Photovoltaic Degradation Risk

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PHOTOVOLTAIC DEGRADATION RISK

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ABSTRACT

The ability to accurately predict power delivery over the course of time is of vital importance to the growth of the photovoltaic (PV) industry. Important cost drivers include the efficiency with which sunlight is converted into power, how this relationship changes over time, and the uncertainty in this prediction. An accurate quantification of power decline over time, also known as degradation rate, is essential to all stakeholders - utility companies, integrators, investors, and researchers alike. In this paper we use a statistical approach based on historical data to quantify degradation rates, discern trends and quantify risks related to measurement uncertainties, number of measurements and methodologies.

1. INTRODUCTION

To sustain the commercial success of photovoltaic (PV) technologies it becomes vital to know how power output decreases with time. An accurate quantification of power decline over time, also known as degradation rate (R_d), is essential to all stakeholders - utility companies, integrators, investors, and researchers alike. Financially, degradation of a PV module or system is equally important, because a higher degradation rate translates directly into less power produced and, therefore, reduces future cash flows. [1] Technically, degradation mechanisms are important to understand because they may eventually lead to failure. The identification of the underlying degradation mechanism through experiments and modeling can lead directly to lifetime improvements. Outdoor field testing has played a vital role in quantifying long-term behavior and lifetime for at least two reasons: it is the typical operating environment for PV systems, and it is thus far the only way to correlate indoor accelerated testing to outdoor results to forecast field performance. We will discuss in this paper the connection of outdoor field measurement uncertainties to financial risk as the primary motivation. Several excellent treatments of uncertainty analysis of PV testing have been done in the past, specifically for outdoor [2, 3, 4, 5] and indoor I-V characterization. [6] We will expand on this work and discuss the impact of the number of measurements on uncertainty. Finally, we will investigate uncertainties associated with continuous data metrics such as the performance ratio and PVUSA method. Specifically, we will demonstrate the influence of data filtering which is a necessary step in the assessment of degradation rate uncertainties.

2. HISTORICAL DEGRADATION RATES

An extensive search resulted in more than 2000 PV degradation rates (R_d) quoted in publications and locations worldwide. Figure 1 shows a summary histogram of degradation rates and provides an update of a more detailed previous report. [7] The summarized rates are long-term degradation rates and usually do not include short-term, light-induced degradation. A decrease in performance is defined as a positive degradation rate. Conversely, a negative rate indicates an improvement. While this histogram needs to be updated frequently as new information becomes available, some general insights can be drawn from it. The distribution is skewed toward high degradation rates with a mean of 0.8%/year and a median of 0.5%/year. The majority of these reported rates, 80% of all data, are below a rate of 1%/year.

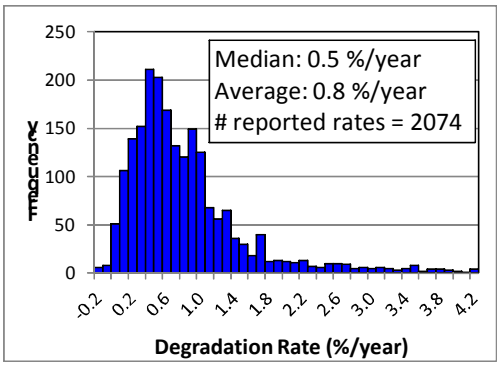

Fig. 1: Histogram of historical degradation rates.

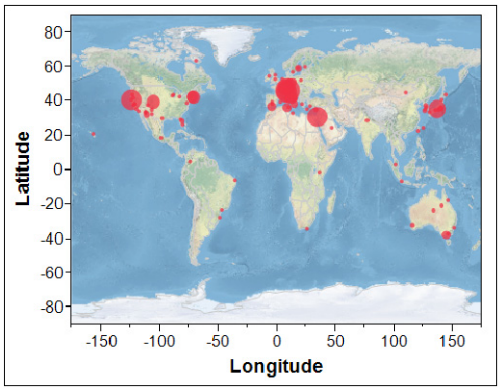

Fig. 2: Geographical distribution of degradation rates.

Figure 2 shows the geographical distribution of the same rates of Fig. 1. The size of the circle indicates the number of reported rates at a given location. The number of cited rates is large enough to allow grouping for installation before and after the year 2000, and by technology as shown in Fig. 3.

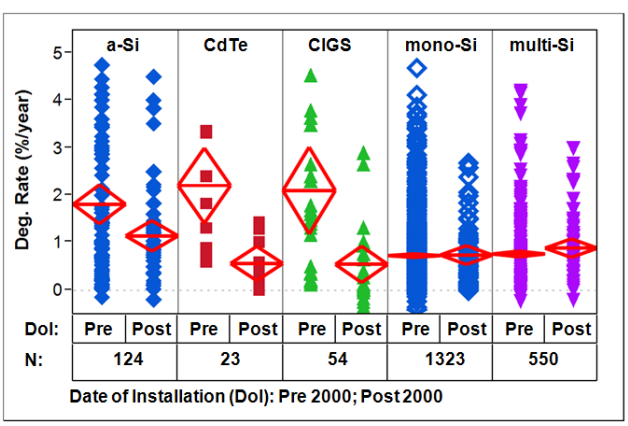

Fig. 3: Historical degradation rates partitioned by technology and date of installation. The number in each category indicates the number of data points. The 95% confidence interval is denoted by the diamonds with the mean as the crossbar.

Crystalline Si technologies (x-Si), mono-crystalline (mono-Si) and multi-crystalline Si (multi-Si), showed very little change between the older and newer data, but each of the thin-film technologies improved significantly during the last decade. Furthermore, Figure 4 compares the field exposure for each of these studies compared to a typical module manufacturer warranty. [8] As module durability increased during the last three decades, module warranties increased accordingly, but only in the last six years have there been studies that meet or exceed a typical module warranty. Offering a warranty that is longer than available field observations can create a state of elevated risk.

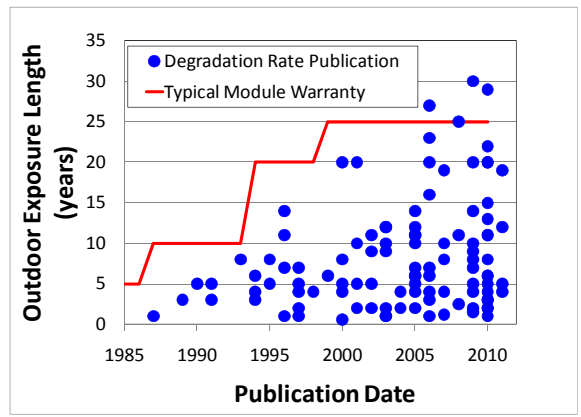

Fig. 4: Outdoor field exposure in years versus date of publication. Module warranty from one manufacturer is shown as comparison.

3. DEGRADATION RATE UNCERTAINTY AND RISK

It is important to distinguish the terms risk and uncertainty. Uncertainty in this paper will be used as the measurement uncertainty of a physical parameter while risk indicates an uncertain state that could lead to a loss, specifically to a financial loss. This section will discuss the connection between these two terms.

Figure 5 shows the evolution with time of the performance of two modules deployed at NREL. It is immediately apparent that the two modules exhibit very different behavior. Module 1 has been deployed for nearly 10 years while Module 2 has been exposed for only 3 years. Module 2 shows strong seasonal fluctuations whereas Module 1 exhibits almost no seasonality. Surprisingly, both modules have the same degradation rate of 0.8%/year. The uncertainties, however, are very different, changing the warranty default risk significantly.

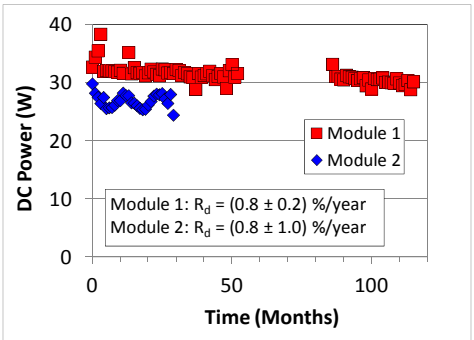

Fig. 5: DC power data from 2 modules located at NREL using PVUSA method. [9]

The lack of certainty has significant impact when the power production is calculated after 25 years according to equation (1).

(1) $\text{Power}(\text{Year}_n) = \text{Power}(\text{Year}_1) \cdot (1-R_d)^n$

A Monte Carlo simulation, shown in Fig. 6, illustrates this point. Typical maximum manufacturer warranties are 80% power production after 25 years of field use, which is indicated by a dashed green line. For the module with the smaller uncertainty the probability to default on the warranty (the integrated probability below the warranty line) is 24% after 25 years. However, the module with the larger uncertainty exhibits almost a 60% chance to default on the warranty despite the fact that both modules have the same degradation rate. This probabilistic approach demonstrates clearly how increased uncertainty in determining physical parameters can have a dramatic impact on risk in the future. The remainder of the paper will investigate various sources of uncertainty.

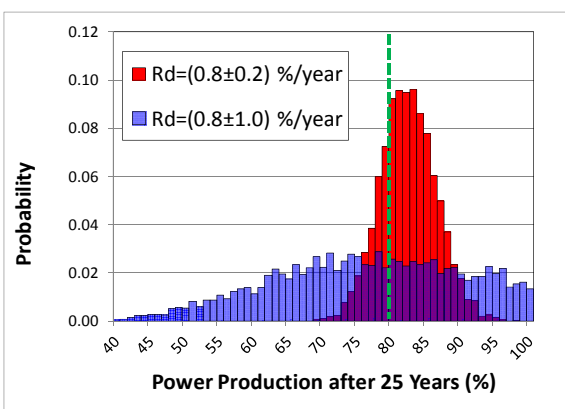

Fig. 6: Monte Carlo simulation for the standard-conditions power production of the two modules after 25 years compared to a typical warranty of 80% indicated by the green dashed line.

4. NUMBER OF MEASUREMENTS

Further insight can be gained by investigating the historical degradation rates with respect to the number of measurements taken to determine degradation rates.

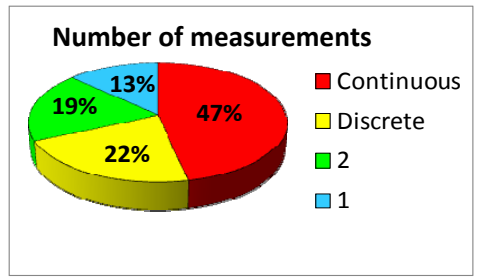

Fig. 7: Percentage pie chart indicating the number of measurements taken to determine degradation rates.

Figure 7 indicates that almost half the studies use continuous data metrics such as the performance ratio (PR) [10], PVUSA or take I-V curves in very short time intervals. [11] The discrete category consists of studies that take more than two measurements but do not acquire data continuously. It is noteworthy, however that a high percentage of references take only one or two measurements to report degradation rates. This situation is often encountered when baseline measurements were never taken or no longer exist today. Thus, modern measurements need to be compared to the original manufacturer's standard test condition (STC) ratings. [12] This approach can add significant uncertainty to the measured degradation rates. [13, 14] To demonstrate the risk resulting from few measurements, I-V data taken on cloudless days every two months for a module deployed at NREL are shown in Fig. 8. I-V curves were irradiance and temperature corrected according to IEC 60891 method 1. [15]

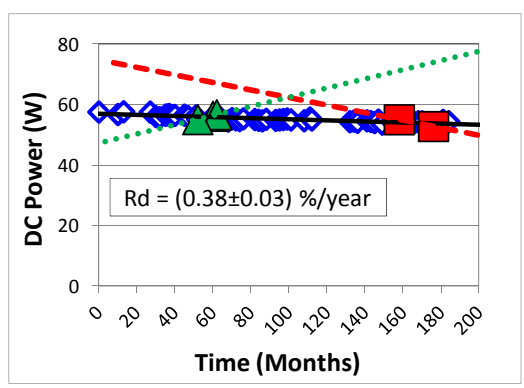

Fig. 8: Quarterly I-V data of a mono-Si module deployed at NREL.

The degradation rate using all available data is determined to be (0.38±0.03) %/year. Subsequently, a specific number of data points are taken randomly from this dataset and the degradation rate calculated. The resulting degradation rate will depend on the number of data points chosen and the time span between them, as illustrated by taking two data points (squares) and three data points (triangles), respectively (Fig. 8). The degradation rate may deviate substantially from the nominal (0.38±0.03) %/year particularly when the time span between taken data points is short. To evaluate the one data point situation a 3% uncertainty was added to the nominal rating in accordance with the Solar America Board for Codes and Standards recommendation. [16] As this procedure is repeated the resulting distribution of degradation rates for a specific time interval and a specific number of data points can be determined. The standard deviation of these distributions is a measure of the uncertainty and is shown in Fig. 9 as a function of the number of data points and number of years between the data points.

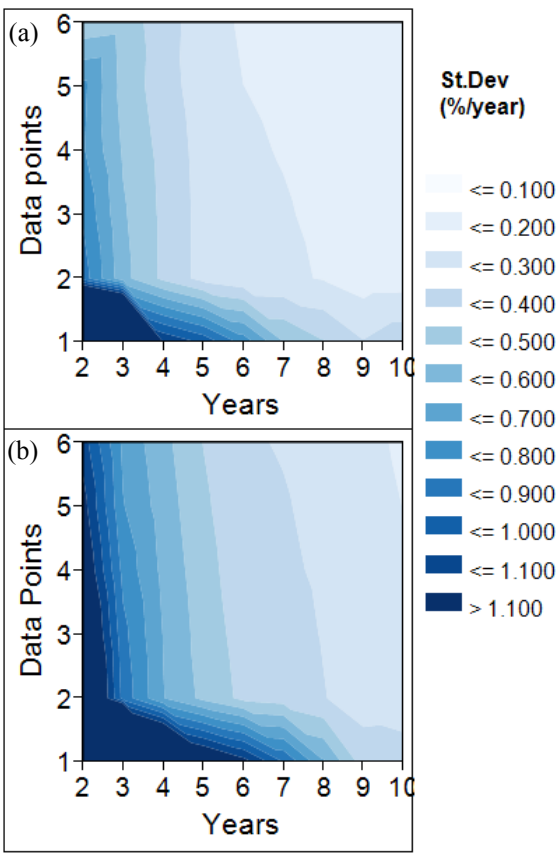

Fig. 9: Contour plot of the standard deviation of the calculated R_d as a function of the number of years and data points from the data set in Fig. 8. No uncertainty was assumed for the temperature correction factor (a); a 20% relative uncertainty in the correction factor was assumed in (b).

As the number of data points and the number of years increases, the calculated degradation rate approaches the rate of Fig 8. For fewer data points and short time spans the R_d distribution and therefore the probability increases significantly that the obtained degradation rate may be misleading (a). The situation is exacerbated when the temperature and irradiance correction is not ideal and includes a relative uncertainty (b).

5. R_d METRICS AND TOTAL UNCERTAINTY

Not only the number of measurements but also the methodology used for quantifying degradation rates can affect uncertainty. No standard exists today to determine long-term degradation rates, therefore a variety of different metrics are used. Examining again the historical data, degradation rate methodologies can be grouped into 4 broad categories, Indoor and Outdoor I-V, PVUSA and Performance Ratio (PR). Figure 10 shows a percentage breakdown of the different methodologies.

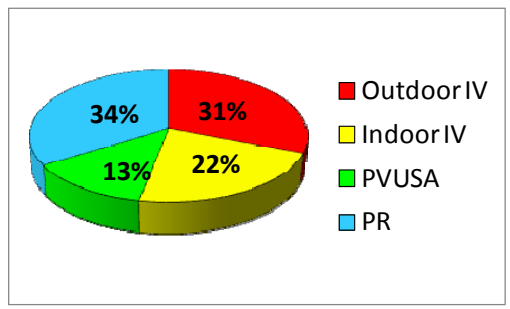

Fig. 10: Pie chart of the number of references deploying the indicated methods to determine degradation rates.

One important aspect for the continuous data metrics PVUSA and PR that is not necessarily applicable to the other metrics is data filtering. Data filtering refers here to any examination or treatment of the data prior to assessing long-term trends. Outdoor I-V curves are typically taken around solar noon on clear days which essentially reflects a type of data filtering by choosing sunny days. Indoor I-V curves are typically taken under the same STC conditions.

After the continuous raw data are collected the question arises as to which subset will be taken to assess long-term performance. Outliers, for instance caused by maintenance events or snow covering the panels may need to be excluded from the assessment. Performance metrics can be determined in different sampling intervals; for example, in monthly, weekly or daily increments. It has been shown that reducing the sampling interval from monthly to weekly increases the number of outliers, but with additional time-series modeling the calculated uncertainty may be reduced. [17] Additionally, utilizing only sunny days has been shown to reduce the uncertainty for the PVUSA methodology. [18]

However, whether other metrics benefit in a similar way is not clear and some of the benefit may depend on what specific metric is utilized.

To answer some of these questions, 4 different performance metrics were investigated on 7 different systems at NREL. The metrics included PVUSA, PR, the median DC Power over plane-of-array irradiance (DC/POA) uncorrected and temperature-corrected and the systems consisted of 3 x-Si and 4 thin-film arrays. The temperature correction was preferably done using the median of several module temperature (Tmod) measurements and corrected to 45º C using temperature coefficients derived from the continuous data. However, not all systems contained consistent multiple module temperature measurements in which case ambient temperature (Tamb) was used and corrected to 20º C, which is approximately equivalent to 45º C Tmod for the climate in Colorado. Since the data quality differed for DC Power and AC Power data for some systems all calculations are based on DC Power data such that direct comparison was possible. However, the following section should also be applicable if only AC Power data are used. All four metrics were investigated in monthly and daily intervals except the shorter interval for the PVUSA methodology was weekly. The impact of using only sunny days versus using all available days was investigated. Sunny days were determined by the clearness index of 0.5 which is the ratio of measured global irradiance over the extraterrestrial beam irradiance on a similarly tilted surface. [19] Filtering by irradiance was done by (1) keeping the upper limit fixed at 1200 W/m^2 with a variable lower limit and (2) keeping both limits flexible resulting in 200W/m^2 irradiance bands. Lastly, different irradiance-level cutoffs ranging from 0 to 800 W/m^2 were investigated. The filtering criteria are summarized in Fig. 11. To investigate the fairly large decision tree of Fig. 11, degradation rates and their statistical uncertainties were determined through automation resulting in 300-500 degradation rates per system.

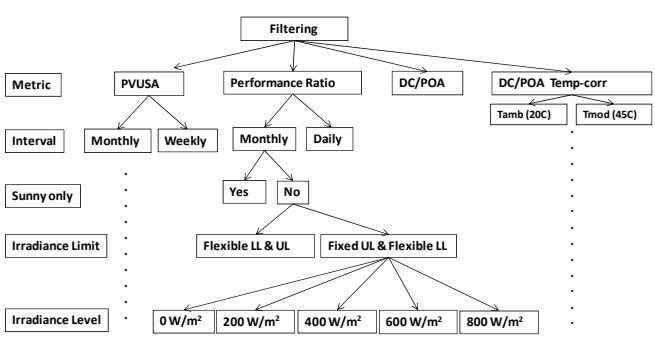

Fig. 11: Decision tree for data filtering.

To assess the impact of the filtering on the degradation rate, a most likely or nominal degradation rate was needed. Since a true degradation rate cannot be determined [20] the nominal R_d was calculated as the median of 5 methods that included time series modeling and measurement of quarterly field I-V curves. [21]

Because performance at low irradiance may differ substantially from technology to technology, especially for thin-film systems only degradation rates at high irradiance (800W/m^2) were further analyzed. Therefore, the group "Lower" in the Irradiance limit (H limit) category in Fig. 12 refers to the flexible lower limit and constitutes an actual filtering interval from 800-1200W/m^2. The group "Upper" refers to a flexible upper limit in addition to a flexible lower limit and an actual filtering interval from 700-900W/m^2. Red dashed lines of 0.2%/year deviation from the nominal degradation rate are added as reference lines to the eye. The difference to the nominal degradation rate for each system and each data filtering category is shown for 4 thin-film systems (top) and 3 x-Si systems (bottom). Because of the lack of knowledge of a true degradation rate the salient feature of this figure is how the different metrics compare under the same filtering conditions.

It appears that the temperature corrected DC/POA ratio falls mostly within or very close to the tight 0.2%/year interval. For the thin-film systems even the uncorrected DC/POA ratio and the PR fall within that same interval. This may be due to the 4 thin-film systems having on average been fielded longer than the 3 x-Si systems. For the x-Si systems the uncorrected DC/POA ratio and the PR show more scatter around the 0.2%/year interval. The PVUSA methodology shows large fluctuations depending on the filtering conditions. A possible reason is that the PVUSA methodology uses a two regression approach. In the first step, the raw data are normalized using POA, ambient temperature and wind speed in typically monthly increments. The second step is to graph the adjusted data in a time series and use a second regression to assess long-term behavior. Typically, the two regressions use a standard least square approach based on minimization of the squared residuals making it susceptible to outliers. It may be possible to improve the methodology by using for example a robust regression approach making it less susceptible to outliers. Another difficulty in the analysis of Fig. 12 is that filtering that gives the lowest uncertainty depends on the data set, since large data sets may still retain substantial data even after heavy filtering, whereas sparse datasets can't tolerate much filtering. In general, this clearly shows that different performance metrics have different sensitivities to data filtering and thus different contributions to uncertainty.

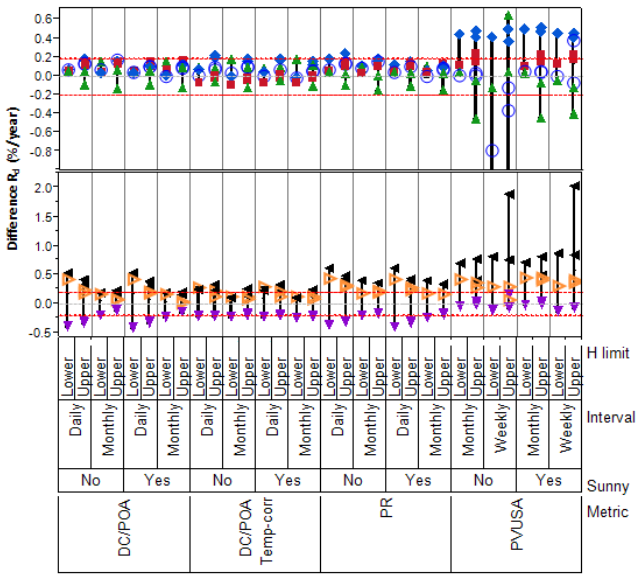

Fig. 12: Difference to nominal degradation rate in %/year for different metrics and data filtering methods. Four thin-film systems are shown on top and 3 x-Si shown at the bottom. Intervals of 0.2%/year interval are indicated by the red dashed lines and range bars for each category are also shown.

6. CONCLUSION

Historical degradation rates show that thin-film technologies narrowed the gap to x-Si technologies during the last decade. It was shown that uncertainty in the degradation rate determination directly impacts the warranty default risk. One third of the surveyed historical degradation rates have been determined based upon 1 or 2 measurements, which can significantly increase the probability of a misleading degradation rate. Continuous data are typically pre-treated, i.e. filtered prior to long-term performance assessment. The choice of filtering results in calculation of different degradation rates and may dominate over other sources of uncertainty to the degradation rate especially if the PVUSA method is used and/or filtering reduces the number of points so outliers become more influential. The simple temperature-corrected power over plane-of-array irradiance ratio seems more robust to data filtering.

7. ACKNOWLEDGMENTS

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