Quantifying Photovoltaic Fluctuation with 5 kHz Data: Implications for Energy Loss via Maximum Power Point Trackers

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***Abstract*—We aim to systematically quantify photovoltaic (PV) variability contained within different frequency bands, primarily for applications in PV maximum power point tracking (MPPT) design. We first discuss the usefulness in quantifying energy capture for various maximum power point (MPP) update rates from nearly 500 days of 5 kHz photovoltaic recordings. Next, we justify the methods used to convert MPP sweep data to single-point, usable, current, voltage, and power values. We discuss fitting methods that yield the MPP under calm irradiance dynamics and explore the approach used during periods of more stochastic changes. This is followed by analysis of raw, high-frequency content and a proposed method to calculate associated energy capture reduction. The conclusion finds an absolute upper bound on solar data variability for a given MPP update rate in terms of energy capture. Finally, we use the previous results and demonstrate an economic analysis that can aid in designing future MPP tracker specifications.**

***Index Terms*—Photovoltaic (PV), solar variability, maximum power point tracking (MPPT), high frequency solar data, frequency domain analysis, energy loss calculation, economic analysis, stochastic energy**

I. Introduction

Capturing the maximum power produced from a photovoltaic (PV) panel has long been a research focus, and many maximum power point tracking (MPPT) algorithms have been designed to fulfill this goal [1-3]. However, in order to maintain maximum power capture, an MPPT device needs to update its measurement of the maximum power point (MPP). This is typically done at a constant rate. As of now, a "necessary" update rate is not clearly defined despite being a fundamental parameter of PV energy capture. Likewise, long-term solar analysis has varying definitions for "high-frequency" update rates ranging from 1 minute [4], to 20 s [5-6], to the higher rates, seemingly topping out around 1 s [7-8]. Since little or no work has gone into quantifying the cost-benefit curve of update rates, some have tried to cater their update rate to the dynamics of the tracking device rather than the solar resource. One approach for a perturb and observe (P&O) MPP tracker balances losses between steady state oscillation (characteristic of P&O) and energy capture reduction due to poor tracking of rapid transients [9]. While this may have short-term merits, we can change future device dynamics or even the MPPT algorithm; in contrast, we cannot meaningfully change the dynamics of the sun, clouds, or birds.

Designers of future MPPT devices may ask themselves, "Is there such a thing as updating the MPP too often, and if so, how fast is 'fast enough' when it comes to update rates?" Determining quantitative answers to these questions has implications primarily for MPPTs, but secondarily for grid stability and dynamic load control as discussed in [10]. In an ideal world, there would be no limit. Knowing the MPP at all times with ultra-fast updates means no source energy would be wasted. In reality, however, more rapid updates necessitate compromises. Higher update rates require faster sampling and more data processing, which may lead to higher overhead energy consumption and higher cost. If the additional energy capture does not compensate for these disadvantages, then it would not make sense to implement an increased update rate. Where is the tipping point between reduced energy capture and the cost of increased update rates? The purpose of this paper is to present a quantitative tool which will answer part of that question. The results of our paper compare update rates to energy capture reduction using long-term, high-frequency solar data collected from atop Everitt Laboratory at the University of Illinois at Urbana-Champaign. The paper steps through the process of data analysis so that similar studies may be performed for other sites.

In this paper, we briefly discuss how the raw 5 kHz solar data were captured. We follow this with broad descriptions of the data processing that transformed the raw sweep data set into single, calculated values. We then discuss the frequency content observed in the data and its implications. Next, we describe our MPPT model that calculates missed energy capture for a given update rate. The calculated value for each MPPT update rate represents a ceiling for the amount of energy capture that is potentially sacrificed by an otherwise ideal MPPT device. Finally, we use the missed energy result as the foundation for an economic analysis that can be used when designing MPPT systems.

II. Solar Data Collection and Processing

Photovoltaic data collection for this experiment was performed by fellow researchers at the University of Illinois at Urbana-Champaign and spans from July 2012 to January 2014 [11]. During data collection, two, identical, rooftop-mounted, 20 W, PV panels, connected to two different meters, were placed side by side to eliminate spatial variation as much as

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possible. One meter was a Keithley 2420 that performed a sweep across the current-voltage (I-V) curve every 2.5-3.9 seconds, and the other was an Agilent 34410A that recorded short-circuit current at 5 kHz.

The data acquisition mechanism is depicted in Fig. 1. The sweeps from the Keithley ("slow") meter enable us to calculate open-circuit voltage (V_{OC}), short-circuit current, and MPP voltage, current, and power (V_{MPP}, I_{MPP}, P_{MPP}). The Agilent ("fast") data provides high-frequency short-circuit current readings (I_{SC}) that, as will be shown, can be used to calculate high-frequency changes in the available power. To clarify, both the Agilent and Keithley meters measured short-circuit current, but in this paper I_{SC} will always refer to the Agilent data. Keithley short-circuit current data was used for verification of measurement accuracy against the Agilent meter and as a check of instrument synchronization.

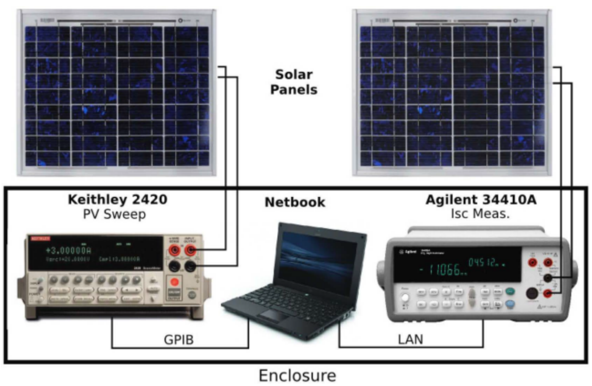

Fig. 1. Solar data acquisition hardware setup [11].

Sampling at 5 kHz seems excessive, but the objective is to capture every possible transient. Common sources of rapid transient creation might be the occurrence of fast clouds, birds, or even airplanes casting flickering shadows on time scales much less than 1 second (faster than 1 Hz). Sampling at 5 kHz means that even in extreme cases we can reconstruct the change in irradiance with multiple samples for each event.

For the analysis performed in this paper, ten different, non-overlapping, 10-day samples (100 total days) were taken at random from the data set such that none contained windows of missing data. The 5 kHz data comes in an immediately usable form, but the slow I-V curve data requires processing to obtain values for short-circuit current, open-circuit voltage, and the various MPP values. Slow short-circuit current data consists of three data points near zero volts, the square symbols in Fig. 2. Open-circuit voltages (V_{OC}) were obtained from the sweeps that crossed the voltage axis, the triangle symbols in Fig. 2.

MPP voltage, current, and power took the most processing. In Fig. 2 the MPP region contains 100 points on the "knee" of the I-V curve. As can be seen in Fig. 3, the measurements contain a combination of high-frequency fluctuations and measurement noise. Simply picking the point with the peak value can lead to misleading and inaccurate MPP values. To alleviate this, a 4th-order polynomial least-squares fit was applied to the data to capture the overall nature of the sweep.

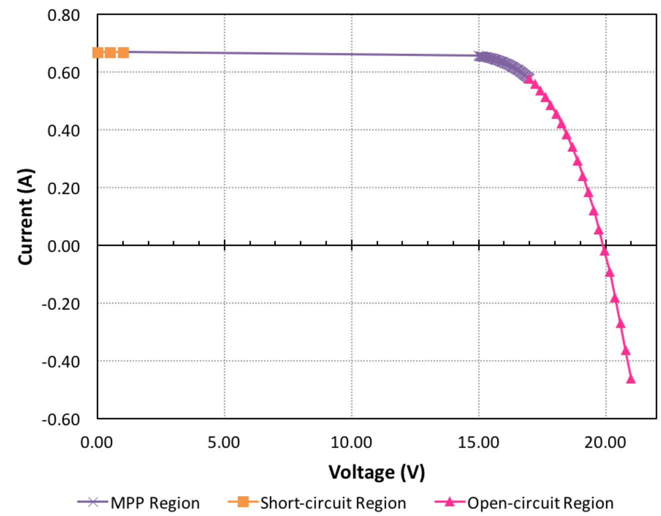

Fig. 2. Slow, current-voltage (I-V), full-range sweep containing data points near the short-circuit, open-circuit, and maximum power point region.

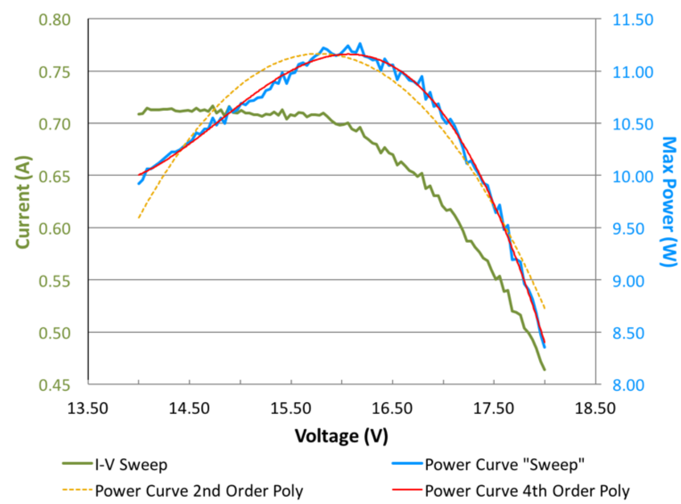

Fig. 3. Slow I-V sweep in MPP region and max power curve with polynomial least squares fits.

Implementing a 4th-order fit instead of the 2nd-order polynomial used in [11] increased the regression coefficient from $R^2 = 0.95$ to $R^2 = 0.995$ for a typical MPP sweep. Higher-order polynomials or other functions may be used instead, but the 4th-order polynomial captures the expected shape of the power curve reasonably well. Rather than solving for the peak algebraically, it was computationally more efficient to evaluate the polynomial function at 500 equally-spaced points over the same range of voltages as the original MPP region and then select the maximum value from this finely-discretized set.

For instances where a peak value was not found, the polynomial kept increasing or decreasing monotonically because the slow meter missed the MPP. In this case, the maximum interpolated value (an endpoint) was chosen as the MPP. An example is provided in Fig. 4 in which three consecutive MPP sweeps are shown with the middle (orange) sweep failing to span the peak power value. This failure is likely due to a sudden drop in irradiance despite a previously increasing trend. Following the procedure mentioned above, the MPP power would be that associated with the power at the left end of the middle curve, or 16.00 V in this specific instance. Sometimes the fluctuations were so fast that within a single sweep, the polynomial approximation generated two peaks (or potentially more if a higher-order polynomial were to be used). Fig. 5 exemplifies such a scenario, where the polynomial was a poor approximation of the raw data. In cases like this, the maximum value of the raw sweep data was chosen instead of the polynomial peak. More generally, polynomial approximations with $R^2 < 0.99$ were deemed invalid and the raw data peak used instead. We assert that using the polynomial fit is only beneficial if it closely represents the original data. Thus, the instance of two peaks in Fig. 5 would be ruled out due to a poor polynomial fit. After computing values from the slow meter data, the results were synchronized with the fast meter measurements using time stamps recorded in both data sets.

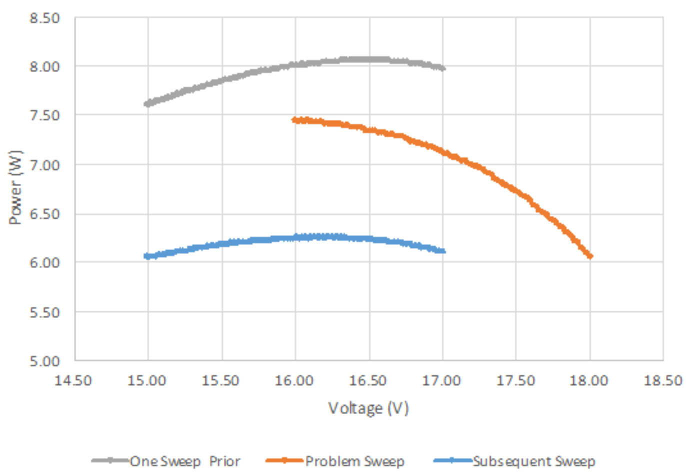

Fig. 4. Three consecutive MPP power curve sweeps with the middle sweep missing the MPP.

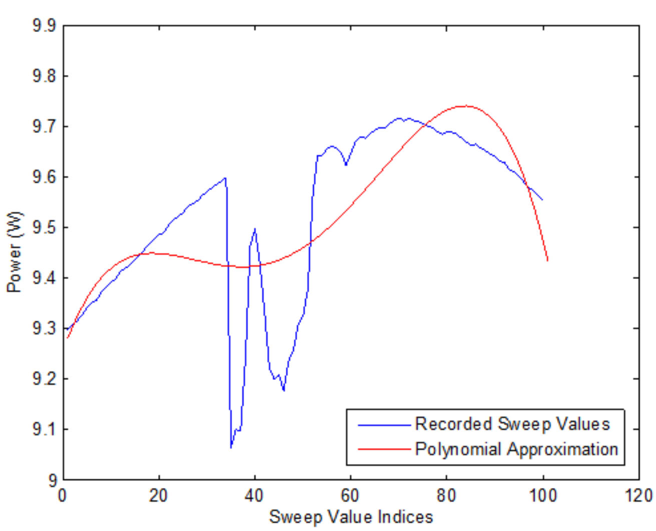

Fig. 5. Rapid transient during MPP sweep and associated poor fit polynomial approximation.

III. Frequency Domain Analysis

Short-circuit current, for which we have high-speed data, is valuable when analyzing the frequency content of solar power; however, the issue is how much variation exists in the *power* coming out of the panel, i.e., we seek the frequency content of I_{MPP} and V_{MPP}. It is known that the ratio of I_{MPP} to I_{SC} is nearly constant, especially over short periods where temperature changes are not significant [12-14]. Fig. 6 provides additional support for interchanging the two metrics through an appropriate scaling factor, by showing the strong correlation between I_{MPP} and I_{SC}. We further demonstrate in Fig. 6 that any deviation from this strictly linear relationship arose from the slow meter sampling rate during periods of rapid insolation change.

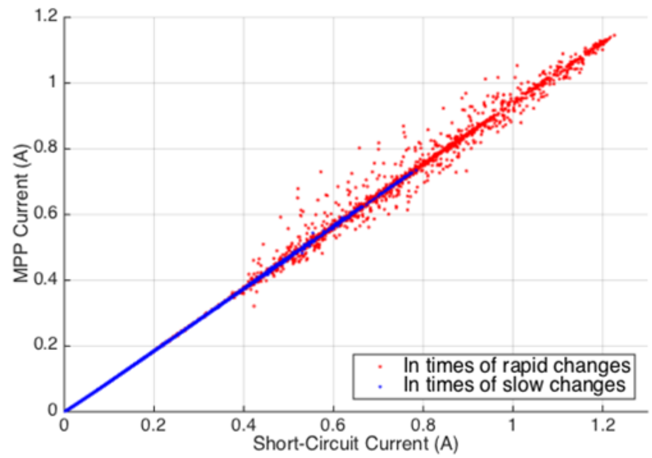

Fig. 6. Linear correlation between slow meter MPP current and fast meter short-circuit current separated into periods of slow and rapid changes.

We must also justify that the MPP voltage does not introduce high-frequency content independent of the current. In [15], the authors step through a mathematical derivation of the MPP voltage (V_{MPP}) and use output characteristics of a solar panel as the following: Voltage at MPP under non-standard conditions is called V'_m, and is a function of two external variables: temperature and irradiance (T and S). There are also parameters for intrinsic properties of the panel (b, c, and e). The results in [15] show that V_{MPP} is predominantly a function of temperature, as in

$$V'_m = V_m \cdot (1 - c\Delta T) \cdot \ln(e + b\Delta S) \qquad (1)$$

We assume in our study that the temperature component of V_{MPP} does not contribute to dynamics faster than the slow meter update rate of 2.5-3.9 s and is thus captured by our metering. Note that only the log term of the irradiance, S, contributes to V_{MPP}, and since irradiance is the primary factor in short-circuit current output, we already have measured irradiance changes from the fast I_{SC} data. To illustrate, Fig. 7 shows that we can bound the variation in V_{MPP} as a function of I_{SC} using two different kinds of days as examples. One day is a smooth day in January, and the other is a noisy day in June. We can bound worst cases from both of these days within approximately 15%

of the I_{SC} regression, and within approximately 20% for all days investigated. This is pessimistic, as the majority of scattered points are much closer to the best fit function. The variance will lead to some uncertainty in the final result for update rates faster than one slow meter sweep.

Since the majority of photovoltaic dynamics should be contained in the fast short-circuit data, then a Fast Fourier Transform (FFT) of I_{SC} provides preliminary information about frequency content in the solar power. We are especially interested in the higher frequencies to see at which point we should expect saturation in energy capture. For instance, an FFT of a 20-minute data sample is plotted in Fig. 8. It indicates that frequency content above about 100 Hz constitutes the noise floor in the measurements, excepting narrow spikes associated with harmonics of the 60 Hz grid frequency. This would indicate that a more rapid update rate in an MPP tracker would not provide increased energy capture beyond 100 Hz. Extended analysis in Section IV will provide a more rigorous argument concerning energy content variability for the whole data set.

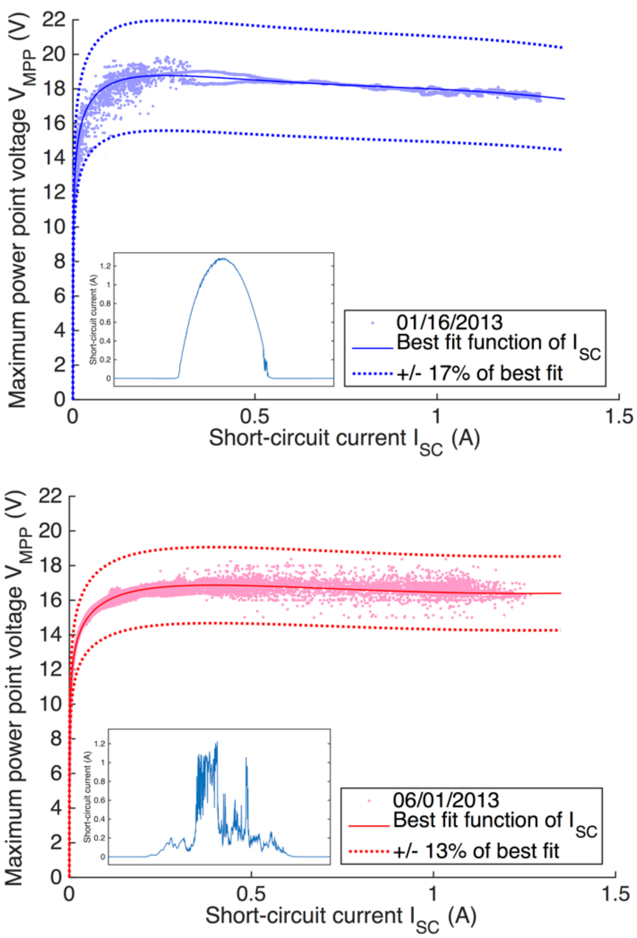

Fig. 7. Correlation between V_{MPP} and I_{SC} for one smooth day (top) and one noisy day (bottom), each with nonlinear regression, bounds of variation about that regression, and inset plot of I_{SC} for day.

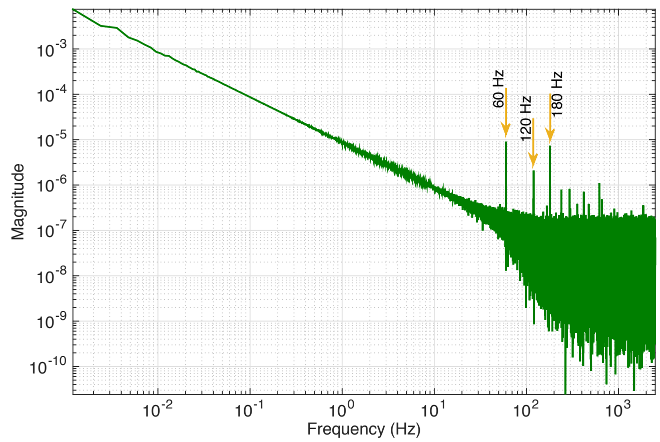

Fig. 8. FFT of ~20 minutes' worth of short-circuit data at ~5 kHz, with labeled peaks at the grid frequency and first two harmonics.

IV. MPPT Operating Model and Economic Implications

While we have thus far discussed variability in terms of power, we now transition to the effect variability has on energy capture. That is, some energy from the PV panel is not captured by the MPP converter if it uses obsolete MPP information. To quantify this missed energy, we envision our PV panels transferring energy through a lossless dc-dc boost converter to a lossless inverter and subsequently to an ideal grid, fixed at nominal voltage, as visualized in Fig. 9.

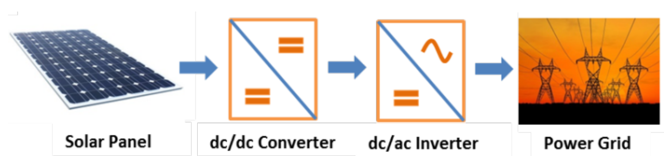

Fig. 9. Idealized process of energy conversion from PV power to grid power.

We assume that each solar panel is equipped with its own microinverter and boost converter so that each panel operates independently. In this set-up, the boost converter is controlled for MPPT at a predetermined update rate. The panel voltage V_{MPP} will be set from the converter active switch duty ratio D as

$$V_{MPP} = V_{in} = (1 - D) \cdot V_{out} \tag{2}$$

For an ideal boost converter and system, missing energy will only occur if there is mismatch between the panel V_{MPP} and the tracker V_{MPP} value, which is held constant through the duration of a sampling period. Sampling period here refers to the duration of time before a new V_{MPP}, and hence duty ratio D, is calculated. In this case, as in a hypothetical depiction of Fig. 10, there will be less energy captured. The reduction could be in either of the shaded regions in Fig. 10 if I_{MPP} were to change but the legacy V_{MPP} value did not update to the optimal MPP.

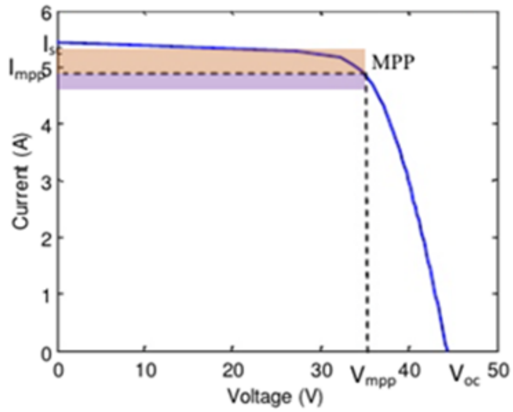

Fig. 10. Hypothetical MPP curve with exaggerated regions of missed energy depicted as the shaded regions.

To create the missed energy capture plot in Fig. 11, we assumed that a baseline MPP update rate of 5 kHz was effectively the same as a continuous update, capturing all possible changes in power output. Then, for a hypothetical MPP tracker that would update every 2, 5, 10, …, 10^6 samples (2500 Hz, 1000 Hz, 500 Hz, …, 0.005 Hz) the amount of energy missed at each time step was summed according to

$$Energy\ Missed = \sum_{m=1}^{S_T/S_U} V_{MPP_k} \cdot \sum_{n=1}^{S_U} \left| \left(I_{SC_n} \cdot I_{SF}\right) - I_{MPP_m} \right| \quad (3)$$

where I_{SF} is the scaling factor between I_{MPP} and I_{SC} (slope in Fig. 6), S_T is the total number of samples in the selected data segment, and S_U is the number of samples per MPP update. Each total sum is then divided by the total amount of energy captured at the baseline rate of 5 kHz. This yields the missed energy fraction from sampling the MPP at a slower rate. Fig. 11 summarizes the results of this calculation for the ten, 10-day periods discussed in Section II, with the mean of these in bolded black. If MPP's are updated at 100 Hz, coinciding with the FFT floor in Fig. 8, about 1 part in 4000 of the available energy will not be captured compared to the baseline case. This is about 63 mW for a 250 W panel. For reference, the noise floor suggests that data resolution is no better than one part in 10000. As another example with the same panel size, a 1 Hz update rate sacrifices an average of about 1 part in 250, about 16 times as much as a 100 Hz update rate. A converter updating at 100 Hz should be able to capture an extra 1 W on average from a 250 W panel compared to a 1 Hz update rate.

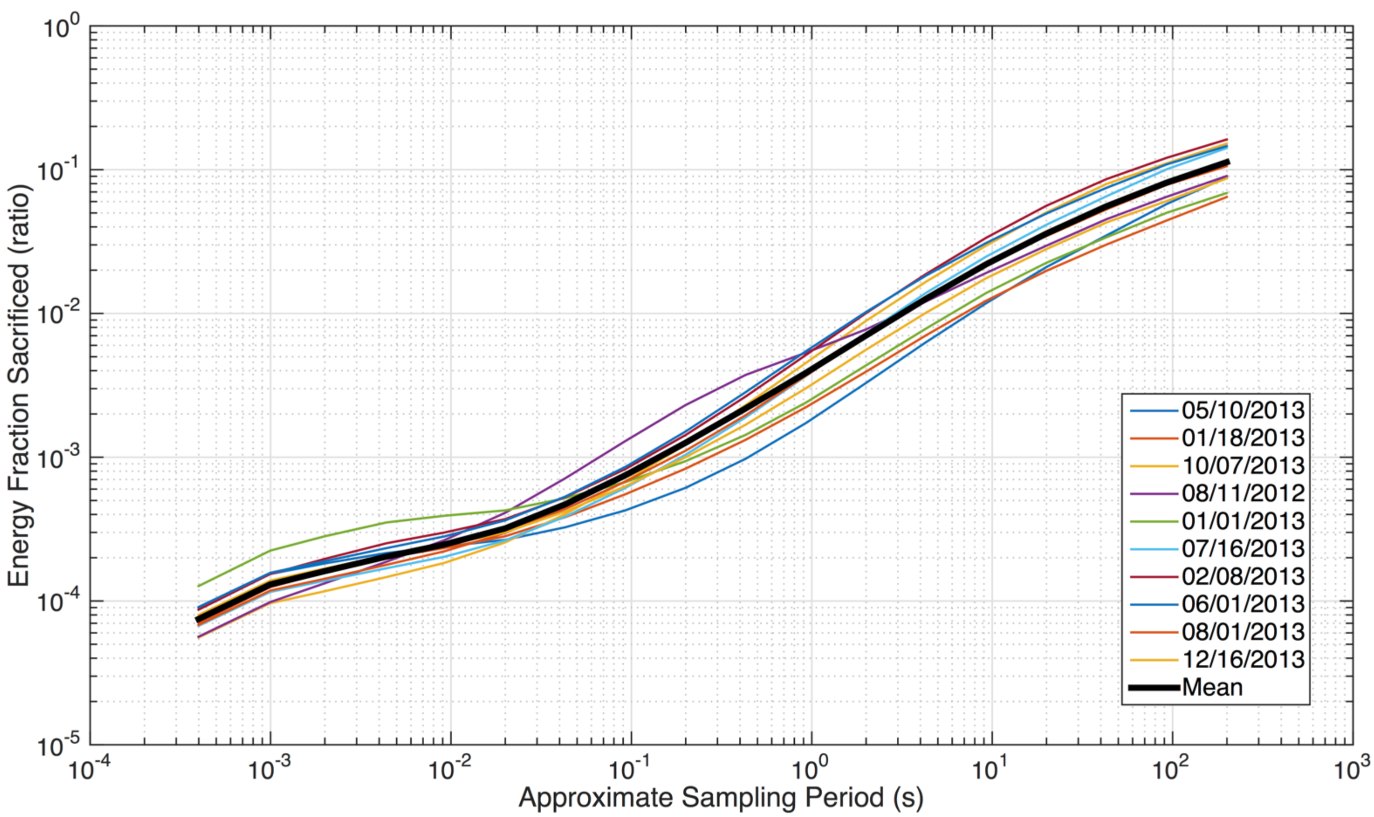

Fig. 11. Modeled energy sacrifice of 10, 10-day samples with varying MPPT update rates and mean in bolded black. Entries in legend represent final day in 10-day series.

Fig. 11 can be used to analyze, in general terms, the economic opportunity cost associated with increased update rates. We compare update rates of 1 Hz and 100 Hz for a hypothetical existing system. Using the relation from Fig. 11 with 1 Hz on the x-axis yields a mean energy fraction sacrifice of 0.41% and 100 Hz input yields a sacrifice of 0.025%. Other assumed parameters are provided in Table I for one PV panel with a built-in microinverter.

Table I. - Economic calculation assumptions

Solar panel rating (W)	Capacity Factor	Hours per year	Lifetime of panel (years)	Electric cost per kWh
245	0.24 [16]	8766	25	$0.11 USD

We calculate the differential cost between the two cases:

$$\begin{aligned} &245\,W \cdot 0.24 \cdot \frac{8766\,hr}{year} \cdot 25\,years \cdot \frac{1\,kWh}{1000\,Wh} \\ &\qquad \cdot \frac{\$0.11USD}{kWh} \cdot (0.41\% - 0.025\%) \\ &\qquad = US\$5.46\ per\ panel \end{aligned} \quad (4)$$

Thus, an incremental cost of a few dollars per panel is worthwhile for increasing update rates from 1 Hz to 100 Hz. Following from (4), even if *all* the remaining 0.025% of energy could be captured, the remaining value to be captured is about US$0.35, so update rates above 100 Hz are unlikely to be cost effective.

V. Conclusion and Future Work

In this paper we described how raw PV data was used to quantitatively determine the variability of energy production for various MPPT update rates. We started with 5 kHz short-circuit current data and slower I-V sweep data from a PV panel exposed to natural conditions for more than a year. We then justified how knowledge of the I-V sweeps together with high-speed short-circuit current was sufficient to be able to determine the dynamics of the MPP within relatively tight bounds. We transformed the panel dynamics into quantifiable missed energy capture due to fixed update rates by modeling an ideal boost converter fed with the raw data. We concluded by performing a basic cost-benefit analysis of MPPT systems to demonstrate one possible use of the energy variability result.

Regarding future work, higher accuracy calculations may be feasible with existing data. In this paper, we treated the effect of irradiance on V_{MPP} as a second-order effect. Future analysis can account for some of the variations faster than one slow meter sweep for days with tight correlations between V_{MPP} vs I_{SC}. Additional work will include filtering and down-sampling of the entire data set for easier handling. We also plan to use this energy content information for analyzing dynamic requirements of solar variability mitigation, such as methods in [17-19].

Acknowledgement

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