Applications

The Character of Power Output from Utility-Scale Photovoltaic Systems

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Power produced by utility-scale solar photovoltaic (PV) systems has fluctuations on both short and long time scales. Power spectral density (PSD) analysis provides information on the character of these power fluctuations. Examination of the correlation and step size of the power output between several PV sites within a multi-site system allows assessment of geographic diversification for addressing intermittency. Both techniques provide insight into the characteristics of firm power and/or demand response required to accommodate large-scale PV deployment. Copyright © 2007 John Wiley & Sons, Ltd.

INTRODUCTION

At large scale, the intermittent character of power generated from sources such as wind and solar photovoltaic (PV) systems can affect power quality and reliability. The effects of PV intermittency on grid voltage have been previously modeled.[1,2] Recently, the effects of PV at high penetration levels in a traditional electricity system have been examined by using hourly average insolation as a proxy for PV power output and real load data with hourly time resolution.[3] Monthly averages of real power output data from large-scale PV power plants have been published.[4,5]

Here, we present analyses of real power output data with 10 s and 1 min resolution from a single 4 MW site and data with 10 min resolution from three ~100 kW sites. The power spectral density (PSD) of the output of large-scale PV can provide insight into the character of both cyclic (daily and seasonal) and non-cyclic

(weather-related) fluctuations associated with array output. Power spectral analysis can give an indication of the type of firm power or demand response appropriate to compliment PV, including required ramp rate.[6] Comparison of the output from several distributed sites provides information about geographic smoothing, previously examined for distributed wind power.[6–9] The statistics of correlation between distributed sites in the time domain can also be used to assess geographic smoothing, an approach used previously to evaluate the impact of site diversity on wind power.[10]

DATA

Data were obtained from two sources (for a description of the data and the handling of data dropouts, see Appendix). The first was a 4·59 MW$_p$ fixed latitude-tilt, south facing array operated by Tucson Electric Power (TEP) on a 44 acre site in northeastern Arizona.[11] Real power output data sampled at 10 s

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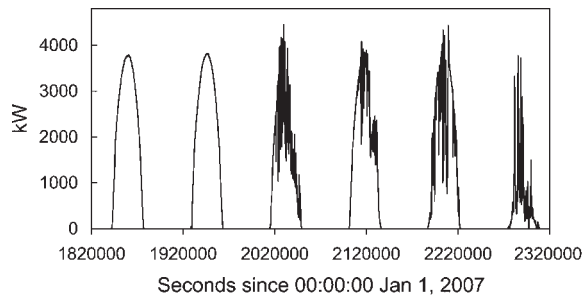†E-mail: apt@cmu.edu

Figure 1. Real power output data from TEP over 6 days at 10-s sampling frequency

Figure 3. Relative locations of the three APS tracking array sites in Arizona

intervals were obtained for two months, January–February 2007: a portion is shown in Figure 1. The observed capacity factor for these two winter months was 18·1%. Real power output data were also obtained with a sampling rate of once per minute for 2 years (January 2004–December 2005). Figure 2 presents an example of power output from the array on 3 June 2004. The observed capacity factor over the 2 years was 19·1%.

The second data source was three single-axis, horizontal tracking (east to west) systems operated by Arizona Public Service (APS): a 228·5 kW$_p$ system in Prescott, Arizona; a 144 kW$_p$ system in Scottsdale, Arizona; and a 121 kW$_p$ system in Yuma, Arizona (relative locations are shown in Figure 3). Approximately 1 month of consecutive data (22 June–27 July 2006) with 10 min sampling frequency was analyzed (4 days of these data are shown in Figure 4). The capacity factors over this summer period were 24·2, 26·7, and 26·8% for the three locations, respectively. We also calculated winter capacity factors for the APS arrays for 21 December 2005 (14:00:00) to 17 January 2006 (08:00:00); they were 13·3, 11·9, and 13·2%, respectively.
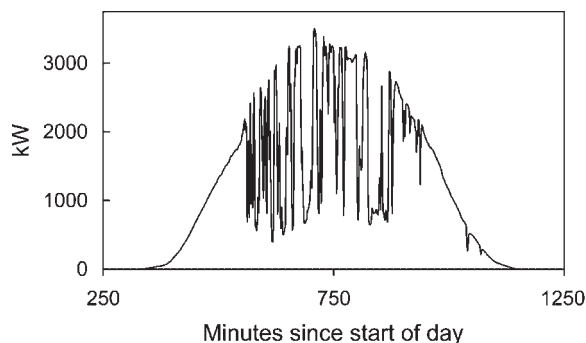
GEOGRAPHIC CORRELATION AND STEP SIZE ANALYSIS

The linear correlation of the real power output between pairs of the three APS sites was computed using data from daylight hours and normalizing the arrays to nameplate peak capacity. The sites exhibit a high degree of positive correlation despite their geographic separation (Table I), which will constrain the use of site diversification for damping fluctuations in this geographic region.

One technique used in wind analysis is to calculate the step size of the difference in power between two consecutive power output samples.[10] As for wind, the average, maximum, and standard deviation of the magnitude of the step sizes decrease for the sum of the three APS sites relative to the sites individually (Table II). The histogram of steps (Figure 5) indicates that some damping of the higher magnitude fluctuations (above about 20% of nameplate capacity) occurs (Figure 5b), as previously observed for wind power output.[8,9] We caution that these data are 10-min samples, and that one array (Prescott) has twice the peak power output either of the other two. Samples at

Figure 2. Real power output data from TEP over one full day in summer (3 June 2004) at 1-min sampling frequency
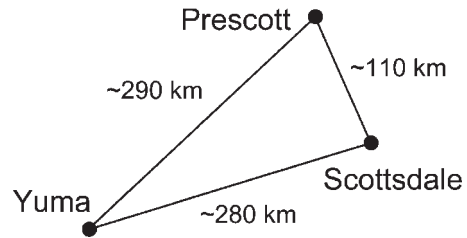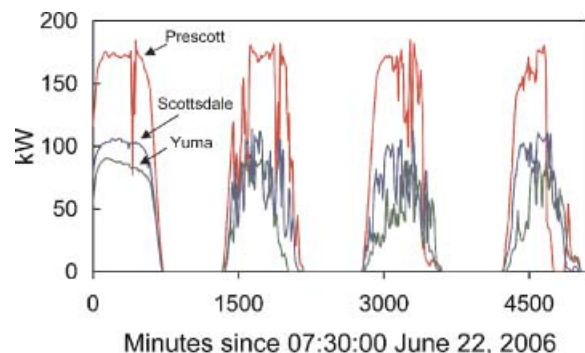

Figure 4. Real power output data from individual APS arrays over ~4 days at 10-min resolution

Table I. Output power correlation between three pairs of
sites in APS for daylight hours over 35 days

	Prescott	Yuma
Scottsdale	0·70	0·73
Yuma	0·57	

higher time resolution may show different behavior,
and the variability of the Prescott data dominates the
sum.

POWER SPECTRA

The method used to estimate the power spectrum of
power output has been described previously.[6] The
power spectrum was estimated for the TEP site for
2 years of 1 min resolution data (Figure 6) and for
2 months of 10 s resolution data (Figure 7). In both, a
peak is observed at a frequency of 1.16×10^{-5} Hz
(24 h) and is an expected result of the cyclic daily
availability of the solar resource; higher harmonics of
1 day are also present, as expected in a Fourier
transform. The linear region of the power spectrum
(frequency f greater than approximately 2×10^{-3} Hz)
is well fit by a function of the form $f^{-1.3}$ for all data
sets. In contrast, the power spectrum of wind turbine
output power is a Kolmogorov spectrum ($f^{-5/3}$).[6]

The flatter PV power spectrum implies that
fluctuations in the 10 min to several hour range are
relatively larger in magnitude for PV than for wind at
the sites examined. Assuming an electric power system
like the one in place today, this implies an increased
need for dispatchable power or dispatchable demand
response to compensate for PV fluctuations in this
frequency region relative to wind, which is likely to
make compensating for the intermittency of PV more
expensive than for wind.

The high frequency attenuation of fluctuations
(above $\sim 5 \times 10^{-3}$ Hz, Figures 6 and 7) may be due

Table II. Comparison of statistics of the absolute value of
the step size as a fraction of maximum output for the three
APS sites individually and the sum of the three sites

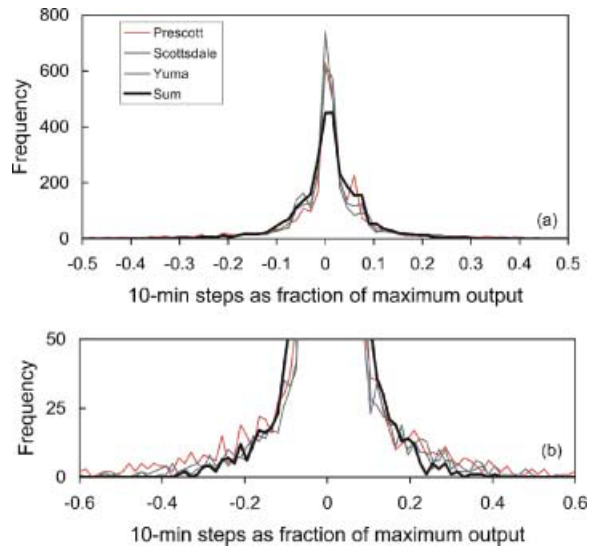|	Prescott	Scottsdale	Yuma	Sum
Average	0·066	0·052	0·049	0·049
Maximum	0·77	0·63	0·64	0·41
Standard deviation	0·10	0·076	0·071	0·055
Stdev, 10% of max and lower	0·026	0·025	0·026	0·026
Stdev, 20% of max and higher	0·12	0·089	0·080	0·047

Figure 5. Change in fluctuation of power output from APS
arrays with site diversity: (a) histogram of 10-min steps
(daylight only) and (b) detail of the tails of this distribution

in part to the time required for a cloud shadow to cross
the full array. If this hypothesis is correct, it might be
expected that the low-pass filtering effect seen in the
PSD of a small portion of the array would be shifted to
higher frequencies relative to the PSD of the full array.
We have examined sub-array data for 2007 at 10-s
resolution, and the power spectrum from a single,
135 kW$_p$ unit within the larger TEP array (Figure 8)
appears to confirm this hypotheses.

The power spectrum for a single APS site is very
similar to that from the three combined sites (Figure 9).
For wind, Nanahara et al.[8] report smoothing when
combining output from six turbines relative to a single
turbine as a change in the slope of the power spectrum;
they report an attenuation of the magnitude of
fluctuations of frequencies above $\sim 1.0 \times 10^{-3}$ Hz.
The available data for the present study limit our
observations to frequencies below 8.3×10^{-4} Hz, but it
appears from the spectral analysis that fluctuations
slower than this frequency (20 min) and faster than
$\sim 2 \times 10^{-5}$ Hz (14 h) are not significantly diminished
due to site diversity over several hundred km.

For wind, at frequencies between 1 h and 2·5 min the
slope of the power spectrum has been reported to be
very close to that of load.[6] Therefore over that interval,
it appears reasonable to treat wind as negative load
(although because load and wind power are not
anti-correlated, this is not the same as stating that the
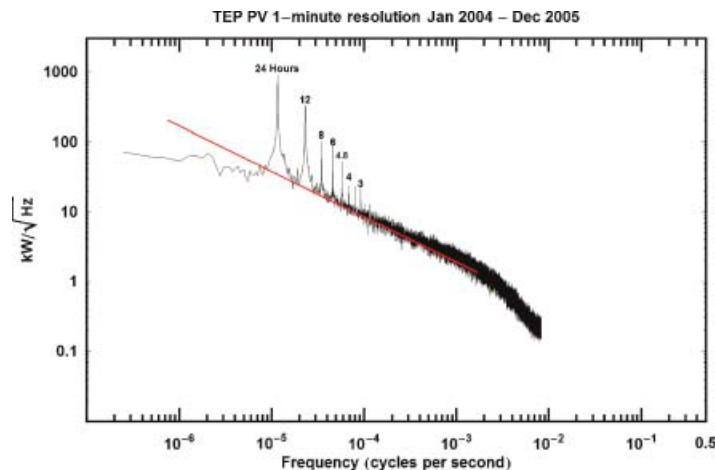two cancel each other out to create a smooth match

Figure 6. Power spectrum of TEP array over 2 years at 1-min sampling frequency with overlaid $f^{-1.3}$ spectrum

between load and supply). PV power output exhibits no similar match in slope with the power spectrum of load in any frequency region, implying a need for increased firm power relative to wind.

DISCUSSION

The intermittency of large-scale PV power for four sites in the American southwest desert is significant, even during daylight hours.[12] These data also imply that site diversity over a ∼280 km range does not dampen PV intermittency sufficiently to eliminate the need for substantial firm power or dispatchable demand response.

The high correlation between geographically dispersed arrays may indicate that high, widespread clouds are responsible for a portion of the intermittency. Observed rapid and deep fluctuations at time scales of 10 s to several minutes may indicate that a component of the intermittency is due to low, scattered clouds with significant opacity. We observe a number
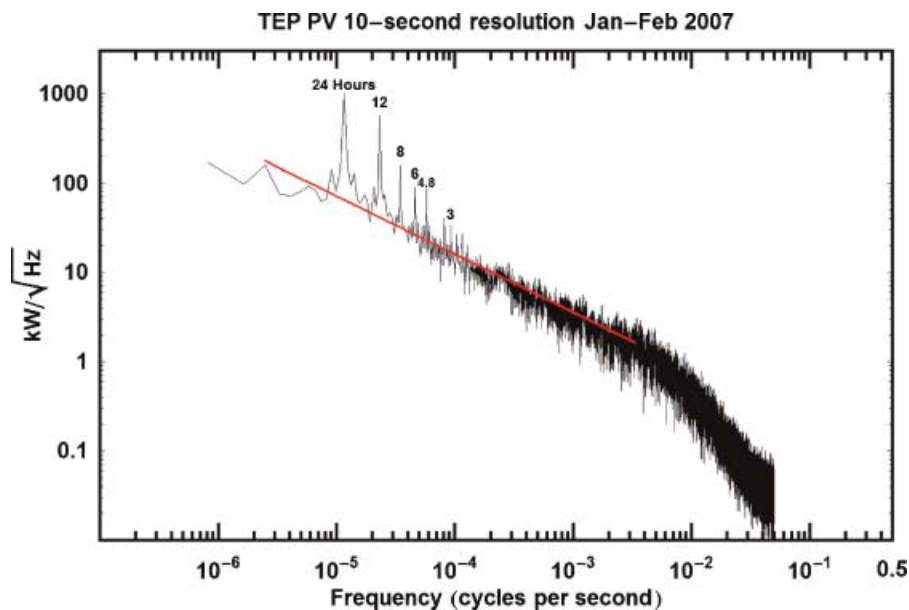

Figure 7. Power spectrum of TEP array over 2 months at 10-s sampling frequency with overlaid $f^{-1.3}$ spectrum
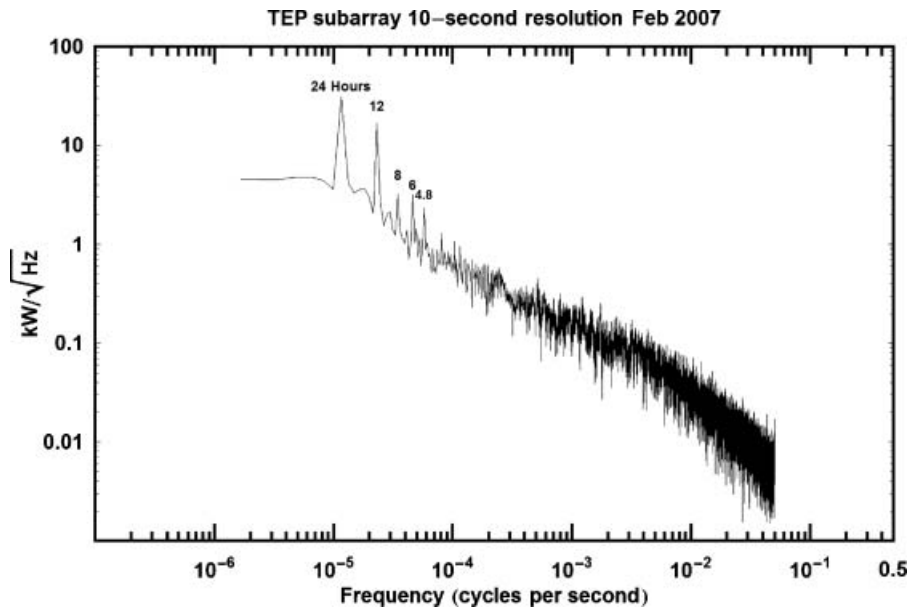
Figure 8. Power spectrum of TEP sub-array for 1 month at 10-s resolution. The sub-array low-pass filter behavior is shifted to higher frequencies relative to the full array (Figures 6 and 7)

of examples of output power rising above nameplate capacity before and after deep drops in power. This may be due to focusing of sunlight around the edges of low clouds.

If PV becomes economically attractive enough to be deployed at large scale, intermittency is likely to be matched with dispatchable power, storage, and/or demand response. It may be argued that the
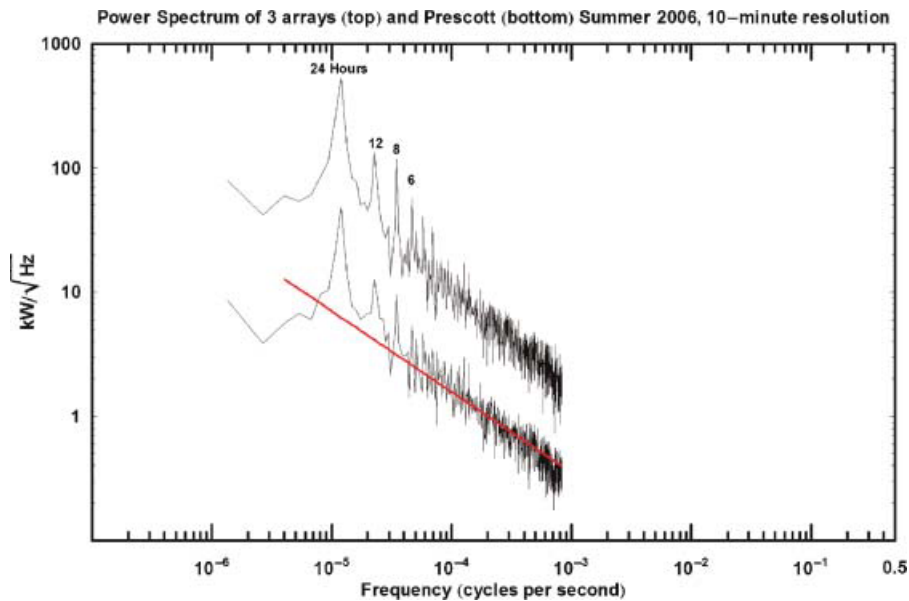

Figure 9. Power spectra of APS PV arrays for 35 days at 10-min resolution. Prescott site (lower spectrum) with overlaid $f^{-1.3}$ spectrum and sum of all three APS sites (upper spectrum). The upper spectrum has been multiplied by 5 to offset the two spectra for clarity

intermittency of solar PV is not an integration issue because wind is also intermittent and has been integrated at scale. In systems with relatively large fractions of wind, control issues are generally solved by fast-ramping assets either within the control area or through an interconnection.[13] Such compensation has economic costs. Knowledge of the character of the intermittency can be used to minimize the costs. As argued previously for the case of wind,[6] an ensemble of generators, energy storage, and demand response would likely be a more economically efficient solution to match the linear region observed in the power spectrum of PV array output power than a source with a single ramp rate.

Acknowledgements

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APPENDIX: DESCRIPTION OF DATA AND HANDLING OF DATA DROPOUTS

In the 2 months of 10-s sampling frequency data from TEP used in this analysis, 3 days (20–22 January 2007) were excluded due to insufficient data acquisition density. The remaining 56 days were used in our analysis. Data dropouts occurred for 0·43% of 483 840 expected points ($\sim$0·42% of daylight points). These missing data were dealt with in one of several ways. For long duration dropouts during daylight hours (greater than several minutes), the data were filled in with a normalized model constructed by averaging several smooth data days (similar to the first two in Figure 1) from the same month as the problem data. This occurred for only 1 day in this data set. For dropouts during daylight hours and duration of less than $\sim$several minutes, data were filled in with a linear regression using three points before and three points after the missing data. For single point dropouts, the average of the point before and the point after was used.

For the 2 years of TEP data with 1-min resolution used in our analysis, data dropouts occurred for 1·4% of the 1 052 640 total expected data points ($\sim$2·2% of daylight data points). Overall, we identified two types of dropouts: (1) missing data points and (2) array output uncorrelated with the independent solar insolation monitor, most often observed as zero output from the array while the monitor indicates that sunlight has not dropped to zero. (TEP believes there are several possible reasons for this second type of dropout. In winter months during early hours of the day, snow that has accumulated over night will melt and fall off more quickly from the independent solar monitors than the full-size modules in the array. At other times of the year or later in the day, the dropouts are due to either system maintenance or to a power outage after which the system only partially returns to operation.) For long duration dropouts during daylight hours (i.e., generally >20 min), the data were filled in with a normalized model constructed by averaging all smooth data days that occurred in the same month as the problem data. For dropouts during daylight hours and duration of less than $\sim$20 min, data were filled in with a linear regression using three points before and three points after the missing data. Where possible, data were filled in by scaling the average array output to the independent monitor information (the ratio was determined by using the average ratio of these values for three points before and three points after the data dropout), but this was much less common than use of the model or a linear regression.

The 10-min sampling frequency data from APS used in our study were free of data dropouts. Since the first and last days of this interval were not used in their entirety, the total number of data points for all three sites was 5046 for the approximately 35 days of consecutive data.