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CHALLENGES ASSOCIATED WITH INCONSISTENT PHOTOVOLTAIC DEGRADATION RATE ESTIMATIONS

Marios Theristis[1,*], Julián Ascencio-Vásquez[2,3], Bruce H. King[1], Marko Topič[3], and Joshua S. Stein[1]
[1]Sandia National Laboratories, Albuquerque, NM 87185, USA
[2]3E sa, Quai à la chaux 6, B-1000 Brussels, Belgium
[3]University of Ljubljana, Faculty of Electrical Engineering, Tržaška cesta 25, 1000 Ljubljana, Slovenia
*corresponding author email: mtheris@sandia.gov

ABSTRACT: Different data pipelines and statistical methods are applied to photovoltaic (PV) performance datasets to quantify the PV module degradation rate. Since the real value of degradation rate is unknown, a variety of unvalidated values has been reported in the literature. As such, the PV industry commonly treats this metric in an assumptive manner based on a statistically extracted range from the literature. However, the accuracy and uncertainty of degradation rate depends on a number of parameters including seasonality in respect to the local climatic conditions and also the response of a particular PV technology. In addition, the selection of data pipeline and statistical method may compound on the accuracy and uncertainty. In order to provide insights, a framework of bulk simulations of PV performance datasets using data from different climates is under development. Known degradation rates are emulated and large parametric studies are conducted in order to observe the convergence time on different PV module types based on several selection criteria such as performance metric, statistical method, etc. The preliminary results that are presented in this paper confirm that, indeed, climates and PV module types with typically lower seasonality can provide accurate degradation rate results in a shorter time period, compared to locations and PV module types that exhibit higher seasonality. As expected, the selection of data pipeline (e.g. metric, temperature correction, etc.) and statistical method also has a strong influence and therefore, introduces additional challenges.
Keywords: photovoltaic, degradation, modeling, simulation, performance

1 INTRODUCTION

Photovoltaic (PV) energy yield predictions require knowledge of the power decay over time (i.e. the degradation rate, R_D). Knowing the R_D value of a system is of utmost importance since its tradeoff with cost and efficiency has a direct influence on the levelized cost of energy.

The real value of R_D is unknown, but it is commonly approximated by applying statistical methods on PV performance timeseries. Such timeseries exhibit a seasonal behavior depending mainly on the location, climate, and also the PV module material. Location and climate affect PV seasonality in respect to irradiance and its spectral composition and angle-of-incidence, ambient temperature, wind speed/direction etc. On the other hand, PV modules respond differently to these conditions depending on their material. For example, crystalline silicon (c-Si) technologies are characterized by a higher temperature dependence (i.e., higher temperature coefficients) compared to thin-film technologies (i.e., lower temperature coefficients). Furthermore, the external quantum efficiency varies among different PV module materials and therefore, the response to spectral variations differs; e.g., amorphous silicon (a-Si) technology is known to be more sensitive to changes in spectrum due to its “narrow” spectral response [1].

In order to reduce seasonality, PV performance timeseries are usually processed in different ways in respect to data normalization, applied corrections, aggregation, etc. These steps, however, are not perfect, and the normalized signals still contain seasonal fluctuations that affect the accuracy and corresponding statistical uncertainty of R_D estimation. Furthermore, seasonal decomposition models can be applied to remove seasonality and extract the trend of PV performance timeseries. To this end, several methods exist in literature, with varying degree of “accuracy” which also depends on the seasonality of PV performance timeseries. In general, it is recommended to allow several cycles to be completed in order to estimate R_D with relatively low uncertainty [2-4]. The number of cycles differs or is often unquantified in literature; this is simply because it depends on climate, location, PV module type, data processing pipeline and applied methodology. Furthermore, other effects such as nonlinear degradation behavior may also exist [5-7] which may increase the statistical uncertainty if the timeseries are fitted with linear models.

Due to the aforementioned challenges of different pipelines of data normalization, corrections, aggregation, statistical methods and undefined “adequate length of timeseries” as well as other challenges such as noise, filtering, etc., there is no proven methodology that would enable a standardized procedure for estimating the PV R_D. As such, irreproducible results among analysts occur, even when the same raw dataset is used [8, 9]. Therefore, accurate knowledge of the real value of R_D is challenging and remains unknown. This, in turn, raises questions regarding the validity of R_D values, which are often used by the industry based on the commonly cited R_D of -0.5%/year for module-level degradation [10]. On the other hand, the well-known PV degradation rate studies conducted by Jordan *et al.* [11, 12] reported average degradation rates between -0.8%/year to -0.9%/year (median -0.5%/year to -0.6%/year). These statistical studies were based on a large sample of unvalidated R_D values from around the world whose accuracy might be challenged, due to the aforementioned issues.

In order to provide insights on how different decisions can influence R_D estimations, and since the real R_D values are unknown, a comprehensive framework for a worldwide parametric analysis is under development. In this paper, specific locations from different Koppen-Geiger-PV (KGPV) climate zones were selected to generate synthetic PV datasets of known degradation rates using weather data over 30 years. The analysis

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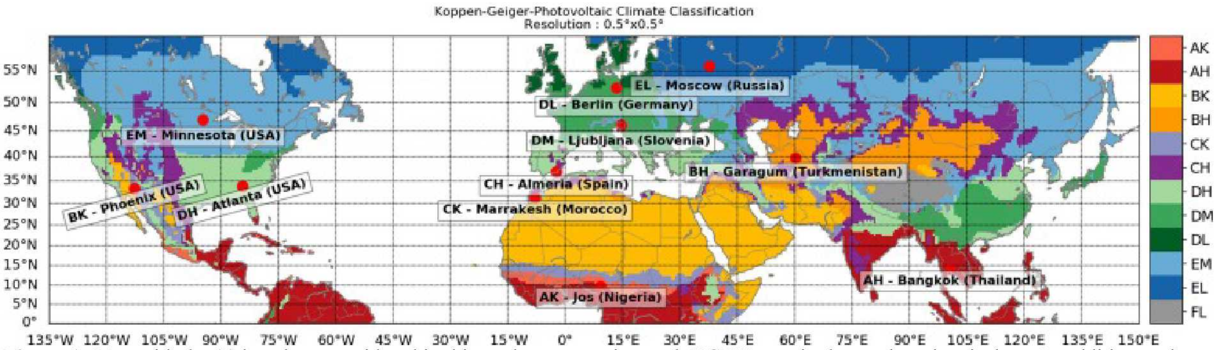

Figure 1: Map with the 11 locations considered in this study representing each KGPV zone in the northern hemisphere. In addition to these, four more locations were added to the analysis: Atacama Desert, Chile (BK) and Gibson Desert, Australia (BK) from the southern hemisphere, Albuquerque, USA (CK) and Lisbon, Portugal (DH). First letter of KGPV classification represents temperature and precipitation (A: Tropical, B: Desert, C: Steppe, D: Temperate, E: Cold, F: Polar) whereas the second letter is based on solar irradiation (L: Low, M: Medium, H: High, K: Very high). Figure courtesy of Ascencio-Vásquez *et al.* [13].

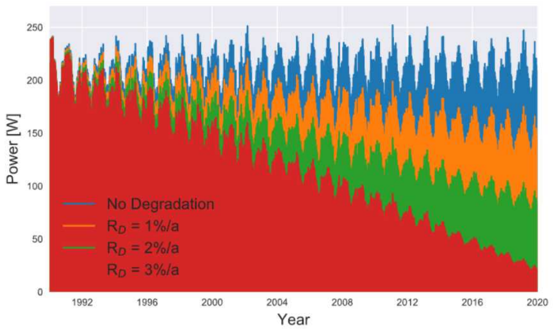

Figure 2: Modeled PV performance data over a 30-year period using ERA5 datasets. Degradation rates ranging from -1%/year to -3%/year were applied to the power data. The case of "no degradation" is also displayed as a reference.

includes different statistical models, timeseries lengths and metrics.

2 METHODOLOGY

15 locations were selected based on the KGPV climate classification that divides the globe into 12 zones with respect to temperature, precipitation and irradiation, and standardizes the PV performance evaluations in regions with similar climatic locations [13] (Fig. 1). Long-term meteorological data (hourly over 30 years) were sourced from the global reanalysis ERA5 of the European Centre for Medium-Range Weather Forecasts (ECMWF) [14]. These data were used as inputs to PV performance models of a monocrystalline silicon (c-Si) and cadmium telluride (CdTe) modules using the Sandia PV Array Performance Model (SAPM) [15] from *pvlib-python* [16]. A linear degradation rate from -1%/year to -3%/year was then applied to the performance data (see Fig. 2) and a parametric analysis including different metrics (performance ratio, *PR*, and temperature corrected *PR*, PR_{TC}), dataset length (2-30 years), and methods (ordinary least square, OLS, classical seasonal decomposition, CSD, seasonal and trend decomposition with LOESS, STL, and Holt-Winters, HW) was performed. Only a nighttime filter was applied to the data (100 – 1200 W/m^2).

Although some of the rates of emulated degradation are not realistic (e.g., linear -3%/year over PV lifetime), they were selected in order to observe whether they influence the convergence time or not. This can also be helpful in the case of nonlinear degradation with rapid performance loss during the initial PV lifetime; for example, light and temperature induced degradation (LeTID) in the case of passivated emitter and rear contact (PERC) PV modules [17].

3 RESULTS

The obtained results are summarized in the form of boxenplots in Fig. 3 and 4. These plots are similar to boxplots, but they provide more information on data distribution and are useful when data are not normally distributed. The largest box represents the interquartile range or 50% of the data (similar to a boxplot) whereas the second largest represents the 1-1/8th percentile (75% of data), the third largest the 1-1/16th percentile (87.5% of data) and so on. The black lines and diamonds represent the median and outlying values, respectively. Fig. 3 demonstrates the minimum number of years needed to converge to degradation rates within 2% of relative percentage error (arbitrary selection) using the four statistical methods. It includes all 15 locations under investigation for both monthly *PR* and PR_{TC} metrics and emulated degradation rates from -1%/year to -3%/year. Overall, it can be observed that each statistical method behaves differently depending on the level of degradation and whether the metric is temperature corrected or not. In respect to the level of degradation, all methods behave similarly achieving faster convergence with increasing degradation rates. The decomposition models (CSD and STL) converge faster with a median number of years ranging from ~ 3 (CSD on PR_{TC} for -3%/year) to ~ 6 years (STL on *PR* for -1%/year). The simplest and most commonly used method of linear regression (i.e. OLS) exhibited the slowest convergence time with median minimum number of years of 7 years (LR on *PR* for -1%/year). HW, which is the least popular method, ranged from ~ 4 to 6 years of minimum number of years. It is worth noting that although the decomposition models demonstrated a faster convergence, the maximum values are well above 15 years, which indicate that the selection of optimum combination of data pipeline and statistical method will not be universal. Further studies will be conducted to investigate this.

The hypothesis relating convergence time with PV material was investigated and the preliminary results are summarized in Fig. 4. Again, it can be seen that for both c-Si and CdTe PV technologies, shorter PV performance time-series are required with increasing degradation rate.

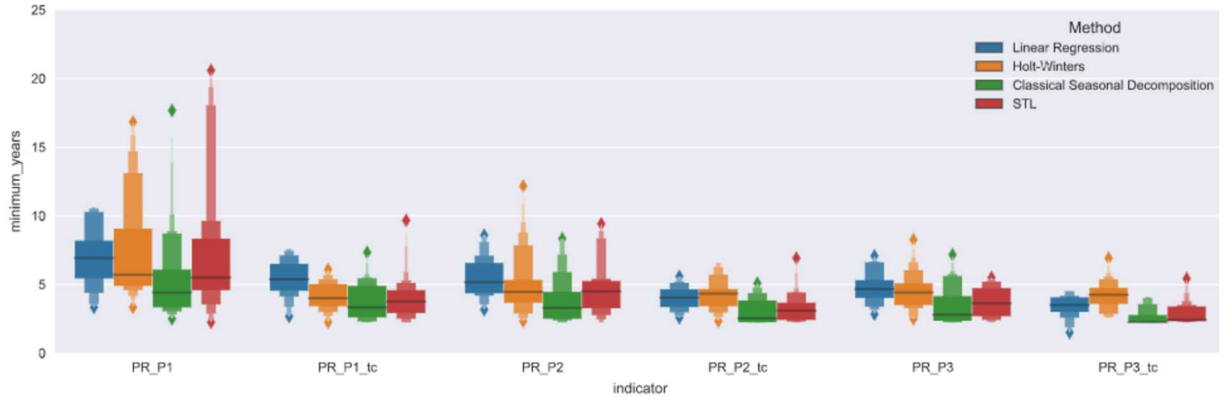

Figure 3: Boxenplot demonstrating the minimum years required to converge within a 2% percentage error of the "real" R_D value taking into account all locations, statistical methods, levels of R_D and both corrected and uncorrected *PR* values.

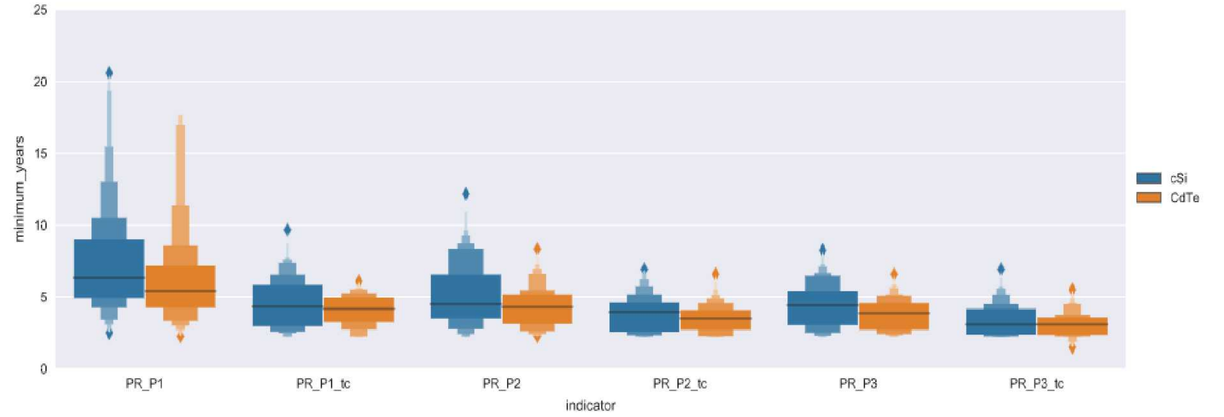

Figure 4: Boxenplot demonstrating the minimum years required to converge within a 2% percentage error of the "real" R_D value taking into account all 15 locations, statistical methods, levels of R_D, both corrected and uncorrected *PR* values and c-Si and CdTe modules.

Furthermore, the reduced seasonality commonly observed on the performance of CdTe technology enables slightly faster convergence time; however, the difference is reduced with increasing rates of degradation.

4 CONCLUSIONS

A new comprehensive framework for a worldwide parametric analysis of PV degradation modeling is under development. The first results using data of known linear degradation rate values on synthetic PV performance datasets demonstrated that each statistical method behaves differently depending on the location, technology, metric and timeseries length. Temperature correction, decomposition models, and CdTe converge faster, due to reduced seasonality. This work will expand and investigate a larger number of locations including additional methods, finer aggregation steps and other metrics. Confidence intervals are equally important to the degradation value itself; this will be reported in future.

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