Photovoltaic Module Performance and Degradation Analysis

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Precise assessment of the degradation rate of photovoltaic systems is vital for evaluating their long-term performance. Determination of the degradation rate allows for effective maintenance and optimisation strategies, ensuring reliable energy generation and maximising the system's economic viability over its operational lifespan. However, degradation rate estimations are critically limited by the absence of a universally accepted methodology.

Using the data collected by the Desert Knowledge Australia Solar Centre in the last 15 years, this study compares the degradation rate estimated using multiple statistical methods and different filters. It is found that the year-on-year method often estimates the lowest degradation rate, while the seasonal and trend decomposition method (using LOESS) yields the highest after applying all filters. It is also shown that the outlier filter has a significant impact on the linear regression method. Nevertheless, after applying all the filters, all the statistical methods yield a similar degradation rate with a standard deviation of around 5.2%.

Introduction

The accurate determination of degradation rates (DR) for photovoltaic (PV) systems is important throughout a system's lifetime. During the design phase, understanding the degradation rate of different PV technologies informs comparisons to select the optimal technology. Furthermore, it also helps evaluate the impact of external factors such as geographical location and weather patterns on performance [1]. In the operational phase, degradation rates can access the overall performance of the system, to precisely forecast energy generation and streamline maintenance protocols [2], thereby ensuring the system operates at its peak potential.

The primary obstacle to estimating degradation rates in PV systems is the lack of a universal baseline for degradation measurements [3]. This absence of a standard reference, combined with the fact that fielded PV systems seldom undergo measurement under standard testing conditions (STC, at 25°C and under 1 Sun illumination using the AM1.5 spectrum), leads to varied results across different analyses and a definitive 'truth' about their degradation remains largely elusive. The wide array of available analytical methods and filters, each with its own specific statistical models, foundational assumptions, and criteria for selecting parameters, further complicates degradation estimations [4]. These diverse characteristics influence the outcomes, thereby impeding a more profound understanding of PV system reliability in real-world scenarios and curtailing the ability to cross-reference reports and studies.

Despite the extensive number of degradation-related studies [4-12], a single comprehensive study comparing primary statistical methods across a variety of PV modules is missing. Additionally, a thorough analysis of the impact of each filtering technique on their behaviour has not been conducted. In this study, the five most prevalent statistical methods were evaluated: linear regression (LR) [13], classical seasonal decomposition (CSD) [14], seasonal and trend decomposition using LOESS (STL) [15], seasonal auto regressive integrated moving average (SARIMA) [16], and year-on-year (YoY) [17]. Furthermore, we include three filters: plane of array (POA), stability, and outlier, and examine how they influence the outcomes of each statistical approach.

Table 1. DKASC dataset description

Site Number	Installation Year	Technology	Mounting	Capacity (kW)
17	2010	Silicon heterojunction (HIT)	Fixed: Ground Mount	6.30
19	2010	Aluminium back surface field (Al-BSF) - mono-crystalline	Fixed: Ground Mount	5.04
20	2010	Al-BSF - multi-crystalline	Fixed: Ground Mount	5.04

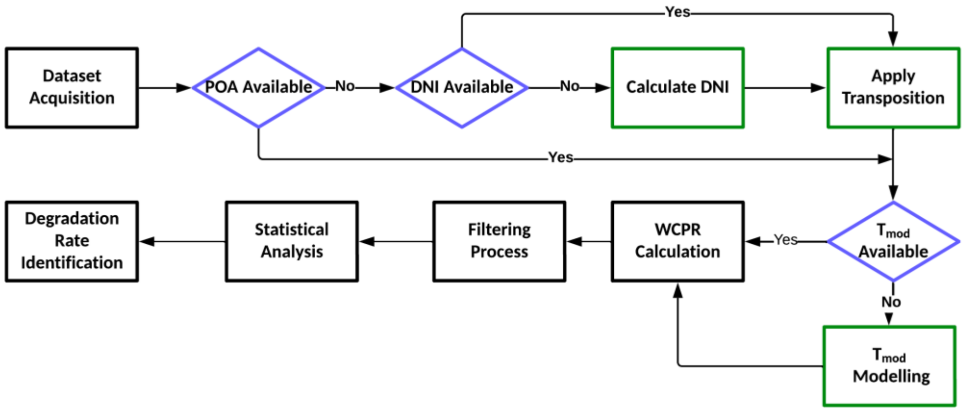

Figure 1. Flowchart of the methodology. DNI is direct normal irradiance, T_{mod} is module temperature.

Methodology

The data from the last 15 years from three different Desert Knowledge Australia Solar Centre (DKASC) [18] sites were used. The main details regarding these sites are summarised in Table 1. Figure 1 outlines the overall methodology employed in this study.

Before applying filtering and statistical analysis, data completeness was checked. If POA irradiance was absent, a transposition model [19] was used to compute it based on the diffused, direct, and global horizontal irradiance data. If module temperature (T_{mod}) was not available, the Sandia modelling technique [20] was applied to estimate it. Subsequently, the weather-corrected performance ratio (WCPR) [6], the ratio of the actual PV system output to the output expected under STC, was used as the metric to evaluate module performance.

Several filtering techniques were then applied: (a) Pre-processing –removing null values and extreme observations (WCPR values outside the range 0.1 to 10); (b) POA Filter – data that falls outside of the 400 lower and 1500 upper limits were excluded. Limits are determined using the 12-month WCPR moving average; (c) Stability Filter – data points were removed if the POA changed by more than 20 W/m^2 per minute [6] or if the module temperature changed by more than 1°C per minute [6], and (d) Outlier Filter – this filter diminishes the effect of measurement inaccuracies and equipment breakdowns. Values outside the 1st (0.15) and 3rd (0.85) WCPR quantile were removed.

After each filter, the five statistical methods (LR, CSD, STL, SARIMA, and YoY) were applied. LR employs the ordinary least squares technique to fit a straight line to the data series [13]. CSD breaks down a time series dataset into three components: trend, seasonality, and residual, offering a clear observation of the underlying patterns and fluctuations [14]. STL is an extension of CSD that adds locally weighted regression (LOESS) [15] to extract the trend, making it more robust to outliers. SARIMA combines autoregressive, integrated, and moving average models, accounting for the seasonality of data [16]. YoY creates a line between two corresponding points in subsequent years, producing a distribution of degradation rates whose central tendency represents the system's long-term performance [17].

Results

The monthly aggregated WCPR between 2010 and 2017 for the three sites are illustrated in Figure 2. Outliers are present for Sites 19 and 20, but not Site 17. As expected, all sites consistently exhibit a gradual decline in WCPR over time. However, WCPR is not 1 even at the early lifetime stage. This can be attributed to issues in production quality assurance, improper design of the PV system, incorrect operation of the system, or flaws that manifest after a short period of usage [21, 22].

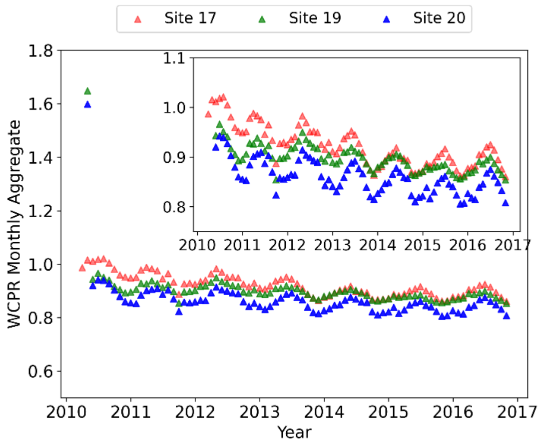

Figure 2. Monthly aggregated WCPR for the three sites

The impact of each filter is demonstrated in Figure 3. Specifically, no filter highlights the pronounced variance in 5-minute WCPR values compared to the 12-month moving average with a mean squared error (MSE) of 0.170. However, once the Stability and POA filters are used, a noticeable decrease in this variance can be observed with an MSE of 0.002. Applying all filters results in WCPR values that only slightly diverge from the 12-month moving average with an MSE of 0.001.

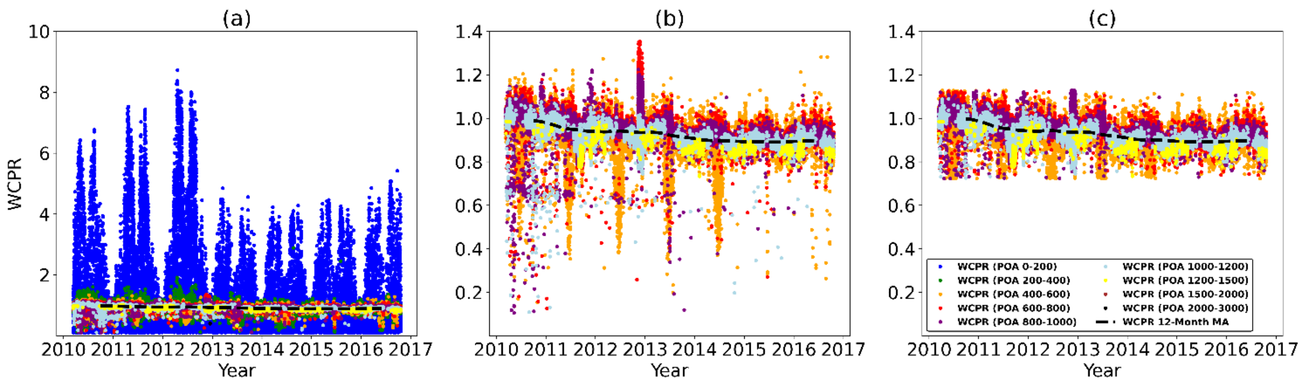

Figure 3. Comparison of applying (a) no filter, (b) POA and Stability filters, and (c) POA, Stability, and Outlier filters. The 12-month moving average is denoted with a black dashed line. WCPR values are distinguished by different colours based on their respective POA ranges.

Figure 4 compares the degradation rates determined by the five statistical methods after each filtering stage. In the presence of significant outliers, the LR method overestimates degradation rates by 0.80 (Site 19) and 0.73% (Site 20) absolute compared to the average of other methods. This drops to 0.03% and 0.05% absolute after applying filter (d). After implementing all the filters, the five statistical methods tend to converge towards similar degradation rates, with standard deviations of 4.9%, 5.4%, and 5.5% for Sites 17, 19, and 20, respectively. The YoY method estimates the lowest rate, whereas STL yields the highest degradation estimation after applying all filters for all sites.

Although it is not the focus of this study, it is interesting to notice the faster degradation rate of Site 17 (HIT technology), with an average of 1.74%, compared to Sites 19 (Al-BSF, mono: 1.04%) and 20 (Al-BSF, multi: 1.17%).

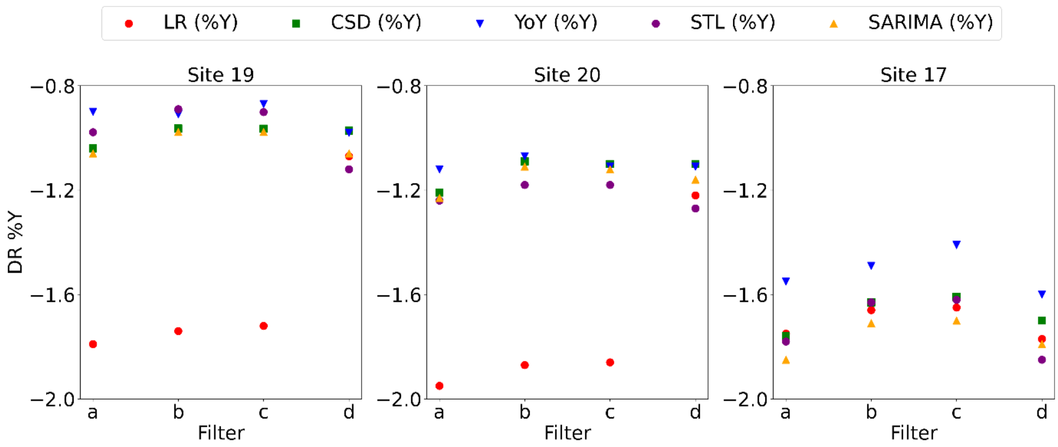

Figure 4. The effect of filtering on the degradation rate for different statistical methods. Filter (a) includes only pre-processing. Filter (b) includes pre-processing and the POA filter. Filter (c) integrates pre-processing, POA, and stability filters. Filter (d) encompasses (c) plus the outlier filter.

Conclusion

To address the lack of an agreed-upon methodology for degradation calculation, a comprehensive study was conducted using 15 years of data from the DKASC. The research examined five statistical methods (LR, CSD, STL, SARIMA, and YoY) and four filters. This research finds that the YoY method typically yields the lowest degradation rate estimates, whereas STL provides the highest after applying all filters. The presence of outliers was found to significantly affect outcomes, particularly for the LR method. However, when all filters were applied, the derived degradation rates from the different methods converged with an average of 5.2% standard deviation. The findings highlight that the preprocessing and filtering methodology can significantly influence the final degradation rate calculation of PV systems. Furthermore, it suggests that employing more complex statistical modelling methods might not always enhance performance analysis. This research not only offers insights into PV degradation rate determination but also sets a benchmark for future studies in this domain.

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