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COMPARISON OF VARIOUS MODELS FOR THE ESTIMATION OF THE PERFORMANCE LOSS RATE OF SEVEN PV TECHNOLOGIES OVER FIVE YEARS IN ALPINE CLIMATE

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ABSTRACT: The interest in methodologies for the estimation of the performance loss rate (PLR) using data from PV systems arises with the aging of an increasing amount of PV installations at different climates. These methodologies must be simple, i.e. involve few quantities as input. Furthermore, the associated uncertainty must be kept low in order to be a reliable tool for the verification of module manufacturers' warranties.
This study compares the PLR of seven PV systems based on different technologies using four different methodologies that are presented and discussed. Results are compared on the basis of the PLR and the respective regression uncertainty. We find that, especially for technologies with a strong seasonal response, the error of the estimated PLR can be significantly reduced using seasonal decomposition methods such as a simple moving average. Other more physical approaches like the PVUSA method to reduce seasonality reduce the error as well, however remaining oscillations that are not captured by the physical description enlarge the error.

Keywords: performance loss rate, degradation, PVUSA, performance ratio, moving average.

1 INTRODUCTION

In this paper we calculate the PLR, expressed as the percentage of the yearly performance loss, of seven PV systems installed at the Airport Bolzano Dolomiti (South Tyrol, North Italy), namely: mono- and polycrystalline Silicon (mc-Si and pc-Si), amorphous Silicon (a-Si), micromorph Silicon, Copper-Indium-Gallium-Selenide (CIGS), Cadmium Telluride (CdTe) and heterojunction with intrinsic layer (HIT). DC-power and weather data are filtered and treated before calculating monthly values of performance metrics. The methodologies used can be summarized as: Performance Ratio (PR) filtered for shading, PR evaluated only at high irradiances G>800W/m^2, PVUSA also evaluated only at high irradiances and the moving average of the shading-filtered PR. A linear regression is performed on a 5-year series of monthly values, in order to estimate the PLR and the associated regression uncertainty. The detailed analysis of the performance loss with different methods is an important step not only to understand the aging behavior of different PV technologies, but more importantly to understand the effect that different computation methodologies have on the value and the accuracy of the performance loss estimation. This information will serve as a valuable source in defining standard of performance loss measurements. Standards are important so that values given by the producer's warranties are verifiable in long term measurements. This in turn will make the economic analysis and the life time yield analysis of a given PV plant more accurate and will give potential investors a better idea of the risk involved in PV investment.

2 METHODS

The purpose of this work is the comparison of four different methods to calculate the performance loss rate (PLR) of seven different PV systems.
In cooperation with the Airport of Bolzano Dolomiti (ABD), EURAC research runs a multi-technology photovoltaic test facility for the detailed performance evaluation of different module technologies and mounting systems.
The site includes 24 technologies and 4 mounting systems. Power monitoring started n summer 2010. The test site has an overall nominal power of 724 kWp. The field orientation is 8.5° West of South, and the modules have a 30° tilt angle. Irradiance variables are monitored by a dedicated weather station. Five years of monitored PV system data are taken into consideration, ranging from January 2011 to December 2015. The DC-power data of the seven considered PV systems was measured by commercial inverters. Data of plane-of-array irradiance, wind speed and ambient temperature were measured by a weather station close to the PV systems and are available as 15-minutes based values. The methods involve the calculation of monthly average values of the performance estimators PR or PVUSA.
The Performance Ratio (***PR***) metric is derived from IEC61724:1998 [1] and is calculated as [2]:

$$PR = \frac{Y_a}{Y_r} = \frac{\sum P_{dc}(i)}{\sum G(i)} \frac{G_{STC}}{P_{STC}} \tag{1}$$

where P_{dc} is the DC-power of the PV system at time i, $G(i)$ is the irradiance measured in the plane of the modules at time i, while G_{STC} is the irradiance under standard test conditions (STC) and P_{STC} is the nominal power of the PV system under STC. The same formula can be written as the ratio of array yield Y_a, i.e. the generated DC-energy per kW of installed PV array, and reference yield Y_r, i.e. the ratio of the irradiation measured on the plane of the modules and irradiance at STC.
The moving average method $\boldsymbol{PR_{mov}}$ involves the use of a monthly value of a symmetrical moving average of the PR over 12 months:

$$PR_{mov}(t) = \frac{1}{2}\left(\frac{1}{12}\sum_{i=t-6}^{t+5} PR(i) + \frac{1}{12}\sum_{i=t-5}^{t+6} PR(i)\right) \tag{2}$$

This method is used in order to decrease the uncertainty associated to the estimation of the PLR as it smooths the seasonal oscillation of PR metric. On the other hand, the values of PR calculated with this technique are computable from the sixth month of data series start, up to the sixth month before the data series end, thus leaving some initial and final gaps in the series used for regression.

PVUSA (Photovoltaics for Utility Scale Applications) metric [3] consists in calculating the best-fit correlation on

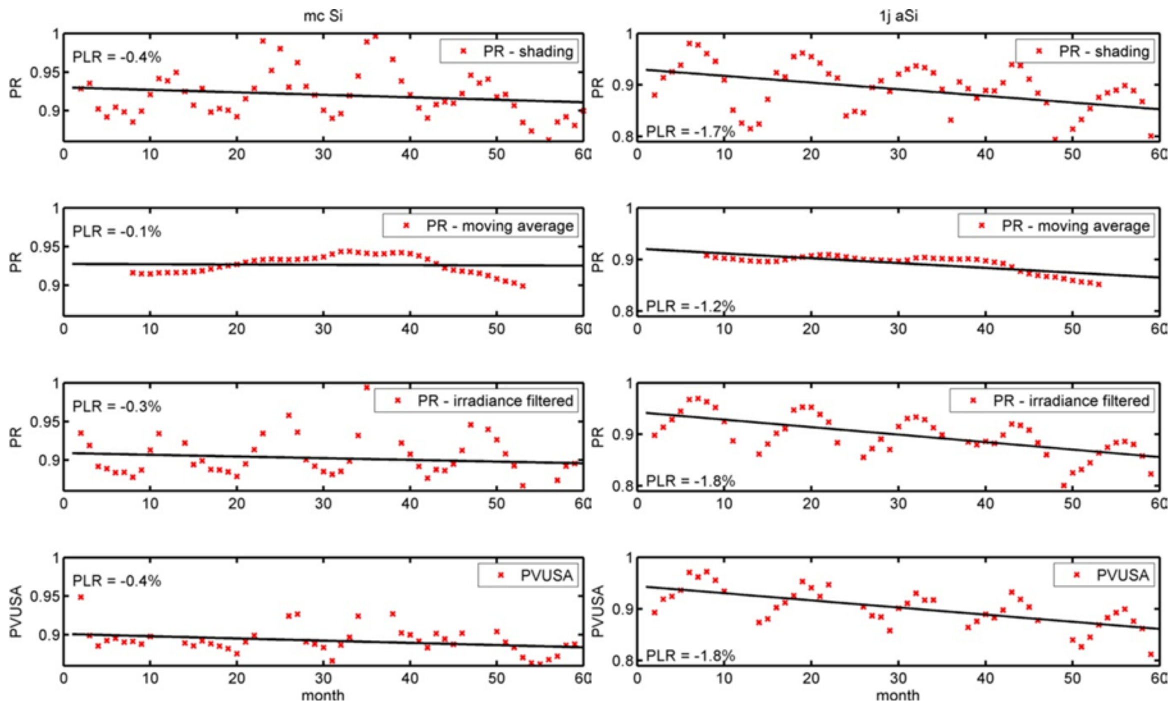

Figure 1 Monthly values of PR and PVUSA according to the four considered methodologies (1 = January 2011; 13 = January 2012; 25 = January 2013; 37 = January 2014, 49 = January 2015): (right) amorphous silicon PV system; (left) monocrystalline silicon PV system. Regression line as well as PLR value are reported. PVUSA values are normalized for the array power at STC, P_{STC}

a monthly base between 15-minutes based values of measured DC-power P_{dc} and 15-minutes based values measured irradiance on the plane of the modules G, wind speed W, and ambient temperature T, according to the following parametrized equation:

$$P_{dc}(i) = G(i)[a + b * G(i) + c * W(i) + d * T(i)] \qquad (3)$$

Parameters a, b and c are then re-fed into Equation 4 in order to estimate the power at Performance Test Conditions (PTC) (G = 1000 W/m^2, T = 20 °C, W = 1 m/s):

$$PVUSA = P_{dc}(PTC) \qquad (4)$$

Different filters are applied to the metrics introduced above. Overall, four different methodologies are applied to the measured data. The methods can be summarized as follows:

- Method 1: PR (Equation 1) filtered only for shading using shading diagram for each array to exclude effects due to close objects which cause the irradiance conditions to be different on the array and the weather station.
- Method 2: moving average of the PR. Equation 2 is applied on the PR values obtained in method 1.
- Method 3: PR (Equation 1) at high irradiances. PR outliers (15-minutes based) are first filtered out using a filter $\overline{PR} \pm \sigma$, where $\overline{PR}$ is the average monthly value of PR and σ is the corresponding standard deviation. Data are further filtered in order to keep only 15-minutes based values of PR corresponding to irradiance values higher than 800W/m^2.
- Method 4: PVUSA: (Equation 3 and 4) at high irradiances. The same filtering technique as Method 3 are used. Here however the PVUSA metric is used instead of PR.

Once the monthly values of the metric are calculated according to the four selected methodologies, a linear regression is calculated and the data is fitted to the linear expression:

$$\bar{P} = at + b \qquad (5)$$

where $\bar{P}$ is the monthly value of the metric PR or PVUSA, t the month number, and a and b are the regression coefficients. The PLR, expressed as the percentage of performance loss in one-year period, is then calculated as:

$$PLR = \frac{12a}{b} \qquad (6)$$

The uncertainty of the linear regression is also calculated according to the procedure proposed by the Guide to the Expression of uncertainty measurement [4] and [5]. The uncertainty of each measurement (y = PR, PR_{mov}, PVUSA) is given as:

$$\sigma_y = \sqrt{\frac{1}{N-2}\sum_{t=1}^{N}(y_t - a\,t - b)^2},$$

where N is the total number of months considered and y stands for the respective performance metric. The uncertainty of the gradient is then given as

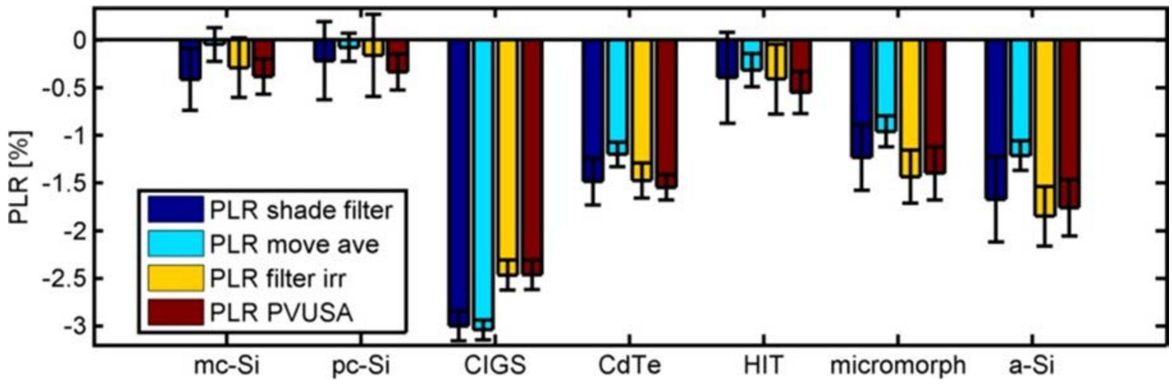

Figure 2 performance loss rates of the 7 technologies with the error for the different methods used: (dark blue) Method 1: PR filtered only for local shading was used for the evaluation, (light blue)Method 2: PR from Method 1 was smoothed using a symmetric 12 month moving average, (yellow) Method 3 PR filtered for high irradiance only, (red) Method 4: the PVUSA performance metric was used

$$\sigma_a = \sigma_y \sqrt{\frac{N}{\Delta}},$$

$$\sigma_b = \sigma_y \sqrt{\frac{\sum t^2}{\Delta}},$$

where Δ is given as

$$\Delta = N \sum t^2 - \left(\sum t\right)^2 .$$

The uncertainty for the PLR is then given as

$$\sigma_{PLR} = \sqrt{\left(\frac{12}{b}\right)^2 \sigma_a^2 + \left(\frac{12a}{b^2}\right)^2 \sigma_b^2}.$$

3 RESULTS

The rates were computed with the methods described above. Figure 1 shows the monthly values of the metrics obtained by the 4 different methods. For space reasons only two of the technologies, namely amorphous silicon (right) and mono-crystalline (left) silicon are shown here in detail. The four graphs from top to bottom show method 1-4 (PR-shading), PR-moving average, PR-irradiance >800W/m^2 and PVUSA). The regression line is plotted for each method and technology and the values of the PLR are given in the figures. For a detailed results the PLR and the corresponding uncertainties are reported in Figure 2 and Table 1.

In general, Methods 1, 3 and 4 present a strong seasonality. They give similar results for PLR. However, method 3 and 4 present gaps in the metric series, since filtering data for irradiance lower than 800W/m^2 tends to exclude all points in winter. On the other hand, Method 2 shows different values of PLR, lower in absolute value. This methodology has a smoothing effect on the metric series, even though it presents a 6-months gap at the beginning and end of the data series.

For all methods used the largest performance loss was measured for the CIGS technology (~2.5-3 %/year), followed by the 1j amorphous silicon (~1.2-1.9 %/year), CdTe (~1.2-1.5 %/year) and the micromorph silicon (~1.0-1.4 %/year). After 5 years of monitoring the thin film show a much larger performance loss than the crystalline technologies such as poly-crystalline (~0.1-0.3 %/year), mono-crystalline silicon (~0.1-0.4 %/year) and HIT (~0.3-0.5 %/year). It is important to mention that the performance loss we found for the CIGS array is unusually high for this technology due to manufacturing problem of this specific product. Typical degradation rates found for CIGS are comparable to those of other thin film technologies [6]. In general the precision of all 4 methods is high taking the error bars into account.

Comparing the uncertainties of the various methods we find the largest uncertainty is found for the PR measurements that are only filtered for shading. Filtering the PR from irradiance larger than 800W/m^2 has no large effect on the error bar. A maximal reduction of the uncertainty to 70% (average reduction to 86%) of that of the former can be achieved. The PVUSA metric reduces the uncertainty by up to about 50% (average reduction to 63%) but not consistently as the physics used by in the computation of the PVUSA metric is not equally accurate for all technologies. The best result in terms of reduction of the uncertainty is achieved using the moving average of the shading-filtered PR. Here the uncertainty can be reduced to up to 33% (average reduction to 46%) of the untreated PR measurements.

4 CONCLUSIONS AND FUTURE WORK

The results found here confirm the general trends in performance loss rates that crystalline technologies age more slowly than thin film technologies. However, the main focus of this work was not the values of PLR but an analysis of various methods of computing them. In previous publication different methods of computing the PLR were explored, see [7] and [8]. In [7] more physical properties were used to reduce the uncertainty related to the PLR computation, taking into account the module temperature and correct for it using the temperature coefficients found in the data sheet. Further [7] presents a study of the influence of the spectral influence on the PLR computations. In contrast to that [8] follows a purely statistical path and uses the XARIMA time series decomposition. Here the PR time series are analyzed and the long term trend is decoupled form seasonal oscillations and a remaining random part.

Our comparison here shows that for the seven technologies under investigation here, simple statistical method based

Table 1 performance loss rates of the different technologies computed with the 4 methods. Lowest error values are found for the PVUSA and the moving average methods. The statistical error of the moving average method is overall lowest, however in contrast to the other methods does not take any physical properties into account to counter balance the fluctuations with cause the errors.

	PLR no filter [%/year]	Error [%/year]	PLR moving average [%/year]	Error [%/year]	PLR filter irradiance [%/year]	Error [%/year]	PVUSA [%/year]	Error [%/year]
mcSi	-0.41	0.32	-0.05	0.18	-0.29	0.31	-0.38	0.18
pcSi	-0.22	0.41	-0.08	0.15	-0.16	0.43	-0.34	0.19
CIGS	-3.00	0.16	-3.04	0.10	-2.46	0.16	-2.46	0.15
CdTe	-1.48	0.25	-1.20	0.13	-1.47	0.18	-1.54	0.13
HIT	-0.40	0.48	-0.32	0.17	-0.41	0.37	-0.55	0.22
micrm	-1.23	0.34	-0.96	0.16	-1.43	0.28	-1.40	0.28
1jaSi	-1.67	0.45	-1.21	0.15	-1.85	0.31	-1.76	0.30

on moving average shows the best results in terms of uncertainty reduction. More advanced methods like ARIMA or LOESS [9] could even strengthen the reduction. Future work will include studies of the effect of ARIMA and LOESS methods alone and in combination with the more physics based approaches described in [7].

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