Performance Model Assessment for Multi-Junction Concentrating Photovoltaic Systems

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Abstract: Four approaches to modeling multi-junction concentrating photovoltaic system performance are assessed by comparing modeled performance to measured performance. Measured weather, irradiance, and system performance data were collected on two systems over a one month period. Residual analysis is used to assess the models and to identify opportunities for model improvement.

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INTRODUCTION

Large photovoltaic systems are typically developed as projects which supply electricity to a utility and are owned by independent power producers. Obtaining financing at favorable rates and attracting investors requires confidence in the projected energy yield from the plant. In this paper, various performance models for projecting annual energy yield from Concentrating Photovoltaic (CPV) systems are assessed by comparing measured system output to model predictions based on measured weather and irradiance data. The results are statistically analyzed to identify systematic error sources.

APPROACH

Sandia National Laboratories (SNL) is engaged in predictive performance model development and evaluation, with the goal of enabling system performance prediction using performance coefficients and weather data sets such as Typical Meteorological Year data sets. Our approach is to concurrently collect solar radiation, weather, and system performance data representing diverse technologies, applications, and locations [1]. The measured weather data is then input to a set of predictive performance models, and the model outputs are compared to measured performance data. SNL has used this process in collaboration with two CPV system manufacturers to evaluate predictive performance models for CPV systems. Residual analysis is used to assess model accuracy as a function of key model inputs, such as irradiance, air mass, and temperature.

PERFORMANCE MODELS

Two CPV performance models that are available in the National Renewable Energy Laboratory's Solar Advisor Model (SAM) [2] are evaluated in this paper. Also evaluated are a simple sun-hour model, for which system output is proportional to system rating and Direct Normal Insolation (DNI), and a model constructed from the translation equation in ASTM E-2527-06 [3].

Sandia PV Array Performance Model

The Sandia PV Array Performance Model [4] is an empirical model with coefficients derived from experimental data from outdoor testing. The model has been applied to flat-plate PV systems and is incorporated in SAM, in PVDesignPro, and in industry proprietary models. This paper describes the application of the model to CPV systems.

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One of the differentiating features of the Sandia model is that it includes four temperature performance coefficients: one each for V_{oc}, I_{sc}, V_{mp}, and I_{mp}. Three coefficients, a, b, and ΔT, are used to calculate cell temperature as a function of ambient temperature, wind speed, and total incident radiation. Additional coefficients determine V_{oc}, I_{sc}, V_{mp} and I_{mp} as a function of effective irradiance and cell temperature. For CPV, effective irradiance is related to direct normal insolation by a 4th order polynomial function of air mass, as shown in figure 1. This air mass function is used to estimate the spectral response of the cell. As shown in the figure, two linear segments may produce a better fit for multi-junction cells. The tests used to determine these coefficients are outlined in reference 4.

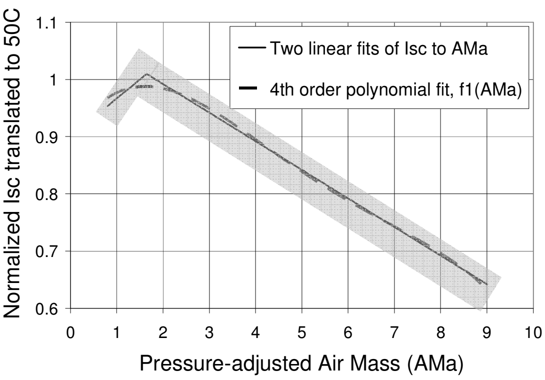

FIGURE 1. Empirical air mass functions representing solar spectral influence on I_{sc} as a function of air mass, measured during nominally clear sky conditions. The shaded area represents typical scatter in data measured over several days.

Solar Advisor CPV Model

When the detailed data required by the Sandia PV Array Performance Model is not available, SAM permits a simplified temperature-compensated approach requiring only module area, dc power at rated conditions, and the maximum power temperature coefficient. The temperature coefficient is used to adjust module output as a function of cell temperature, which is determined using nominal a, b, and ΔT coefficients from the Sandia model above. Setting the temperature coefficient to zero creates the simple sun-hour calculation in which system output is proportional to system rating and DNI.

Sandia Inverter Model

The Sandia Inverter Model [5] is used in SAM to estimate inverter efficiency as a function of input power level and array V_{mp}, as determined by the array model. The coefficients for this model are derived from test data published on-line by the California Energy Commission.

Shading and Derate Factors in SAM

The Solar Advisor Model permits entering shading factors by hour of the day and month of the year, but these factors must be calculated externally. In the initial evaluation of model accuracy presented in this paper, periods when the concentrators are shaded have been eliminated from the data. Concentrator spacing typically causes self-shading, so evaluating shading estimates and concentrator response are an important model evaluation activities for future research.

Within SAM, pre-inverter and post-inverter derate factors are used to estimate losses due to mismatch, diodes and connections, dc wiring, soiling, sun tracking, ac wiring, and the ac transformer. In the residual analysis below, these factors have been set to match total modeled energy production to measured energy production over the period of observation.

Translation Equation Model

ASTM E-2527-06 provides the following translation equation to translate measured data to rated conditions:

$$P = E \cdot (a_1 + a_2 \cdot E + a_3 \cdot T_a + a_4 \cdot n) \qquad (1)$$

This equation requires a regression analysis to generate the coefficients from measured data. System data measured over several clear days have been used to create coefficients for each system. Then, the translation equation was used as a performance prediction model. This approach directly models the ac output of the system.

DATA COLLECTION

Solar irradiance, weather, and system performance data were collected at 5-minute intervals for a period of approximately one month in the fall of 2009 on two CPV systems: an Amonix 7500 system located in Las Vegas, NV; and an Emcore system located in Albuquerque, NM. Since the focus of this paper is model evaluation, data were screened to eliminate periods of operation where the systems were not operational, key data were missing, or, as noted above, the concentrators were shaded. Future work will include data collection over a greater range of environmental conditions and will include modeling of self-shading by neighboring concentrators.

Generation of the performance coefficients for the Sandia PV Array Performance Model requires dc characterization of module operation on a two-axis tracker or within a system. For both systems, data used in this paper were collected from the tracking systems, rather than from a module test at Sandia. For Amonix, a 24 cell mini-module was also characterized on SNL's 2-axis tracker in Albuquerque. The results for the mini-module and for a MegaModule tested within the Amonix system in Las Vegas were consistent within experimental error. Inverter coefficients were derived from CEC-published test data. These inverter coefficients are included in the database distributed with the Solar Advisor Model.

ANALYSIS

System design data and the measured and filtered weather and irradiance data were input to an analysis package that contains the models described above. For the Solar Advisor Model, performance was modeled using the component models described above. The system derate factors required by SAM can be estimated, calculated externally, or based on experience. We chose the latter approach, and set the derate factors so that modeled output summed over the performance period matched the measured output. A similar derate factor was applied to equation 1. This permits examination of the impact of individual parameters on hourly performance predictions, as shown below.

RESULTS

To eliminate the difference in concentrator sizes, the data is presented in the form of normalized residuals:

$$\text{Residual} = (P_{mod} - P_{meas})/P_{rating} \quad (W/W_p) \qquad (2)$$

where P_{rating} is the nominal ac output of the concentrator. Table 2 shows that all the models worked reasonably well over the short duration of data collection. A longer period of data collection with greater variation in input parameters might show greater differences. The coefficients for the translation equation from the ASTM standard, in particular, were the result of regression analysis during the test period, while the data used to generate coefficients for the Sandia model were not contemporaneous with the test period.

Table 2. Standardized Deviation of Normalized Residuals.

	Sun-hour	Temp Comp	ASTM	SNL
System 1	0.0458	0.0508	0.0499	0.0343
System 2	0.0516	0.0538	0.0502	0.0476

A valid model should produce residuals that are randomly distributed with respect to all variables in the analysis. Correlation between residuals and model inputs indicates areas where the model could be improved. Figure 3 shows the normalized residuals vs. air mass for two of the models: the sun-hour model and the Sandia model. The correlation of residuals and air mass is clear, especially for the sun-hour model. Charts for the simple CPV model with temperature compensation and for the model using the ASTM translation equation are similar to the sun-hour model. None of these models include an air-mass function. Less correlation of residuals with air mass is seen for the Sandia model, which has an air mass function.

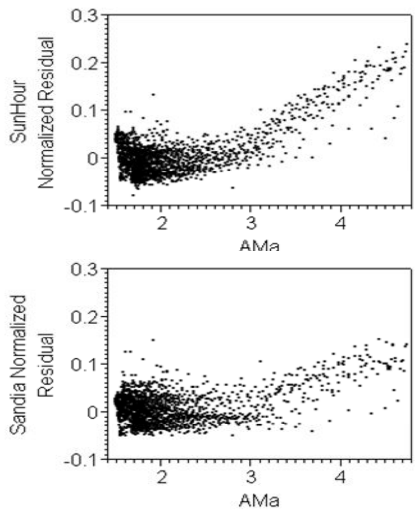

Figure 3. Normalized Residuals vs. Air Mass for System 1

Stepwise regression was applied to the modeling results to evaluate the sensitivity of normalized model residuals to model inputs. Stepwise regression is based on performing a stepped series of linear regressions of the form:

$$Y = b_o + \sum_{j=1}^{P} b_j X_j \qquad (3)$$

where Y is a vector of dependent variables and X is a set of P vectors of independent variables included in the stepwise model and j represents the step. In the first step, the method tests the linear regression between Y (in our case, model residuals) and a set of independent variables (DNI, air mass, wind speed, air temperature) to see which variable results in the best linear fit (highest R^2). For the second and subsequent steps, additional independent variables are added to the regression in order of which variable provides the highest R^2 value for each step. The process of examining additional variables continues until the probability that an effect could be due to chance is reached (5%).

Figures 4 and 5 show the stepwise results for the systems as simulated by each of the four models considered. For each model run, the parameters and their associated incremental R^2 values represent opportunities for improving the model. The largest incremental R^2 value for each model is the fraction of the residual variance that would be reduced by including a linear correction based on that parameter. The best models will have the lowest incremental R^2 values. The second highest R^2 value for each model (step 2) represents the variance reduction relative to the variance remaining after the first parameter is included. For system 1, air mass is the parameter with the largest R^2. The Sandia model, the only model which includes a correction for air mass, produces the lowest R^2 value. The next two variables for the sun-hour model are wind speed and ambient temperature. This is expected since these parameters have an effect on cell temperature, and that model has no temperature correction. However, the effect is small since the temperature coefficient for multi-junction cells is small. For system 2, air mass is the most sensitive parameter for all models except for the ASTM model, for which air temperature appears to account for about 8% of the variance.

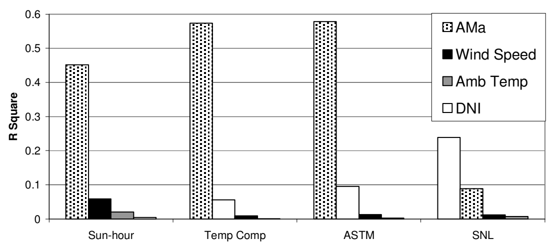

Figure 4. Stepwise Analysis of Normalized Residuals vs. Model for System 1.

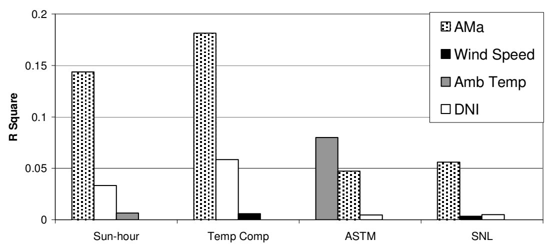

Figure 5. Stepwise Analysis of Normalized Residuals vs. Model for System 2.

CONCLUSIONS

All the models, even the simple sun-hour model, worked well when applied to the short period of data collected for this paper. A longer test with greater variations in input parameters and with multiple locations might produce different results. Only the Sandia model includes an air mass function. Stepwise analysis of the residuals of the others generally showed the strongest correlation was to air mass. Analysis of system 1 showed some correlation of the residuals for the sun-hour model to air temperature and wind speed, indicating the value of temperature correction as found in the other models.

Additional work is needed to validate performance models for CPV, including extending the validation period to include a wider range of environmental conditions, and expanding the number of systems and locations. While this paper focused on evaluating model sensitivity to the input parameters, future work should examine model bias error and the application of derate factors. Also, a field of systems will shadow each other in the morning and afternoon. Evaluation of shading algorithms is needed.

ACKNOWLEDGMENTS

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