

**CRACK DETECTION IN PHOTOVOLTAIC PANEL
ELECTROLUMINESCENCE IMAGE USING MATCHED
FILTER FOR PERFORMANCE LOSS ESTIMATION**

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Abstract

The long-term use of renewable energy investments which have gained importance in recent years, can be realized by tracking errors and malfunctions. It is very important to determine the cracks, microcracks and flaws that occur especially during the production and use of solar energy panels. Errors in the panels can seriously affect the energy production performance of the installed system. According to the panel arrangement in the power plant, flaws in any panel not only affect the energy production of a single panel, but also reduce the production of the entire series to which it is connected. Cracks and faults in solar panels cannot be seen with the naked eye, but can be determined by electroluminescence images. However, detecting these errors requires special expertise and a long examination time. In this study, fractures, microcracks and connection errors are detected automatically from electroluminescence images taken from photovoltaic panels. Before analyzing the images taken with the electroluminescence device, some preprocessing is required. Since the images taken from the installed power plants are not standard in terms of layout, background removal, size and perspective correction are required. In the study, the panels are not examined as a whole, but cell-based examination is carried out. For this reason, the panels are divided into cells. By applying the Matched filter to the dividing cell images, the fractures and cracks are highlighted and the features are extracted. The obtained features are evaluated statistically and the cell status is determined. An accuracy of 98.6% is achieved in determining cell damage status. The losses in the power generation performance of the panel

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are calculated according to the status of all cells on the panel. The calculated values are compared with the measured I-V values. As a result, efficiency loss was calculated with an accuracy rate of 96.2%.

Key words: photovoltaic systems, matched filter, performance estimation, flaw detection

Introduction. The use of carbon-based energy sources causes global warming by inflicting damage that is difficult to repair in our world [1]. However, these energy resources are not unlimited in our world. It is known that after a while, when these energy sources are exhausted, renewable energy sources will be needed in order to continue our lives. For this reason, the whole world has turned to renewable energy sources. Because of this, solar power plants have been established extensively all over the world recently.

Solar energy systems produce energy with 16–18% efficiency in the most ideal conditions with today's technology [2]. Factors such as deterioration in the system or panels and panel temperature, solar radiation and weather conditions can affect efficiency. Particularly, panel failures seriously affect panel efficiency.

Microcracks, solder joint errors, ribbon slips and connector failures can be found in solar panels [3]. The most common panel failures are microcracks [4]. Microcracks that occur in the panels can occur during panel production as well as in the use process due to thermomechanical factors in the power plant area over time [5]. Failures other than this usually occur during the production process and assembly stage.

Detection of the mentioned errors is usually not possible by eye. While visual errors of some serious malfunctions can be seen, many of them cannot be visually understood. Therefore, thermal and electroluminescence (EL) images are used to detect errors. Electroluminescent images are used especially in the detection of errors in the production process. Electroluminescence images are also used to identify malfunctions that occur during use in the field.

Detection and identification of errors by analyzing EL images requires expert personnel and takes a long time. For this reason, panel controls have gained importance recently as the installation of solar power plants has become widespread. For this reason, many studies are carried out on the automation of these processes with computer systems.

In [6], solar panel cells are separated by edge detection methods in EL images. ANWAR and ABDULLAH [7] detected microcracks in polycrystalline panels with image segmentation and anisotropic diffusion filter. In the study of TSAI et al. [8] cracks were determined by extracting features from the panel image with Independent Component Analysis. In the study of SPATARU et al. [9], a matched filter was used to reveal the visibility of the cracks.

In recent years, errors have been determined from EL images by using artificial intelligence methods apart from traditional image processing applications.

AKRAM et al. [10] detected errors in the panel with convolutional neural network from EL images. Similarly, TANG et al. [11] also used deep learning methods to detect errors in PV panels. Cell errors were found with CNN models. Image processing algorithms and GAN models were used to augment the data set before model training. With the trained model, damaged cells could be detected with 83% accuracy.

In the study of RAJPUT et al. [12], EL images taken from solar panels were evaluated on a cell basis. Cell energy performance was calculated based on the luminance value. In addition, panel performance was determined by I-V measurements. By comparing the calculated value with the measured value, an estimate was made with an accuracy of 77%. In [13], features were extracted from cell images with deep learning methods and classification was made with machine learning algorithms. In [14], the data set made available to the public was used. In the study, cells were divided into 2 and 4 different classes. The best results were obtained with SVM. An accuracy of 94.52% was obtained in separating into two classes and 89.63% in separating into four classes. In the study of KARIMI et al. [15], 90 EL panel images were divided into cells after preprocessing. The features were extracted from the cell images and separated into three classes with SVM with 99% accuracy. BODNÁR et al. [16] used EL images to examine the performance degradation of installed panels. The relationship between the performance values obtained by I-V measurements and the errors in the EL images was determined. A new method called generalized quantitative electroluminescence (g-QUEL) has been proposed to determine the effect of EL images on performance [17]. The performance loss was determined by calculating the PV panel parameters mathematically. Performance estimation was made with approximately 3% error.

In this study, fractures, microcracks and connection errors are determined with EL images in PV panels. Detection of errors in panels is performed on a cell basis. Matched Filter is used to reveal the characteristics of the errors in the panel for the analysis of the images. With the appropriate parameters selected, faulty areas in the image are highlighted and other parts are suppressed. In this way, automatic error detection will be possible. The effect of the errors detected depending on the panel layout on the panel energy production performance is calculated. In order to evaluate the power loss caused by the errors determined as a result of the analysis, I-V measurements of the tested PV panels are taken. The I-V measuring device provides the measurement of the output voltage and current of the PV modules under certain radiation. It is possible to determine the performance of the whole module with the I-V curve drawn with the data obtained as a result of the measurement. Thus, the performance of the proposed method will be evaluated.

Method and dataset. In this study, five PV panels taken to the warehouse for long-term control in the power generation area and five PV panels directly

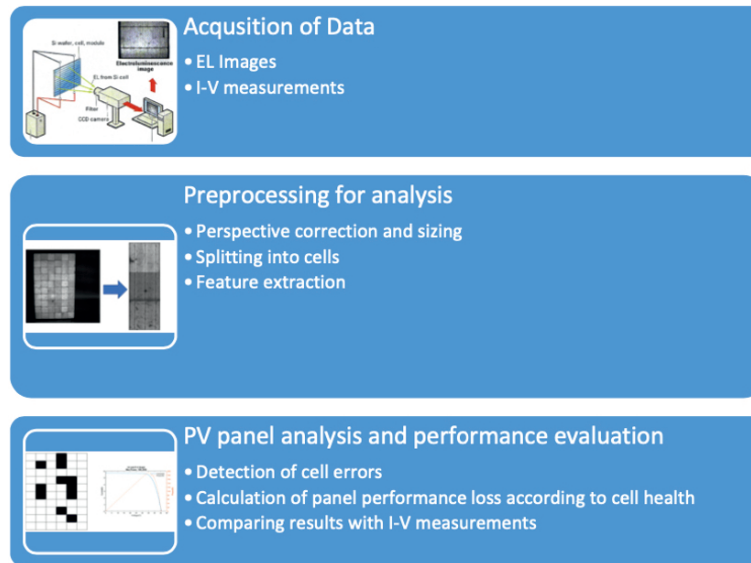


Fig. 1. Flowchart of proposed method

taken from the factory production line were used. EL images of these panels were taken with the Greateyes Lumisolar Outdoor Line-Powered device [18]. The connection applied during the image acquisition process is shown in Fig. 1. The images taken when the PV panel is energized in a dark environment are 2048×2048 in size. In the PV panel with high voltage, the faults in the cells have different brightness values. These differences are used to detect errors in the panel. The EL image of a panel taken from the field is cropped, cleared of the background, and then perspective corrected.

The images used in the study are not taken in standard and fixed environments. Therefore, they need some preprocessing before they can be used for analysis. First of all, perspective distortion in the images due to the viewing angle is eliminated. Afterwards, all of the PV panel images are fixed in size. The next step is to separate the cells in the panels. The PV panels used in the study are placed in the form of 6×10 cells. In this way, it evaluates 600 cells for ten panels.

Matched Filter is applied to visually reveal the cracks and micro-cracks in the cells. In this way, necessary features are extracted to detect errors. In the next step, faults on the panels are determined by performing edge detection. A score is given to the cell according to the amount of error determined. In the last stage of the study, the performance loss to be experienced in the panel will be calculated according to the health status of the cells. Verification of the calculated value will be done according to the I-V measurement values of the panel. The general working diagram of the method proposed in the study is shown in Fig. 1.

The two-dimensional comparison filter (2D Matched Filter) is created by using the Gaussian function given in [19]

$$(1) \quad g(x, y) = 1 - \exp\left(-\frac{x^2 + y^2}{2\sigma^1}\right).$$

It outputs in the image to highlight the crack profile-like visuals. It is actually a filter bank created by combining many Gaussian filters. The filters reveal cracks of different thickness and orientation in the image. 3, 7 and 11 size filters are created to detect cracks of different sizes in the filter bank. Twelve different filters are obtained by rotating the filter whose size is determined in the range of 0–180° at 15° intervals as stated in

$$(2) \quad R_\theta = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}.$$

In this study, 0°, 90° and 180° angles should not be perceived as broken since they are the angles of the panel edge lines. For this reason, filters belonging to these angles are removed and processed.

Thresholding is used to split the flawed areas in the filtered images. Since the average brightness of the images is not the same, the adaptive threshold value should be determined. For this reason, the Otsu algorithm is used to determine the threshold value depending on the brightness variance value in the image. As a result of the thresholding process, defects and microcracks in the cell image will be completely exposed.

In the next step, the cell will be marked as healthy or defective according to the amount of defective pixels determined in the cell. The performance loss of the panel is calculated by determining the effect on the panel performance according to the location and health status of the cells. In PV panels, cells are connected in a matrix manner as rows and columns [20].

Cells in rows are connected in series, while in columns there are parallel connections. In this case, the defective panel in a row affects the entire column. The performance of the panel is calculated as expressed in

$$(3) \quad P = \sum_{i=1}^m \left(\bigcap_{j=1}^n \text{Cell}_{j,i} \right) \frac{\text{TotalPower}}{m},$$

where P indicates the power that can be obtained from the panel, m is the number of columns, and n is the number of rows. Cell value represents the health information of the cell. TotalPower value indicates the maximum amount of power that can be obtained from the panel.

The accuracy of the proposed method is determined by comparing the calculated power value for the tested PV panel with the measured I-V value.

Experimental results. EL images and I-V measurements used in the study were taken at the GAP Yenev research center. The tests of the proposed method were carried out on a computer with Intel i9 processor, 64 Gb Ram and Tesla K40C graphics card. The application was written and run with Matlab program.

First of all, the images taken in the study should be prepared before the analysis. It is corrected for this purpose. The panels are then divided into cells.

Initially, a matched filter is applied to Cell images. With the parameters expressed in the matched filter method section used in the study, abnormal pixel changes, other than the lines in the nature of the panel, become evident. These transitions are known to be cracks and fractures. Threshold value is calculated with Otsu algorithm for the obtained image. The image is converted to binary image with the calculated threshold value. Some small noises are cleared in the image and the exact defective parts are determined. The state of the cell is determined according to the number of pixels determined as cracked or broken in the binary image. The cell is marked as damaged if there are more than 5% of the total pixel count of the cell image with cracked pixels. The decision is made based on the number of pixels marked as abnormal, regardless of the type or location of cracks in the cell.

The matched filter output (Fig. 2b) and thresholded sample cell are shown in Fig. 2. In the resulting Fig. 2c image, after the noises are cleared, the defective areas in the cell remain.

Figure 3 shows the state of the cells in the two panels. In the panel in Fig. 3a, it is seen that three out of six columns are defective. In this case, it is calculated that there is a 50% power loss. However, in Fig. 3b, only one column of defective cells is detected. The performance loss in this panel is approximately 16.6%. In Figure 3c and d, I-V graphics of the panels given are shown.

In this study, panels of the same type were used in the experiments. Five of these panels are new and five of them are used and evaluated separately. The results obtained in the experiments carried out on panels with 350 W power are

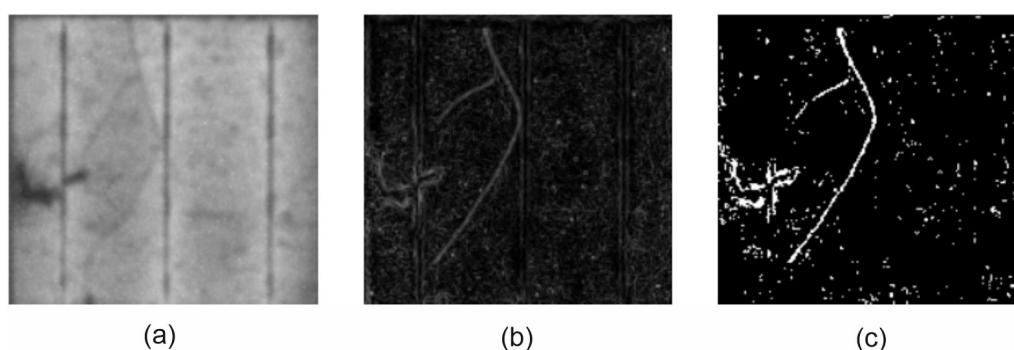
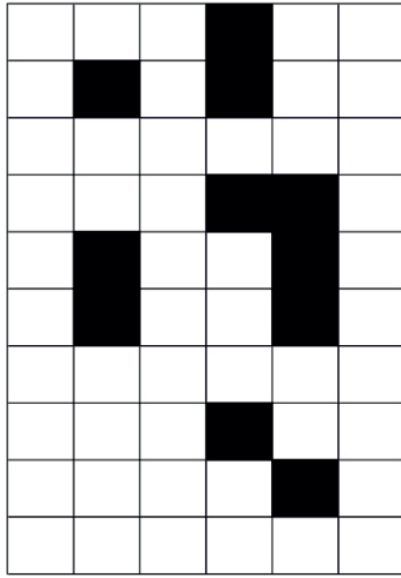
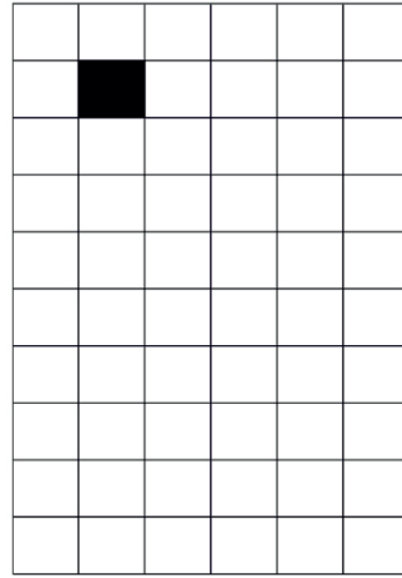


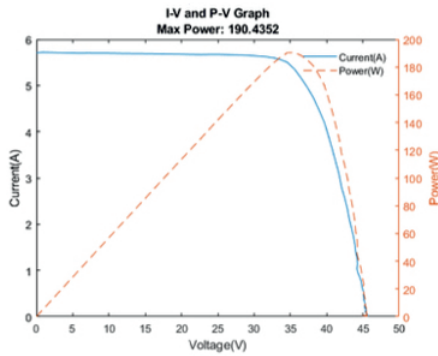
Fig. 2. (a) Cracked cell image; (b) Output of matched filter; (c) Output of thresholding operation



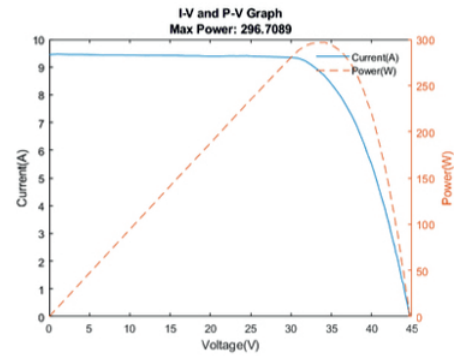
(a)



(b)



(c)



(d)

Fig. 3. (a) Defective cells in a used panel; (b) Defective cells in a new panel; (c) I-V graph of the panel shown in (a); (d) I-V graph of the panel shown in (b)

shown in Table 1. According to the results given in Table 1, it is seen that the power loss is higher in used panels. It is seen that the panel power estimated by the proposed method for used panels is different from the measured panel power. This is because used panels have more broken or cracked areas. This makes it difficult to identify cracks completely. The presence of fewer cracks in the new panels allows to calculate the panel performance loss more accurately.

In the tests performed, ten different panels were used with the proposed method. The panel performance determined by the method was compared with

T a b l e 1

Estimated panel power values and the difference with the actual value

	Panel name	PV Panel No	Catalogue performance value of the panel	Estimated performance value with proposed method	Performance value measured with I-V	Absolute difference between estimate and measured value (W)	Difference between estimated and measured value (%)
Used panels	PV1	350	233.33	220.00	13.33	5.71	
	PV2	350	175.00	165.00	10	5.71	
	PV3	350	175.00	190.00	15	8.57	
	PV4	350	233.3	223.00	10.33	4.43	
	PV5	350	291.67	310.00	18.33	6.29	
	Used panel average					13.398	6.142
New panels	PV6	350	291.67	296.00	4.33	1.49	
	PV7	350	350.00	355.00	5	1.43	
	PV8	350	291.67	289.00	2.67	0.91	
	PV9	350	291.67	297.00	5.33	1.83	
	PV10	350	350.00	345.00	5	1.43	
	New panel average					4.466	1.418
All panels average					8.932	3.78	

the I-V measurement. In the tests performed, 98.6% accuracy was achieved in the detection of defective and healthy cells. The panel performance calculated according to the detected defective cells was 96.2% accuracy compared to the measured performance value.

The results obtained with the proposed method in this study are at a level that can compete with the studies in the literature. Bodnár et al. [16] and PURANIK et al. [17] have shown that performance evaluation can be made from EL images. In [17], the panel technical features were used in performance evaluation, so it gave more successful results. The proposed method makes performance estimation independent of the panel technical features. Tang et al. [11] and DEMIRCI et al. [13], using the features extracted with deep learning models, determined the cell state by machine learning algorithms. Better results were obtained with the estimation success performed in this study. In addition, these methods require extra effort because they require a training process before classification. In the study of Karimi et al. [15], after pre-processing the panels separated into cells, an estimate of the panel status was made with 99% success. However, in our study, panel energy production performance is calculated depending on the cell status.

Conclusion. In this study, it was seen that the status of PV panels can be determined by EL images. Cell-based analysis is performed to determine the con-

dition of the panels. The performance of the panel was calculated by considering that if there are damaged cells in the columns due to the panel structure, the performance of the entire column will suffer. The results obtained were compared with the I-V measurements and it was seen that acceptable results were achieved.

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