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Performance Loss Rate Estimation of Fielded Photovoltaic Systems Based on Statistical Change-Point Techniques

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***Abstract*—The accurate evaluation of performance loss rate (PLR) of photovoltaic (PV) systems is crucial to reduce investment risks and to further increase the bankability of the technology. Until recently, the PLR of fielded PV systems was mainly estimated through the statistical extraction of a linear trend (de-trending) from a time series of performance indicators. However, in real operating systems a lot of performance outliers (reflecting to PV module failures, initial degradation, shading and soiling) cause variability in the performance and may bias the PLR results obtained from linear trend techniques. Change-point (CP) methods were thus introduced to identify nonlinear trend changes and behaviour. The scope of this work is to perform a comparative analysis among different CP techniques for estimating the annual PLR of eleven different grid-connected PV systems installed in Cyprus. Outdoor field measurements over an 8-year period (June 2006–June 2014) were used for the analysis. The obtained results when applying different CP algorithms to the monthly performance ratio time series demonstrated that the extracted trend may not always be linear but sometimes can exhibit nonlinearities. The application of different CP methods resulted to PLR values that differ by up to 0.85% per year (for the same number of CPs/segments).**

Keywords*—*performance loss rate, change-point methods, photovoltaics

I. INTRODUCTION

The accurate estimation of the performance loss rate (PLR), defined as the decrease of system performance over time, of photovoltaic (PV) systems is crucial for assessing the lifetime output performance, reducing financial risks and further increasing the bankability of the technology [1]. PV degradation is evidenced at all levels (cell, module, array and system) and is attributed to many environmental factors, such as temperature, module soiling, humidity, snow, precipitation, solar irradiation and to parameters relating to their constituent instruments [2]. The various degradation mechanisms impose significant stress over the lifetime of a PV system, resulting in the reduction of durability and output power production [3].

Over the years, various statistical and comparative trend extraction methods have been proposed in the literature for estimating the PLR (or the degradation rate, R_D) of fielded PV systems [2], [4]. Such trend extraction methods include the ordinary least squares (OLS) method, the classical seasonal decomposition (CSD), the Holt-Winters (HW) exponential smoothing, the non-parametric filtering method of LOcally wEighted Scatterplot Smoothing (LOESS), the year-on-year (YoY) comparative technique, the autoregressive integrated moving average (ARIMA) and the principal component analysis (PCA) [5]. A review paper conducted by Phinikarides et al. [2] showed that the PLR estimation was mainly influenced by data integrity, PV module technology and the applied methodology.

Another important underlying assumption been made in most published studies in the PV reliability field was that the consequent trend was linear. However, during actual field exposure and operation of PV systems, many performance variations (module failures, initial degradation as in the case of thin-film technologies, shading and soiling) were observed causing nonlinearities that bias the performance loss (or the degradation) rate estimation. Recently, change-point (CP) algorithms (e.g., Facebook Prophet) were used to identify changes in PV performance time series and profiles [1], [6]–[8]. Such CP methods can identify the nonlinear power losses, mitigate the effect of abrupt changes that bias the results and finally estimate both the linear and nonlinear PLR (or R_D). In these cases, the effectiveness of the selected technique strongly depends on the modelling capabilities of the method for decomposing and modelling the given time series of performance indicators and detecting abrupt changes.

The aim of this work is to perform a comparative analysis among common CP techniques for PLR estimation of PV systems. The PLR evaluation was performed using different nonlinear trend extraction methods applied on the monthly performance ratio (PR) time series of eleven fielded PV systems in Nicosia, Cyprus. The outdoor field measurements were obtained over an 8-year evaluation period (June 2006–

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June 2014). The linear and nonlinear PR trend was extracted by detecting and quantifying changes in the variability of time series, which, in turn, results in defining different segments of the extracted trend. Each segment is then analysed to compute the corresponding PLR.

II. Experimental Setup

Field data from eleven grid-connected PV systems of approximately 1 kW_p capacity each were used for this investigation. The systems are installed at a fixed-tilt angle of 27.5° facing due South in Nicosia, Cyprus. Modules of the test PV systems include monocrystalline silicon (mono-c Si), multi-crystalline silicon (multi-c Si), and thin-film technologies. Table I lists the main technical characteristics of each PV system under investigation.

The performance of each PV system and the prevailing meteorological conditions are recorded according to requirements set by the IEC 61724-1 [9] and stored with the use of a measurement monitoring platform. The monitoring platform comprises of solar irradiance, wind, temperature and electrical operation sensors. It records data at every second and stores them as 1-, 15-, 30- and 60-minute average measurements. The recorded meteorological measurements include in-plane irradiance (G_{I}), ambient temperature (T_{amb}), module temperature (T_{mod}), wind speed (S_{w}) and direction (a_w). The PV electrical data include the array DC current (I_A), voltage (V_A), and power (P_A), and AC power to the utility grid. Additional yields and performance metrics such as the final PV system yield (Y_f), the reference yield (Y_r) and the PR were also calculated [10].

The PV systems and pyranometers were cleaned on a seasonal basis and after dust events to minimize soiling effects. Systematic recalibration of the sensors was performed as specified by the manufacturers. Periodic cross-checks against closed by sensors were also conducted to identify sensor drifts.

Over the 8-year evaluation period (June 2006–June 2014), different failures and degradation mechanisms occurred during the service operation of PV systems. More specifically, the BP Solar and Solon PV systems suffered from partial shading during the 2nd, 3rd and 4th year of operation [11]. The incident logs of Sanyo and Suntechnics PV systems reported a failure occurrence due to water ingress in March 2009 and June of 2009, respectively. Finally, results obtained from performance time series analysis of the investigated PV systems showed a pronounced loss of performance (i.e., high initial degradation) for the First Solar (CdTe) and MHI (a-Si) thin-film systems due to the stabilization processes attributed to the Staebler-Wronski effect (SWE) [12], [13].

TABLE I. Main Technical Characteristics of the PV Systems Under Investigation

Manufacturer	**Technology**	$\mathrm{N_{SERIES}} \times \mathrm{N_{PARALLEL}}$	**Rated Power ($\mathrm{kW_p}$)**
Mono-crystalline silicon (mono-c Si)			
Atersa	mono-c Si	6 × 1	1.02
BP Solar	mono-c Si (Saturn)	6 × 1	1.11
Sanyo	mono-c Si (HIT cell)	5 × 1	1.03
Suntechnics	mono-c Si (back-contact cell)	5 × 1	1.00
Multi-crystalline silicon (multi-c Si)			
Schott Solar	multi-c Si (MAIN cell)	6 × 1	1.02
Schott Solar	multi-c Si (EFG)	4 × 1	1.00
SolarWorld	multi-c Si	6 × 1	0.99
Solon	multi-c Si	7 × 1	1.54
Thin-film			
Würth Solar	CIGS	6 × 2	0.90
First Solar	CdTe	3 × 6	1.08
MHI	a-Si (single cell)	2 × 5	1.00

III. Methodology

The data quality processing methodology was initially applied on the acquired 15-minute average field measurements to ensure data validity and filter out invalid measurements [14]. To avoid introducing bias, a maximum threshold of 5% of missing data rate was set. Irradiance filtering conditions were then applied to the measurements to include only irradiance values between 0 W/m^2 and 1300 W/m^2 [15]. The data quality process did not include the application of data inference techniques and neither temperature/spectral corrections were applied to the data.

The second step taken was to create the PV datasets of each system by aggregating the data into monthly blocks [15]. Daily aggregation was not preferred due to larger fluctuations. Then, the DC PR time series of the systems under study were created from the acquired G_I and P_A measurements [10]. The PR at the AC side was not chosen as it would represent PV system degradation which is not the objective of this analysis. Following the creation of the monthly PR time series, an outlier filter was applied to remove values outside the three standard deviations using the Sigma (σ) rule method [16].

The final step was to estimate the PLR of the investigated systems using different statistical techniques.

A. Statistical Method and PLR Estimation

The PLR values were obtained by analysing each PR time series using the LOESS method and CP detection techniques. The LOESS method extracts the trend from locally weighted polynomial fitting [17]. It decomposes the time series into seasonal, trend and remainder components by applying a LOESS smoother. To estimate the PLR, the OLS method is then applied on the smoothed time series. LOESS advantages include the robust estimation of the trend and seasonal components that are not distorted by outliers and missing values, while also the extracted trend shows the trend of changes beyond the seasonality [2].

The LOESS method can also be used for estimating nonlinear relationships [17]. In this work, the trend extracted by the LOESS method was used as an initial screening for identifying CPs within the given time series through visual inspection.

Four different CP approaches were then used to detect changes in the slopes of PV trends and estimate the linear/nonlinear PLR. In particular, the pruned exact linear time (PELT), the Breakpoints (BCP), the Facebook prophet (FBP) and the Bayesian estimation of abrupt change, seasonality, and trend (BEAST) algorithms were used.

The PELT algorithm was used to detect multiple CPs in the mean of the PR time series [18]. The PELT is based on an algorithm for optimal partitioning of data and CPs are detected by minimizing the sum of a penalized cost function [19]. The PELT algorithm requires an input features the penalty values to avoid overfitting (e.g., identifying noise as CPs). In this work, the CPs for a range of penalties (CROPS) was selected. The minimum and maximum penalty values were set to 0.001

and $\log_{10}(n)$ – where n is the number of months in the PR time series. To estimate the significance of the detected CPs found using PELT, the small sample hypothesis t-test was used [20].

The BCP algorithm detects multiple changes within linear regression models [21]. It computes the number and location of CPs in regression relationships by minimizing the residual sum of squares (RSS) [22]. The approach used in this study comprises of an algorithm that tests for simultaneous estimation of multiple CPs in time series regression models based on the Bellman principle [22]. It is a dynamic programming approach, and the main computational effort is to compute a triangular RSS matrix with the corresponding residual sum of squares for each segment. To determine the optimal number of breaks, the Bayesian information criterion (BIC) estimator of the number of CPs was used. By post-processing the BIC estimates for different numbers of CPs, we can determine the optimal number of segmentations and hence the optimal number of CPs within the time series (which is the one with the lowest BIC).

The BEAST algorithm decomposes the time series into three components: abrupt changes, periodic/seasonal changes and trends [23]. The BEAST is an ensemble algorithm that enables the detection of CPs and nonlinear trend analysis. The trend is modeled as a piecewise model, while the seasonal signal is approximated as a piecewise harmonic model. Then posterior inference of CPs, seasonality and trends is performed by using the Bayes theorem assuming an empirical distribution for k CPs [23]. In this work, the BEAST algorithm was provided only with the period of the cyclic component - an integer number that indicates the number of observations per cycle (e.g., for complete and monthly sampled annual time series, the period of the cyclic/seasonal component is set to 12) and the maximum number of allowed trend CPs in the time series (which was set to 3). Further information about the BEAST calibration process can be found in [7].

The FBP algorithm is an additive decomposition model, which decomposes the time series into trend, seasonality, and holidays [24]. A piecewise linear model is by default applied for modeling the trend component, while the seasonality is modeled as an additive component (like the exponential smoothing of HW). The algorithm distributes 25 CPs uniformly placed in the first 80% of the time series. Then it compares the slopes against a set threshold level to decide whether there is a significant CP or not (by capturing statistical changes in slopes of the time series). The FBP tuning was performed as reported by Theristis et al. [1] to optimally capture the behavior of the PV systems under study. Since the investigated PV systems exhibited similar seasonal behavior, the FBP seasonality settings (i.e., daily, weekly, yearly, custom) were set as "TRUE", to fit daily, weekly and yearly seasonality.

After the CP algorithms application, the trend was divided into different segments (depending on the number of the detected CPs) and the OLS method was finally applied to estimate the PLR of each segment.

IV. Results

A. PLR Using the LOESS Method

The non-parametric filtering method of the LOESS was applied on the constructed monthly PR time series (see Fig. 1) to extract the trend of each PV system and estimate the annual PLR. By visually inspecting the extracted trend by the LOESS method, obvious trend changes can be seen at least for the BP Solar and thin-film PV systems. This initial screening indicates the presence of nonlinear power loss and the existence of CP(s) within the given PR time series. Since the extracted trend can exhibit nonlinearities, the application of CP algorithms is required for more accurate PLR estimations.

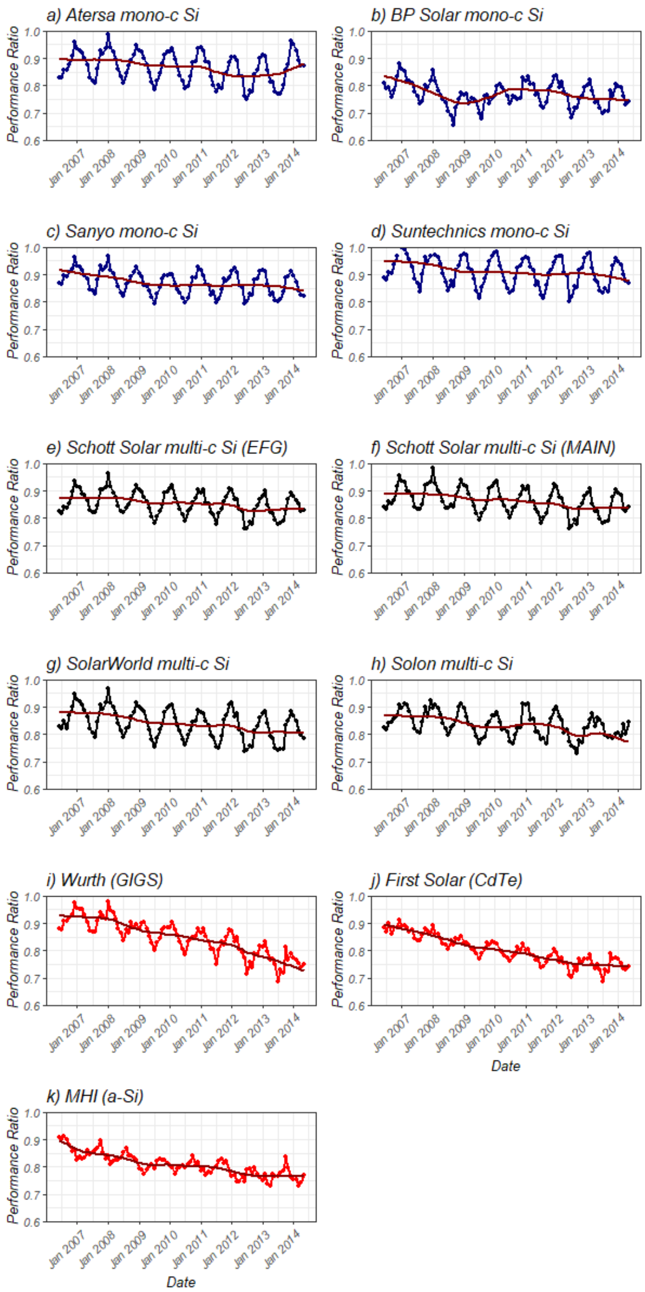

Fig. 1. Monthly PR time series and extracted trend (coloured in maroon) using the LOESS method for the investigated PV systems over the period June 2006-June 2014. The purple, black and red lines indicate the mono-c Si, multi-c Si and thin-film PV module technology systems, respectively.

The PLR results from the LOESS application are summarised in Table II. The average PLR for the mono-c Si, multi-c Si and thin-film PV systems was -0.72%/year, -0.93%/year and -2.01%/year, respectively. The PLR estimations ranged from -0.60 to -0.78%/year and -0.68 to -1.09%/year for the mono-c Si and multi-c Si PV technologies, respectively. All crystalline Silicon PV systems exhibited

TABLE II. ANNUAL PERFORMANCE LOSS RATE OF PV SYSTEMS EVALUATED BY APPLYING THE LOESS METHOD

System	Annual PLR (%/year) ± Standard Error
Atersa mono-c Si	-0.78 ± 0.00
BP Solar mono-c Si	-0.60 ± 0.01
Sanyo mono-c Si	-0.74 ± 0.00
Suntechnics mono-c Si	-0.75 ± 0.00
Schott Solar multi-c Si (MAIN)	-0.84 ± 0.00
Schott Solar multi-c Si (EFG)	-0.68 ± 0.00
SolarWorld multi-c Si	-1.09 ± 0.00
Solon multi-c Si	-1.09 ± 0.00
Würth Solar CIGS	-2.52 ± 0.03
First Solar CdTe	-2.04 ± 0.00
MHI a-Si	-1.46 ± 0.00

annual PLR lower than 1%/year. In contrast, the thin-film technologies showed higher annual PLR compared to the crystalline silicon systems, ranging from -1.46 to -2.52%/year.

Since the seasonal component was extracted from the de-trended time series, the remainder component was then checked for Gaussian white noise (GWN) properties using the remainder autocorrelation (ACF) and partial autocorrelation function (PACF) plots [13]. The remainder ACF and PACF plots of the thin-film technologies' models and Atersa mono-c Si have shown evidence that the remainder of LOESS exhibited GWN properties because all autocorrelation coefficients were within the 95% confidence interval bounds. On the other hand, the rest of the systems' model remainders failed to reject the null hypothesis of no autocorrelation in the model remainders, because one or more autocorrelation coefficients (apart from lag 0 which is always unity) exceeded the 95% confidence interval bounds. It was also evident from the remainder ACF and PACF plots that most systems' model remainder had significant autocorrelation at the seasonal frequency (lag 12), signifying the need for better seasonal adjustment.

B. PLR Using CP Techniques

CP algorithms were then applied on the PR time series to extract the nonlinear trend (by detecting changes in the slopes of PV trends) and estimate the PLR of the test PV arrays.

The PELT algorithm detected at least one CP for all the investigated PV arrays (see Table III). The Sanyo, Suntechnics, Schott Solar (MAIN), SolarWorld and Solon PV systems exhibited two segments, whereas the Atersa, Schott Solar (EFG), Würth Solar, First Solar and MHI systems exhibited three segments. The CP that was detected after 2 years of operation for the Würth Solar, First Solar and MHI systems may be caused due to the initial degradation affecting thin-film technologies. Finally, the BP Solar system exhibited four segments. For the BP Solar mono-c Si system the CPs that were detected during the 2nd and 3rd year may be caused due to the partial shading affecting the system during the respective years. Similarly, the CP detected during the year 2009 for the Solon multi-c Si system may be attributed to partial shading affecting the performance of the system. Information extracted from the maintenance logs, did not report any major issue for the remaining PV systems and therefore, the detected CPs may be attributed to an actual degradation mechanism (i.e., change in degradation rate).

The CP results demonstrated that the extracted trend may not always be linear but can exhibit nonlinearities. For visualisation purposes, the detected CPs by the PELT technique for the BP Solar (mono-c Si) and MHI (a-Si) PV systems are shown in Fig. 2. The PELT results indicated the presence of nonlinear power loss and the existence of CPs in the PR time series of these two PV systems, confirming the suspicions generated by the initial screening of the LOESS trend for trend changes.

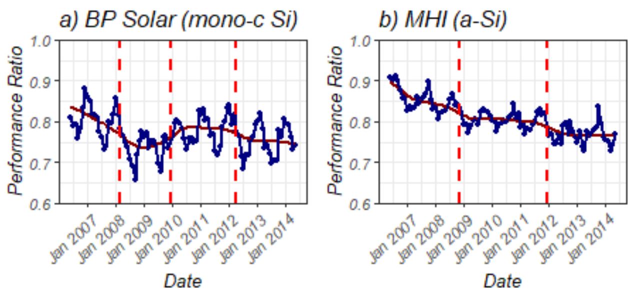

Fig. 2. Monthly PR time series for the a) BP Solar (mono-c Si) and b) MHI (a-Si) PV systems. The solid maroon line indicates the extracted trend by the LOESS method, while the detected CPs are depicted by red dashed vertical lines.

The BCP algorithm detected one CP for all the c Si PV systems, except for the BP Solar system (see Table IV). Two CPs were detected for the BP Solar PV system during the 2nd and 3rd year (the respective years that the system suffered from partial shading). For the thin-film PV systems (Würth Solar, First Solar and MHI), three CPs were detected. For the MHI thin-film system, the first two detected CPs (during the years 2007 and 2008) may indicate the initial degradation of the technology.

The PLR results from the BEAST algorithm application are summarised in Table V. A linear power loss was detected

TABLE III. CHANGE-POINTS DETECTED BY THE PELT ALGORITHM

System	Number of CPs	Location of CPs
Atersa mono-c Si	2	04/2011, 10/2013
BP Solar mono-c Si	3	03/2008, 12/2009, 04/2012
Sanyo mono-c Si	1	04/2008
Suntechnics mono-c Si	1	04/2008
Schott Solar multi-c Si (MAIN)	1	02/2011
Schott Solar multi-c Si (EFG)	2	05/2012, 09/2012
SolarWorld multi-c Si	1	03/2009
Solon multi-c Si	1	02/2009
Würth Solar CIGS	2	04/2008, 03/2012
First Solar CdTe	2	04/2008, 04/2011
MHI a-Si	2	11/2008, 12/2011

TABLE IV. CHANGE-POINTS DETECTED BY THE BCP ALGORITHM

System	Number of CPs	Location of CPs
Atersa mono-c Si	1	04/2011
BP Solar mono-c Si	2	03/2008, 08/2009
Sanyo mono-c Si	1	04/2008
Suntechnics mono-c Si	1	04/2008
Schott Solar multi-c Si (MAIN)	1	02/2011
Schott Solar multi-c Si (EFG)	1	03/2012
SolarWorld multi-c Si	1	03/2009
Solon multi-c Si	1	02/2009
Würth Solar CIGS	3	04/2008, 04/2010, 04/2012
First Solar CdTe	3	03/2008, 02/2010, 01/2012
MHI a-Si	3	10/2007, 12/2008, 12/2011

TABLE V. CHANGE-POINTS DETECTED BY THE BEAST ALGORITHM

System	Number of CPs	Location of CPs
Atersa mono-c Si	2	09/2011, 10/2013
BP Solar mono-c Si	2	09/2008, 03/2010
Sanyo mono-c Si	1	09/2010
Suntechnics mono-c Si	1	08/2009
Schott Solar multi-c Si (MAIN)	0	NA
Schott Solar multi-c Si (EFG)	2	01/2009, 02/2012
SolarWorld multi-c Si	0	NA
Solon multi-c Si	2	02/2009, 02/2012
Würth Solar CIGS	1	07/2012
First Solar CdTe	1	06/2012
MHI a-Si	3	09/2008, 11/2009, 12/2011

for the Schott Solar (MAIN) and SolarWorld PV systems. The Sanyo and Suntechnics PV systems once again exhibited two segments along with the Würth Solar and First Solar systems. For the Suntechnics mono-c Si system, the detected CP (during August 2009) may be due to the failure occurrence affecting the system during June 2009. For the MHI thin-film system, three CPs were detected. The detected points after 2 and 3 years of operation may be attributed to early degradation of the thin-film PV technology. For the remaining PV systems (Atersa, BP Solar, Schott Solar EFG and Solon) two CPs were detected. The maintenance logs reported performance issues only for the BP Solar and Solon PV systems.

The FBP analysis demonstrated a linear trend for the Atersa, Schott Solar (MAIN and EFG) and SolarWorld systems, while eight CPs were detected for the remaining PV systems (see Table VI). A CP in the trends of the Sanyo and Suntechnics systems was detected by the FBP due to a maintenance event as reported by the maintenance logs. A CP was also detected for the thin-film PV systems that may be due to an actual degradation mechanism, since the maintenance logs did not report any major issues/failures. Finally, for the PV systems affected by failures, the FBP detected two CPs for the BP Solar mono-c Si system, while a CP was detected for the Solon multi-c Si PV system.

Since the FBP algorithm has already been validated against synthetic PV performance datasets and proved to be a robust algorithm for estimating the R_D of PV systems [1], [25], we proceed the analysis with estimating the linear/nonlinear PLR by applying the FBP algorithm on the given time series data. The annual PLR results from the FBP application are summarized in Table VII. By comparing the linear PLR estimates of LOESS with FBP, differences of up to 0.14% were observed.

TABLE VI. CHANGE-POINTS DETECTED BY THE FBP ALGORITHM

System	Number of CPs	Location of CPs
Atersa mono-c Si	0	NA
BP Solar mono-c Si	2	12/2008, 05/2011
Sanyo mono-c Si	1	07/2009
Suntechnics mono-c Si	1	04/2009
Schott Solar multi-c Si (MAIN)	0	NA
Schott Solar multi-c Si (EFG)	0	NA
SolarWorld multi-c Si	0	NA
Solon multi-c Si	1	05/2011
Würth Solar CIGS	1	06/2011
First Solar CdTe	1	08/2009
MHI a-Si	1	04/2010

TABLE VII. ANNUAL PERFORMANCE LOSS RATE (%/YEAR) OF PV SYSTEMS EVALUATED BY APPLYING THE FBP ALGORITHM WITH 95% CONFIDENCE INTERVALS

System	*Linear FPB*	*FPB PLR₁*	*FPB PLR₂*
Atersa mono-c Si	-0.83 ± 0.01	NA	NA
Sanyo mono-c Si	NA	-1.35 ± 0.01	-0.45 ± 0.01
Suntechnics mono-c Si	NA	-1.07 ± 0.00	-0.61 ± 0.00
Schott Solar multi-c Si (MAIN)	-0.96 ± 0.00	NA	NA
Schott Solar multi-c Si (EFG)	-0.80 ± 0.00	NA	NA
SolarWorld multi-c Si	-1.23 ± 0.00	NA	NA
Solon multi-c Si	NA	-1.21 ± 0.01	-0.90 ± 0.01
Würth Solar CIGS	NA	-2.52 ± 0.00	-2.66 ± 0.01
First Solar CdTe	NA	-2.80 ± 0.00	-1.99 ± 0.04
MHI a-Si	NA	-1.78 ± 0.01	-1.48 ± 0.00

Finally, the PLR of each PV system was estimated using the other CP methods. The estimated PLR values differ by up to 0.85% per year (for the same number of segments/CPs) depending on the selection of the applied method. The results indicate that by applying CP algorithms to the monthly PR time series, the extracted trend may not always be linear but can exhibit nonlinearities that need to be accounted, especially for thin-film technologies. Furthermore, different number and location of CPs were detected depending on the applied technique, indicating that the nonlinear PLR estimation is methodology dependent. A comparative analysis is thus required using synthetic PV performance datasets with known degradation behaviour and emulated fault conditions to derive the most accurate method for degradation studies.

It is worth noting here that the linear/nonlinear PLR estimated value directly affects the project's economics. Thus, the development of more sophisticated models to estimate the PLR of fielded PV systems is required to reduce financial risks. As recently stated in [26], the PLR is the third most important factor influencing the levelized cost of energy (LCOE), after the discount rate and capital cost.

V. CONCLUSIONS

In this paper, the performance loss rates of different technology PV systems were estimated using the LOESS and CP methods, after 8 years of outdoor operation. The application of LOESS resulted in an average PLR of -0.72%/year, -0.93%/year and -2.01%/year for the mono-c Si, multi-c Si and thin-film PV systems, respectively. Visual inspection of the trend extracted by the LOESS method provided initial insights for the potential presence of CPs within the investigated time series.

The application of CP algorithms proved to be an effective statistical technique for identifying nonlinear power loss in PV systems. The different CP algorithms could detect changes in the slopes of PV trends. However, different number and location of CPs were detected depending on the applied technique. The detected CPs may be attributed to failures affecting the PV systems, maintenance events or actual degradation mechanisms. The PLR values obtained over the 8-year period differ by up to 0.85% per year (for the same number of segments/CPs) depending on the applied method. This indicates the methodology dependency of the nonlinear PLR estimates and the need for more sophisticated models to estimate accurately the PLR of fielded PV systems, thus reducing financial risks. Future work will focus on comparing the CP algorithms for PLR estimates using synthetic PV performance datasets with known degradation behaviour and emulated fault conditions. Furthermore, future investigation will focus on extracting the PV performance trend and combining the seasonal trend decomposition with LOESS for estimating nonlinear relationships and PLR.

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References

[1] M. Theristis, A. Livera, C. B. Jones, G. Makrides, G. E. Georghiou, and J. S. Stein, "Nonlinear Photovoltaic Degradation Rates: Modeling and Comparison Against Conventional Methods," *IEEE J. Photovoltaics*, vol. 10, no. 4, pp. 1112–1118, 2020, doi: 10.1109/JPHOTOV.2020.2992432.

[2] A. Phinikarides, N. Kindyni, G. Makrides, and G. E. Georghiou, "Review of photovoltaic degradation rate methodologies," Renew. Sustain. Energy Rev., vol. 40, pp. 143–152, Dec. 2014, doi: 10.1016/j.rser.2014.07.155.

[3] A. Livera, M. Theristis, G. Makrides, and G. E. Georghiou, "Recent advances in failure diagnosis techniques based on performance data analysis for grid-connected photovoltaic systems," Renew. Energy, vol. 133, pp. 126–143, 2019, doi: 10.1016/j.renene.2018.09.101.

[4] D. C. Jordan, M. G. Deceglie, and S. R. Kurtz, "PV degradation methodology comparison - A basis for a standard," *Conf. Rec. IEEE Photovolt. Spec. Conf.*, vol. 2016-Novem, no. Ci, pp. 273–278, 2016, doi: 10.1109/PVSC.2016.7749593.

[5] A. Livera, A. Phinikarides, G. Makrides, and G. E. Georghiou, "Impact of Missing Data on the Estimation of Photovoltaic System Degradation Rate," *44th IEEE Photovolt. Spec. Conf.*, pp. 1954–1958, 2018, doi: 10.1109/pvsc.2017.8366442.

[6] M. Theristis *et al.*, "Modeling nonlinear photovoltaic degradation rates," in *47th IEEE Photovoltaic Specialist Conference (PVSC)*, 2020, pp. 0208–0212, doi: 10.1109/PVSC45281.2020.9300388.

[7] L. Micheli *et al.*, "Improved PV Soiling Extraction through the Detection of Cleanings and Change Points," *IEEE J. Photovoltaics*, vol. 11, no. 2, pp. 519–526, 2021, doi: 10.1109/JPHOTOV.2020.3043104.

[8] I. Romero-Fiances *et al.*, "Impact of duration and missing data on the long-term photovoltaic degradation rate estimation," *Renew. Energy*, vol. 181, pp. 738–748, 2022, doi: https://doi.org/10.1016/j.renene.2021.09.078.

[9] IEC, "IEC 61724-1:2021: Photovoltaic system performance - Part 1: Monitoring," 2021.

[10] M. Theristis, V. Venizelou, G. Makrides, and G. E. Georghiou, "Chapter II-1-B – Energy yield in photovoltaic systems," in *Kalogirou, S.A. (Ed.), McEvoy's Handbook of Photovoltaics, third ed. Academic Press*, 2018, pp. 671–713.

[11] G. Makrides, B. Zinsser, M. Schubert, and G. E. Georghiou, "Energy yield prediction errors and uncertainties of different photovoltaic models," *Prog. Photovoltaics Res. Appl.*, vol. 21, pp. 500–516, 2013, doi: 10.1002/pip.121

[12] G. Makrides, B. Zinsser, M. Schubert, and G. E. Georghiou, "Performance loss rate of twelve photovoltaic technologies under field conditions using statistical techniques," *Sol. Energy*, vol. 103, no. October 2016, pp. 28–42, 2014, doi: 10.1016/j.solener.2014.02.011.

[13] A. Phinikarides, G. Makrides, B. Zinsser, M. Schubert, and G. E. Georghiou, "Analysis of photovoltaic system performance time series: Seasonality and performance loss," *Renew. Energy*, vol. 77, pp. 51–63, 2015, doi: 10.1016/j.renene.2014.11.091.

[14] A. Livera *et al.*, "Data processing and quality verification for improved photovoltaic performance and reliability analytics," *Prog. Photovoltaics Res. Appl.*, vol. 29, pp. 143– 158, 2021, doi: 10.1002/pip.3349.

[15] A. Livera, M. Theristis, E. Koumpli, G. Makrides, J. S. Stein, and G. E. Georghiou, "Guidelines for ensuring data quality for photovoltaic system performance assessment and monitoring," in *37th European Photovoltaic Solar Energy Conference (EU PVSEC)*, 2020, pp. 1352–1356, doi: 10.4229/EUPVSEC20202020-5DO.2.4.

[16] A. Livera, M. Florides, M. Theristis, G. Makrides, and G. E. Georghiou, "Failure diagnosis of short- and open-circuit fault conditions in PV systems," in *45th IEEE Photovoltaic Specialist Conference (PVSC)*, 2018, pp. 0739–0744, doi: 10.1109/PVSC.2018.8548161.

[17] R. Cleveland, W. Cleveland, J. McRae, and I. Terpenning, "STL: A seasonal-trend decomposition procedure based on Loess," *J. Off. Stat.*, vol. 6, no. 1, pp. 3–73, 1990.

[18] R. Killick, P. Fearnhead, and I. A. Eckley, "Optimal detection of changepoints with a linear computational cost," *J. Am. Stat. Assoc.*, vol. 107, no. 500, pp. 1590–1598, 2012, doi: 10.1080/01621459.2012.737745.

[19] B. Jackson *et al.*, "An algorithm for optimal partitioning of data on an interval," *IEEE Signal Process. Lett.*, vol. 12, no. 2, pp. 105–108, 2005, doi: 10.1109/LSP.2001.838216.

[20] S. Academy, *Introductory Statistics*, V. 1. Saylor Academy, 2012.

[21] J. Bai and P. Perron, "Estimating and Testing Linear Models with Multiple Structural Changes," *Econometrica*, vol. 66, no. 1, p. 47, 1998, doi: 10.2307/2998540.

[22] J. Bai and P. Perron, "Computation and analysis of multiple structural change models," *J. Appl. Econom.*, vol. 18, no. 1, pp. 1–22, 2003, doi: 10.1002/jae.659.

[23] K. Zhao *et al.*, "Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A Bayesian ensemble algorithm," *Remote Sens. Environ.*, vol. 232, no. April, 2019, doi: 10.1016/j.rse.2019.04.034.

[24] S. J. Taylor and B. Letham, "Forecasting at Scale," *Am. Stat.*, 2017, doi: 10.1080/00031305.2017.1380080.

[25] M. Theristis *et al.*, "Comparative analysis of change-point techniques for nonlinear photovoltaic performance degradation rate estimations," *IEEE J. Photovoltaics*, vol. 11, no. 6, pp. 1511–1518, 2021, doi: 10.1109/JPHOTOV.2021.3112037.

[26] D. C. Jordan, T. J. Silverman, B. Sekulic, and S. R. Kurtz, "PV degradation curves: non-linearities and failure modes," *Prog. Photovoltaics Res. Appl.*, vol. 25, no. 7, pp. 583–591, 2017, doi: 10.1002/pip.2835.