Predictive Network Modeling for Design of PV Module Materials with Increased Durability, Performance, and Lifetime

Laura S. Bruckman, Timothy J. Peshek, Roger H. French
Material Science and Engineering, SDLE Center, Case Western Reserve University, Cleveland OH, USA

Introduction

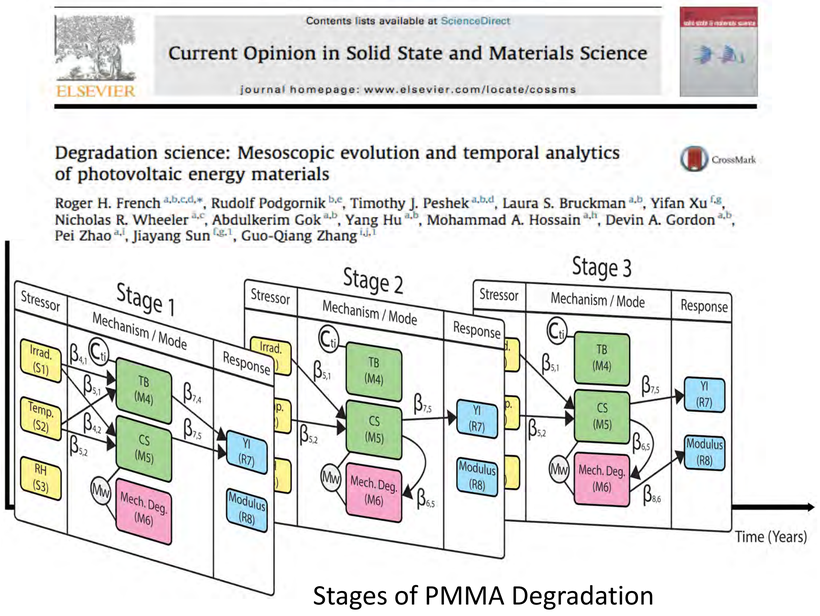
Accurately model the lifetime and performance PV modules
- essential for predicting the levelized cost of energy.

Generalized network models
- provide quantitative predictions
- framework for integration of multiple experiments, data types, and study designs.

Network model development
- big data analytics approach
- combining data from PV modules exposed to real-world and accelerated, lab-based weathering
- diverse set of studies with differing study designs and data types

Graph-theory informed network modeling
- for larger complex systems such thousands of PV plants spread
- across diverse climatic zones,
- to enable more precise understanding of the stressors
- PV plants actually spend their lifetime under.

Network Modeling & semi-gSEM Model

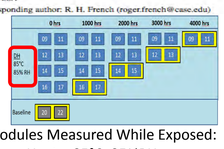


Stages of PMMA Degradation
1) Tinuvin Bleaching,
2) Chain Scission,
3) Mechanical Degradation
With Change-point Transitions

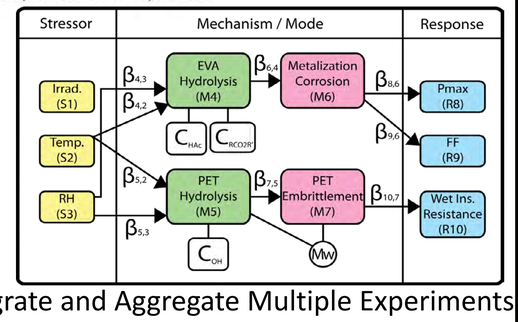
PV Module Network Model

Statistical and Domain Analytics Applied to PV Module Lifetime and Degradation Science

LAURA S. BRUCKMAN[1], NICHOLAS R. WHEELER[2], JUNHENG MA[3], ETHAN WANG[4], CARL K. WANG[4], IVAN CHOU[5], JIAYANG SUN[3], AND ROGER H. FRENCH[6] (Member, IEEE)
Corresponding author: R. H. French (roger.french@case.edu)



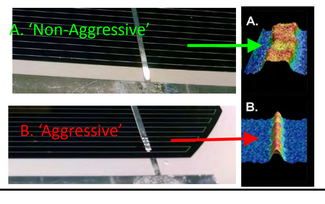
16 Modules Measured While Exposed:
Damp Heat – 85°C, 85%RH
UV – 60°C, ~80W/m2
Every 1000 Hours, 2 Modules:
Destructively Disassembled & Evaluated
Final Dataset:
15 Variables Total
2 Different Stress Conditions

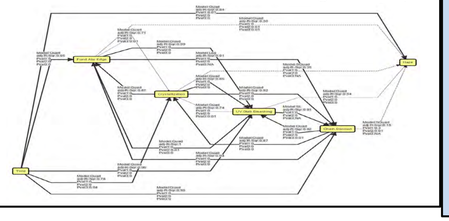


Network Models Can Integrate and Aggregate Multiple Experiments

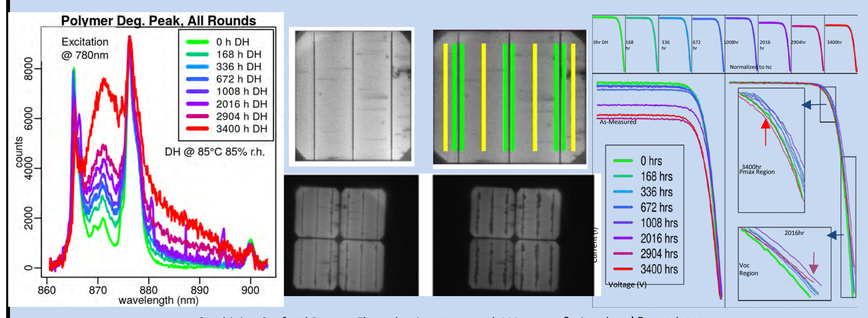
Metallization Corrosion
Corrosion of screen printed Ag gridlines
I-V, EL, Raman Confocal Microscopy

PET Degradation
Hazing of UV Stabilized PET in ASTM G154
UV, heat and dark condensing humidity





Metallization Corrosion



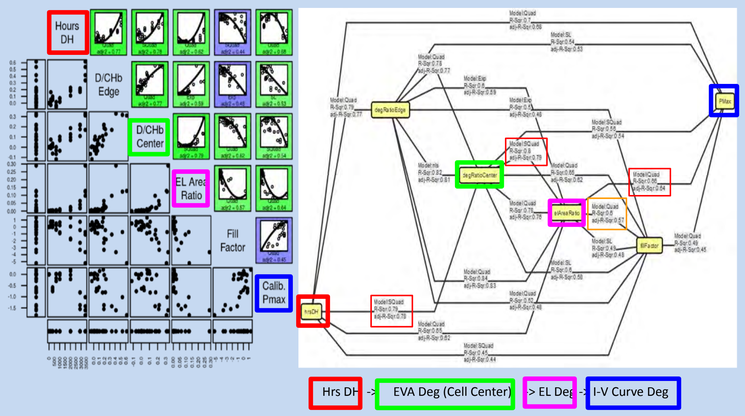
Combining Confocal Raman, Electroluminescence and I-V => System Level Power Loss

Mechanism & Pathway Equation Coefficients For

$$PMax \sim intC + CC*(intB + CB*(intA + IA*(hrsDH^2)) + IB*((intA + IA*(hrsDH^2))^2)) + IC*((intB + CB*(intA + IA*(hrsDH^2)) + IB*((intA + IA*(hrsDH^2))^2))^2)$$

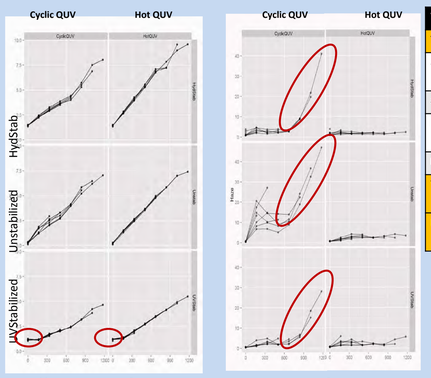
Agg $PMax \sim 0.46 - 3.10e{-}06*hrsDH^2 + 1.13e{-}05*hrsDH^4 - 6.20e{-}12*hrsDH^6 - 1.03e{-}05*hrsDH^8$

NAgg $PMax \sim -0.28 - 1.51e{-}06*hrsDH^2 + 7.41e{-}06*hrsDH^4 - 1.59e{-}12*hrsDH^6 - 9.12e{-}06*hrsDH^8$



1. $degRatioCenter \sim intA + IA*(hrsDH^2)$
2. $elAreaRatio \sim intB + CB*degRatioCenter + IB*(degRatioCenter^2)$
3. $PMax \sim intC + CC*elAreaRatio + IC*(elAreaRatio^2)$ → $PMax \sim intC + CC*(intB + CB*(intA + IA*(hrsDH^2)) + IB*((intA + IA*(hrsDH^2))^2)) + IC*((intB + CB*(intA + IA*(hrsDH^2)) + IB*((intA + IA*(hrsDH^2))^2))^2)$

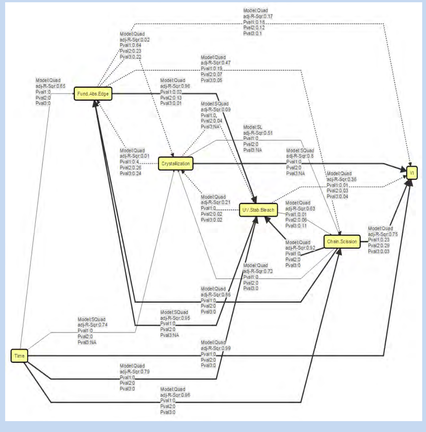
PET Degradation



Yellowing of 3 PET Grades

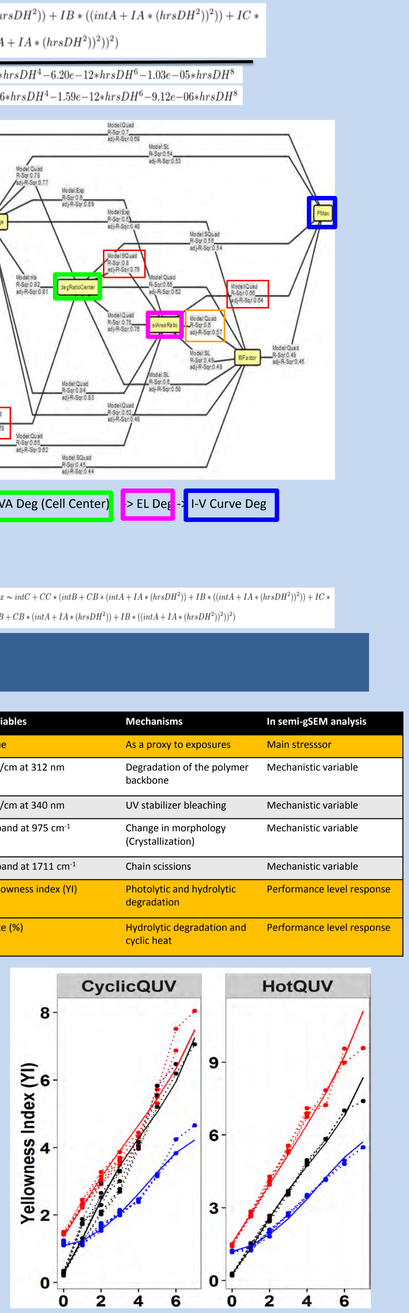
Haze of 3 PET Grades

Variables	Mechanisms	In semi-gSEM analysis
Time	As a proxy to exposures	Main stresssor
abs/cm at 312 nm	Degradation of the polymer backbone	Mechanistic variable
abs/cm at 340 nm	UV stabilizer bleaching	Mechanistic variable
IR band at 975 cm^{-1}	Change in morphology (Crystallization)	Mechanistic variable
IR band at 1711 cm^{-1}	Chain scissions	Mechanistic variable
Yellowness index (YI)	Photolytic and hydrolytic degradation	Performance level response
Haze (%)	Hydrolytic degradation and cyclic heat	Performance level response



Yellowing of UV Stabilized PET in Hot QUV

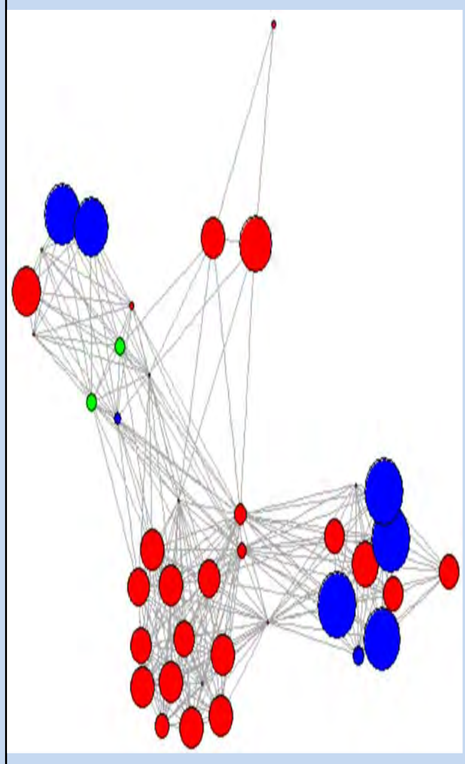
Chain Scission and Crystallization
Produce Yellowing
Confirmatory Evidence From IV and DSC measurements



Mixed Effect & Fixed Effect Modeling
Predictive Modeling

Graph Modeling of PV Module Power Data

Graphs are structures to model pairwise relationships btwn objects.
Nodes/Vertices are connected by Edges
In a Graph Network Model of PV Power Plants,
each inverter is represented as a Node
the correlations between them are the Edges.



Pearson's Correlation Coefficient:
The degree of the relationship between linear related variables
Assumes that both variables are normally distributed
For 2 lists, X and Y:
- Where n is the # of observations

$$r = \frac{\sum XY - \frac{\sum X \sum Y}{N}}{\sqrt{\left(\sum X^2 - \frac{(\sum X)^2}{N}\right)}\sqrt{\left(\sum Y^2 - \frac{(\sum Y)^2}{N}\right)}}$$

Minute by Minute Data
loaded in from HBase
→ is Averaged daily
To create a Data Frame
with 365 values per inverter
42 powerplants
AC_power data taken from 2013
Edge deletion threshold:
correlation of .4
Nodes sized based on number of modules
Nodes colored based on location:
Red: Northeast United States
Blue: Southern California
Green: Southeast United States
Fruchterman-Reingold layout algorithm

Conclusions

Network Modeling allows for large data sets
- To model degradation and performance
- To predict lifetime for current PV modules & materials
- To predict lifetime of new technologies

Network Modeling shown for
- PV modules
- PET
- Metallization Corrosion
- PV Module Power Data

References

L. S. Bruckman et al., "Statistical and Domain Analytics Applied to PV Module Lifetime and Degradation Science," in IEEE Access, vol. 1, no. , pp. 384-403, 2013. doi: 10.1109/ACCESS.2013.2267611
RH French,et al. "Degradation science: Mesoscopic evolution and temporal analytics of photovoltaic energy materials", Current Opinion in Solid State and Materials Science, Volume 19, Issue 4, August 2015, Pages 212-226, ISSN 1359-0286 http://dx.doi.org/10.1016/j.cossms.2014.12.008.

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