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Image Processing-based Assessment of Dust Accumulation on Photovoltaic Modules

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***Abstract*— Numerous environmental factors significantly affect the energy yield of solar photovoltaic (PV) power plants. Among these, solar irradiance, photovoltaic module temperature, dust and shading are prominent. The level of soiling is directly related to the installation site of the PV plant. In this study, to investigate the impact of dust shading factor on energy efficiency, artificial light source in laboratory environment is used and power outputs are compared for three different densities of dust accumulation on the module surface. For each level of dust accumulation, images are obtained from PV modules. From the PV module images obtained by a camera for different levels of dust accumulation, new features are obtained based on Gray Level Co-occurrence Matrix. The obtained data with new features are classified on the basis of Artificial Neural Networks to determine dust level and its effect on PV module performance.**

Keywords*— *Soiling, dust deposition, Photovoltaic module, solar energy

I. INTRODUCTION

Solar energy is a free, abundant and clean energy source [1]. Due to these advantages, a number of studies have been conducted throughout the world on efficient photovoltaic (PV) modules to make more use of solar energy. PV module is comprised of semiconductor diodes exposed to light to convert sunlight to usable energy. The efficiency of the energy conversion process is directly related to various factors such as the type of PV cell, orientation and inclination angle of PV module, installation type, location, cell temperature, shading, deposition of dust and pollution on module surface [2]. The dust accumulation on the cover glass of PV module traps solar irradiance and causes reflecting [3]. Soiling includes not only dust accumulation but also surface pollutions such as plant products, soot, salt deposits and bird droppings [4].

The regions with the highest annual sunlight are mainly desert regions. In these regions, the main reason for the decrease in efficiency is the difficulty of cleaning the deposited dust on the surface of PV modules due to the low rainfall [5]. This degrades the performance of the PV system [6]. The result of an eight-month survey in Saudi Arabia showed that power generation in PV arrays decreased by 32% due to dust accumulation [7]. In another study, a six-day PV module monitoring performed outdoor resulted a decrease by 17% of energy efficiency [8].

The objective of this study is the classification of soiling factor which is a prominent parameter affecting the electricity production of PV modules and determination of its effect on energy efficiency. According to this, dust is deposited artificially on the surface of a 60 watt PV module at high, medium and low densities. Afterwards, an artificial light source is used and power output values for each dust level is compared. Hence, the effect of dusting factor on the efficiency of PV module is evaluated in real time. At the same time, for three different levels of deposited dust, images are taken from the module and from the images new features are obtained employing Gray Level Co-occurrence Matrix (GLCM). Afterwards, classification is made based upon artificial neural network (ANN).

This paper is organized as follows. Section 2 describes section system implementation. Section 3 introduces GLCM based estımatıon of soiling on PV module. In section 4, experimental results discussed. Finally, section 5 presents our conclusions.

II. PROPOSED SYSTEM IMPLEMENTATION

PV module test system shown in Fig. 1 is established to trace and evaluate the effect of dust accumulation on PV module in real-time.

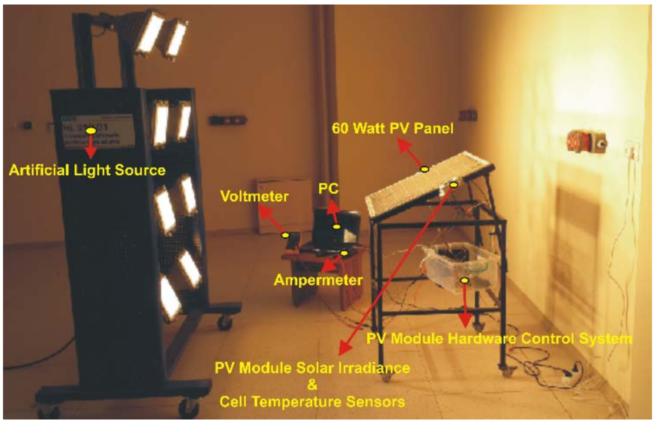

Figure 1. Outline of PV module test system

In the PV module testing system, an ARM based STM32F103C8T6 development card has been used to receive data from the sensors and to process these data. The STM32F103C8T6 development board has an ARM-based 32-bit cortex M3 based microprocessor with a maximum frequency of 72 MHz. In addition, the embedded system board includes communication interfaces such as I2C, USART, SPI, CAN and USB. Within the scope of the study, linear current sensor of ± 75A from Alegro that has magnetic effect is used. This sensor outputs 3.3V analog voltage (18.5mV / A) or 5.5V (28mV / A), with a margin of error less than 2%. An electronic circuit with voltage monitor is designed with the LM741 op-amp circuit to monitor PV module voltage values. In addition, the PV module used in the system is connected to the battery charging system with maximum power point tracking (MPPT). A 12V 18Ah battery is thus efficiently charged during the tests.

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The voltage and current values obtained from the output of the PV module are directly related to the solar irradiation and the PV cell temperature. The power output of the PV module increases with an increase in the quantity of solar irradiation. In contrary, the power output of PV module decreases with an increase in cell temperature. In the PV module test system, Si-01TC-T type irradiation and cell temperature sensor from IMT SOLAR is used. Images are acquired with a camera to determine the degree of pollution of the designed PV module. Figure 2 shows the block diagram of the PV module test system in detail.

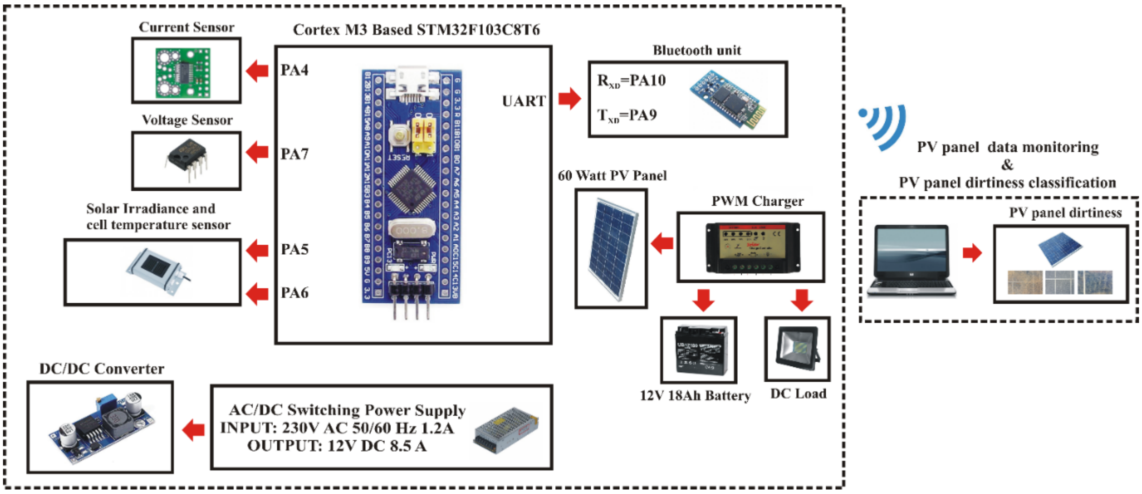

Figure 2. Prototype electronic board designed for the control of overall PV module system

III. GLCM BASED ESTIMATION OF SOILING ON PV MODULE

Humans can make some inferences by perceiving the environment with the help of visual systems. For example, looking at a PV module, one can make a rough judgment about whether it is dirty or clean. However, it is not possible to make any inferences about the extent of the effect of pollution level on energy efficiency. Because in such cases, based on numerical variables and long-term monitoring, a number of measurable quantities of PV modules must be utilized. Within the scope of this study, the degree of PV module pollution was classified using artificial intelligence techniques without any human intervention. In order to make this classification, the textures obtained from the PV module were evaluated. Texture is an important feature for identifying the relevant regions in an image. Gray level co-occurrence matrix (GLCM) is one of the effective methods used to classify the texture. This method is one of the best statistical approaches that can describe the second order statistical properties of texture image. These statistical properties are extracted by means of the GLCM matrix generated by considering the spatial relationship of the pixels in the image. Fig. 3 shows the GLCM-based ANN classifier algorithm scheme used in the PV system.

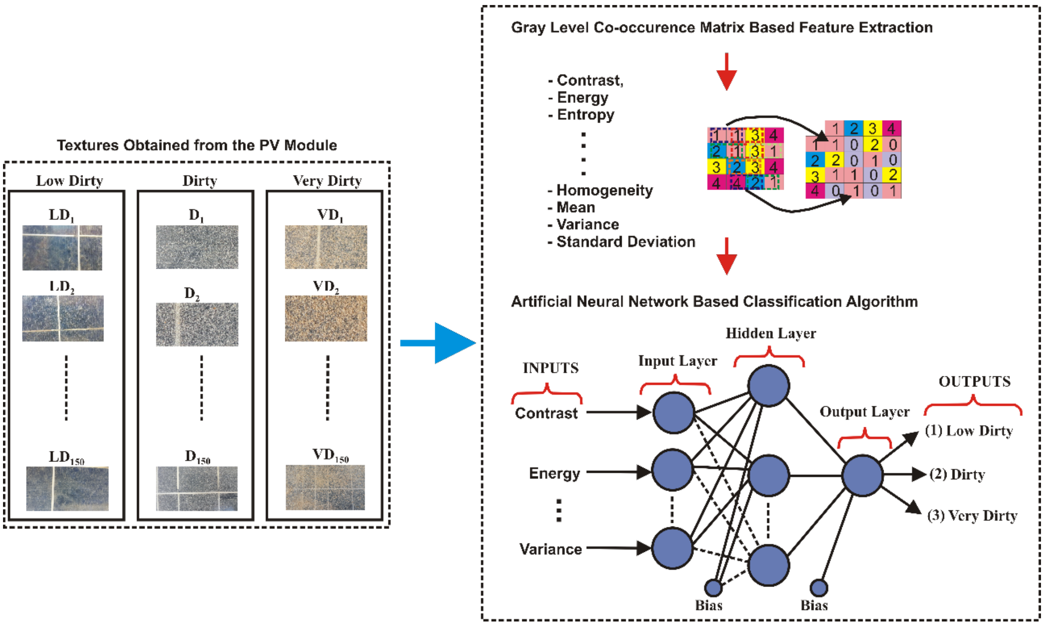

Figure 3. The algorithm diagram of GLCM based ANN classifier

IV. EXPERIMENTAL RESULTS

In this study, the PV module was artificially polluted at three different pollution levels. Afterwards, the test system was operated using the artificial light source and MPPT-based battery charging, and a number of system data such as PV module voltage and current, solar irradiation and cell temperature were obtained for three different pollution levels. Fig. 4 shows the variation of PV cell temperature during the test performed at different levels of pollution.

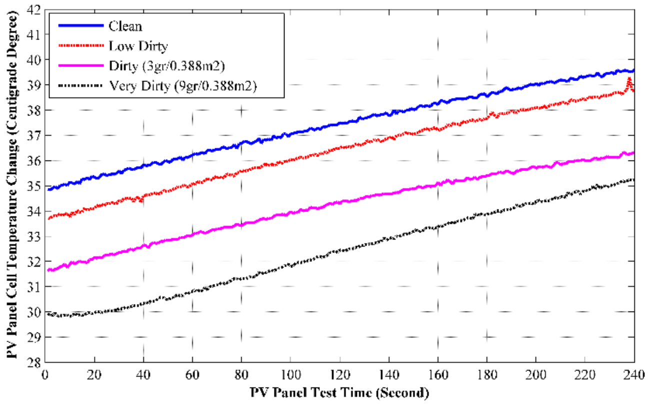

Figure 4. PV cell temperature change

In order to be able to accurately evaluate the effect of the pollution factor on the conversion efficiency of the PV system, the artificial solar irradiation values must be very close to each other. Fig. 5 shows the artificial solar irradiation values of the tests performed at different levels of pollution.

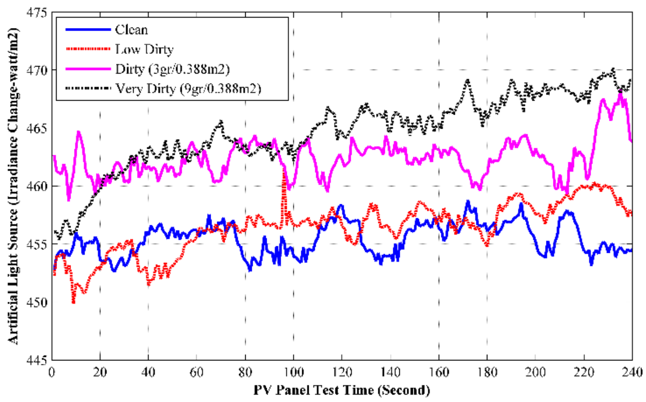

Figure 5. Variation of solar irradiation on PV module

Variable parameters such as current and voltage at 3 different pollution levels were obtained in real time from the designed PV system for 4 minutes. The obtained data were used to acquire power values of the module for the same artificial solar irradiation values. It is clear that the cell temperature and the artificial solar irradiation values on the PV module should be approximately at the same value so that the results obtained from the tests can be interpreted correctly. This case was taken into consideration in the study. Figure 6 depicts the electrical power outputs from the PV module for different levels of pollution in real time. As shown in Figure 6, when the PV module is clean, the electrical power output is approximately 20 watts, whereas 16 watts when it is less dirty, 14 watts when it is dirty and 12 watts when it is very dirty. As can be seen from the results, as expected, the efficiency of the system decreases as PV pollution level increases.

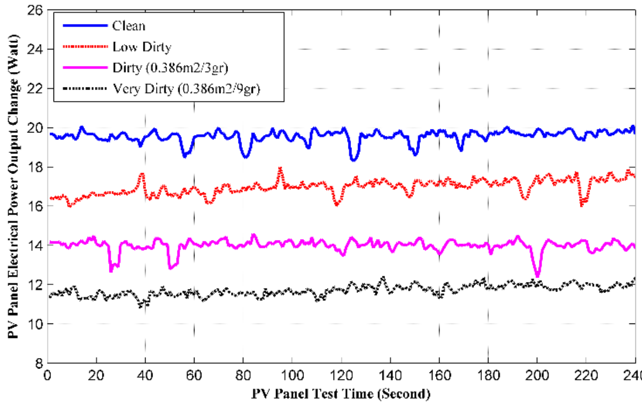

Figure 6. Variations of PV module electrical power outputs

Texture images have been obtained for 3 different levels of pollution in PV system. New features based on GLCM have been obtained from PV module pollution images taken by a camera. These new features were classified by artificial neural networks and the degree of pollution of PV modules was classified. Variable parameters in the artificial neural network are Hidden Layer Neuron Number (HLNN), Learning Rate (LR) and Activation Function (AF). In addition to these variables of the neural network system, the selection of Momentum Constant (MC) is also vital. Because, in order to accelerate neural network training, heuristic approaches such as momentum or variable/adaptive learning rate have been used [9]. Therefore, a value of 0.9 for MC was kept constant in the neural network model. Finally, the number of iterations was taken as 1000.

The employed ANN structure is a feed-forward and multilayer network that is trained with back-propagation algorithm. The neural network model used consists of the input layer, hidden layer and output layer. Since the input of the system consists of 19 features, there are 19 nodes in the input layer. The number of neurons in the output layer was taken as 1. Thus, the output value is converted to 3 different outputs according to the activation function used. In order to increase the sensitivity of the neural network, the values of 6, 7, 8, 9, 10 for the number of intermediate neurons, and the values of 0.4, 0.6, 0.8, 1.0, 1.2 for the learning rate were tested. In addition, operations were performed based on the values from which the optimum result was obtained for all folds. Different activation functions (tansig and purelin) were used for neurons in hidden and output layers. Thus, the objective was to determine the most appropriate predictive network structure. Training and test process was performed using a value of 0.001 for stop criterion.

First of all, the performance of the classification results in case of different LR and HLNN for the tangent sigmoid activation function is summarized in Table 1. As seen in Table 1, the highest performance in the neural network model used to estimate the degree of pollution in PV system was obtained when LR = 0.8 and HLNN = 7. Finally, for the pollution estimation of the PV system, experiments have been conducted for purelin activation function and the data related to these trials are detailed in Table 2. As shown in Table 2, the highest performance in the neural network model used for estimating the degree of pollution in PV system was obtained when LR = 0.4 and HLNN = 7.

TABLE I. ESTIMATION RESULTS IN PERCENT FOR TANSIG ACTIVATION FUNCTION

HLNN	Performance Criteria	FN	LR=0.4	LR=0.6	LR=0.8	LR=1.0	LR=1.2
6	Accuracy (%)	19	96.29	95.71	95.71	95.71	95.71
	Test Time (s)		24.49	26.42	26.34	26.51	25.14
	Standard Deviation		2.71	3.09	2.78	3.37	3.09
7	Accuracy (%)	19	96.86	96.57	96.86	96.29	96.29
	Test Time (s)		30.17	29.27	28.63	32.47	29.51
	Standard Deviation		2.11	3.51	2.11	3.58	3.31
8	Accuracy (%)	19	96.00	95.43	95.43	95.43	94.86
	Test Time (s)		28.62	31.23	28.75	30.07	30.21
	Standard Deviation		2.76	2.41	2.41	3.07	2.63
9	Accuracy (%)	19	96.29	96.57	95.71	96.57	96.29
	Test Time (s)		26.12	24.22	26.57	30.03	27.61
	Standard Deviation		3.58	3.51	3.63	3.51	3.82
10	Accuracy (%)	19	94.86	95.14	94.86	95.14	94.86
	Test Time (s)		29.80	28.63	29.52	29.48	30.89
	Standard Deviation		3.24	3.31	3.24	3.31	3.24

TABLE II. ESTIMATION RESULTS IN PERCENT FOR PURELIN ACTIVATION FUNCTION

HLNN	Performance Criteria	FN	LR=0.4	LR=0.6	LR=0.8	LR=1.0	LR=1.2
6	Accuracy (%)	19	89.14	89.14	89.14	89.14	88.57
	Test Time (s)		21.35	24.46	22.63	20.42	22.09
	Standard Deviation		5.68	5.68	5.68	5.68	5.04
7	Accuracy (%)	19	91.43	90.86	90.86	90.86	90.86
	Test Time (s)		19.89	19.38	20.27	19.46	20.97
	Standard Deviation		4.26	4.22	4.43	4.43	4.22
8	Accuracy (%)	19	90.00	90.00	90.00	89.71	90.57
	Test Time (s)		25.47	23.11	24.48	24.23	25.69
	Standard Deviation		4.31	4.31	4.31	4.30	4.87
9	Accuracy (%)	19	88.00	88.00	88.00	88.86	87.43
	Test Time (s)		21.47	19.83	20.26	19.60	22.71
	Standard Deviation		5.18	5.68	5.68	5.29	5.59
10	Accuracy (%)	19	88.86	89.14	89.83	89.43	88.86
	Test Time (s)		22.16	21.63	22.02	22.04	26.57
	Standard Deviation		5.63	5.99	5.72	6.18	5.63

Considering the performance values obtained from Table 1 and Table 2, in terms of the classification of the degree of PV module pollution, the highest performance was obtained in the tansig activation function for LR = 0.8 and HLNN = 7. Therefore, the artificial neural network model structure was carried out by considering these parameters.

V. CONCLUSION

The present study was designed to evaluate the performance degradation of PV module. With the help of image processing techniques, the degree of PV module pollution was predicted. As a result of this investigation, an inference has been obtained regarding the level of PV module pollution, which significantly affects the power output of the PV module. The realized system can quickly and effectively determine the degree of pollution that significantly affects the PV module conversion efficiency. On this basis, the findings of this study can be used to judge the necessity or cleaning cycle of the front cover of PV module. Therefore, the operation of PV module can be provided in more efficient conditions. The study can progress by designing robotic systems for cleaning purposes.

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