# QUANTIFYING THE EFFECTS OF AVERAGING AND SAMPLING RATES ON PV SYSTEM AND WEATHER DATA

Daniel M. Riley, Christopher P. Cameron, Joshua A. Jacob, Jennifer E. Granata, Gary M. Galbraith
Sandia National Laboratories, Albuquerque, NM

## ABSTRACT

When modeling photovoltaic (PV) system performance data, modelers typically reduce the amount of data analyzed by reducing the sampling frequency below the maximum sampling frequency of their instruments (under-sampling), averaging a number of samples together, or a combination of these two methods. A sampling frequency which is too low may not provide enough fidelity to accurately model system performance, while a sampling frequency which is too high may provide unnecessarily high data fidelity and increase file size and processing complexity. This paper strives to quantify the errors caused by reduced sampling and averaging frequencies through the comparison of modeled high temporal resolution weather data and low resolution weather data.

## INTRODUCTION

Predictive models can be used in many stages of PV system design, purchase, installation, and operation. For instance, a model may be used to choose one technology instead of another, to estimate power output for power purchase agreements (PPA), or to monitor a system's health in real-time. In all of these cases, some form of weather and irradiance input is used to predict system performance. This weather and irradiance data can come from many sources such as historical typical meteorological year (TMY) data, real-time data from instruments, satellite derivations, or can be generated using transition matrices [1]. In each case, the user of the data must make a decision regarding an appropriate rate at which to sample the data. A high sample rate will increase data fidelity at the expense of larger data file sizes and analysis computation time. In order to reduce the file size, the user may sample less frequently (under-sample), or sample frequently and average samples together. If the reduced data is used in a predictive model, and the output is compared to the same predictive model output for non-reduced (higher temporal resolution) data, the reduced data output will have errors which can be attributed to the use of fewer samples of weather data. Furthermore, under-sampling and averaging will produce distinctly different error patterns.

It has been shown that the averaging of weather data into larger time bins can over predict insolation, the integration of irradiance over time, at low light levels [1]

[2]. This skewed insolation distribution, when combined with the fact that modules have a non-linear response to irradiance can lead to incorrect performance predictions. Variation in insolation due to plane of array (POA) irradiance is shown in [2]. Figure 1, below, shows the percent of annual direct insolation received on a 2-axis tracker by direct normal irradiance in Albuquerque, NM. Notice that as the same irradiance data is averaged into larger time bins, more energy appears to be generated at medium irradiance levels, and this averaging can grossly under estimate low irradiance insolation by 5%. Note that Albuquerque has a relatively large amount of clear weather. In a climate with more partly-cloudy weather, this effect would be expected to be even greater. The effect shown could cause disparities when using models to compare concentrated PV modules to "standard" one-sun PV modules. Only direct beam irradiance and insolation are shown in Figure 1, but the same effect can be seen with global irradiances which may cause disparities when using models to compare modules with different responses to irradiance.

If significant weather changes are randomly dispersed throughout the day, sample rates less than a few hours should not appreciably alter the distribution of high and low irradiance periods throughout the year (irradiance being the primary driver of PV system output) as happens when data is averaged. However, sampling at a given rate generally will produce less accurate weather information than sampling at a faster rate and averaging to the same sample period. It should also be noted that the method of interpolation between sampled points can greatly affect the induced error. For the purposes of this paper, all sample interpolation uses a "zero order hold" or a "sample and hold" method, which assumes that all data at times in between samples are at the same value as the previous sample.

While these effects have been shown to exist, it is unclear how this skew will affect PV predictive models.

**%of Annual Direct Insolation Received by Irradiance**
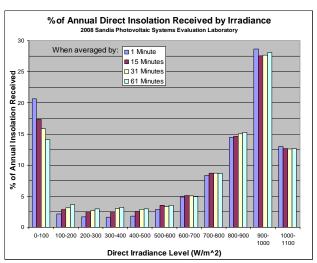2008 Sandia Photovoltaic Systems Evaluation Laboratory

Figure 1: Percent of annual direct insolation received by the irradiance at which it was received, based on averaging period length for Albuquerque, NM 2008

### PROCEDURE

### Data collection

In an effort to quantify the errors associated with reduced sample rates and averaging, weather data was collected at Sandia National Laboratories' Photovoltaic Systems Evaluation Labs (PSEL) in Albuquerque, NM. Sandia's weather station collected irradiance, temperature, wind speed and other meteorological data approximately every three seconds for several days in late August to mid-September, 2008. The weather data was then used in a simple irradiance algorithm to obtain irradiance on a tilted plane. Finally, the POA irradiance and meteorological data were input to Sandia's Photovoltaic Array Performance Model [3] to simulate the performance of a single 215 $W_p$ mono-crystalline module which had been tested at Sandia in 2006.

The highest resolution weather data and the model output corresponding to that data are considered the "real-time" data set. This "real-time" data set is considered to be the gold standard to which all other data will be compared and comparison statistics will be generated. The three second weather data was then re-sampled at a lower rate, known as the sampling window. Sampling windows were generated from 10 to 3600 seconds in 10 second increments. For example, a sampling window of sixty seconds would sample every twentieth point and assume that the sampled value is held for the following sixty seconds. The under-sampled weather data was then up-sampled to the same rate as the "real-time" data in order to allow a point for point comparison. In order to average the weather data, the day was similarly divided into time bins the size of the sampling window, but all weather points which fell within the bin were averaged and the average value was used for the entirety of the time bin. The under-sampled and averaged weather data sets were

then used to model the performance of a single module, and the model outputs of the under-sampled and averaged weather data were compared to the model outputs for the "real-time" weather data. Figure 2, below, shows the modeled module maximum DC power, Pmp, on a sunny day in Albuquerque using the high resolution "real-time" weather data. Also shown is the modeled maximum power for weather data that was under-sampled and averaged. The error between under-sampled or averaged Pmp and the "real-time" Pmp was calculated through comparison statistics. Since the time interval used in Figure 2 is 3600 seconds (1 hour) the total error between the "real-time" and sampled graphs would correspond to a point at sampling window = 3600. Note that for a day with little variability, the under-sampled data under predicts power in the morning and over predicts power in the afternoon, but will generally have the correct total energy over a day.
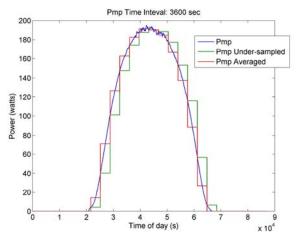


Figure 2: Modeled module maximum DC power, Pmp, on a sunny day with low variability, shown with model output from 1 hour averaging and 1 hour under-sampling of weather data

### Comparison statistics

After modeling the under-sampled and averaged weather data sets, the output was compared to the "real-time" modeled output with a number of error statistics. The root mean squared deviation (RMSD), mean absolute error (MAE), and daily energy deviation (DED) were computed as follows:

$$\text{RMSD} = \left[ \frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)^2 \right]^{0.5} \qquad (1)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} |y_i - x_i| \qquad (2)$$

$$\text{DED} = \sum_{i=1}^{n} \left[ (y_i - x_i) * (t_{i+1} - t_i) \right] \qquad (3)$$

where
n = the number of samples in the day
$y_i$ = the ith under-sampled or averaged output $P_{MP}$
$x_i$ = the ith "real-time" output $P_{MP}$
$t_i$ = the time (in seconds) of the ith sample

The mean bias error (MBE) was also computed, but is extremely similar in nature to the daily energy deviation since the time between samples is approximately equal. In most cases these error values have been normalized by the measured module power at standard test conditions ($W_p$) for the module in order to make the output scalable to a PV array of any size. When normalized by $W_p$ the DED becomes a daily energy yield error measured in Whr/$W_p$.

**Daily variability binning**

It was also hypothesized that the resulting errors would be positively correlated to the daily variability. Thus a "daily variability factor", $F_{DV}$, had to be used to separate the days of high variability from the days of low variability. For this variability factor, direct beam transmittance, $K_n$, was chosen as the input although a number of similar inputs could be used [4]. $F_{DV}$ was computed as the variance of the difference of all $K_n$ values from the prior $K_n$, as shown in equation (5).

$$K_n = I_n / I_o \qquad (4)$$
$$F_{DV} = VAR\left(K_{n_{i+1}} - K_{n_i}\right) \qquad (5)$$

where
$I_n$ = the direct normal irradiance at Earth's surface
$I_o$ = extraterrestrial direct irradiation

For all of the days where $F_{DV}$ was computed, the days were sorted into four groups by variability. The highest variability days had $F_{DV} \geq 4.5 \times 10^{-4}$. Two groups of less variability were found such that $2.5 \times 10^{-4} \leq F_{DV} < 4.5 \times 10^{-4}$ and $2 \times 10^{-5} \leq F_{DV} < 2.5 \times 10^{-4}$. The least variable days were found such that $F_{DV} < 2 \times 10^{-5}$. These variability bins were respectively referenced qualitatively as "no variability", "little variability", "moderate variability", and "high variability" for ease of reading. The days with the least variability were perfectly clear days, although similar $F_{DV}$ values could be obtained from days which were uniformly overcast. Figure 3, below, shows $K_n$ values for representative days in each variability bin. Each bin contained three days of similar $F_{DV}$ values, and the following results section will show the average errors of the three days within each variability bin.
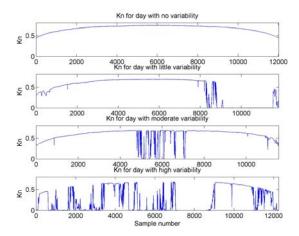


Figure 3: $K_n$ values for representative days in all 4 variability bins

**RESULTS**

**Effect of averaging vs. under-sampling**

Throughout the process, it was found that averaging and under-sampling do not produce similar amounts of error. Figure 4 and Figure 5, below, show that under-sampling produces approximately twice as much MAE for days with little variability, but these variations seem to average out and there is not a large difference between under-sampling and averaging on the energy yield error.
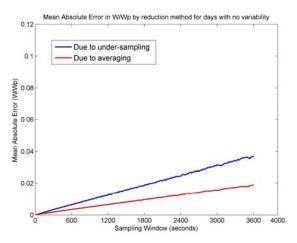
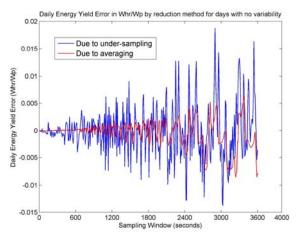

Figure 4: MAE for days with no variability.

Figure 5: Daily energy yield error for days with no variability.



Figure 7: Daily energy yield error for days with high variability.

For days with moderate or high variability, however, the MAE is typically increased by about 50% when an under-sampling reduction method is used instead of an averaging method. In these cases, the errors are not averaged throughout the day, and the daily energy yield error of an under-sampling method is about 2-2.5 times larger than that of an averaging method. It is also worth noting that the energy errors of a high variability day due to under-sampling were approximately evenly distributed on either side of zero ($\mu_{under-sample}$ = 0.011), while the energy errors due to averaging were always positive ($\mu_{average}$ = 0.071). MAE and daily energy error for days with high variability are shown below in Figure 6 and Figure 7.
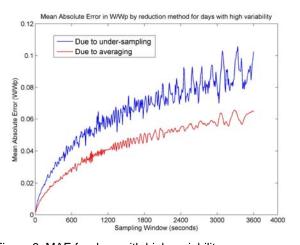
Under all conditions, the under-sampling method produced a much more erratic error function for varying sample rates.

**Effect of daily variability**

Daily variability plays a large part in determining the errors associated with sampling rates. A day with low variability is typically insensitive to sample rate since the conditions which govern system output, namely irradiance, are changing slowly. The high frequency nature of the conditions on a highly variable day greatly increases the error sensitivity to sample rate. As previously mentioned, twelve days were evenly binned into four variability groups. The under-sampling method produces a more erratic error function. In order to improve readability, the error due to daily variability is only shown here as generated by the averaging of weather data.

Figure 8, Figure 9, and Figure 10 respectively show the RMSD, MAE, and daily energy yield errors for the different variability bins.
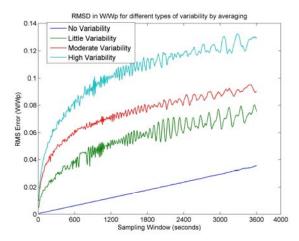


Figure 6: MAE for days with high variability.

Figure 8: RMSD in W/$W_p$ for days of differing variability
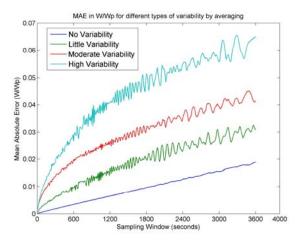


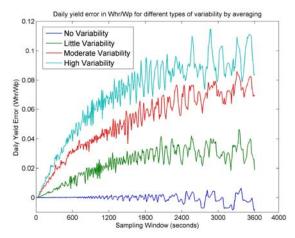Figure 9: MAE in W/$W_p$ for days of differing variability



Figure 10: Daily energy yield error in Whr/$W_p$ for days of differing variability

These figures clearly show that increased daily variability leads to increased errors on a sample by sample basis and that these sample errors lead to an over

prediction of energy for a mono-crystalline module. Furthermore, as indicated by the MAE in Figure 9, modeling errors of up to 6% may be experienced during high variability days even if the weather data is measured at a three second interval and averaged into one hour bins, which is similar to the method used for gathering of irradiance data in TMY data sets [5].

**Effect of different types of modules**

Modules typically exhibit a nonlinear response to POA irradiance with respect to their rating at a given test condition. Figure 11, below, shows the modeled performance differences with varying effective irradiance (Ee) when other conditions are held at PVUSA test conditions [3]. A module with perfectly linear response to Ee would overlay the x-axis of Figure 11. The non-linearities observed, combined with the aforementioned averaging of high and low light levels, which causes more annual insolation at medium irradiances, can cause models using averaged irradiance data to over predict energy generation for modules with increasing efficiency at low light levels [1] [2].
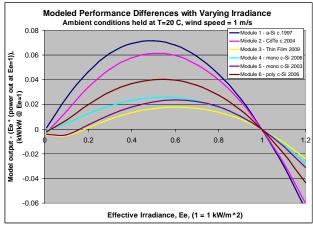


Figure 11: Performance differences for 6 modules with varying effective irradiance. Note that modules shown may not be indicative of current production modules.

Up to this point, all error statistics have been shown for module 4 (215 $W_p$ mono c-Si). Figure 12, below, shows the daily energy yield error for module 1 and module 4 for a range of variability conditions. In both cases, the averaging of weather and irradiance data causes the model to over predict energy output. However, the over prediction is significantly larger for the module with high performance at lower light levels (module 1). For days of little and moderate variability, the energy error for module 1 is approximately 2 times the energy error for module 4; this increases to about 2.5 times for days of high variability. Thus, the nonlinear response of a module is compounded by the averaging of highly variable irradiances to cause higher errors in energy prediction.
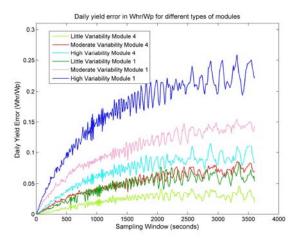
Figure 12: Energy yield error over a range of averaging window sizes and variability conditions, for two different modules using identical input weather data

## CONCLUSIONS

When measuring weather and irradiance data for use in PV modeling, either as a predictive tool, comparative tool, or as a monitoring tool, the weather instrumentation is typically sampled at a low rate or sampled and averaged in order to reduce the amount of data collected. Each method of data reduction induces more errors as the sampling or averaging size becomes larger. It is evident from the results presented that sampling less frequently causes larger errors than sampling more frequently and averaging.

It was also shown that the errors induced by the averaging of weather data are a function of the daily variability, as defined by direct beam transmittance in equation 5. This seems intuitive, as a signal with higher frequency content requires a higher sampling frequency in order to avoid aliasing. However, the results show that MAE of up to 0.06 $W/W_p$ (6% at STC) can be induced by averaging data into 1 hour averages on high variability days. Energy yield errors of up to 0.2 $Wh/W_p$ per highly variable day were also found. Energy yield errors of 0.2 $Wh/W_p$ can be significant, especially for highly variable days which receive low daily insolation. For a single day (not shown), an energy yield error of 0.38 $Wh/W_p$ was found, which accounted for a 7.9% over prediction of energy throughout the day. While this was the "worst-case" of all 16 possible days of data, combining high variability and low insolation, it can serve as an indicator of the energy errors which may be induced by a reduced sampling rate.

As modules respond non-linearly to changes in irradiance, they are affected by the averaging of irradiance data which blends high and low irradiances into periods of medium irradiance. Modules which show higher efficiencies at medium irradiance (around 500 $W/m^2$) will benefit from the averaging of irradiance data by over predicting energy generation due to medium irradiance conditions. Conversely, modules with lower efficiencies at medium irradiance will be negatively impacted as models which average irradiances will under predict energy generation (or over predict by less, as is shown in this paper).

## FUTURE WORK

Further improvements in the method presented may be made by refining the variability binning process, modifying the error statistics used, or looking at a larger sample of models, modules, and input weather data. Linear interpolation of the reduced data points may also be examined as an alternative to the "sample and hold" methods used here.

In the future, it may be possible to estimate an average number of days a particular site may have within each variability bin, thus defining the average variability of a site. Based on the site variability, a sampling or averaging rate may be selected such that measurements are expected to not exceed a given error threshold. More generally, it is hoped that the results presented will inform system modelers as they select a sampling and averaging rate, such that they may have data with accuracy appropriate to their needs.

Since most modelers depend on hourly data sets such as TMY3 data, the effect of hourly averaging for a range of climates and module types is of interest. The possibility of synthesizing sub-hourly data from hourly data to improve modeling accuracy will also be investigated.

## REFERENCES

[1]  S. Ransome, "How Well Do PV Modelling Algorithms Really Predict Performance?", *Twenty-Second European PVSEC*, Milan, 2007

 [2]  S. Ransome, and P. Funtan, "Why Hourly Averaged Measurement Data is Insufficient to Model PV System Performance Accurately", *Twentieth European PVSEC*, Barcelona, 2005

[3]  D.King et al., "Photovoltaic Array Performance Model", SAND 2004-3535, 2004

[4]  E. Maxwell, "A Quasi-Physical Model for Converting Hourly Global Horizontal to Direct Normal Insolation", SERI/TR-215-3087, 1987

[5]  S. Wilcox and W. Marion, "Users Manual for TMY3 Data Sets", NREL/TP-581-43156, Revised May 2008

## ACKNOWLEDGEMENTS