three systems are shown in Figures 6, 8, and 10. Not every participant analyzed every system, and model *n* for system 1 is not necessarily the same as model *n* for system 2 in these figures.

Comparisons of modeled to measured annual energy production are shown in Figures 7, 9, and 11. These are provided to illustrate the range of results obtained by users with varying levels of experience; they do not necessarily indicate modeling error within the model or in the hands of an experienced user. Selection of derate factors had significant impact on these results. Also, models were run in various configurations. For example, one participant ran PVWatts in a version that permitted the user to change the temperature coefficient, which is not the case in public versions of PVWatts.

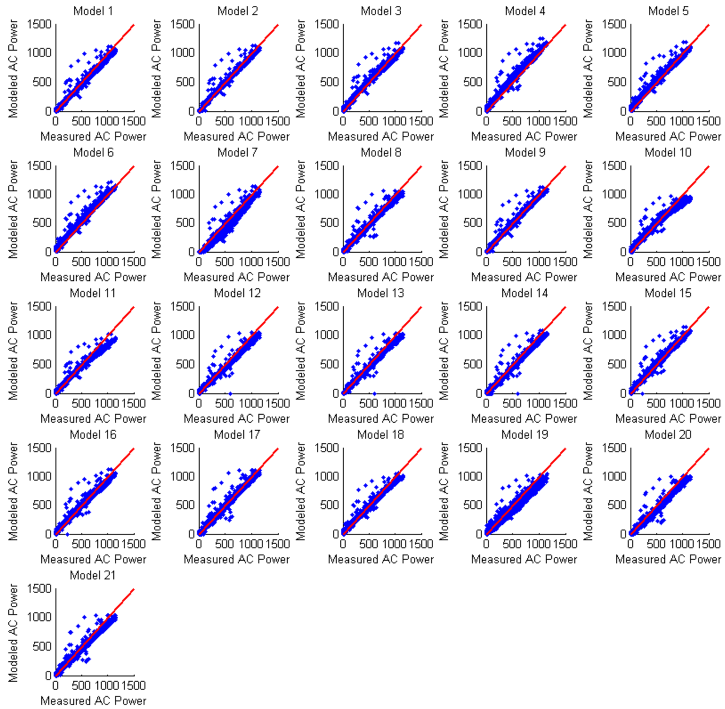


Figure 6. Hourly Comparisons (System 1).

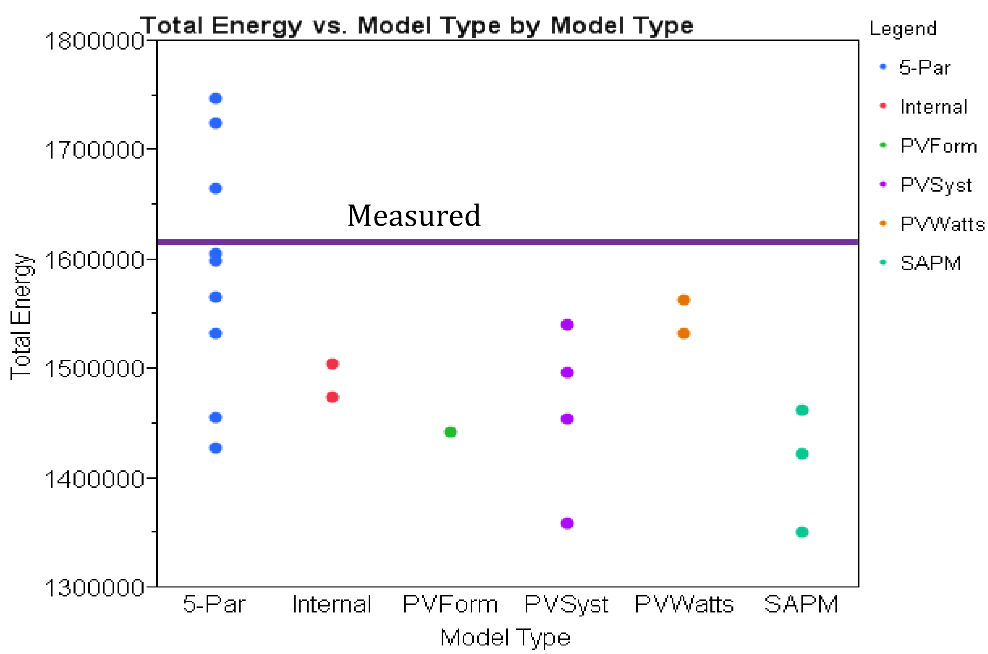


Figure 7. Predicted Annual Output by Model Type (System 1).

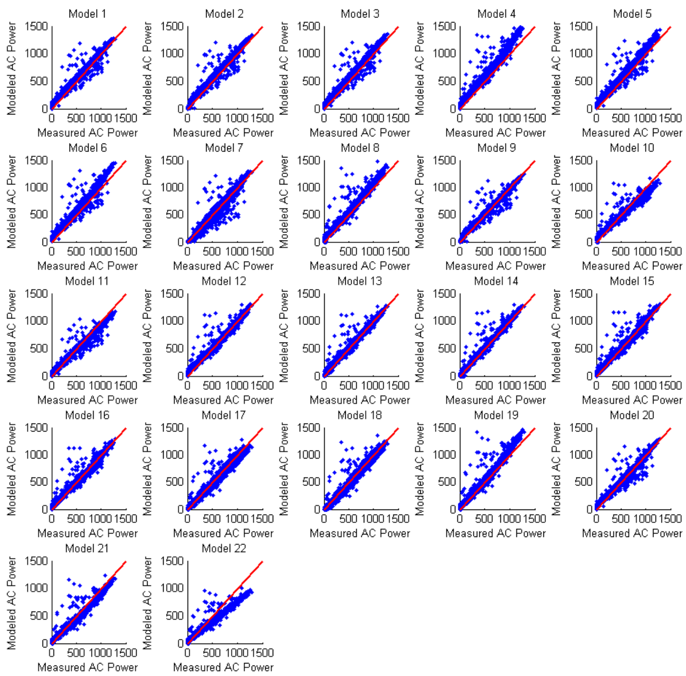


Figure 8. Hourly Comparisons (System 2).

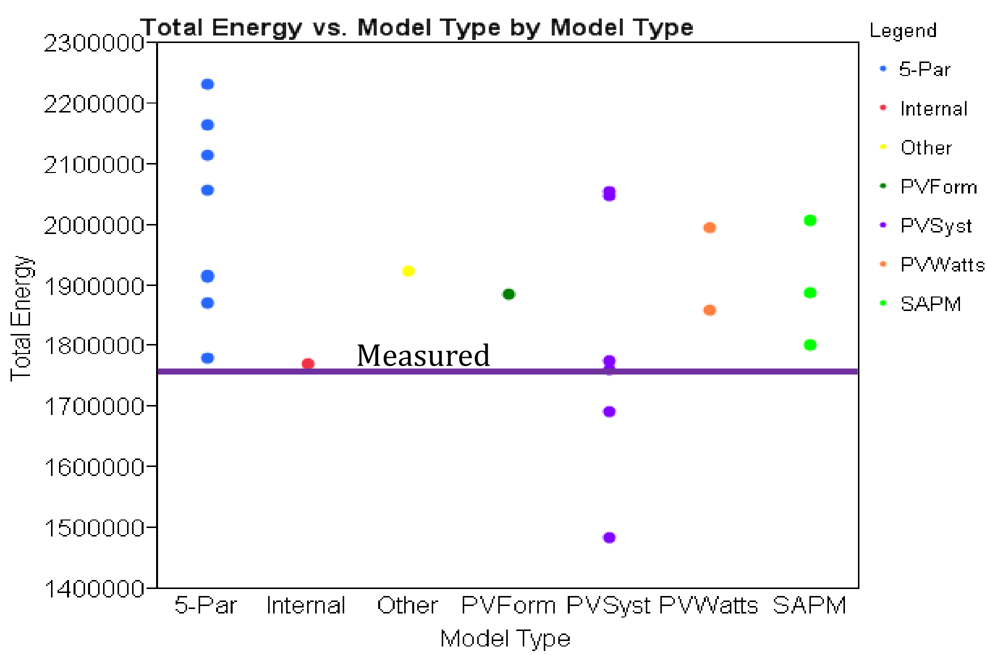


Figure 9. Predicted Annual Output by Model Type (System 2).

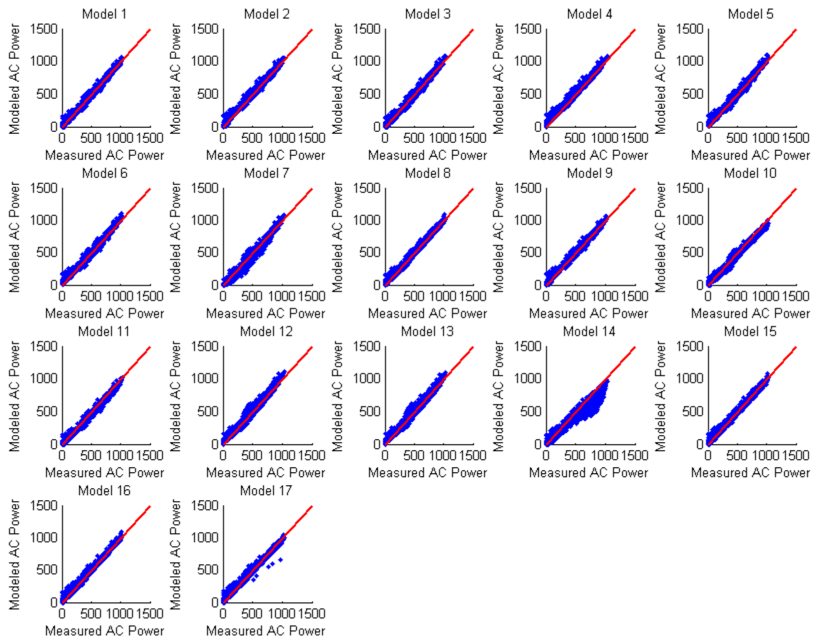


Figure 10. Hourly Comparisons (System 3).

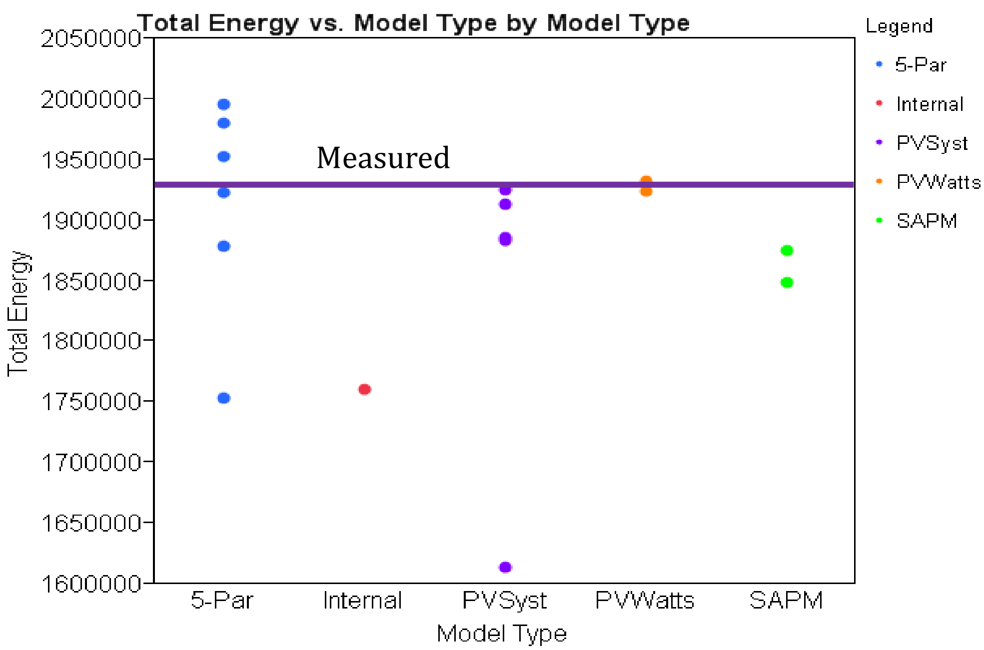


Figure 11. Predicted Annual Output by Model Type (System 3).

An example of the analysis of an internal value is shown in Figure 12, where the module temperature calculated by the models (when available in the output) is compared to the measured back-surface module temperature. Most module temperature models appear to behave well. The mean bias error range was -0.17 to 3.6 °C and the standard deviation range was 2.0 to 2.5 °C.

The varying input requirements and output formats of the various models presented difficulties for both participants and the analyst. As time permits, a formal analysis of each participant's results is being prepared and offered to them. An example is given in Appendix D.

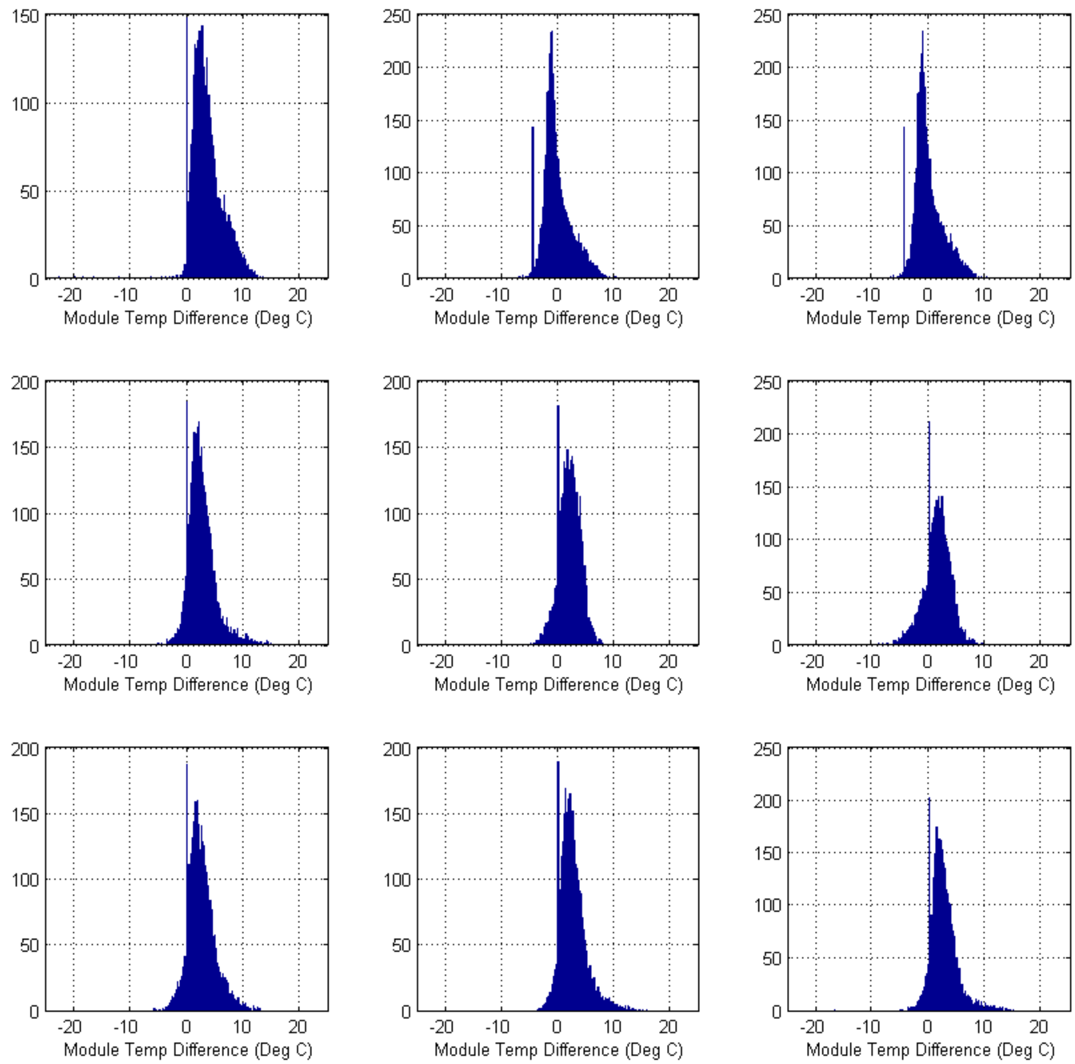


Figure 12. Example Module Temperature Results (System 3).

2.1.3 Modeling the Module

The next section of presentations provided an overview of several models that focus on the module algorithms. Brief overviews of the presentations are included here. The reader is referred to the presentations for more detail.

Overview of PV*SOL and Plans for US Market (Paul DeKleermaeker, Valentin Software)

Valentin Software, developer of PV*SOL, is currently supported by ~50 staff, primarily engineers and developers. The modeling application has become a leading PV simulation tool in Europe, particularly in Germany where more than 70% of installed systems in 2009 are reported to have been designed using PV*SOL. The company offers two primary software packages, one for solar thermal (T*SOL) and PV*SOL for PV. The latter offers three levels of tools to fit users' needs as well as a free on-line calculator for 10 locations in the United States.

Valentin provides both packaged software and customized design tools. Key features of the various PV*SOL packaged versions include:

PV*SOL Basic

- Residential and commercial grid-connected systems up to 1,000 modules
- Automatic inverter selection and configuration
- Roof layout
- Incentive rates and energy tariffs
- Wire size calculation and losses

PV*Sol Pro

- Residential, commercial and power plant systems up to approx. 100MWp
- Grid-connected and off-grid
- 2-D shade analysis

PV*Sol Expert

- Capabilities and features of PV*SOL Pro plus 3-dimensional visualization

Standard component databases behind PV*SOL software currently include more than 5,000 modules and 1,200 inverters, with automatic updates integrated and distributed weekly. Climate modeling is based on standardized climate data from 1,020 U.S. TMY3 locations and 8,000 global locations. Users can create or modify standard component and climate data as necessary. The software also provides users the option to define tariffs and incentives in order to model system financials.

PV*SOL offers flexibility in array design, including capabilities for multiple and diverse technologies, configurations, and orientations. Sub-models in PV*SOL include:

(1) Irradiance Model - Hay and Davies model with monthly albedo
(2) Module Model - includes options for an incident angle modifier for reflection; module efficiency curve for maximum-power point (MPP) calculated at all irradiance levels; complete current-voltage (I-V) characteristics for non-MPP operation points; efficiency

and temperature-corrected I-V curves using three temperature coefficients; and linear or dynamic temperature model options.

(3) Module Technologies - provides options to model numerous technologies based on unique characteristics; includes standard data sets for c-Si, amorphous Silicon (a-Si), cadmium telluride (CdTe), CIS, heterojunction with intrinsic thin layer (HIT), mc-Si, ribbon

(4) Inverter Model - includes voltage-dependent correction and ability to model multiple quantities and types of inverters

(5) Configuration and Automatic Inverter Optimization – allows modeling based on one inverter with multiple sub-arrays using different sizes, modules, and orientations; multiple inverter types; and automatic selection of appropriate configurations and/or inverter sizing and selection

(6) Simulation Frequency – models in hourly increments, with shade calculated in 10-minute intervals

(7) Shading – Imported or user-defined horizon; or 3-D model which is area-based, models near and horizon shade in 10-minute intervals, and calculates impact per string of cells in each module

(8) Losses & Derate Parameters – Module mismatch, diodes & module quality; wiring losses calculated from cable data; deviation from standard spectrum; and soiling.

Report output options may be viewed in the presentation.

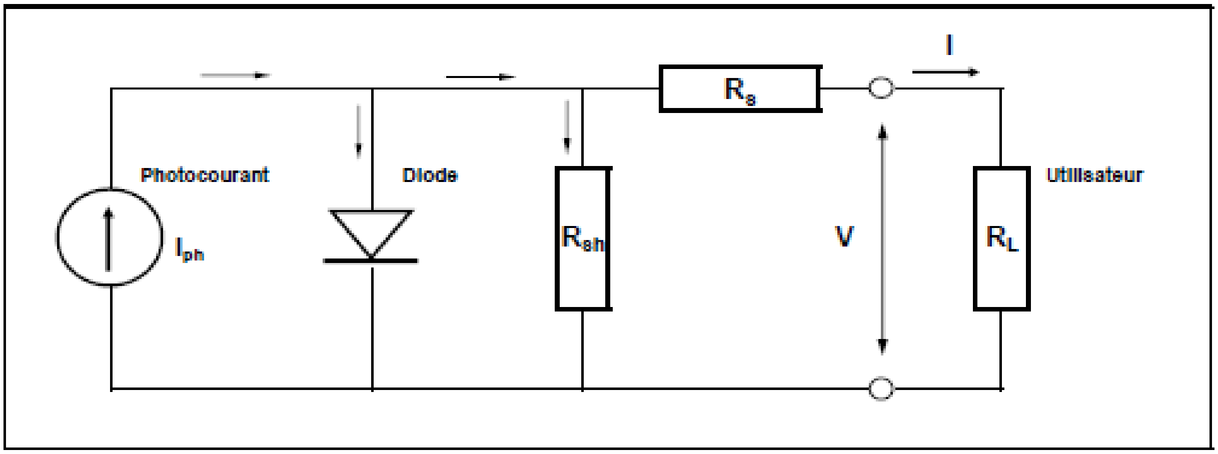
An Overview of the Module Model in PVsyst (Andre Mermoud, Institute of the Environmental Sciences, University of Geneva)

PVsyst was developed as a model for general simulation and is widely used in the PV industry, in part because of the many features built into the model. The goal of the module model in PVsyst is to represent I-V behavior of PV modules of any technology, in any irradiance and temperature conditions. PVsyst is based on the one-diode model and includes parameters from manufacturer product data sheets, plus several additional parameters as identified in Figure 13.

Module parameters used can be derived from an I-V curve or from manufacturer's data. Some module suppliers generate their own module parameters rather than using those provided in the database. Additional parameters are added as follows:

- Exponential correction to Rsh, applied for all modules
- Recombination correction, $d^2 \mu\tau$, for amorphous silicon, μ-crystalline silicon and CdTe
- Spectral correction for amorphous and μ-crystalline silicon

Outdoor measurements are reproduced to within 1 to 1.6% root mean square deviation for all technologies. However, it is noted that results are generated from one measured module, not from the manufacturer's specifications; model accuracy should not be confused with parameter accuracy.



$$I = \underbrace{Iph}_{\text{Photocurrent}} - \underbrace{Io\,[\exp(q \cdot (V+I\cdot Rs) / (N_{cs}\cdot\gamma\cdot k\cdot Tc)) - 1]}_{\text{Current in the diode}} - \underbrace{(V + I\cdot Rs) / Rsh}_{\text{Current in Rsh}}$$

Where

- I = module current [A]
- V = module voltage [V]
- Iph = Photocurrent [A], proportional to the irradiance
- Io = Diode saturation current, dep. on temperature
- Rsh = shunt resistance
- Rs -- series resistance
- γ = Diode quality factor, normally between 1 and 2
- q = Electron charge = 1.602 · 10-19 Coulomb
- k = Bolzmann constant = 1.381 · 10-23 J/K
- Ncs = Number of cells in series
- Tc = Effective cell temperature (Kelvin)
- q/kT = 26 mV at 300 K

Figure 13. The One-Diode Model.

[Improvements to the CEC/Wisconsin *n*-Parameter Model](#) (Bill Beckman, University of Wisconsin)

Bill Beckman is Director Emeritus of the Solar Research Laboratory at the University of Wisconsin and former director of the university's Solar Energy Laboratory, co-author of *Solar Engineering of Thermal Processing*[9], and developer of the 5-parameter PV performance model. The 5-parameter model is also derived from the one-diode model, but uses a different approach to estimating the coefficients. In the latest version of the model, two parameters have been added to the original five.

[9] J.A. Duffie, W. A. Beckman, *Solar Engineering of Thermal Processes.* Third ed. John Wiley & Sons Inc., New York, 2006.

In early uses of the model, conducted using CEC data from ~2,000 modules, the temperature coefficient of power did not always agree with experiments. As shown in the presentation, the parameter δ is added to the series resistance calculation in the model and selected such that that the maximum power temperature coefficient calculated by the model matches the measured value:

$$R_s = R_{s,\,ref}\,[1 + \delta\,(T_c - T_{c,\,ref})],\ \text{with } \delta \text{ chosen so that } \gamma_{model} = \gamma_{measured}$$

Recently, a seventh coefficient (*m*) has also been added by fitting the model output at 200 W/m^2 and 25 °C cell temperature. The goal of the seventh coefficient is to improve modeling of thin-film modules:

$$\frac{I_o}{I_{o,ref}} = \left[\frac{G}{G_{ref}}\right]^{m} \left[\frac{T_c}{T_{c,ref}}\right]^3 \exp\left[\frac{1}{k}\left(\left.\frac{E_g}{T}\right|_{T_{ref}} - \left.\frac{E_g}{T}\right|_{T_c}\right)\right]$$

The coefficient generator is not publicly available at present. Coefficients are determined for the CEC from manufacturer's data or, more recently, independent test data and are made available in models such as SAM and the CECPV Calculator[10].

Overview of the Module Model in PVWatts (Bill Marion, National Renewable Energy Laboratory)

The widely used online simulation tool, PVWatts, was developed by Bill Marion, Principal Scientist at the National Renewable Energy Laboratory's (NREL's) Performance and Reliability Research and Development Laboratory. The tool is based on an earlier Sandia model, PVForm (Sandia National Laboratories, 1985).

PVWatts uses a linear irradiance function corrected for cell temperature above 125 W/m^2 and a quadratic function below 125 W/m^2. The adjustment for conditions <125 W/m^2 conditions is based on reductions in output observed by Sandia for c-Si modules in low irradiance. The available online versions of PVWatts assume a maximum power point temperature coefficient of -0.5%/ °C. A web-service version of the model, accessed by the California Solar Incentive CSI Standard PV Calculator (www.csi-epbb.com), uses the module manufacturer's value for the temperature coefficient. An AOI correction from the Sandia PV Array Performance Model[11] is also applied, but no air mass correction is included.

$$P_m = \frac{E_e}{E_0} \cdot P_{m_0} \cdot \left[1 + \gamma \cdot (T - T_0)\right]$$

PVWatts model irradiance >125 W/m^2

[10] http://www.gosolarcalifornia.org/tools/nshpcalculator/index.php

[11] D.L. King, W.E. Boyson, and J.A. Kratochvil (2004). "Photovoltaic Array Performance Model." 41 pp.; Sandia Report No. 2004-3535. (http://photovoltaics.sandia.gov/docs/PDF/King%20SAND.pdf)

$$P_m = \frac{0.008 \cdot {E_e}^2}{E_0} \cdot P_{m_0} \cdot \left[1 + \gamma \cdot \left(T - T_0\right)\right]$$

PVWatts model for irradiance <125 W/m²

where E = plane-of-array irradiance, W/m^2; T = PV cell temperature, ºC; γ = P_m correction factor for temperature, ºC^{-1}; zero subscripts denote performance at Standard Rating Condition; and the e subscript denotes an "effective" irradiance, which in the case of PVWatts means corrected for AOI but not spectrum.

In the presentation, the value of adding a third parameter was examined. This parameter, k, is experimentally determined from testing at 200 W/m^2, where

$$k = \frac{0.2 \cdot P_{m_0} - P_{200}}{P_{m_0}}$$

k is applied as a non-linear correction below 200 W/m^2 and as a linear correction above 200 W/m^2 as shown in Figure 14. Experimentally determined values of k are 0.011 for a Mobil mc-Si module, 0.009 for a SunPower c-Si module, and 0.030 for a Shell CIS module. Addition of this module-specific parameter improved the agreement of PVWatts with the Sandia PV Array Performance Model. Since a power measurement at 200 W/m^2 is now required by the International Electrotechnical Commission's (IEC's) standards 61215 and 61646, this improvement could be made to a future version of PVWatts.

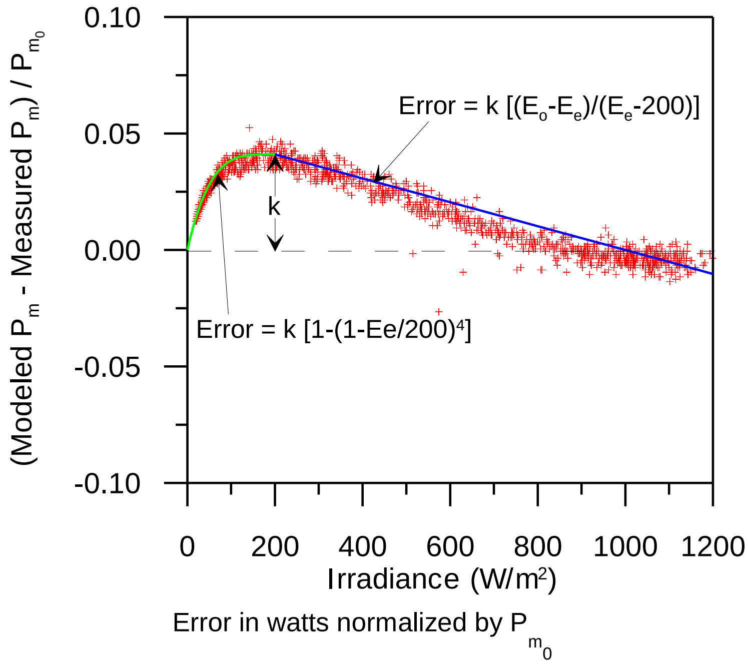


Figure 14. Application of New PVWatts Correction Factor, *k*.

Overview and Background on the Sandia PV Array Performance Model (Dave King, DK Solar Works)

Dave King, retired Distinguished Member of Technical Staff at Sandia National Laboratories and now an independent consultant, played a pivotal role in developing the Sandia PV Array Performance Model. This model was developed to address the limitations of the one-diode circuit model. Though the Sandia model is based on fundamental cell performance characteristics, it requires only outdoor I-V measurements and meteorological data to empirically calculate performance coefficients.

As described in the presentation, the model uses effective irradiance in its electrical calculation. In the model, effective irradiance is calculated from the incident beam radiation, corrected by an angle-of-incidence function, and combined with the incident diffuse radiation, with the sum corrected by an air-mass function.

In the calculation of electrical output, four separate temperature coefficients are used: one each for I_{sc}, I_{mp}, V_{mp} and V_{oc}. Cell temperature is calculated from the total incident irradiance (E), ambient temperature (T_{amb}), wind speed (WS), and ΔT_{1000}, which is the difference between the module back temperature and the cell temperate at an incident irradiance of 1000 W/m^2, as shown in Figure 15. The coefficients for this calculation are specific to the module structure and mounting configuration.

$$T_m = E \cdot \left\{ e^{a + b \cdot WS} \right\} + T_{amb}$$

$$T_c = T_m + \frac{E}{1000} \cdot \Delta T_{1000}$$

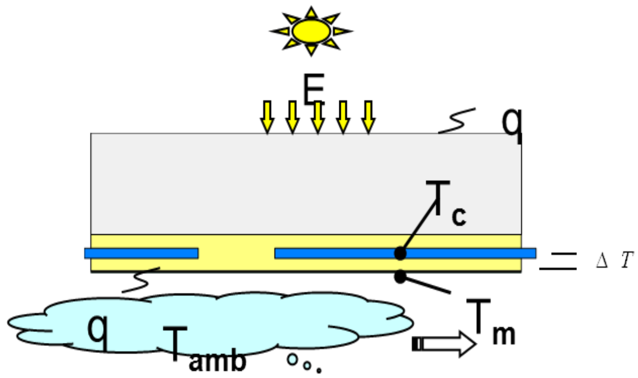


Figure 15. Empirical Thermal Model to Determine Cell Temperature.

SAPM is used in the System Advisor Model, PV DesignPro, and in some industry internal models such as SunPower's PVSim. Use of this model has been hampered by the limited number of modules in the required database of performance coefficients. To remedy this situation, Sandia has partnered with TÜV Rheinland PTL, LLC in Phoenix, Arizona. Both Sandia and TÜV Rheinland PTL are now able to characterize new modules.

Modeling and Measuring Nominal Cell Operating Temperature (NOCT) (Matt Muller, National Renewable Energy Laboratory)

The standard test conditions under which PV modules are rated [1,000 W/m^2, air mass 1.5, and cell temperature of 25 °C] rarely occur during normal system operation. An alternate rating condition, Nominal Operating Cell Temperature (NOCT), sets conditions of 800 W/m^2, 20 °C ambient temperature, and 1 m/s wind speed and is used in combination with the P_{mp} temperature coefficient to estimate the effect of cell temperature on performance. Manufacturers publish NOCT for modules, and some models use those stated NOCT values in calculating performance.

Matt Muller, staff engineer at NREL, provided an overview of IEC 61215, the procedure used to determine NOCT, and discussed uncertainty in NOCT. Heat transfer theory suggests that modules that are in open circuit and having the same basic package of materials should have similar NOCT. However, independent laboratory test measurements such as those in the module database from the CEC (included in the System Advisor Model) report NOCT values for rack-mounted standard silicon modules in a glass/Tedlar package that range from 41.6 to 52.3 °C. At 1000 W/m^2, modeling a module assumed to operate at a 10 °C higher temperature with a power coefficient of 0.5%/°C will lead to a 5% lower estimate of output power. The uncertainty associated with the NOCT procedure is ±4 °C.

Over an eight-month analysis for a single module, the range of NOCT averaged over a three-day period ranged from 45.3 to 49.8 °C. In reality, however, only 10 days over the eight-month period were actually suitable for NOCT testing. When comparing three c-Si modules over three 3-day periods, the range of NOCT was 1.9 to 3.2 °C, well within the expected ±4 °C. During side-by-side testing these three modules were found to have average NOCT ranging from 48.6 to 48.9 °C, but the values of NOCT determined by independent laboratories and reported in the CEC database were 42.4 °C, 47.9 °C, and 52.3 °C.

This work is continuing, but preliminary conclusions reached were:

- The IEC 61215 procedure does not guarantee repeatable results.
- Eight months of NREL data result in NOCT values ranging from 45.3 to 48.9 °C.
- A steady state heat transfer model supports that a 10 °C variation in NOCT can result from changing sky, ground, and ambient temperatures.
- Three modules with previously reported NOCT values of 42.4 °C, 47.9 °C, and 52.3 °C show identical NOCT values in side-by-side testing.

Future work will include examination of suggested changes to the IEC procedure and continuation of data gathering at NREL.

Modeling Module Temperature in the System Environment (Ty Neises, University of Madison – Wisconsin)

University of Wisconsin masters student Ty Neises (now on staff at NREL) is studying various models to predict cell temperature in both building integrated PV (BIPV) and open rack configurations. The study compares predictions from numerous models, including a steady-state energy balance equation with conduction, convection, and ground and sky radiation components; the Duffie and Beckman model (2006)[12] which includes NOCT temperature; the Skoplaki model (2008)[13] which includes a parameter for mounting configuration; and the King model (2), which includes mounting- and panel-specific coefficients.

All of the included models performed well for a rack-mounted c-Si module located at Sandia in Albuquerque, New Mexico. The study found overall that cell temperature model results for open rack panels are consistent and accurate when compared against the 5-parameter model with measured backside temperature input. The largest discrepancy of modeled to measured results occurred for BIPV modules tested at the National Institute of Standards and Technology in Gaithersburg, Maryland.

The results of Neises' study underscore the importance of modeling modules relative to their mounting configuration. In a 2010 study using the Sandia PV Array Performance Model, Sandia found that the difference in output of a rack-mounted system vs. a system with an insulated back was as much as 10% in Phoenix, Arizona[14]. Even in an open field, First Solar reports variations of 10 °C in temperature between the edge and the center of large arrays (see earlier presentation).

[12] J.A. Duffie, W. A. Beckman, *Solar Engineering of Thermal Processes.* Third ed. John Wiley & Sons Inc., New York, 2006.

[13] E. Skoplaki, A. G. Boudouvis, and J. A. Palyvos, A simple correlation for the operating temperature of photovoltaic modules of arbitrary mounting, *Solar Energy Materials and Solar Cells*, vol. 92, no. 11, pp. 1393–1402, 2008.

[14] C. P. Cameron and A. C. Goodrich, "The Levelized Cost of Energy for Distributed PV: A Parametric Study," Proceedings of the 35th IEEE Photovoltaics Specialists Conference, Honolulu, Hawaii, June, 2010.

Understanding Modeling Errors Using Residual Analysis (Josh Stein, Sandia National Laboratories)

As discussed in Stein's presentation on "A Proposed Approach to PV Performance Model Validation," Sandia is employing residual analysis to identify potential sources of model error. Sandia's intent is to offer each participant from the pre-workshop exercise a personalized model validation report using residual analysis. In this presentation, Stein reviewed residual analysis from participants' use of SAPM, PVsyst, the 5-Parameter Model, and PVWatts.

As shown in Figure 16, residual analysis of these examples show that two of the models overpredict power at low temperatures (below 20 °C) and underpredict at high temperatures (above 20 °C). No distinct trends were observed in the models prediction of module temperature, so this might suggest the temperature coefficients used to correct performance for temperature are too large. The results for the two PVWatts examples were inconsistent. This illustrates the need to observe these patterns for multiple systems before conclusions may be reached.

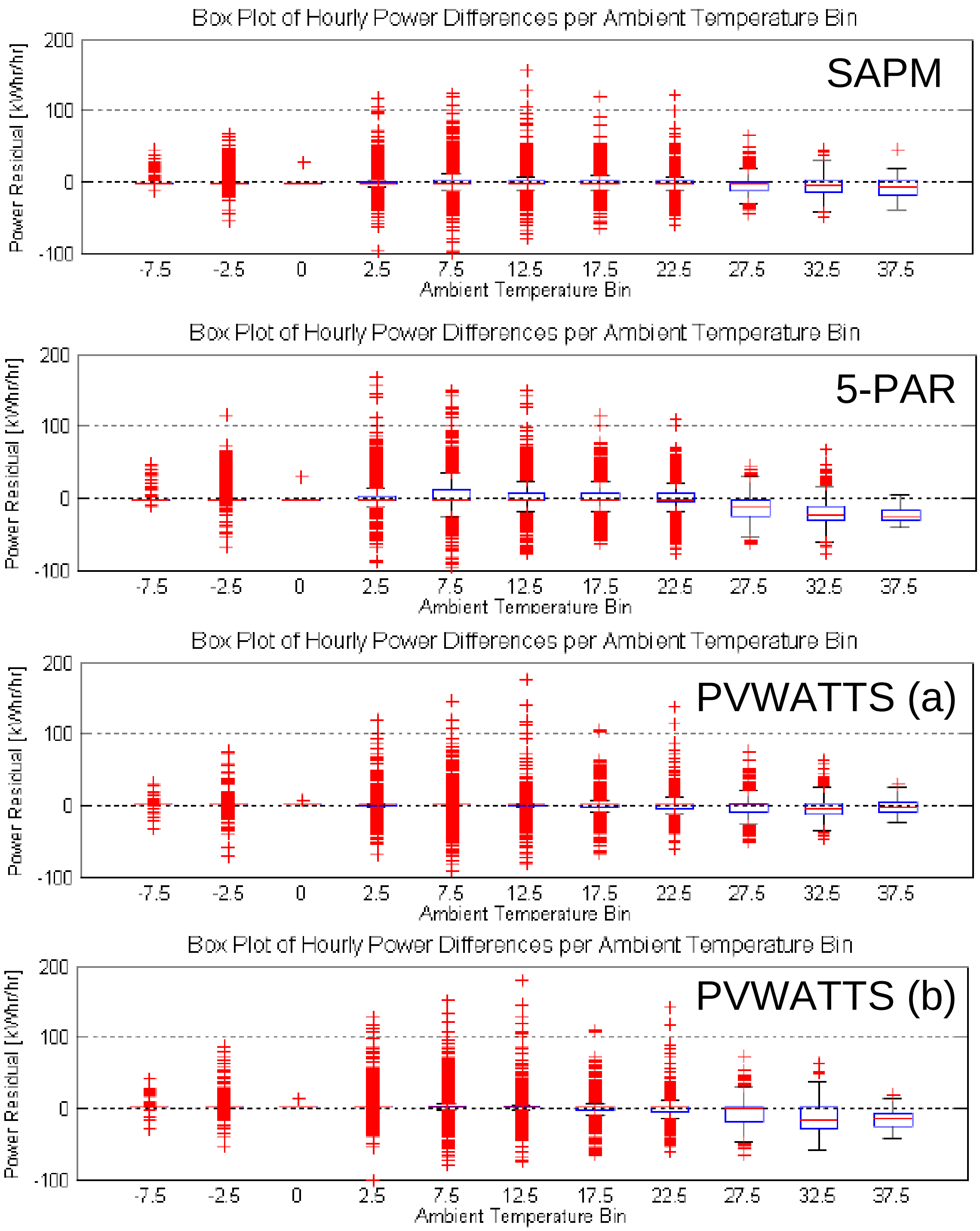


Figure 16. Hourly Power Differences as a Function of Ambient Temperature.

2.1.4 Facilitated Discussion – Day One

Facilitated discussion at the conclusion of day one focused on two primary issues: specific attributes needed to improve module performance testing, and the prioritization of future efforts, roles, and responsibilities. Additional discussion included streamlining and standardizing models, and third-party verification.

When the group was asked what must be done to improve module performance modeling, a number of suggestions were made ranging from more standardization of data to more reliance on systems-related approaches. Some specific needs identified by participants include:

Module testing

- Module testing should be performed by independent third parties to improve bankability.
- A set of standard tests should be developed that could be used to generate performance coefficients for all available performance models.
- Standard tests should also include data at non-STC conditions.
- Test data and the resulting performance coefficients should be published in a publicly-accessible location.
- Data should represent more than one module, perhaps a statistically significant number of modules rather than just one or a few.
- Rapid development of new test protocols is needed for new products.
- Several participants suggested that manufacturers add efficiency specifications and ISO audit information to product datasheets in an effort to help reduce compliance costs and account for differences among production runs, technologies, and degradation.

Uncertainty

- The uncertainties that most impact model output should be identified.
- Performance coefficient databases need to include coefficient uncertainty to enable propagation of uncertainty through the models.
- Risk analysis and stress testing of results that can satisfy the needs of the investment community and improve bankability of projects should be performed.

Module Modeling

- Better analysis and calculation should be performed around how module modeling affects system modeling and can drive system design, selection of inverter sizes, etc.
- Models are needed that can calculate performance at other than maximum power point for modules that are mismatched due to shading or multiple orientations, or when grid considerations require operation away from maximum power point.
- Rapid development of models is needed for new products.

System Modeling

- Models should be developed with a better understanding of audience needs and potential tailoring of output for different users: manufacturers, engineers, integrators, consumers.
- Suitable models and third-party data should be available for all audiences.

- Independent engineers suggested that their efforts could be enhanced by models that are based on independently tested and verified data and used across the industry. Currently, independent engineers are often asked to evaluate output and data from industry models, which are based on external assumptions and manufacturer-provided datasheets.

Model Validation

- Third-party, independent datasets for assessment of models are needed, including datasets for different locations and seasons, potentially using standardized test configurations and cleaning processes for reference cells and sensors.
- Model evaluation processes should begin at the module level and then go through the system piece-by-piece to prioritize attributes in descending order of effect on the model. Higher-priority elements should be examined first.
- A streamlined process for achieving model validation is needed so as not to delay implementation of models or have them lag technology.
- Models should use of inputs and generate outputs that are relevant to and well-understood by the financial community.

Standards Development for Model Validation

- Participants stressed the importance of the modeling community's participation in the standards process, including with a new IEC standard currently in development.

2.2 Day 2: Thursday, September 23

2.2.1 Modeling System Performance

Beyond the Module - Modeling System Performance - Introduction (Chris Cameron, Sandia National Laboratories)

This introductory presentation summarized the output of day one and set the stage for day two of the workshop, in which discussions moved beyond the module model to the systems model. A systems model has many sub-models, as shown in the center of Figure 17. Ideally, users would enter the design data shown in the left of the figure and the systems model would predict system output. The reality is that users may have a choice of sub-models and associated databases for some calculations, such as the radiation translation and module models. Other inputs such as expected soiling losses must be estimated by the user. All of these choices affect the model output, as illustrated by the results of the model inter-comparison exercise reported above.

Modeling Systems Losses in PVsyst (Andre Mermoud, Institute of the Environmental Sciences, University of Geneva)

In a continued discussion about PVsyst, Andre Mermoud discussed the modeling of system losses and model improvements currently underway. Mermoud emphasized the importance of identifying and planning for losses in PV system simulation, which can be model- or input-driven. As shown in Figure 18, PVsyst provides detailed analysis of all losses – optical, array, and system – with each simulation, which helps the user check the pertinence of input parameters.

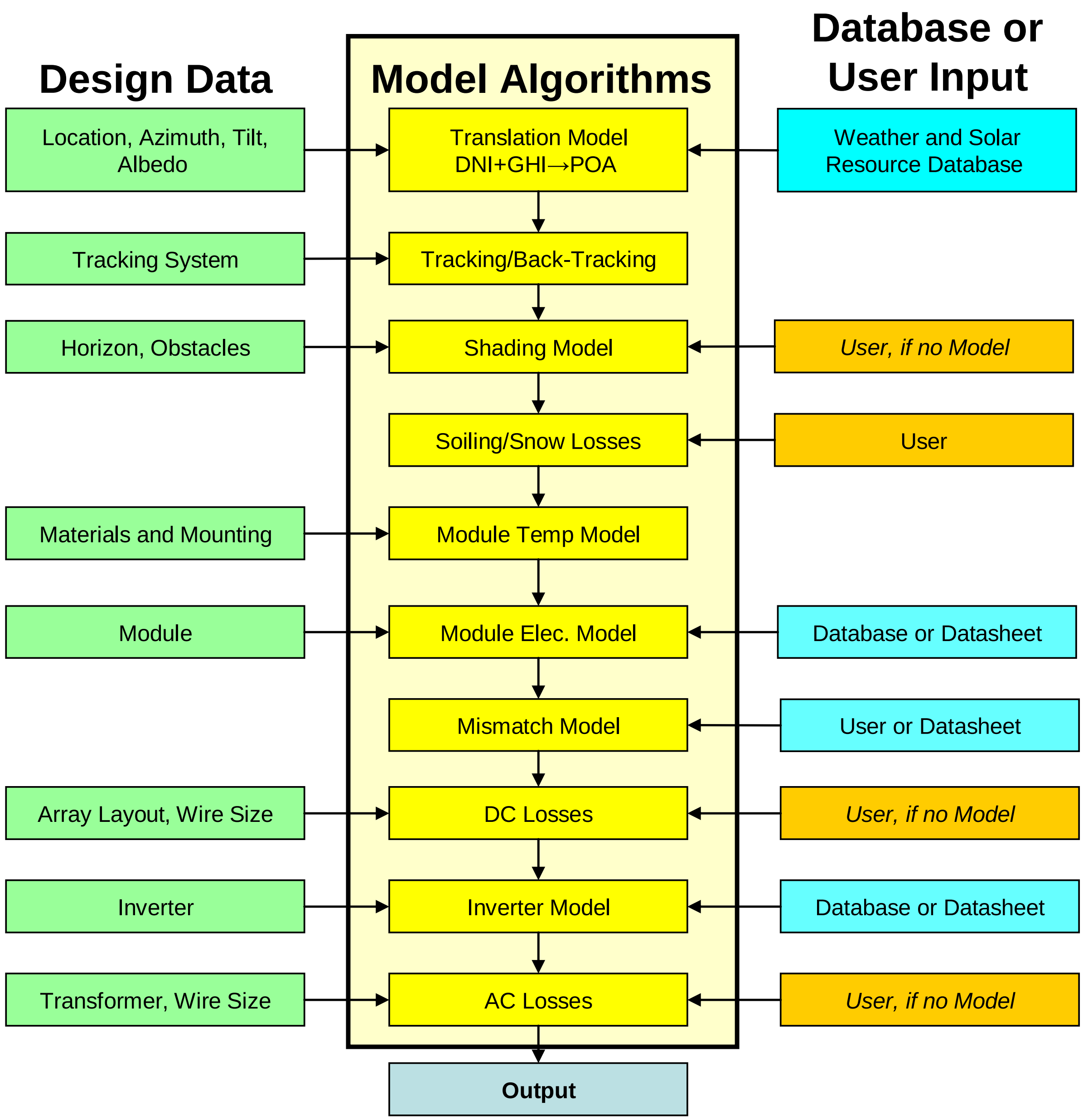


Figure 17. Performance Model Process Outline.

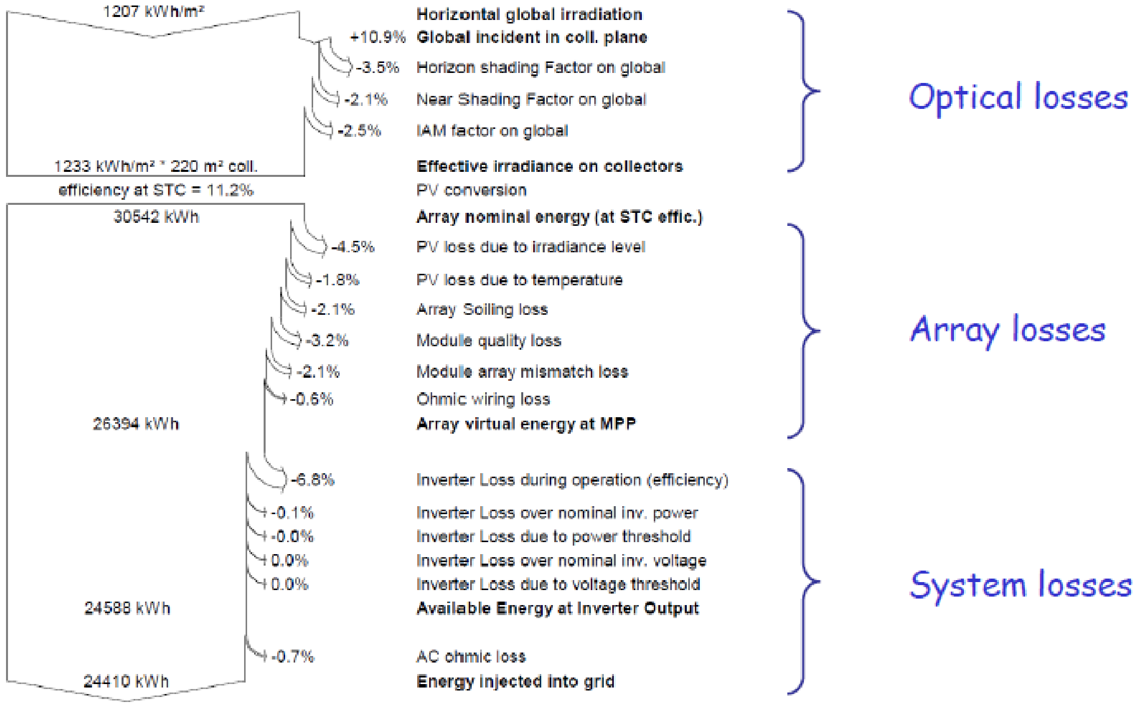


Figure 18. Loss Analysis Overview from PVsyst.

PVsyst models both far and near shading losses. Near shading requires knowing the dimensions and position of objects near the array and computing the impact of shading on each sub-module of each PV sub-array connected to each MPP inverter output. Near shading may be modeled as three-dimensional structures and obstructions.

Far shading includes obstacles that are at a distance typically greater than ten times the array size. These are modeled as a horizon line that blocks the direct beam component as a function of sun position. The horizon line can be captured from GIS sketches or by instruments such as Solmetric's SunEye.

PVsyst also calculates inverter losses and allows the user to input wire lengths and cross sections to enable calculation of wiring losses. Other losses require user estimates including soiling loss, in yearly or monthly values; module degradation; mismatch loss; and availability loss. Default values are provided for each of these loss factors.

Despite PVsyst's advanced capabilities, its simulations still experience the same uncertainties as many other models: meteorological data sources and accuracy, and validity/uncertainty of module specifications provided by manufacturers.

Mermoud concluded his presentation by asking participants for input and discussion on the rising number of requests for P50/P90 performance estimates. Calculation of these uncertainty estimates requires stochastic modeling methods.

Characterizing Shading Losses and the Impact of Sub-array MPPT (Chris Deline, National Renewable Energy Laboratory)

Shading leads not only to power loss, but also current mismatch within a series string and voltage mismatch between parallel strings. Chris Deline is a staff engineer at NREL conducting modeling and analysis of PV module and array shading and mismatch resulting from orientation, manufacturing tolerance, aging and soiling.

Depending on the reverse bias characteristics, shading of just 25% of the area of one cell can lead to bypass diode turn-on, which will remove the power from the 15-20 cells found within the diode-protected substring. Power loss is greater in proportion to the amount of shade on the system, and detailed modeling is required to predict the power loss. For example, 30% power loss from shading was observed in a string where only 12.5% of the string was shaded. Since the system I-V curve is built from individual substring I-V curves in series and in parallel, partial shading can lead to local and global maxima as shown in Figure 19. Further reduction in power output can occur if an inverter's maximum-power point tracking (MPPT) algorithm locks in on a local (rather than global) maximum.

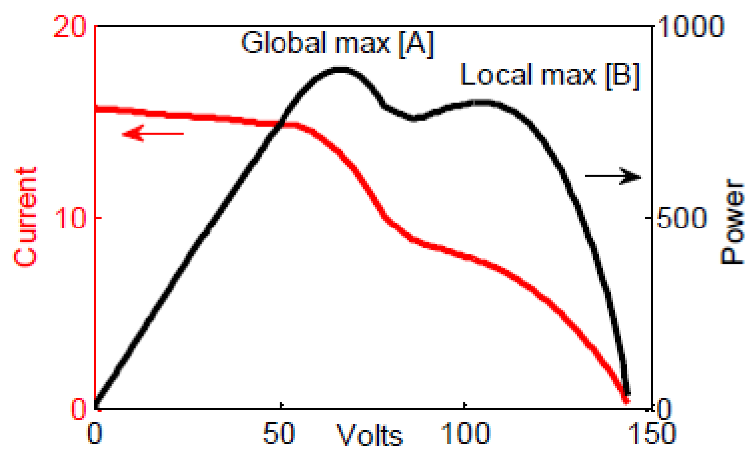


Figure 19. Demonstration of How Shading Can Distort the I-V curve (black) and Lead to Local Maxima in the Power Curve (red).

Deline discussed numerous issues related to shading, including foliage changes throughout the year, spatial resolution, evaluation of opaqueness, position uncertainty for nearby objects, and the time commitment involved to complete three-dimensional shade modeling. Electrical circuit models can also take a great deal of time to run, especially for large systems, so Deline recommends using a simplified 3-parameter model or a shade opacity look-up table.

Deline's work focuses on utilizing individual sub-string I-V curves in series and in parallel to build a system I-V curve and evaluate shading effects. The simulation uses PVWatts with an added shade derating factor, which is based on empirical relationships between extent of shade and overall power loss. Modeled results compared favorably with measured data on representative sunny days and annual results show close agreement with site survey's solar resource fraction, though Deline acknowledges this is not always the case. Deline is continuing to improve shading simulation and will be creating a simulation feature for SAM. He is also performing test and evaluation of DC-DC converters and micro-inverters to determine the performance improvement that can be achieved with these devices.

[Modeling and Evaluating Sub-Array MPPT]() (Sara MacAlpine, University of Colorado)

Sara MacAlpine is a graduate student in the Civil, Environmental, and Architectural Engineering department at the University of Colorado in Boulder. Her research focuses on using a combination of tests and modeling approaches to characterize shading response under non-uniform shading conditions and evaluating the effects on energy production.

One of MacAlpine's examples analyzed the impact of shading on various string configurations. For example, Figure 20 shows two system layouts. In one, only one string is shaded. In the other, both strings are shaded. Her analysis of the impact of shading, presented in Figure 21, shows that the layout with two horizontal-strings produces more energy when the system is heavily shaded (95% of the irradiance is blocked), but the side-by-side configuration produces more power when only 50% of the irradiance is blocked. This example illustrates the complexity of modeling shading effects.

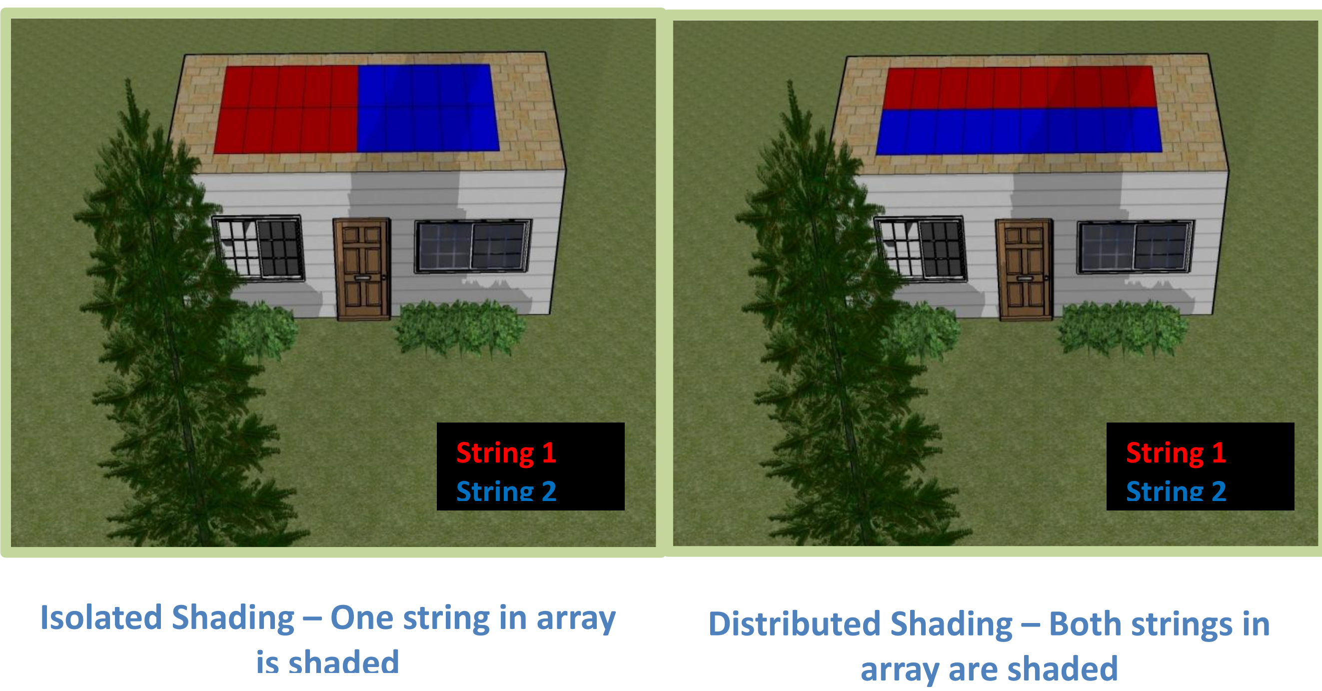


Figure 20. Partially-shaded Array.

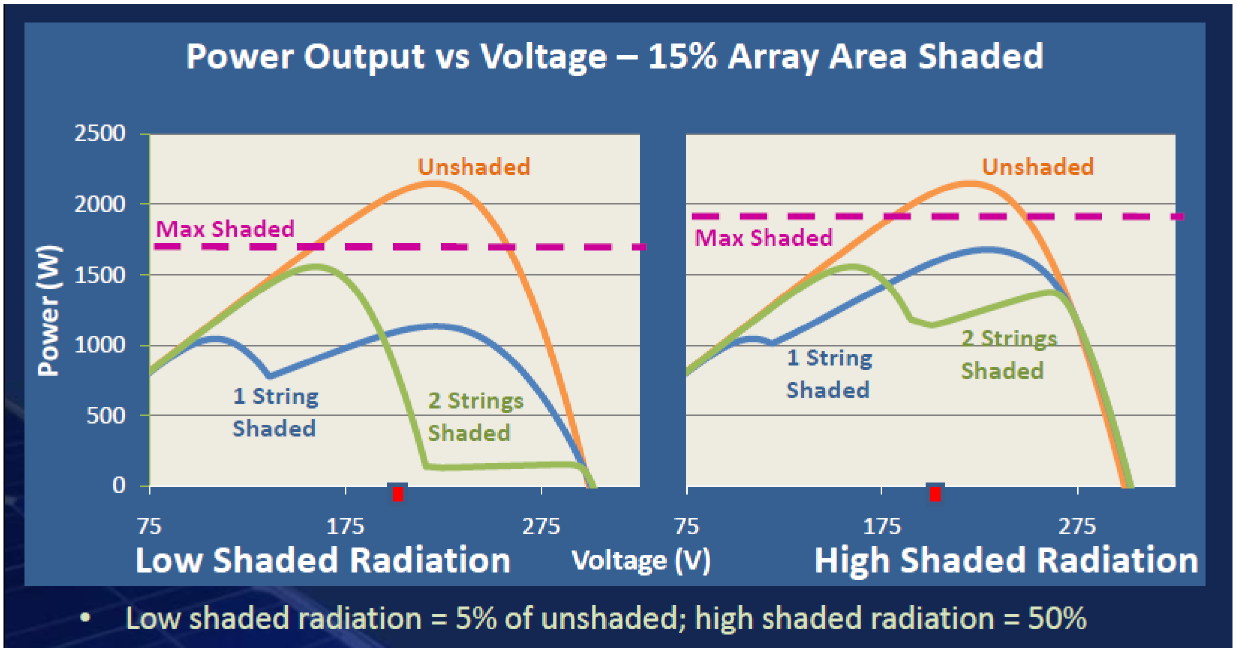


Figure 21. Effect of String Configuration on Performance with Partial Shading.

MacAlpine then examined the potential benefit of using Distributed Maximum Power Point Tracking (DMPPT) to alleviate variability caused by disproportionate losses, which are often caused by mismatch within a system. The results are presented in Table 4 and show that, when there is significant shading, DMPPT can improve performance but the degree of improvement is a function of system configuration. When shading was more moderate, no advantage was seen with DMPPT because of the insertion loss associated with the devices.

Table 4. Impact of DMPPT on Shaded System Performance.

Object Position	String Division	% Shading Loss with Prototype Converters	Shaded System %Output Difference -- Prototype Converters vs None	Shaded System Max Potential %Output Difference -- Modular vs Central MPPT
Corner	Left-Right	15%	3%	8%
	Top-Bot	15%	8%	13%
Center	Left-Right	21%	10%	15%
	Top-Bot	21%	31%	37%

MacAlpine showed simulations of annual array energy capture, shading loss, and power recovery potential using MATLAB models at the panel, power converter, and inverter levels. The simulation included TMY-3 hourly irradiance and NOCT data for Boulder, Colorado. Preliminary results indicate the potential for shade impact factors (SIF) to be used to accurately model DMPPT, with the most promising results occurring when SIF is implemented at the bypass diode substring level.

Modeling Needs for Very Large Systems (Joshua Stein, Sandia National Laboratories)

Most system performance models assume a point measurement for irradiance and that, except for the impact of shading from nearby obstacles, incident irradiance is uniform across the array. Module temperature is also assumed to be uniform across the array. For small arrays and hourly-averaged simulations, this may be a reasonable assumption. Stein is conducting research to characterize variability in large systems and to develop models that can better accommodate large system factors.

In large, multi-MW arrays, passing clouds may block sunlight from a portion of the array but never affect another portion. Figure 22 shows that two irradiance measurements at opposite ends of a multi-MW PV plant appear to have similar irradiance (left), but in fact the irradiance is not always the same (right). Module temperature may also vary across the array, with modules on the edges being cooler because they have greater wind exposure. Large arrays will also have long wire runs and will be subject to associated losses. Soiling patterns may also vary, with modules closer to the source of soiling, such as an agricultural field, receiving more dust load.

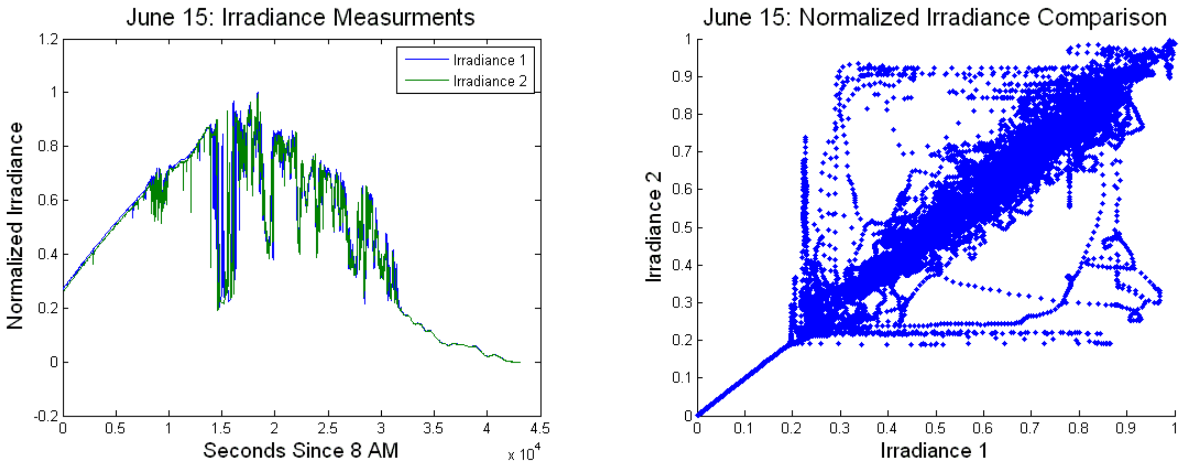


Figure 22. Irradiance Differences between Two Sensors.

One of the primary concerns associated with this effort is how to work with integrators to gain access to better and more comprehensive data for model development and validation.

How Does Uncertainty in Input Parameters Affect Model Output? (Cliff Hansen, Sandia National Laboratories)

The output of most PV performance models is presented as a deterministic result without any estimate of error or uncertainty, but both uncertainty and variability in model inputs affect results. Uncertain parameters have fixed but imperfectly known values, such as parameters related to performance (e.g., P_{mp}) and parameters related to empirical approximations (e.g., the model coefficients relating I_{mp} to irradiance). Variable parameters characterize inherently variable quantities, such as weather data.

Cliff Hansen, a Distinguished Member of Technical Staff at Sandia National Laboratories, is working with Joshua Stein and Steve Miller (also from Sandia) to address issues associated with quantifying model input uncertainties. By doing so, efforts can be made to reduce those uncertainties and validate model outputs that drive decisions related to technology, system design, costs, and financing.

The initial study presented was focused on model sensitivity of the Sandia PV Array Performance Model, which contains many empirically-determined performance coefficients (illustrated in Figure 23). The methodology used Monte Carlo statistical methods to assign uncertainty ranges to model inputs and investigate correlations between those inputs and the model output. In order to reduce unknown variability in the study, weather data was fixed and a single SunPower PV module was analyzed for three different locations: Phoenix, Arizona; Alamosa, Colorado; and Detroit, Michigan.

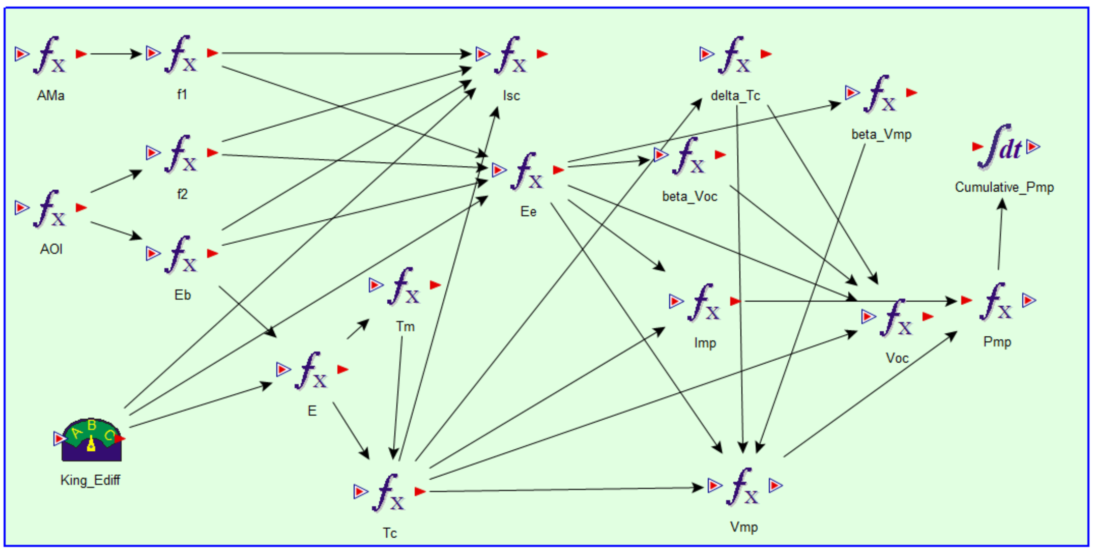


Figure 23. Schematic Representation of the Sandia PV Array Performance Model.

In a study of 16 uncertain parameters in the Sandia PV Array Performance Model, those shown to be most significantly correlated to uncertainty in output (cumulative power) were maximum power point error, the Angle of Incidence correction factor, the Air Mass correction factor, and the C_0 coefficient (relating I_{MP} to effective irradiance). This study is being continued and expanded to additional modules technologies and performance models. Understanding the impact of uncertainty will both inform model users of the sensitivity of the models and will help focus efforts to improve the models on the most important parameters.

[Model of Models](#) (Doug Payne, SolarTech)

Doug Payne is the executive director of SolarTech, a collaborative organization comprised of solar stakeholders including industry, financiers, local governments and utilities.
The group focuses on six primary areas related to advancing the solar market: performance, workforce, financing, interconnection, permitting, and interconnection. Of these, Payne indicates modeling is estimated to have the most significant impact on the financing and performance areas.

Payne discussed a 'model of models' proposed by SolarTech and shown in Figure 24. The initial model design uses a family of cumulative kWh projection curves and allows uncertainty to be factored in using various methods. SolarTech suggests that this model be updated quarterly in order to reduce uncertainty.

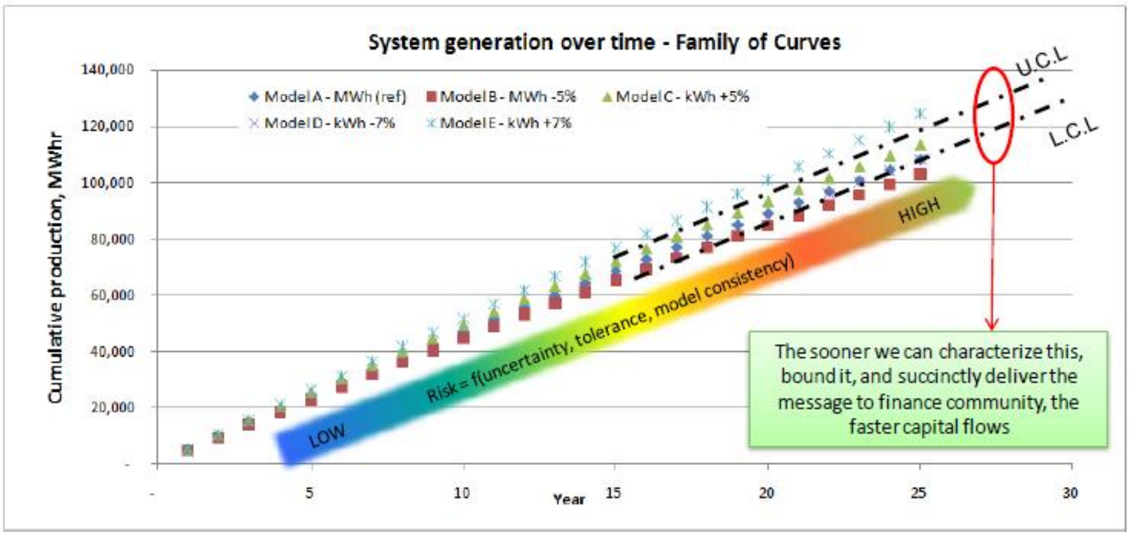


Figure 24. SolarTech's 'Model of Models'

The objectives of SolarTech's approach are to use standard performance metrics and energy production tools to drive faster buying decisions, reduce transaction costs, and enhance due diligence for developers.

2.2.2 Facilitated Discussion – Day Two

The facilitated discussion for the second day focused on model validation, whether and how to include uncertainty in model outputs, and prioritization of future efforts to model system losses.

Discussion opened with a recap of the information survey results from day one, in which participants voted for the most important elements to include in future modeling efforts. The two most voted for were: (a) review of existing standards and development of standardized tests for industry that are not model-driven; and (b) inclusion of non-STC conditions in modeling and testing.

Implementing suggestion (a) includes conducting a full inventory of existing standards to address elements that characterize power production. The objective would be to identify gaps in test standards with respect to modeling and determine whether the solar industry is sufficiently employing standards (i.e., are the incentives for using them – or penalties for not using them – adequate enough to drive more consistent use?).

The group did not come to agreement as to whether manufacturers could conduct this audit and, if so, whether manufacturers' processes and results should be open to third-party scrutiny and enforcement. There was consensus, however, that individual components of solar systems should be isolated for testing and modeling and that doing so could help modelers capture aspects that are consistent across systems of varying sizes and configurations. The group also agreed that there is a need for prompt and independent datasets for new technologies.

Data for Model Validation

The discussion about standardization and third-party datasets motivated a dialogue about how to validate and evaluate such elements, and who will fund and own the data. One suggestion included DOE working with the General Services Administration to install identical systems on federally-owned buildings and then make data from those systems publicly available. Concerns about this option included disagreement about the necessary number of installations and inevitable differences in climate and building characteristics that would keep the installations from being uniform. As an alternative, the group recommended collecting data from projects installed under DOE's Solar America Cities and similar programs where political and financial capital has been invested, and/or developing the suggested federal installation program but using only portions of installations for data and analysis. The group also suggested writing requirements for the data collection system procurement process to include standardized data systems, and noted that the use of uncertainty analysis to identify the most critical parameters will define the instrumentation needs.

Despite the group's overall agreement that standardization would help alleviate modeling error, the concern remained that different classes of materials and types of systems could continue to require varying models. How and whether to develop a standard approach relies heavily on whether such an approach can effectively cover current and future technology, either through protocols that can cover a broad range or through the inclusion of elements that can be tailored without disrupting the model. Participants also noted that characterization should go beyond components to include evaluation of entire systems, and that uncertainty analyses be conducted for all system scales: utility, commercial, and residential.

Model Improvement

When asked for a 'wish list' from the modeling community in terms of revising current and developing future models, participants narrowed their requests to four specific items:

- The ability to run multiple years and then separate them readily
- The ability to input the user's measured data to models
- Parametric analysis and sensitivity analysis capabilities

- Model output that can feed readily into a wide variety of financial models and rate schedules

Access to reliable, quality data was acknowledged as a key shortcoming for the modeling community. Chris Cameron asked participants interested in supporting future development to collaborate with Sandia and other model developers to determine how to best improve access to data and information.

The workshop concluded with an optional tour of Sandia's Photovoltaic Systems Evaluation and Distributed Energy Technologies Laboratories.

APPENDIX A: AGENDA

PV PERFORMANCE MODELING WORKSHOP
September 22 and 23, 2010

Phillips Technology Institute Collaboration Center
on Maxwell Ave SE, one block north of Gibson Blvd SE
Kirtland Air Force Base, Albuquerque, NM

Wednesday, September 22, 2010		
9:00	Welcome and Purpose	Chris Cameron, SNL
9:15	A Review of System Performance Models	Bradley Hibberd and Tarn Yates, Borrego Solar
9:35	Needs and Issues in System Performance Modeling - Manufacturer/Integrator	Ben Bourne, SunPower
9:50	Needs and Issues in System Performance Modeling - Manufacturer/Integrator	Adrianne Kimber, First Solar
10:05	Needs and Issues in System Performance Modeling - Independent Engineer	Jeff Newmiller, BEW Engineering
10:20	**Break**	
10:35	Recent Studies of PV Performance Models	Steve Ransome
11:00	A Proposed Approach to PV Performance Model Validation	Joshua Stein, SNL
11:30	Results of Model Inter-Comparison - Predicted vs. Measured System Performance	Joshua Stein, SNL
12:00	**Lunch** Luncheon Presentation: Overview of PV*SOL and Plans for US Market	Paul DeKleermaeker, Valentin Software
1:00	An Overview of the Module Model in PVsyst	Andre Mermoud, PVsyst
1:20	Improvements to the CEC/Wisconsin n-Parameter Model	Bill Beckman
1:40	Overview of the Module Model in PVWatts	Bill Marion, NREL
2:00	Overview and Background on the Sandia PV Array Performance Model	David King
2:20	Modeling and Measuring Normal Cell Operating Temperature	Matt Muller, NREL
2:35	Modeling Module Temperature in the System Environment	Ty Neises, U. of Wisconsin
2:50	**Break**	
3:05	Understanding Modeling Errors for Module Models Using Residual Analysis and Application to the Results from Model Inter-Comparison	Joshua Stein
3:50	Facilitated Discussions of Results	
	• What must be done to improve module performance modeling?	
4:30	• Prioritization of future efforts, roles, and responsibilities	
5:00	Adjourn	

PV PERFORMANCE MODELING WORKSHOP
September 22 and 23, 2010

Phillips Technology Institute Collaboration Center
on Maxwell Ave SE, one block north of Gibson Blvd SE
Kirtland Air Force Base, Albuquerque, NM

Thursday, September 23, 2010		
8:30	Beyond the Module - Modeling System Performance - Introduction	Chris Cameron, SNL
8:40	Modeling Systems Losses in Pvsyst	Andre Mermoud, PVsyst
9:05	Characterizing Shading Losses and the Impact of Sub-array MPPT	Chris Deline, NREL
9:25	Modeling and Evaluating Sub-Array MPPT	Sara MacAlpine, U. of Colorado
9:45	Modeling Needs for Very Large Systems	Joshua Stein, SNL
10:00	Break	
10:20	How Does Uncertainty in Input Parameters Affect Model Output?	Cliff Hansen, SNL
10:40	Facilitated Discussion	
	• Industry-led Market Transformation: FY2011 Performance/Finance Framework (Doug Payne, SolarTech)	
	• Validating models and inputs - are new standards needed?	
	• Should uncertainty be included in model outputs?	
	• Ensuring quality in model inputs	
	• Validating model accuracy and uncertainty	
	• Prioritization of future efforts to model system losses	
11:40	Closing Discussion and Action Items	
12:00	Lunch	
1:00	Depart by Bus **ONLY** for Tours of Sandia Inverter and Outdoor Module Test Laboratories *Please note: All tour participants must travel by bus. Cell phones and other electronics are not permitted on the tour and cannot be left in the meeting room. They can be left on the bus, which will remain at the tour location. The group will return to the Phillips Technology Institute Collaboration Center at the end of the tour.*	
~3:30	End of Tours and Workshop	

APPENDIX B: PARTICIPANT LIST

PV PERFORMANCE MODELING WORKSHOP
September 22 and 23, 2010

Abound Solar	Larry Knipp
American Capital Energy	Ryan McDonald Tom Anderson
BEW Engineering	Jeff Newmiller Rhonda Bailey
Black and Veatch	Evan Riley
Borrego Solar	Bradley Hibberd Tarn Yates
BP Solar	Jay Miller Jeff Meyer
Clean Power	Andrew Parkins
First Solar	Adie Kimber
Hoes Engineering	Charles Hoes
Independent analyst / consultant	Steve Ransome Dave King
Luminate	Nick Lemon
Miasole	Roger Balyon Aaron Schultz
Navigant	Graham Stevens
National Institute of Standards and Technology	Tania Ullah Matt Boyd
National Renewable Energy Laboratory	Nate Blair Matt Muller Aron Dobos Chris DeLine Bill Marion

Sandia National Laboratories	Chris Cameron Jennifer Granata Charlie Hanley Geoff Klise Josh Stein Steve Miller Cliff Hansen
SENTECH / SRA International, Inc.	Coryne Tasca
SolarTech	Doug Payne
SoloPower	Sankaran “Jay” Jayanarayanan John Foreman
SunEdison	Bob Wimbrow
SunPower	Ben Bourne
Uni-Solar / Solar Integrated	Kevin Beernink Riley Caron
University of Arizona - AzRISE	Joseph Simmons
University of Colorado - Boulder	Sara MacAlpine
University of Geneva	Andre’ Mermoud
University of New Mexico	Mark Harris
University of Wisconsin – Madison	Ty Neises Bill Beckman
U.S. Department of Energy	Michael Cliggett
Valentin Software	Paul DeKleermaeker
Yingli	Kenneth Sauer

APPENDIX C: PV SYSTEM DATA DOCUMENTATION FOR MODELING WORKSHOP PRE-WORK

This document describes the design of three fixed tilt PV systems that participants of Sandia's modeling workshop (Sept 2010) are being asked to simulate system performance (Watt-hr per hr) for a one-year period based on measured weather data from each site. The design descriptions are found in Section 1. The weather data format is described in Section 2, and the requested format of the results is described in Section 3 at the end of the document. Participants are asked to simulate each of the systems using the model or models of their choice. Derate factors must be estimated by the modelers based on expert judgment. We have provided module parameters along with the system descriptions.

Section 1: PV System Descriptions

System 1: *Shell Solar CIS Grid-Connected System*

Location:	NREL Outdoor Test Facility, Golden, Colorado
Latitude:	39.74°N
Longitude:	105.18°W
Elevation:	1785 m
Time Zone:	MST(-7)
Installation Date:	January, 2006
Nameplate Rating:	1120 Wdc
Array Tilt:	40°
Array Azimuth:	180°
PV Module:	Shell Solar CIGSS model Eclipse 80. Pmax = 80 W. Sandia PV Array Performance Model parameters estimated by Dave King are included in the file 'Eclipse CIS 80-C.xlsx' and listed in Table 1. Manufacturer datasheet is included with the data files.
PV Array:	Consists of two 560 W source circuits. A source circuit has seven modules connected in series with a resultant maximum power point voltage of 232 V at STC.
Inverter:	1.8-kW Sunny Boy model SWR 1800U. The minimum input voltage for peak power tracking depends on the grid voltage, and ranges from 138 Vdc for a grid voltage of 105 Vac to 171 Vdc for a grid voltage of 132 Vac. Maximum input voltage for peak power tracking is 400 Vdc.
Notes:	

Table 1. Sandia PV Array Performance Model Coefficients for Shell Solar Eclipse 80-C module.

Parameter	Value	Units		Parameter	Value	Units
Module	Shell Solar Eclipse 80-C			A0	0.921	
Area	0.86	m^2		A1	0.071815	
Material	CIS			A2	-0.014619	
Series_Cells	84			A3	0.00125	
Parallel_C-S	1			A4	-3.74E-05	
Isco	2.68	A		B0	1	
Voco	46.6	V		B1	-0.002438	
Impo	2.41	A		B2	0.0003103	
Vmpo	33.2	V		B3	-1.25E-05	
aIsc	0.00013			B4	2.112E-07	
aImp	-0.00041			B5	-1.36E-09	
C0	0.972			d(Tc)	3	C
C1	0.028			fd	1	
BVoco	-0.181			a	-3.47	
mBVoc	0			b	-0.0594	
BVmpo	-0.149			C4	0.982	
mBVmp	0			C5	0.018	
n	1.752			Ixo	2.63	A
C2	0.50877			Ixxo	1,71	A
C3	-2.954			C6	1.045	
				C7	-0.045	

System 2: *Mobil/ASE EFG Silicon Grid-Connected System*

Location:	NREL Outdoor Test Facility, Golden, Colorado
Latitude:	39.74°N
Longitude:	105.18°W
Elevation:	1785 m
Time Zone:	MST(-7)
Installation Date:	February, 1995
Nameplate Rating:	1430 Wdc
Array Tilt:	40°
Array Azimuth:	180°
PV Module:	Mobil Solar Ra 280-50 H EFG Silicon. Pmax = 286 W. (Very similar to the module: Schott Solar ASE-300 DFG-50 (280) 2007(E), which is in the Sandia Module Database (included with SAM). Manufacturer datasheet is included with the data files.

PV Array: Consists of five source circuits (five PV modules in parallel). A source circuit consists of one PV module with a maximum power point voltage of 50 V at STC.
Inverter: 2.5-kW Xantrex model SunTie STXR2500. The minimum input voltage for peak power tracking is 42 Vdc and the maximum is 85 Vdc.
Notes:

System 3: *SunPower Grid-Connected System*

Location: Sandia National Laboratories, Albuquerque, NM
Latitude: 35.05°N
Longitude: 106.54°W
Elevation: 1657 m
Time Zone: MST(-7)
Installation Date: April 1, 2007
Nameplate Rating: 1085 Wdc
Array Tilt: 35.05°
Array Azimuth: 180°
PV Module: SunPower SPR-210-WHT, Pmax = 217 W. This module is included in the Sandia Module Database. Manufacturer datasheet is included with the data files.
PV Array: Consists of five source circuits (five PV modules in parallel). A source circuit consists of one PV module with a maximum power point voltage of 40 V at STC.
Inverter: 2.5-kW SunPower Corp (Originally Mfg. – PV Powered): model SPR-2500 240 V. The minimum input voltage for peak power tracking is 140 Vdc and the maximum is 450 Vdc.
Notes: System and weather data are presented in order by month rather than chronological order (Jan 2008 – March 2008 –April 2007 – Dec 2007). Leap day data was removed from the dataset. This was done so that the data could be represented in TMY2 format, which requires a full calendar year. Please submit simulated performance in same 8760 hour format.

Section 2: Weather Data Format

Weather data is supplied for each of the systems in TMY2 format and in comma delimited files with the following columns containing 8760 hourly values (Jan 1 – Dec 31):

1. Year: Year of measurement (e.g., 1996)
2. Month of measurement (1-12)
3. Day of month of measurement (1-31)
4. Hour of measurement (1-24)
5. Direct normal irradiance (W/m^2). Hourly average from previous hour.
6. Diffuse horizontal irradiance (W/m^2). Hourly average from previous hour.
7. Global horizontal irradiance (W/m^2). Hourly average from previous hour.
8. Tdry (dry bulb temperature in degrees C). Hourly average of period +/- 30 min.

9. Wind (wind speed in m/sec). Hourly average of period +/- 30 min.
10. WindDir (wind direction in degrees clockwise from North, E=90, S=180, W=270). Hourly average of period +/- 30 min.
11. Pres (air pressure in mbar). Hourly average of period +/- 30 min.

During periods when weather instruments or array output was not ideal or normal, weather and performance data have been adjusted to make sure that the models will predict zero power during these periods. For example, several systems experienced shade at certain times of the year. Weather data (and power output data) for these time periods have been altered so that irradiance and output power values are set to zero. Also during these times periods, other weather variables were set to reasonable values that are not expected to alter performance calculations.

Section 3: Performance Model Results Format

Workshop participants are asked to simulate the hourly output in Watt-hours AC per hour for these three systems and report their results back to Sandia before the workshop. Results will then be analyzed together to characterize the amount of variance between different models. Sandia will keep the source of the model results anonymous from other workshop participants and will identify individual results with a code number or letter (e.g., Simulation A, B, C, or 1, 2, 3, …).

Model results should be expressed in a table listing 8760 hourly values for each system. The primary output of interest is **AC power**, but **DC power**, **Module and Cell Temperature**, **Voltage and Current** may also be of interest. I have included a template in Excel that can be used to report back performance model output results. The first page (sheet) of the template is meant to record information about the model used and allow any comments on the simulation you might want to provide (e.g., derate assumptions). There are three other sheets where you can paste your modeling results for each of the PV systems. You are free and encouraged to run multiple models; simply fill out one template per model used. The more results the better.

APPENDIX D: PV PERFORMANCE MODEL VALIDATION SAMPLE REPORT

Postworkshop Evaluation of Submitted PV Model Exercise Validation Analysis by: Joshua S. Stein

Table of Contents

Chapter 1. Introduction

The Sandia National Laboratories photovoltaic program is tasked with evaluating and improving PV performance models. One of our evaluation approaches is to compare the measured output of a PV array to the modeled output, where the modeling is performed with weather data measured coincident with the output measurements. Typically, the weather data is hourly data provided in Typical Meteorological Year (TMY-2) format. Comparison of measured to modeled data is performed to assess the validity of the model used to simulate the performance of the systems.

One might expect a perfect model to exactly reproduce the measured performance. However, since all measurements have some inherent uncertainty and associated error distribution, even a perfect model will not exactly match the measured performance. Unfortunately the measurement uncertainty is usually not well characterized and therefore comparisons between measured and predicted performance are more difficult and imprecise. If the uncertainties are known and the model is perfect, the model residuals, defined as the difference between measured and modeled power, should reflect the uncertainty distribution. In practice, when the uncertainty is not well characterized, the distribution of residuals reflects the combination of measurement and model uncertainties.

In most cases, the input data will be scrubbed of unusual circumstances that would interfere with model validation, such as missing power data. For such data, the effect of the data on model evaluation is removed by forcing both the irradiance and power data to zero. In the data presented in this report, data was not available for the month of December, as reflected in the figures.

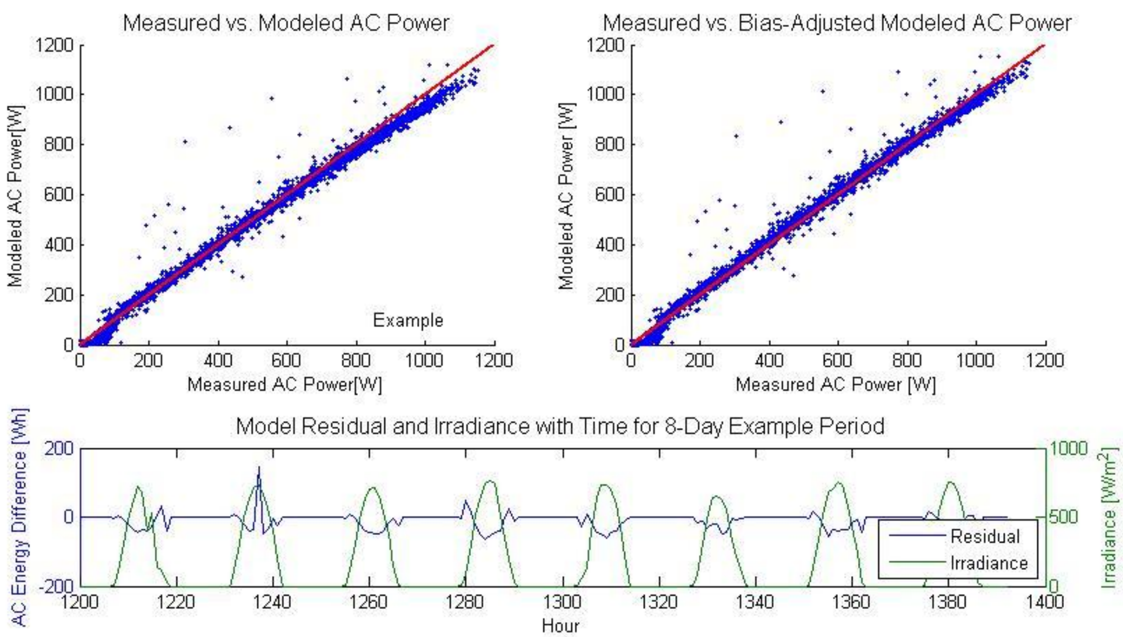
Chapter 2. Overview of Validation Methods

Several analysis methods will be applied in a typical report. These will generally be illustrated with a series of figures and calculated values. For each array, modeled values of AC and DC power will be compared with measured data. Examples of each type of analysis are described in the rest of this section.

Scatter Plot Analysis

The first step in PV model validation is generation of a scatter plot of modeled power vs. measured power for each time interval (one hour in this case). An example of such a plot is shown in the top left scatter plot in the figure below. The red line has a slope of 1 and represents exact equality between measured and modeled values. Points that fall above the line indicate that the model is overestimating power from the array and points below the line indicate that the model is underestimating power. Sometimes most of the points are to one side or the other of the line, which indicates that there is a model bias. The magnitude of the bias can be estimated by solving for the factor that when multiplied with the modeled power, results in the sum of the adjusted residuals equaling zero. The scatter plot on the upper right of the figure below shows bias-adjusted modeled power against measured power. The bias adjustment is listed at the bottom of the figure.

The plot at the bottom of the figure shows irradiance and model residuals plotted against time for an example 8-day period, where throughout the report, residual = modeled – measured value. A positive residual indicates the model is predicting a higher value than the measured data. The plot shows whether there is a repeatable pattern in the residuals with diurnal cycles (morning, midday, and afternoon). Such patterns, if they exist, can help to identify systematic errors in the model.



Total Measured Energy = 1607885 Whr
Total Modeled Energy = 1563618 Whr
Percent Energy Difference (Modeled-Measured) = -2.7531%

Bias Adjustment Factor (Sum of Residuals = 0) = 1.0283

Figure D-1. Example Scatter Plot Figure.

Residual Distribution Analysis

The next analysis performed is to examine the distribution of the model residuals (modeled - measured) with a probability plot (left) and a histogram (right). If the model is valid, the distribution of residuals should be normal with a small amount of variance equal to the measurement uncertainty. Deviations from normality can indicate problems with the model.

A normal distribution plots as a straight line on the probability plot. Deviations typically occur in the tails of the distribution, as is shown in the example below. These outliers may indicate a problem with the model but also may simply reflect data quality issues, such as a bird perching on an irradiance sensor for part of the measurement interval.

The histogram is shown along with a best-fit normal distribution for reference. This example below shows that the model does a pretty good job matching the measured data. The RMS error is shown below the figure.

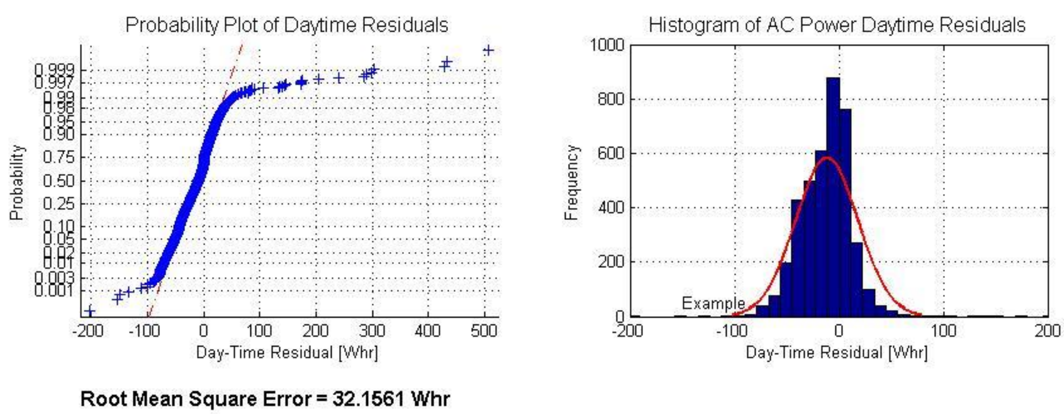


Figure D-2. Example Residual Distribution Figure.

Residual Run Plot Analysis

A residual run plot shows the residuals as a function of daylight time (night time periods are stripped from the dataset). This plot is useful for determining whether there is a long-term trend in the residuals. Such a trend could indicate problems with sensor drift and data quality. If soiling is a problem on the array, this might be visible on this plot as periods when residuals increase in magnitude (soiling) and abrupt decreases in residuals (cleaning by rain). A seasonal trend in the residual run plot might indicate a systematic problem with the model related to seasonal patterns of temperature, solar elevation angle, etc.

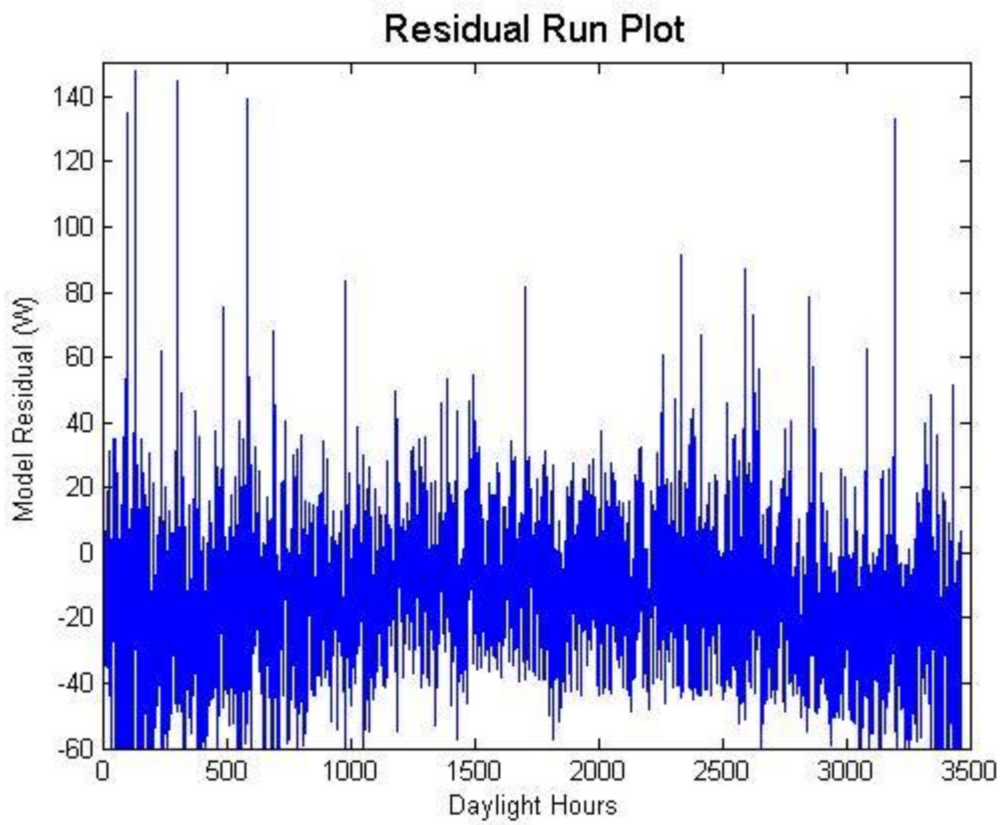


Figure D-3. Example Residual Run Plot.

Lag Plot Analysis

Lag plots provide information about whether the model residuals are autocorrelated in time. A lag plot provides one check on whether a data set or time series is random or not. Random data should not exhibit any identifiable structure in the lag plot (e.g. correlation). Non-random structure in the lag plot or residuals indicates that the underlying data are not random and suggests that the model has a systematic error in time.

Below are two examples of lag plots, one for a lag of 1 hour and the other for a lag of 6 hours. Both exhibit little to no correlation and indicate a random pattern in the time series of residuals. The concentration of points near and along the zero axes of the plots can be explained by the fact that the residuals tend to be small at the beginning and end of the day when power output is very low. Note that in this example, the bias error is negative (model is generally underpredicting power) and thus most points on the lag plots are located in the SW quadrant of the plot where both residuals are negative.

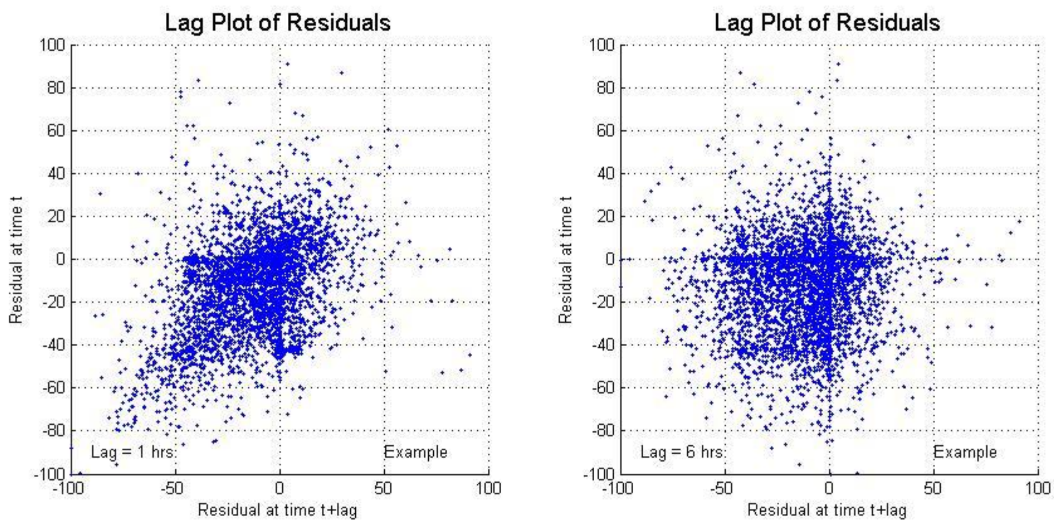


Figure D-4. Example Residual Lag Plots.

Graphical Residual Analysis

Graphical residual analysis is used here to explore correlations between residuals and input variables for the model. The input variables considered in this analysis include: month of year, hour of day, irradiance (global horizontal), ambient air temperature, wind speed, angle of incidence of sunlight on the array, and air mass.

Below are two example of the type of plots used to examine these correlations.

For the first trio of plots, the top bar graph indicates the percent of the total energy produced by the array in each month. The middle bar graph shows the energy difference (model - measured) expressed in percent of the array capacity at STC.

In this example, these differences are quite small and all negative, which indicates that the model is underpredicting the monthly energy slightly for all months. A more pronounced pattern in these differences might indicate a problem with the model. For example, a seasonal variation in the residuals could indicate that the model is not accurate in correcting performance as a function of temperature.

The lower plot is a box plot that shows the distribution of hourly residuals within each month bin. On each box, the central mark is the median, the edges of the box are the 25th and 75th percentiles, the whiskers extend to the most extreme data points not considered outliers, and outliers are plotted individually. Outliers are assumed to be outside the ~99% confidence interval, which is estimated as ranging from $q3 + w\cdot(q3 - q1)$ to $q1 - w\cdot(q3 - q1)$, where q1 and q3 are the 25th and 75th percentiles, and w is a user-defined factor (set to 1.5 for the plots in this report).

The next set of plots are configured the same but residuals are binned by global horizontal irradiance. In this example, there is a larger (negative) disagreement between model and measured performance at very low irradiance values, indicated by the large (negative) blue bar in the lowest irradiance bin.

In the body of the report that follows, the results are presented by an automatic report generator. Interpretation of the results is left to the modeler.

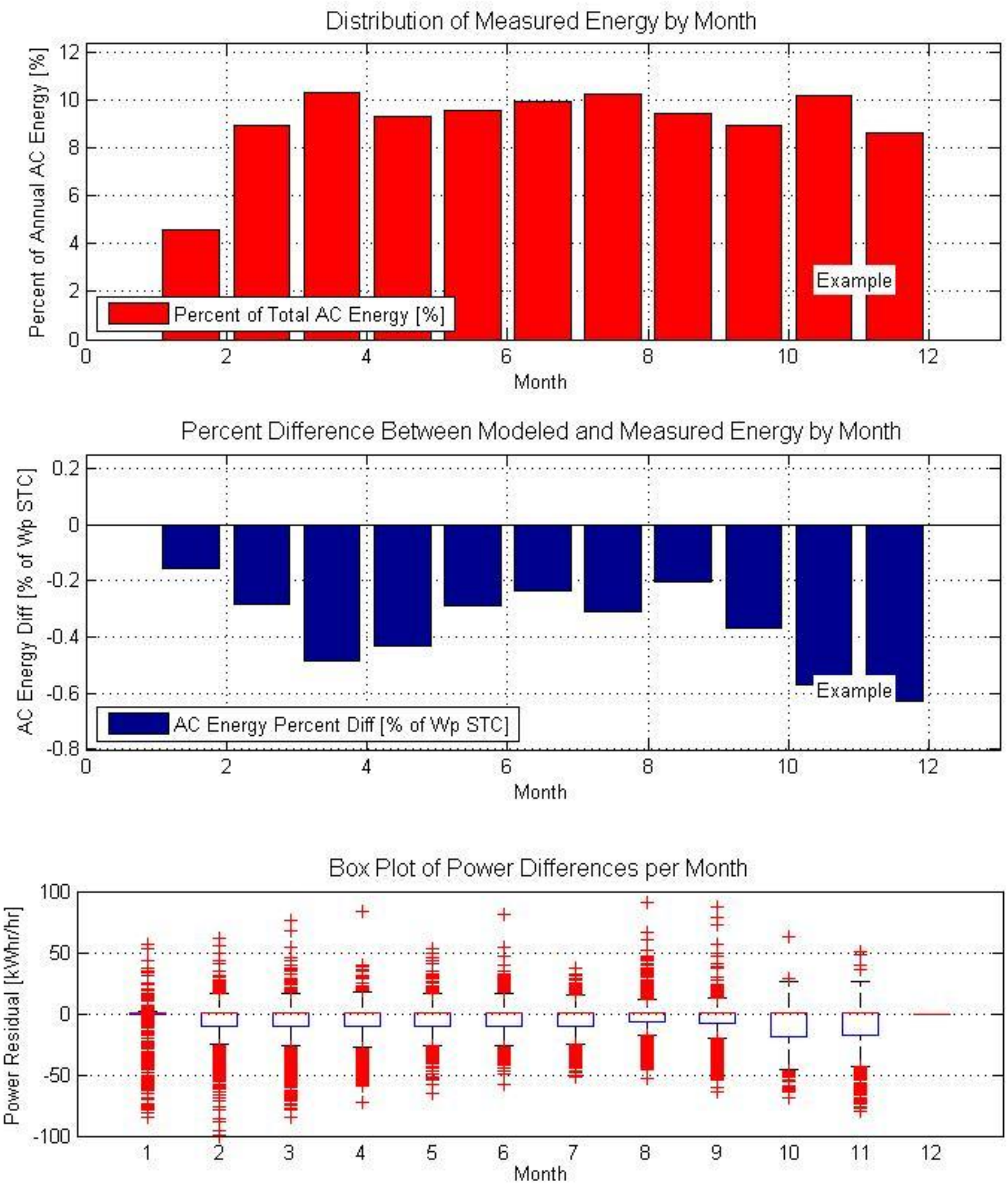


Figure D-5. Example Graphical Residual Analysis by Month.

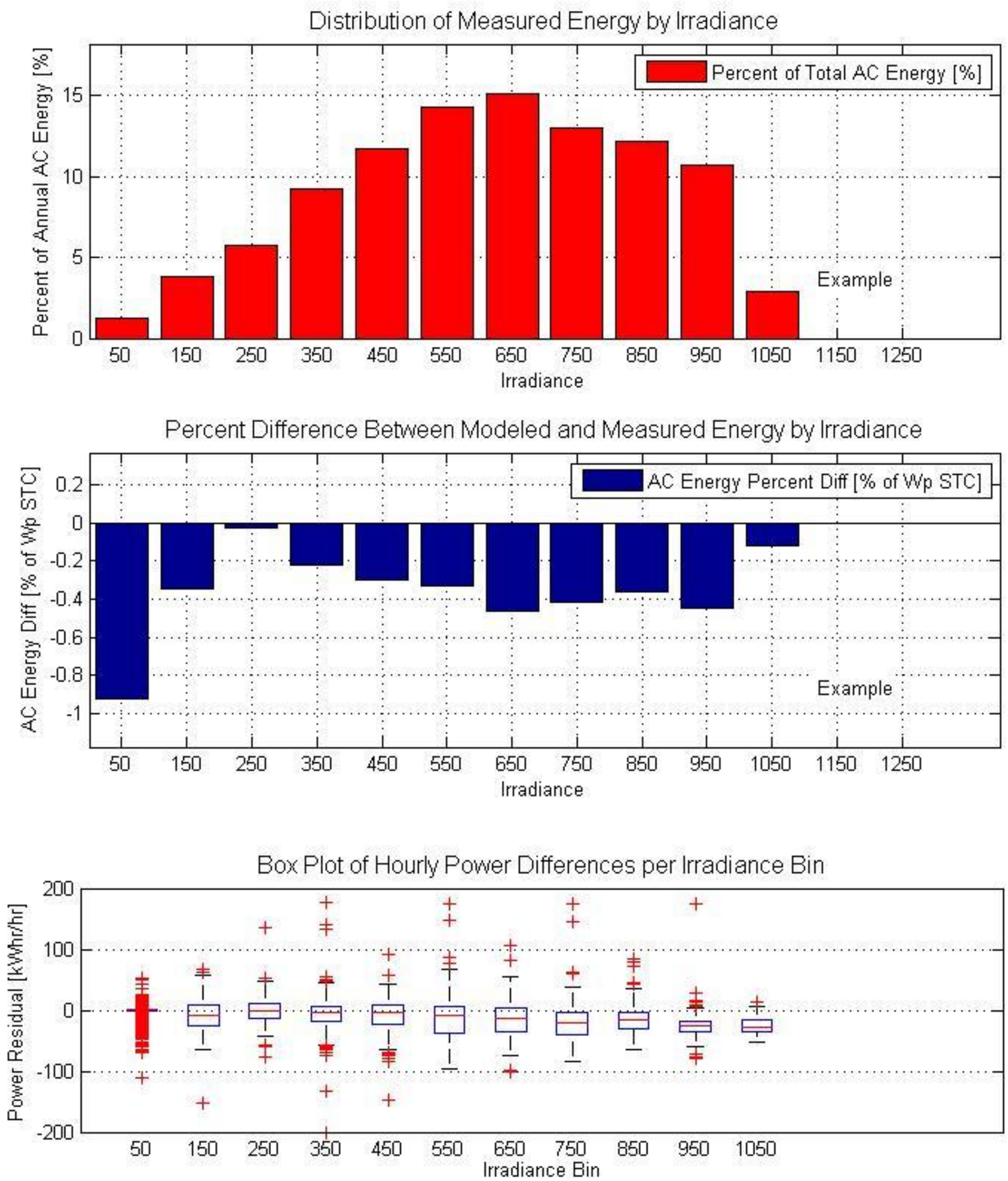


Figure D-6. Example Graphical Residual Analysis by Global Horizontal Irradiance.

Chapter 3. Model Validation Results

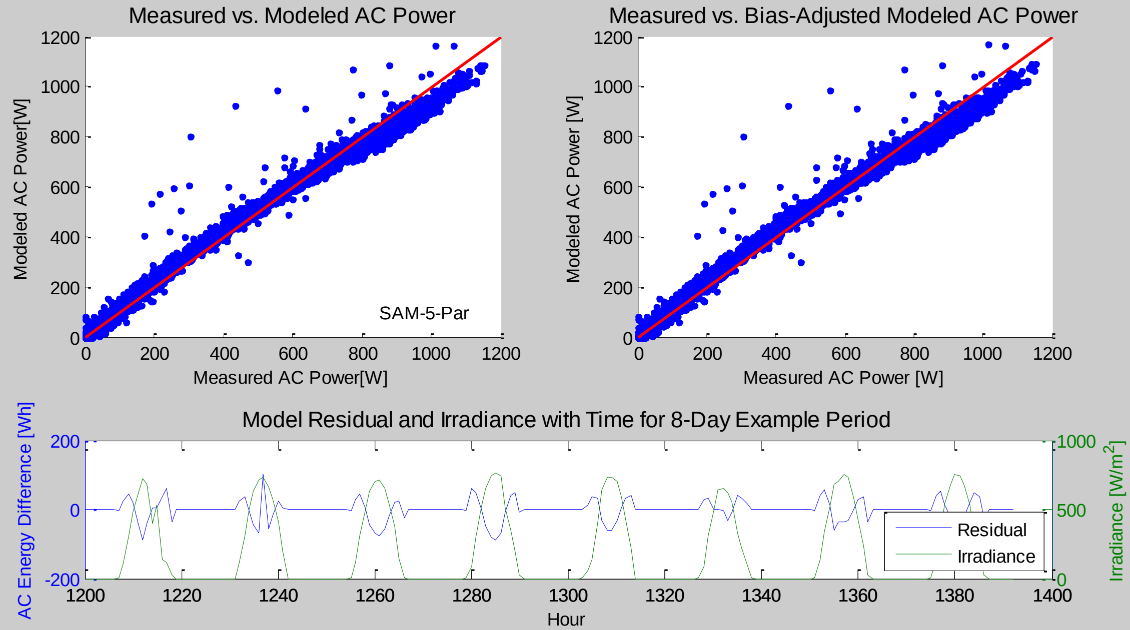
Model = SAM-5-Par

Participant = Cameron

Array 1: Shell

Site parameters describe the latitude, longitude, and elevation of the site. Array parameters, such as tilt angle and azimuth angle are also specified. Site parameters are used in the calculation of sun position and absolute air mass. Latitude = 39.7400 deg Longitude = -105.1200 deg Elevation = 1785 m Array Tilt = 40 deg Array Azimuth = 0 deg

Quantity Analyzed: AC Power



Total Measured Energy = 1607885 Whr
Total Modeled Energy = 1606033 Whr
Percent Energy Difference (Modeled-Measured) = -0.11518%

Bias Adjustment Factor (Sum of Residuals = 0) = 1.0012

Right plot is raw data. Left plot is bias-adjusted data (modeled power multiplied by an adjustment factor).

Figure D-7. Scatter Plots Showing Modeled vs. Measured AC Power.

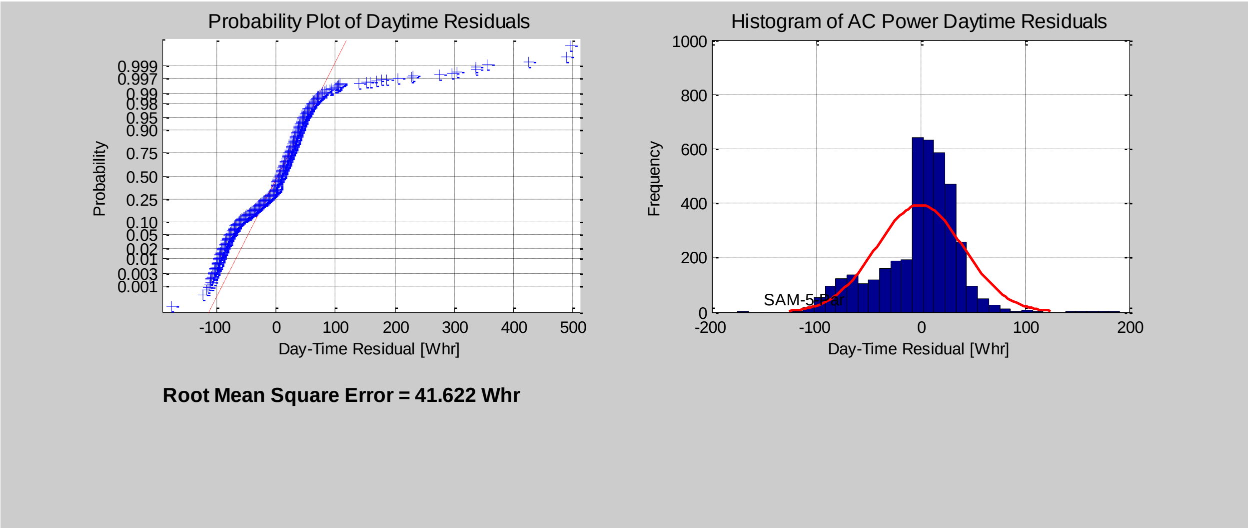


Figure D-8. Distribution Plots of Bias-Adjusted Residuals of AC Power.

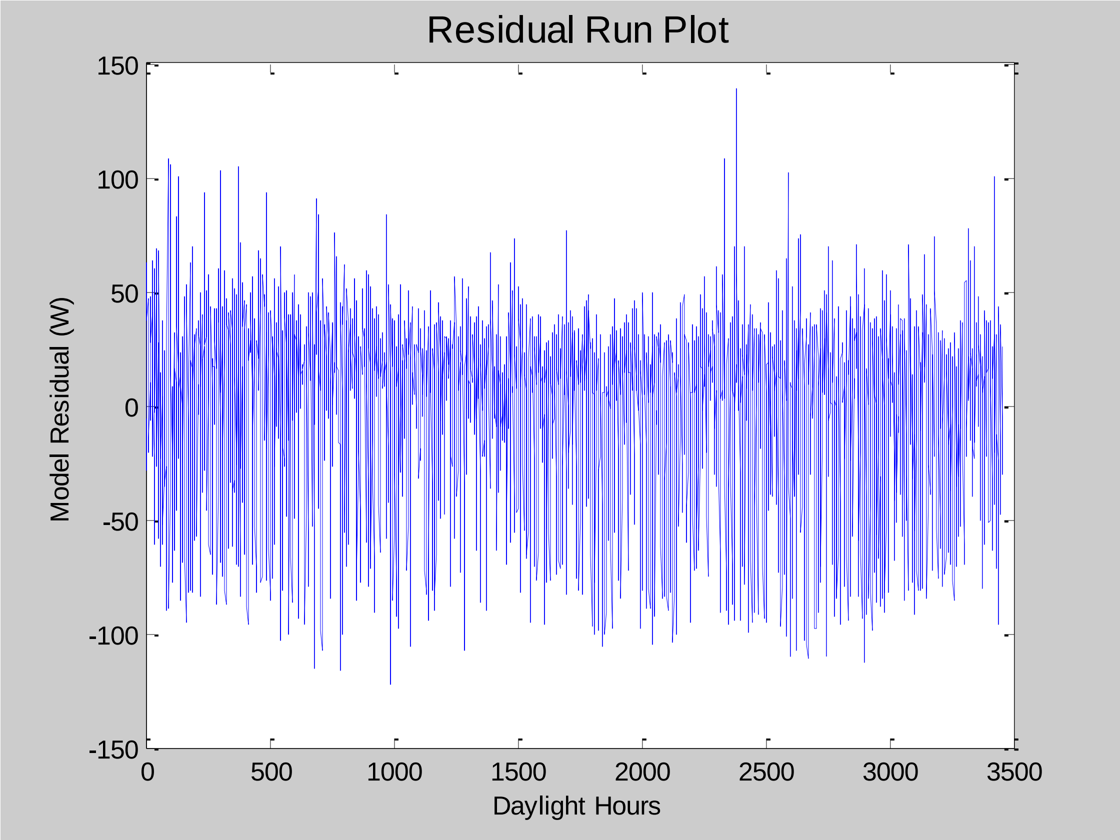


Figure D-9. AC Power Residual Run Plot.

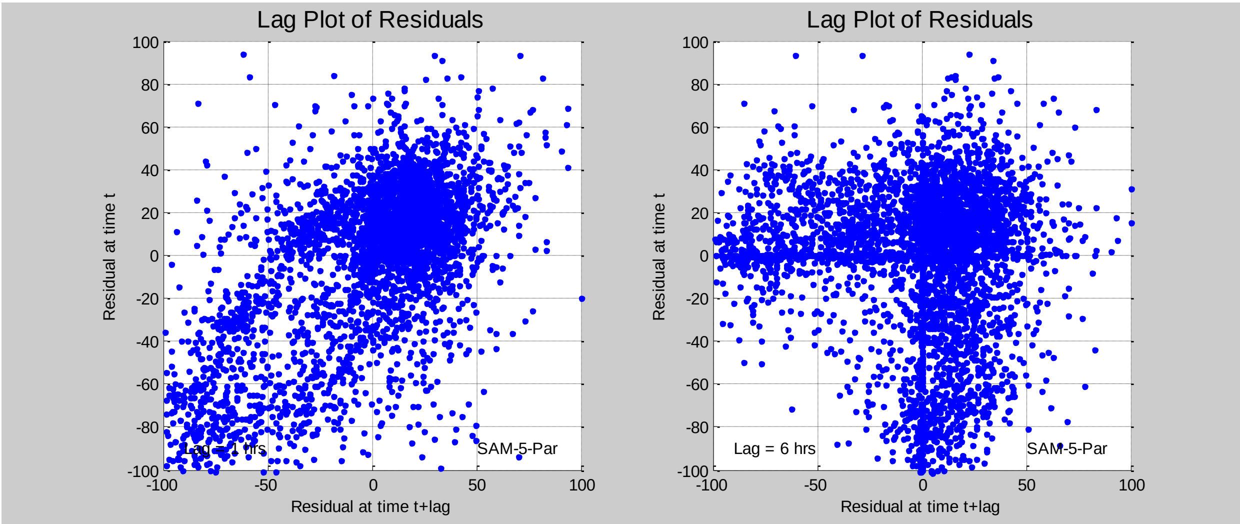


Figure D-10. Lag Plots of Residuals: AC Power.

Residual Analysis for AC Power

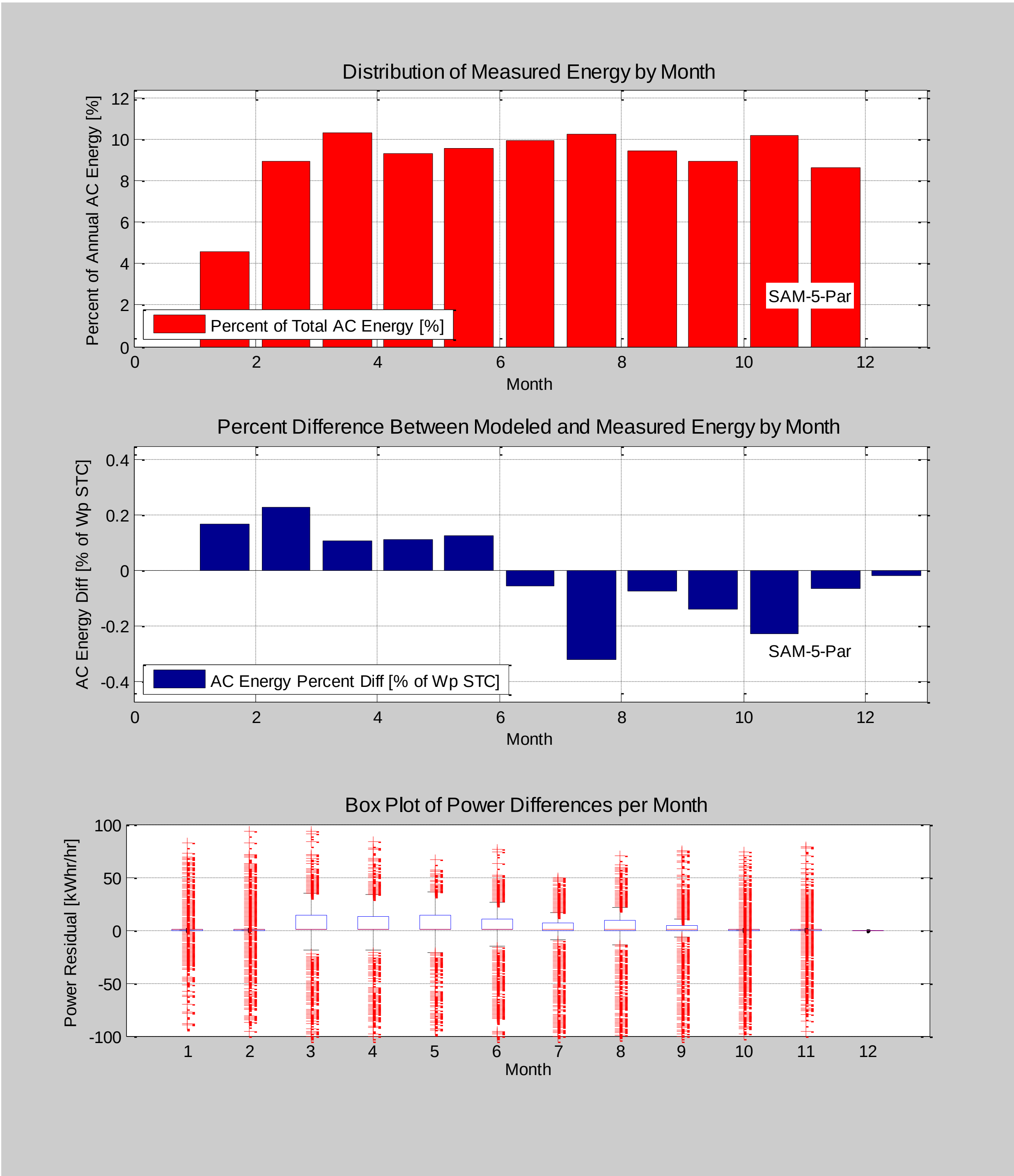


Figure D-11. AC Power Residuals by Month.

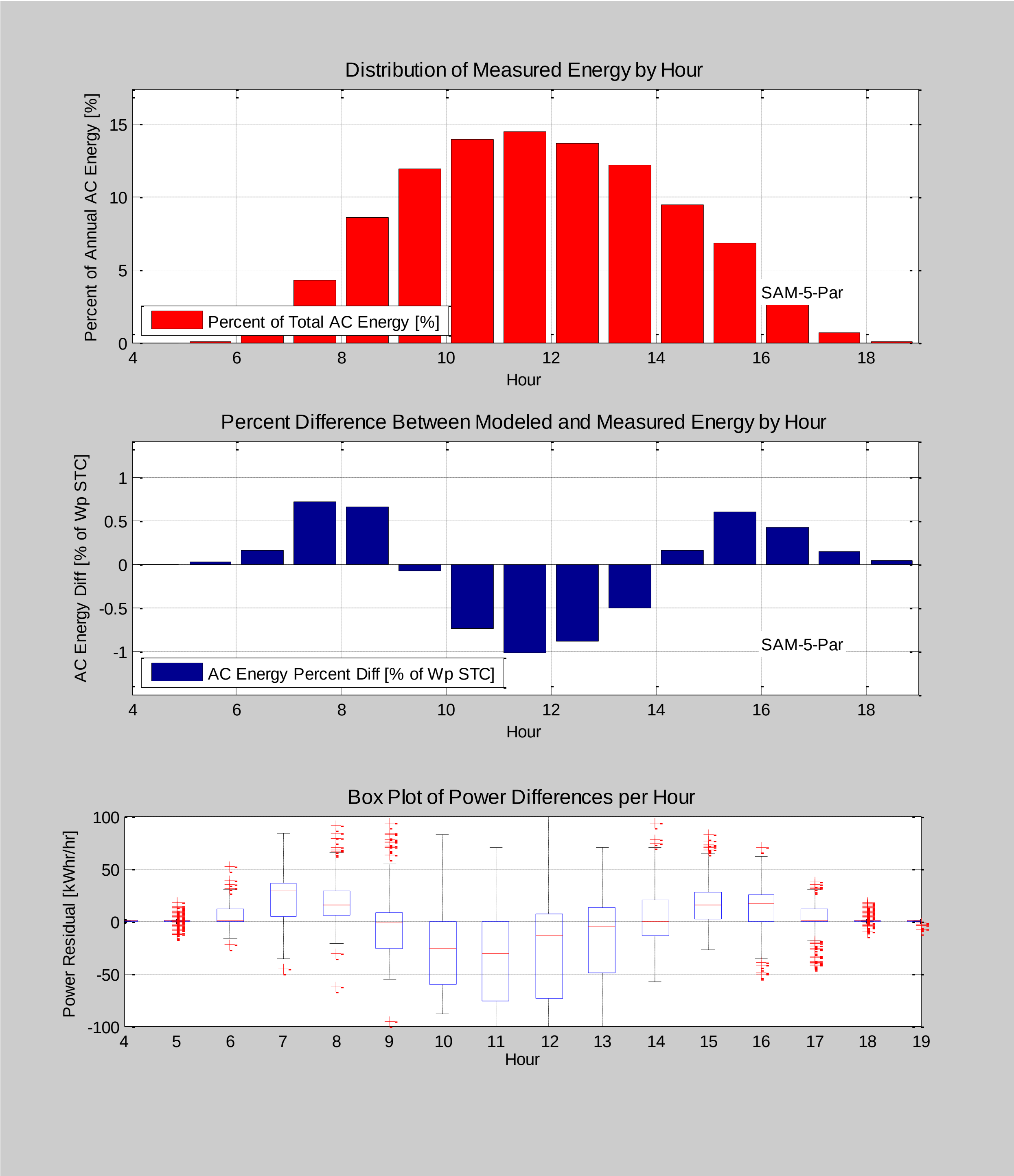


Figure D-12. AC Power Residuals by Hour.

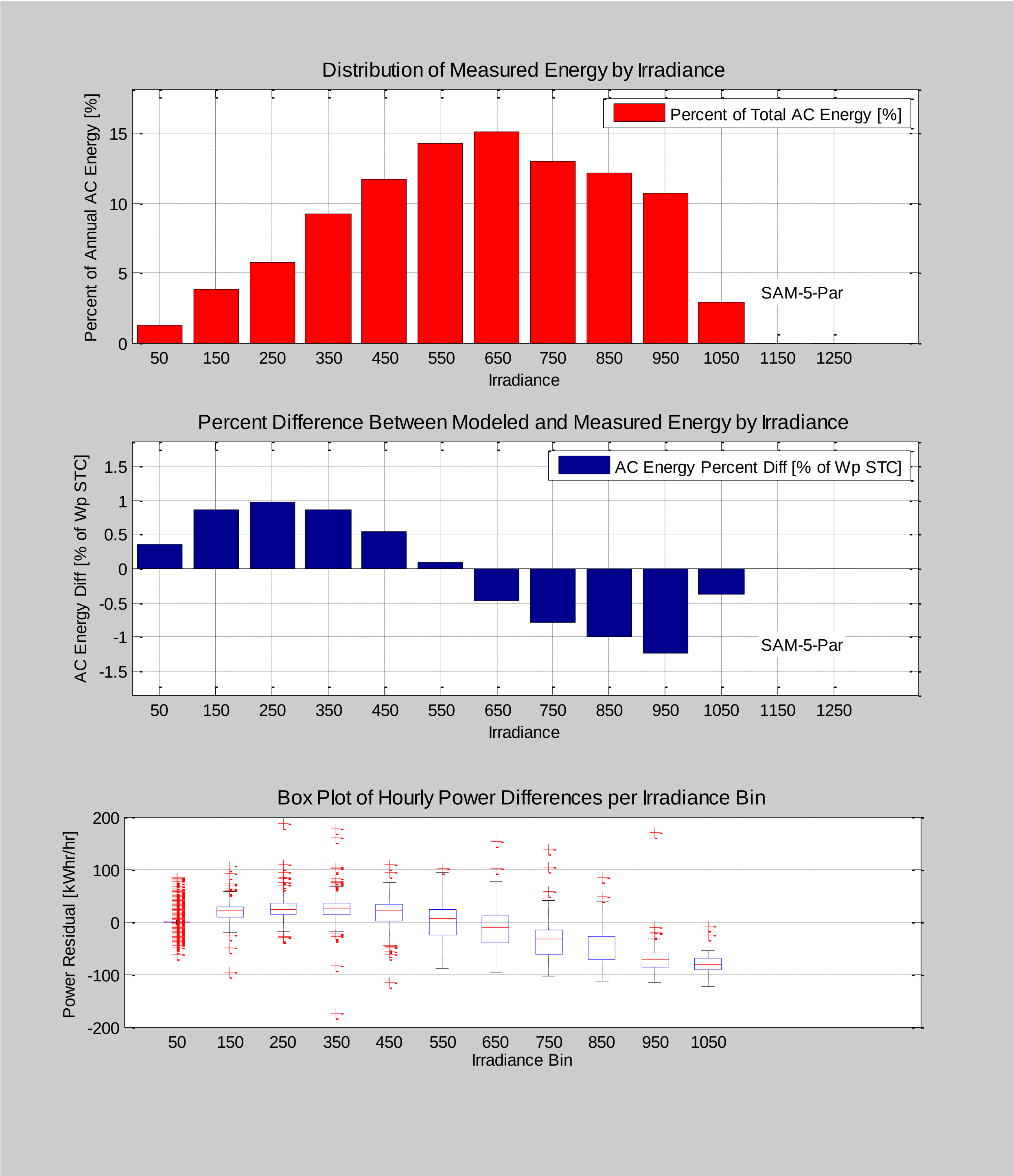


Figure D-13. AC Power Residuals by Irradiance.

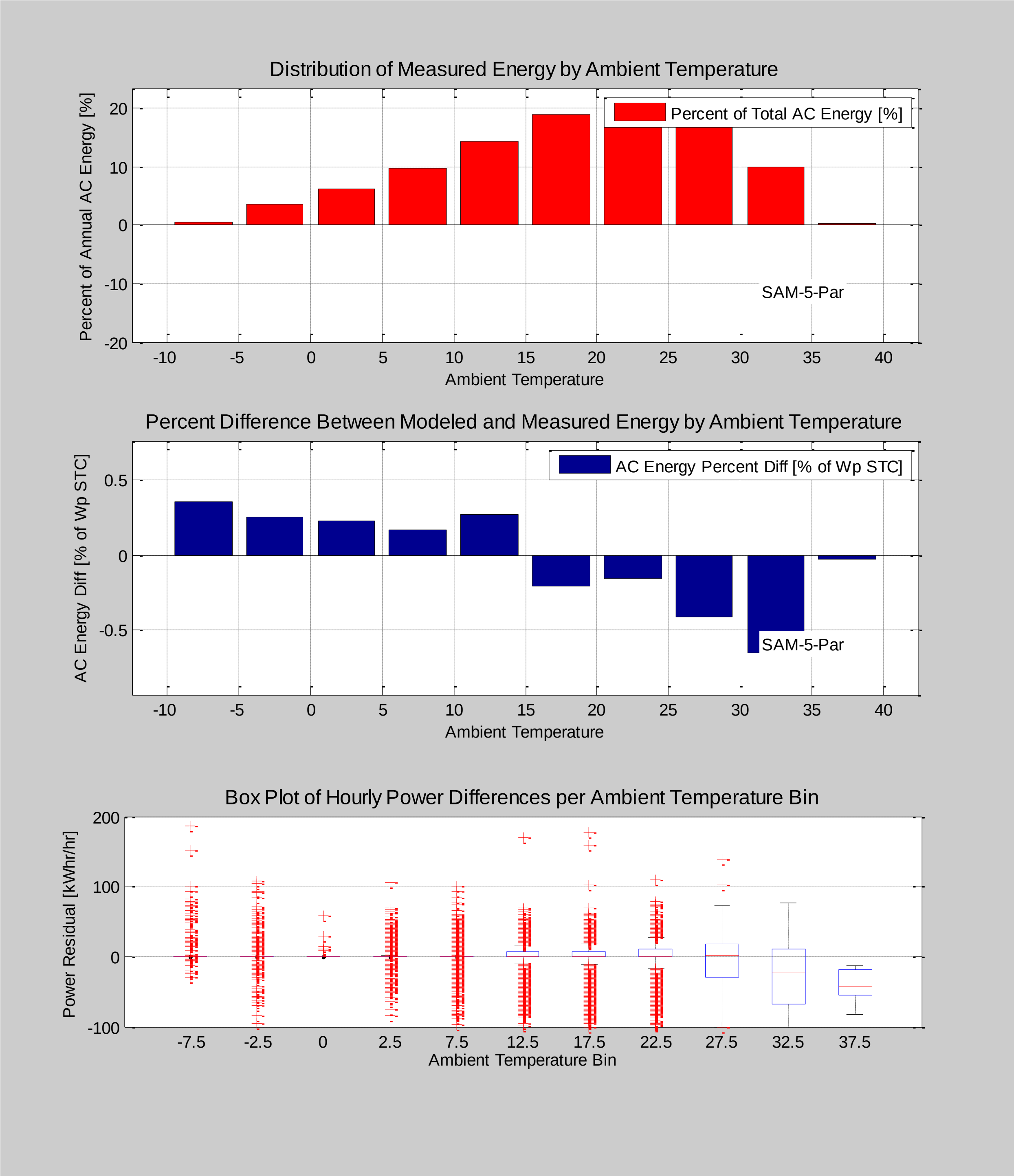


Figure D-14. AC Power Residuals by Air Temperature.

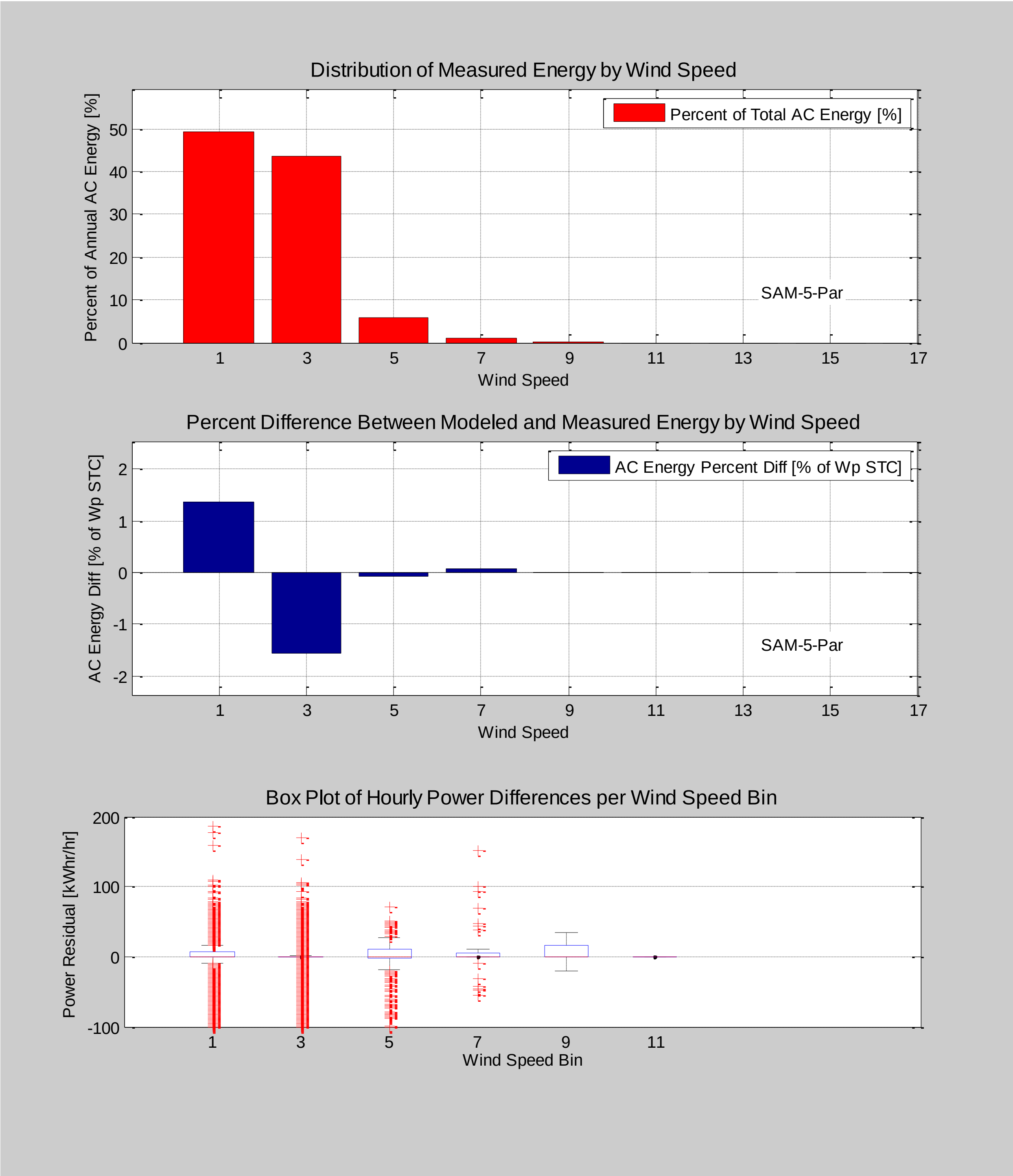


Figure D-15. AC Power Residuals by Wind Speed.

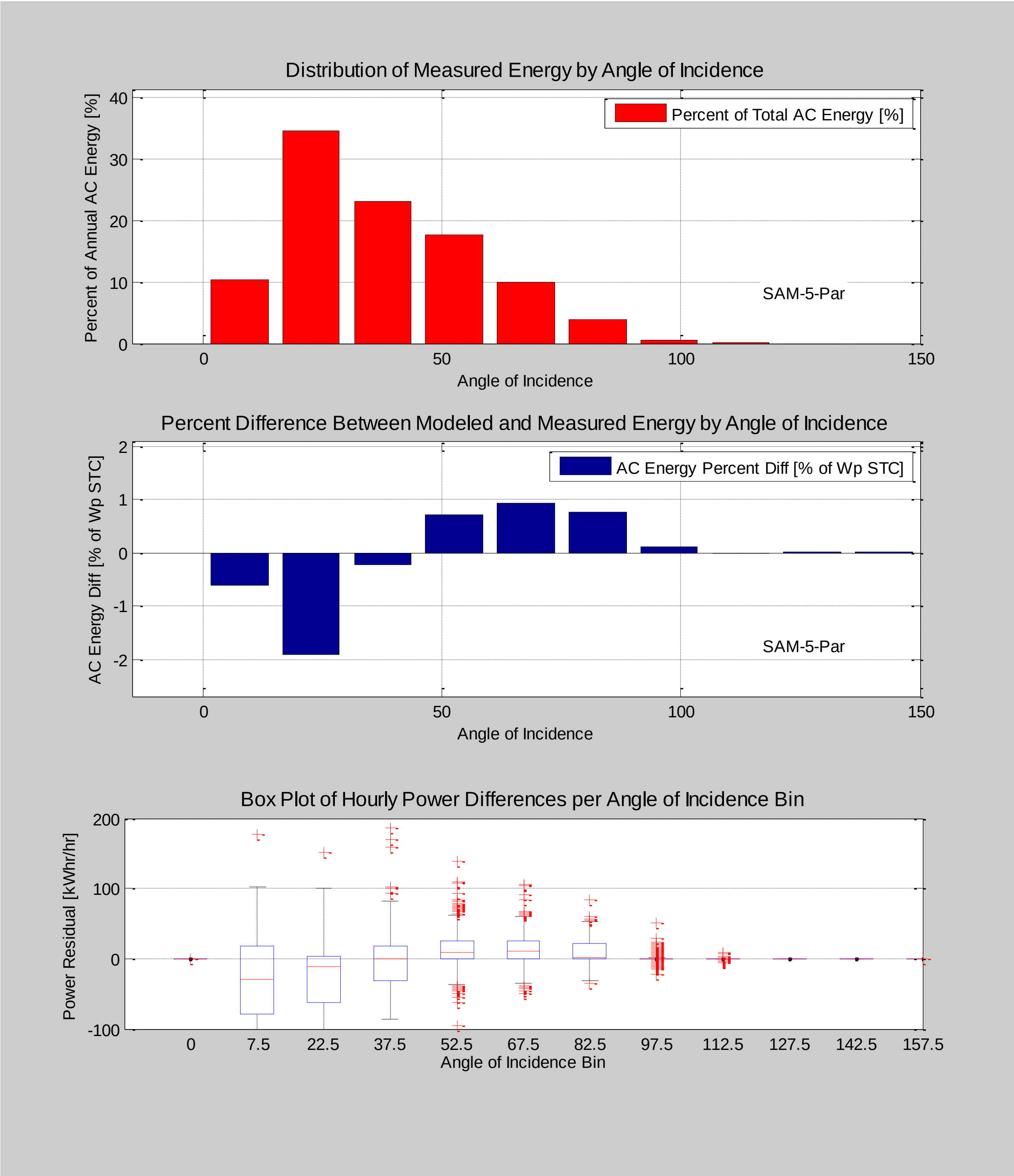


Figure D-16. AC Power Residuals by Angle of Incidence.

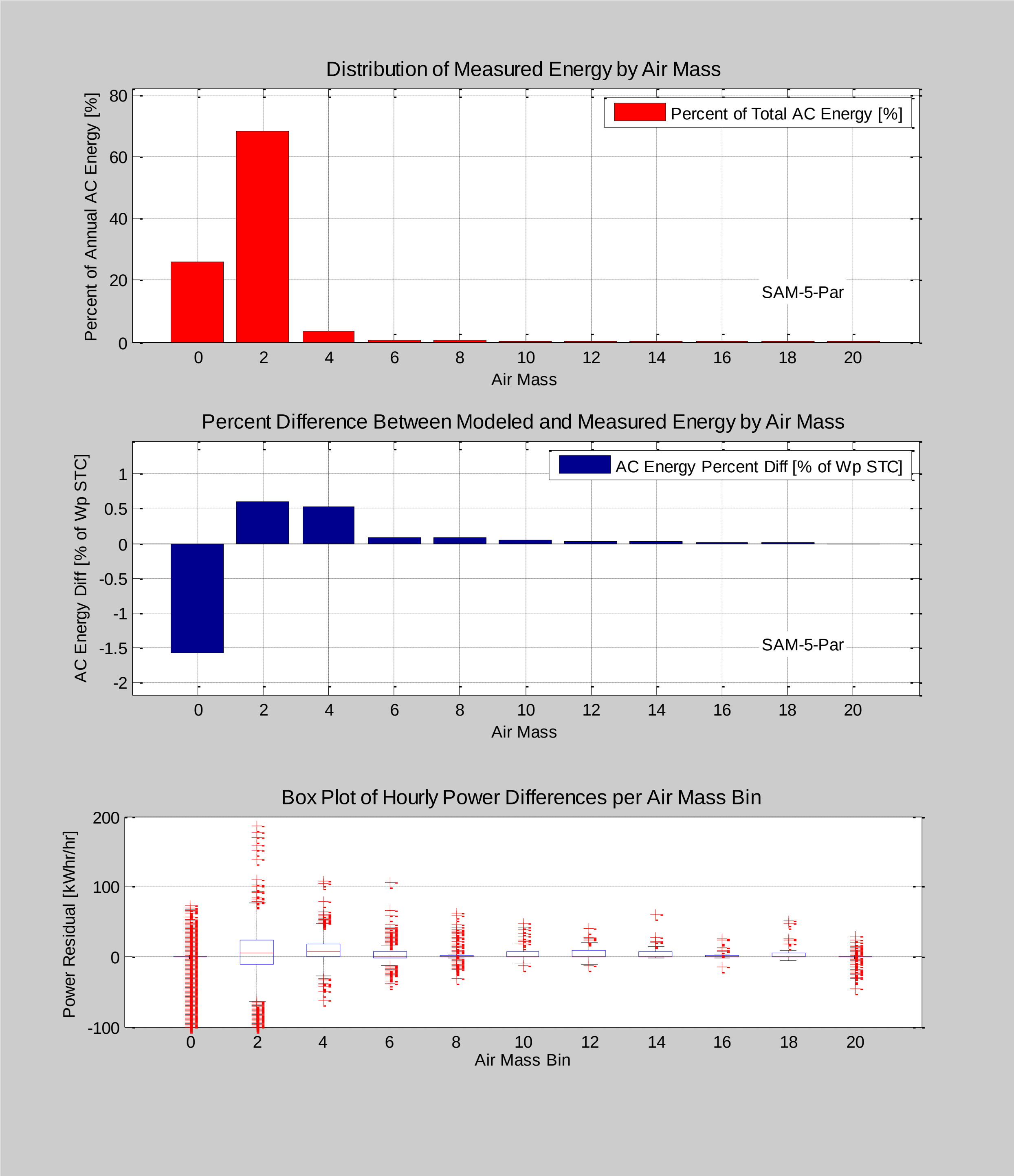
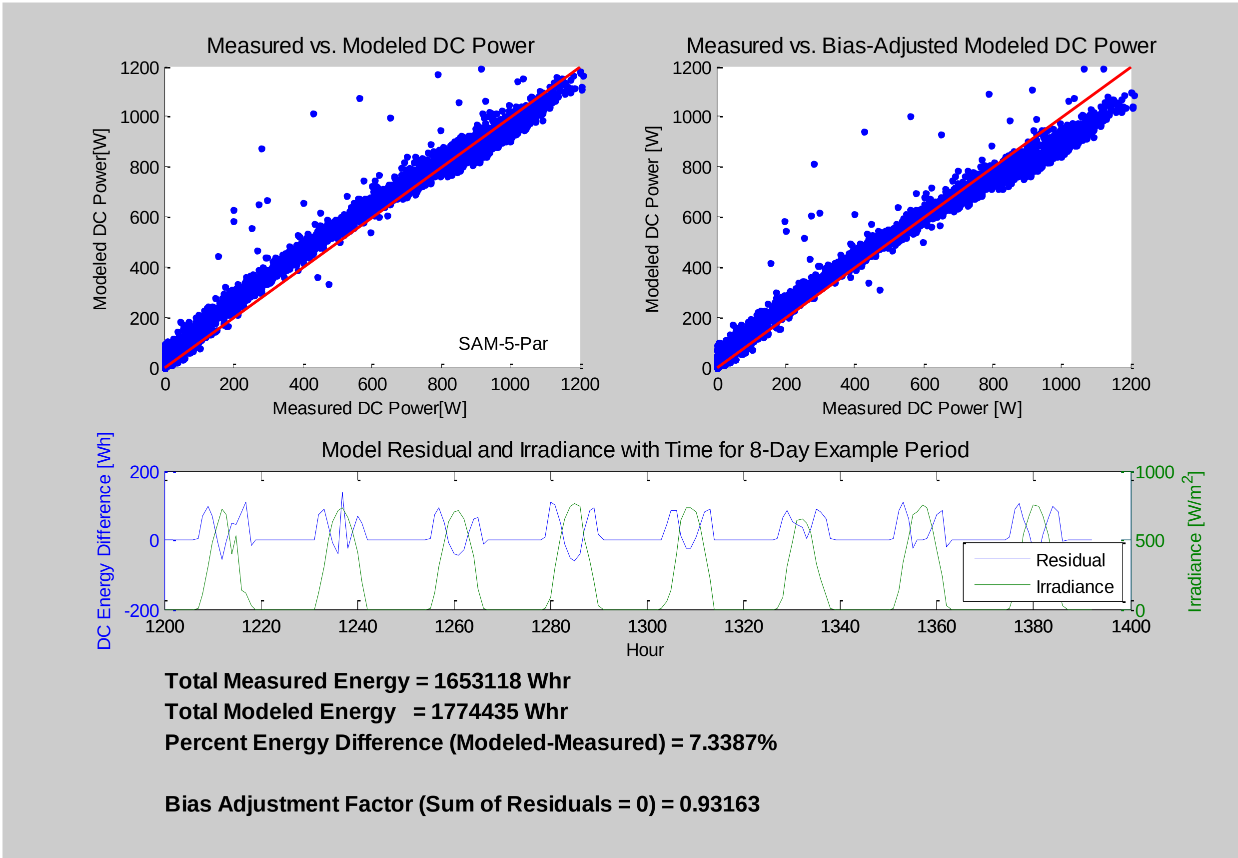


Figure D-17. AC Power Residuals by Air Mass.

Quantity Analyzed: DC Power



Right plot is raw data. Left plot is bias-adjusted data (modeled power multiplied by an adjustment factor).

Figure D-18. Scatter Plots Showing Modeled vs. Measured DC Power.

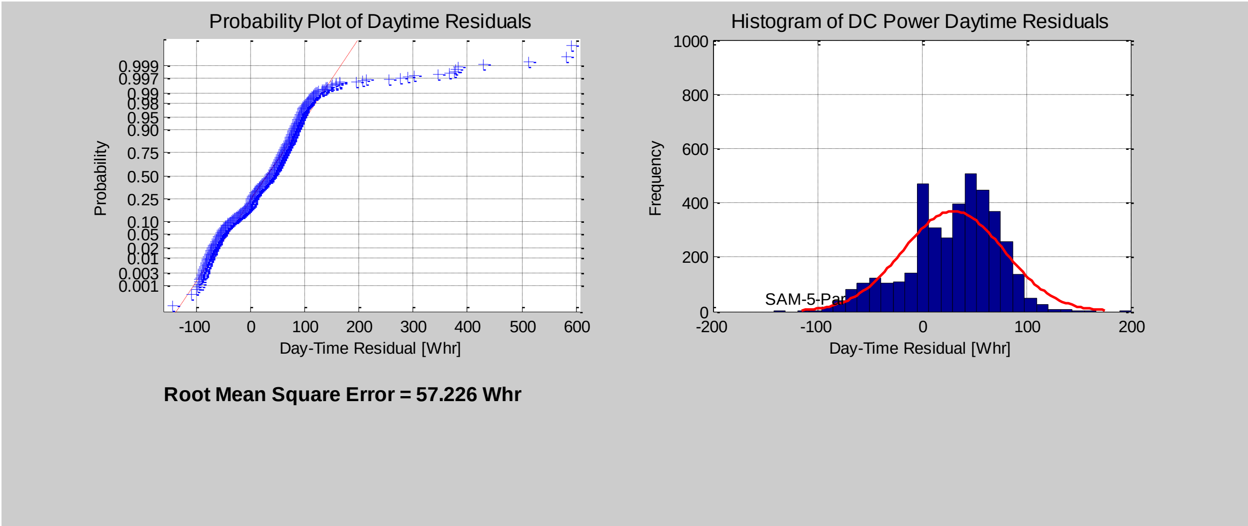


Figure D-19. Distribution Plots of Bias-adjusted Residuals of DC Power.

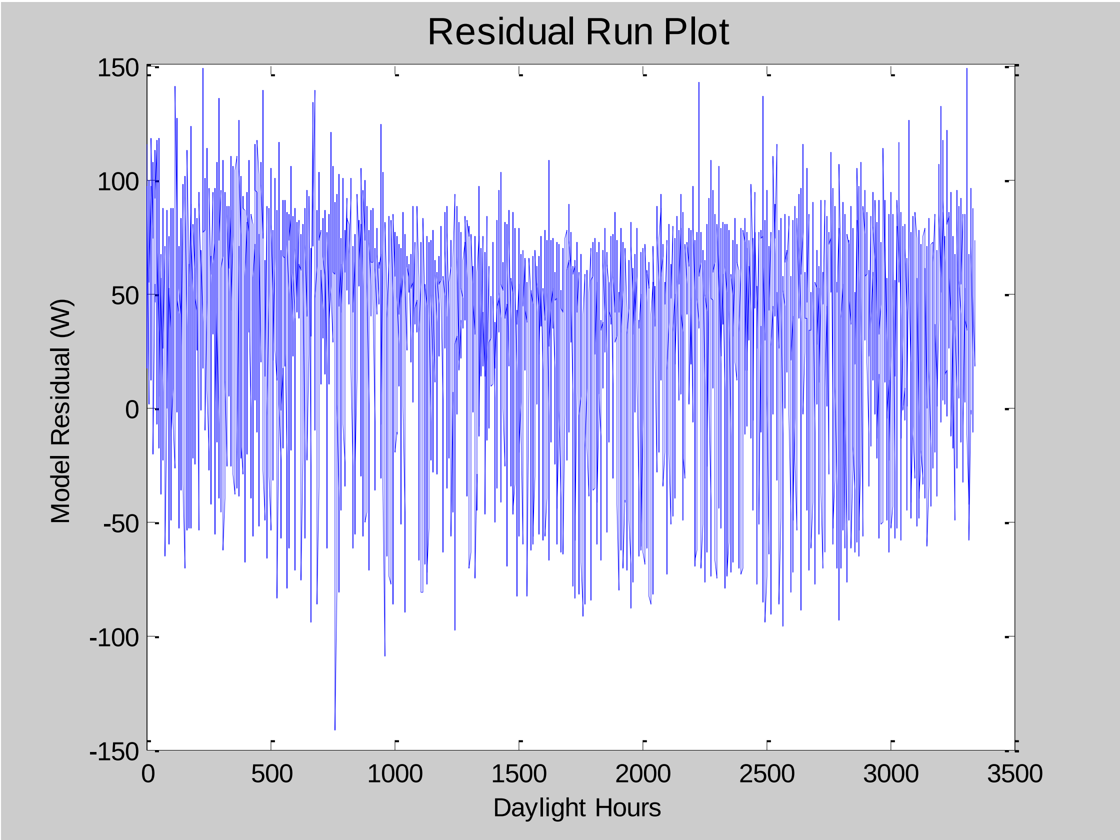


Figure D-20. DC Power Residual Run Plot.

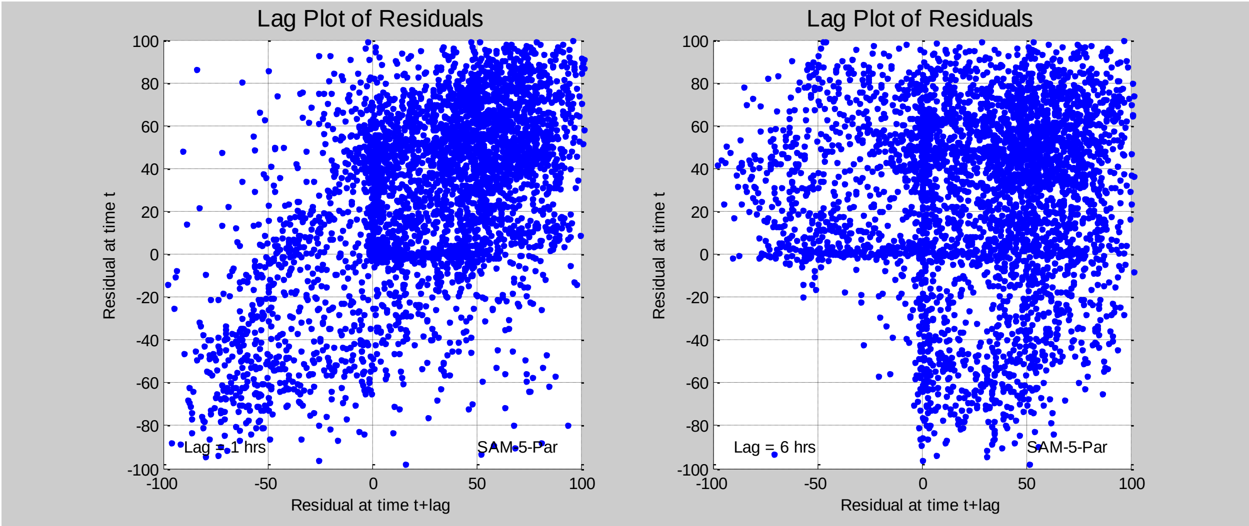


Figure D-21. Lag Plots of Residuals: DC Power.

Residual Analysis for DC Power

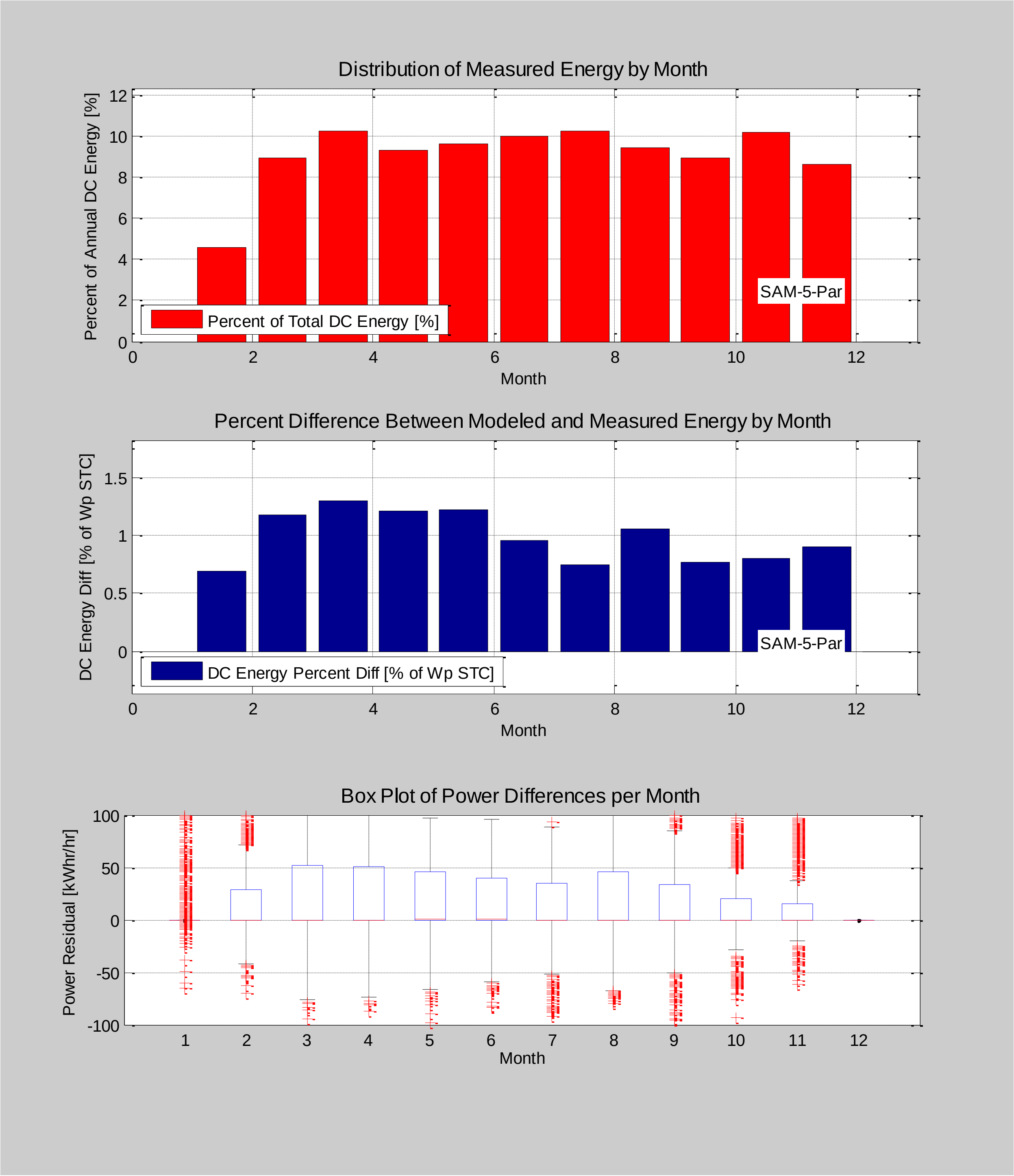


Figure D-22. DC Power Residuals by Month.

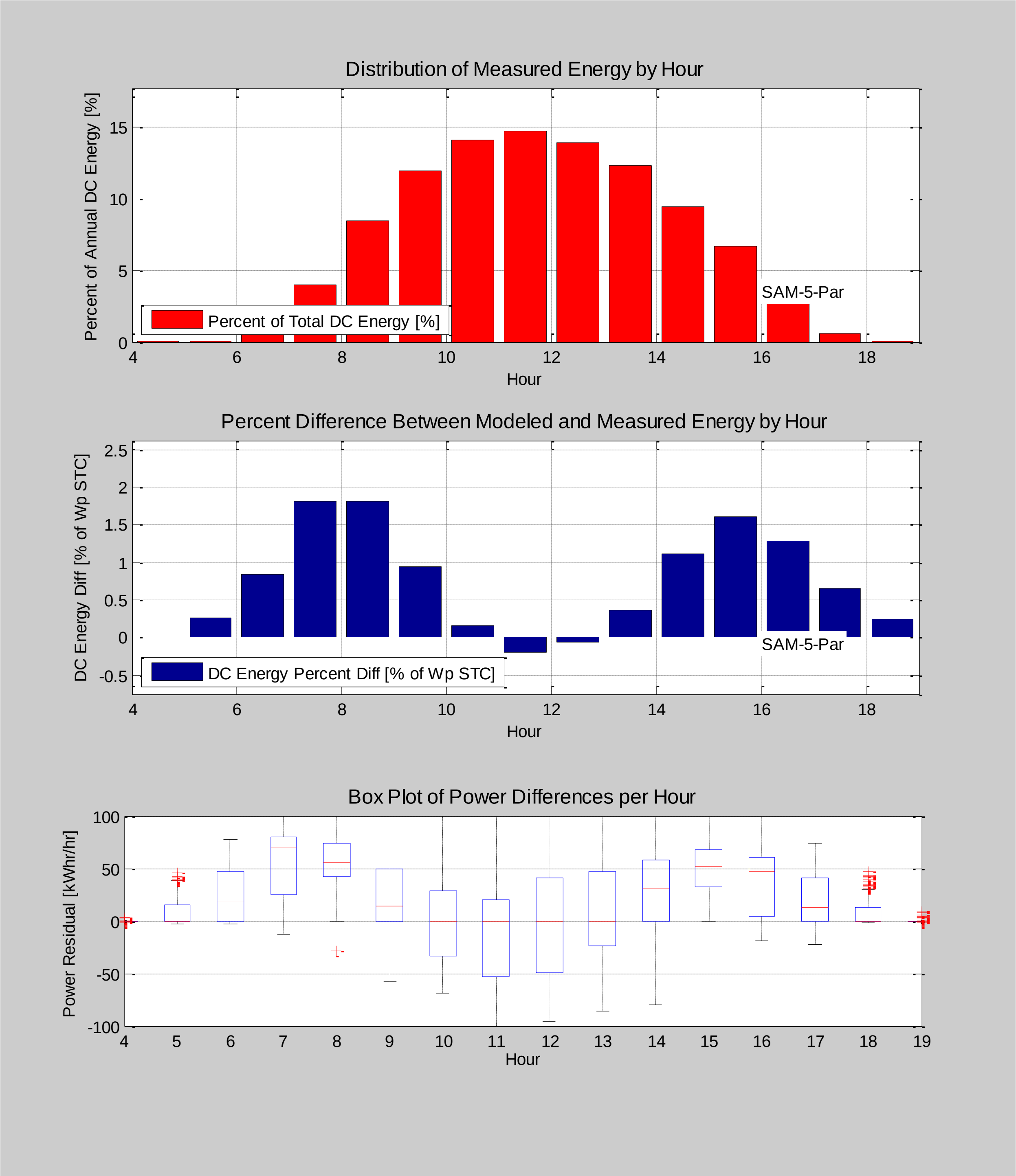


Figure D-23. DC Power Residuals by Hour

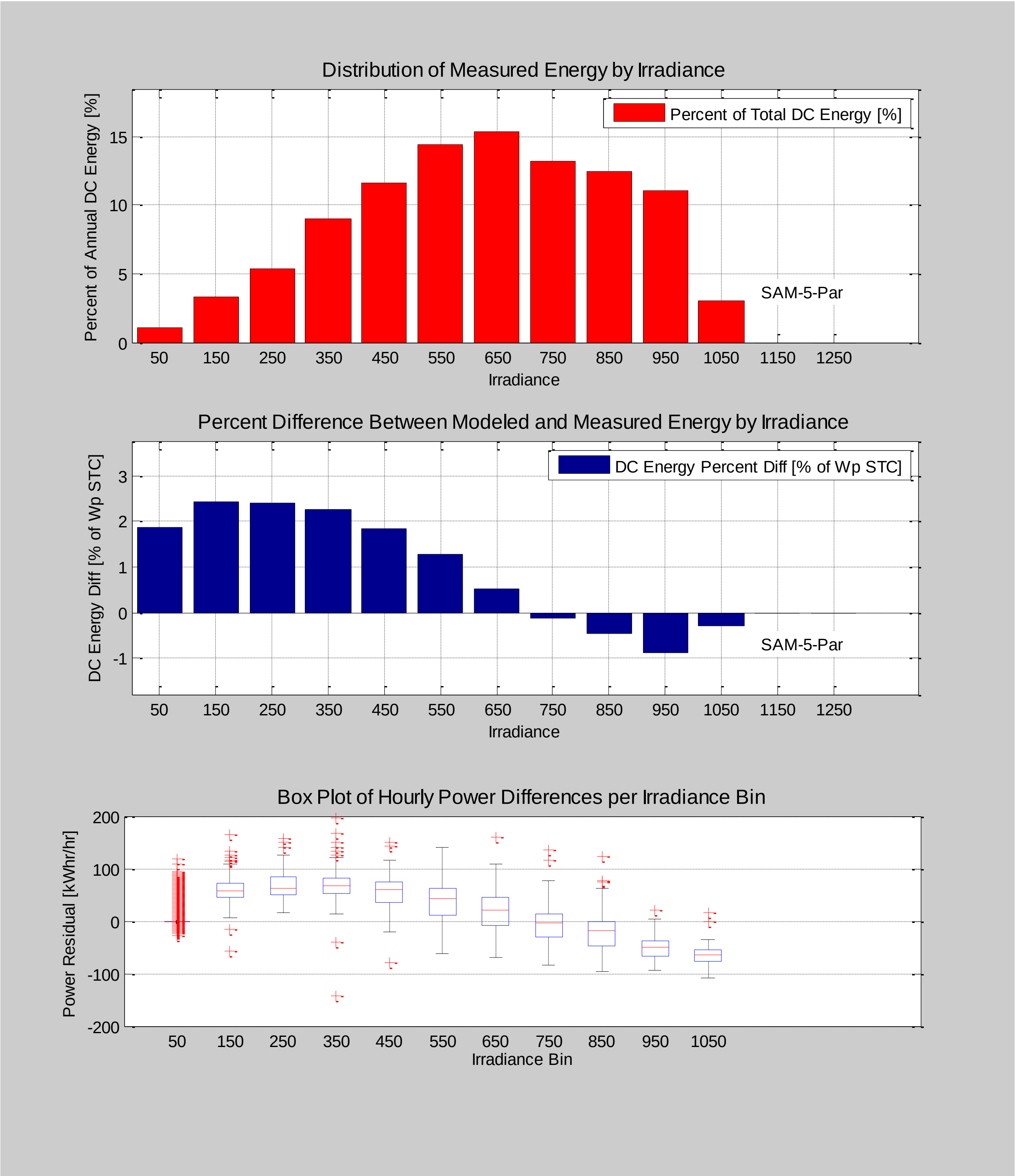


Figure D-24. DC Power Residuals by Irradiance.

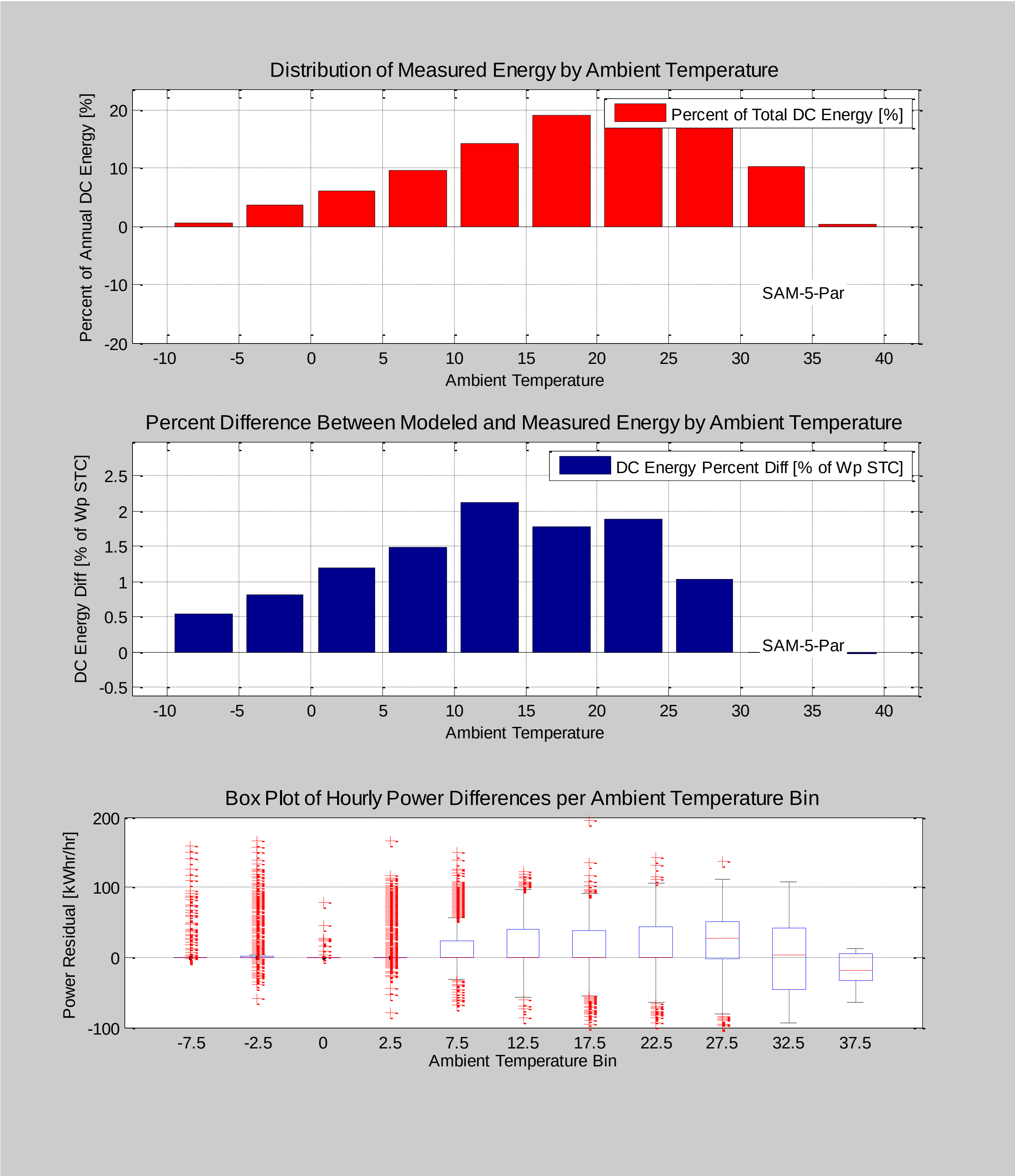


Figure D-25. DC Power Residuals by Air Temperature.

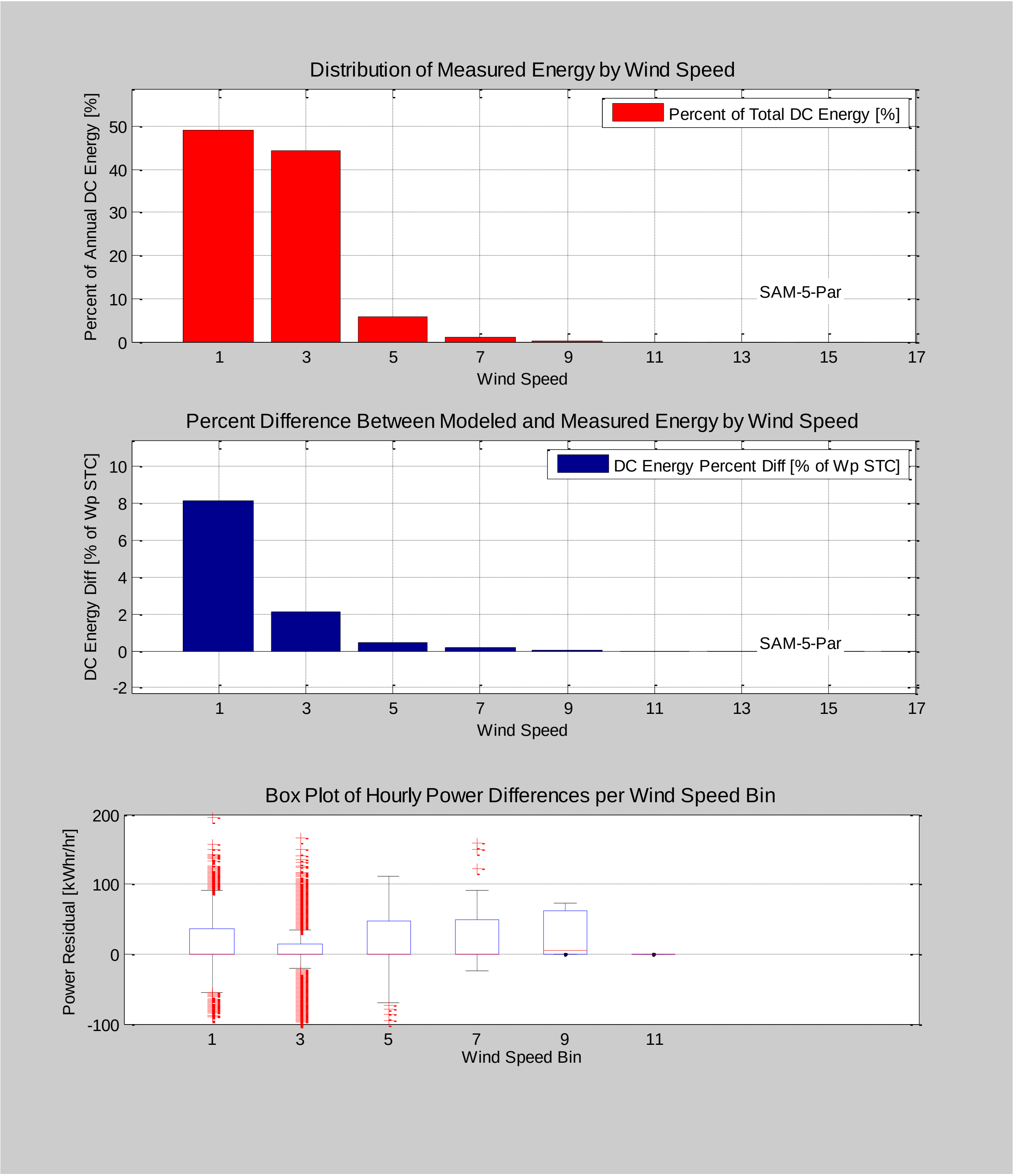


Figure D-26. DC Power Residuals by Wind Speed.

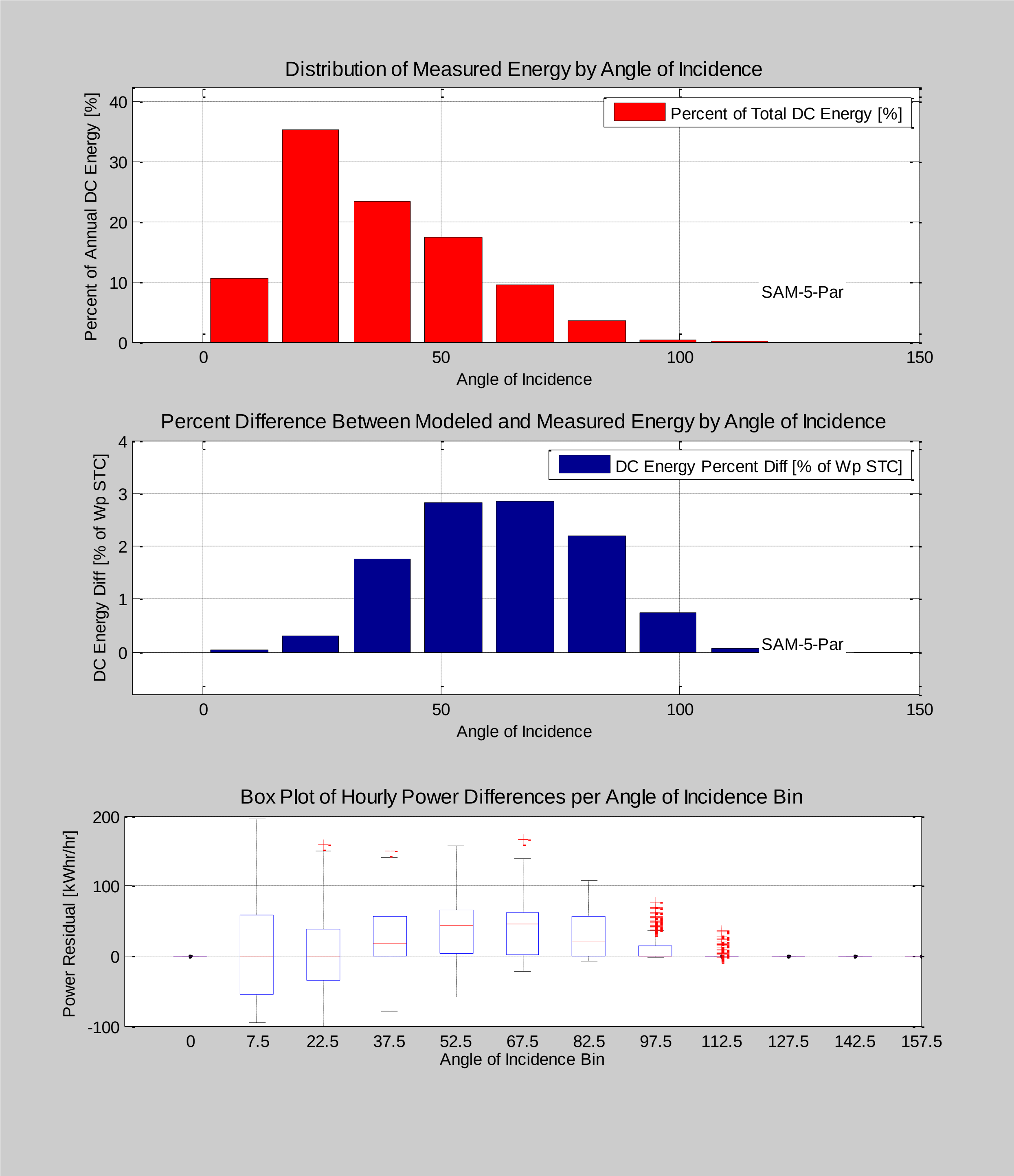


Figure D-27. DC Power Residuals by Angle of Incidence.

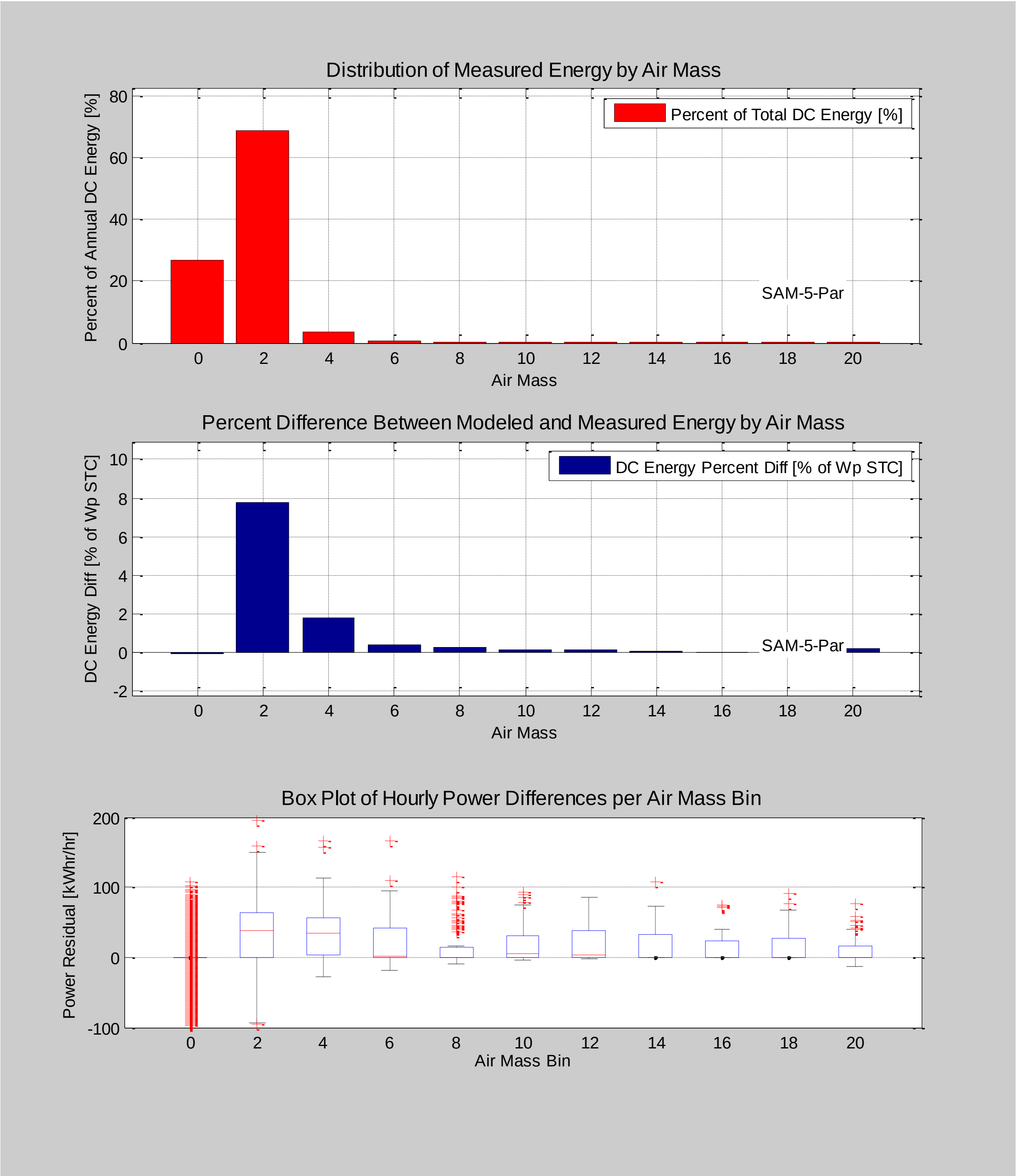


Figure D-28. DC Power Residuals by Air Mass.

Chapter 4. Summary and Conclusions

This report has presented a personalized example of a standardized analysis of PV performance model validation for an example PV system included in a modeling exercise that was part of Sandia National Laboratories' PV Performance Modeling Workshop. It was created using Matlab's Report Generator to allow rapid creation of such reports.

The Sandia PV Modeling and Analysis Team hopes that this report is valuable for participants to evaluate the performance of their models. We encourage any feedback on improvements and additional information that would increase the value of such reports.

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