Field Inspection of PV Modules
Quantification of EVA Browning Level using an Image Processing Tool

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Field Inspection of PV Modules: Quantification of EVA Browning Level using an Image Processing Tool

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Abstract — PV plant inspections are important to identify and quantitatively determine the impacts of various visual defects on module performance. One of the dominant visual defects is EVA (ethylene vinyl acetate) (encapsulant) browning, which affects the light transmittance and thus output of PV modules. The present study deals with development of an image processing tool to quantify the browning and which is then used to quantify the short circuit current (Isc) of the browned modules without disconnecting the modules from their arrays. This MATLAB tool removes human subjectivity, accurately quantifies browning level, predicts Isc, and reduces time required for field inspection.

Index Terms — Browning and PV performance correlation, Browning Index, EVA browning quantification, Image Processing, MATLAB tool.

I. INTRODUCTION

There are as high as 86 different types of defects that can be found in the PV modules installed in various climates and most of them can be visually observed. However, a quantitative determination of performance impact or financial risk of each of identified defect is a challenging task. Thus, it is utmost important to quantify the risk for each of the visual defects without any human subjectivity. The best way to quantify the risk of each defect is to perform current-voltage (I-V) measurements of the defective modules installed in the plant but it requires disruption of plant operation, use of expensive measuring equipment and intensive human resources.

The NREL visual inspection checklist is one of the best ways to identify visual defects and qualitatively categorize the intensity of each defect [1]. Though this checklist is simple and greatly useful for quick analysis, the defect intensity categorization is very subjective as the perception differs from one person to the other, and may really become a tedious task when considering millions of modules in large power plants. Thus, developing image processing tools which quantify these visual defects is very important for the booming solar PV industry.

One of the most risky and dominant visual defects is EVA (encapsulant) browning, which affects the PV module performance (current and power) due to transmittance loss. The present study deals with the development of an image processing tool to quantify browning level and study the impact of browning on performance without disruptively disconnecting the modules from or at the plant. In this work, the quantified browning level (browning index [BI]) impact on performance has also been experimentally validated through a correlation study using short-circuit current of browned PV modules retrieved from aged plants/systems installed in the hot-dry climatic condition of Arizona.

II. METHODOLOGY

A. Browning Analysis and Correlation—Process Overview

Photographic images of several field aged modules installed on a manual 2-axis tracker were obtained outdoor during bright sunny times. The MATLAB based image processing tool developed in this work involves two parts. In the first part, as shown in Fig. 2, a six-step image cropping/processing tool was developed and used to obtain the “cells-only-image” of the entire module. In the second part, the browning level (also known as browning index) was determined using the pixel count and pixel weight of the cells-only image of the module. In the last step, the performance parameter (Isc) was correlated with the browning index calculated using the developed tool.

A.1. Image Processing—Part 1

A basic image is made up of small rectangular elements called pixels as shown in Fig. 1. Every pixel carries information about a specific color. Colors are perceived using various color systems (RGB, HSV, HSI, YUV, and others). The other important quality of an image is called resolution. Resolution is the amount of pixel required to make a specific area of an image. Higher resolution implies more information about the image.

Fig. 1. Example pixel level image [2]
The aim of the first part of this project is to obtain an image that can be processed for browning and thus eliminating other elements in the image.

The six steps of part 1 image processing are as shown in Fig. 2 and are as follows: 1) raw input photograph/image, 2) converting raw photograph image into binary (black and white) raw image using the “thresholding” function, 3) converting the binary raw image of step 2 into another binary raw image using the “Imfill” function which converts all the black patches (in this case, cells) surrounded by white pixels (in this case, inter cell areas) on all sides of the defined area (in this case, module area) into white patches with an exception to the black patches which are surrounded by white pixels and are laying around the edges and away from the defined image area (in this case, all the surroundings except module area), 4) converting the binary raw image of step 3 into another binary raw image using the “filtering” function which is used to convert all the surrounding (of the defined module area) into black pixels, 5) converting the binary raw image of step 4 into a raw module-only photograph image using the “module-only cropping” function which crops out all the area except the module area, and 6) converting the module-only cropped photograph image of step 5 into the cell-only photograph image using the “cell-only cropping” function again. The cropped module image shown in step 5 contains all the components/materials such as, module frame, inter-cell backsheets, fingers, and inter connects which should not be considered for encapsulant browning level analysis. To obtain the step 6 image, a cell isolation factor of 150 is used to get rid of these irrelevant materials. The cell isolation factor is a fixed numerical factor which has been experimentally fixed based on the module samples used. The effect of cell isolation factor is that all the pixels with at least two of the R, G, or B values is greater than or equal to 150 are converted into black pixels. The cell-only image is then used for the part 2 image processing analysis to determine the quantitative browning level/index.

A.2. Image Processing – Part 2

Part 1 of the image processing gives an image that only contains cells and the browning on them. Part 2 deals with calculating the Browning Index (BI). The whole color space is infinite. To quantify and qualify the color space, the color space is divided into finite divisions for understanding and calculating browning index.

The color palette can be developed based on any color model/system, but works best with HSV or HSI color systems as they are closest to the human perception. In this work, HSV or HSI color systems/models are used in processing of the final part 1 cell-only image for calculating the Browning Index (BI). The color space is divided in “n” different bins using the color system components and are represented by “n” different colors. Thus, we have a color palette with “n” colors which can be used for processing. The colors ranges were divided based on the H and V component values of the HSV color system as they are very closely replicating the color variation behavior as seen in Fig. 3 and Fig. 4.

![Fig. 3. Comparison of variation of Hue component (on right image) with variation in browning in the original image (on left)](image)

![Fig. 4. Comparison of variation of Value component (on bottom image) with variation in browning in the original image (on top)](image)

A.2.1. Pixel Weight

The color palette with “n” colors only describes the number of colors/bin available but does not give any information about the quality/extent/intensity of browning of a specific bin/color. Pixel weights are random logical numbers assigned to
every color/ bin in the color palette which describes the quality/extent/intensity of browning. The higher the pixel weight, higher the level of browning.

The color palette with different colors, pixel weights is as shown in Fig. 5.

A.2.2. Pixel Count

The pixel count refers to the number of pixels that fall in a specific bin out of the total number of pixels available in the image. Pixel count are obtained by using the histogram plot of an image component as shown in Fig. 6.

A.3. Browning Index Calculation

The browning index is calculated is dependent on two parameters, Pixel count and Pixel weight as shown in the below equation.

\[
Browning\ index\ (BI) = \frac{\sum \text{Pixel count} \times \text{Pixel weight}}{\sum \text{Pixel count}} \quad (1)
\]

B. Performance Parameters

I-V curves of all the 21 modules were taken on a day with clear and sunny conditions (800-1000W/m2). Isc of the measurement is used for correlation. Dark I-V have been measured to calculate the series resistance of the modules. Modules with encapsulant delamination have been identified by observing the I-V curves with mismatch as shown in Fig. 7.
true browning-only Isc loss. The modules with delamination defect can be detected in the field visually or by using a handheld reflectance spectrophotometer and with excessive series resistance issue can be detected using the IR imaging.

Saturation of colors: The saturation as shown in Fig. 8 is due to the limitation of number of colors available in color palette of the first iteration for segregating the brown colors with respect to intensity of browning. To tackle this the number of colors in the second iteration has been increased to 30 colors divided based on H and V values of the HSV color system.

Moire Pattern: The curved white/ shiny lines on the image as shown in Fig. 9 are called moire patterns. The patterns are a result of Aliasing effect. The basic reason for the occurrence of this effect in module image is due to the presence of very closely packed silver finger. MATLAB has inbuilt tools to minimize the effect of moire patterns with Anti-Aliasing filters (AA filters) namely cubic, bicubic, bilinear. Lanczos2, and Lanczos3 filters.

The correlation with browning index was skewed and the reason for this result is with the over refinement of the actual data using various tools and will be discussed in detail in the results and discussion section.

B.1.3 Third Iteration- Cell Level

As the module level iterations were having major hindrance with moire patterns, to go around moire patterns cell level images have been taken, a module with series connected cells, highly browned cells would dominate or dictate the overall Isc of the module. The worst looking cells were picked manually by visual inspection of the module. 2 to 4 different cells were picked from each module for the 3rd iteration. Only Lanczos3 filter was used in the 3rd iteration as it had the best correlation in the second iteration. 24 MP camera with wide and zoom lens were used in this iteration, along wetting of front glass of the module.

The area with maximum BI in a cell would generate the least amount of current. Based on this logic, in the third iteration, only the maximum BI of each cell was considered instead of all the BIs of entire module.

III. RESULTS AND DISCUSSION

The MATLAB tool developed in this work went through a lot of modifications from first iteration to final third iteration. The tool is best understood when the results are studied in sequence for each iteration.

First Iteration: The initial iteration had a color palette in which the whole color range was divided into 8 segments and applied for calculating the BI for the module. The correlation of the calculated BI with measured Isc of the 21 modules came out to be 0.093, by eliminating the modules with high series resistance the correlation was improved to 0.411, by further eliminating the modules with mismatch errors the correlation developed to 0.535, by further manually picking and eliminating the clear outliers the correlation has improved to 0.818 as shown in Fig. 10. The reason for the outliers is believed to be the limitation of the color palette with 8 colors and the moire patterns on the images.
resolved by developing a new color palette with 30 colors instead of 8 colors and updated pixel weights. The moire patterns were tried to be minimized by using AA filters inbuilt in MATLAB, the procedure visually could minimize the moire patterns on the images as shown in Fig. 11.

Fig. 11. Moire patterns before (top) and after (bottom) using AA filters

The correlation of BI with the performance parameter (Isc) was adversely affected the correlation after the improvements in decreasing the moire patterns. Upon eliminating the data of modules with other defects and manual outliers, the maximum recorded correlation was about 0.503. Lanczos3 filter was found to be the best.

The primary reason for the high drop in correlation was found to be the over purification/ manipulation of the data by using AA filters with low zoom out factor. An AA filter requires 2 specific inputs, zoom out factor and filter type. Zoom out factor is the factor by which the total number of pixels in both X and Y axis of the original image are reduced to as shown in Fig. 12. Filter type (Lanczos3) is the logical algorithm which determines the way in which the complete data from original image is condensed to the zoomed out final image. 0.7 and 0.98 zoom out fractions were experimentally (manual visual inspection of various images) determined to work best for the project. Thus, 0.7 zoom out fraction was used for the second iteration.

Third Iteration: The primary aim of this iteration was to find a way around moire patterns and improve the correlation between BI and Isc. The Cell level images of the worst browning have been considered for calculating the BI. Lanczos3 filter with 0.98 zoom out factor was used for minimizing any moire patterns. The primary reason for having lesser intensity of moire patterns is due to the use of higher pixel camera (24MP) and cell level images. Cell level images help the camera in clearly differentiating between different fingers on the cell and highly minimizing moire patterns. The images were taken in 3 ways, with zoom lens, wide lens, and with a thin layer of water on the module glass to make it highly transparent (wide lens).

As multiple images were taken for each cell and also multiple cells in a module, maximum BI calculated from each cell is taken as the BI of that cell and maximum of all the maximum BI’s calculated for all the cells of the module is taken as the maximum BI for the module (maximum of maximum, referred as “max”) and average of all the maximum BI’s calculated for all the cells of the module is taken as the average BI for the modules (average of all maxima, referred as “avg”). Upon removal of the outliers and data of modules with other defects, a remarkable Isc correlation coefficient of 0.928 was obtained as shown in the last column of Fig. 13.

Fig. 13. Third iteration - Correlation with no high Rs, mismatch, and outlier modules, 11 AZ Modules, Age – 18 Years

Thus, it has been experimentally determined that the photographs taken after spraying a thin layer of water on the glass surface (referred as “wet-cell”) works the best for the image processing as compared to the dry glass surface (referred as “dry-cell”; Fig. 14). Fig. 15 clearly shows how the processed images obtained using the wet-cell approach have distinct colors and boundaries for two different browned modules. As shown in Fig. 15, the unprocessed dry-cell image (on the left) is mostly covered by both whitish/bluish and brownish colors
and is slightly covered by a blackish color at the bottom edge and bottom right corner. The processed dry-cell image (on the right) still shows the blackish color. However, the unprocessed image of the wet-cell does not show any whitish or blackish color at all. Similarly, the processed image does not show any blackish color at all. The exact reason for the appearance of the blackish color of the dry-cell at the bottom edges and bottom right corners is not known but it may be attributed to the surface roughness caused by the wind-born sand blowing on the glass surface over 18 years in the desert climate or to the formation of a thin layer of cemented soil on the glass surface over 18 years.

Fig. 14. Processed image obtained using the dry-cell approach

Fig. 15. Photographic (left) and processed (right) images of a cell in a module obtained using dry-cell and wet-cell approaches

Upon carefully studying all 3 iterations, it is important to note that a combination of iteration 2 with wet-cell approach seems to work the best provided the photograph is taken before the thin water layer gets dried up.

The standard operating procedure (SOP) of the MATLAB tool developed in this work involves only three human input: identify the file location of the photographic image to be processed; input or use default module detection factor (MDF); input or default relative size factor (RSF). The browning index value and processed image are generated in about 30-300 seconds after hitting the “Run” button. Images taken with a cell phone camera (13 MP) takes about 30 seconds to generate the BI. The high resolution DSLR camera (24 MP) images takes about 300 seconds to generate the BI.

IV SUMMARY

An accurate but quick image processing MATLAB tool to quantify the impact of encapsulant browning on the short-circuit current of field aged PV modules is presented through the determination of browning index (BI). This tool is expected to serve as a key inspection tool in the PV power plants. This tool removes the human subjectivity, accurately quantifies the browning level (current/power loss level or annual degradation rate due only to browning) and reduces the workforce time required for field inspection. The photographs taken with the second iteration on wet glass surface is recommended to be used for image processing to improve the accuracy of the results.

REFERENCES
