Photovoltaic Testing for Energy Yield Predictions with Sensitivity to Spectral Shifts

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***Abstract*—Solar spectra change depending on location, weather, and time of day around the world. These spectral variations affect the performance of photovoltaic (PV) cells and modules and are not captured by standard testing procedures. We introduce a method to classify spectra and use this classification to develop a testing procedure to reproduce spectral conditions of locations within various climate zones. With LED solar simulators becoming commercially available and representative sets of outdoor spectra found, the gap between real world outdoor testing and indoor testing is closing. With LED-based testing of CdTe, Si, and GaAs PV cells, we show that the effects of spectral shifts on short circuit current are captured, demonstrating the potential use of this method for more accurate testing of solar modules indoors.**

***Index Terms*—solar spectrum, LED solar simulators, testing standards**

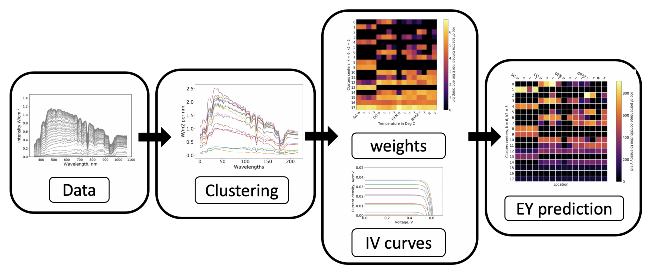

Fig. 1. RISE Classification method: 1. Align data, 2. Cluster data, 3. Find IV curves and weights for each cluster center, 4. Predict Energy Yield (EY).

I. Introduction

Standard testing conditions (STC) of photovoltaic (PV) devices do not take all outdoor operating conditions into account using only one specific temperature, 25 degrees Celcius, and one specific spectrum, AM 1.5G. [1] [2] There are efforts to capture and standardize variations in outdoor climate through temperature coefficients, and number of sun hours per location. [3] However spectral variations are often still neglected, even if studied widely. [4]. However, thus far in standard testing, these spectral differences are not taken into account.In this work we propose a method to uniquely classify spectra, and use this classification to select a representative set of spectra that can be used for location specific energy yield predictions. This method is called Representative Identification of Spectra and the Environment (RISE). [5] Through this work millions of outdoor spectra are condensed into 10 to 20 different spectra with which we can test solar cells indoors. In this paper we explain the RISE through simulation and then demonstrate how these spectra capture differences between materials by testing of Cadmium Telluride (CdTe), Silicon (Si), and Gallium Arsenide (GaAs) PV cells.

II. RISE Method

The RISE method is explained in Figure 1. It uses millions of measured solar spectra as input and outputs a representative set of spectra. For this work we have obtained data from four locations representing different climate zones including cold arid, fully humid equatorial, equatorial with dry summer, and fully humid warm temperate. Each of these locations has very different spectra conditions, and with these millions of spectra, we find a small number of spectra that represent the entire data set to some accuracy. In this work, we first bin the spectra by irradiance with half as many spectra allotted to each successively higher irradiance bin. This captures the irradiance differences, but not any of the differences in the shapes of the spectral curves. Therefore, within each irradiance cluster, a machine learning clustering algorithm called k-means is run to capture secondary spectral difference such as red and blue shifts. With these two steps, we have captured two physically interpretable effects, intensity variations and spectral shift.

We model two types of solar cells, CdTe and Si to understand how well the representative spectra predict energy yield (EY) when compared to using all millions of spectra to calculate EY. To accomplish this, we first create models for CdTe and Si using the one-diode model below equations. [6]

$$I = I_{ph} - I_0(e^{-q(V+IR_S)/(nk_bT)} - 1) - (V + IR_S)/R_{sh} \quad (1)$$

with I_{ph} as the photocurrent found using Equation 2, I_0 as the dark saturation current found using Equation 4, q as the elementary charge ($1.602 * 10^{-19}C$), V as voltage, I as current, R_S as series resistance, n as ideality factor, k_b as Boltzmann constant ($1.380 * 10^{-23}J/K$), T as temperature, and R_{sh} as shunt resistance.

$$I_{ph} = \sum((EQE(\lambda) * Irr(\lambda))/E_{ph}(\lambda)) \quad (2)$$

with EQE as external quantum efficiency resolved by wavelength, λ, Irr is the irradiance falling on the cell resolved by wavelength, and E_{ph} as the photon energy resolved by wavelength as found with Equation 3.

$$E_{ph} = (hc * 10^9)/\lambda_{EQE} \quad (3)$$

with h as Planck's constant ($6.626*10^{-34}Js$), c as the speed of light ($3 * 10^8 m/s$), and λ_{EQE} as the wavelength.

$$I_0 = I_{0,STC}(T/T_{STC})^3 * e^{((qE_g/nk_bT)*(1/T_{STC}-1/T))} \quad (4)$$

with $I_{0,STC}$ as the dark saturation current at standard testing conditions (STC), T as temperature, T_{STC} as the temperature at STC, q as the elementary charge ($1.602 * 10^{-19}C$), E_g as the band gap of the material, n is the ideality factor, and k_b as Boltzmann constant ($1.380 * 10^{-23}J/K$).

From these models in Equations 1 - 4, IV curves are found with temperature and spectral data of the representative clusters

This material is based upon work partially supported by the U.S. Department of Energy and NSF joint QESST grant. MISTI funding also supported this work. Erin Looney acknowledges support by the National Science Foundation Graduate Research Fellowship.

for both Si and CdTe with parameters shown below. We then apply temperature coefficients to these cells shown below in the modelling parameters table. These IV curves are used to find energy yield (EY).

$$EY[Wh/m^2] = \sum_{i=1}^{N} \eta(\Delta n, T, P(\lambda), ...)P_{in}t \qquad (5)$$

with η as efficiency of the solar cell which is dependent on minority charge carrier injection, Δn, (number of electrons or holes injected due to excitation of solar power hitting material), temperature, T, power per wavelength, P(λ), and more. P_{in} is the total power into the cell in W/m^2 which can be found by integrating $Irr(\lambda)$, t is time in hours, and N is total number of measured spectra evaluated over.

The silicon and cadmium telluride cells were modeled to have the same efficiency for direct comparison. A list of the parameters for these models is in the table below.

Modeling Parameters, and STC results		
Parameter	Silicon	CdTe
Efficiency, %	18.2	18.2
Fill Factor, %	82.6	75
Open Circuit Voltage, V	0.618	0.848
Short Circuit Current, mA/cm^2	40.1	27.6
Temperature coefficient, % performance lost per degree K	-0.41	-0.32
Series Resistance, ohm/cm^2	1.3	1.215
Shunt Resistance,ohm/cm^2	500	500
Band Gap	1.12	1.5

III. Classification Results

The results shown are for intensity bins (K1), K1 = 6, and k-means bins (K2), K2 = 3, making a total of 18 representative bins to describe all of the data from the four locations.

As can be seen in the top left of Figure 2, these spectra have intensity (K1), and shape (K2) differences. There are 6 distinct intensities with 3 different shapes in each one, as is expected. The number of spectra from the full data set that belong in each bin are shown in the bottom left. First we can see, that many more spectra occur in the lower intensity bins, as seen in bin 0 outlined in orange. This makes sense as both morning and night, as well as cloudy days product low intensity spectra. We can also see there is a segregation of data according to location that the algorithm natural finds. For instance, bin 16, outlined in pink, is mostly indicative of Singapore data (Af), with very few Colorado, Brazil or Denmark data belonging in bin 16. The fact that the algorithm picked up on these differences indicates the spectral shape differences for the different locations.

Using the Si and CdTe models and the binned spectra, IV curves shown in the top right of Figure 2 are calculated. Using these IV curves along with the weights from the bottom right of Figure 2, we calculate energy yield results using Eqn.5. These results can again be made into a heat map with percent contribution to EY. As can be seen, the segregation between locations persists, but now the higher intensity bins are the most prominent because they contribute the most to energy yield even though the frequency of occurrence is less.

With these results we can compare the RISE method with the "ground truth" which is here the EY found using every single measurement in the dataset. This is also compared to the standard testing condition results found with modeling the cell under STC and multiplying be the number of sun hours for each location. In Figure 3 we see these EY results for Denmark, Colorado, and Singapore.

As can be seen in Figure 3, the RISE method captures the ground truth with less than one percent error as compared to STC estimates that have errors as much as 20 percent (Singapore, Si). It should be noted that these results use the modeling parameters from the methods section, so both technologies have the same baseline efficiency under STC. Looking at the Singapore results, it can be seen that CdTe outperforms silicon greatly, and the STC overestimates Si energy yield and underestimates CdTe energy yield. It is also worth noting that

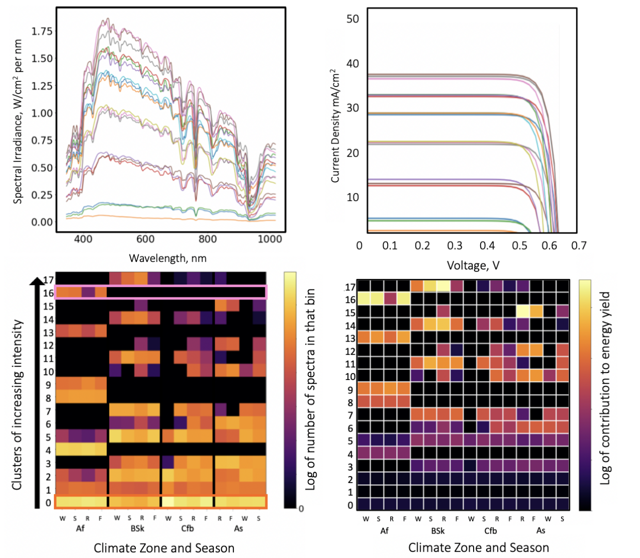

Fig. 2. Top left: Representative spectra (bins) found using the RISE method, Top Right: calculated IV curves, Bottom Left: Weights of number of spectra in each bin for different locations and seasons, Bottom Right: Contributions to EY of each bin for different seasons and locations.

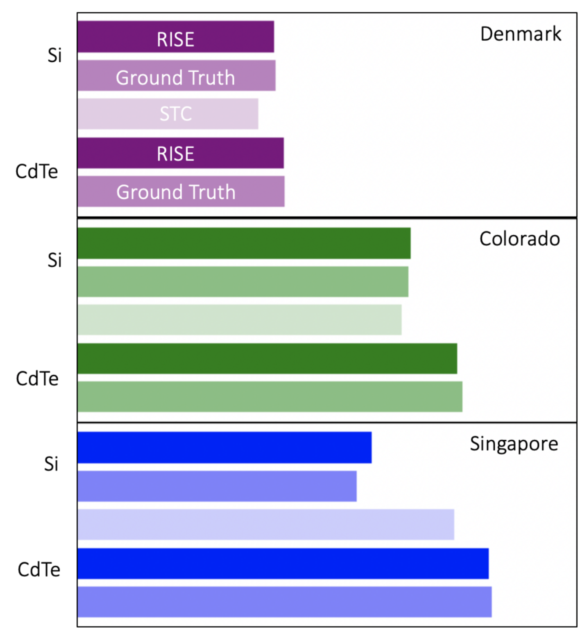

Fig. 3. EY predictions for three different locations using all data ("ground truth"), the RISE method with 18 spectra and average temperatures from each bin, and standard testing conditions.

the largest difference between the technologies is in Singapore as compared to Colorado and Denmark. This can be explained by Si's sensitivity to humidity and heat when compared to the more tolerant CdTe. Furthermore, the only location where Si is competing relatively well with CdTe is in Denmark where there is a colder climate. However, Denmark being fairly humid also has some advantages for CdTe. The discrepancy between RISE and ground truth is believed to arise from the temperature averaging done for the RISE method, whereas each measured module temperature is accounted for in the "ground truth". One way this could be mitigated in the future is by testing each of the representative RISE spectra at several temperatures during module testing to capture these differences.

IV. LED-RISE Experiments

To test out this methodology on PV cells, we procured a Wavelab Sinus 70 LED-based solar simulator, [7] and test the representative spectra found using the RISE method on several PV technologies. The three tested technologies are Si reference cells from Fraunhofer Institute of Solar Energy (ISE), CdTe cells from First Solar (FSLR), and GaAs cells from ISE. The equipment used to test these cells is the Wavelab Sinus 70 which has 21 individual LED's to tune to the representative spectra. This can be seen in Figure 4.

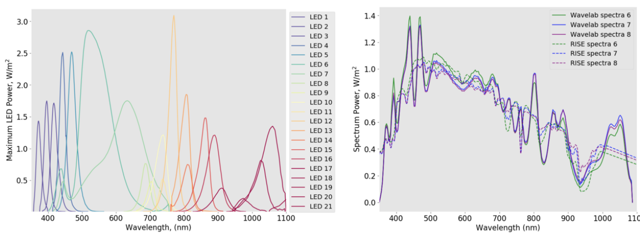

Fig. 4. Left: Maximum power of LED's in Wavelab Sinus 70. Right: Fit of these LED's to representative spectra.

Next, these cells are tested under the representative spectra to compare short circuit current (Jsc) between technologies. We expect differences between the performance of CdTe and Si under different climate zone conditions. This is what we see in the experimental results in Figure 5 with a comparison of Jsc normalized by STC AM1.5G for CdTe and Si technologies. This normalization means that the Jsc found for each technology and for each spectra is divided by the Jsc found with STC for that technology to get a relative difference from baseline. In this figure, if the number on the x-axis is positive, then Si performs relatively better in that location in terms of Jsc. As can be seen in Figure 5, CdTe Jsc's are relatively better than Si in Singapore. This makes physical sense as this is the most humid location where CdTe would expect to outperform Si. It can also be seen the Si Jsc's are best in Colorado which can be understood due to its relatively dry climate, and for Denmark there is more of a split between CdTe and Si Jsc's.

Capturing these spectral difference in Jsc with indoor testing of solar modules is a proof of concept for this technique. With the representative spectra found and programmed into an LED solar simulator, Jsc differences are measured corresponding to those seen outdoors. This demonstrates an opportunity for these methods to be used within industry or academia to test PV technologies for different climates zones.

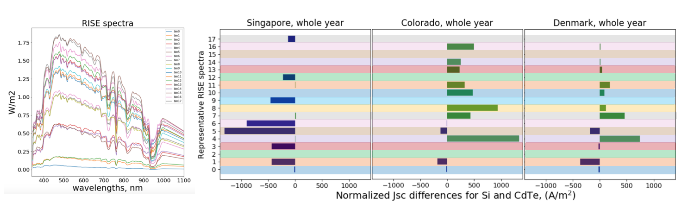

Fig. 5. Normalized Short Circuit current (Jsc) differences between CdTe and Si technologies.

V. Discussion of Significance to Field

With the advent of new LED based solar simulators that more accurately reflect the sun's light, we can have more accurate testing of PV cells and modules indoors. Along with this advance, clustering techniques from the field of machine learning have become widely available and can be used to reduce millions of experimental spectra into a number that can realistically be tested on PV cells indoors. In this work, EY's found using representative spectra demonstrate close accuracy to energy yield predictions found using the full data set. We test these representative spectra with LED-based solar simulators to confirm this method. The Jsc differences expected from these different spectra on Si vs. CdTe are captured by these experiments. From these results, changes to how PV devices are tested in research and development settings and potential alterations to international standards are envisioned with LED-based solar simulators and spectra that represent the worlds climate zones accurately leading the way.

VI. Summary

In this work, we demonstrate the RISE method for finding a representative set of solar spectra that can be used to more accurately test PV cells indoors for outdoor conditions capturing sensitivities to spectra that are not captured in current standard testing conditions. Using this method, we show that EY predictions are within less than one percent of "ground truth" found with all of the experimental data. We test these spectra experimentally using a LED-based solar simulator to demonstrate this capability. The LED-RISE experiments capture different materials' sensitivities to variations in spectra in a way that current standards do not. With these new advances, more accurate testing of PV cells and modules within laboratories can be used for PV device design and optimization.

Acknowledgments

We would like to thank all of our collaborators for providing empirical data for this work. The climate and spectral data from Denmark was provided by Nicholas Riedel at the Technical University of Denmark, Department of Photonics Engineering. The Singapore climate and spectral data were supplied courtesy of the Solar Energy Research Institute of Singapore (SERIS), Dr. Andre Nobre and Dr. Lu Zhao. The Colorado data was provided by the National Renewable Energy Lab's Measurement and Instrumentation Data Center. We gratefully acknowledge these organizations and the many individuals involved in the collection and maintenance of these valuable solar data sets. We would also like to greatly thank FSLR and ISE for provided devices for this research.

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