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Electroluminescence Based Metrics to Assess the Impact of Cracks on Photovoltaic Module Performance

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***Abstract* — Solar cell cracking is a potential reliability concern that may affect the long-term performance of modules that experience mechanical stress in the field. We present a methodology that utilizes EL images to predict power loss due to cell cracking. We explored pixel intensity histogram normalization methods to generalize this approach to a wide range of measurement conditions. The final optimized EL metric exhibits a strong correlation with power loss for a range of module technologies where a 1% increase in the dark area due to cracks results in a 3% loss in performance. This approach enables field EL mapping to translate to module P_{max} mapping across a system.**

***Index Terms* — module reliability, mechanical durability, electroluminescence, cell cracking.**

I. Introduction

Long-term reliability of photovoltaic modules and systems is critical for solar energy to be a cost competitive alternative to traditional energy sources. Cell cracking has become a major concern in recent years due to cost related module design changes that have increased cells' susceptibility to breakage, including declines in wafer thickness, increased module areas, and increased wafer diameters [1], [2]. The long-term impact of cell cracking is not yet clear. To quantify the impact of cell cracking on long term performance, modules with crack damage will need to be monitored over time as they age in the field. Unfortunately, obtaining accurate power data on large numbers of modules in the field is time consuming and often cost prohibitive. In this work we aim to develop electroluminescence (EL) based metrics that can be used as a proxy for electrical performance measurements.

II. Experimental

To develop a correlation between power loss and any EL based metric, a large dataset of EL images and performance data are needed that cover a broad range of module performance conditions. To achieve this, we utilized the *LoadSpot* system from BrightSpot Automation which allows for *in-situ* module performance characterization during mechanical loading[3]. EL images were captured using a modified DSLR camera, and current-voltage (I-V) data was collected using a Sinton FMT-350. The module bias used for EL imaging was the nameplate short-circuit current, and the bias current was kept constant during the mechanical test sequence. Data was collected as a front side load was applied to the module in steps of 400Pa up to a maximum of 5400Pa. This process was carried out for several modules over a range of manufacturers and technologies.

To derive a quantitative metric from an EL image, the image pixel intensity histogram was used. A threshold was applied to the histogram, and any pixel intensity below that threshold was characterized as contributing to a "dead area" that was quantified as an area fraction in percentage terms. Using the same threshold for the entire sequence of images, the "dead" area fraction calculated for each image was plotted against the relative power as determined by the I-V measurements. An example of this plot is shown in Fig. 1. From this type of plot, it becomes possible to relate area fraction determined from the EL image to the relative power loss for that particular module.

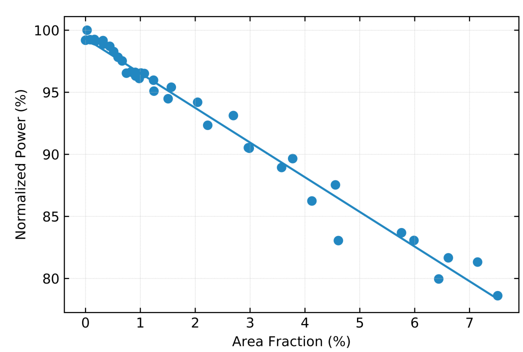

Fig. 1. Normalized module power vs. "dead" area fraction for one module using each step in the mechanical loading sequence as one point of the graph. The best-fit line for the data is also displayed to show the strong linear correlation.

III. Histogram Normalization

The objective of this work was to develop a generic methodology that could be applied to a variety of module types and that was not tied to a specific set of measurement conditions (*e.g.* exposure time, bias current, temperature, etc.). To achieve this, we explored several methods to normalize the

EL histograms prior to an application of threshold. We studied two main approaches to histogram normalization involving identification of key regions within the pixel intensity histograms. The first method was to identify the peak value and use that as the reference point. The second approach was to find the maximum and minimum intensities observed within the image, excluding noise, and use both of those points as a reference.

An example of the raw pixel intensity histograms for a series of EL images, along with the resulting histograms for both normalization methods, are shown in Fig. 2. As is seen with the original histograms, there is some variability that could be the result of temperature variation during the testing or due to the constant bias conditions during the experiment even though the module performance was degrading as cracks were generated within the cells. Each of the normalization methods used resulted in a better alignment of the histograms. After normalization, the threshold used for calculating the "dead" area fraction is applied consistently across all images.

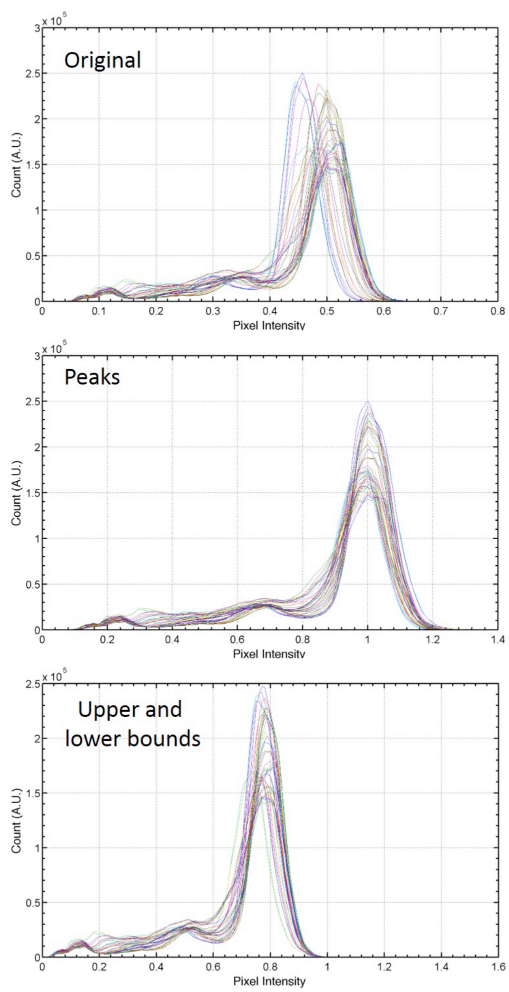

Fig. 2. Example of the EL pixel intensity histograms, including the original (*i.e.* un-corrected) and after both normalization methods. Each line on the graph represents a unique image captured for one module at each step during the mechanical loading sequence.

IV. Threshold Determination

When assessing the impact of cracks on module performance, it is common to look for dark areas in an EL image that signify regions that have been isolated from the interconnect wires. To quantify this so called "dead area", previous work has explored the use of an intensity threshold in which any pixel below this threshold is used to calculate an area fraction associated with these "dead" region[4]. This approach required the use of a reference cell or module, characterized using the same measurement settings to determine the appropriate intensity threshold value that was only relevant for the particular module type. In this work we aim to generalize this approach so that no prior knowledge is required to identify what intensity threshold to select for a given EL image. We achieved this by utilizing the normalization methods described above.

To determine the most appropriate threshold, the area fraction was calculated for each threshold value for the entire range of intensity values. Using each image and the associated I-V measurement at each step of the mechanical loading sequence, plots of area fraction vs power were generated. Power was normalized considering the initial, non-degraded measurement as 100%. An example of this type of plot is shown in Fig. 1. The quality of the correlation for each plot was determined using the r^2 value for a linear-fit applied to the data. This process was carried out for all threshold values.

Plots of r^2 vs. threshold were then generated for each module and each normalization method. These plots allow us to identify which threshold, and corresponding area-fraction, is most predictive of module power degradation. An example of this plot, prior to any histogram normalization, is shown in Fig. 3 for one module used in this work. The best correlation, determined from the highest r^2 value, was found in the lower range of pixel intensities.

For every module used in this work, the same analysis was performed. The correlation between the area fraction and relative power was improved after normalization of the pixel intensity histograms. Before normalization r^2 values ranged from 0.67 to 0.93. After normalization r^2 values ranged from 0.88 to 0.98, with several modules exceeding 0.95. These results emphasize the importance of the normalization process. For modules with poor quality linear fits (*i.e.* low r^2 values) prior to normalization, superior results were obtained using the upper and lower bounding normalization method instead of the peak normalization method. This can be explained by the presence of new cracks, generated during the mechanical loading sequence, that effectively shift the peak of the histogram lower as more pixels have lower EL intensity due to partially disconnected regions.

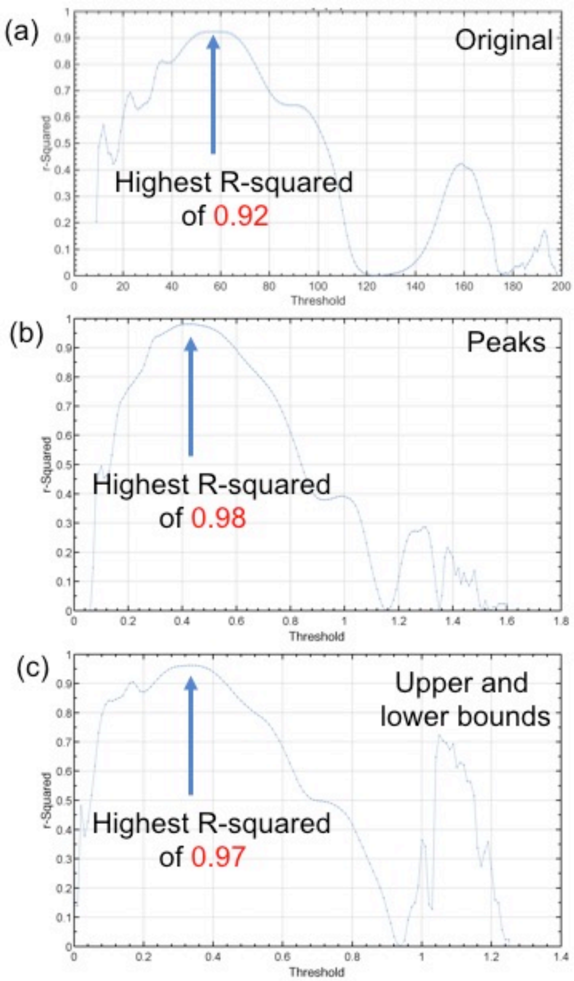

Fig. 3. Example of r^2 as a function of threshold value for the same module as in Fig. 2 for (a) the original, uncorrected histograms, (b) the peak normalization method, and (c) the upper and lower bound normalization method. The peak r^2 value, corresponding to the best linear fit, is highlighted. The threshold axis in (a) corresponds to the intensity range of 0-256 for a standard 8-bit image. The threshold axis in (b) and (c) are scaled according to the normalization method.

In a final step to generalize our findings, the optimal threshold values obtained for the modules were compared to see if they were consistent. We found that when utilizing the upper and lower bounding normalization method, the optimal threshold was in the range of 0.28 and 0.31. This implies that for a range of module types including both mono and multi-crystalline technologies, a consistent threshold could be used as a metric to quantify the effective "dead area" due to cell cracking. Examples of the resulting EL images with the "dead area" highlighted in red are shown in Fig. 4. It is interesting that the "dead area" determined using a purely mathematical evaluation of the histograms corresponds quite well to what would be perceived as "dead area" by a skilled researcher.

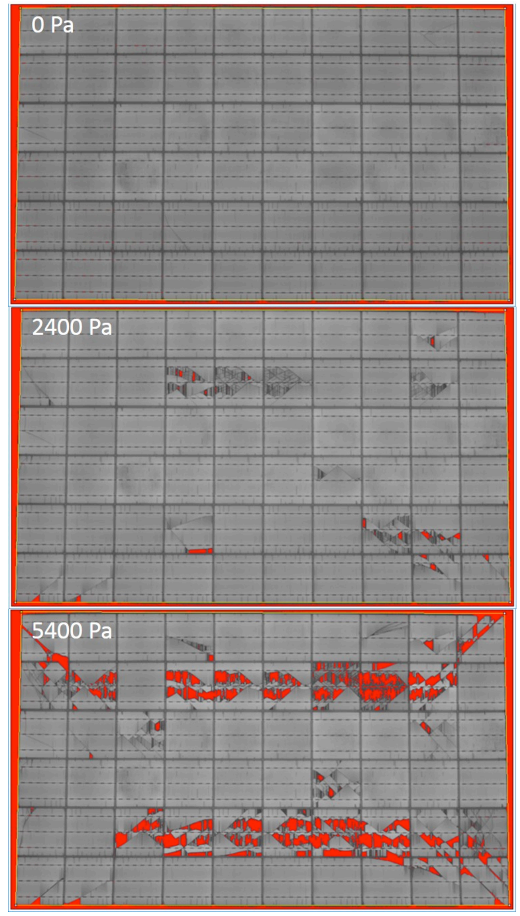

Fig. 4. Example of EL images with "dead area" highlighted in red.

V. Correlation With Power

The final step to a comprehensive metric is to determine the correlation factor between the area fraction and normalized power. The optimal threshold value was determined to be 0.29 when averaging results after the histograms were normalized using the upper and lower bounding method (*i.e.* the upper bound is set to 1 and lower bound is set to 0). The power vs. area fraction for one group of mono-crystalline modules is shown in Fig. 5. For this group of modules, a consistent correlation factor of approximately 3% degradation per every 1% increase in the "dead area" fraction was determined.

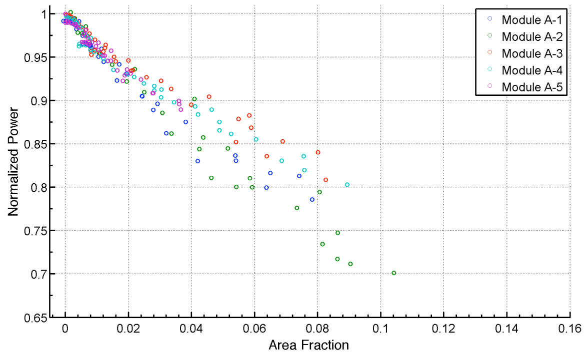

Fig. 5. Plot of normalized power vs. area fraction for a group of mono-crystalline modules using the upper and lower bounding histogram normalization process and the optimized threshold of 0.29.

VI. Conclusions

This work presented a methodology that can be used to quantify the "dead area" in EL images due to cell cracking and relate this metric to power loss. We explored methods to normalize EL pixel intensity histograms to make the process generic to a wide variety of measurement conditions. Although this technique was specifically tailored to cracks, the same type of analysis could be used for other degradation mechanisms as well.

With the availability of systems that can capture EL images for field installed modules, this analysis could be used in place of module I-V measurements. This would allow for a quick evaluation of performance loss that system operators could utilize after weather events like hurricanes, hail, or severe snow to evaluate the cell crack damage or on regularly scheduled basis for modules that are known to be prone to cell cracking. This could guide decisions on the necessity of module replacement or for selection of specific modules for additional performance characterization.

References

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