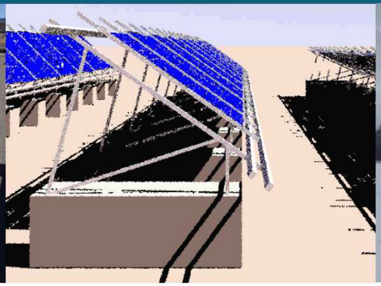
SAND2020-5877C

Modeling nonlinear photovoltaic degradation rates



PRESENTED BY

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Outline

- Motivation
- Overview of approaches for detecting and quantifying nonlinear degradation rate
- Performance analysis of change-point detection approaches
- Application of field data and impact on levelized cost of energy (*LCOE*)

Introduction

- Accurate prediction of lifetime performance of photovoltaic (PV) is crucial for determining the financial payback of a project

- PV systems degrade in the field and therefore, the power degradation rate (R_D) has to be accurately quantified

- R_D estimation depends on data availability, quality, and applied methodology

- Although common practices assume a constant R_D over time, field experience has shown that this is unrealistic

- Identifying and separating trend-based performance losses from failures can improve O&M strategies, increase system availability and hence, further reduce *LCOE*

Using constant degradation rate values may increase financial risks

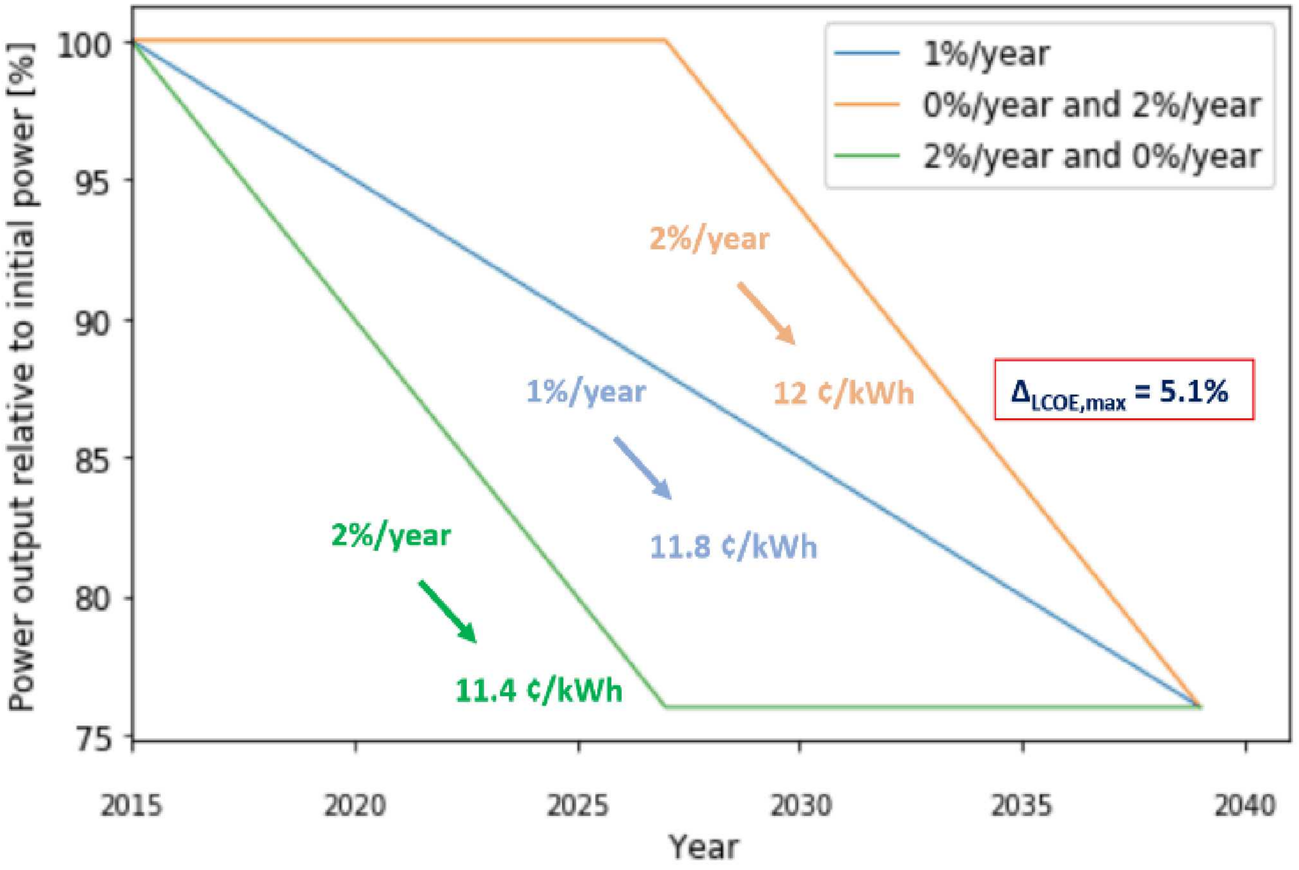


Figure recreated from:
J. S. Stein, C. Robinson, B. King, C. Deline, S. Rummel, and B. Sekulic, "PV Lifetime Project: Measuring PV Module Performance Degradation: 2018 Indoor Flash Testing Results," in *2018 IEEE 7th World Conference on Photovoltaic Energy Conversion (WCPEC) (A Joint Conference of 45th IEEE PVSC, 28th PVSEC & 34th EU PVSEC)*, 2018, pp. 0771-0777.

Change-point detection methodologies

Facebook Prophet (FBP) and RBeast* libraries

Decomposition model → Change-point analysis → OLS at each segment

Segmented or Piecewise Regression (SegmR) methodology

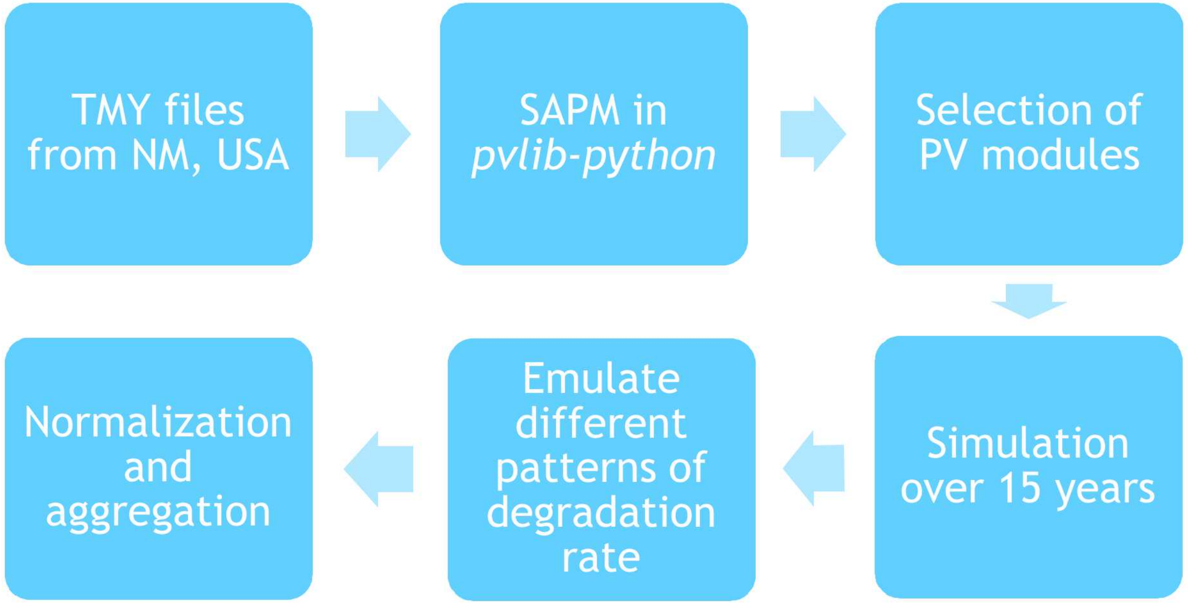
Decomposition model → Piecewise function → Curve fitting

*Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST)

Generation of synthetic datasets

Real degradation rate value, number and location(s) of change-points are “unknown”

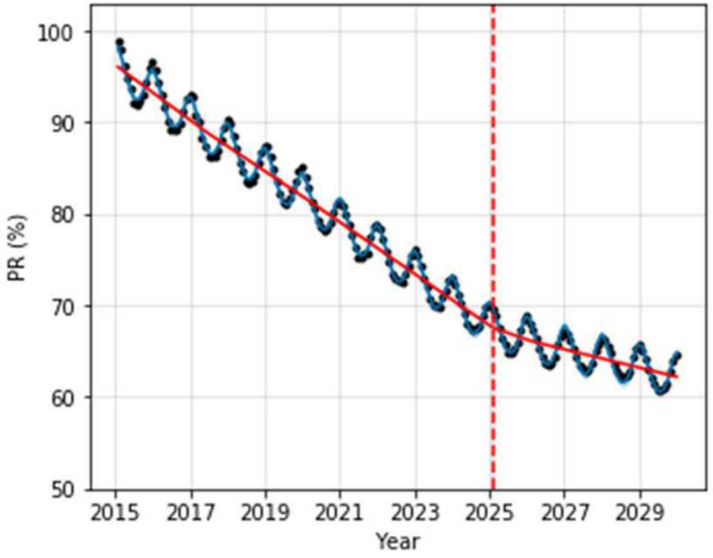
Synthetic datasets of known behavior were generated prior to applying the methods on real data



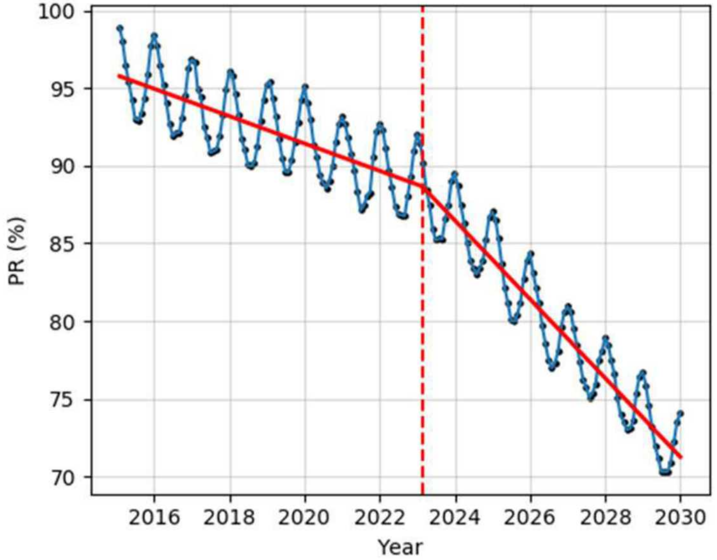
Scenarios considered for nonlinear degradation rate

Scenario	Change-point date/position	$R_{D,1}$ (%/year)	$R_{D,2}$ (%/year)
a	Jan-17 (24)	-5	-1
b	Jan-19 (48)	-0.5	-3.5
c	Jan-21 (72)	-1	-0.5
d	Jan-23 (96)	-1	-2.5
e	Jan-25 (120)	-3	-1

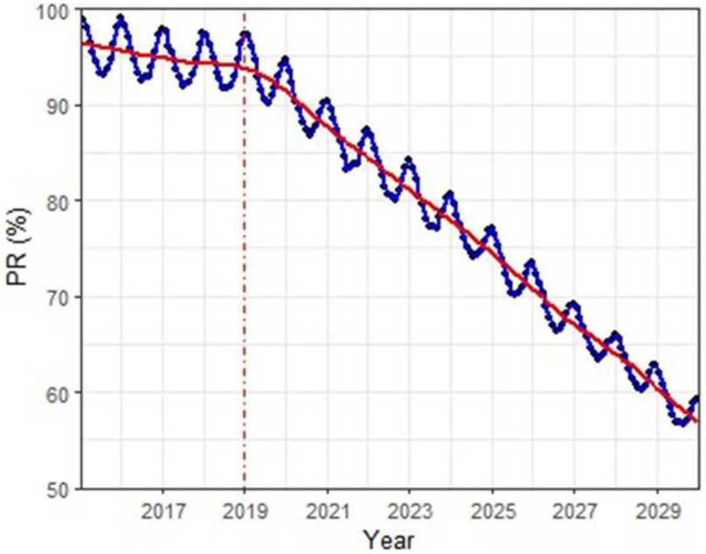
Some examples:



FBP (Scenario *e*)



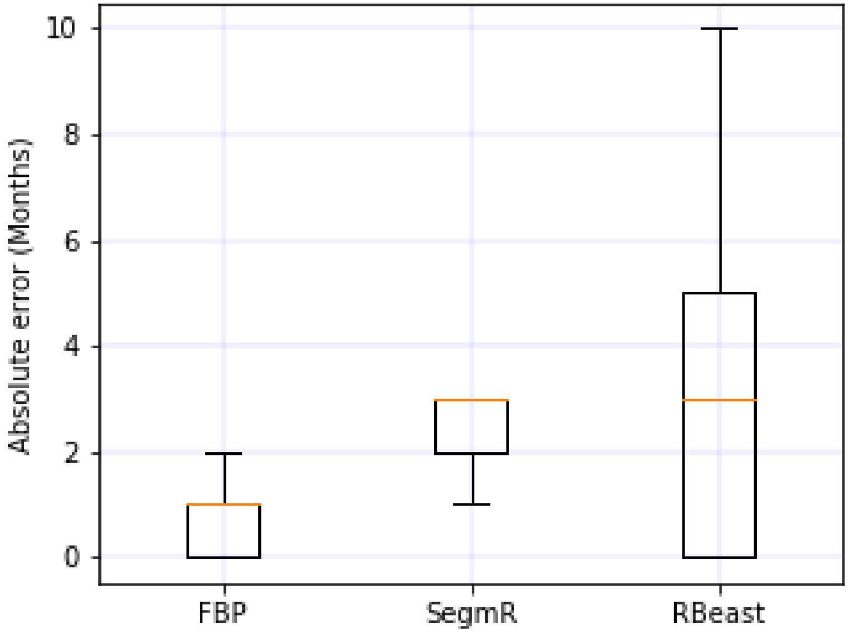
SegmR (Scenario *d*)



RBeast (Scenario *b*)

Performance comparison in locating the change-point positions

- Absolute error varied from 0 to 10 months
- Median absolute errors of 1 Month for FBP and 3 months for SegmR and Rbeast
- Mean absolute error (MAE) of 0.8, 2.4, 3.6 Months for FBP, SegmR and RBeast, respectively

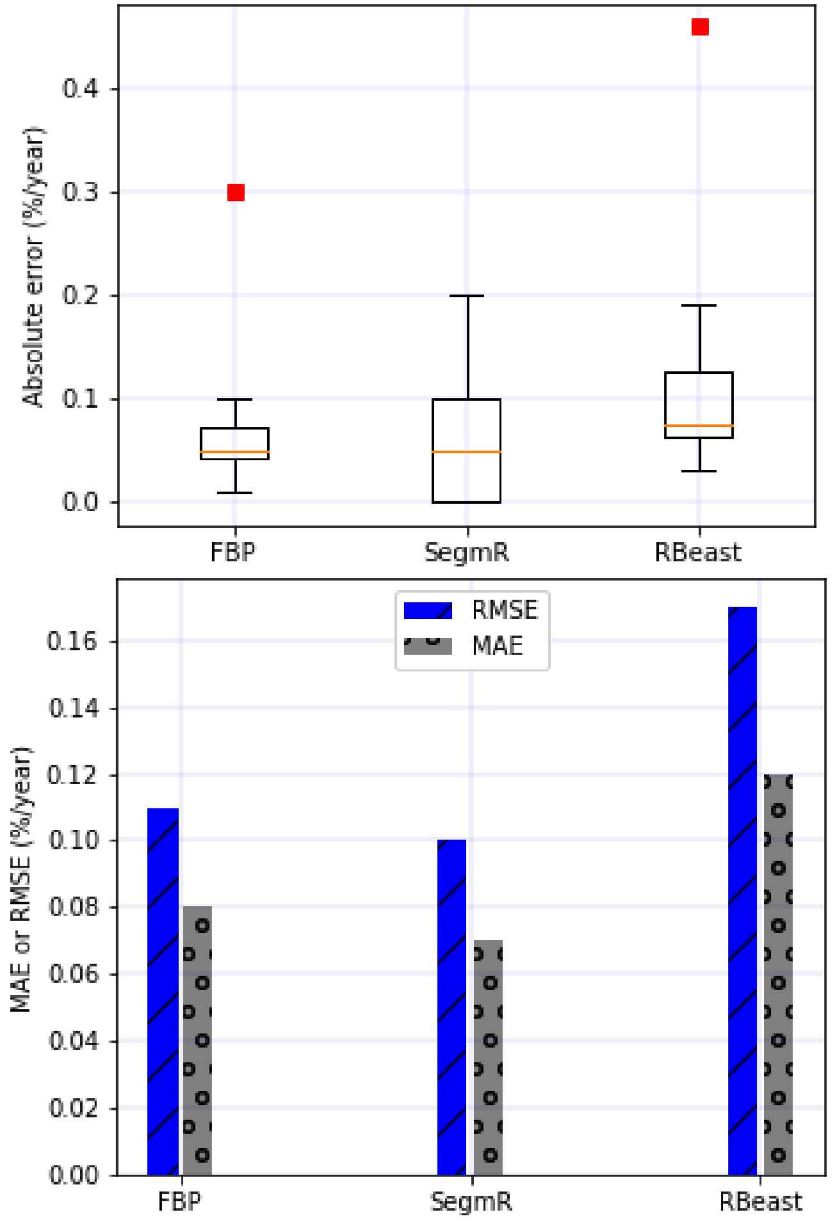


FBP is the most accurate in detecting change-point locations.

Performance comparison in estimating the degradation rates in the different segments

- Median absolute errors of 0.05%/year for FBP and SegmR whereas Rbeast exhibited 0.075%/year
- MAE was 0.08%/year, 0.07%/year, 0.12%/year for FBP, SegmR and RBeast, respectively
- RMSE was 0.11%/year, 0.10%/year, 0.17%/year for FBP, SegmR and RBeast, respectively

➡ SegmR is the most accurate in estimating degradation rates in corresponding segments.



Demonstration of FBP on 9 systems over 8 years of field exposure

Site and systems' description

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

Location: Nicosia, Cyprus

Period: 2006 – 2014

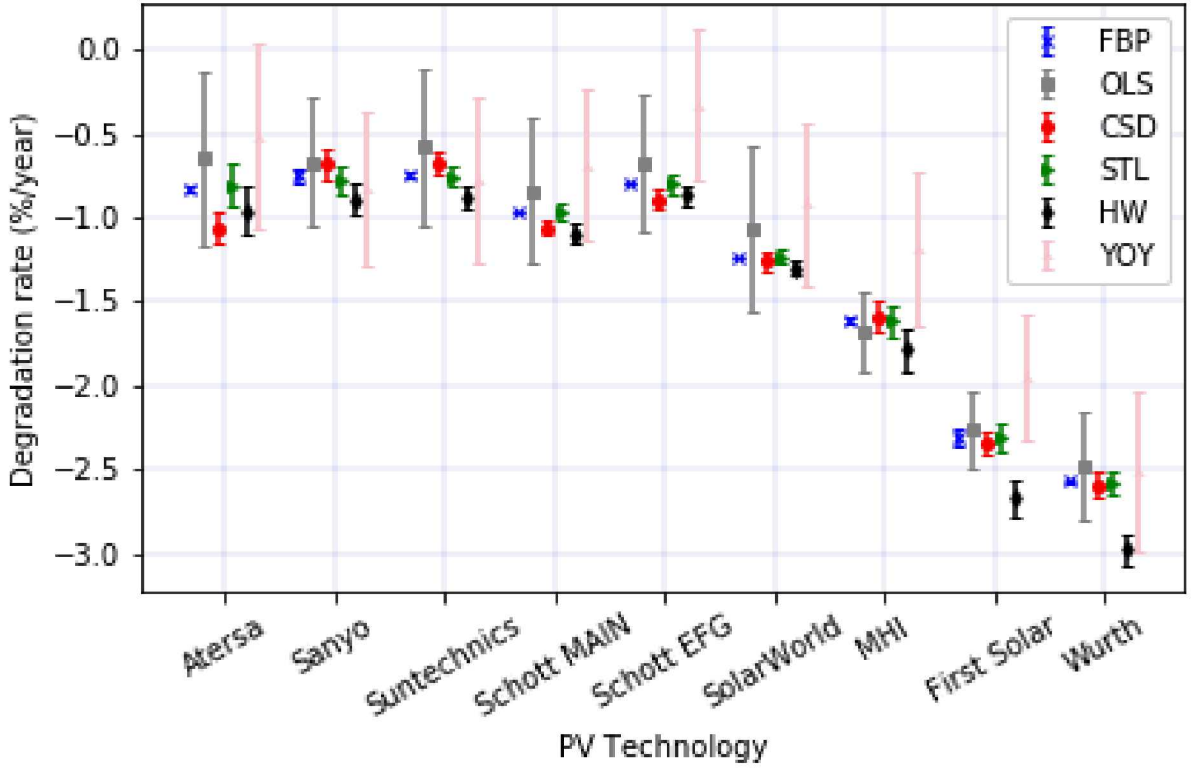
Climate: *BSh* (hot semi-arid)

Recording according to IEC 61724

Monthly performance ratio

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 Journal of Photovoltaics,* pp. 1-7, 2020.

Comparison of computed degradation rates for all systems using different methods

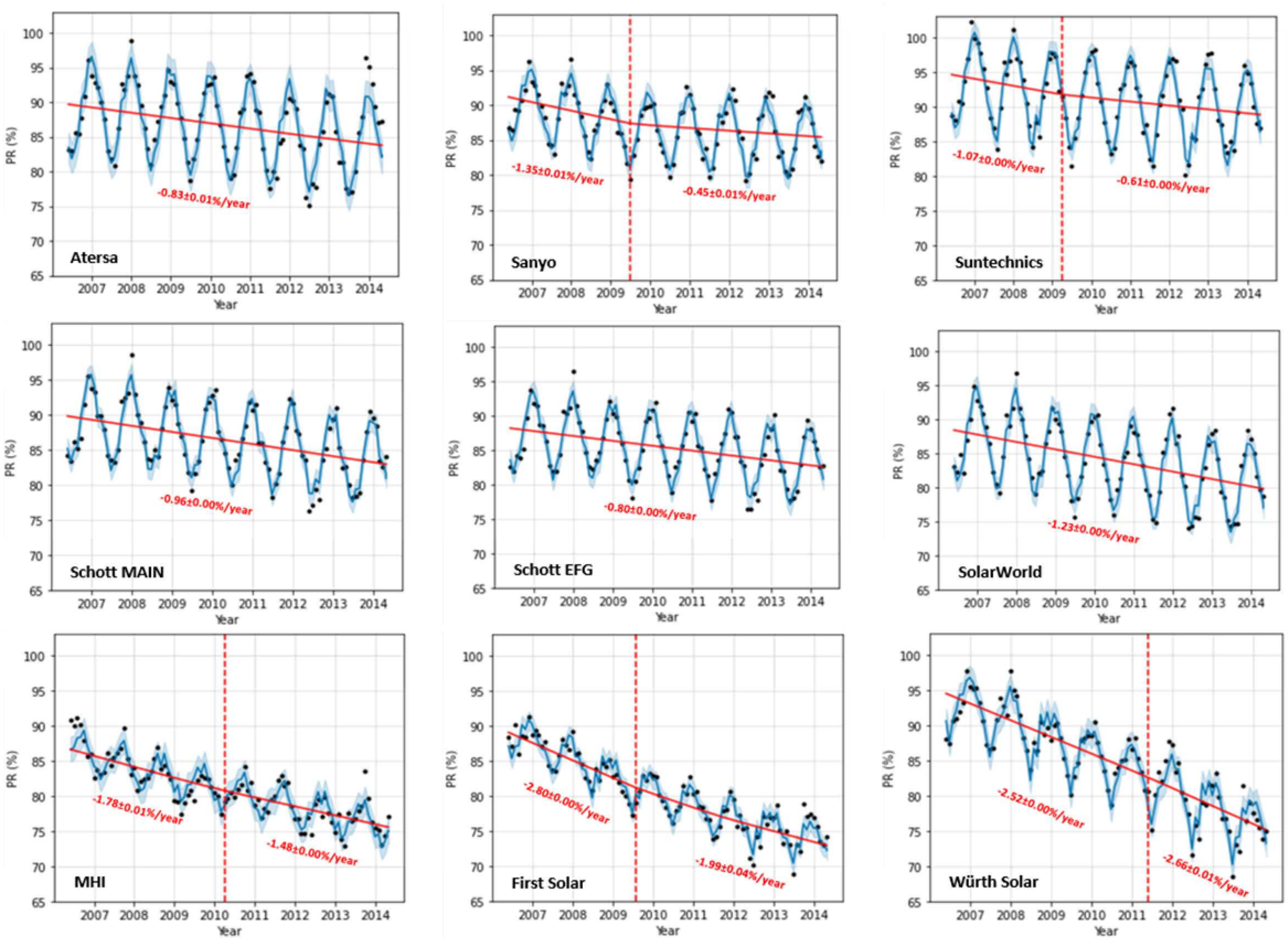


All methods assume linear behavior and the error bars are 95% confidence intervals of the statistical uncertainty.

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 Journal of Photovoltaics,* pp. 1-7, 2020.

Application of FBP on 8-year field data

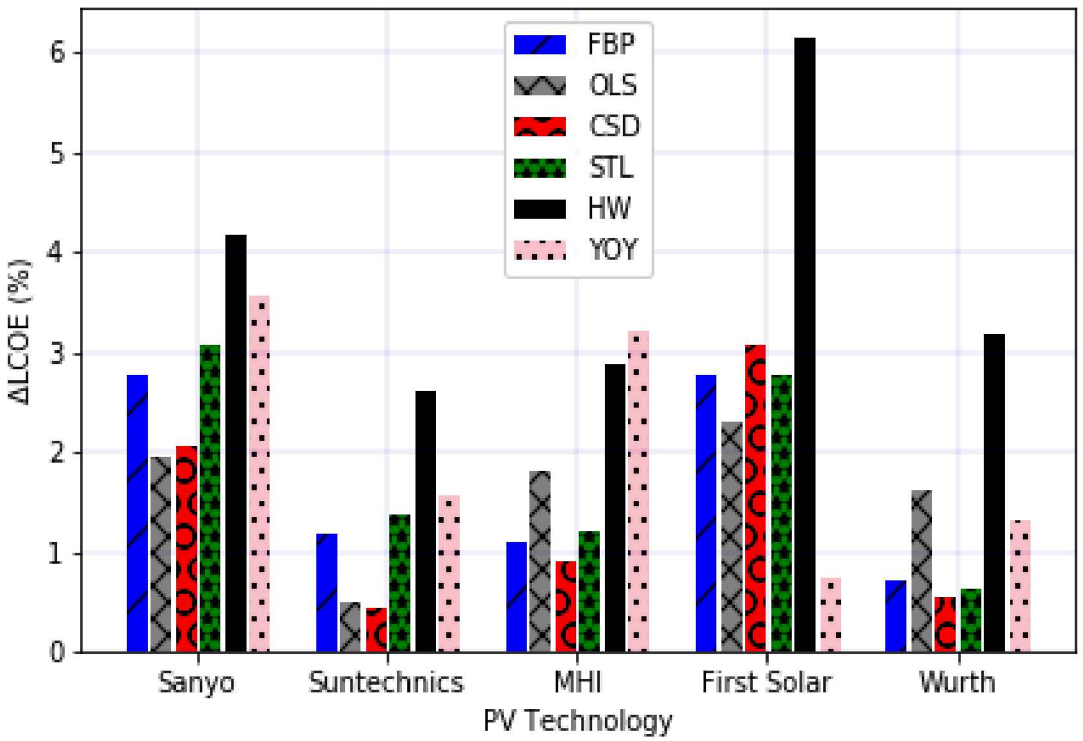
- Actual PR time-series (black dots)
- Linear and non-linear PR trend segments (red solid lines)
- Prophet fit (blue line) and associated uncertainty (shaded blue)
- Change-points (red dashed vertical lines) for all systems.



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 Journal of Photovoltaics,* pp. 1-7, 2020.

Impact of nonlinear degradation rate on *LCOE*

Nonlinear FBP method is compared against all statistical methods that assume linear behavior (including the linear version of FBP).



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 Journal of Photovoltaics,* pp. 1-7, 2020.

Conclusions

- Nonlinear PV degradation was successfully detected and quantified using three different methods
- Overall, all methods demonstrated good performance
- FBP exhibited the lowest prediction errors in locating the positions of change-points
- SegmR was the most accurate in computing the corresponding degradation rates
- Different change-point detection models may be more appropriate depending on the particular case
- Relatively high *LCOE* deviations were exhibited when nonlinearity was neglected

Future work

- Future work (manuscript preparation under progress) will expand on this study to include:
  - additional change-point techniques
  - longer list of scenarios including three-step or greater degradation rate behavior
  - different PV module technologies

- Application of all methods to larger scale PV power plants to enable stronger benchmarking

- Differentiating failures from degradation modes

- Investigate change-point techniques for detecting other trend-based performance losses such as soiling*

*see also submission by Micheli *et al.*, "Segmentation of Deposition Periods: An Opportunity to Improve PV Soiling Extraction," in *47th IEEE Photovoltaic Specialists Conference (PVSC)*, 2020.

Thank you for your attention!

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