

EFFECT OF TIME AVERAGING ON ESTIMATION OF PHOTOVOLTAIC SYSTEM PERFORMANCE

Clifford W. Hansen
 Sandia National Laboratories
 P.O. Box 5800 MS 1033
 Albuquerque, NM 87185
 e-mail: cwhanse@sandia.gov

Joshua S. Stein
 Sandia National Laboratories
 P.O. Box 5800 MS 1033
 Albuquerque, NM 87185
 e-mail: jsstein@sandia.gov

ABSTRACT

Power from proposed photovoltaic power systems is commonly estimated by a performance model using hourly averaged weather data, such as TMY data. Use of hourly averaged weather data introduces error in model estimates independent from other sources of error. We isolate and quantify the error in DC energy that results solely from using time-averaged model inputs. We demonstrate that error in estimated energy arises from two separate approximations: 1) the approximation of PV performance as linear in time-averaged inputs, such as irradiance; and 2) the treatment of time-averaged inputs for partially-lit hours including sunrise and sunset. We show that the net error in DC energy from these approximations can be predicted from characteristics of the PV modules and the frequency of clear-sky conditions. For a typical cSi PV module, error in annual energy ranges between -0.3% for locations with primarily clear-sky conditions to +2.0% for locations with highly variable conditions; errors are greater for systems with amorphous silicon modules and less for systems with CdTe modules. Our analysis permitted quantifying the error, identifying the underlying causes, and proposing a model to estimate the error in annual energy resulting from time-averaged weather data. With current modeling practices, the error in annual energy resulting from time averaging is substantially reduced by use of weather data at 15 minute intervals or less.

1. INTRODUCTION

Power from photovoltaic (PV) systems can be calculated, using one of several models (e.g., [1], [2], [3]), from measurements of weather data such as irradiance, air temperature and wind speed. Weather measurements are generally obtained as averages over time intervals ranging from a few seconds to as long as an hour. Models for

power generally assume that the PV system responds rapidly to changes in external variables, and thus power is calculated at discrete times corresponding to the averaged weather values.

Uncertainty in model output may result from uncertainty in: (i) model parameters that characterize the PV system; (ii) model inputs such as irradiance and temperature; and (iii) misspecification of the model itself, referred to as model uncertainty. Quantifying uncertainty in model output is currently of interest because such uncertainty informs decisions about investment risk for large-scale PV power plants.

Power from a PV module is not precisely described by a linear function of the incident irradiance, as is demonstrated by the nonlinearities formulated in the various models of PV module performance. Also, the inputs to performance models do not change linearly in time; for example, irradiance under clear skies tends to follow a sine curve. Because calculating power and energy from time-averaged inputs implicitly assumes (as we will illustrate) a linear relationship between inputs and outputs, using time-averaged inputs introduces some amount of uncertainty in the model results that is separate from other sources of uncertainty.

In our analysis we regard the error introduced by time-averaged inputs as model uncertainty, because it results primarily from the implied assumption of linearity. To isolate this uncertainty from other sources of uncertainty, we will assume that the system parameters are known exactly, and the model inputs (e.g., irradiance) are known precisely on any time interval over which the input has been averaged. By this assumption we exclude any effects of error in measurement of array characteristics or of weather, or from the models used to transform weather measurements into inputs to the array performance model.

2. METHODS

We obtained one month of measured data as follows:

- global horizontal irradiance (GHI), direct normal irradiance (DNI), diffuse horizontal irradiance (DHI), air temperature and wind speed recorded at three-second intervals in Albuquerque, NM;
- GHI, air temperature and wind speed recorded at one-minute intervals in Las Vegas, NV;
- GHI, DNI, DHI, temperature and wind speed recorded at one-second intervals in Lanai, HI.

In each case, the recorded values represent averaged measurements over the stated time interval.

For each location, we also calculated one year of clear-sky irradiance at one-minute intervals using a clear-sky model. We paired the estimated clear-sky irradiance with a constant temperature of 25°C and wind speed of 1 m/s.

Using these data we computed the beam and plane-of-array (POA) diffuse irradiance in order to run the Sandia Array Performance Model (SAPM) [1] to estimate array power and energy. In all cases, we assumed a flat-plate PV system at latitude tilt. For Albuquerque, NM, and Lanai, HI, we calculated beam irradiance by multiplying DNI by the cosine of the solar angle of incidence on the panel, and we calculated POA diffuse irradiance using an empirical model developed by Sandia. For Las Vegas, NV, we calculated DNI from GHI using the DISC model [4], obtained DHI as the difference between GHI and DNI, and then estimated POA diffuse irradiance using the Perez model [5].

We used the Sandia model to estimate cell temperature from beam and POA diffuse irradiance, air temperature and wind speed. We then created averages of beam, POA diffuse irradiance and cell temperature for a range of averaging intervals, ranging from one minute to one hour.

In order to estimate power using SAPM, we still needed to determine values for the solar angle of incidence (AOI) and air mass (AMa); SAPM uses these quantities with empirically determined functions to calculate *effective irradiance*, which is the irradiance available to converted to electricity within a module ([1], Eq. 1). Consistent with common modeling practices [6], for each time interval that does not include sunrise and sunset, AOI and AM were determined using geometric models at the midpoint of each interval. For intervals during which sunrise or sunset occurs, AOI and AM were determined at the midpoint of the sunlit portion of the interval. As we will show, the approximations inherent in estimating effective irradiance, by combining time-averages of beam and POA diffuse irradiance with these representative

values, have a substantial effect on the error in calculated energy.

With all necessary inputs in hand, we applied SAPM to representative latitude-tilt PV systems, each comprised of a single module, for a range of module technologies. We selected modules which have been characterized through Sandia's outdoor characterization test processes, and for which well-calibrated coefficients for SAPM are available. We calculated power for time series of weather for a range of averaging intervals, from original data to one-hour averages, and computed the corresponding hourly and daily energy. We regard the power calculation for the original data as exact, i.e., not subject to error of any other source, in order to isolate the errors resulting from using time-averaged input data. Specifically, for each averaging interval, we determine the error in energy as the difference between the energy estimated for time-averaged data and the energy calculated with the original data.

3. RESULTS

Following these methods, a lengthy analysis was conducted of the errors in power and energy that result from using time-averaged data [7]. For a representative 230W cSi module, the left panels of Figure 1 show power for a clear day and a day with variable irradiance, for three-second and hourly-averaged inputs. For each day, the right panels of Figure 1 illustrate error in energy for each hour, for 15-minute and hourly-averaged data. Energy error is substantially different on days with clear skies than on days with variable irradiance. On clear days, error in hourly energy appears primarily during early and late hours, whereas for days with variable irradiance the largest errors occur in the middle of the day. By analyzing intermediate steps in the calculation of energy, we determined that the errors in early and late hours for clear-sky days result from approximations involved in determining effective irradiance, whereas the errors for variable day calculations arise primarily from the implied assumption of linear module performance.

3.1. Error from Approximation of Effective Irradiance

Effective irradiance (E_e) is the solar radiation that is captured by the module's cells. For the Sandia Array Performance Model, effective irradiance is calculated in watts by ([1], Eq. 21):

$$\begin{aligned} E_e &= E_e(E_b, E_{diff}, AMa, AOI) \\ &= f_1(AMa)(E_b f_2(AOI) + f_d E_{diff}) \times SF \end{aligned} \quad (1)$$

where $f_1(AMa)$ is the air mass (AMa) dependent spectral correction; $f_2(AOI)$ is the angle-of-incidence correction; E_b and E_{diff} are the beam and diffuse irradiance, respectively, incident on the module; f_d is the fraction of diffuse irradiance captured by the module (typically $f_d = 1$); and SF is the soiling derate factor ($SF = 0.98$ in this analysis).

E_b and E_{diff} are calculated from available irradiance measurements (e.g., direct normal irradiance or global horizontal irradiance) using various models as described earlier. AMa and AOI are typically calculated deterministically using only the solar ephemeris ([8]).

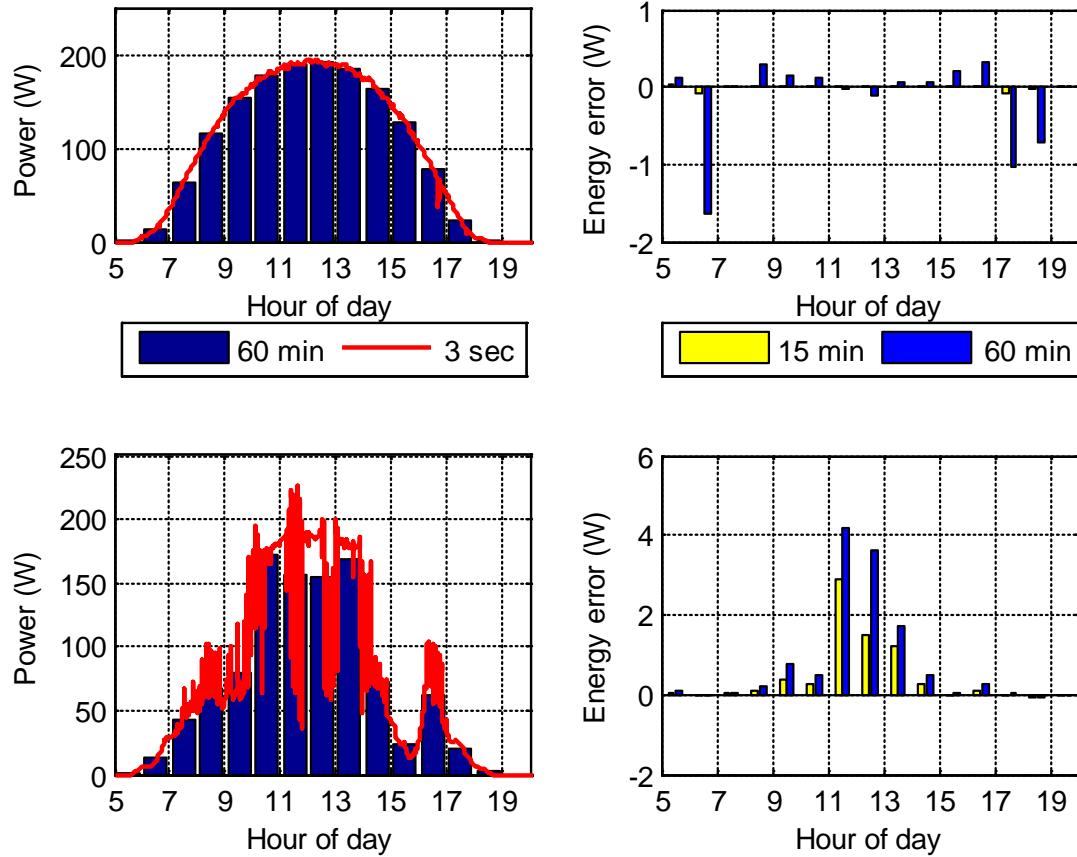


Fig. 1. Power and Error in Energy for a Clear Day and a Variable Day (Albuquerque, NM).

As is common practice, we averaged E_b and E_{diff} over various time intervals to obtain \bar{E}_b and \bar{E}_{diff} , respectively, and we associated the values of AMa and AOI at each interval's midpoint, denoted by AMa^* and AOI^* , respectively, to the entire interval, with modification for intervals containing sunrise or sunset. We then used Eq. (1) to calculate a single value \hat{E}_e of effective irradiance for each interval.

The value of \hat{E}_e which results from time-averaged data is not equal to the average \bar{E}_e of effective irradiance E_e over an interval because E_e is not linear with respect to the independent variables (Eq. (1)). We found that the error in energy for early and late hours (e.g., between 6 am and 6 pm in Fig. 1, top row) results almost entirely from the inexact approximation of \bar{E}_e by \hat{E}_e .

The error due to the approximation of effective irradiance can be significantly reduced by decreasing the interval for time averaging, as shown in Fig. 1. We explored whether other methods, such as a regression model for the errors, could be used to correct the error. We used a clear-sky model for Albuquerque, NM, to estimate irradiance at one minute intervals, and calculated power for a single representative cSi module at latitude tilt assuming a constant ambient temperature of 25 °C and a constant wind speed of 1 m/s. For various time averaging intervals, we calculated the error in energy for each hour of the year and normalized the error to each day's total energy. Fig. 2 shows that the normalized hourly error varies in a complex manner throughout the year; Fig. 3 shows the normalized error for one day selected from Fig. 2 and illustrates that the error may be positive and negative for different hours of the same day. For other locations (Lanai, HI, and Las Vegas, NV) we found different, yet similarly complex, patterns of normalized error, indicating that any correction method must take site location into account. However, for all locations we observed that the error is significantly reduced for all days when the averaging time interval is reduced from one hour to 15 minutes. Due to the complex pattern evident for normalized error at long averaging times, and the dependence of this pattern on site location, we did not pursue other methods for correcting this error.

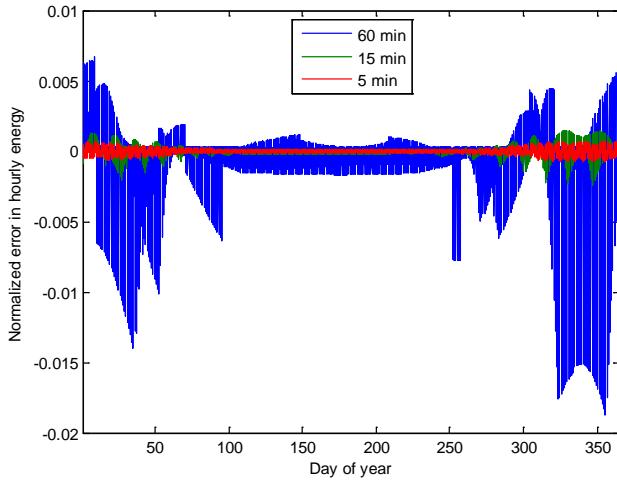


Fig. 2. Normalized Error in Hourly Energy for One Year of Clear-Sky Days (Albuquerque, NM).

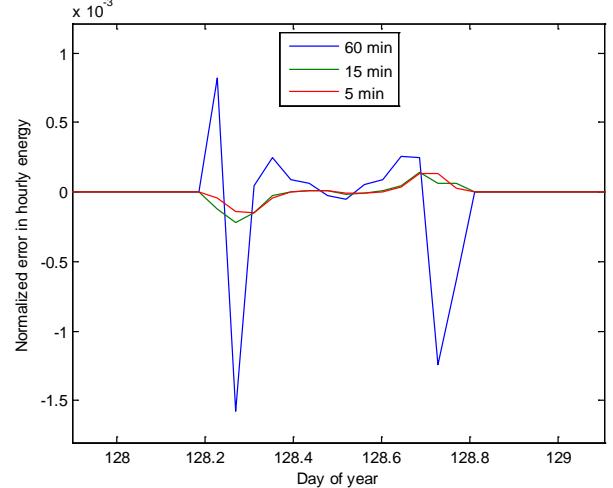


Fig. 3. Normalized Error in Hourly Energy for One Day (Albuquerque, NM).

3.2. Error from Assumption of Linear Module Performance

Conceptually, we can represent the calculation of power from a PV module by a function, P , which takes as input the effective irradiance E_e , temperature (cell, module or ambient), parameters which describe the module's electrical characteristics (e.g., current at the maximum power point and standard test conditions), and possibly other inputs. Power calculated from time-averaged weather data, denoted by $P(\bar{E}_e, \dots)$ is an approximation to the time-average of power, denoted by $\bar{P}(E_e, \dots)$ that is calculated from weather data at each time step:

$$P(\bar{E}_e, \dots) \approx \bar{P}(E_e(t_i), \dots) = \frac{1}{N} \sum_{i=1}^N P(E_e(t_i), \dots); \quad (2)$$

where

$$\bar{E}_e = \frac{1}{N} \sum_{i=1}^N E_e(t_i), \quad (3)$$

$E_e(t_i)$ indicates the value of effective irradiance at time t_i , and the time average is computed over t_1, \dots, t_N . Thus,

calculation of power (and energy) from time-averaged inputs implicitly introduces error associated with the approximation in Eq. 2.

The approximation results because module performance, described by the function P , is not exactly linear in the various inputs. Fig. 4 illustrates how this approximation can be in error due to the curvature in the module's response to effective irradiance. The concave downward shape of the module's response at high levels of effective irradiance is typical of semi-conductor photovoltaic devices. Current generally increases proportionally with effective irradiance ([1], Eq. 1 and Eq. 2), while voltage generally increases with the logarithm of effective irradiance and decreases linearly with temperature ([1], Eq. 4), with the net effect being that power increases sublinearly with increasing effective irradiance and decreases linearly with increasing temperature. Irradiance and temperature tend to increase together, and because changes in effective irradiance have a greater effect on power than do changes in cell temperature, the net result is that power increases sublinearly with increasing effective irradiance. The concave downward curvature evident in Fig. 4 reflects the combined effects of changes in both effective irradiance and temperature.

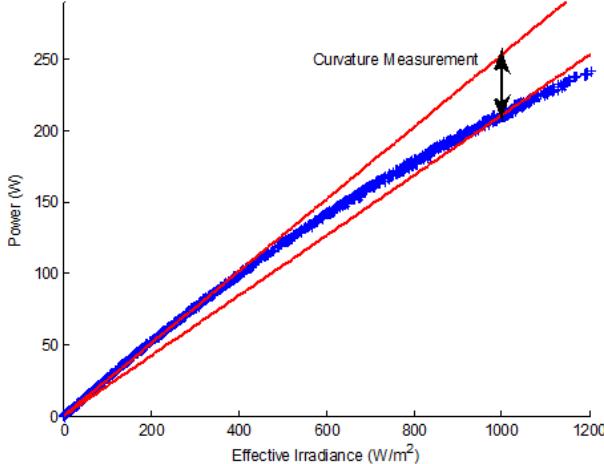


Fig. 4. Illustration of Curvature in a Representative Module's Response to Effective Irradiance

We measured the degree of curvature in a module's response to effective irradiance by the difference between power at effective irradiance of 1000 W/m^2 , and power projected by a line fit to power for effective irradiance less than 400 W/m^2 , scaled by the module's maximum power at standard test conditions. We remark that the smallest value of the measure (0.004) was observed for a Cu-In-Se module, and the greatest values (0.2) were associated with several triple junction amorphous silicon modules; with crystalline and multi-crystalline modules

spanning the range between these two extremes. Additional values are given in [7], Table 4.

Because the effective irradiance vs. power curve is concave downward, power calculated from average effective irradiance will inherently be greater than the average of power computed at each value of effective irradiance. More formally, if E_{e1} and E_{e2} are two irradiance values, we have

$$P\left(\left(\frac{E_{e1} + E_{e2}}{2}\right), \dots\right) \geq \frac{1}{2}(P(E_{e1}, \dots) + P(E_{e2}, \dots)) \quad (4)$$

as is illustrated by Fig. 5.

The error due to the assumption of linear performance will be most significant during hours when changes in irradiance are large in magnitude. During midday hours with clear sky conditions (e.g., between 11 am and 2 pm on Fig. 1, top row), the error in energy arising from the approximation of time-averaged power is relatively small because there is little variability in irradiance.

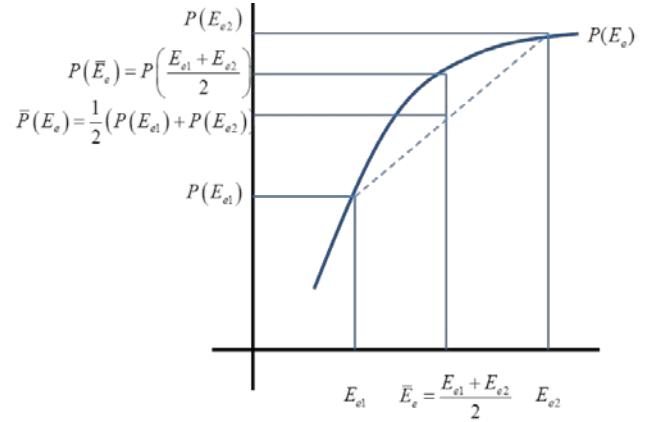


Fig. 5. Effect of Time Averaging on Power Calculation.

Each irradiance measurement in a time interval is similar to the average irradiance over the interval; thus power computed from the time-average of irradiance is similar to the time-average of power. However, when irradiance is variable within the time interval (e.g., between 11 am and 2 pm on Fig. 1, bottom row), time-averaged power (and hence energy) are overestimated from time-averaged weather. Error magnitude decreases with decreasing averaging interval.

3.3. Net Error in Energy

The net error in energy results from the combined effects of the two approximations discussed above. Fig. 4 also shows that the magnitude of the net error is influenced by

the degree of curvature in the effective irradiance vs. power curve, and Fig. 5 indicates that the frequency of variable irradiance conditions also will affect the net error. We explored these relationships by computing error in daily energy, for various averaging intervals, for one month of measured irradiance and temperature in Las Vegas, NV and Lanai, HI, for a selected group of PV modules for which well-calibrated coefficients for SAPM are available. We chose modules to obtain a wide range of values for the measure of curvature indicated in Fig. 4.

Fig. 6 illustrates the relationship between module curvature and average (over one month) error in daily energy for Lanai, HI. For each averaging interval, the relationship is remarkably linear, increasing as module curvature increases. Moreover, the slope and intercept of each least-squares fit line changes in a regular manner as the averaging interval increases. However, different results were obtained for Las Vegas, NV (Fig. 7). The linear relationship between module curvature and error remains evident. Unlike the results for Lanai, HI, the slope and intercept of the best-fit lines do not change regularly; at hourly averages, the slope increases sharply and the intercept becomes negative. This different behavior results because the weather in Las Vegas, NV, included many clear days. During clear days, when hourly averages are used, the contribution to error resulting from the linearity assumption is small relative to the contribution to error from the approximation of effective irradiance during early and late hours, which itself is negative (underestimates energy) for the particular month chosen.

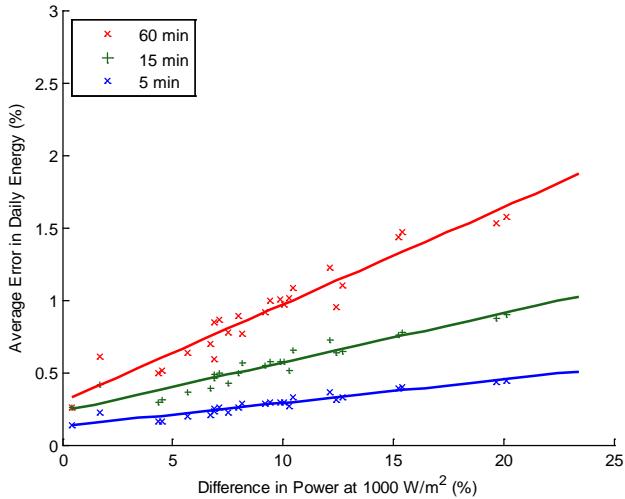


Fig. 6. Average Error in Daily Energy as a Function of Module Curvature: Spring Weather in Lanai, HI.

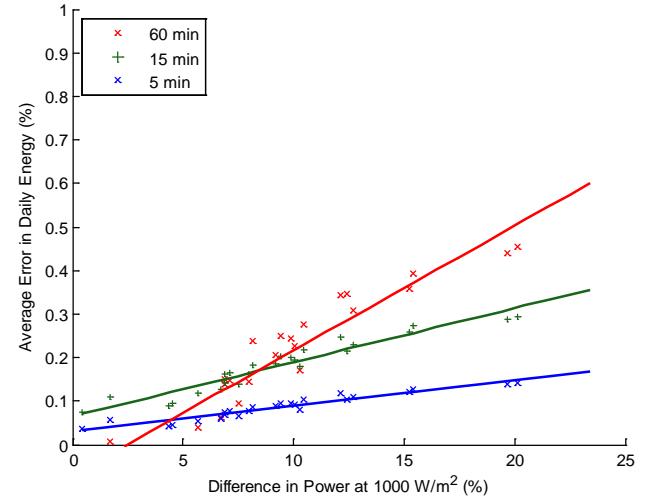


Fig. 7. Average Error in Daily Energy as a Function of Module Curvature: Spring Weather in Las Vegas, NV.

3.4. Model for Net Error in Annual Energy Resulting from Time Averaging

Analysis of the components which comprise the net error resulting from time averaging allow us to propose an empirical model for the range of values for this error, as a function of module curvature and the relative frequency of variable and clear-sky conditions. During clear-sky conditions, the error will be dominated by the approximation of effective irradiance, and will tend to underestimate annual energy (as is suggested by Fig. 2 and Fig. 3). Accordingly, we calculated a lower bound for the error in annual energy by using a clear-sky model for both Lanai, HI and Albuquerque, NM, and obtained approximately the same values for the error in annual energy for a given module curvature.

When irradiance conditions are frequently variable, the net error in annual energy will be dominated by the error resulting from the linearity assumption, and this error will overestimate annual energy. We calculated an upper bound for the error in annual energy by considering one year of weather recorded at Lanai, HI, as a surrogate for sites with consistently variable irradiance conditions. For a site with conditions between these two extremes, we considered one year of weather measured in Las Vegas, NV, where clear days interspersed with days showing variable irradiance conditions.

The proposed model for error in annual energy involves selecting a surrogate site from those listed in Table 1, then linearly interpolating between the error values for the averaging interval and module curvature desired. We did not find that a regression surface fit to these data (with curvature and averaging interval as predictors) resulting

in a useful model for any site, because of non-linear changes of error either as a function of curvature or of averaging interval. Moreover, a regression model that subsumes selecting a surrogate site would require a predictor to indicate the frequency of variable irradiance conditions.

Table 1. Proposed Model Quantifying Error Associated with Time-Averaged Weather Data

Location: Irradiance condition	Av'ing. Interv'l (min)	Curvature (fraction of power at 1000 W/m ²)		
		1.7%	9.6%	20.1%
Lanai, HI (2010): Consistently variable throughout the year	5	0.17	0.3	0.36
	15	0.28	0.6	0.61
	60	0.37	0.8	1.8
Las Vegas, NV (2010): Many clear days with infrequent cloudy periods	5	0.02	0.03	0.06
	15	0.04	0.09	0.17
	60	-0.04	0.04	0.34
Lanai, HI (clear sky model): Completely clear	5	-0.002	- 0.003	-0.003
	15	-0.012	-0.01	-0.014
	60	-0.23	-0.3	-0.19

4. SUMMARY AND CONCLUSIONS

We isolated the error in performance predictions of a PV module that results from using time-averaged inputs. We found that the error results from two approximations that underlie performance predictions:

- The approximation of effective irradiance by the combination of average irradiance values and representative values for air mass and angle-of-incidence. This error is greatest in magnitude during early and late hours of a day, and tends to underestimate energy.
- The approximation, inherent in the use of time-averaged data, that a module's response to effective irradiance is linear. This error is of greatest effect when irradiance is variable during mid-day hours, and tends to overestimate energy. We show that this error in energy depends on the degree of curvature in a plot of effective irradiance vs. module power, with errors increasing as the curvature increases.

We propose a model to quantify the error in annual energy resulting from the use of time-averaged inputs. For hourly-averaged data, the error ranges between -0.3% for locations where clear-sky conditions dominate, to +2.0% for locations with consistently variable irradiance and for systems with modules that have significant curvature.

Due to the complex behavior of the two components of error over the course of a year, and their offsetting effects, we do not believe it will be practical to develop an effective correction of these errors without reducing the time interval for input data. However, errors for 15-minute averages of weather are substantially reduced compared to hourly averages. Consequently, if correction of these errors is desired, we recommend use of weather data at intervals of 15 minutes or less.

5. ACKNOWLEDGMENTS

Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

6. REFERENCES

- (1) King, D. L., W. E. Boyson, J. A. Kratochvill, Photovoltaic Array Performance Model: SAND2004-3535, Albuquerque, NM, Sandia National Laboratories. 2004
- (2) De Soto, W., S. A. Klein, and W. A. Beckman, Improvement and validation of a model for photovoltaic array performance: *Solar Energy*, Vol. 80, pp. 78-88, 2006
- (3) Mermoud, A., T. Lejeune, Performance Assessment of a Simulation Model for PV Modules of Any Available Technology: *Proc. of the 25th European Photovoltaic Solar Energy Conference*, Valencia, Spain, September 2010
- (4) Maxwell, E. L., A Quasi-Physical Model for Converting Hourly Global Horizontal to Direct Normal Insolation: SERI/TR-215-3087, Solar Energy Research Institute, Golden, CO, 1987
- (5) Perez, R., Ineichen, P., and Seals, R., Modeling Daylight Availability and Irradiance Components from Direct and Global Irradiance, *Solar Energy* Vol. 44, pp. 271-289, 1990
- (6) Private communication with Solar Advisor Model (SAM) developers at National Renewal Energy Laboratory, Sept. 2011
- (7) Hansen, C. W., Stein, Joshua S., and Riley, D. M., Effect of Time Scale on Analysis of PV System Performance: SAND2012-1099, Sandia National Laboratories, Albuquerque, NM. 2012
- (8) Lorenzo, E., Energy Collected and Delivered by PV Modules, in *Handbook of Photovoltaic Science and Engineering* 2ed, ed. A. Luque and S. Hegedus, Wiley, 2011