

# MEASURING DEGRADATION RATES WITHOUT IRRADIANCE DATA

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## ABSTRACT

A method to report photovoltaic (PV) system degradation rates without using irradiance data is demonstrated. First, a set of relative degradation rates are determined by comparing daily AC final yields from a group of PV systems relative to the average final yield of all the PV systems. Then, the difference between relative and absolute degradation rates is found using a Bayesian statistical analysis. This approach is verified by comparing to methods that utilize irradiance data. This approach is significant because PV systems are often deployed without irradiance sensors, so the analysis method described here may enable measurements of degradation using data that were previously thought to be unsuitable for degradation studies.

## INTRODUCTION

Measurements of PV system degradation rates are needed by many stakeholders such as PV component manufacturers, PV system owners, investment firms, and insurance companies. Knowledge of degradation rates guides decision-making on PV manufacturing processes, PV system hardware selection, investment terms and warranties. Therefore additional measurements of degradation for different PV systems in various environments are increasingly in demand.

However, existing methods for field testing [1-10] cannot be used to report degradation rates of many PV systems due to lack of irradiance data. Irradiance sensors are not deployed with most PV systems because irradiance sensors are expensive and require expertise to install, operate, maintain, and calibrate. Therefore it would be advantageous to have a method for measuring PV system degradation rates without using irradiance data. This is a challenge because the annual solar radiation can fluctuate by 10% from year to year [11], while PV system degradation rates are often less than 0.5% per year.

We have developed and tested a method to measure the individual degradation rates for a group of PV systems using only data from the AC power generated by each PV system. First we describe the PV systems and datasets we studied. Then we explain methods we used to determine relative degradation rates and the uncertainty in these values. Next we describe how to find absolute degradation rates from relative degradation rates without using irradiance data. Finally, we use irradiance data to verify this method and discuss the results.

## PV SYSTEMS AND DATA

We studied degradation rates for 22 grid-tied PV systems based on data provided by Tucson Electric Power. All 22 PV systems are located in Tucson, Arizona, and have been monitored with revenue-grade kWh meters since 2003. Ignoring data before or after system hardware changes still leaves data spanning at least three years for 19 systems. The PV module material, manufacturer, model number, the system nameplate power rating, the duration of data utilized from each system, and results from our degradation studies are listed in Table 1.

The PV systems in our study all use maximum power point tracking inverters. The modules all face south at the latitude angle of 32°. The first 16 PV systems in Table 1 are at the TEP solar test yard shown in Fig. 1. Unlike TEP's Springerville generating station [12], the TEP PV test yard has a large variety of different systems, most of which are 1 to 2 kW. The other four systems are located within 10 miles of the TEP solar test yard.

The final yield of each day (kWh/kW) for System 6 is plotted in Fig. 2 for a duration of four years. The quantity known as final yield,  $Y_f$ , is described in reference [1] and is calculated from the measured energy output (kWh) divided by the nameplate power (kW) of a PV system. This helps to compare systems with different nameplate ratings.



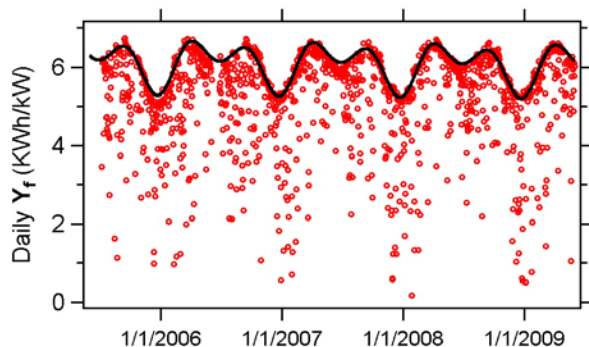
**Figure 1. The TEP solar test yard. Over 600 PV modules from 20 different manufacturers are grid-tied, for a combined 90 kW<sub>peak</sub>. The yard, located at 4350 E. Irvington Rd, Tucson, AZ 95702, was commissioned in 2003. Photo credit: Alex Cronin, NREL PIX 17433.**

One observes two maxima per year in the daily final yields. These maxima occur near the equinoxes because on those dates the fixed-angle latitude-tilt modules in Tucson receive the most radiant energy. Temperature is important for PV system performance, but temperature effects are less significant than irradiance for determining the final yields shown in Fig. 2. The black curve plotted on top of the data in Fig. 2 is a model of  $Y_f$  based on a solar

Material	Sys. #	Make (Model)	KW	yrs	Change %/yr WOI	Change %/yr WI
CIS/CIGS	1	Global Solar (GG-112,13309)	1.44	5	-3.2 ±0.5	-2.9 ±0.5
	2	Shell Solar (ST40)	1.52	5	-3.0 ±0.5	-2.9 ±0.5
a-Si	3	Solarex (MST-43MV)	3.00	3	-0.2 ±1.1	-0.2 ±0.6
MJ-Si	4	BP Solar (MST50MVHS)	1.50	5	-4.8 ±0.6	-4.5 ±0.3
	5	BP Solar (MST50 MVHS)	1.50	3	-1.6 ±0.9	-2.5 ±0.6
	6	UniSolar (US-64)	1.54	3	-0.2 ±1.4	0.2 ±0.7
HIT (Si)	7	Sanyo (HIP-G751BA2)	1.34	5	-1.4 ±0.5	-1.0 ±0.2
	8	Sanyo (HIP-J54 BA2)	1.44	5	-0.7 ±0.5	-0.2 ±0.2
px-Si	9	BP Solar (BP 3150U)	1.50	4	-0.7 ±0.5	-1.2 ±0.8
	10	BP Solar (SX140S)	1.40	3	0.2 ±0.7	0.2 ±1.6
	11	Kyocera (KC150G-A)	1.35	3	0.4 ±0.8	0.8 ±1.6
	12	Schott (ASE-300-DGF/50)	1.26	2	0.0 ±2.6	-0.1 ±4.5
	13	Schott (ASE-300-DGF/50)	1.20	3	-1.6 ±0.5	-1.3 ±0.8
	14	Schott (ASE-300-DGF/50)	22.7	4	-2.4 ±0.8	-2.6 ±0.6
	15	Schott (ASE-300-DGF/50)	22.7	5	-2.0 ±0.6	-2.6 ±0.6
x-Si	16	AstroPower (API-165-MCB)	1.48	3	-0.7 ±1.4	-2.6 ±2.4
unknown	17	Unknown; 10 mi from yard	21.6	4	-2.2 ±0.9	-1.7 ±0.4
	18	Unknown; 6.5 mi from yard	108	3	-4.3 ±0.8	-2.6 ±1.2
	19	Unknown; 6.5 mi from yard	108	4	-3.4 ±0.7	-3.0 ±0.5
	20	Unknown; 2.0 mi from yard	1.20	5	-1.0 ±0.5	-1.0 ±0.4

**Table 1. PV module types and degradation rates for each system. The duration of data used from each system is listed under (yrs). Degradation is listed for methods without irradiance (WOI) and with irradiance (WI) data.**

position algorithm combined with a thermal de-rating that fluctuates smoothly throughout each year. This undulating function will be used later as a tool to study degradation rates. Sunny days result in high  $Y_f$  near the value predicted by the model (black line), while dips below the model are typically the result of cloudy days.



**Figure 2. Daily  $Y_f$  for System 6 (red circles) and a model based on a solar position algorithm (black line).**

### ANALYSIS OF RELATIVE DEGRADATION

To study relative degradation rates, we introduce a new quantity: daily relative final yield,  $Y_\phi$ , based on daily final yield normalized by the yard average. Here 'yard average' refers to the average final yield for all the PV systems operating at the TEP solar test yard on that day.

For completeness we show the defining equation for final yield [1].

$$Y_f = \frac{E}{P_0} \quad (1)$$

where  $E$  (kWh) is the net AC energy output (in our case, the daily net energy output), and  $P_0$  (kW) is the nameplate DC power rating of the PV array. We construct a daily yard average of final yields,  $\langle Y_f \rangle$ , defined as

$$\langle Y_f \rangle = \frac{1}{N} \sum_{j=1}^N Y_{f,j} \quad (2)$$

where  $j$  indexes the individual systems in the yard (In our case,  $N$  was typically 10 to 12 systems operating on a

given day. Only systems located at the TEP test yard were included in this average, i.e. systems 17-20 were not included). We then define daily relative final yield

$$Y_{\phi} = \frac{Y_f}{\langle Y_f \rangle} \quad (3)$$

The relative final yield,  $Y_{\phi}$ , is plotted in Fig. 3 for System 6. Fig. 3 shows less scatter than Fig. 2 because cloudy days affect all the PV systems similarly.

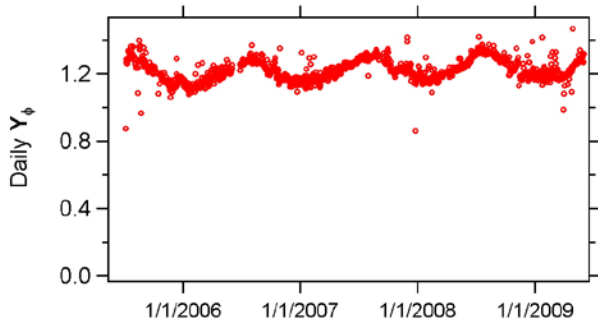


Figure 3. Daily relative final yield,  $Y_{\phi}$ , for System 6.

Normalizing by the yard average cancels out the effects of cloudy days and irradiance fluctuations. Normalizing by the yard average also cancels out many effects of seasonal variations as well. There are no longer two maxima per year. Remaining undulations in Fig. 3 (with maxima once per year) are due to the way the particular system (System 6) performs differently than the rest of the PV systems used to define the average,  $\langle Y_f \rangle$ . For example, differences in thermal deratings between different systems contribute to the residual undulations in Fig. 3.

To determine relative degradation rates we made linear fits to  $Y_{\phi}$ . Since the data were normalized by the yard average, these linear fits have a positive slope for approximately half of the PV systems. This means that roughly half the systems are improving compared to the yard average. As we justify later, a shift of 1.9 %/year is subtracted from the relative degradation rates in order to report absolute degradation rates. These shifted values are reported in Fig. 4 and Table 1 as rates of change (%/yr) without irradiance data (WOI).

The way we choose to estimate uncertainty in relative degradation rates is to repeat the linear fits twelve times with the start and stop date shifted by one month each time. This provides a distribution of best fit rates, with the spread in the distribution related to the residual annual fluctuations. This uncertainty does not include systematic errors such as calibration drift in the meters.

The shift from relative to absolute degradation rates (nominally -1.9 %/yr) causes additional uncertainty (of approximately 0.41 %/yr). We added 0.41 %/yr in quadrature with the uncertainty from each relative rate of change to report the error bars in Fig. 4 and Table 1. The calculation of this additional 0.41 %/yr uncertainty is discussed later.

### ANALYSIS OF ABSOLUTE DEGRADATION

To check our estimate for the -1.9 %/yr shift between relative and absolute degradation rates, we also analyzed absolute degradation rates with the aid of irradiance data. The highest quality irradiance data that we could obtain for the relevant dates came from the Tucson, Arizona Meteorological Network, (AZMET) station [13]. Unfortunately this is global horizontal irradiance, not plane of array irradiance. Furthermore, the AZMET data were reported hourly and were obtained from a meteorological station approximately 8 miles north of the TEP solar test yard.

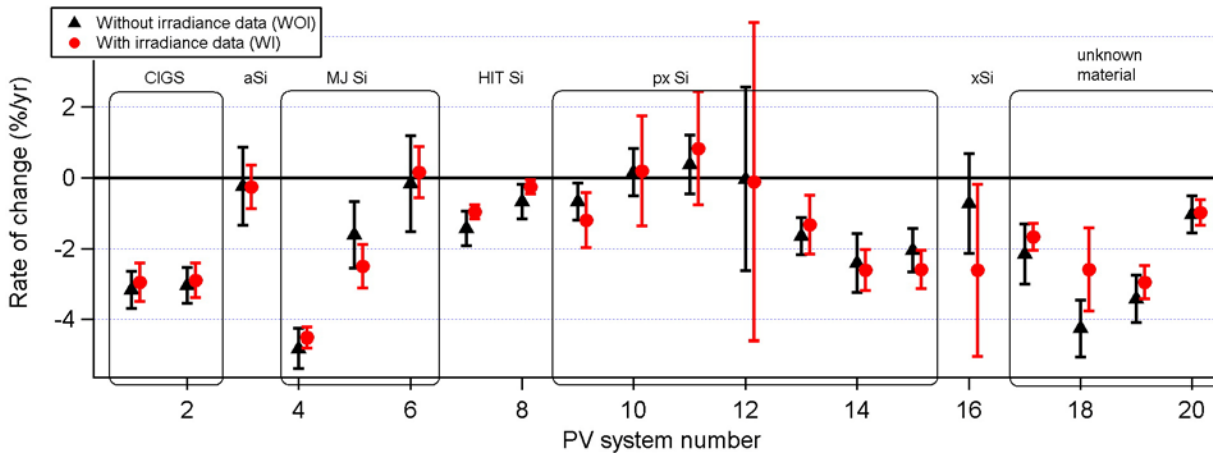


Figure 4: Degradation rates for 20 PV systems. Rates determined without irradiance data (black triangles) have an uncertainty comparable to the method that utilized irradiance data (red circles) even after including the 0.41 %/yr uncertainty in the *shift* parameter.

To correct for the angle mismatch between the irradiance sensor (horizontal) and the PV system modules ( $32^\circ$ ), we followed two different approaches that gave consistent results. The first approach is simpler, but resulted in larger uncertainty. The second approach was more involved, but reduced the uncertainty.

The first approach used a cloudiness index for each day that was determined by comparing the daily AZMET insolation data with a model for predicted horizontal insolation each day of the year. The model is based on a clear-sky and a solar position algorithm and no year-to-year fluctuations. The cloudiness index therefore captures both the effects of weather and the year-to-year fluctuations (trends) in irradiance. Once the cloudiness index for each day was found, then the final yields (see Fig. 2) were normalized by this cloudiness index.

The second approach we explored in order to report absolute degradation rates took one additional step. This was to normalize the final yields also by the undulating function, the model, shown in Fig. 2. We plot the values from this method in Fig. 4 (red circles), and tabulated the uncertainty for these values in Table 1. Uncertainties for these rates of change for  $Y_f$  data were estimated with the same method (12 start and stop dates) as uncertainty in the rates of change for  $Y_\phi$ .

### FINDING ABSOLUTE DEGRADATION WITHOUT IRRADIANCE

Determining the degradation rate of a system from final yields without irradiance data requires estimating the difference between relative degradation rates and absolute degradation rates. One simple method to find this difference is to assume that the “the best” PV system exhibiting the smallest loss in annual yield is stable, i.e.

not degrading at all. However, we suggest that more accuracy can be obtained by allowing for occasionally erroneously high (sometimes positive) rates of change that result from noise in the data and limitations of our analysis.

A rigorous statistical investigation of the shift between relative and absolute degradation begins with a probability distribution function (PDF). We define the parameter *shift* as the difference between the real degradation rate of the system and the measured degradation rate relative to the dataset, and  $P_{shift}$  as the PDF of *shift*.

To help determine  $P_{shift}$  we introduce another PDF,  $P_A(k_a)$ , for the probability of various rates of change  $k_a$  of each system. The analysis presented here assumes  $P_A(k_a)$  for each system is the same, independent of the module and inverter type. The unknown PDF was estimated by a function with a single fit parameter,  $\mu$ . However, functions with fixed parameters, i.e. a lognormal with pre-chosen values for mean and standard deviation, were also tried and found to give similar results for  $P_{shift}$ .

There is a need to limit the number of variable parameters used in the function that describes  $P_A(k_a)$  since determining several best fit parameters requires datasets with more systems. For our dataset of 20 systems the function  $P_A$  was limited to a single-parameter model, but large datasets could potentially use a  $P_A(k_a)$  PDF which takes more parameters. For example, an improvement to this method in the future might be to use different a priori PDFs  $P_A(k_a)$  for systems with different PV materials.

In order to limit the number of parameters, the probability of rates of change greater than zero was assumed to be zero. The PDF chosen thus allows degradation but not improvement. By using a maximum entropy argument from statistics, this PDF will have the form of Eqn. (4) [14]. This argument assumes the function is bounded by zero, and that a mean value of the PDF,  $\mu$ , can be specified.

$$P_A(k_a|\mu) = \begin{cases} 0 & k_a \geq 0 \\ -\frac{1}{\mu} \exp\left(\frac{-k_a}{\mu}\right) & k_a < 0 \end{cases} \quad (4)$$

where the parameter  $\mu$  is negative.

The relative degradation rate PDF,  $P_R(k_r)$ , can then be found by adding a constant, *shift*, that accounts for the difference between relative and absolute degradation rates.

$$k_r = k_a + shift \quad (5)$$

$$P_R(k_r|shift, \mu) = \begin{cases} 0 & k_r \geq shift \\ -\frac{1}{\mu} \exp\left(\frac{shift-k_r}{\mu}\right) & k_r < shift \end{cases} \quad (6)$$

Furthermore, there is uncertainty in the measured relative degradation rate, so a noise term,  $k_\sigma$ , is added which has a Gaussian PDF to get the measured relative degradation rate,  $k_m$ .

$$k_m = k_r + k_\sigma \quad (7)$$

$$P_\sigma(k_\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{k_\sigma^2}{2\sigma^2}\right) \quad (8)$$

where  $\sigma$  is the uncertainty in the measurement. Using the product rule to calculate the measured degradation rate PDF,  $Prob_M(k_m)$ , results in a convolution:

$$P_M(k_m | shift, \mu) = \int_{-\infty}^{\infty} P_\sigma(k_\sigma) P_R(k_m - k_\sigma | shift, \mu) dk_\sigma \quad (9)$$

By assuming each system is mutually independent, the PDF for the entire dataset can then be written as

$$P_{\{M\}}(\{k_m\} | shift, \mu) = \prod_{i=1}^N P_M(\{k_m\}_i | shift, \mu) \quad (10)$$

where  $\{k_m\}_i$  is the measured degradation rate of an individual system,  $k_m$ , in the dataset,  $\{k_m\}$ .

Using Bayes' theorem, a joint PDF is calculated; Eqn. (11).

$$P(\text{shift}, \mu | \{k_m\}) = \frac{P_{\{M\}}(\{k_m\} | \text{shift}, \mu) \times P(\text{shift}, \mu)}{P(\{k_m\})} \quad (11)$$

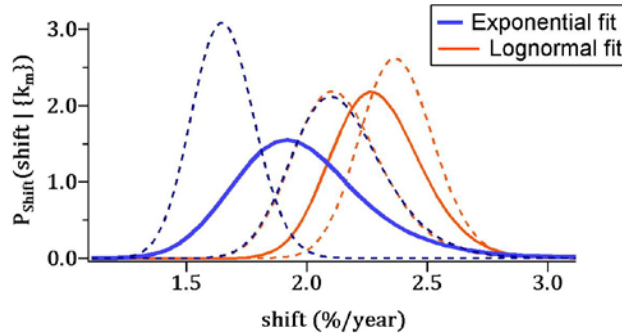
In Bayesian statistics, the function  $P(\text{shift}, \mu)$  is called the prior and represents our state of knowledge prior to any data being taken [14]. For simplicity we assume independence of  $\text{shift}$  and  $\mu$ , resulting in Eqn. (12).

$$P(\text{shift}, \mu) = P(\text{shift}) \times P(\mu) \quad (12)$$

We have treated  $P(\text{shift})$  and  $P(\mu)$  in two different ways. In our fixed parameter models, we have treated the PDF  $P(\mu)$  as a delta function,  $\delta(\mu - \mu_0)$ , and  $P(\text{shift})$  as a uniform PDF. In our variable parameter models, we have treated the PDF's for both  $\mu$  and  $\text{shift}$  as being exponential functions similar to Eqn. (4).

From the joint PDF  $P(\text{shift}, \mu | \{k_m\})$  in Eqn. (11) the desired PDF,  $P_{\text{Shift}}(\text{shift} | \{k_m\})$ , can be calculated as shown in Eqn. (13) and is plotted for the TEP data in Fig. 5.

$$P_{\text{Shift}}(\text{shift} | \{k_m\}) = \int_{-\infty}^0 P(\text{shift} | \mu, \{k_m\}) d\mu \quad (13)$$



**Figure 5. Plot of  $P_{\text{Shift}}(\text{shift} | \{k_m\})$  using the exponential function of Eqn. (4) where  $\mu$  is a free parameter (solid blue). Results from fixed parameter models are shown with dashed lines (which depict the results of using parameters one half and twice the value found in the free parameter models).**

Figure 5 shows that when the functional form of  $P_A(k_a)$  is assumed to be the exponential of Eqn. (4), the peak in the PDF occurs at 1.9 %/year with a standard deviation of 0.24 %/year.

## DISCUSSION

We attempt to make a complete list of the assumptions built into the model below. We assume:

1. The uncertainties in the measured relative degradation rates are correct.

2. The degradation rate is constant for each system, in other words there is no time-dependence in the degradation rate.
3. The degradation rate PDF is the same for all systems, independent of module and inverter type.
4. The PDF for the rate of change of a system can be described by  $-1/\mu \times \exp(-k/\mu)$  where the PDF is nonzero only for negative  $k$ , i.e., only degradation is allowed.

The results from this model depend on the uncertainties associated with the measured relative degradation rates of each system. If the uncertainty associated with an outlier is less than the correct value, then it will be weighted heavier in the calculation and have a strong effect on the result.

Assumptions 2 through 4 can be considered a list of possible improvements that could be made to the model, in that each one of these items could be eliminated or improved by adding parameters to the model. For example, a separate  $\mu$  could be determined for every system with a specific module and inverter type to eliminate assumption 3. Ultimately, however, the number of parameters added to any model should be limited by the number of systems in the study and the number of years in the datasets. We believe a single-parameter model is appropriate for a data set with 20 PV systems.

In regards to the function used in assumption 4 [Eqn. (4)], we have attempted to capture the general character of degradation rates. We wanted a PDF that goes to zero as the degradation rate goes to infinity. A lognormal PDF,  $P_A(k_a | \mu, \sigma) = \frac{1}{k_a \sigma \sqrt{2\pi}} \exp(-(\ln(k_a) - \mu)^2 / 2\sigma^2)$ , would meet this requirement, and other than adding an additional parameter, we do not have a compelling argument against using a lognormal PDF.

Additionally, we attempted to estimate how much uncertainty is in our results due to the possibility that the exponential function used in Eqn. (4) is the wrong functional form. This was done by calculating the standard deviation of a set of fixed parameter model results, that included results from both a lognormal function and the exponential function of Eqn. (4). Some of these results are plotted in Fig. 5. This resulted in an additional 0.33 %/yr uncertainty. When added in quadrature to the 0.24 %/yr result of the previous section, the combined uncertainty was 0.41 %/yr.

In our model, the PDF describing degradation rates was meant to be as general as possible, in that we avoided using results from specific studies which may have resulted in a PDF dependent on system characteristics that might not be entirely known in the beginning of a degradation rate study. We acknowledge that rates of change may not be constant throughout a PV system's lifetime, and in particular there may be positive rates of change (improvements) during certain durations. A PDF

that handles this condition would require the addition of multiple parameters and detailed knowledge of the behavior of a system, and is left for a future study.

### SUMMARY OF RESULTS

We introduced a new quantity named relative final yield,  $Y_{\phi}$ , to describe daily final yields relative to a group of PV systems. We then described a method to find degradation rates based on relative final yields. We accomplished the challenging task of finding the shift between these relative degradation rates and absolute degradation rates by using a Bayesian statistical analysis for the probability of the shift given the data and some general assumptions. We made a complete list of assumptions in the discussion. The degradation rates found according to this method without using irradiance data are in good agreement with degradation rates determined in a more traditional manner utilizing irradiance data. This supports the claim that one can accurately measure absolute degradation rates without irradiance data.

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