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Non-linear photovoltaic degradation rates: modeling and comparison against conventional methods

Marios Theristis, Andreas Livera, C. Birk Jones, George Makrides, George E. Georghiou, and Joshua S. Stein

***Abstract*—Although common practice for estimating photovoltaic (PV) degradation rate (R_D) assumes a linear behavior, field data have shown that degradation rates are frequently non-linear. This study presents a new methodology to detect and calculate non-linear R_D based on PV performance time-series from nine different systems over an 8-year period. Prior to performing the analysis and in order to adjust model parameters to reflect actual PV operation, synthetic datasets were utilized for calibration purposes. A change-point analysis is then applied to detect changes in the slopes of PV trends, which are extracted from constructed performance ratio (*PR*) time-series. Once the number and location of change-points is found, the ordinary least squares (OLS) method is applied to the different segments to compute the corresponding rates. The obtained results verified that the extracted trends from the *PR* time-series may not always be linear and therefore, "non-conventional" models need to be applied. As expected, all thin-film technologies demonstrated non-linear behavior whereas non-linearity detected in the crystalline silicon systems is thought to be due to a maintenance event. A comparative analysis between the new methodology and other conventional methods demonstrated levelized cost of energy (*LCOE*) differences of up to 6.14%, highlighting the importance of considering non-linear degradation behavior.**

***Index Terms*—non-linear degradation, photovoltaics, modelling, change-point analysis, levelized cost of energy**

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M. Theristis, C. B. Jones, and J. S. Stein are with Sandia National Laboratories, Albuquerque, NM 87185, USA (e-mail: mtheris@sandia.gov; cbjones@sandia.gov; jsstein@sandia.gov).

A. Livera, G. Makrides, and G. E. Georghiou are with the PV Technology Laboratory of the FOSS Research Centre for Sustainable Energy and the Department of Electrical and Computer Engineering, University of Cyprus, Nicosia 1678, Cyprus (e-mail: livera.andreas@ucy.ac.cy; makrides.georgios@ucy.ac.cy; geg@ucy.ac.cy).

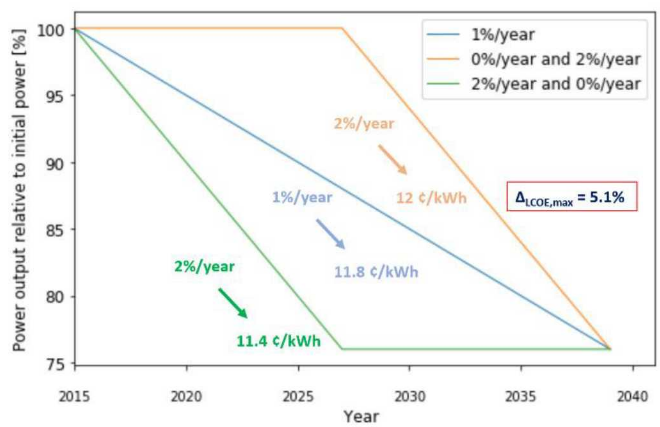

Fig. 1. Theoretical comparison of different degradation rates and the impact on *LCOE* (assuming discount rate 4%, operation &maintenance of 2%, installation costs of 3 $/W, annual irradiation of 1700 kWh/kWp). This figure was recreated from Stein *et al.* [1].

I. Introduction

Accurately predicting the lifetime performance of photovoltaic (PV) systems is critical for determining the financial payback of the project. One of the parameters that influence PV performance prediction is the Degradation Rate (R_D) or Performance Loss Rate (*PLR*) defined as the decrease of system efficiency over time. Knowledge of this metric is important for reducing uncertainties and financial risks [2].

Although seemingly simple, the R_D estimation is not trivial for systems under real operating conditions due to several factors (i.e. data quality, integrity, processing, methodologies, etc.) that can influence its calculation [3]. Recently published investigations aim to reduce computational inconsistencies among analysts [4, 5] that use different data pipelines and degradation rate estimation methods that have been extensively analyzed elsewhere [6, 7]. Furthermore, common practices assume a constant R_D over time when applying various statistical techniques on PV performance time-series.

Field experience has shown that constant R_D is unrealistic mainly due to the initial and wear-out degradation that may occur. Known degradation modes such as Light and elevated

TABLE I
PV TECHNOLOGIES AND SIZES OF INVESTIGATED SYSTEMS

No.	Manufacturer	Model	Technology	$N_{SERIES} \times N_{PARALLEL}$	Size (kW_p)
1	Atersa	A-170M24V	mono-c-Si	6 × 1	1.020
2	Sanyo	HIP-205NHE1	mono-c-Si (HIT cell)	5 × 1	1.025
3	Suntechnics	STM 200 FW	mono-c-Si (back-contact cell)	5 × 1	1.000
4	Schott Solar	ASE-165-GT-FT/MC	multi-c-Si (MAIN cell)	6 × 1	1.020
5	Schott Solar	ASE-260-DG-FT	multi-c-Si (EFG)	4 × 1	1.000
6	SolarWorld	SW165 poly	multi-c-Si	6 × 1	0.990
7	MHI	MA100T2	a-Si (single cell)	2 × 5	1.000
8	First Solar	FS60	CdTe	3 × 6	1.080
9	Würth Solar	WS 11007/75	CIGS	6 × 2	0.900

Temperature Induced Degradation (LeTID) [8], Light Induced Degradation (LID) [9] and Staebler–Wronski [10] effects occur early in the life of a PV module and then cease once an equilibrium has been reached. The path traveled to a certain performance loss has a significant economic impact on the levelized cost of energy (*LCOE*). Fig 1 shows an example of three possible degradation pathways resulting in the same total loss but with different *LCOE* values. A sensitivity analysis based on Monte Carlo simulation and theoretical degradation rate curves was conducted by Jordan *et al.* [11, 12] where an *LCOE* difference of ~1.1 ¢/kWh was found, establishing the R_D as the third most important factor influencing the *LCOE*, after the discount rate and capital cost [12].

Non-linear drops in performance may affect contractual agreements between operation and maintenance (O&M) contractors and PV asset managers where key performance indicators (KPIs) are agreed to in order to quantitatively monitor the health state and performance of a particular power plant. Such *LCOE* differences and significant uncertainties in PV performance models highlight the importance of developing more sophisticated non-linear degradation rate models in order to reduce financial risks.

A new methodology is proposed for estimating non-linear R_D based on a decomposition model coupled to a change-point analysis. This is achieved by detecting and quantifying changes in the variability of performance ratio (*PR*) time-series, which, in turn, results in defining different segments of the extracted trend. Each segment is then analyzed to compute the corresponding degradation rates which are then compared against conventional methods using *LCOE* as a criterion.

II. METHODOLOGY

A. Outdoor Test Facility (OTF)

Operational data from nine grid-connected PV systems of approximately 1 kWp capacity each were used for this investigation. Modules included mono-crystalline silicon (mono-c-Si), multi-crystalline Si (multi-c-Si) and thin-film technologies (see Table I). The systems were installed and commissioned in June 2006, in a hot semi-arid climate (Köppen climate classification: *BSh*), in Nicosia, Cyprus. Identical inverters connected all systems to the grid to avoid mismatches in tracking the maximum power point (MPP).

The performance of each PV system and the prevailing meteorological conditions were recorded according to the IEC 61724 [13], at a resolution of one second and stored as 1- and 15-minute averages of irradiance, meteorological and electrical measurements. The meteorological data include in-plane irradiance from a broadband pyranometer, ambient temperature, wind speed and direction, while the PV operational data include the MPP DC current, voltage and power (P_A) of the array, AC power to the utility grid and back-of-module temperature. The systems are ground-mount, fixed-tilt at an inclination angle of 27.5° facing due South, at the OTF of the University of Cyprus (UCY) in Nicosia, Cyprus.

The recording period used for this investigation was 8 years (i.e. 2006 – 2014), which was considered acceptable since several complete annual cycles allow spectral [14] and temperature variability to average out in order to be able to provide R_D estimations with relatively low uncertainty [15, 16].

All PV arrays and sensors were kept clean to minimize any soiling effects. Furthermore, all sensors were inspected and calibrated periodically to minimize systematic errors (e.g. due to sensor drifts). Finally, it should be noted that the degradation rates obtained in this study may not be indicative of different climates and PV technologies.

B. Data Quality Processing and Verification

Data quality routines (DQRs) were applied to the 15-min average datasets to ensure data validity and filter out erroneous measurements.

The DQRs process includes: initial data statistics, identification of monitoring availability, outliers, missing, duplicate, and erroneous data. In order to avoid bias introduction, a maximum threshold of 5% of missing data was set. Once the power datasets were normalized to each repective systems' rated power, an outlier filter was applied to remove *PR* values outside 2 standard deviations using the Sigma Rule method. Further filtering is applied to include irradiance values between 50 W/m^2 and 1300 W/m^2 and P_A within 10% and 130% of power under standard test conditions (P_{STC}). The process did not include the imputation of data to estimate missing values and temperature or spectral corrections were not applied to the data. The time-series were then resampled and aggregated to construct a dataset of monthly DC *PR* values where the R_D modelling was performed. Daily aggregation was not preferred due to larger fluctuations. AC *PR* was not chosen as it would represent PV *system* degradation which is not the objective of this analysis.

C. Modeling R_D Using Conventional Statistical Methods

Conventional statistical methods assume a constant rate of power decrease over time and the relative degradation rate is calculated by multiplying the ratio of the slope to intercept by 12 or 365 for monthly or daily aggregation, respectively.

In this study, five different methods were used for the comparative analysis. Four of these are freely available on the PV Performance Modeling Collaborative (PVPMC) website [17]: a) linear regression with ordinary least squares (OLS), b) classical seasonal decomposition (CSD), c) seasonal and trend decomposition using locally weighted scatterplot smoothing, LOWESS, (STL) and d) Holt-Winters (HW) triple-exponential smoothing. In addition to these, the e) year-on-year (YOY) comparative approach that is available through the Python Library "RdTools" [18] is also used. The theory, merits and demerits of each method have been reported elsewhere [6, 7, 19]. Each of the five methods was applied to the OTF datasets to serve as a baseline for comparison. The same data normalization, filtering, and aggregation was used for all methods in order to enable a comparative analysis.

D. Modeling Non-Linear R_D Using Facebook Prophet

Facebook Prophet (FBP) Algorithm was selected to model the *PR* trends and subsequent change-points for estimating non-linear R_D in this work [20]. FBP is an open-source library, available in Python and R, used to forecast time-series based on an additive (i.e. when the seasonal variation is relatively constant over time) decomposition model where trend, seasonality and holidays are combined as follows:

$$y(t) = g(t) + s(t) + h(t) + e_t \tag{1}$$

where $g(t)$ is the trend, $s(t)$ and $h(t)$ represent the seasonal and holiday (not used in this study) components respectively, and e_t accounts for the error. The trend model is using a piecewise linear model by default whereas the seasonal model is similar to the exponential smoothing in the conventional HW technique. This model performs well with long time-series that have high seasonality and it is robust to outliers and missing data [20]. The main reason for selecting the FBP model is its ability to perform change-point analysis [21] on the time-series trend either automatically or by modifying a number of parameters.

The resulting trends of the monthly *PR* time-series were analyzed using the change-point technique, embedded in FBP, which identifies the amount and location of change-points by capturing statistical changes in the slopes of defined segments. By default, the FBP algorithm distributes 25 "potential" change-points uniformly along the selected range of the time-series' trend and then compares the slopes against a set threshold level in order to decide whether there is a "significant" change-point or not. In this study however, the number of potential change-points, threshold level, and flexibility were optimized to capture the PV behavior (see Section II-E). Once the trend was sliced into different segments, the ordinary least squares (OLS) method [22] was applied in order to compute the different R_D values for each segment.

E. FBP Calibration Against Synthetic Datasets

Time-series decomposition is used to remove the seasonality effect from a given dataset. This is achieved by separating trend, seasonality and error. Change-point analysis is then applied on the trend to detect changes in slope. However, change-point detection depends highly on the flexibility of the extracted trend, number of potential change-points, and range. Since the real R_D, number and location(s) of change-points are unknown, an iterative process was followed to calibrate FBP against synthetic data that were generated with known combinations of given degradation rates and change-point locations.

Specifically, 15 typical meteorological year (TMY) datasets from different locations in New Mexico (NM), USA were randomly sampled and used as consecutive inputs to a PV performance model of silicon and thin-film module technologies using the Sandia PV Array Performance Model (SAPM) [23] from pvlib-python [24]. Non-linear degradation rates were then applied to the performance predictions and a parametric analysis was performed to optimize the FBP model parameters.

The number of potential change-points were uniformly distributed along the time-series and set equal to the number of month-to-month transitions in the dataset (i.e. *n_changepoints* = 95) and the flexibility was adjusted until changes in R_D of at least 0.5%/year in the synthetic datasets were identified but not overfit (*changepoint_prior_scale* = 0.07). Since the analysis does not project trends into the future, the *changepoint_range* argument was set to 1. With these parameter inputs, FBP was able to detect the optimum number and location of the imposed

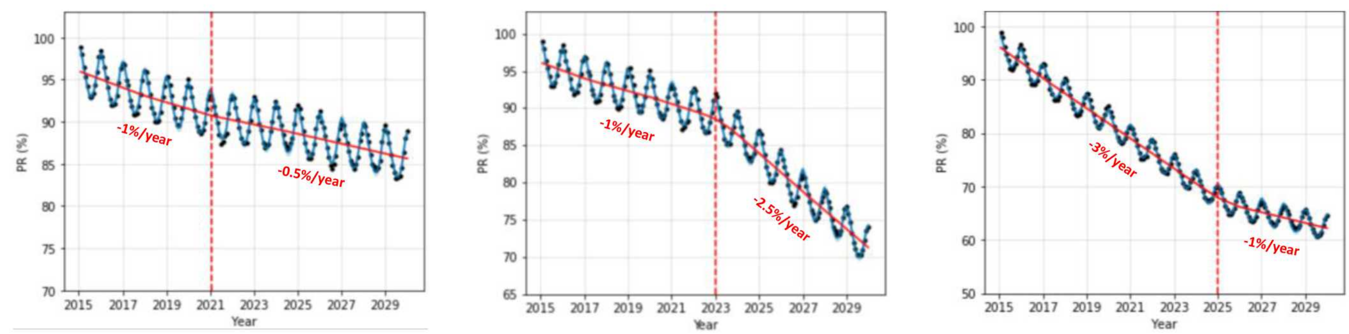

Fig. 2. Change-point detection on synthetic datasets with different non-linear degradation rate combinations and change-point positions. The synthetic datasets were simulated using the SAPM on PVLIB with 15 TMY datasets from around NM, USA.

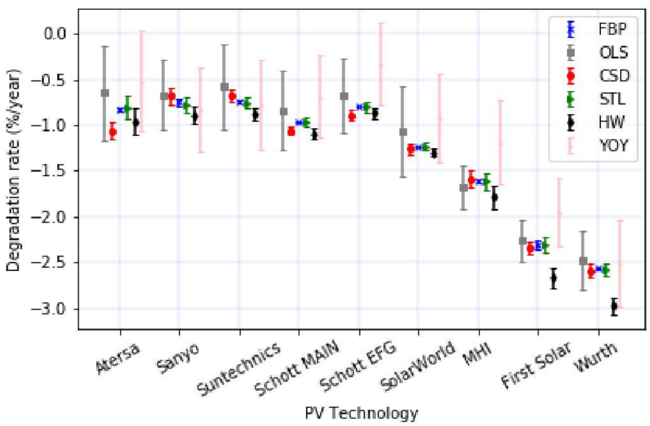

Fig. 3. Comparison of computed degradation rates for all systems using different methods. All methods assume linear behavior and the error bars are 95% confidence intervals of the statistical uncertainty.

change-points in all examined cases, as seen in a representative sample of the synthetic datasets in Fig. 2.

F. Financial Impact on LCOE

LCOE is defined as the lifetime costs divided by the lifetime energy generation, typically expressed in currency/kWh. Although it has been criticized in literature for not adequately reflecting project economic feasibility [25], it is a useful and simple metric for comparing costs and benefits between different technologies.

While the financial impact of non-linear trends was investigated by Jordan *et al*. [11, 12] using theoretical curves, a comparison is presented here, based on observed non-linear degradation rates. The simplified equation used to calculate the *LCOE* is given by [26]:

$$LCOE = \frac{\sum_{t=0}^{T} C_t/(1+r)^t}{\sum_{t=0}^{T} E_t \cdot (1-R_D)^t/(1+r)^t} \qquad (2)$$

where t is time, C_t includes the initial investment and costs associated to O&M, E_t is the lifetime energy multiplied by the degradation rate, and r is the discount rate.

III. Results And Discussion

A. Comparative Analysis Assuming Linear R_D

FBP was initially used to calculate R_D assuming linearity by applying OLS on the whole trend of the decomposed time-series. In Fig. 3, the estimated R_D using FBP, OLS, CSD, STL, HW and YOY are shown for all the systems under investigation. The error bars are 95% confidence intervals of the statistical uncertainty assuming a normal distribution.

The minimum and maximum absolute mean (among all methods) linear degradation rates were observed in the Suntechnics back-contact cell technology (0.74%/year) and Wurth Solar CIGS system (2.62%/year), respectively. Averaging the computed linear degradation rates of each technology, resulted in -0.77%/year, -0.94%/year, -2.17%/year for the mono-c-Si, multi-c-Si and thin-film systems, respectively.

With respect to the applied methods, HW and YOY demonstrated the largest deviations from the means. As expected, the OLS and YOY methods exhibit the widest confidence intervals overall, whereas the remaining statistical models result in relative degradation rates of lower statistical uncertainty mainly due to their removal of seasonality. YOY is a comparative approach which requires finer aggregation (e.g. weekly or daily) and temperature correction for best performance. Furthermore, FBP and STL seem to be the most consistent, robust (i.e. lowest deviation from the mean) and have the lowest uncertainty compared with the other statistical techniques, a result that agrees with findings from other investigations [7].

B. Non-Linear R_D Estimations Using FBP

The application of FBP to the monthly *PR* time-series of the nine systems without assuming linearity revealed different trend behaviors with some systems exhibiting different slopes for each segment, verifying the presence of non-linear power loss. More specifically, Fig. 4 shows the 8-year *PR* time-series (black dots), FBP fit (blue line), trend (red line), uncertainty (blue shade) and change-points (red dashed vertical lines) for

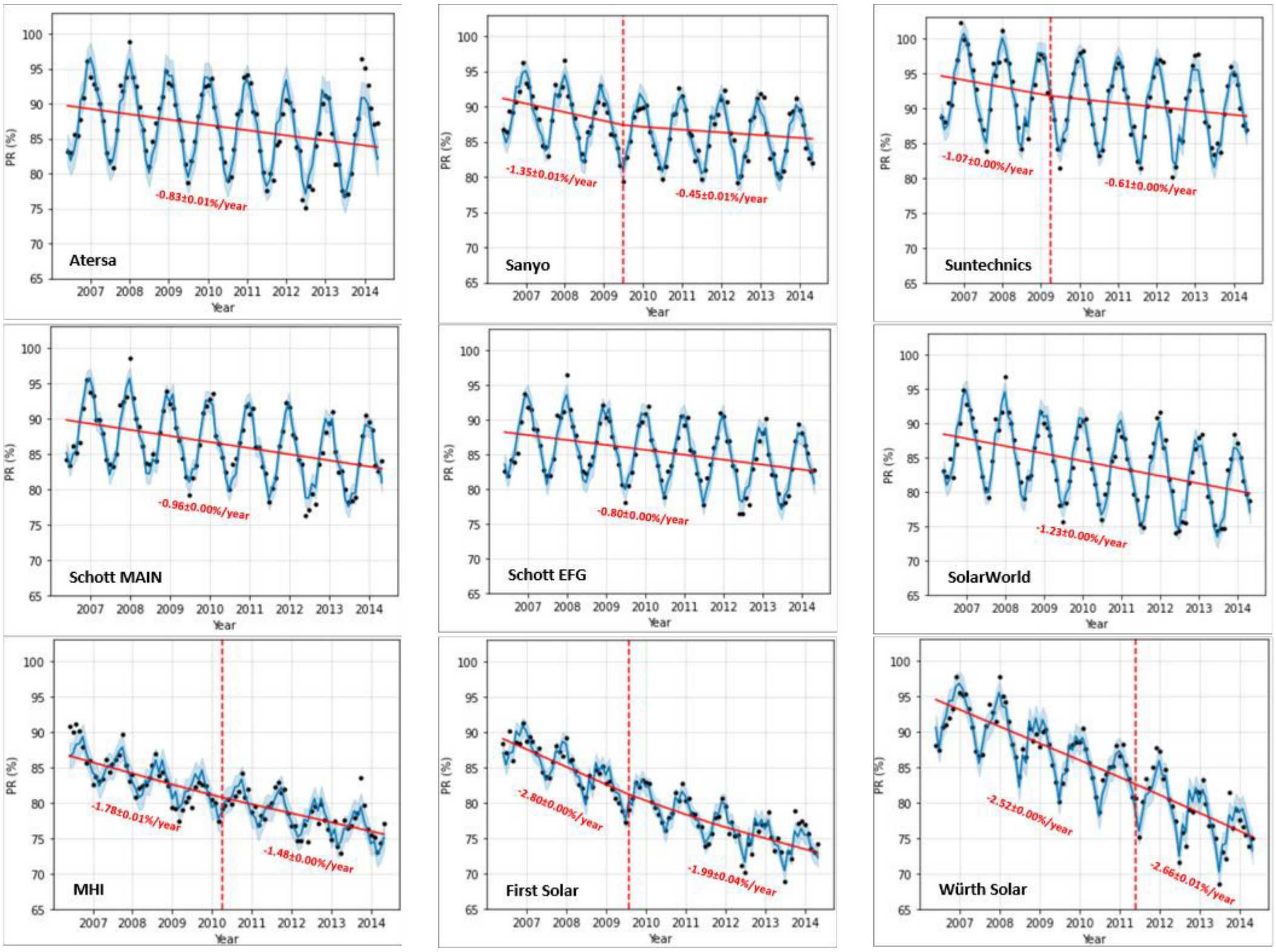

Fig. 4. Linear and non-linear PR trend (red solid lines) segments with actual PR time-series (black dots), Prophet fit (blue line) and associated uncertainty (shaded blue) and change-points (red dashed vertical lines) for systems 1-9 from Table I.

each system. The Sanyo, Suntechnics (mono-c-Si) and MHI, First Solar, Wurth (thin-film) systems exhibited two segments whereas the remaining mono-c-Si (Atersa) and multi-c-Si (Schott MAIN, Schott EFG, SolarWorld) systems demonstrated a linear power decline.

The analysis revealed that three out of five change-points (Sanyo, Suntechnics, First Solar) occurred in 2009 which raises the question whether this change-point is due to a maintenance event or an actual degradation mechanism. Information extracted from the maintenance logs of the UCY OTF indicated an issue in the Sanyo and Suntechnics systems during March and June of 2009. The issue was repaired, but correlation of the maintenance to the degradation rate has not been established. Therefore, it can be assumed that the change-points in the trends of Sanyo and Suntechnics systems were due to a maintenance event, verifying the ability of FBP to detect change-points in PV *PR* time-series. Differentiation of failures from degradation modes will be part of a future investigation. With respect to the First Solar system, maintenance logs did not report any major activities and therefore, the change-point can be attributed to a change in degradation rate. Overall, $|\Delta R_D|$ of 0.90%/year, 0.46%/year, 0.30%/year, 0.81%/year and 0.14%/year were observed for the Sanyo, Suntechnics, MHI, First Solar and Wurth systems, respectively. Furthermore, Wurth Solar was the only system that exhibited increased degradation rate, compared to the initial value.

Table II summarizes the 8-year annual degradation rate results of all methods and systems assuming linear and non-linear trends. Due to the difficulty of a fair "apples-to-apples" comparison between linear and non-linear degradation rates, the difference will be highlighted using the *LCOE* as a criterion.

C. *Impact on LCOE*

As mentioned by Jordan *et al*. [11] and shown in (2), the degradation rate directly affects the *LCOE* (see also the theoretical curves in Fig. 1). Assuming that the change in the rate of performance degradation occurs once (e.g. -1.35%/year for the first 3 years and -0.45%/year for the remaining, in the

TABLE II
SUMMARY OF COMPUTED NON-LINEAR R_D (%/YEAR) WITH CORRESPONDING 95% CONFIDENCE INTERVALS USING DIFFERENT STATISTICAL METHODS.

	Non-linear R_D		*Assuming linear R_D*					
System	***FPB $R_{D,1}$***	***FPB $R_{D,2}$***	***FPB***	***OLS***	***CSD***	***STL***	***HW***	***YOY***
Atersa	NA	NA	-0.83±0.01	-0.65±0.52	-1.06±0.09	-0.81±0.13	-0.96±0.14	-0.52±0.55
Sanyo	-1.35±0.01	-0.45±0.01	-0.75±0.04	-0.67±0.38	-0.68±0.09	-0.78±0.08	-0.89±0.10	-0.83±0.46
Suntechnics	-1.07±0.00	-0.61±0.00	-0.74±0.02	-0.58±0.47	-0.67±0.07	-0.76±0.06	-0.88±0.07	-0.78±0.50
Schott MAIN	NA	NA	-0.96±0.00	-0.84±0.43	-1.06±0.05	-0.97±0.05	-1.10±0.06	-0.69±0.45
Schott EFG	NA	NA	-0.80±0.00	-0.67±0.41	-0.89±0.06	-0.80±0.06	-0.87±0.06	-0.33±0.45
SolarWorld	NA	NA	-1.23±0.00	-1.07±0.49	-1.26±0.06	-1.23±0.05	-1.30±0.04	-0.92±0.49
MHI	-1.78±0.01	-1.48±0.00	-1.61±0.02	-1.68±0.24	-1.59±0.09	-1.62±0.09	-1.79±0.13	-1.19±0.46
First Solar	-2.80±0.00	-1.99±0.04	-2.31±0.05	-2.26±0.23	-2.34±0.07	-2.31±0.09	-2.67±0.11	-1.95±0.38
Würth	-2.52±0.00	-2.66±0.01	-2.57±0.01	-2.48±0.32	-2.59±0.08	-2.58±0.07	-2.98±0.09	-2.51±0.48

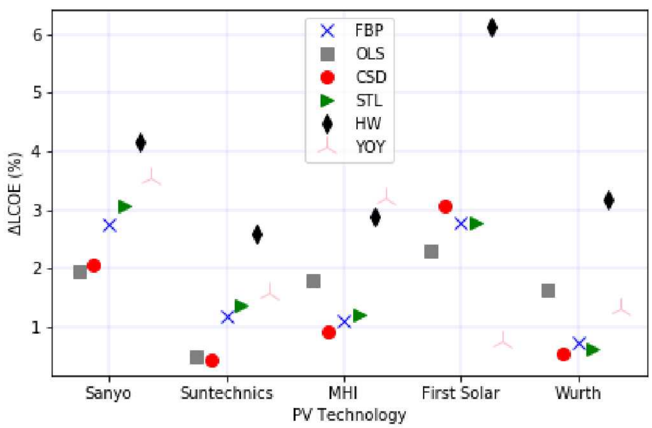

Fig. 5. Impact of non-linear degradation rate on LCOE. Non-linear FBP method is compared against all statistical methods that assume linear behavior (including the linear version of FBP).

case of Sanyo system), a comparative analysis based on linear and non-linear degradation rates was conducted in order to highlight the impact on *LCOE* over a 25-year project lifetime. Input parameters to (2) are the same as in Fig. 1.

The results of this analysis are illustrated in Fig. 5 for all methods. It should be noted that the linear version of FBP (i.e. by ignoring the change-point analysis and simply applying OLS on the extracted trend) is also compared with the non-linear case. *LCOE* percentage differences (*ΔLCOE*) of up to 6.14% have been found in the case of the HW method on the First Solar system. Furthermore, and as expected (see Section III-A), HW is the method with the greatest impact, but this is due to the poor performance in estimating the degradation rates. The least impacted system was the one from Suntechnics with an average of 1.28% whereas the First Solar and Sanyo systems demonstrated the highest mean differences of 2.97% and 2.92%, respectively. MHI and Wurth follow with 1.85% and 1.34%, respectively. If HW is excluded from the analysis, all methods exhibit differences lower than 3.6% whereas the method with the lowest difference in the mean was the CSD.

An additional analysis was performed to compare *LCOE* calculated using the non-linear R_D values to *LCOE* calculated assuming degradation rate ranges reported in literature; i.e. -0.5%/year to -0.9%/year for the c-Si modules [11]. The results showed that the *LCOE* for the Sanyo system differed between 0.19% to 4.26%. The *LCOE* for the Suntechnics system varied between 1.33% and 2.80%. These results indicate a significant difference in estimating *LCOE* that could impact financial calculations.

This *LCOE* analysis highlights the potential importance of not assuming constant rates of power loss during a project's lifetime. Using more sophisticated models (different methods, metrics, assumptions, distributions instead of single values, etc.) may more accurately reflect PV power plant project economics.

IV. CONCLUSIONS

This study successfully detected and quantified the impact of non-linear PV degradation on *LCOE* by applying the FBP change-point algorithm on trends of monthly *PR* time-series. This is important since identifying change-points in the PV performance trend may mitigate the bias in the R_D computations when applying statistical analysis techniques that assume linearity. Interestingly, all thin-film PV technologies demonstrated a change in the slope of their corresponding trends. Future research focused on degradation change-points of thin-film modules may reveal the underlying causes that enable more accurate performance predictions.

The application of OLS on the different trends' segments enabled the quantification of R_D at different PV lifetime phases. A comparative analysis between FBP and conventional models demonstrated the robustness of the STL and FBP methods. In order to highlight the impact of non-linear degradation rates, an *LCOE* analysis was performed exhibiting differences up to 6.14%.

The analysis showed that, two out of six c-Si PV systems exhibited a coincident change-point in 2009. The changes suggest that the systems experienced similar issues at the beginning of life that were rectified at a similar point in time. This example indicates the potential for verifying successful maintenance procedures for avoiding significant degradation rates. In addition, the approach can be used to identify system failures or soiling patterns that may not be detectable using daily time-series data. Overall, the approach provides a more detailed analysis of system performance that could support more accurate financial models. In the future, this methodology will be applied to larger scale PV power plants to enable stronger verification and benchmarking.

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