DuraMAT
Durable Module Materials Consortium

Assessing Factors Underpinning PV Degradation Through Data Analysis

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DuraMAT Webinar

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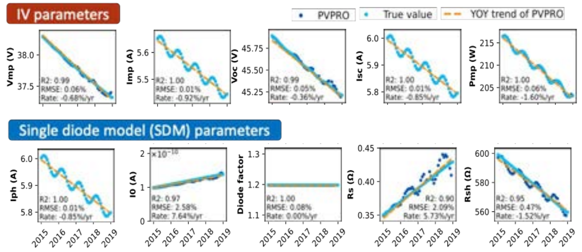
Field PV data mining using PVPRO for degradation Analysis



Degradation trend of IV and SDM parameters estimated by PVPRO using synthetic dataset

PART 1

Electroluminescence (EL) image analysis with computer vision

OUTLINE:

- **Automatic pipeline of identifying defective cells**
  – Case study: Field survey of a solar farm

- **Quantified crack feature extraction from EL images**
  – Case study: Does QualPlus test lead to more severe cracks?

PART 1

Electroluminescence (EL) image analysis with computer vision

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Automatic pipeline of identifying defective cells

Motivation

- Field survey is important to report degradation mode and evaluate system health
- Electroluminescence imaging is a fast and non-destructive method commonly used to identify cell-level defects (e.g., cracks, solder disconnection)
- However, PV system have 100K ~ 1M modules, making human inspection inefficient

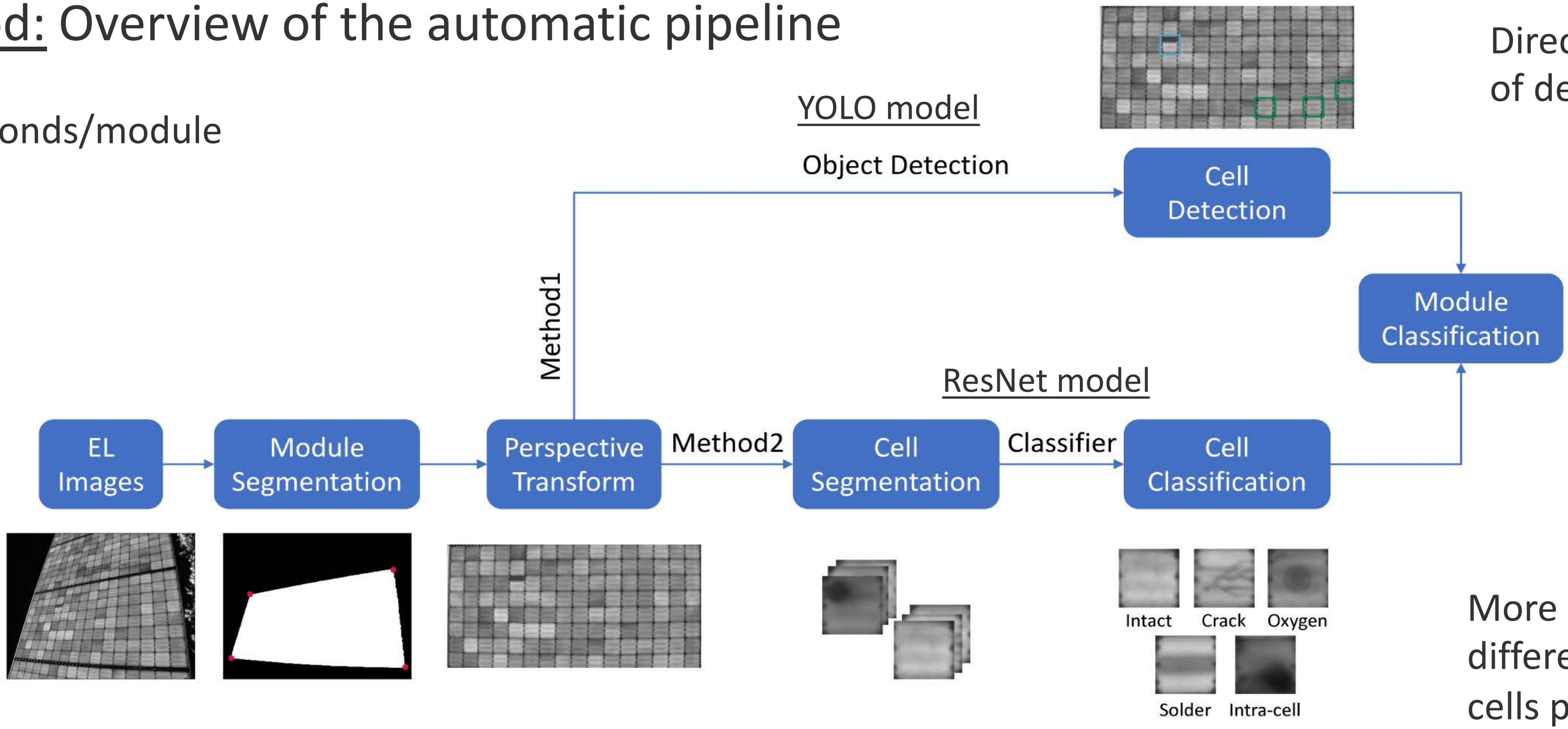
A large-scale solar farm

Goal: Enable automatic inspection of EL images with a computer vision pipeline

Automatic pipeline of identifying defective cells

Method: Overview of the automatic pipeline

~ 0.5 seconds/module



Direct visualization of defect positions

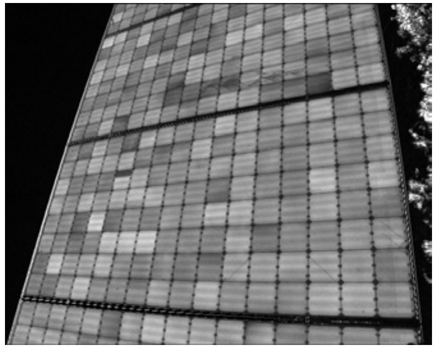
More robust to different number of cells per module

Architecture of the identification pipeline

Automatic pipeline of identifying defective cells

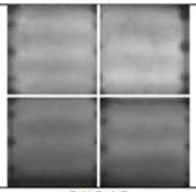
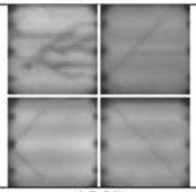
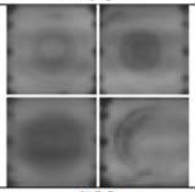
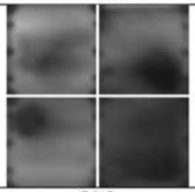
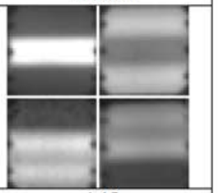
Method: computer vision models development

- Dataset: 1,025 EL images of IBC solar modules

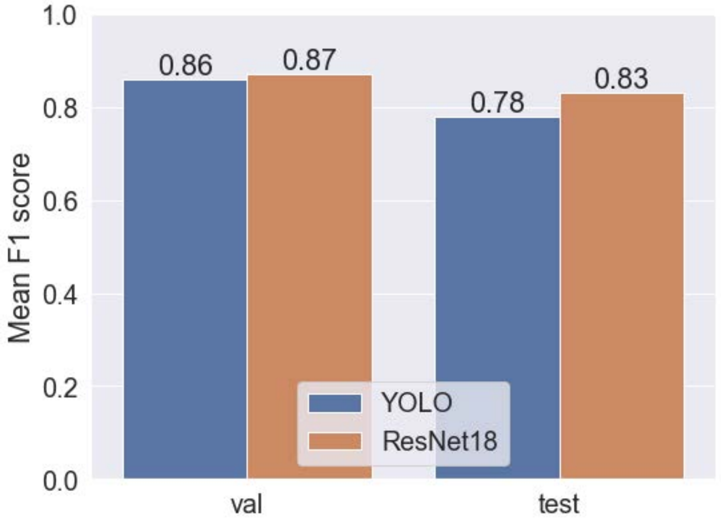


Field EL image
~4 mm/pixel

Note: those targets are what our collaborators are interested in. The pipeline can be extended to detect other defects

Category	Intact	Crack	Oxygen	Intra-cell	Solder
Image					
Training 762 modules	95048 97.44%	1367 1.40%	709 0.73%	279 0.29%	143 0.15%
Validation 134 modules	16618 96.87%	345 2.01%	127 0.74%	47 0.27%	18 0.10%
Testing 129 modules	16082 97.4%	244 1.48%	126 0.76%	45 0.27%	17 0.10%

- Evaluation



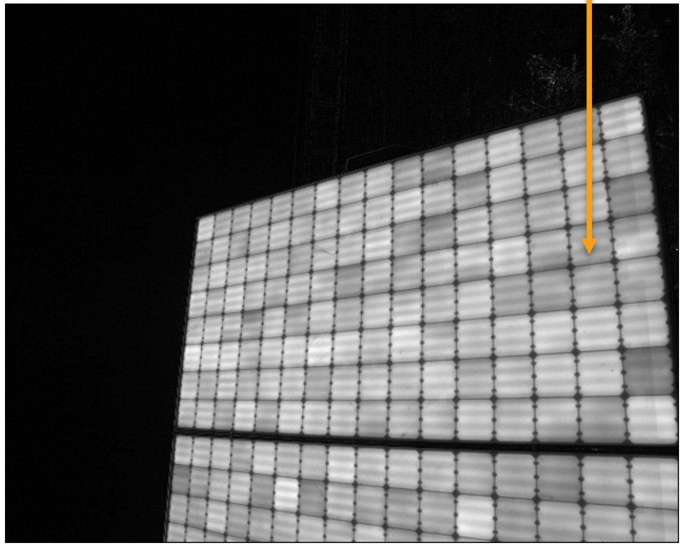
F1 score evaluates how many targets are detected and how precise the detection is

Performance of object detection model and classification model is comparable, but classifier generalizes (i.e., work on new data) better

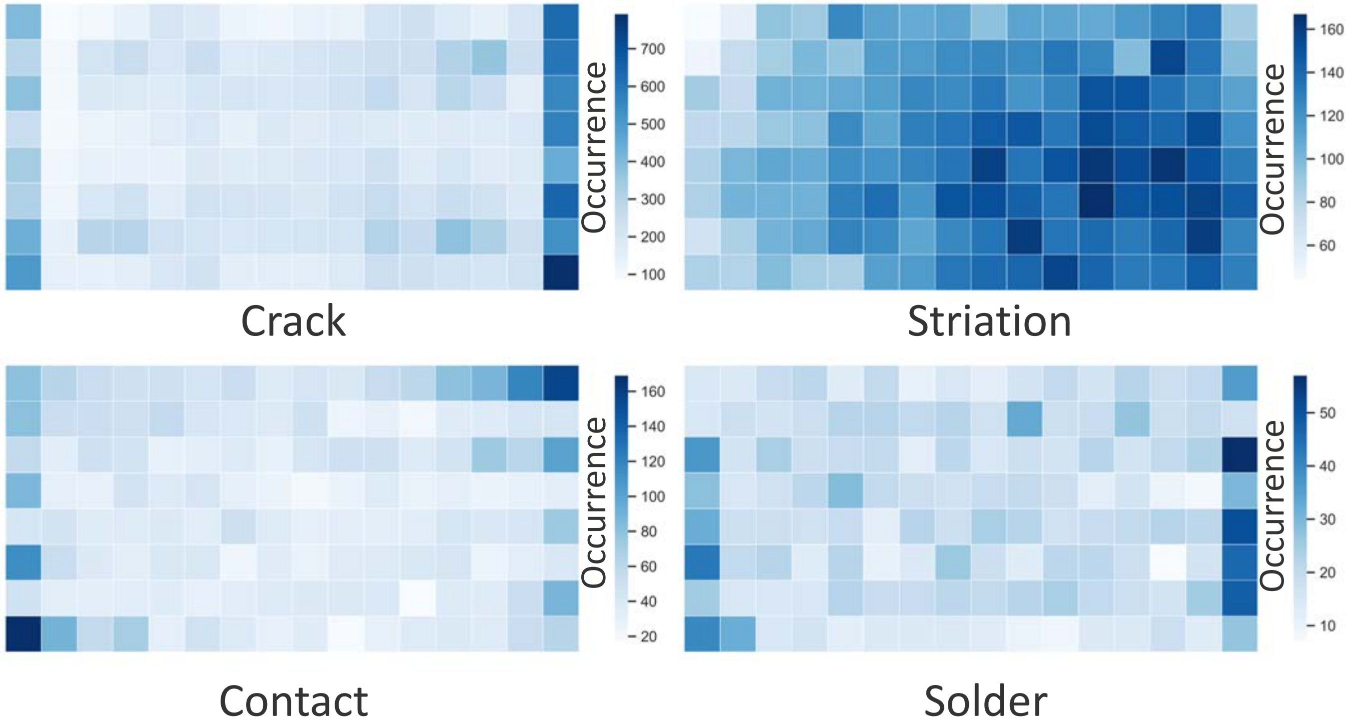
Automatic pipeline of identifying defective cells

Case study: Filed inspection of bushfire damage

Closer to bushfire



18,825 PV modules affected by fire are analyzed by YOLO model.



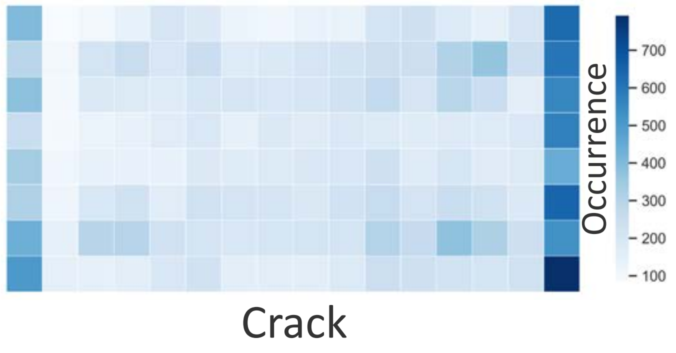
Distribution of defects on solar module

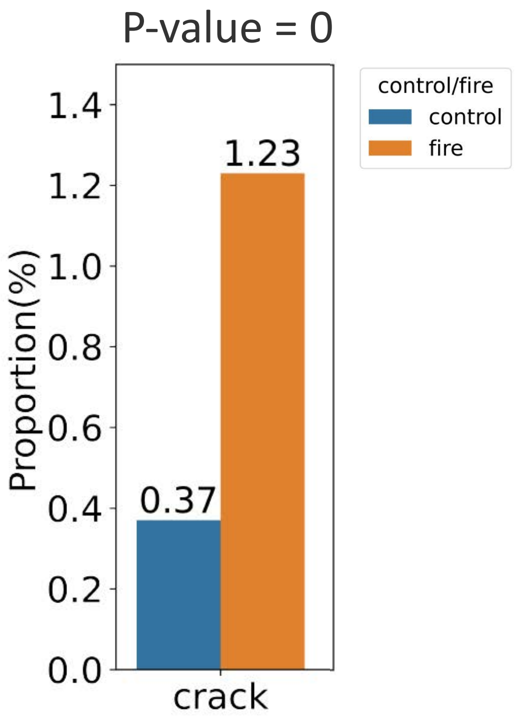
Tendency of distributing on fire-effected side

Automatic pipeline of identifying defective cells

Case study: Filed inspection of bushfire damage

	Fire-effected	Control group
Module number	18,825	129
Description	The control group were installed in the same site, but at a different part of the plant that wasn't influenced by the fire.	





Thermal stress induced by fire may cause an increase of cracks

PART 1 Electroluminescence (EL) image analysis with computer vision

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  - Case study: Field survey of a solar farm

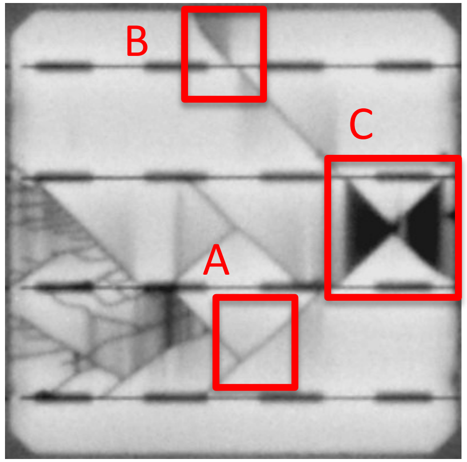
- **Quantitative crack feature extraction from EL images**
  - Case study: Does QualPlus test lead to more severe cracks?

Quantitative crack feature extraction from EL images

Motivation

- Degradation of cracked modules varies from 3%/yr ~ 8%/yr in field[1]
- Cracks have a delayed effect on module power and can recover during cycling
- It is unclear how to quantify crack impact on PV performance due to complex crack features

Cracks don't necessarily lead to power loss



EL image of a cracked cell (~0.4 mm/pixel) cropped from module image. Crack A is uncritical; B causes partial disconnection; C causes complete isolation.

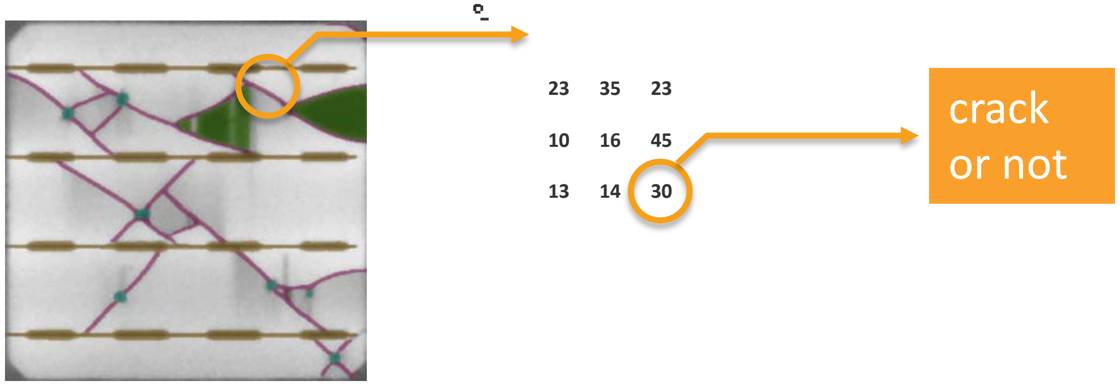
Goal: Automatically extract quantitative crack features from EL images

1. M. Köntges, *et al.*, *Report IEA PVPS Task 13,* (2017)

Quantitative crack feature extraction from EL images

Method: Semantic segmentation

- Counting number of cracked cells is not enough to quantitatively describe cracks
- Pixel-scale crack features are needed



Extracted crack masks can be used to design crack descriptors

Quantitative crack feature extraction from EL images

Method: Computer vision model development

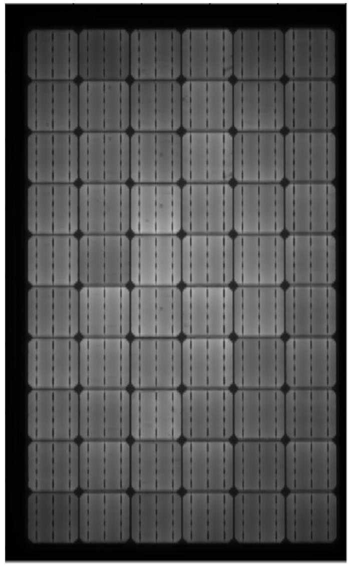
Automatic Crop | Sample | Split

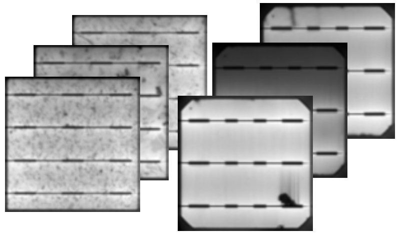
445 modules → 29,664 cells → 1,837 cells →

- Train: 1272 — Train model →
- Val: 206 — Select model →
- Test: 359 — Test generalization →
- Test (crack only): 322

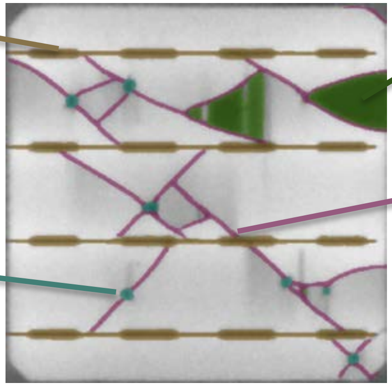
UNet model

Manual annotation





- Mono/poly-c Si
- Various numbers of busbars and cells

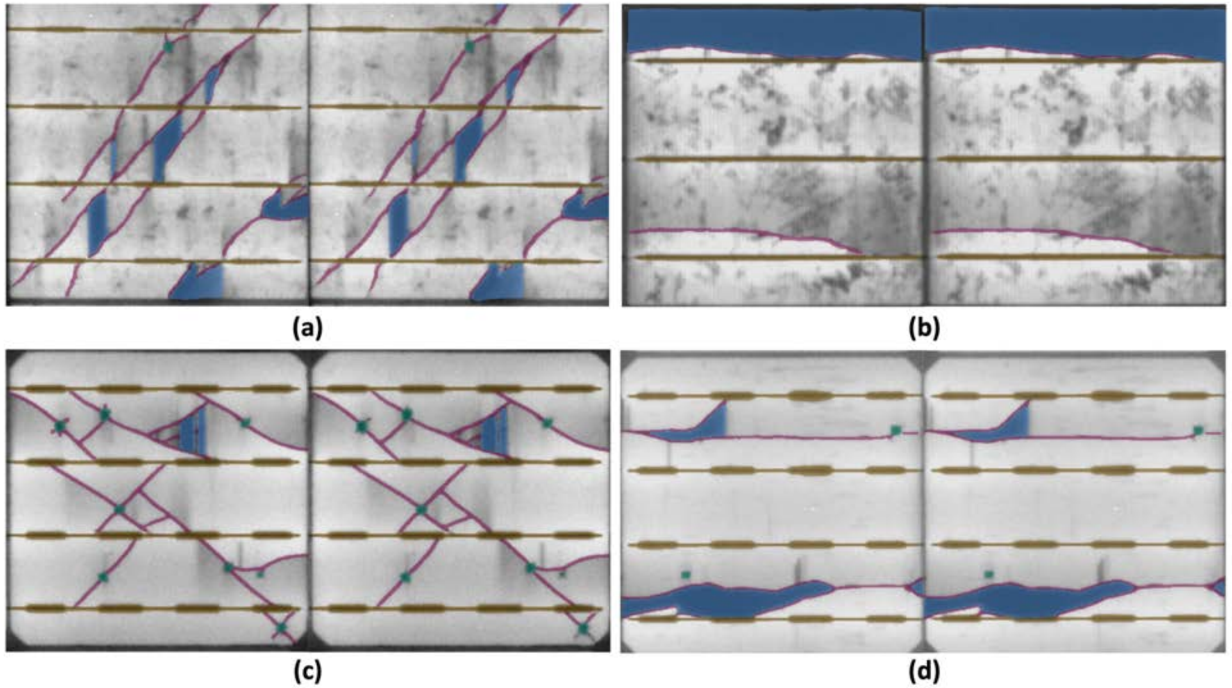


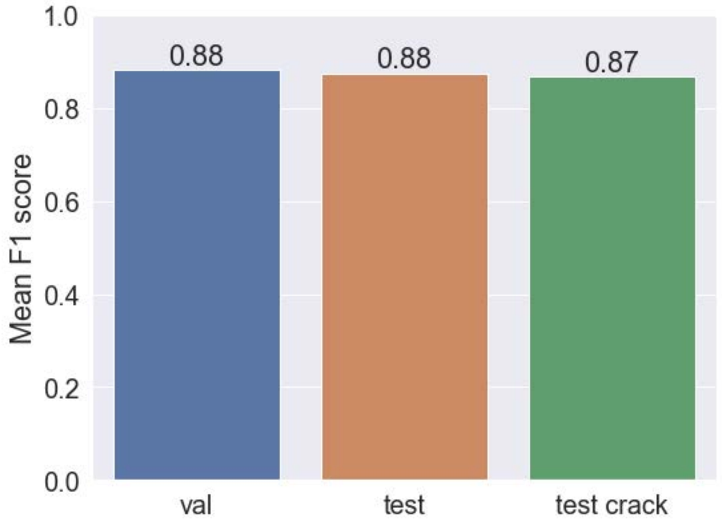
Note: Another better algorithm was designed to extract dark area

Quantitative crack feature extraction from EL images

Evaluation: Computer vision model development

Left: ground truth Right: prediction



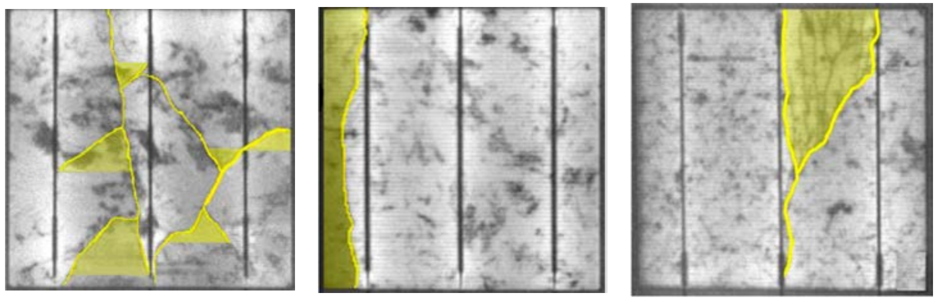


- High performance on validation set
- Robust performance on testing set shows generalization (i.e., work on new data)

Quantitative crack feature extraction from EL images

Method: Crack feature extraction

- Crack isolation influences photogenerated current depending on isolated area and increases the series resistance depending on the severity of the crack disconnection
- In the worst case, isolated part becomes totally inactive



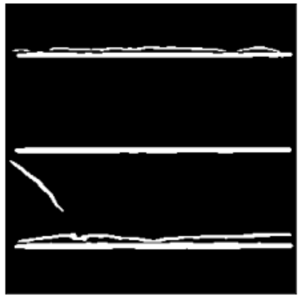
MBJ, “MBJ Services - Solar Module Judgment Criteria EL,” 2019.

Isolated area and EL intensity (related to crack resistance) might be good descriptors of cracks to represent crack damage

Crack and busbar masks predicted from UNet model can be utilized to compute crack features

Quantitative crack feature extraction from EL images

Method: Crack feature extraction



Cracks and busbars predicted from UNet model

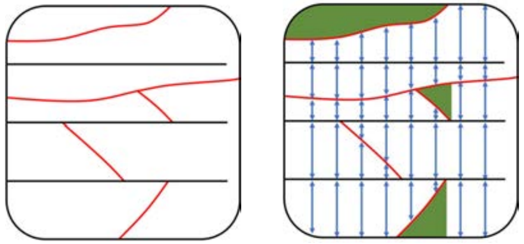
Crack length

Pixel numbers of skeletonized cracks predicted by crack segmentation model

Isolated area proportion

Max-isolated area prediction algorithm

$$p(\%) = \frac{\mathrm{Area}_{iso}}{\mathrm{Area}_{cell}} \times 100$$



Brightness of isolated region

Mean grayscale value (normalized to 0-1) of isolated area using max-isolated area prediction algorithm

$$Avg_{iso} = \frac{Sum_{iso}}{Area_{iso}}, \text{1 for intact cell}$$

Quantitative crack feature extraction from EL images

Case study: Crack damage in QualPlus test

- Standard accelerated aging test may not be enough to capture crack failures in solar modules
- Extended aging test (QualPlus) is suggested to evaluate module resistance to static and dynamic loading
- Does QualPlus really cause more crack damage? How to quantify it?

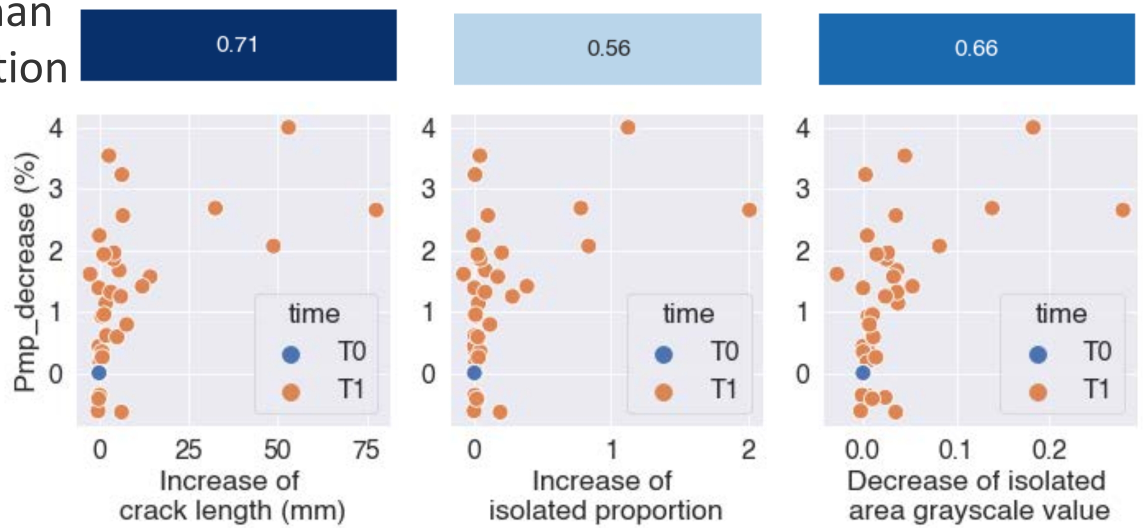
		T0	Accelerated aging testing				T1
Standard	Sequence1 (6 modules)	EL, IV	UV precondition		Thermal cycle, 50 cycles	Humidity freeze cycle, 10 cycles	EL, IV
Standard	Sequence2 (6 modules)	EL, IV			Thermal cycle, 200 cycles		EL, IV
Qual Plus	Sequence3 (12 modules)	EL, IV	UV precondition	Dynamic mechanical load,1000 cycles	Thermal cycle, 50 cycles	Humidity freeze cycle, 10 cycles	EL, IV
Qual Plus	Sequence4 (12 modules)	EL, IV			Thermal cycle, 500 cycles		EL, IV

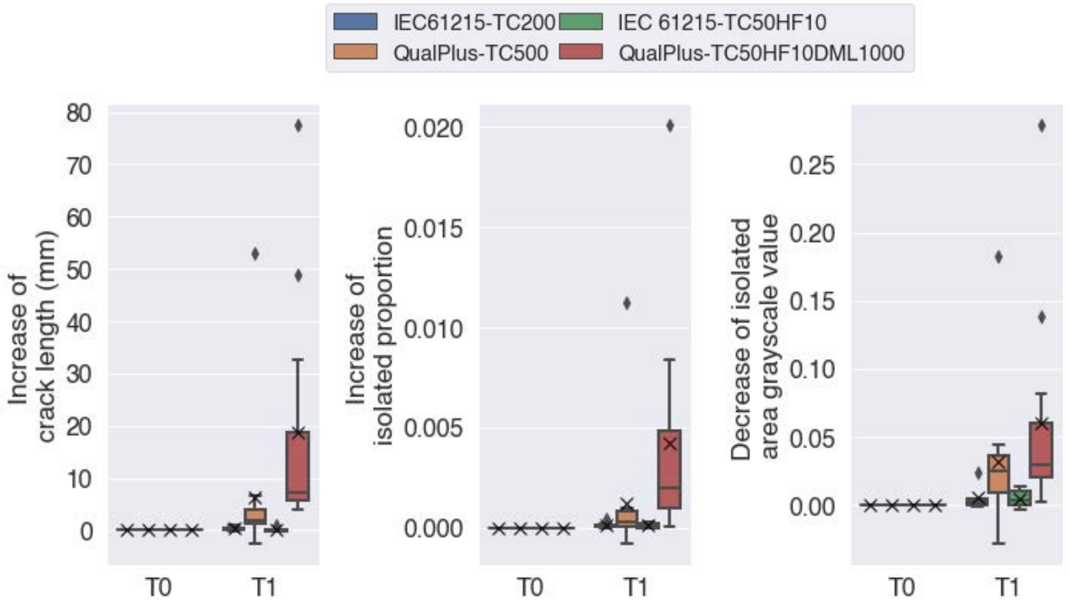
36 modules went through different aging test sequences. EL and IV data are collected in the beginning (T0) and after tests (T1).

Quantitative crack feature extraction from EL images

Case study: Crack damage in QualPlus test

Spearman correlation





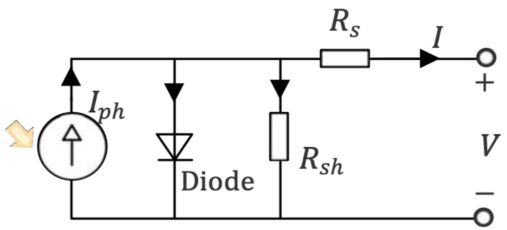
- Extracted crack features show correlation with power loss
- Isolated area's correlation is weak (possibly due to the reason that isolated area causes negligible power loss if metal contacts are still connected)

QualPlus leads to more significant change of crack length, isolated area and isolated resistance

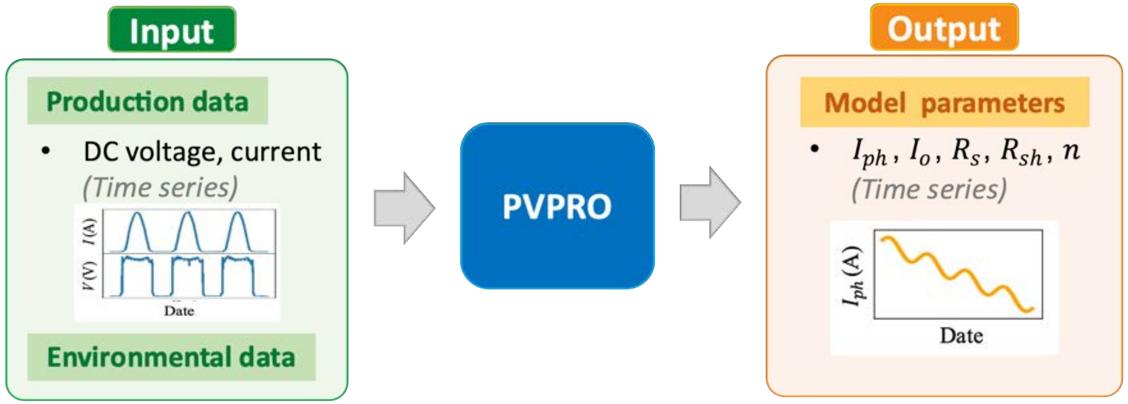
PART 2

Field PV Data Mining Using PVPRO for Degradation Analysis

Background:



- **Physics-based circuit parameters** (Rs, Rsh) are essential for the degradation analysis of PV systems
- Calculating these parameters typically requires a **full I-V curve**, which is **not commonly available** at PV system level
- A methodology (**PVPRO**) is developed to estimate the parameters using **only operation** (DC voltage and current) and **weather data** (irradiance and temperature).



Background

Relevant research in the literature

- **Killam et al. [1]:** Suns-Voc method to estimate parameters and reconstruct pseudo I-V curves from meteorological data and open-circuit voltage
- **Chakar et al. [2]:** Teaching-Learning-Based Optimization technique to extract circuit parameters
- **Sun et al. [3]:** Suns-Vmp method to extract the model parameters by fitting the double-diode model using time-series maximum power point (MPP) data.

Limitations

- Requires Voc (hard to measure)
- Complex training
- Limited generalization
- Restrict monotonic degradation trend
- Slow fitting
- Simple preprocessing

PVPRO

Step 1

Step 2

[1] A. C. Killam, et al., "Monitoring of Photovoltaic System Performance Using Outdoor Suns-VOC," *Joule*, vol. 5, no. 1, 2021
[2] J. Chakar, et al., "Determining solar cell parameters and degradation rates from power production data," *Energy Conversion and Management: X*, vol. 15, 2022
[3] X. Sun, et al., "Real-time monitoring and diagnosis of photovoltaic degradation only using maximum power point—the Suns-Vmp method," *Progress in Photovoltaics: Research and Applications*, 27, 1, 2019

Method: Pre-processing

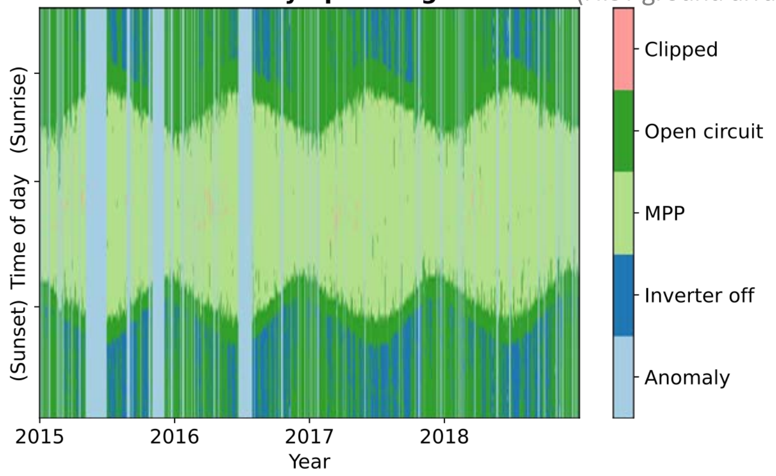
Daylight saving time (DST) correction

- If field data contains DST shifts, DST gets corrected using Solar data tools [1].

Identification of operation condition

- PVPRO uses data at maximum power point (MPP)
- Identify condition based on electrical and weather data

Identified PV array operating condition (NIST ground array)



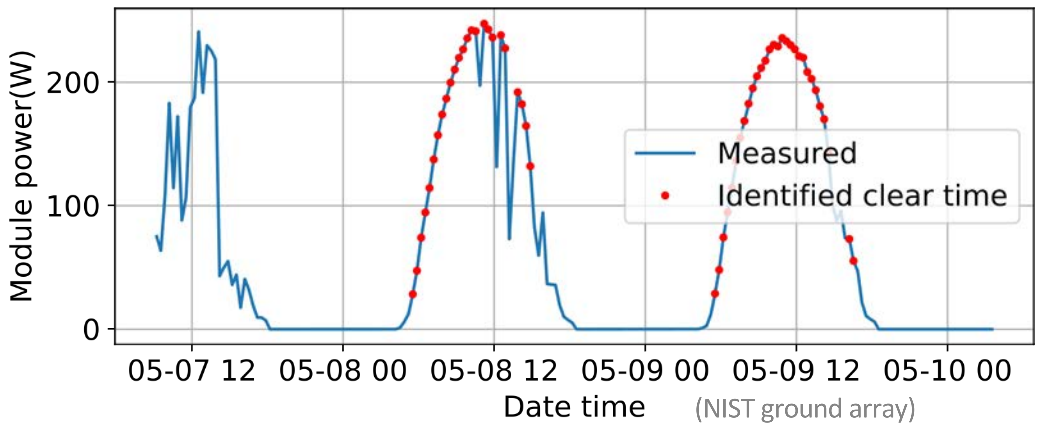
Clear time detection

- Rapid change of G → higher error of predicted operation point

  (due to spatial difference and imperfect synchronization between sensor and PV array)

- Statistical clear sky fitting (SCSF) algorithm[1] is applied

  (free of geometric modeling & resilient to shading)



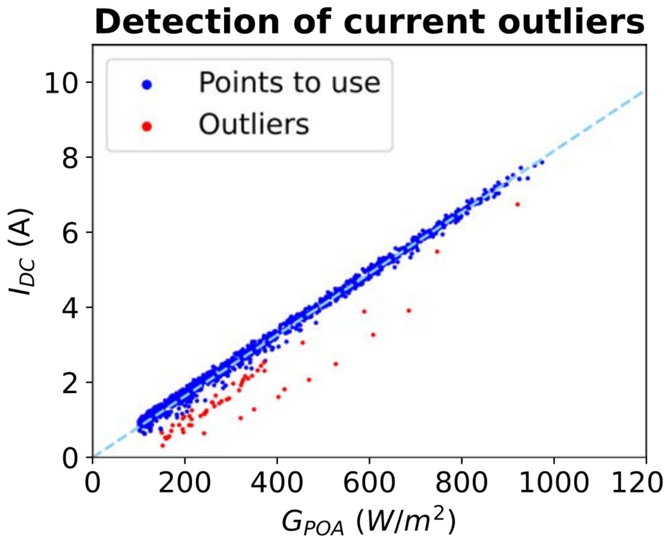
(NIST ground array)

[1] https://github.com/slacgismo/solar-data-tools

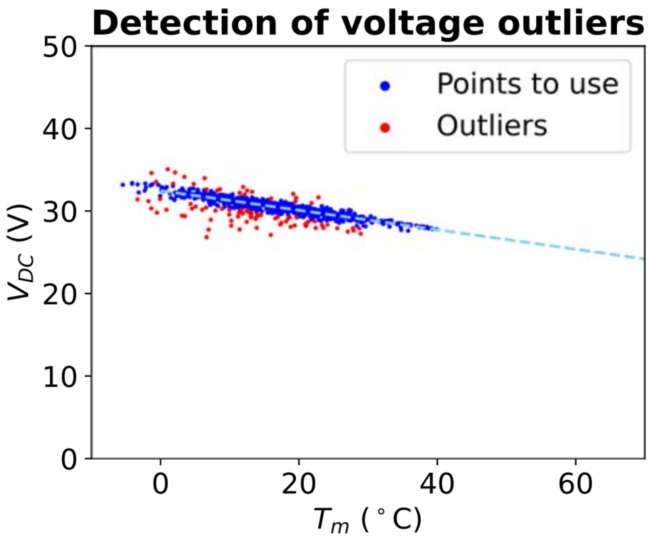
Method: Pre-processing

Current irradiance & Temperature voltage filter

- DC current (I_{DC}) is expected to be proportional to plane-of-array (POA) irradiance (G_{POA}).



- DC voltage (V_{DC}) and temperature (T_m) should be linearly related.

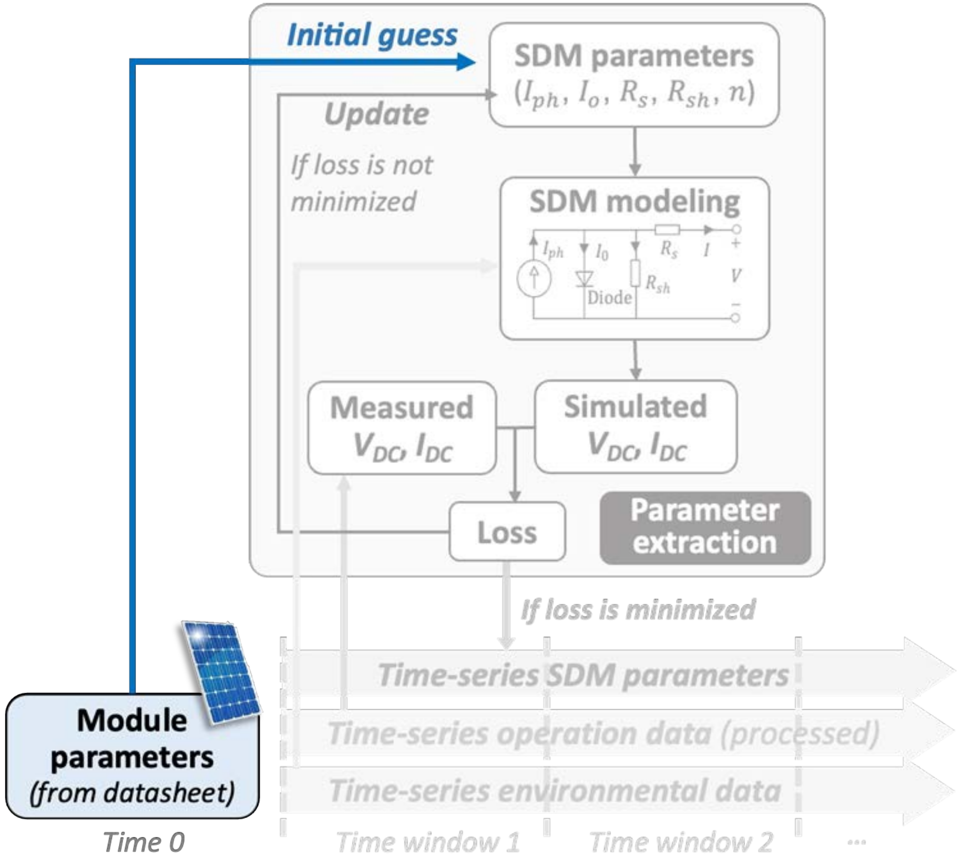


Deviations can occur if:
- MPP tracking errors.
- MPP tracking window limits
- Measurement anomalies

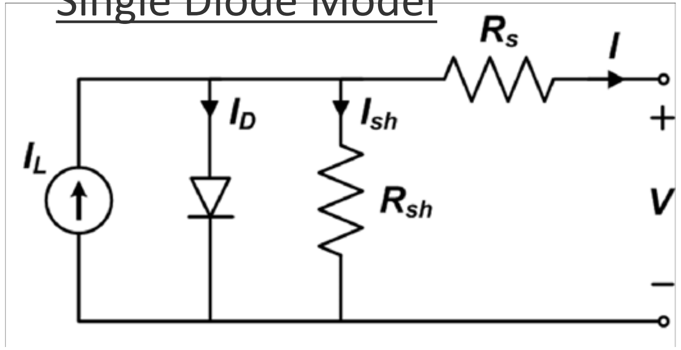
- **Method:** Use **Huber regressor** (robust to outliers in the fitting procedure) to perform a **linear regression** to classify points as points to use or outliers.

Method: Parameter estimation

Initial guess of SDM parameters



Single Diode Model



$$I = I_L - I_O\left[\exp\left(\frac{V + IR_S}{nV_{th}}\right) - 1\right] - \frac{V + IR_S}{R_{SH}}$$

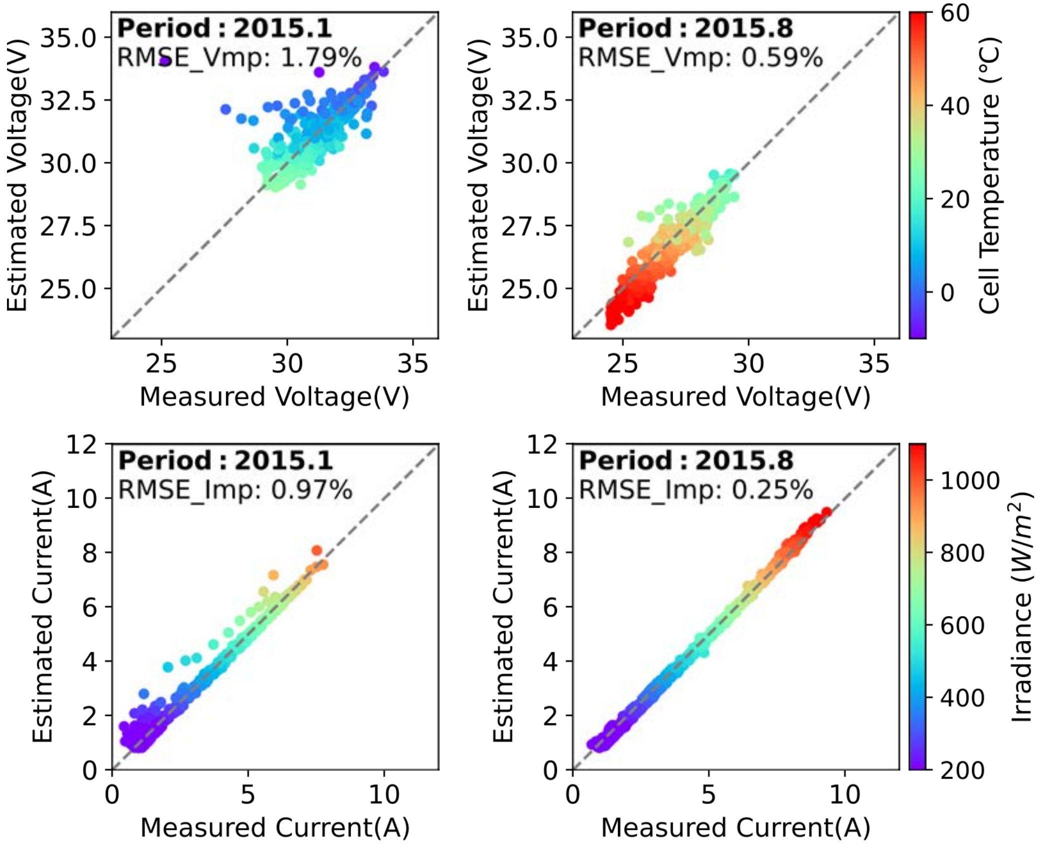
PVPRO uses 5 fit parameters:

- Saturation current at reference conditions (Io)
- Photocurrent at reference conditions (IL)
- Series resistance (Rs)
- Extra shunt resistance (Rsh)
- Diode factor (n)

Method: Parameter estimation

Initial guess of SDM parameters

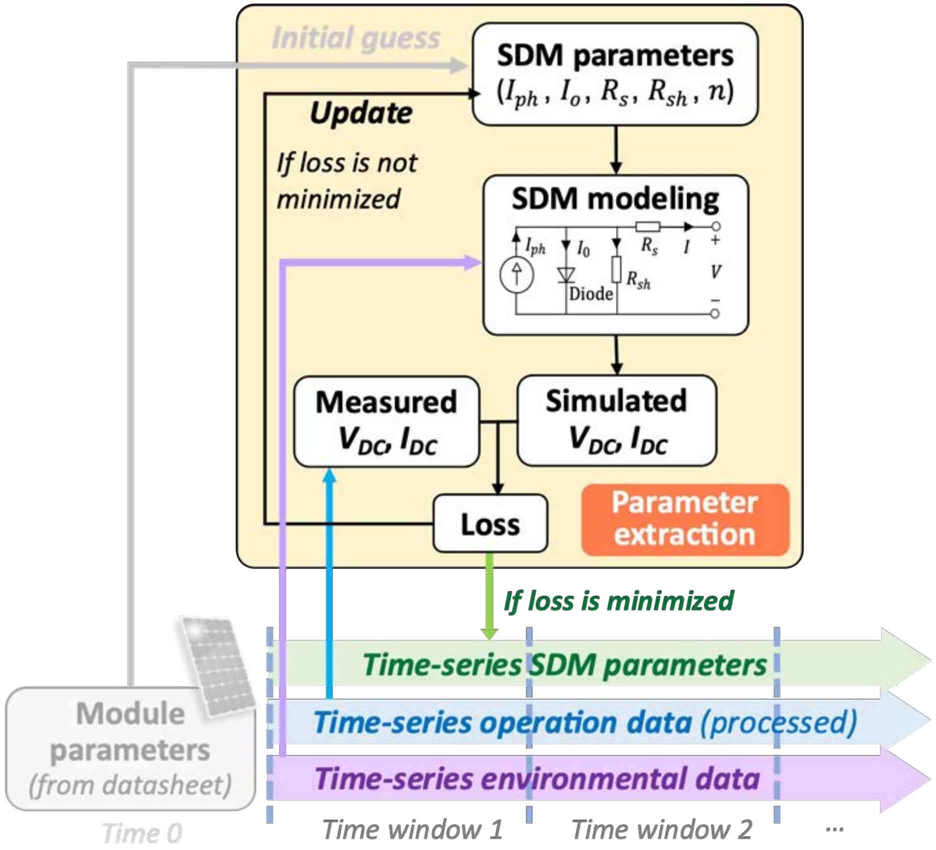
- Using initial parameters, SDM can **predict** module output under **any environmental conditions**.
- RMSE of voltage and current **varies** when using **different periods** of data
- SDM parameters need to be determined **dynamically** based on the data of **each time period**



- *Root mean squared error (RMSE)*

(NIST ground array)

Method: Parameter estimation

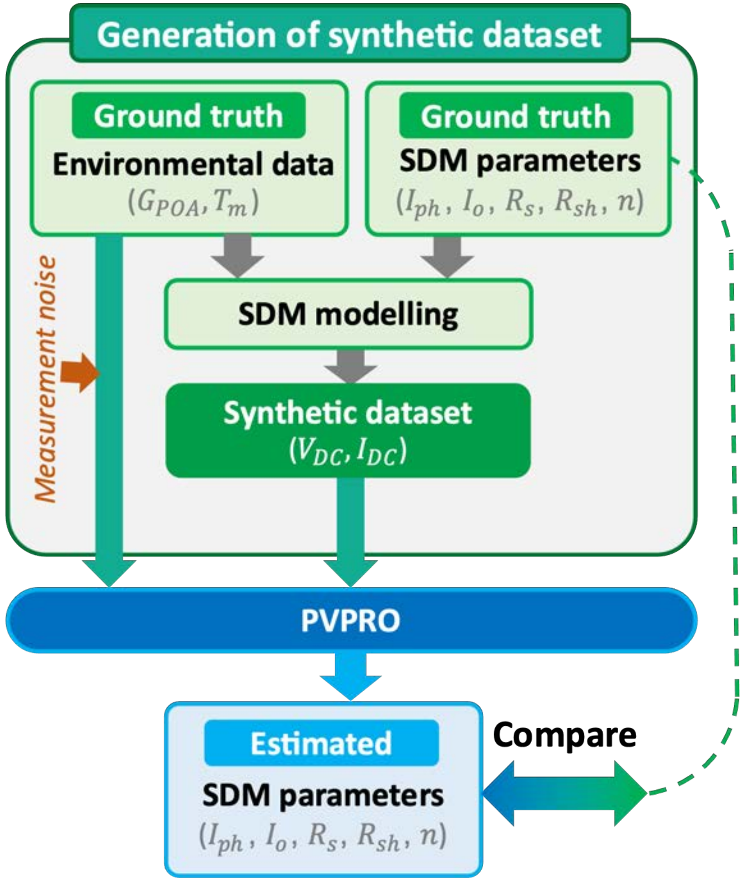


$$L2\_Loss = \left[\left(\frac{V_{DC}^{modeled} - V_{DC}^{measured}}{V_{DC}^{median}}\right)^2 + \left(\frac{I_{DC}^{modeled} - I_{DC}^{measured}}{I_{DC}^{median}}\right)^2\right]/2$$

- L-BFGS-B as the solver
- Lower and upper bounds
- Time window set as 2 weeks (14 days)

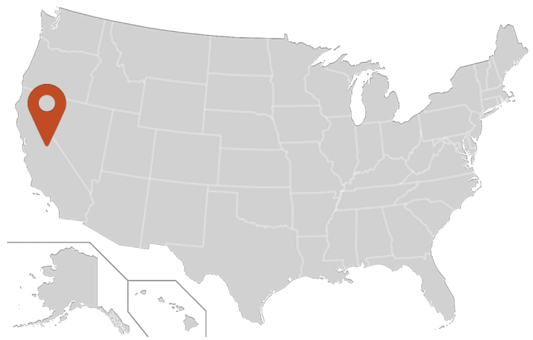
Application: Synthetic PV data

Methodology



Data:

- Simulate an 11kW PV array of 50 sc-Si modules over time
- Weather data (4 years) from NSRDB database [1]



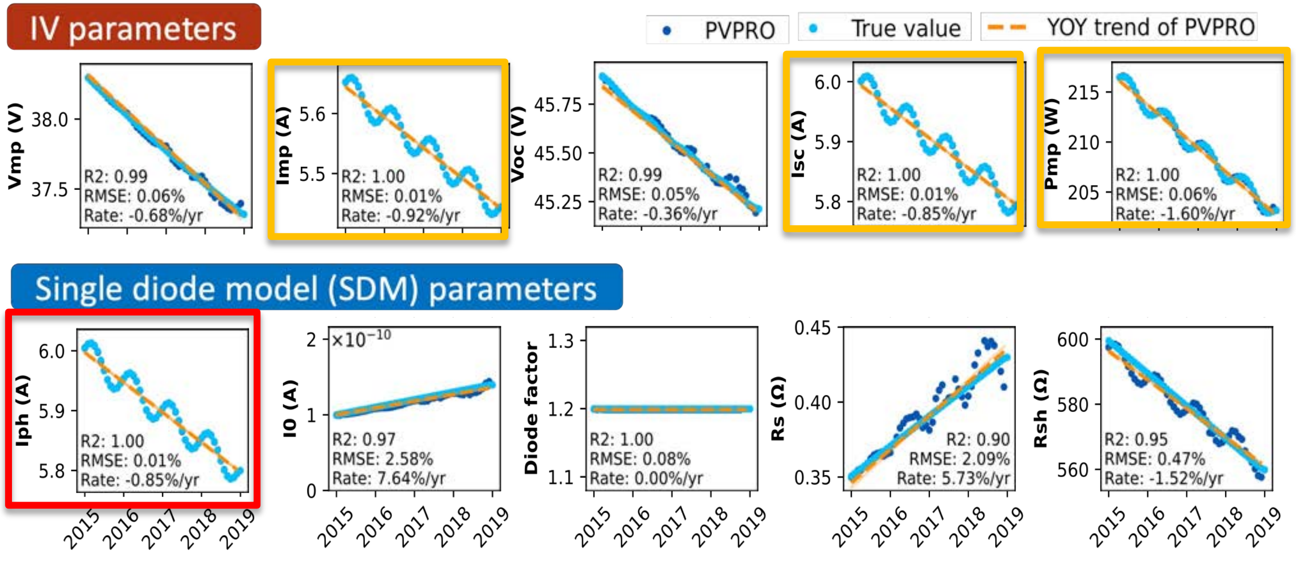
- Artificial degradation over time introduced to SDM parameters (I_{ph}, I_o, R_s, and R_{sh})

[1] https://nsrdb.nrel.gov/

Application: Synthetic PV data

Estimated trends of IV and SDM parameters

(using a synthetic dataset modeling an 11kW PV array)



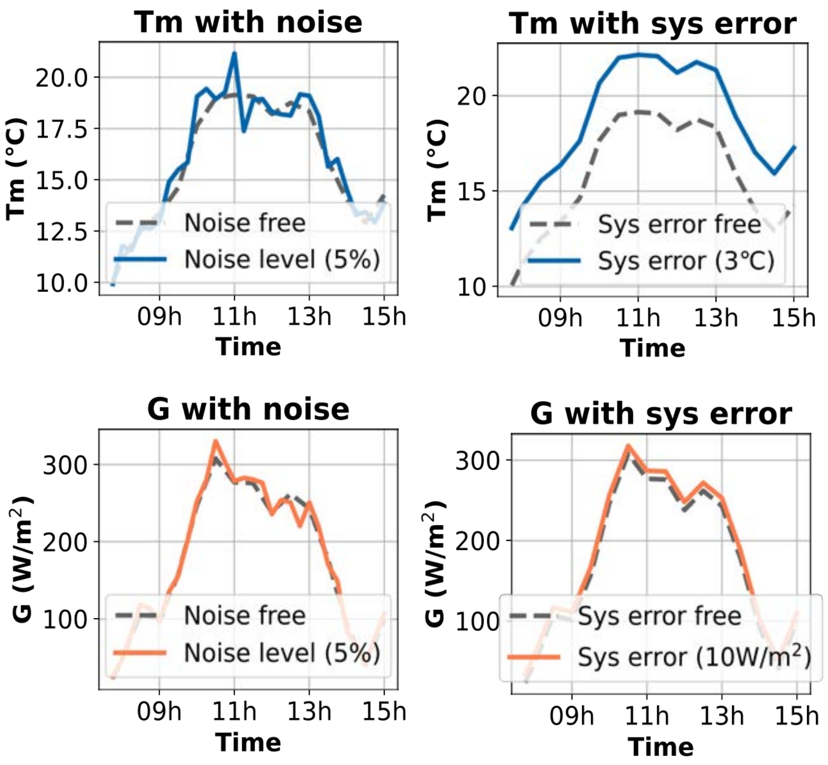
Degradation trend of IV and SDM parameters estimated by PVPRO using synthetic dataset

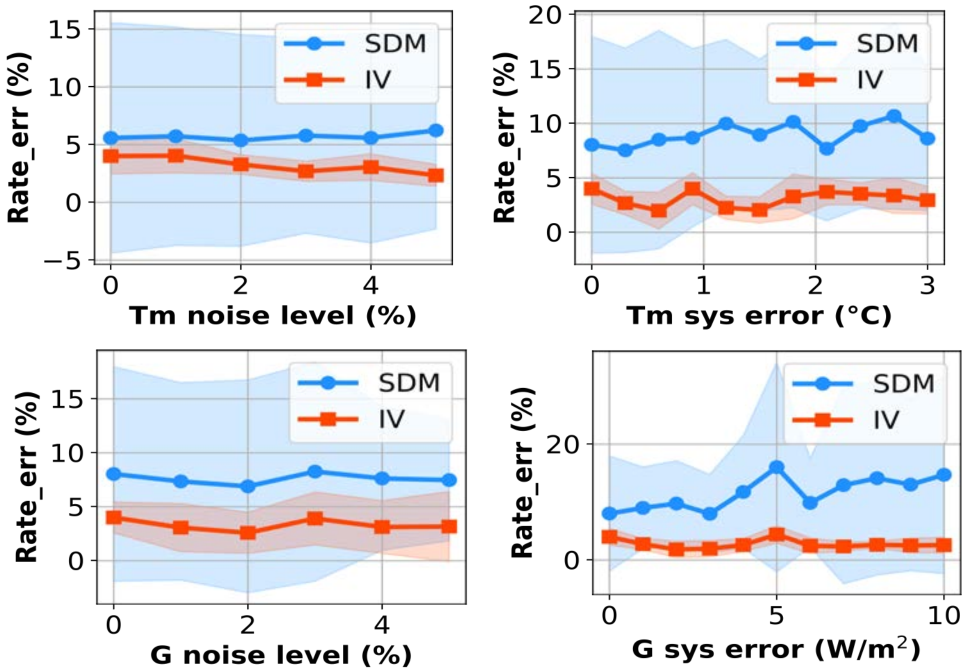
- Periodic wave of I_{ph} impacts the current-related parameters (I_{mp}, I_{sc}, and P_{mp})
- IV parameters are better estimated (r^2 = 1)
- Oscillation presents in R_s and R_{sh}
- Overall, average relative RMSE 0.55% and the r^2 score of 0.98

Application: Synthetic PV data

Impact of measurement noise

- 2 types of noises added on G and Tm





- The **estimated degradation rate** is **robust** to random noise and systematic errors

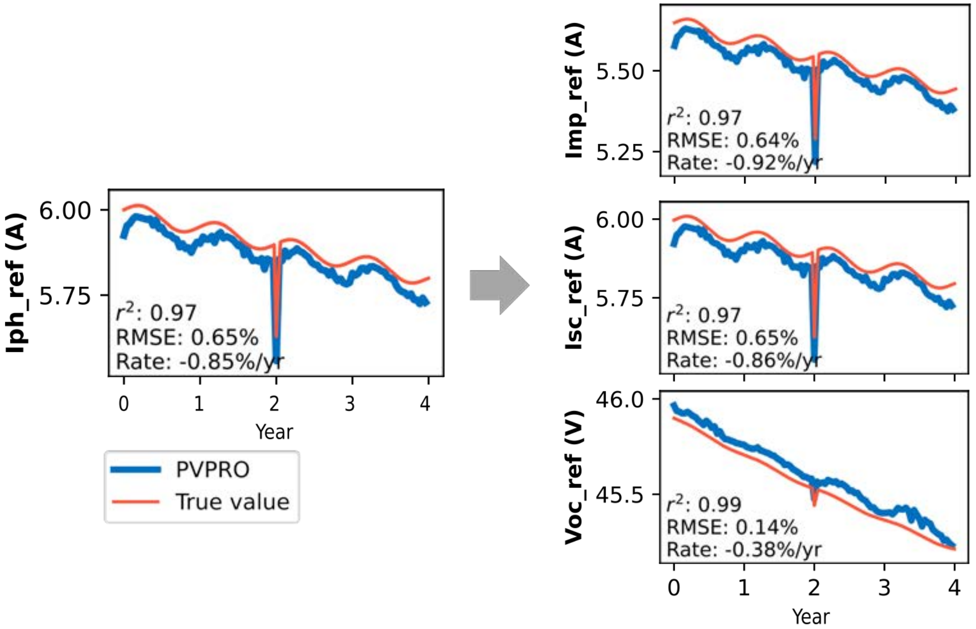
Application: Synthetic PV data

Impact of synthetic faults on SDM parameters

- Add some sudden changes to simulate the occurrence of faults in the PV array

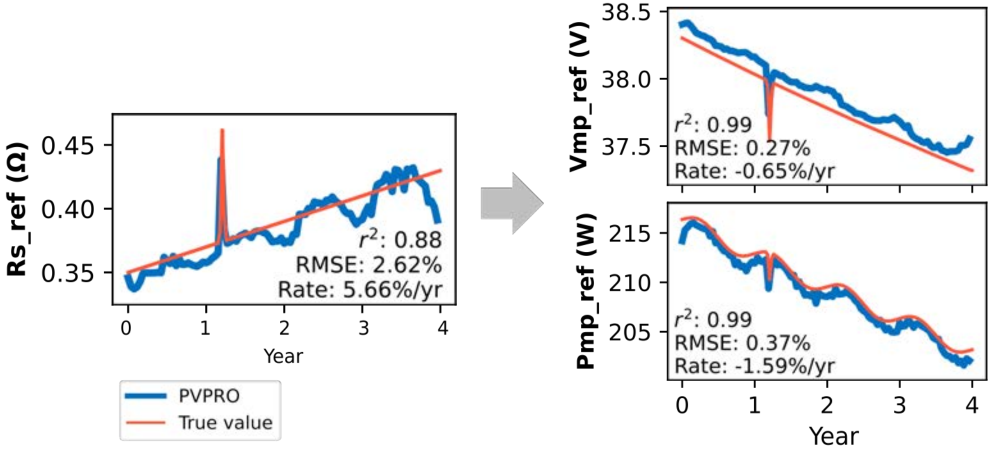
A **decrease** set for I_{ph}

(usually caused by shading or soiling)



An **increase** for R_s

(generally due to the solder band failure)

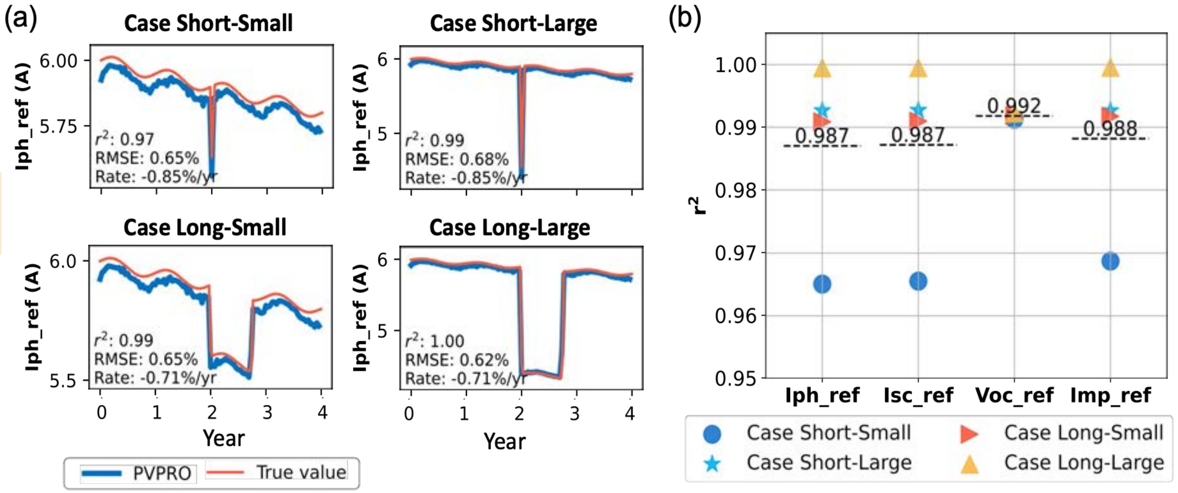


Application: Synthetic PV data

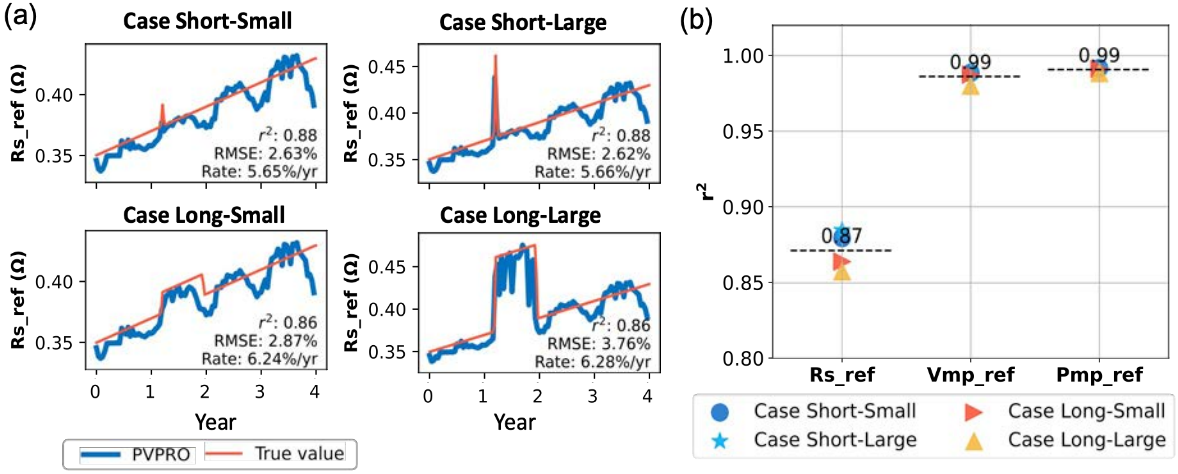
Impact of synthetic faults on SDM parameters

- Study 4 cases of change
  (different duration and magnitude)

I_{ph}



R_s



- PVPRO can closely capture the trend under all the cases
- r^2 of I_{ph} > 0.98, r^2 of R_s > 0.86
  (in the presence of noise)

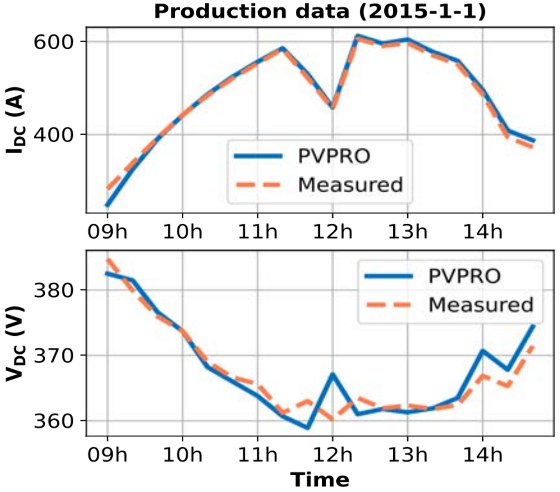
Application: Field PV data

- PVPRO is validated on NIST ground array dataset

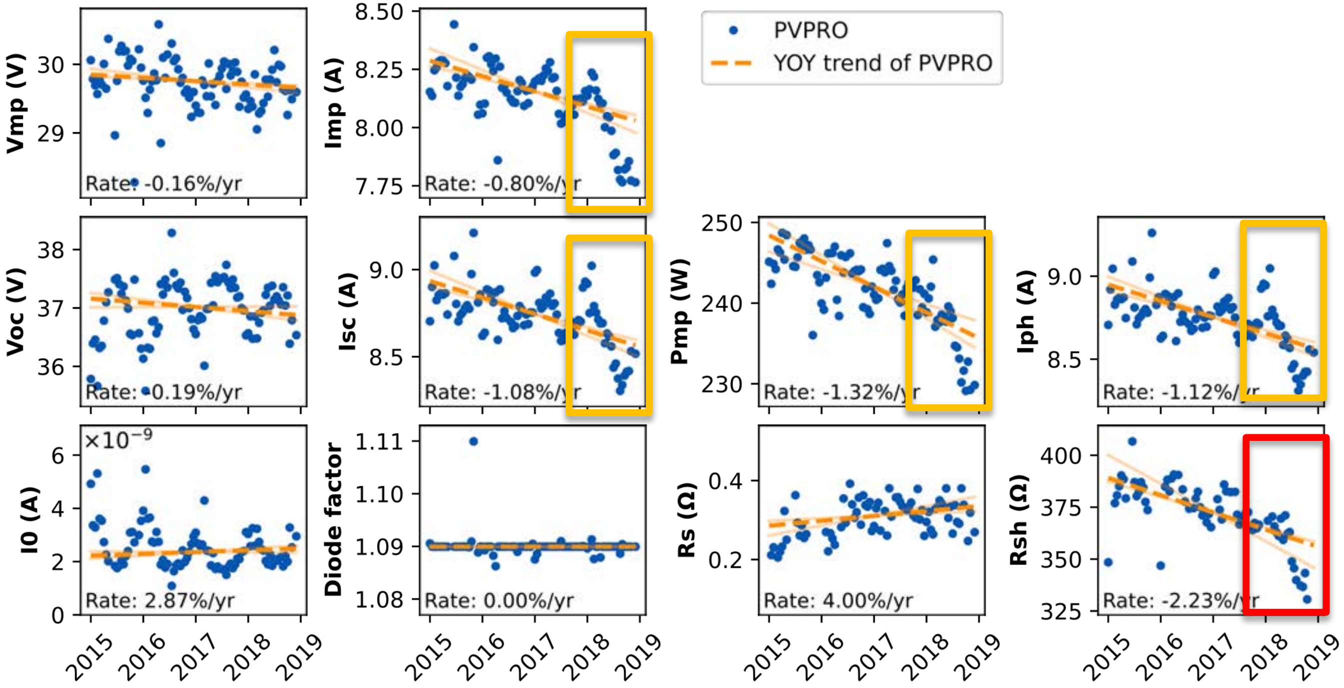
National Institute of Standards and Technology U.S. Department of Commerce

- 1152 modules
- 271 kW

- Relative error between estimated and measured V_{DC} and I_{DC} < 1%



- Degradation trends of IV and SDM parameters are extracted
- Abnormal behaviors of parameters are identified



Past and future outputs

Past publications

[1] Chen, Xin, Todd Karin, and Anubhav Jain. "Automated defect identification in electroluminescence images of solar modules." Solar Energy 242 (2022): 20-29.

[2] Li B., Chen X., Karin T., Jain A. Estimation and Degradation Analysis of Physics based Circuit Parameters for PV Systems Only Using DC Operation and Weather Data [C]. Proceedings of the 49TH IEEE PVSC. Philadelphia, PA, US, 2022. **Best Poster Award**

Future publications

[1] X. Chen, et al., A. Jain "Automatic Crack Segmentation in Electroluminescence Images of Solar Modules and Maximum Inactive Area Prediction", IEEE Journal of Photovoltaics (reviewed manuscript under revision)

[2] Li B., Karin T., Meyers B., Chen X., et al. Determining Circuit Model Parameters from Operation Data for PV System Degradation Analysis: PVPRO (to be submitted)

Q&A and thank you!

PVPRO: B. Li*, T. Karin*, X. Chen,, A. Jain, C. Hansen, M. Deceglie, B. Meyers, L. Schelhas, B. King, D. Jordan, S. Moffitt

PV-Vision: X. Chen*, T. Karin, A. Jain, C. Libby, R. Sundaramoorthy, M. Deceglie, T. Silverman, N. Bosco, M. Owen-Bellini, E. Young, X. He, E. Bernhardt, P. Hacke, M. Bolen, D. Fregosi, W. Hobbs, PVEL company

PV-Vision *on Github*

PVPRO *on Github*

DuraMAT Webinar

November 14, 2022