

# Interdisciplinary and Multi-Faceted Research Aimed at Accelerating the Adoption of Solar Energy Technologies

### Prof. Kristopher O. Davis

Contributors: <u>Dylan Colvin; Mengjie Li</u>; Max Liggett; Jarod Kaltenbaugh; William Oltjen; Xuanji Yu; Manjunath Matam; Hubert Seigneur; Andrew Gabor; Philip Knodle; Greg Horner; Laura Bruckman; Roger French

Organizations: University of Central Florida; Case Western Reserve University; BrightSpot Automation; Tau Science



College of Engineering and Computer Science



CREOL, The College of Optics and Photonics





BrightSpot Automation





### University of Central Florida





**CREOL, The College of Optics and Photonics** 







### UCF Team Members and Key Collaborators



**CWRU SDLE Team at UCF** 





### Interdisciplinary Research Strategy for Photovoltaics (PV)



### Problem: Charge Carrier Recombination at Metal Contacts

- A key loss mechanism in photovoltaics is charge carrier recombination at the metal/semiconductor interface of the electrical contacts
- This sets a ceiling on the voltages one can obtain and P = IV





M Li et al. <u>https://doi.org/10.1109/JPHOTOV.2020.3003792</u>

### Passivating, Carrier-Selective Contacts

- A key loss mechanism in photovoltaics is due to charge carrier recombination at the metal/semiconductor interface of the electrical contacts
- Our group is exploring new approaches and materials that can passivate surface defects and are selective to either electrons or holes (i.e., carrier-selectivity) ٠
- UCF Collaborators: Prof. Banerjee (MSE, REACT), Prof. Jurca (Chemistry, REACT), Prof. Kumar (Mechanical), Prof. Kar (CREOL), Prof. Schoenfeld (FSEC, CREOL), Prof. Kushima (MSE) •
- External Collaborators: Fraunhofer ISE, Schmid Group, Beneg, ANU, UC-Berkeley, University of Melbourne ٠



Atomic Layer Deposition of Atomic Layer Deposition of Hole-Selective MoO<sub>x</sub>



G. Gregory et al., Advanced Materials Interfaces, 2020.

Atomic Layer Deposition of Hydrogenated Al<sub>2</sub>O<sub>3</sub>/MoO<sub>y</sub>





### Passivating, Carrier-Selective Contacts APCVD of Electron-Selective Polycrystalline Silicon Films



- Our group is exploring new approaches and materials that can passivate surface defects and are selective to either electrons or holes (i.e., carrier-selective = block one carrier type, allow the other to pass)
- This can be accomplished by growing a very thin silicon oxide (SiO<sub>x</sub>) film (~1.5 nm) followed by either an electron- or hole-selective material
- Atmospheric pressure chemical vapor deposition (APCVD) is a low cost, high throughput process well suited for the PV industry, and we are using this to deposit doped polycrystalline silicon (poly-Si) films that serve as electron-selective layers
- Collaborators: Dr. P. Banerjee (MSE, REACT), Dr. R. Kumar (Mechanical), Dr. A. Kar (CREOL), Schmid Group, Rutgers, ANU



Invited: JF Mousumi et al. https://doi.org/10.1088/1361-6463/ac0e5c



UCF

c-Si

### Passivating, Carrier-Selective Contacts APCVD of Electron-Selective Polycrystalline Silicon Films



- Our group is exploring new approaches and materials that can passivate surface defects and are selective to either electrons or holes (i.e., carrier-selective = block one carrier type, allow the other to pass)
- This can be accomplished by growing a very thin silicon oxide (SiO<sub>x</sub>) film (~1.5 nm) followed by either an electron- or hole-selective material
- Atmospheric pressure chemical vapor deposition (APCVD) is a low cost, high throughput process well suited for the PV industry, and we are using this to deposit doped polycrystalline silicon (poly-Si) films that serve as electron-selective layers
- Collaborators: Dr. P. Banerjee (MSE, REACT), Dr. R. Kumar (Mechanical), Dr. A. Kar (CREOL), Schmid Group, Rutgers, ANU



### Photonic Curing of Silver Metallization Printing and Laser Sintering High Viscosity Silver Pastes



- Printed silver (Ag) pastes undergo a thermal sintering process to coalescence µm-nm scale particles and improve electron transport
- Some of these passivating heterojunction materials are very temperature sensitive, so the low sintering temperature process leads to high bulk resistivity
- Ag is expensive and the high bulk resistivity means a larger volume of Ag is needed
- Collaborators: Dr. R. Kumar (Mechanical), Dr. A. Kar (CREOL)





### Multifunctional Nanomaterials Self-Assembled Al<sub>2</sub>O<sub>3</sub> Nanostructures: Electronic + Photonic Functionality

- Can we develop new materials with unique properties that can serve multiple functions?
- Yes we showed how self-assembled Al<sub>2</sub>O<sub>3</sub> nanostructures can electronically passivate surfaces provide improved light trapping, electronic + photonic functionality
- Collaborators: Dr. P.G. Kik (CREOL), Brookhaven National Laboratory







Nanopillars



Hossain et al. https://doi.org/10.1515/nanoph-2021-0472



SEM

### Multifunctional Nanomaterials Self-Assembled Al<sub>2</sub>O<sub>3</sub> Nanostructures: Electronic + Photonic Functionality

- Can we develop new materials with unique properties that can serve multiple functions?
- Yes we showed how self-assembled Al<sub>2</sub>O<sub>3</sub> nanostructures can electronically passivate surfaces provide improved light trapping, electronic + photonic functionality
- Collaborators: Dr. P.G. Kik (CREOL), Brookhaven National Laboratory



Hossain *et al.* <u>https://doi.org/10.1515/nanoph-2021-0472</u>



Nanopillars

SEM Images



### Multiscale Characterization of PV Modules in the Field



# **Reliability and Durability Challenges**

- Complex combinations of materials susceptible to a wide range of degradation pathways
- Technologies are changing rapidly, along with the materials and manufacturing processes used
- Demands for high volume and low cost limit where and how in-line metrology can be used
- Different climate zones have different stressors, but cost pressure precludes tailored designs for specific climates
- Nevertheless, warrantied lifetimes are typically 25+ years with a push to go to 50 years





12

### Multiscale Characterization of PV Modules in the Field



# Data Challenges

#### Challenges

- Many samples of various types featuring different device technologies and materials
- Drilling down to the materials-level is expensive, so sampling needs to strategic and guided by the data
- Diverse datasets of different types and large in magnitude
  - Time-series vs. asynchronous
  - Data collected at the system-, module-, device-, and materials-level
  - Point data, curves, and images
  - In some cases, physical models known and well understood, while others this isn't the case

#### Needs

- Scalable data sources that are fast and information dense
- Automated analysis pipelines for each of these data streams
- Effective means of storing data, models, and results to make links across different samples and measurement types





# UCF Florida Solar Energy Center – Cocoa, Florida

- Long-standing PV test facility for the DOE and the DOE Regional Test Center for Hot-Humid Climates
- Many diverse types of modules installed at various times
- Great access co-located with indoor module characterization labs





# Florida Gulf Coast University – Fort Myers, Florida

- 2 MW PV system installed at Florida Gulf Coast University (FGCU) in Fort Meyers, Florida
- We performed imaging on this system before and after Hurricane lan



### CWRU Sunfarm – Cleveland, OH

Project collaborator: Prof. Roger French and Prof. Laura Bruckman

- 50 kW test site operated by CWRU
  - 148 modules installed in 2013
  - 20 brands with 6 replicates of each



17

### CWRU MCCo – Cleveland, OH

1 MW power plant owned by Case Western

- ~4,000 modules on site installed 2016
- 2 brands
  - Each about <sup>1</sup>/<sub>2</sub> of site



### Time Series Team

Methods

• Remote time-series electrical performance and weather data





### **Time Series Team**





UCF

### **Time Series Dashboard**

Development of automated interactive dashboard (Will Oltjen et al. at CWRU)

- Missingness and data quality
- Performance loss rate calculation
- System information

Grade:				23:00
Outlier %	Missingness %	Longest Missing Gap	Length Requirement	21:00
В	А	С	Р	17:00

Performance Loss Rate:

• -1.093 ± .215 %

Method

- XbX + Universal Temperature Correction
  - Year on Year Regression
- Bootstrapped Uncertainty



15:0

13:00

09:00

07:00

05:00

03:00







### Time Series Analysis – Extreme Weather







P<sub>loss</sub> ~1%

Before

After

UCF

22

### Indoor Module Characterization Team

- Current-voltage (I-V) or current density-voltage (J-V) curves curves under illuminations
- Electroluminescence (EL) image performed in the dark under bias



UCF

### Indoor Module Characterization Team

- Current-voltage (I-V) or current density-voltage (J-V) curves curves under illuminations
- Electroluminescence (EL) image performed in the dark under bias







24

### Illuminated J-V Curves – Simple Models

- Photogenerated current density, J<sub>G</sub> (A/cm<sup>2</sup> or mA/cm<sup>2</sup>)
- Diode current density,  $J_D$  (A/cm<sup>2</sup> or mA/cm<sup>2</sup>)
- Saturation current density, J<sub>0</sub> (A/cm<sup>2</sup> or fA/cm<sup>2</sup>)
- Ideality factor, *n* or *m*
- Series resistance,  $R_{\rm S}$  ( $\Omega$  or  $\Omega \cdot \rm cm^2$ )
- Shunt resistance,  $R_{SH}$  ( $\Omega$  or  $\Omega \cdot cm^2$ )
- Boltzmann constant, k
- Charge of an electron, q

$$J = J_G - J_0 \left( e^{\frac{q(V+JR_S)}{kT}} - 1 \right) - \frac{V+JR_S}{R_{SH}}$$





### Illuminated J-V Curves – Loss Mechanisms



26

### **Measurement Methods**

- Illuminated *J-V* and Suns-*V*<sub>oc</sub> measurements
- Electroluminescence (EL) imaging



### EL Image Analysis Approaches Developed

Efforts to make EL image analysis more quantitative and less subjective

- EL sweep Turn EL images of modules measured at different currents into dark J-V curves of cells to extract  $R_s$  and  $J_0$
- Pixel  $R_{\rm S}$  Use that in turn to determine the local  $R_{\rm S}$  of each pixels in the EL image
- EL defect segmentation Use supervised deep learning for semantic segmentation of EL images based on different defect classes



### **EL Sweep**



- 1. Obtain EL images at increasing bias currents
- 2. Calculate voltage for each cell within each image
- 3. Repeat for each image to build dark *I-V* curve for each cell
- 4. Analyze dark *I-V* curves to extract performance characteristics

D.J. Colvin, et al. https://doi.org/10.1016/j.solener.2022.08.043

### EL Sweep of Two M55 Modules - $R_{\rm S}$ and $J_{\rm O}$ Maps





1.0

1.4

1.2

- 1.0

0.8

0.4

- 2.4

2.2

J01- Dark Saturation Current (A/cm2)

J01- Dark Saturation Current (A/cm2

# Pixel R<sub>s</sub> – Control M55 Module

M. Li et al. https://dx.doi.org/10.2139/ssrn.4367178



UCF

### Pixel R<sub>S</sub> – Degraded M55 Module



# Pixel R<sub>S</sub> - Comparison

#### **Control M55 Module**







0

#### **Degraded M55 Module** Module EL





L 10

### Data-Driven Approach to Defect Classification and Localization

- Supervised deep learning model with CNN (Deeplabv3 model with a ResNet-50 backbone)
- Model trained with 17,064 EL images fully annotated dataset
- Defect classes shown below 95.4% pixel-level accuracy achieved

(a) Cracks



(b) Common contact defects



#### (c) Interconnect defects



#### (d) Rare contact defects



J. Fioresi, et al. https://doi.org/10.1109/JPHOTOV.2021.3131059



### Examples



### **Resistive interconnects**

J. Fioresi, et al. https://doi.org/10.1109/JPHOTOV.2021.3131059



# Complete EL Image Analysis Sequence







#### **EL Defect Segmentation**



# Module Characterization – Coring

- Module characterization guides us to select regions for extracting cell samples
- Curves tell us more on the loss mechanisms and magnitude of the power loss
- Images tell us the location of possible defects and the patterns can indicate the possible root cause



### **Device and Materials Characterization**



UCF

### **Device and Materials Characterization**

• Multi Al-BSF







39

### Automated Analysis of SEM Images

- Semantic segmentation of cross-sectional SEM images
- Again goal is to make the evaluation of these images more automated and less subjective



### Multiscale Characterization of PV Modules in the Field



## Field Inspection Team

- Methods
  - Pole-mounted IR imaging
  - Pole-mounted UV fluorescence (UVF) imaging
  - Drone-based UVF imaging
  - Scanning photoluminescence (PL) and non-contact electroluminescence (EL)

42

### **Pole-Mounted IR Imaging**



Outdoor installation during daytime

Pole-mounted IR imaging setup



# **Pole-Mounted UVF Imaging**



Pole-mounted UVF imaging setup



44

# **Pole-Mounted UVF Imaging**

- What do you do with the images?
- Need to make sense of them, but there are too many to manually inspect
- Subject matter experts establish a process to interpret the patterns observed
- Then, images can become useful information
- Again, the analysis must be automated

   there are far too many images to
   evaluate them all manually



UCF

# **UVF Image Analysis**

Input Image



#### Mask-RCNN Mask



#### **Planar Output**





UCF

## Drone-Based UVF with UV LEDs

- BrightSpot has performed several drone flights using a UV-LED payload
- Good for a low volume sites and for panels that fluoresce brightly







### Outdoor PL and EL Imaging







UCF

# Need for Data FAIRification

#### Making Datasets & Models FAIR

• By "FAIRification"

#### **Enables Models to find Data**

And Data to find Models

#### So that they can advance

• Without human intervention

#### This is an aspect of the Semantic Web

- And Resource Description Framework
- Hbase triples are an example of RDF

#### FAIR Data very active in Europe

• U.S. efforts just starting now





### Future Work

 Through MDS<sup>3</sup> Center of Excellence with CWRU and Sandia (Elliott Fowler and Matthew Kottwitz), looking to adapt some of these process to electronic component reliability





### Acknowledgements

UCF

Faculty: Kristopher O. Davis, Mengjie Li, Mubarak Shah Postdoctoral Researchers: Dylan J. Colvin, Eric J. Schneller, Haider Ali Students: Geoffrey Gregory, M. Jobayer Hossain, Nafis Iqbal, Jannatul F. Mousumi, Max Liggett, Rafaela Frota, Joseph Fioresi, Sofia Oliveira

Collaborators CWRU: Roger H. French, Laura Bruckman, Jen Braid, Ina Martin Tau Science: Greg Horner BrightSpot Automation: Andrew Gabor, Phil Knodle Sandia: Elliott Fowler, Matthew Kottwitz

Funding



DE-EE0008155, DE-EEE0008172, DE-EE0009347



DE-NA0004104

