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Review of photovoltaic degradation rate methodologies

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ABSTRACT

This paper provides a review of methodologies for measuring the degradation rate, R_D, of photovoltaic (PV) technologies, as reported in the literature. As presented in this paper, each method yields different results with varying uncertainty depending on the measuring equipment, the data qualification and filtering criteria, the performance metric and the statistical method of estimation of the trend. This imposes the risk of overestimating or underestimating the true degradation rate and, subsequently, the effective lifetime of a PV module/array/system and proves the need for defining a standardized methodology. Through a literature search, four major statistical analysis methods were recognized for calculating degradation rates: (1) Linear Regression (LR), (2) Classical Seasonal Decomposition (CSD), (3) AutoRegressive Integrated Moving Average (ARIMA) and, (4) LOcally wEighted Scatterplot Smoothing (LOESS), with LR being the most common. These analyses were applied on the following performance metrics: (1) electrical parameters from IV curves recorded under outdoor or simulated indoor conditions and corrected to STC, (2) regression models such as the Photovoltaics for Utility Scale Applications (PVUSA) and Sandia models, (3) normalized ratings such as Performance Ratio, R_P, and P_{MPP}/G_I and, (4) scaled ratings such as P_{MPP}/P_{max}, P_{AC}/P_{max} and kWh/kW$_p$. The degradation rate results have shown that the IV method produced the lowest R_D and LR produced results with large variation and the largest uncertainty. The ARIMA and LOESS methods, albeit less popular, produced results with low variation and uncertainty and with good agreement between them. Most importantly, this review showed that the R_D is not only technology and site dependent, but also methodology dependent.
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Contents

1. Introduction

Photovoltaics (PV) is one of the most important renewable energy sources, simply due to the abundant and, most-importantly, predictable solar irradiation reaching the Earth's surface.

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The technology can become even more attractive for consumers and investors if the cost is minimized, while at the same time keeping reliability and durability at top level. As is valid for all PV technologies, any breakthroughs in the improvement of durability and, subsequently, the lifetime of PV modules will instil confidence in the technology, whose economic viability is based on the capability of delivering rated power, P_{max}, over the expected service lifetime. This is the main driver behind the growing interest in the accurate calculation and prediction of degradation of PV under real operating conditions, either through testing in the field or through accelerated aging.

Performance degradation is evidenced at all levels, i.e. cell, module, array and system with different factors and degradation mechanisms apparent at each level. In all cases, the main extrinsic factors related to performance degradation in field operation include: temperature, humidity, precipitation, dust, snow and solar irradiation. At the array level, all these and additionally shading and module mismatches contribute to degradation. The aforementioned factors give rise to various degradation mechanisms [1–5] and impose significant stress over the lifetime of a PV system, resulting in the reduction of durability, which must be quantified through the measurement of the rate of performance degradation.

More specifically, at the PV cell level the main mechanisms behind performance loss and possible failure are corrosion, light-induced degradation, contact stability and cracked cells. At the module level, degradation occurs due to the reliability issues of the individual cells and in addition due to glass breakage, delamination, busbar failure, broken interconnects, front surface discoloration, moisture ingress, reduced interlayer adhesion, diode failures and hot-spots. The majority of studies on the crystalline Silicon (c-Si) technology report that the calculated P_{max} degradation was mainly attributed to short circuit current, I_{SC}, losses, followed by smaller decreases in the fill factor, FF [6–9]. I_{SC} degradation associated with the reduction of P_{max} was most commonly caused by delamination and discoloration [10,11]. Hishikawa et al. [9] showed that the reduction in I_{SC} was due to discoloration or delamination at the cell/ethylene-vinyl acetate (EVA) interface, front glass breakage and increased series resistance, R_S, due to the degradation in electrode soldering. A study by the National Renewable Energy Laboratory (NREL) suggested that the degradation rate and associated I_{SC} decline were caused by ultraviolet (UV) light absorption at or near the top of the silicon surface, which causes discoloration [12]. Sanchez-Friera et al. [7] attributed the large degradation rate and I_{SC} losses to delamination of the cell-encapsulant interface, oxidation of the front metallization grid and the antireflection coating of the cells and front glass soiling. On the other hand, for thin-film technologies, there was a higher degradation rate of the FF in comparison to the c-Si case [13]. Finally, at the system level, degradation was the result of individual module failures, array shading, potential induced degradation (PID) [14] and other balance-of-system effects such as inverter efficiency loss, interconnect and cabling losses.

Gradual degradation of the performance when exposed to field conditions is defined as the inability of the PV device to produce its rated power, following exposure to extrinsic factors [15]. Long-term testing of PV has proven that gradual degradation affects the rated power of PV and although it can be clearly observed through long-term monitoring of PV devices in the field, accurate physical, mathematical or empirical representations do not yet exist due to the multitude of physical factors and mechanisms associated with degradation. In other sectors, such as the automotive, materials, paint and coating industries, long-term degradation is tested through weathering. In this regard, weathering is very different from the existing International Electrotechnical Commission (IEC) qualification testing standards on PV modules that test for “infant mortality” [16,17] and needs to be established for PV as well. Even if a PV module passes qualification testing, it does not prove that it will offer its theoretical useful lifetime in every operating environment. Some advancements have been made in the form of proposals such as the American Society's for Testing and Materials (ASTM) proposal, ASTM WK25362, “New Practice for Accelerated Life Testing of Photovoltaic Modules” [18], which describes procedures for accelerating the failure mechanisms of PV modules caused by mechanical, electrical, and environmental stresses. ASTM states that the results of test protocols described in ASTM WK25362 will help designers and manufacturers identify and quantify the failure mechanisms that can limit the service life of PV modules, as well as provide methods to evaluate the rate of performance degradation. Other proposals have been made by the IEA PVPS Task 13 team on the “Performance and Reliability of Photovoltaic Systems” [19,20] in order to build a data bank of PV system measurements and analyze the data to assess their performance and degradation.

The objective of this paper is to review the current state of degradation rate evaluation methodologies, providing details of each reported method, their advantages, disadvantages and uncertainties and to report the degradation rates resulting from each method. The reviewed methodologies were classified based on the testing conditions (field exposure or artificial conditions) and compared based on measurement data qualification and filtering criteria, performance ratings and statistical analyses required to reduce uncertainty and variability of the results. A direct comparison between the methodologies was made based on the estimated uncertainty of the results.

2. Degradation of terrestrial photovoltaics

The extent by which the various degradation mechanisms affect the different PV technologies does not appear to be identical but depends on the technology, the operating topologies and the cumulative history of exposure to meteorological conditions as a result of the geographical location of the installation. Consequently, the rated power of PV degrades at different rates. The term degradation rate, R_D, is defined as the rate of maximum performance reduction over time and is denoted as a positive quantity. It is commonly expressed in %/year and represents the reduction of P_{max} expected from a PV cell, module, array or system in the field [21]. Measures of degradation rates are essential in assessing the effective lifetime of a PV module, given the 25-year long warranties offered by manufacturers, which guarantee a maximum of 20% reduction of the datasheet P_{max} at the end of the 25 years. As of lately, the maximum degradation rate per year is also warranted. Some manufacturers guarantee that the PV module will not experience performance degradation higher that 1%/year for the first ten years of operation (linear warranty), but they do not specify the tests necessary for assessing a potential claim by the customer. Even by measuring the module's performance at Standard Test Conditions (STC), the measurement uncertainties are high enough that a difference lower than 3–4% from the rated P_{max} cannot be held in certainty. The warranties by themselves are high enough and the fact that recently produced modules have not been tested to the end of their lifetime in the field further validates the need for establishing a standardized methodology for calculating accurate degradation rates of PV modules and systems in the field.

Jordan et al. have compiled a comprehensive review of published degradation rates [22]. In summary, from 1751 published studies for c-Si, the average degradation rate was calculated at 0.7%/year and the median at 0.5%/year, with the majority of studies published before 2000, whereas for 169 published studies for thin-film technologies the average and median were higher, at 1.5%/year and 1%/year respectively, with the majority of studies published after 2000. These results did not include initial degradation (minimum three years of measurement data). Although the average for thin-films was 1.5%/year, the rates were spread from 0.2 to 4.2%/year, whereas for c-Si the rates were mainly concentrated around the median. This signifies a very large variation in reported degradation rates, which may be attributed to the small number of field studies and the variability in degradation rate calculation methodologies [23,24]. Interestingly, the study found degradation rates for systems which were sometimes lower than the rates reported for modules and not the other way around as one might expect, given that balance-of-system components, dust and snow accumulation and shading could result in higher degradation rates [25–28].

Methods for calculating R_D vary widely with the performance metric used to rate the power of the PV module/array/system and also the test conditions (outdoors and indoors). Indoor testing at STC (1000 W/m^2 irradiance, AM1.5 spectrum and 25 °C cell temperature) using solar simulators is less often used as it is time consuming and inefficient for large PV systems. Often, only a small sample of PV modules is tested at STC [16,17] in order to calculate the degradation of a large PV system, hence adding significant error to the calculation.

The methodologies presented in this paper are classified into field based, by monitoring the long-term performance of PV in the field and indoor based, by applying stress under accelerated conditions.

2.1. Calculation of degradation rates of PV systems and modules in the field

2.1.1. PV performance metrics

The calculation of degradation rates relies on the analysis of chronological ratings of the performance of PV devices. Evaluation of the performance of PV in the field typically includes the recording of measurements such as: (1) direct current (dc) current and voltage at the maximum power point (MPP) of the module or array, I_{MPP} and V_{MPP} and subsequently the dc power, P_{MPP}, as a calculated quantity, (2) alternating current (ac) power, P_{AC}, of grid-connected systems, (3) short-circuit current, I_{SC}, open-circuit voltage, V_{OC}, fill factor, FF, series resistance, R_S, and shunt resistance, R_{SH}, from IV characterization of modules and arrays and, (4) meteorological measurements such as the plane of array global irradiance, G_I, module, T_m, and ambient, T_{am}, temperatures, wind speed, S_w, and wind direction, a_w, and relative humidity, H_{rel} [29].

Common performance metrics used to rate the performance the PV technologies can be grouped into four categories, (1) electrical parameters from IV curves recorded under outdoor or simulated indoor conditions and corrected to STC, (2) regression models such as the Photovoltaics for Utility Scale Applications (PVUSA) and Sandia models [30,31], (3) normalized ratings such as Performance Ratio, R_P, and P_{MPP}/G_I and, (4) scaled ratings such as P_{MPP}/P_{max}, P_{AC}/P_{max} and kWh/kW$_p$ [32].

2.1.1.1. IV characterization. Outdoor IV curves are usually obtained periodically, whereas indoor IV curves are obtained under STC at variable intervals [33]. From an IV curve, degradation can be observed on the individual electrical parameters [34]. As detailed in the previous section, degradation of an electrical parameter can be correlated to the existence of certain physical defects. Further validation of the existence of these physical defects can also be performed indoors, with techniques such as electroluminescence and dark lock-in thermography. Outdoors IV characterization is currently performed purely for research purposes, with the modules ideally held at MPP between IV scans, in order to simulate the full load condition [6]. Indoor IV characterization is less commonly used as it is time consuming and inefficient for PV systems. Furthermore, regular indoor IV characterization carries the risk of module failure due to mishandling, while being transported to a testing facility or while being handled in the lab. Thus, it is more efficiently used for single field-exposed modules, deployed alongside a larger PV system [35]. When using indoor IV characterization, the degradation rate can be calculated by the percentage error (PE) between two consecutive temporal ratings [36].

2.1.1.2. Regression modeling. Regression models are empirical models that stem from the linear relationship of PV system parameters with meteorological parameters [37]. One of the most popular regression models is the PVUSA model [38]. The model requires the selection of measurements at high irradiance on the plane of the array (at, or above 800 W/m^2), fitting these measurements of P_{MPP} or P_{AC}, G_I, T_{am} and u_W to Eq. (1) and calculating the coefficients a, b, c and d via multivariate regression. More commonly, multiple linear regression is used, although more robust methods could be used to minimize the error of the regression residuals. The coefficients are calculated for monthly blocks of data and then monthly ratings at PVUSA Test Conditions (PTC), P_{PTC}, are calculated by substituting $G_I = 1000$ W/m^2, $T_{am} = 20$ °C and $u_W = 1$ m/s in Eq. (1).

$$P_{MPP} = G_I(a + bG_I + cT_{am} + du_W) \tag{1}$$

The model is accurate for c-Si PV, but not for thin-film technologies. A modified model for thin-films was proposed in [39], which uses Eq. (2) and adds a constant loss factor, where a, b, c, d and e are regression coefficients with measurements at irradiance levels equal or greater than 50 W/m^2. An indirect advantage of this modified model is that less data is filtered out, resulting in more accurate realization of the temporal characteristics of the PV system under a larger operating range of irradiance.

$$Y_A = G_I(a + bG_I + cT_{am} + du_W) - e \tag{2}$$

2.1.1.3. Normalized and scaled ratings. Normalized [40] and scaled [32,41,42] ratings are used for direct comparisons between different PV technologies, PV system capacities and geographical locations [43]. The most popular metric is R_P, which is defined in Eq. (3) as the ratio of the final energy yield of the PV system, Y_f, and the reference yield, Y_r [29]:

$$R_P = \frac{Y_f}{Y_r} \tag{3}$$

where Y_f is defined as the yield of the PV system, when P_{AC} is used and of the array if P_{MPP} is used, divided by the rated power, P_{max}, of the PV array and Y_r is calculated by dividing the total irradiation on the plane of the array, H_I, by the reference irradiance at STC (1000 W/m^2). The main advantage of R_P and the other normalized and scaled metrics over the PVUSA method is that they can be expressed in yearly, monthly, weekly and any other arbitrary time unit.

With respect to degradation rates, a comparison of the published rates obtained using PVUSA and R_P, showed similar results for different technologies [44], but some studies have shown substantial differences between the PVUSA and R_P [40,45]. Different results have also been observed by using temperature correction and different averaged time units on the R_P. It has been shown that the application of temperature correction results in higher degradation rates, in comparison to non-temperature-corrected measurements [40,46], with the higher degradation rates in line with degradation rates obtained from indoor IV characterization. Also, the usage of a smaller time unit resulted in the increase of the variability of the resulting degradation rates [40].

2.1.2. Measurement qualification and filtering

The measurements of the meteorological parameters and the electrical parameters of PV systems in the field are very sensitive to the type of sensors used, their accuracy and calibration and also the presence of soiling and sporadic errors and faults. The measurements are usually filtered to select favorable meteorological conditions [47] and averaged to remove bad measurements and noise. Studies have shown that data filtering improved the calculated power rating of PV at PVUSA Test Conditions (PTC) and reduced uncertainties [30] by removing invalid and out-of-calibration measurements, outages and shading periods from the evaluation. The lowest uncertainties were evaluated when selecting clear days, above 400 W/m^2 irradiance from a reference cell in comparison to a pyranometer, and using the Behnke, Erdman & Whitaker Engineering (BEW) linear method [48] in the summer and the PVUSA method in the winter, for all technologies. For specific technologies, the King 3-Part model showed the lowest uncertainties except for multi-c-Si which was on par with PVUSA. Outliers, especially due to shading, in the measurement data were discussed in [49] and it was shown that they can be identified using the I_{SC} and the G_I as a method to reduce uncertainty in R_D calculations. Another study reported the analysis of the performance of PV arrays using imperfect or incomplete input data [50]. The study proposed interpolation of missing meteorological data from the calculation of the nominal operating cell temperature (NOCT) using available data and identifying bad PV measurement data by normalization and visual representation through contour plots. Correcting outliers in the measurement data adds complexity to the methodology and is time-consuming, but it has the advantage that the uncertainty of calculated R_D is reduced significantly. This is of particular importance for short testing periods, where there are larger uncertainties due to the small amount of measurement data. On the other hand, overcorrection of PV measurements can lead to unrealistic expectations by introducing bias to the calculations [51]. Also, filtering out a significant amount of measurements or selecting a very small subset of measurements reduces the sample size and the statistical significance of the results [52]. A more recent study discussed how data filtering affected the calculated degradation rate of a grid-connected PV system at NREL in the US [40]. The study used the degradation rate calculated by measuring the P_{max} indoor at STC, before field deployment and after six years of exposure, as its basis. It was found that the temperature corrected P_{MPP}/G_I and R_P metrics, combined with a stability (i.e. irradiance and temperature rate of change) filter and outlier filter resulted in degradation rates in line with the indoor measured degradation rate at STC. The non-temperature-corrected R_P showed negative bias on the resulting degradation rate. Using the PVUSA rating the resulting degradation rates were far away from the indoor degradation rate, whether filtering was applied or not.

2.1.3. Statistical analysis

Statistical methods for estimating the trend of the performance metric over time have the largest impact on the resulting R_D. The goal of the statistical analysis is to calculate the trend of the PV performance time series and translate the slope of the trend to the annual degradation rate, in units of %/year. Model-based methods such as Linear Regression (LR), Classical Seasonal Decomposition (CSD), Holt–Winters (HW) exponential smoothing and AutoRegressive Integrated Moving Average (ARIMA) require the specification of a stochastic time series model whereas non-parametric filtering methods, such as LOcally wEighted Scatterplot Smoothing (LOESS) do not require specification of a model and are popular because of their simplicity.

The most commonly used method in the literature is linear regression (LR). LR is used to fit Eq. (4) to the PV performance time series

$$\hat{y} = \alpha t + \beta \tag{4}$$

where $\hat{y}$ represents the fitted values, α is the slope of the trend and β is the y-intercept. The LR algorithm tries to fit Eq. (4) by minimizing the sum of squared residuals, by most commonly using ordinary least squares. It is very sensitive to outliers and seasonal variations and can thus have a very large uncertainty. An alternative to ordinary least squares is the Theil–Sen estimator [53,54] which is a robust estimation technique that chooses the median slope among all lines passing through the data points. Its main advantage is that it is much less sensitive to outliers.

The following methods more advanced than LR have been proposed in the literature [46,55–57], in order to extract the underlying trend from the PV performance time series and overcome the limitations of the LR method:

- The CSD method is based on the application of a centered moving average and computation of seasonal indices by averaging the extracted seasonal component for each month. It therefore assumes that the seasonal component of PV performance is stable year after year. It requires either the additive model in Eq. (5) or the multiplicative model in equation depending on the stability of the seasonal component.

$$\hat{y} = T_t + S_t + e_t \tag{5}$$

$$\hat{y} = T_t S_t e_t \tag{6}$$

  where T_t is the trend, S_t is the seasonal and e_t is the residual component. Due to the fact that the LR and CSD methods fit a fixed model, particular characteristics of each time series are therefore not captured and this results in significant autocorrelations in the model residuals.
- Another model-based method is HW, in which triple exponential smoothing is applied to the time series. Triple exponential smoothing takes into account seasonal changes, as well as trends, through the minimization of the squared one-step ahead prediction error, in contrast to CSD, which bases the calculation of trend, seasonal component and residuals on a centered moving average. HW exponential smoothing requires the general additive model in Eq. (7), where m_n is the level component, b_n is the slope component and c_{n-S+1} is the relevant seasonal component, S is the seasonal period, and are given in Eq. (8), Eq. (9) and Eq. (10) respectively.

$$\hat{y}_{n+l|n} = m_n + b_n + c_{n-S+l} \quad l = 1, 2, \ldots \tag{7}$$

$$m_t = \alpha_0 (y_t - c_{t-S}) + (1 - \alpha_0)(m_{t-l} + b_{t-l}) \tag{8}$$

$$b_t = \alpha_1 (m_t - m_{t-l}) + (1 - \alpha_1) b_{t-l} \tag{9}$$

$$c_t = \alpha_2 \frac{y_t}{m_t} + (1 - \alpha_2) c_{t-S} \tag{10}$$

  where α_0, α_1 and α_2 lie between 0 and 1.
- The most advanced model-based method reported in the literature is multiplicative ARIMA [58,59]. The ARIMA method is more flexible than classical methods since it can effectively deal with seasonal variations, random errors, outliers and level shifts and can therefore be used to specify a model which removes all autocorrelations in the model residuals. The general model for multiplicative ARIMA is given in Eq. (11) and is

Table 1
Published R_D calculation methods, emanating from field exposure.

Performance rating	Measurement data filtering criteria	Statistical analysis	References
Monthly W/W$_p$, from STC corrected dc P_{MPP}	P_{MPP} at AM1.5 and noon	PE[a] of 1st year between sequential Junes	[45]
Monthly dc R_P	–	LR on time series	[45]
Monthly dc R_P	P_{MPP} at $G_I>800$ W/m^2, excluding outages	LR on time series	[45]
Monthly PVUSA ratings, from dc P_{MPP}	–	LR on time series	[45]
Monthly PVUSA ratings, from module IV P_{MPP}	P_{MPP} at $G_I>800$ W/m^2	LR on time series	[24,56]
Monthly PVUSA ratings	P_{MPP} at $G_I>800$ W/m^2	CSD (additive) on time series and LR on the extracted trend	[56]
Monthly PVUSA ratings	P_{MPP} at $G_I>800$ W/m^2	ARIMA(1,0,0)(0,1,1) modeling of the time series, CSD on modeled data and LR on the extracted trend	[56]
Monthly dc R_P	Correction of outages	Optimal seasonal ARIMA and LR on the trend component	[55]
Monthly dc R_P	Correction of outages	HW exponential smoothing	[55]
P_{MPP}, from outdoor module IV and indoor IV at STC	–	PE[a] of P_{MPP}	[36]
P_{MPP}, from outdoor module IV	P_{MPP} at T_m=NOCT and $G_I>800$ W/m^2	PE[a] of P_{MPP}	[6]
Annual ac R_P	–	PE[a] of R_P	[74,75]
P_{MPP}, from indoor IV at STC	–	PE[a] of P_{MPP}	[76–78]
Daily dc R_P	–	LOESS[b] regression on time series and LR on separate degradation regions	[35]
Monthly and daily dc R_P	–	LR on time series	[46]
Monthly and daily dc R_P	–	CSD (additive) on time series	[46]
Monthly and daily dc R_P	–	LOESS on time series	[46]
Monthly and daily dc R_P-TC[c]	–	LR on time series	[46]
Monthly and daily dc R_P-TC[c]	–	CSD (additive) on time series	[46]
Monthly and daily dc R_P-TC[c]	–	LOESS on time series	[46]
Weekly means of P_{MPP}, I_{SC}, V_{OC}, FF, I_{MPP} and V_{MPP}, from outdoor module IV and correction to 1000 W/m^2 and T_m=45 °C	P_{MPP}, I_{SC}, V_{OC}, FF, I_{MPP} and V_{MPP} at $800<G_I<1100$ W/m^2	LR on time series	[79]
Daily ac kWh	–	PV system ac yield normalized by relative final ac yield and LR on time series	[21]
Modified monthly PVUSA ratings, from P_{AC} corrected to STC	P_{AC} at $G_I>500$ W/m^2	LR on time series, $R_D=\frac{x_1 \tau_{regress}}{x_2}100$ where $P=x_1t+x_2$ is the linear fit equation.	[80]
Modified weekly PVUSA ratings, from P_{AC} corrected to STC	P_{AC} at $G_I>500$ W/m^2	LR on time series, $R_D=\frac{x_1 \tau_{regress}}{x_2}100$ where $P=x_1t+x_2$ is the linear fit equation.	[80]
Modified monthly PVUSA ratings, from P_{AC} corrected to STC	P_{AC} at $G_I>500$ W/m^2	CSD on time series, $R_D=\frac{x_1 \tau_{regress}}{x_2}100$ where $P=x_1t+x_2$ is the linear fit equation.	[80]
Modified weekly PVUSA ratings, from P_{AC} corrected to STC	P_{AC} at $G_I>500$ W/m^2	CSD on time series, $R_D=\frac{x_1 \tau_{regress}}{x_2}100$ where $P=x_1t+x_2$ is the linear fit equation.	[80]

[a] PE: percentage error
[b] LOESS: LOcally wEighted Scatterplot Smoothing
[c] R_P-TC: performance ratio using temperature corrected P_{MPP}.

abbreviated as ARIMA(p,d,q)(P,D,Q), where p is the autoregressive (AR) order, d is the differencing order, q is the moving average (MA) order, P is the seasonal AR order, D is the seasonal differencing order and Q is the seasonal MA order.

$$\Phi(T)\Phi_S(T^S)\nabla^d\nabla_S^D y_t=\theta(T)\theta_S(T^S)e_t \tag{11}$$

In order to find the optimal ARIMA model, the time series must be checked for stationarity and then transformed using differencing to achieve stationarity, as necessary. The lags p, q, P, Q of the model are determined from the autocorrelation function (ACF) and the partial autocorrelation function (PACF). The model selection procedure can yield multiple models that fit the data well. The optimum model is the one with the lowest order (i.e. parsimonious), with the lowest mean-square-error (MSE) and the minimum value of the corrected Akaike information criterion (AICc). Due to the complex nature of ARIMA, it is entirely implemented in software [60,61]. One of the most widely used software packages is X-13 ARIMA [62], which was developed by the U.S. Census Bureau. X-13 ARIMA implements the parametric X-11 ARIMA method [63,64] which automatically detects additive outliers and level shifts in the data and has been proven to calculate statistically accurate degradation rates [55]. The ARIMA method was investigated for forecasting the R_P of different PV technologies [65]. Through model validation, residual analysis and minimization of the forecasting error, the study showed that each PV system was modeled more accurately with different model orders. Another study tested the sensitivity of the methodologies to outliers and data shifts [56]. Shifts in the measurements were fixed by selecting a range of corrective scaling factors and minimizing the residual-sum-of-squares (RSS) of errors with respect to the various scale factors. The ARIMA(1,0,0)(0,1,1) model was pre-selected and the results showed that it performed very well with outliers and could be used to calculate similar R_D to the simple LR method with as little as two years of field measurements in a semi-arid climate.

- Non-parametric filtering methods are different than model-based methods because an explicit model is not specified. One such method is LOESS, which extracts the trend from locally weighted polynomial fitting [66,67]. LOESS provides robust estimates of the trend and seasonal components that are not distorted by outliers and missing values [68]. A comparison of R_D found using LR, CSD and LOcally wEighted Scatterplot Smoothing (LOESS) on monthly and daily R_P and temperature-corrected R_P (R_P-TC) time series of 5 years of c-Si and thin-film PV system performance has shown that LR was the least robust method since it was heavily influenced by the type of performance metric used and by temperature correction of P_{MPP}. Using as a criterion the lowest variation of R_D, the best method for c-Si was the monthly R_P-LOESS which resulted in an average degradation rate of 0.95%/year, while for thin-films it was the daily R_P-LR method, which resulted in an average degradation rate of 2%/year [46].

From these results, it can be deduced that different technologies might require different R_D calculation methods because of the inherent differences in their seasonal components, temperature coefficients and metastability (Staebler–Wronski effect, thermal annealing, light soaking and dark rest).

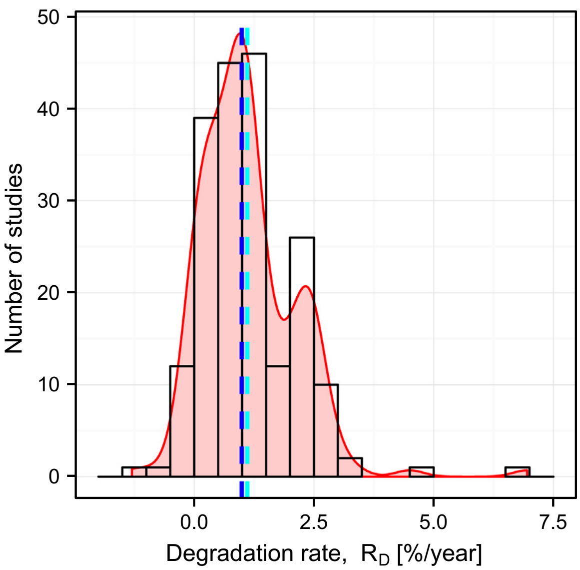

Fig. 1. Distribution of degradation rates of all technologies and all methods, from the sources cited in this paper. The blue vertical line represents the median and the cyan vertical line represents the mean R_D. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.1.4. Uncertainties

Each methodology for calculating the degradation rate of PV systems in the field carries different uncertainties. For example, the LR method on R_P carries the uncertainty of the regression and the calculation of R_P, which in turn carries the uncertainties of the V_{MPP}, I_{MPP}, P_{AC}, G_I, T_{am} and T_m sensors used. Correction of outages and filtering measurements in order to exclude low-quality data reduce the degradation rate uncertainty due to the sensing equipment, shading (snow, dust) and outages [40,55,69].

On the other hand, the short observation time, the presence of outliers in the measurements and the data shifts related with hardware changes, increase the uncertainty of the calculation [56]. A minimum testing period of 3–5 years was found to be necessary in order to obtain accurate R_D from field measurements, due to seasonal variations and higher initial degradation [70]. More specifically, the uncertainty of the statistical method used to calculate the R_D is reduced with increasing observation time, as more sample data is recorded and therefore random variations and seasonality have a smaller impact on the underlying trend. In addition, the methodology used can affect uncertainty and therefore the width and shape of the R_D distribution. A larger uncertainty is related to larger variance and thus results in a broader distribution. Granata et al. [71] found that the calculated R_D were within the experimental uncertainty, which means that they were statistically insignificant, given the specific measuring equipment and calculation method. The experimental uncertainty can be quite high, as the irradiance measurement carries the largest contribution to uncertainty. Translated into R_P, the uncertainty can reach up to 4.5% [72]. This further proves the need for employing a methodology which minimizes the uncertainty, especially given that a linear R_D less than 0.5%/year is required to satisfy long-term warranties [73].

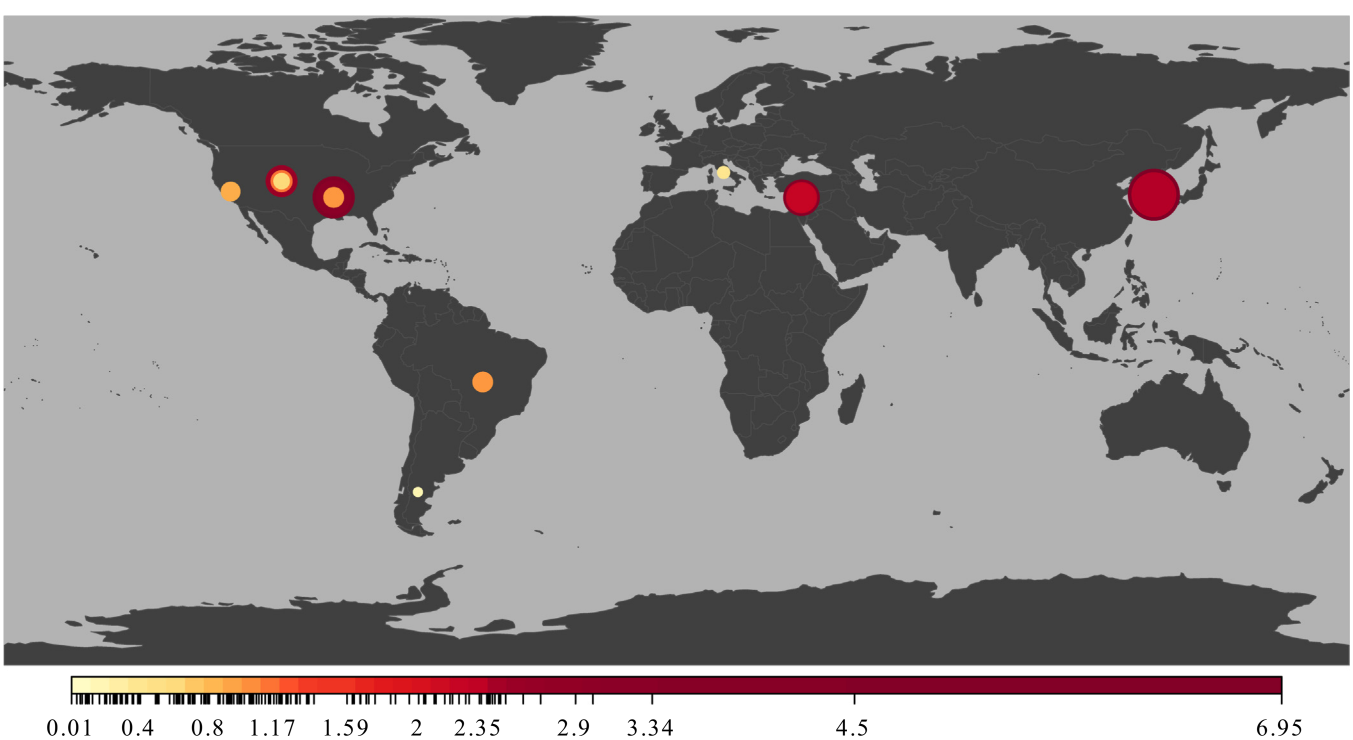

Fig. 2. Worldwide rates of degradation [%/year] from the results of the studies listed in Table 1. The color and size of the bubbles represent the degradation rate value. (For interpretation of the references to color in this figure legend, the reader is referrred to the web version of this article.)

Trend extraction techniques reduce the degradation rate uncertainty by removing noise and seasonal effects from the time series. The more complex the trend extraction technique, the better is the removal of the seasonal and noise components. CSD, being a fixed technique, suffers from these pitfalls. It assumes that the seasonal component is stable each year and makes no corrections to the model based on the residuals. This is not valid for a-Si technologies as they experience periods of lower efficiency due to the Staebler–Wronski effect and then periods of increased efficiency due to thermal annealing. It is also not valid for meteorology, as the annual global irradiation reaching the Earth's surface varies according to the well-known 11-year solar cycle and other random fluctuations.

2.1.5. Degradation rate analysis for PV systems in the field

Table 1 summarizes the commonly employed analytical R_D calculation methods used for PV systems and modules installed outdoors, as reported in the bibliography. From this table it is clear that there is a multitude of methods used to calculate the R_D of PV. It is thus evident that a comprehensive study must be performed where each and every method is tested on the same PV modules/arrays/systems and compared in multiple locations, in order to formulate an accurate and robust methodology.

The R_D results from all the sources cited in this paper are shown in the histogram of Fig. 1, where a positive R_D indicates loss of performance. The mean R_D of all technologies was found to be 1.1%/year and is indicated by the cyan dashed line. The median R_D of all technologies was 0.99%/year (indicated by the blue dashed line). For individual technologies, the mean R_D for mono-c-Si was 0.89%/year, for multi-c-Si was 0.81%/year, for a-Si was 1.34%/year, for CIGS was 1.86%/year, for CdTe was 1.70%/year and for other thin-film technologies the mean R_D was found to be 2.24%/year. From the differences in the mean degradation rates, it is evident that a distinction must be made, based on the PV technology.

The same degradation rates are shown on the map of Fig. 2. From the map it can be seen that the highest degradation rates were found in Korea and the Mediterranean region and the lowest in Brazil and Italy. The geographical representation should not be taken as relative, but rather as absolute values, as the degradation rates were calculated from a multitude of systems with vastly different field exposure history and using much different degradation rate calculation methods.

The R_D results extracted from the investigations listed in Table 1 were further categorized by technology and statistical analysis method and presented in Fig. 3, where the black dashed horizontal line represents the median R_D of all technologies. It can be seen that for all technologies, the IV method with PE resulted in the lowest degradation rates and low variation, except for mono-c-Si. LR resulted in the largest variations and uncertainties, especially for a-Si/a-Si, CdTe and CIGS, and produced slightly lower median R_D. LOESS and ARIMA, albeit less frequently used, were shown to produce good results with low variation, for all technologies. Lastly, CSD produced the highest degradation rates for mono-c-Si and multi-c-Si.

2.2. Degradation rates of PV modules through accelerated aging

2.2.1. Weathering

As mentioned in the previous section, degradation studies in the field need several years of field exposure in order to yield credible results but they still carry large variability, as shown by the published R_D results, even for the same technologies and manufacturers. Keeping in mind the continuous improvement of PV cells and modules and the introduction of new module revisions to the market, long-term testing of every PV module revision is impractical and unrealistic. For this reason, their reliability is estimated through accelerated aging and statistical sampling, from tried and tested techniques developed for the materials industry. In this regard, qualification test procedures were created specifically for PV modules [16,17] resulting in pass/fail criteria. Although these procedures formulate the standard conditions for qualification of all PV modules, it is impossible to simulate all degradation mechanisms that occur naturally in the field and are thus unable to test module reliability and durability. On the other hand, degradation mechanisms that do not normally appear in the field can manifest due to unrealistic stress levels. As mentioned before, future standards will recommend procedures for quantifying the durability and of PV modules through weathering [18].

Regarding accelerated indoor testing, studies have shown that 1000 h at damp-heat conditions at 85 °C and 85% H_{rel} were able to simulate a P_{max} drop of about 10% [81,82] due to moisture ingress which causes corrosion and delamination. Therefore, if a mean, linear degradation rate of 0.8% is assumed for c-Si [22], this is equivalent to 12.5 years of outdoor exposure. The advantage of this method is that it reveals degradation of P_{max} due to corrosion and delamination in a short amount of time but due to the unknown acceleration factor, AF, degradation cannot be correlated to normal operation in the field, as different climates have varying effects on the field exposure history [34]. Furthermore, a high AF means that the PV module will be exposed to a much harsher environment than what will normally be encountered in the field. In this case,

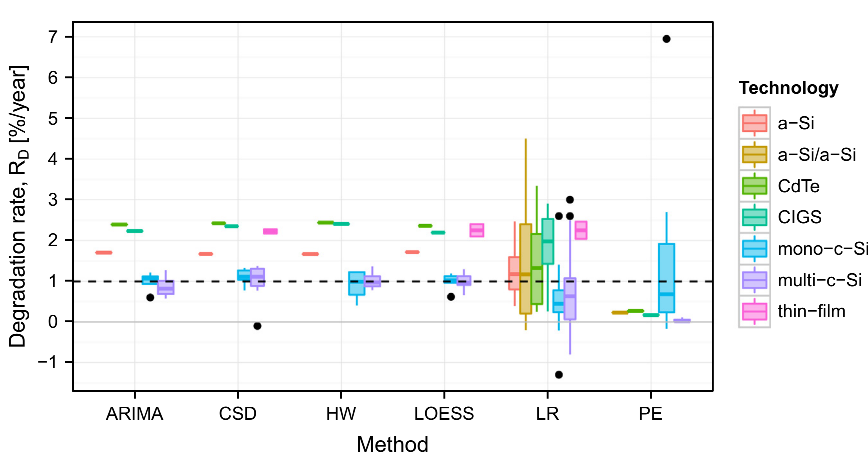

Fig. 3. Degradation rates from the sources cited in this paper, categorized by the PV technology and statistical analysis method. The dashed black horizontal line represents the median R_D of all technologies.

Table 2
Published studies on power loss during indoor and outdoor PID testing.

Indoor PID testing	Outdoor PID testing
Between −10 and −99% change in power for 9 c-Si modules out of 13, after 48 hours. PID module test configuration: front aluminum foil, −1000 V between the foil and the front contact of a PV cell, modules placed in a climatic chamber at 50 °C and 50% humidity [87].	−35% change in power for a back-contact c-Si PV module experiencing +160 V at the high potential end of a series string, after several months, in Germany [88].
−52.2% power loss for framed a-Si modules after 1340 h. PID module test configuration: −600 V applied to the shorted output leads of the module, modules placed in environmental chamber at 60 °C and 85% humidity [89].	−11% change in power for c-Si modules under −600 V system voltage bias (applied logarithmically with irradiance), after ~10 months, in Florida, USA [90].
	−25.7% power loss for c-Si modules under −1500 V system voltage bias, after one year, in Florida, USA [91]. Power degradation of up to −51% for multi-c-Si solar modules biased to −1000 V at daytime, within 25.5 weeks, in Alzenau, Germany [92].

the correlation between accelerated aging and field aging becomes even weaker, because of degradation mechanisms unique to the extreme environment. More recently, the effect of thermal cycling was studied by predicting the R_D under accelerated stress [83]. The results showed that degradation was observed on the solder interconnections and in comparison to normal operation, the acceleration factor was found to be equal to 6, for temperature cycles between −40 °C and 85 °C.

2.2.2. *Potential induced degradation*

An important externally induced factor that causes excessive degradation in PV modules is the potential induced degradation (PID), which was discovered in the last few years by the PV community. PID is accelerated under hot and humid conditions [84] and is a critical factor leading to significant loss of power in PV. Due to its relatively recent discovery, there is lack of data on this degradation mechanism of PV modules deployed in the field. Only recently, the first attempt towards calculation of the R_D of PV modules under high system voltage operation in the field was presented in a publication by Kaul et al. [85]. The 2.5 year outdoor monitoring of glass-to-glass Cu–In–Ga–Se (CIGS) thin-film modules in the hot and humid climate of Florida, revealed a significant R_D of 5.13 ± 1.53%/year and 4.5 ± 1.46%/year using PVUSA type regression analysis for the positive and negative strings, respectively. Table 2 summarizes some of the studies on loss of power during outdoor and indoor PID testing. Most companies perform indoor PID tests using criteria that they have set themselves. Therefore, there is a great need for an international experimental procedure to be included in qualification tests to allow the comparison of test results. An independent IEC standard for PID of c-Si modules (IEC 62804) is under discussion by the PID committee for standardization and is expected to be finalized in 2014–2015 [86]. A brief description of the first draft of the IEC 62804 is: 96 h under specified system voltage, 58–62 °C and 80–90% humidity, for c-Si modules with their frame grounded [87]. The test samples must then pass the insulation test and the test for insulation resistance when wet, as well as the power test, per IEC 61215, and a visual inspection, per IEC 61730.

3. Conclusions

The accurate and efficient evaluation of performance degradation of PV technologies is the next logical step to reaping the benefits of PV, as new, more efficient technologies emerge with unstudied and undefined durability and weatherability. Understanding of the performance degradation under real operating conditions is a key requirement for their successful characterization under varying meteorological conditions. The outcome of PV degradation assessments and the comparison of different PV technologies provide useful insight on the durability of each technology and their efficiency throughout their lifetime. In this paper it has been shown, from a number of published studies, that researchers are creating momentum with the degradation of PV and subsequently, their long-term durability.

Through the analysis of published works, this review has shown that the degradation rate is not only technology dependent, but also methodology dependent. Many different methodologies for calculating degradation of different technologies were presented as well as their results in the form of degradation rates. In the case of degradation rates and long-term durability, the recognized research directions are pointing towards the standardization of methods for degradation rate assessment including experimental uncertainty limits, measurement data qualification and filtering, averaging, outlier detection and performance rating techniques required in order to reduce uncertainty and variability and to establish the standardized reporting of degradation rates for different technologies.

Finally, this review paper identified and presented the four major statistical analysis methods for the calculation of degradation rates: (1) Linear Regression (LR), (2) Classical Seasonal Decomposition (CSD), (3) AutoRegressive Integrated Moving Average (ARIMA) and, (4) LOcally wEighted Scatterplot Smoothing (LOESS) and the different performance metrics used in conjunction with these methods: (1) electrical parameters from IV curves recorded under outdoor or simulated indoor conditions and corrected to STC, (2) regression models such as the Photovoltaics for Utility Scale Applications (PVUSA) and Sandia models, (3) normalized ratings such as Performance Ratio, R_P, and P_{MPP}/G_I and, (4) scaled ratings such as P_{MPP}/P_{max}, P_{AC}/P_{max} and kWh/kW$_p$. A statistical analysis of the results of the methodologies has shown that the IV method with PE produced the lowest R_D. The LR method produced results with considerable variations and uncertainty. The CSD method produced the highest R_D for mono-c-Si and multi-c-Si but with lower uncertainty than LR, whereas the ARIMA and LOESS methods, albeit less popular, produced results with low variation and uncertainty and with good agreement between them for all technologies.

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