DuraMAT
Durable Module Materials Consortium

Accelerating a sustainable, just, and equitable transition to zero-carbon electricity generation by 2035.

# Assessment of Accelerated Stress Testing Data for Silicon Photovoltaics using Tensor Decomposition Methods

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Central Data Resource

## Project Overview

The photovoltaic (PV) industry is simultaneously targeting long warranties and new materials/designs for high-energy-yield modules, requiring an advanced methodology to forecast long-term durability of products with un-proven materials combinations. Extended, sequential, and combined stress testing methods are gaining popularity for assessing durability of PV modules/materials beyond the early-stage mortalities. Importantly, multiple degradation mechanisms can proceed simultaneously, and their separate contributions to the overall power loss should ideally be quantified. This work examines the use of data-driven tools towards developing a strategy for faster learning cycles in accelerated stress testing.

**Goal:** Characterize and quantify the evolution of distinct degradation modes in silicon PV modules undergoing accelerated stress testing

**Approach:** Leverage two-dimensional matrix and higher-order tensor decompositions to extract interpretable modes from image stacks across accelerated stress testing stages

## Data Details

Investigated 8 mini-modules with varying encapsulant and packaging structures

- Photoluminescence (PL) images (808nm light, 1 Sun)
- Electroluminescence (EL) images (0.9A and 9A)
- Current-Voltage (IV) metrics

Modified IEC TS 63209-2:2022 sequential stress procedure:

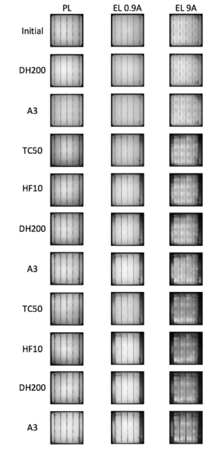
DH200: Damp heat for 200 hours with 85 C and 85%-RH

A3: Full-spectrum light exposure under 65 C chamber temperature, 90 C black panel temperature, 0.8 W/m2-nm intensity at 340nm, and 20 %-RH for 2000 hours

TC50: Thermal cycling from 85 to -40 C with ramp rates defined in IEC 61215, and current injection equivalent to short-circuit current

HF10: Humidity-freeze for 10 cycles between 85 C with 85 %-RH and -40 C with non-controlled humidity

- Data obtained from "Degradation Pathways in Glass/Glass Bifacial PV With Emerging Encapsulants and Half-Cut Cells" DuraMAT project

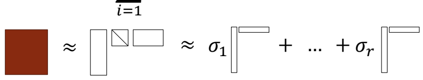



## Data Decomposition Methods

### Singular Value Decomposition (SVD)

- SVD computes an orthogonal, rank-1 decomposition of matrix[1]
- Decomposition modes are ordered and quantified by their contributions to the original matrix
- Foundational technique for principal component analysis (PCA) and proper orthogonal decomposition (POD)

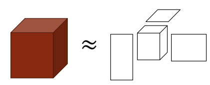
$$\mathbf{X} \approx \mathbf{U}\,\boldsymbol{\Sigma}\,\mathbf{V}^{\top} = \sum_{i=1}^{r} \sigma_i\, \mathbf{u}_i\, \mathbf{v}_i^{\top}, \quad \sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r = 0$$




### Tucker Decomposition

- Tucker decomposition generalizes the SVD to higher-order tensors by replacing singular values with a smaller (but dense) tensor of the same order as original[3,4]
- Difficult to quantify contributions of modes to different dimensions of the data

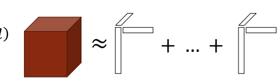
$$\mathcal{X} \approx \mathcal{G} \times_1 \mathbf{U}_1 \times_2 \dots \times_N \mathbf{U}_N$$




### Canonical Polyadic Decomposition

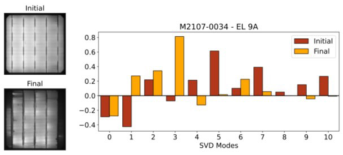
- Reduces the Tucker decomposition by assuming central tensor is super-diagonal[3,5]
  - Decomposes full tensor into sum of rank-1 tensors
- Contributions of modes to different dimensions of the data are easily extracted from mode vector norm

$$\mathcal{X} \approx \sum_{i=1}^{r} \mathbf{a}_i^{(1)} \circ \cdots \circ \mathbf{a}_i^{(d)}$$

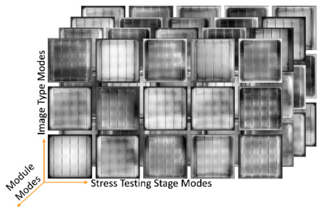



## Interpreting Modal Decompositions

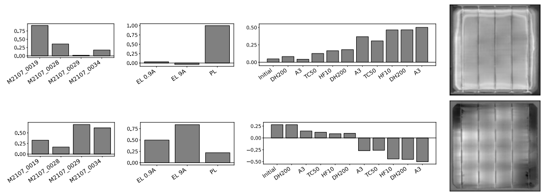
### SVD




### Tucker Decomposition



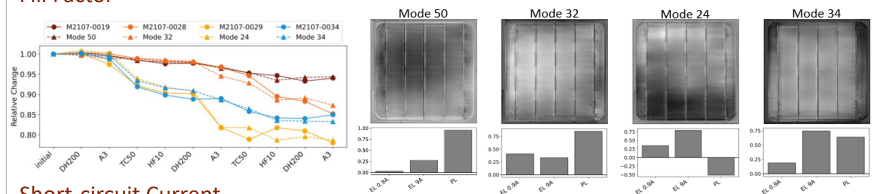

### CP Decomposition



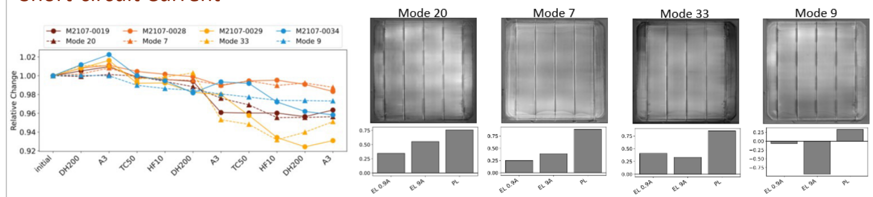

- SVD can only consider a single parameter at time and modes do not exhibit physical relationships with data
- Tucker captures evolutions along different parameters but are not easily interpretable
- CP modes can be explicitly quantified in terms of their contributions to each parameter

## Correlating Modes with Performance Metrics

### Fill Factor




### Short-circuit Current




- Fill factor degradation exhibit stronger correlations with identified linear modes than short-circuit current
  - Correlated modes highlight delamination found PL images for glass/transparent-backsheet modules and cracking found in the high-current EL images for glass/glass modules
- Modes for short-circuit current vary more in highlighted degradations, including crowding features and delamination modes

## Outcome & Impact

- Tensor approaches identify and isolate meaningful degradation modes from stress testing datasets
  - Compared tensor decompositions to matrix-based SVD, which produces efficient modes for data reconstruction but provide limited interpretability
  - Tensor-based approach enables the consideration of multiple imaging types, stressing procedures, module characteristics, etc.
- Generalizable methods can be used to characterize degradation across many materials and devices
- Correlate contributions of CP modes to IV metrics across stress testing stages
  - Delamination and cracking modes correlate most strongly with evolution of fill factor during testing and highlight appearance in PL and high-current EL imagining
  - Short-circuit current showed weaker correlation with linear modes and may require more complex methods to identify key drivers of performance degradation

## References

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## Acknowledgements

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE) under the Solar Energy Technologies Office Award Number 38259. This research was performed using computational resources sponsored by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy and located at the National Renewable Energy Laboratory. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.