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 timescales. Power spectral density 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 required firm power and / or demand response required to accommodate large-scale PV deployment.

KEY WORDS: grid-connected PV systems, intermittency, spectral analysis

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1. 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 photovoltaic power plants have been published.[4, 5]

Here, we present analyses of real power output data with 10 second and 1 minute resolution from a single 4 MW site and data with 10 minute 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]

2. DATA

Data were obtained from two sources. 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 second intervals were obtained for two months, January - February 2007: a portion is shown in Figure 1.[12] 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 June 3, 2004.[13] The observed capacity factor over the two 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[14] (relative locations are shown in Figure 3). Approximately one month of consecutive data (June 22 - July 27, 2006) with 10 minute sampling frequency was analyzed (four 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 December 21, 2005 (14:00:00) to January 17, 2006 (08:00:00); they were 13.3, 11.9, and 13.2%, respectively.

3. GEOGRAPHIC CORRELATION AND STEP SIZE ANALYSIS

The linear correlation of the real power output between pairs of the 3 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 1), 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 2). 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-minute samples, and that one array (Prescott) has twice the peak power output either of the other two. Samples at higher time resolution may show different behavior, and the variability of the Prescott data dominates the sum.

4. 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 minute resolution data (Figure 6) and for 2 months of 10 second resolution data (Figure 7). In both, a peak is observed at a frequency of 1.16×10^{-5} Hz (24 hours) 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 minute 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 ~ 5×10^{-3} Hz, Figures 6 and 7) may be due 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 second 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. 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 ~1.0×10^{-3} Hz.[8] The available data for the present study limits our observations to frequencies below 8.3×10^{-4} Hz, but it appears from the spectral analysis that fluctuations slower than this frequency (20 minutes) and faster than ~2×10^{-5} Hz (14 hours) are not significantly diminished due to site diversity over several hundred km.

For wind, at frequencies between 1 hour and 2.5 minutes 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 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.

5. DISCUSSION

The intermittency of large-scale PV power for four sites in the American southwest desert is significant, even during daylight hours. 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 seconds to several minutes may indicate that a component of the intermittency is due to low, scattered clouds with significant opacity. We observe a number 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 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.[15] 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 photovoltaic array output power than a source with a single ramp rate.

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11. For details see http://greenwatts.com/pages/solaroutput.asp.
12. Three days (January 20-22) were excluded due to insufficient data acquisition density. The remaining 56 days were used in our analysis. Data dropouts occurred for 0.4% of 483,840 expected points (~0.4% 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 only for one day in this data set. For dropouts during daylight hours and duration of less than ~several minutes, data were filled in with a linear regression using 3 points before and 3 points after the missing data. For single point dropouts, the average of the point before and the point after was used.
13. Data dropouts occurred for 1.4% of the 1,052,640 total expected data points (~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 minutes), 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 ~20 minutes, data were filled-in with a linear regression using 3 points before and 3 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 3 points before and 3 points after the data dropout), but this was much less common than use of the model or a linear regression.

14. 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.
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TABLES

Table 1. Output power correlation between 3 pairs of sites in APS for daylight hours over 35 days.

	Prescott	Yuma
Scottsdale	0.70	0.73
Yuma	0.57	

Table 2. Comparison of statistics of the absolute value of the step size as a fraction of maximum output for the 3 APS sites individually and the sum of the 3 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

FIGURES

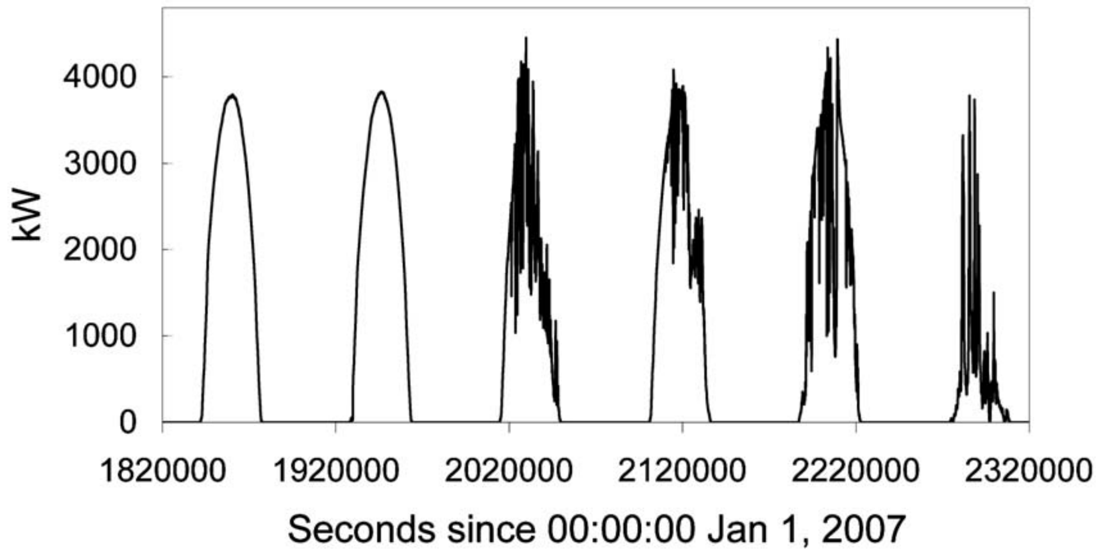

Figure 1. Real power output data from TEP over 6 days at 10 second sampling frequency.

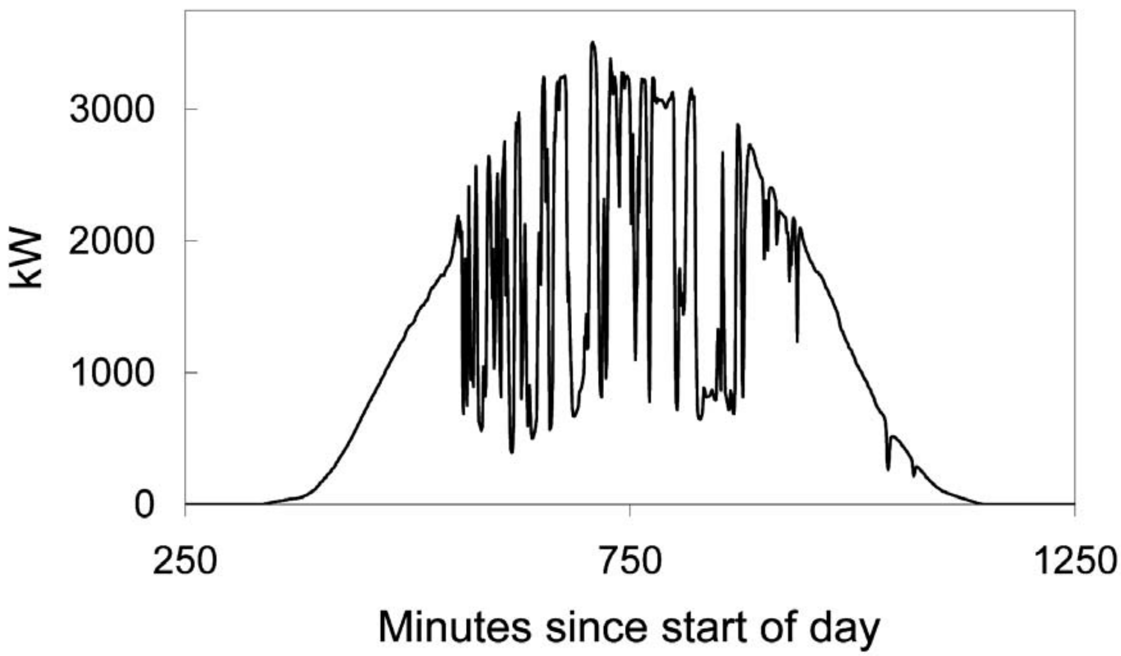

Figure 2. Real power output data from TEP over one full day in summer (June 3, 2004) at 1 minute sampling frequency.

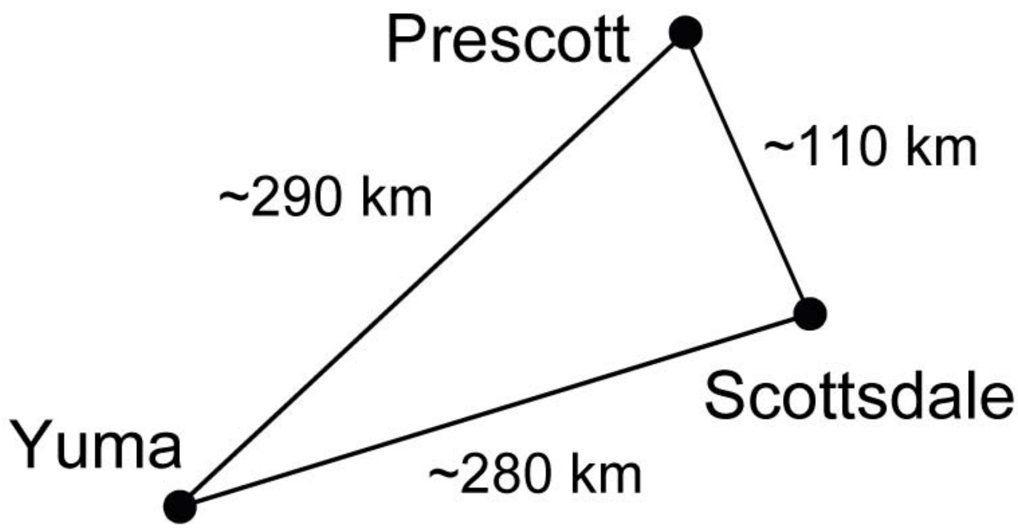

Figure 3. Relative locations of the three APS tracking array sites in Arizona.

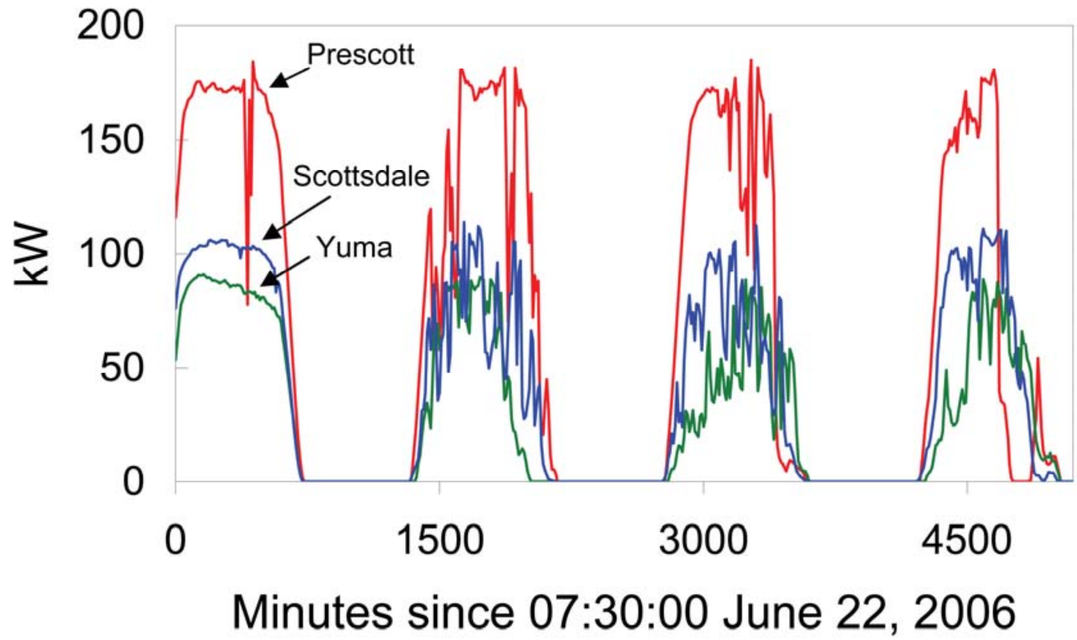

Figure 4. Real power output data from individual APS arrays over ~4 days at 10 minute resolution.

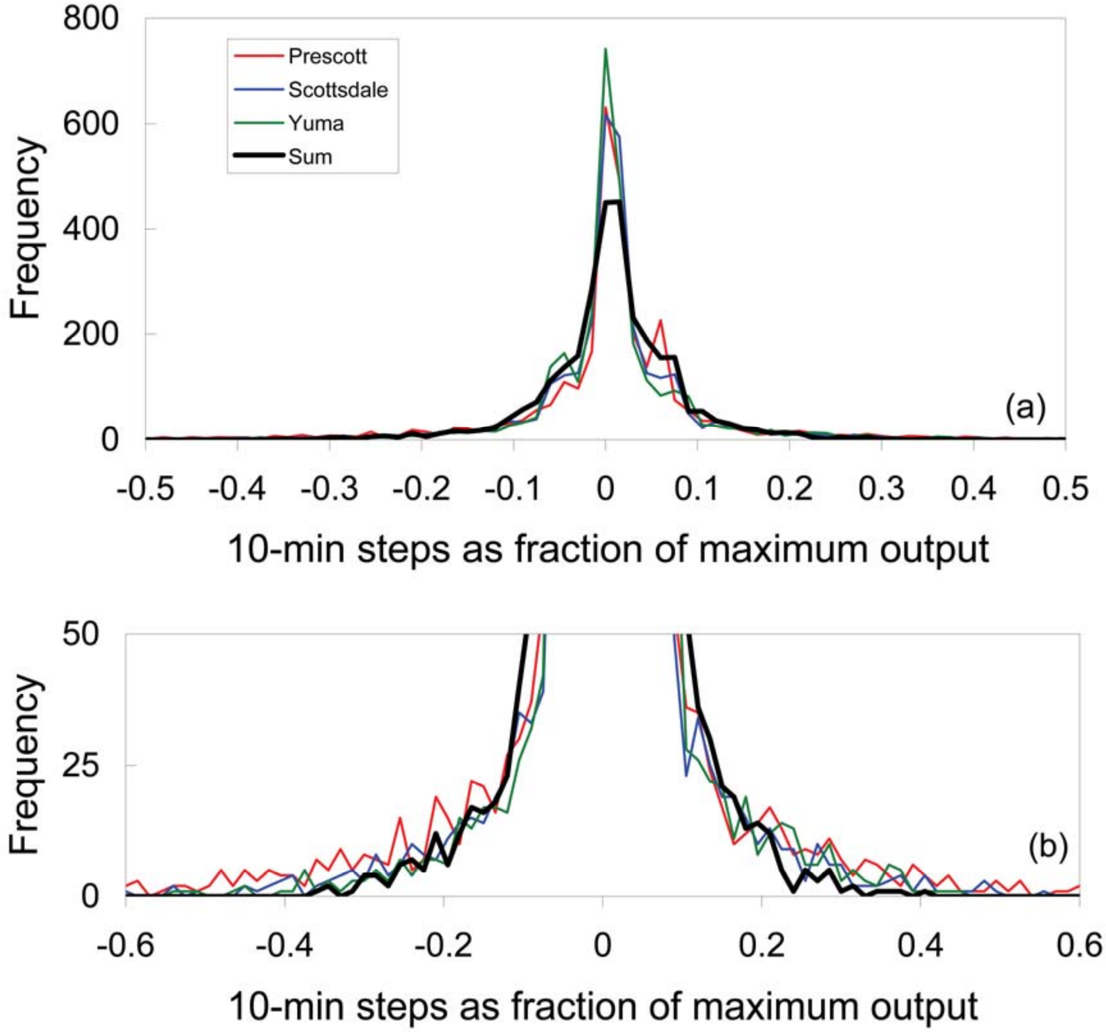

Figure 5. Change in fluctuation of power output from APS arrays with site diversity: (a) histogram of 10 minute steps (daylight only) and (b) detail of the tails of this distribution.

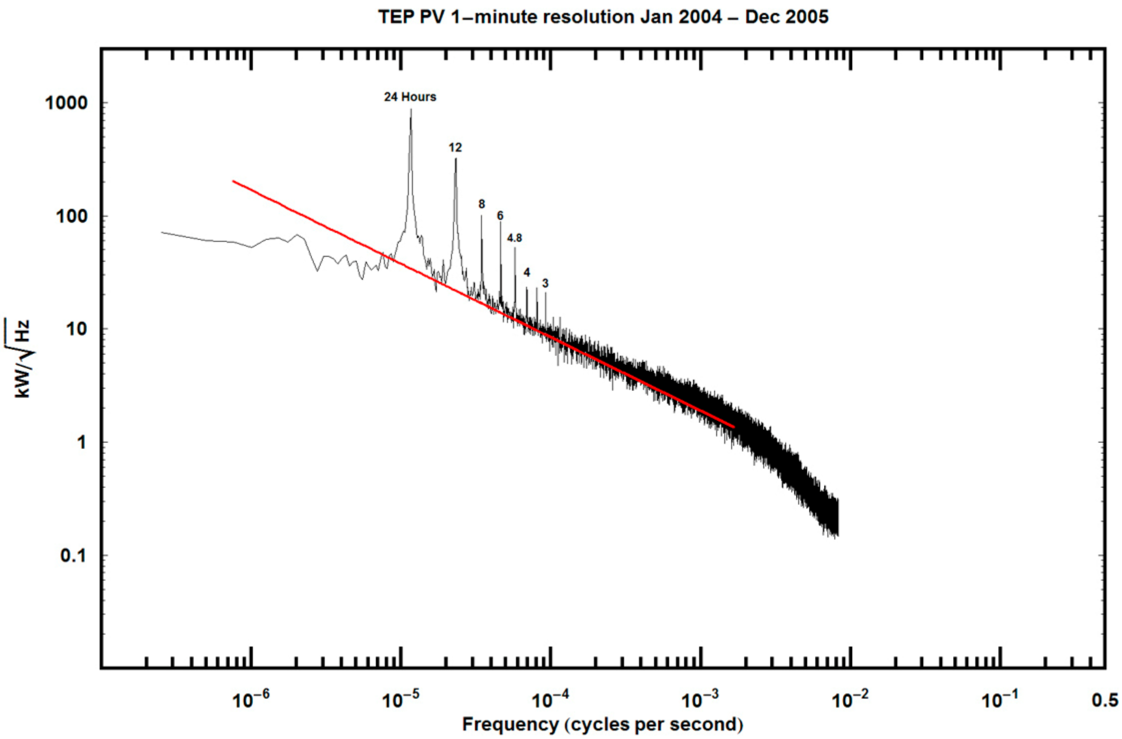

Figure 6. Power spectrum of TEP array over 2 years at 1 minute sampling frequency with overlaid f $^{-1.3}$ spectrum.

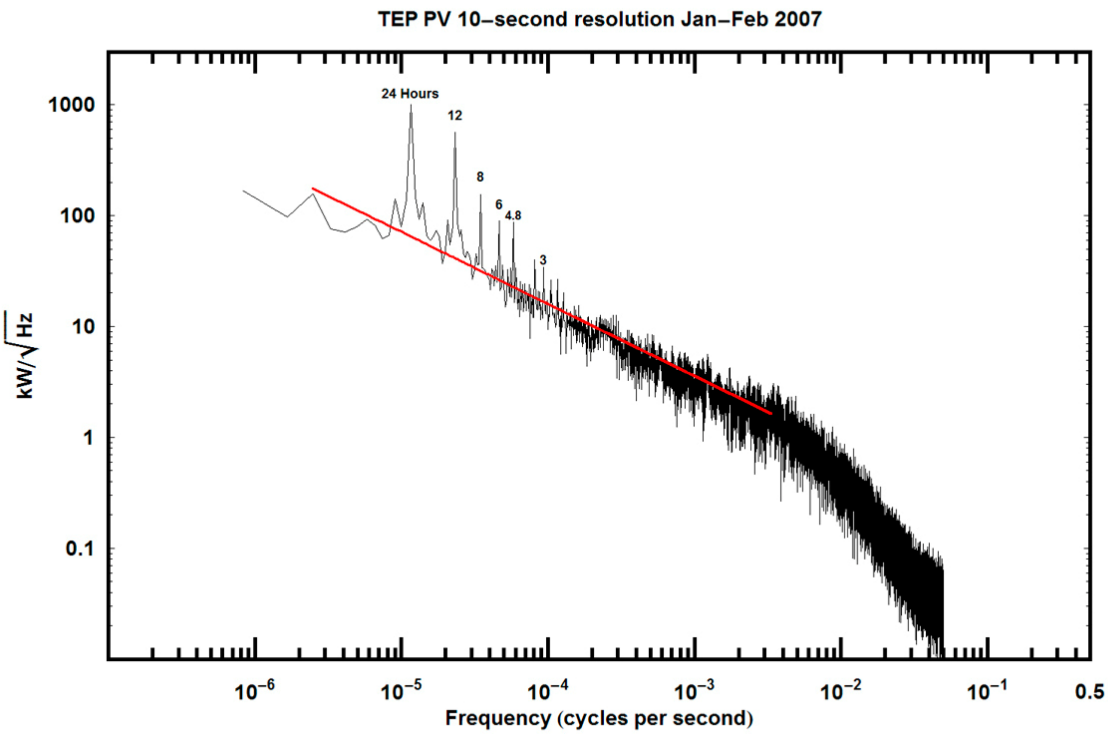

Figure 7. Power spectrum of TEP array over 2 months at 10 second sampling frequency with overlaid f $^{-1.3}$ spectrum.

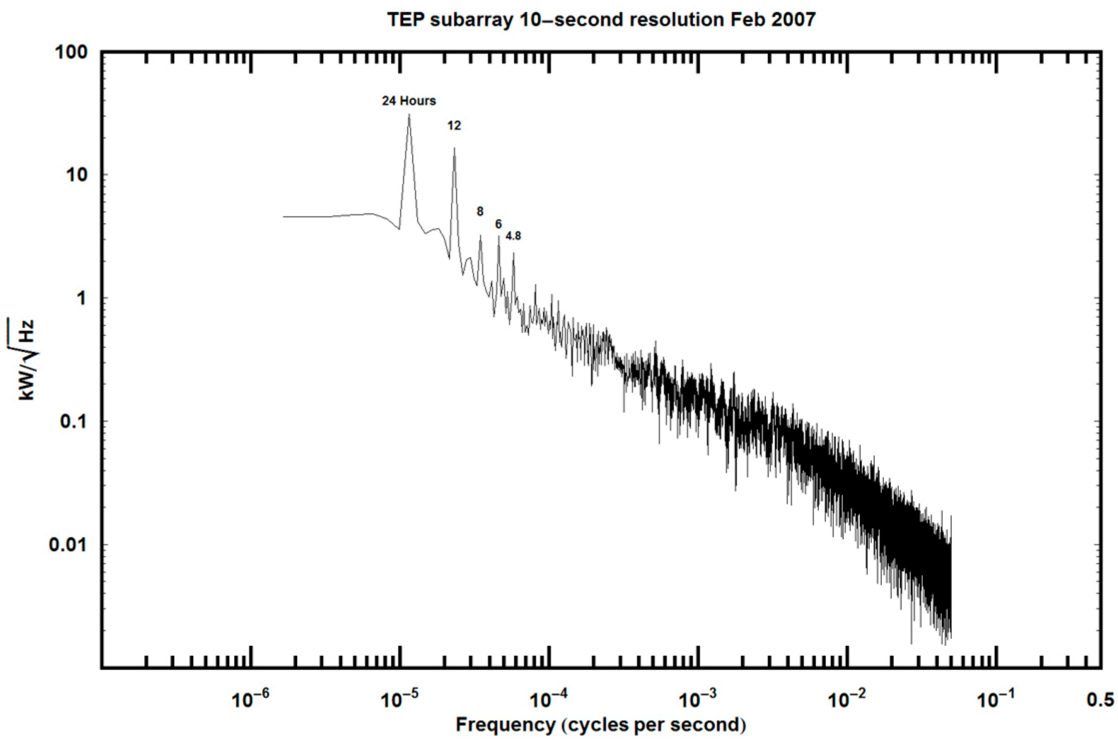

Figure 8. Power spectrum of TEP sub-array for 1 month at 10 second resolution. The sub-array low-pass filter behavior is shifted to higher frequencies relative to the full array (Figs. 6 and 7).

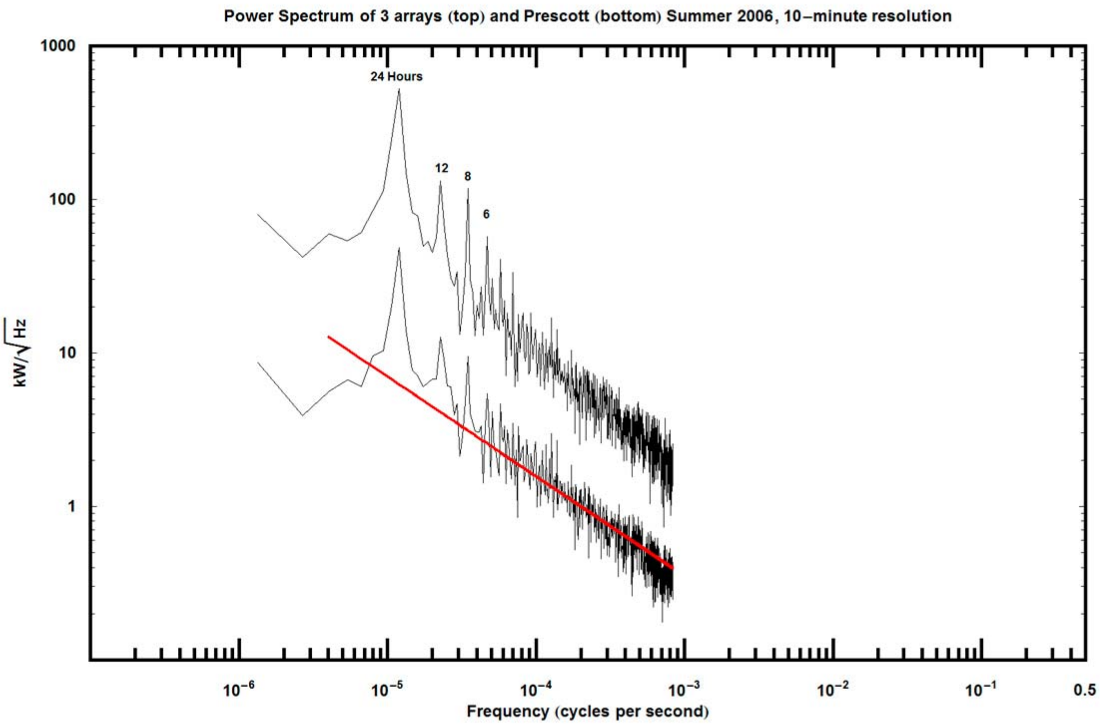

Figure 9. Power spectra of APS tracking PV arrays for 35 days at 10 minute resolution. Prescott site (lower spectrum) with overlaid $f^{-1.3}$ spectrum and sum of all three APS sites (upper spectrum). The upper spectrum has been multiplied by 5 to offset the two spectra for clarity.