Module Level Exposure and Evaluation Test (MLEET) for Real-World & Laboratory-Based PV Modules: Common Data and Analytics for Quantitative Cross-Correlation and Validation

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MLEET Tasks

Task 1: Identify candidate PV modules for outdoor and indoor analytics and testing

Prior to data ingestion, identify and catalog the candidates for study for BP1. These candidates include three potential sources: outdoor PV power plants and modules, modules for accelerated lab testing, and fabrication of new modules for study.

Task 2: Outdoor Lifetime Performance Prediction: Temporal analytics of outdoor I-V, P_{mp} datastreams leading to validated exposure conditions

Acquire and ingest all retrospective I-V, P_{mp} datastreams from partner sites spanning at least fifty power plants over at least three climate zones plus I-V curves from at least four climate zones. Reserve a sub-set of data to be excluded from model training for later model validation and lifetime performance prediction.

Task 3: Indoor Lifetime Performance Prediction: Degradation pathway models to define indoor tests

In BP1, we will focus on constant stressors applied at constant stress levels, such as uniform and non-uniform irradiance, high heat, and high heat + humidity.

Task 4: Validation and cross-correlation: Indoor and outdoor cross-correlation, and lifetime performance prediction

Comparison of I-V features acquired in outdoor and indoor exposures.

Task 1: World-wide Data Acquisition

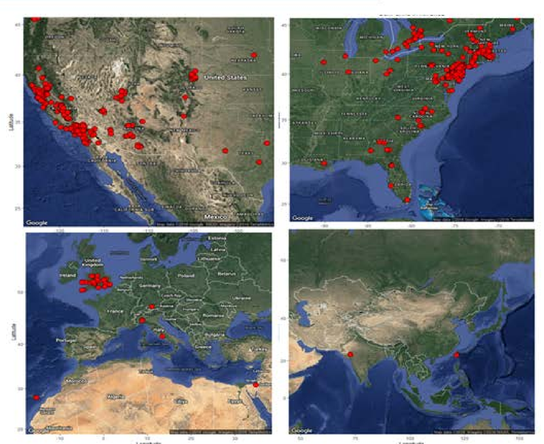
Collection and storage of data related to PV degradation, including:
- **Power time series**
- **I-V time series**
- **Point in time data**
- **EL images**
- **Accelerated testing**
- **Weather data**

From diverse outdoor and indoor sources

Task 1: Global SunFarm Network

SDLE PV Data Covers ~3.4 GW Encompasses 1.92% of Global PV Power
- 787 PV Project Sites
- 5638 PV Systems (Inv. & Modules)
- 60 PV Module Brands/Models
- 38 PV Inverter Brands/Models
- Across 13 Köppen-Geiger Climatic Zones
- Single Modules to 265 MW plants
- Going Back Up To 15 years

Epidemiological PV Population Of Time-series data streams
- Real-world power production
- Real World Exposure Conditions
- Operating Over Real Time-scales



Task 1: Fraunhofer Data Set

I-V curve measurement every 5 minutes
P_{mp} measurements in between

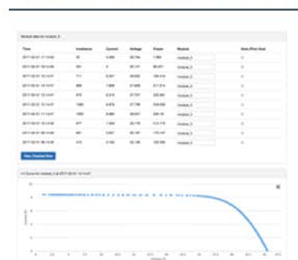
Gran Canaria (GC)
- 2010-2015
- Arid-Steppe-Cold (BSK)
- 0.75 million I-V curves

Mount Zugspitze (UFS)
- 2010-2015
- Polar-Tundra (ET)
- 0.85 million I-V curves

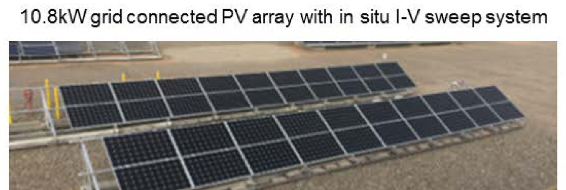
Negev Desert (NEG)
- 2012-2015
- Arid-Desert-Hot(BWh)
- 0.55 million I-V curves

Two module samples on each site
Two different brands on the same site
The same brands across three sites

Task 1: Sandia PV Array Testbed

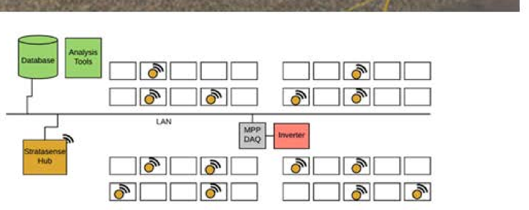


10.8kW grid connected PV array with in situ I-V sweep system



Automatic data collection provides visual interface

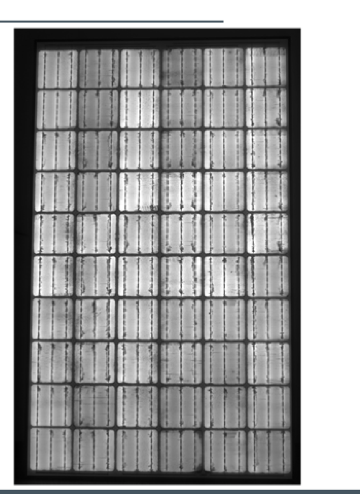
Stratasense perform automatic module level I-V sweeps



Task 1: SunEdison

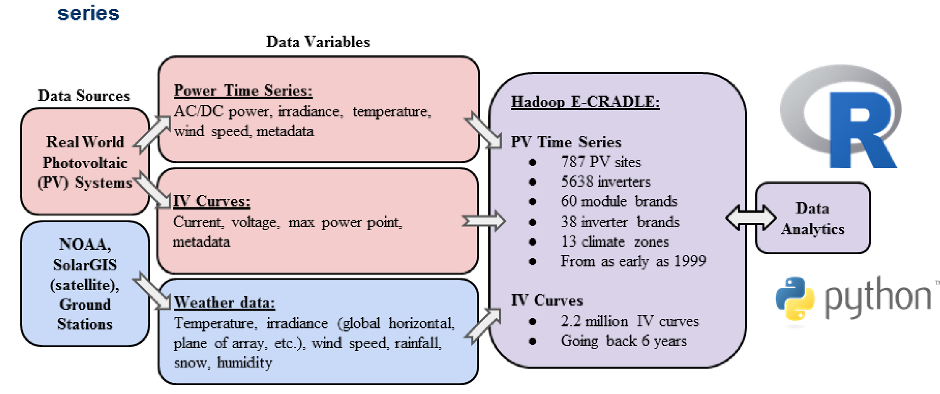
5 Brands
3 Wafer Materials
- **Mono-Si Al-BSF**
- **Multi-Si Al-BSF**
- **Mono-Si PERC**

5 Exposure Types
- **Damp-heat**
  - 3000 hours, 500 hour steps
  - Extended exposure to 4200 hours, 300 hour steps (4 samples)
- **Thermal cycling**
  - 600 cycles, 200 cycle steps
  - Extended exposure to 1000 cycles, 100 cycle steps (4 samples)
- **PID +1000V**
- **PID -1000V**
- **Ultra-violet**
  - 90 kWhs, 30 kWhs step



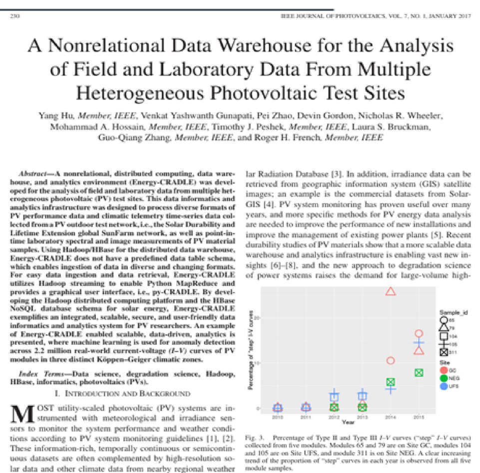
Task 2: Outdoor PV Degradation

Utilize High Performance Computing to run data analytics on massive data scopes and scales to find degradation and operation features in power and I-V time series



Task 2: Result from I-V-Stats model

- Analyzed 2.2m I-V curves
- No step I-V curves detected initially
- Proportion of type I and type II curves increases over time
- Most significantly in Gran Canarias (GC) location

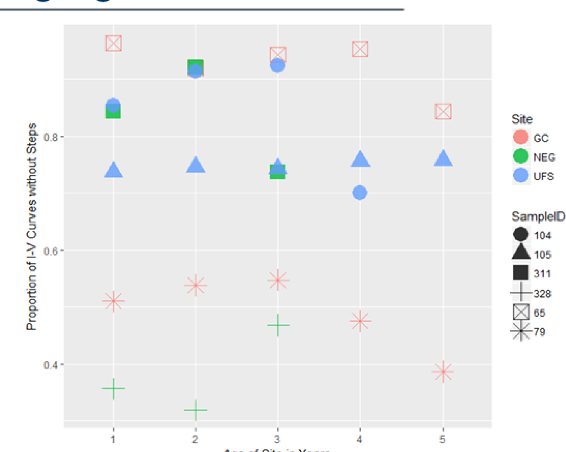


A Nonrelational Data Warehouse for the Analysis of Field and Laboratory Data From Multiple Heterogeneous Photovoltaic Test Sites

Yang Hu, Member, IEEE, Venkat Yashwanth Gunapati, Pei Zhao, Devin Gordon, Nicholas R. Wheeler, Mohammad A. Hossain, Member, IEEE, Timothy J. Peshek, Member, IEEE, Laura S. Bruckman, Guo-Qiang Zhang, Member, IEEE, and Roger H. French, Member, IEEE

Task 2: Result from I-V-SegReg Model

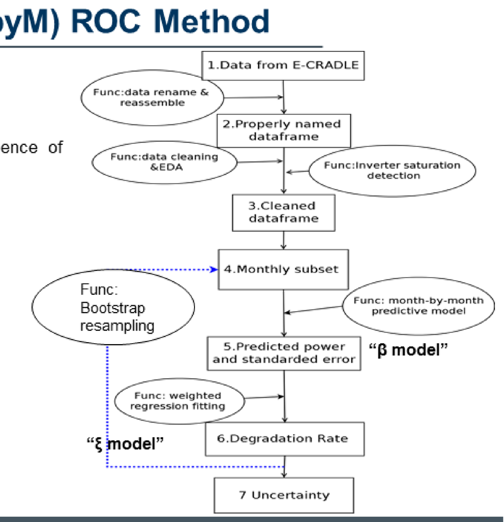
- Data
  - Negev Desert site: 3 yrs
  - UFS: one sample has no data available after 4 years
- Gran Canarias site:
  - decrease in the proportion
  - hot climate
- Negev Desert site:
  - inconclusive
  - only 3 year of data
- UFS site
  - no conclusive signs of change
- Some sample (* . +)
  - high proportion of step I-V curves



Task 2: Month-by-Month (MbyM) ROC Method

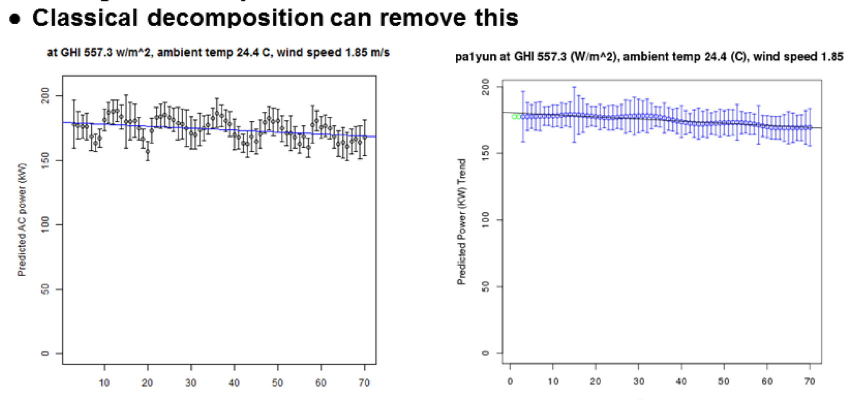
Underlying assumption:
- System performance change is a long-term phenomena
- There is no obvious degradation within 30 days,
- Train a regression model without considering the consequence of observations.

Data analytic procedure:
- Use all data, not filtering
  Noon time, morning and afternoon
- Categorize data by age
  Every 30 days from the first operation date considered a month
- Develop predictive model for each pseudo-month
  (β model) Linear regression model
  These models serve as a snapshot of the system status
- Normalize system performance to same climate condition
  Use monthly regression models
- Do not assume linear degradation rate
  Look at the profile of the monthly predicted value
  (ξ model) piecewise linear model
- Use bootstrap approach to estimate the uncertainty



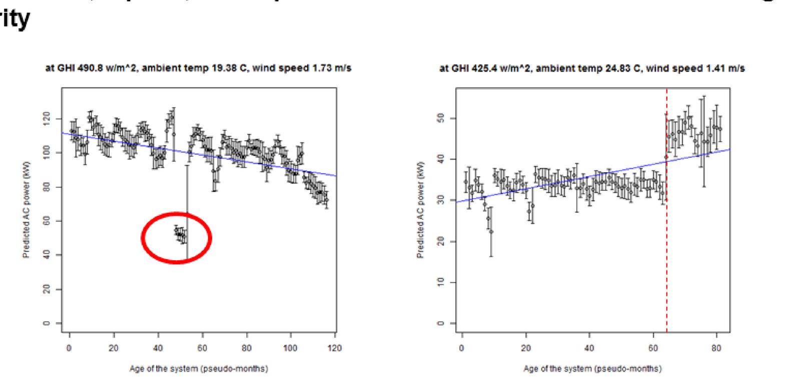
Task 2: Seasonal Decomposition

- **Strong seasonality can be seen in the trends**
- **Classical decomposition can remove this**



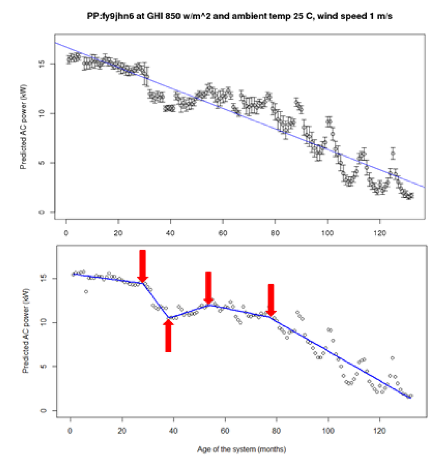
Task 2: Operation Features

In longer time series of commercially fielded systems, features of operation such failures, repairs, and replacements can be seen that create strong non-linearity



Task 2: Non-Linearity

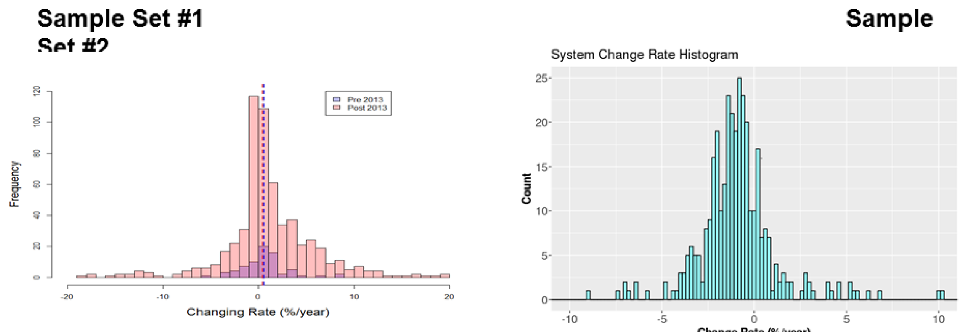
- **Analysis shows that nonlinear trends are quite common**
- **Traditional PV analysis methods would cut most of these features out**
- **Features like this are important in understanding the operation of real systems**



Task 2: ROC Distributions

Rate of change (ROC) distributions from two sample sets of data, SS#1 of 655 systems, and SS#2 of 353 systems.

Sample Set #1 **Sample Set #2**



Task 3: Indoor Degradation

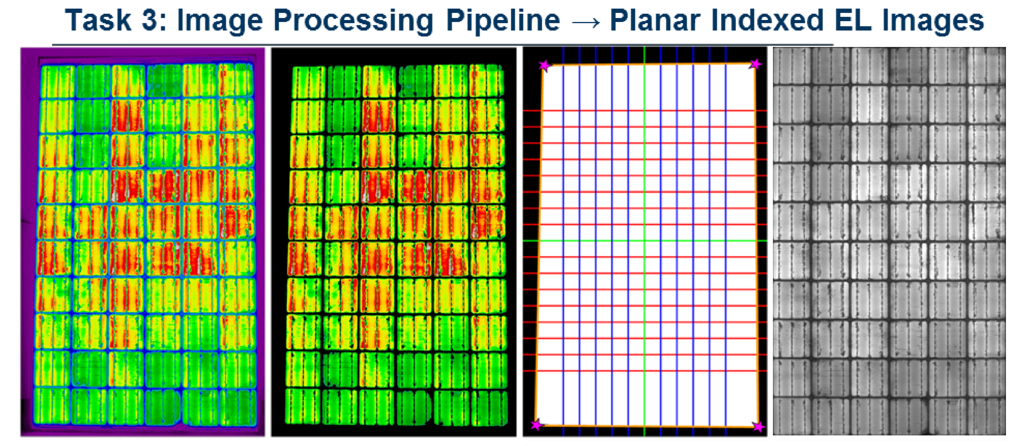
Quantification of EL measurements with comparisons to I-V and power features

Automated image analysis and classification

I-V curve feature extraction, including step I-V proportion

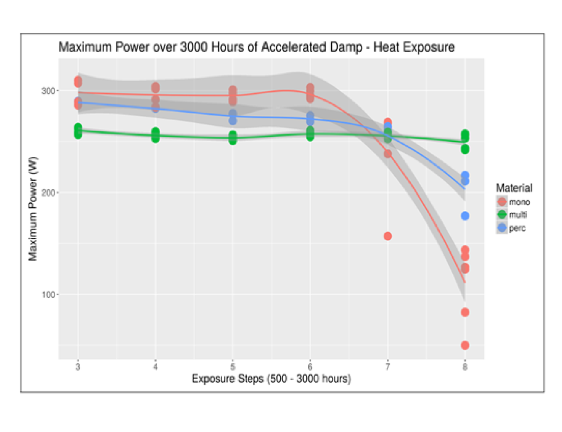
Accelerated testing under diverse conditions with comparisons to outdoor data

Task 3: Image Processing Pipeline → Planar Indexed EL Images



Median Filter (Spectral Color Mapping)	Background Threshold (Spectral Color Mapping)	Convex Hull/ Corner Finding	Planar Indexed EL Image (Perspective Transformed)

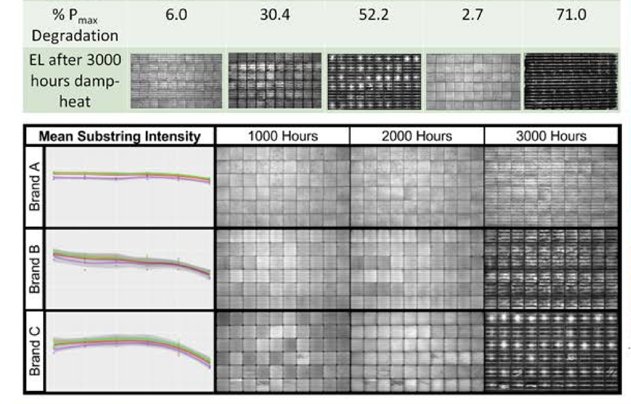
Task 3: Max. Power Degr. from damp heat exposure & thermal cycles



- damp-heat
  - undergone 3000 hours
  - future extension to 4200 hours (four 300 hours)
- thermal-cycled
  - undergone 600 cycles
  - future extension to 1000 cycles (four 100 cycles)
- The extension of exposures will allow for much greater insight into the end-of-life (EOL) performance of these materials

Task 3: Data Integration - SunEdison EDA

Sample	A	B	C	D	E
Material	Multi	PERC	Mono	Multi	Mono
% P_{max} Degradation	6.0	30.4	52.2	2.7	71.0
EL after 3000 hours damp-heat					



Rsh	0.36	0.35	0.32	0.46	0.56	0.53	0.39	0.13	-0.42	-0.29
0.36	FF	0.47	0.42	0.64	0.59	0.61	0.18	-0.14	-0.64	-0.56
0.35	0.47	ELmed	0.99	0.85	0.76	0.79	0.17	-0.3	-0.88	-0.66
0.32	0.42	0.99	ELmn	0.79	0.7	0.73	0.15	-0.28	-0.81	-0.62
0.46	0.64	0.85	0.79	Vmp	0.94	0.97	0.49	-0.03	-0.93	-0.65
0.56	0.59	0.76	0.7	0.94	Imp	1	0.68	0.16	-0.84	-0.51
0.53	0.61	0.79	0.73	0.97	1	Pmp	0.65	0.14	-0.86	-0.54
0.39	0.18	0.17	0.15	0.49	0.68	0.65	Isc	0.76	-0.23	0.15
0.13	-0.14	-0.3	-0.28	-0.03	0.16	0.14	0.76	Voc	0.35	0.56
-0.42	-0.64	-0.88	-0.81	-0.93	-0.84	-0.86	-0.23	0.35	Rs	0.75
-0.29	-0.56	-0.66	-0.62	-0.65	-0.51	-0.54	0.15	0.56	0.75	ELsd

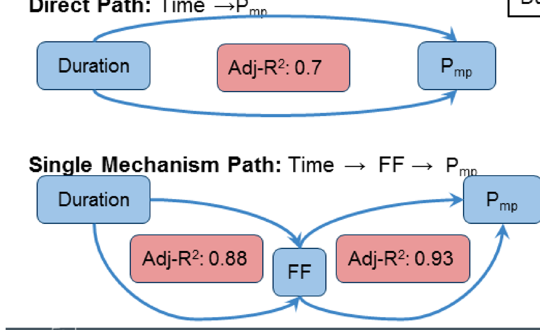
-1 -0.8 -0.6 -0.4 -0.2 0 0.2 0.4 0.6 0.8 1

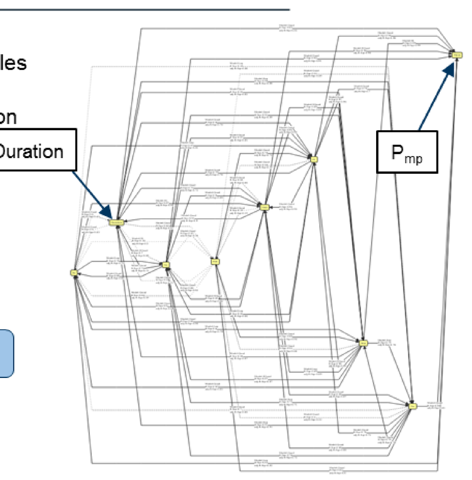
Task 3: netSEM

Semi-supervised Structural Equation Modelling
- A network model of multiple continuous variables
- Using six common functional form fits
- Adjusted R^2 for univariate relationship selection

Direct Path: Time $\rightarrow P_{mp}$

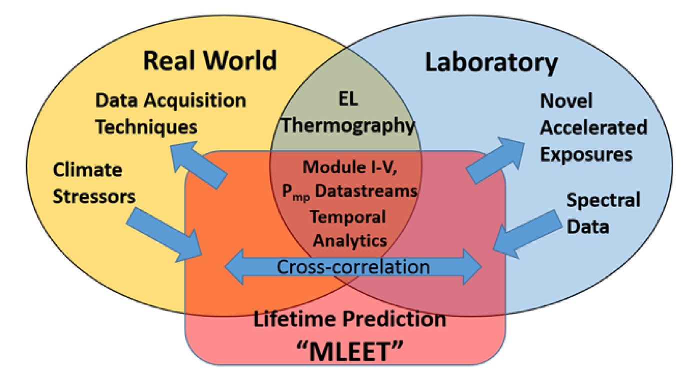
Single Mechanism Path: Time → FF → P_{mp}





Task 4: Cross-correlation and Validation

Validation of indoor and outdoor models and Cross-correlation between indoor and outdoor models



Task 4: Power ROC Model Comparison, MbM vs. Responsivity

Location	Method	Time Step 1 Measurement (Watts)	% Diff.	Time Step 2 Measurement (Watts)	% Diff.
GC	Measured Standard Power	179.75 (36 months)	0.0%	172.0 (57 months)	0.0%
GC	MbM	180.24 (36 months)	0.27%	175.53 (57 months)	2.0%
GC	NREL	182.54 (36 months)	1.6%	179.32 (57 months)	4.3%
UFS	Measured Standard Power	222.3 (30 months)	0.0%	253.2 (44 months)	0.0%
UFS	MbM	242.3 (30 months)	9.0%	253.9 (44 months)	0.28%
UFS	NREL	248.0 (30 months)	11.5%	248.5 (44 months)	-1.9%

Comparison of model results at set times (~3 yr. And ~ 5 yr.)
- MbM shows increased accuracy at all times selected.

- Hu.Yang et al. 'Modeling the Long-term Temporal Change of Power Production for Real-world Photovoltaic Systems" IET Renewable Power Generation, submitted
- D. C. Jordan and S. R. Kurtz. Data filtering impact on PV degradation rates and uncertainty (poster). In PV Module Reliability Workshop, 28 February - 2 March 2012, Golden, Colorado, 2012. URL http://nrelpubs.nrel.gov.
- Iec 60891 ed2.0 – photovoltaic devices – procedures for temperature and irradiance corrections to measured i-v characteristics | iec webstore | publication abstract, preview, scope. URL http://webstore.iec.ch/webstore/webstore.nsf/Artnum_PK/43615.

Task 4: Comparison of Models

Results of Model Comparison:
- Segmented MbM gives more confident models than assumed linear responsivity.
- Segmented fit handles models irregular data much better than the assumed linear fit.
- Stable data still shows a strong linear trend, segmented fits not needed in all cases.
- *MbM prediction is closer (>5%) to measured standard power readings at all points.*
- *All uncertainty measurements for each MbM model exclude 0 as a possible change rate.*
- Classical Time-series Decomposition added

	GC	UFS
Time Step 1	83%	22%
Time Step 2	53%	85%

Table showing the percent improvement in the MbM method estimation of the measured standard power vs. the Responsivity method.

Green values are a closer prediction than the Responsivity, red values indicate a worse prediction.

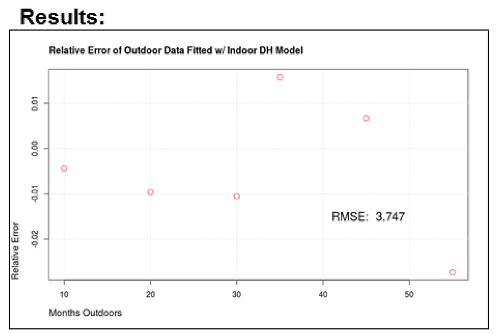
Task 4: Cross Correlation of Indoor and Outdoor Modules

The Data Used:

	Outdoor	Indoor
Exposure Conditions	CSa/BSk	Damp heat
Cell Type	Multi	Multi
Name Plate Power (W)	280	266
Irradiance (W/m^2)	~980-1020	~1000

Model Used:
- $P_{mp} = 254 + 320536 * D - 14648460512 * D^2$
  - netSEM best fit of "A"

Results:



RMSE = 3.747
Rel. $Error_{max}$ = 2.7%
* Assumed 3000 hrs indoor ~ 5 years outdoors for scaling time

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