Accepted Manuscript

Reliable fault detection and diagnosis of photovoltaic systems based on statistical monitoring approaches

Fouzi Harrou, Ying Sun, Bilal Taghezouit, Ahmed Saidi, Mohamed-Elkarim Hamlati

PII: S0960-1481(17)30911-4

DOI: [10.1016/j.renene.2017.09.048](https://doi.org/10.1016/j.renene.2017.09.048)

Reference: RENE 9246

To appear in: *Renewable Energy*

Received Date: 21 March 2017

Revised Date: 29 August 2017

Accepted Date: 14 September 2017

Please cite this article as: Harrou F, Sun Y, Taghezouit B, Saidi A, Hamlati M-E, Reliable fault detection and diagnosis of photovoltaic systems based on statistical monitoring approaches, *Renewable Energy* (2017), doi: 10.1016/j.renene.2017.09.048.

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

Reliable fault detection and diagnosis of photovoltaic systems based on statistical monitoring approaches

Fouzi Harrou^a, Ying Sun^a, Bilal Taghezouit^b, Ahmed Saidi^c, Mohamed-Elkarim Hamlati^c

^aKing Abdullah University of Science and Technology (KAUST)

Computer, Electrical and Mathematical Sciences and Engineering (CEMSE) Division, Thuwal 23955-6900, Saudi Arabia

Tel: +966.12808.0602, Fax: +966.12802.1386, E-mail: fouzi.harrou@kaust.edu.sa

^bCentre de Développement des Energies Renouvelables, CDER, B.P. 62, Route de l'Observatoire, Bouzaréah, Algiers, 16340, Algeria, E-mail: b.taghezouit@gmail.com

^cSmart Grids and Renewable Energie (SGRE) Laboratory, Electrical Engineering Department, Tahri Mohammed University, BP 417 Route de Kenadsa, Béchar, Algeria

Abstract

This study reports the development of an innovative fault detection and diagnosis scheme to monitor the direct current (DC) side of photovoltaic (PV) systems. Towards this end, we propose a statistical approach that exploits the advantages of one-diode model and those of the univariate and multivariate exponentially weighted moving average (EWMA) charts to better detect faults. Specifically, we generate array's residuals of current, voltage and power using measured temperature and irradiance. These residuals capture the difference between the measurements and the predictions MPP for the current, voltage and power from the one-diode model, and use them as fault indicators. Then, we apply the multivariate EWMA (MEWMA) monitoring chart to the residuals to detect faults. However, a MEWMA scheme cannot identify the type of fault. Once a fault is detected in MEWMA chart, the univariate EWMA chart based on current and voltage indicators is used to identify the type of fault (e.g., short-circuit, open-circuit and shading faults). We applied this strategy to real data from the grid-connected PV system installed at the Renewable Energy Development Center, Algeria. Results show the capacity of the proposed strategy to monitor the DC side of PV systems and detect partial shading.

Keywords: Fault detection, Partial shading, Photovoltaic systems, One-diode model, statistical monitoring charts.

1. Introduction

Renewable energy is a key challenging problem increasingly gaining attention worldwide. Renewable energy sources, such as solar and wind, are promising alternatives to conventional fossil fuels because they are clean, sustainable, safe, and environment-friendly with zero CO₂ emissions. For instance, [1] showed that 100 gigawatts of photovoltaic (PV)-generated power in Europe in 2012 kept more than 53 million tons

of CO₂ from being emitted into the atmosphere. Furthermore, solar PV energy, which is one of the most sustainable and economically competitive renewable energy sources, increases a countries' energy security by reducing their dependency on fossil fuels.

Although the high progress in PV systems technology to ensure their optimal operations, in practice several factors can affect significantly the PV system performance by decreasing its efficiency. Indeed, PV systems are frequently exposed to different sources of faults and failures that affect the power generated by the PV modules (e.g., short-circuit, open-circuit and shading faults). These faults could reduce considerably both their production efficiencies and lifespan [2]. This is mainly due to external interferences or faults resulting from dust accumulation on the PV modules [3], aging of PV modules [4], shading [5], MPPT error [6], and inverters faults [7]. Faults in DC side of PV systems are often difficult to avoid and can result in energy loss, system shutdown or even in serious safety concerns [8, 9]. For example, two PV facilities in the US (a 383 KWp PV array in Bakersfield, CA and a 1.208 MWp power plant in Mount Holly, NC) burned in 2009 and 2011, respectively [8]. The source for these accidents was a fault on the DC side that was not identified early [10, 11]. Therefore, it is crucial to detect and identify possible faults or failures in the monitored PV systems as early as possible. Hence, an accurate and prompt fault detection and diagnosis strategy is required to improve PV system efficiencies, avoid the high cost of maintenance, and reduce risks of fire hazards which could affect both personnel and installed equipment.

Keeping a PV system running smoothly and safely and generating the desired power remains a major challenge in grid-connected PV systems [12]. Therefore, monitoring in PV systems has lately received special attention from researchers and practitioners in the field of safety engineering. Increased attention to fault detection and safety has led to the development of several fault detection techniques that can be grouped into two main families: model-based and data-based fault detection techniques [13, 14, 15, 16, 17, 18]. Data-based methods use implicit empirical models derived from analysis of available data and rely on computational intelligence and machine learning methods. The approaches in this category are mostly based on artificial neural network [13, 19], fuzzy logic [18] and Bayesian neural network [20]. Such methods require a minimal a prior knowledge about a PV system, but depends on the availability of quality input data. On the other hand, Model-based approaches compare analytically computed outputs with measured values and signal an alarm when large differences are detected [21, 10]. Model-based fault detection methods include, one-diode-based fault detection approaches [22, 21], Kalman filter [23], and Fourier series [24]. Of course, the effectiveness of model-based fault-detection approaches relies on the accuracy of the used models.

To enhance PV system operation, we want to not only monitor the system in an efficient manner, but

also successfully identify the type of faults. Faults in PV systems may result in performance degradation of PV plants, reliability reduction, and profitability decrease, therefore, it is of great importance to monitor accurately PV systems performances. Statistical process monitoring charts are some of the tools that have been applied to achieve these objectives. It is a major tool for monitoring sequential systems to make sure that they work stably and satisfactory.

In this work, we propose a practical and simple scheme to monitor the DC side of PV system. A new fault detection method for monitoring PV systems based on statistical control charts is presented. This method merges the flexibility of one-diode model and the greater sensitivity of the univariate and multivariate exponentially-weighted moving average (EWMA) control charts to insidious changes. Specifically, the residuals, which are the differences between the measured and predicted MPP for the current, voltage and power, obtained from the one-diode model are used as the input data of the MEWMA chart to reveal abnormalities. MEWMA charts, incorporates information from the entire process history, rather than just using the most recent observations, so that they are more sensitive to small changes. These charts take the correlations between variables into account and monitor a set of cross-correlated variables simultaneously. Moreover, the main advantage of MEWMA chart is that it can be easily implemented in real time because of the low computational cost. However, the main drawback of the MEWMA chart is that it cannot identify the fault type. To overcome this drawback, the adopted method allows also identification of the type of fault by using univariate EWMA based on current and voltage indicators. We validate our fault detection strategy using measurements from the 9.6 kWp PV plant at the Renewable Energy Development Center in Algiers, Algeria.

The following section gives a brief overview of the grid-connected PV plant that provided data for this study and our data acquisition techniques. In Section 3, we review one-diode model. Section 4 briefly reviews the univariate and multivariate EWMA charts. We then introduce new fault detection and diagnosis strategy in Section 5. In Section 6, the performances of the proposed methods are illustrated in a real data application, and Section 7 concludes with a discussion.

2. Description of case study data

The geographical location of Algeria provides it a high solar potential and good solar energy exposure (see Figure 14). Indeed, Algeria with abundant solar radiation throughout the year is more suitable for solar energy production. By receiving an average of 3000 hours/year of solar radiation, Algeria has the highest solar potential of the Mediterranean basin (169440 TWh/year) [25]. Algeria intends to invest even more in

the near future to the renewable resources of energy, although the oil and gas production is still in a high level. By 2030 more than 37% of national electricity in Algeria is expected to be produced by solar energy.

Figure 1: Global Horizontal Irradiation in Algeria.

In this study, we validated our fault detection method using practical data collected from a grid-connected photovoltaic (GCPV) system located at Renewable Energy Development Center (CDER) in Algiers, Algeria. This PV system of 90 PV modules, which is 9.6 kW rated system, has an output DC voltage of 125-450 V and an output AC voltage of 220 V. It consists of three sub-arrays of 30 PV modules each (see Figure 2).

Figure 2: CDER grid-connected PV system composed of three sub-arrays.

Each sub-array, which is connected to a 3 kW (SMA Sunny Boy TL-3000) single-phase inverter (see Figure 2), consists of 30 Isofoton (106 W-12 V) PV modules grouped into two parallel strings of fifteen PV

modules in series. Irradiance on titled plane (27°) and PV module temperature measurements are collected with a SMA Sunny SensorBox. A Sunny WebBox collects and documents all electrical data from inverters and the meteorological data measured by sensorbox, thus permitting interruption-free monitoring of the PV plant, a safety control box and a meter. The Sunny WebBox provides the operator with all recorded data via an Internet connection. When the utility grid is not energized the inverter immediately stops providing power to the grid. The main components of the GCPV system are shown in Figure 3.

Figure 3: The main components of grid-connected PV system used in this study.

We used data from one sub-array to simulate both healthy and faulty operating conditions under various meteorological conditions. The electrical and physical characteristics of the Isofoton 106-12 PV module are summarized in Table 1. The real measurements (ie., MPP voltage and current) were collected every five minutes.

2.1. Typical faults in PV systems

Generally, a PV system can be affected by different types of faults that can result in significant loss of power in a PV system. According to the fault duration, two types of faults can be distinguished: temporary and permanent faults (see Figure 4). Temporary faults, such as shading, disappear after a certain period of time or after being manually cleared in cases of dust, leaves or bird dropping. The PV system then returns to its normal operating conditions. On the other hand, permanent faults, including short circuits and open circuits are persistent or ongoing. Indeed, a short-circuit fault can affect PV cells, bypass diodes or PV modules. It is mainly due to the infiltration of water into PV modules or to bad wiring between the PV module and the inverter.

Table 1: Electrical and physical characteristics of the Isofoton 106-12 PV module under standard test condition.

Electrical characteristics of the solar panels tested in this study	Value
Electrics specifications	
Peak power (P_{MPP})	106 W
Voltage at maximum power point (V_{MPP})	17.4 V
Current at maximum power point (I_{MPP})	6.10 A
Open circuit voltage (V_{oc})	21.6 V
Short circuit current (I_{sc})	6.54 A
Physics specifications	
Dimensions	1310*654*39,5mm
Weight	11,5 kg
Number of PV cells in series	36
Number of PV cells in parallels	2
Nominal operating PV cell temperature (800 W/m ² , 20°C, am 1.5,1m/s)	47°C
Standard test conditions (STC)	
Solar irradiance	1000 W/m ²
PV module temperature	25°C

Additionally, aging of the PV module, which is caused by long-term operation of the PV system, is one of the main sources of short-circuit faults. Unlike a short-circuit fault, an open-circuit fault may occur if any current path that is in series to the load is accidentally removed or opened from a closed circuit. Such a situation mainly occurs due to a break in wire between PV modules or PV solar cells. On the other hand, A partial shading fault occurs when part of the PV array is shaded while the other part is lightly energized. This occurs due to several reasons including passage of clouds, dirt on the PV module, snow, or any other light barrier. Nearby obstacles might also interfere and cast shadows, resulting in reduced power output. Even a small amount of shade can dramatically reduce the output amperage of a PV system. Another fault usually occurs in PV systems, which is termed degradation faults, is essentially due to aging of PV modules. This fault can be happened when series resistance between PV modules increases over the time. This is mainly due to contacts' adherence reduction in one side and water vapor's corrosion effect .

3. PV module modeling

The one-diode model (ODM) is the most common model used to predict energy production from PV cells [26]. This model is based on modelling the PV solar cell as a light-generated current source connected in parallel with a diode with series and parallel resistance accounting for resistive losses (see Figure 5).

ODM determines the resulting current and voltage given the parameters of the solar PV cell [27] by

Figure 4: Faults in PV systems.

Figure 5: One diode model of solar PV cells and PV modules.

equation (1):

$$I = I_{ph} - \underbrace{I_0 \left[\exp \left(\frac{q(V + R_s I)}{n k_B T} \right) - 1 \right]}_{I_d} - \underbrace{\frac{V + R_s I}{R_{sh}}}_{I_{sh}}, \quad (1)$$

where I and V are the generated current and voltage of the solar PV cell, respectively. I_{ph} , also called the photogenerated current, corresponds to the amount of current generated by incoming photons; it is proportional to the irradiance and the area of the solar PV cell. I_0 is the dark saturation current, n is the diode's ideality factor. R_s and R_{sh} are the series and shunt resistances, respectively. k_B is Boltzmann's constant ($k_B \approx 1.38064852 \times 10^{-23} JK^{-1}$). T is the PV cell's temperature and q is the electronic charge ($q \approx 1.60217662 \times 10^{-19} C$).

The impacts of meteorological conditions, irradiation and temperature, on the current and voltage output of a PV panel are considered by the OMD. Specifically, it can be seen from Equation (1) that the exponential term, $\exp \left(\frac{q(V + R_s I)}{n k_B T} \right)$, depends on temperature, T . Furthermore, the photocurrent given by equation (3) depends on both the solar irradiance and the PV cell temperature [28].

$$I_{ph} = \frac{G}{G_{ref}} \left[I_{ph,ref} + \mu_I (T - T_{ref}) \right], \quad (2)$$

where G is the irradiance (W/m^2), $G_{ref} = 1000W/m^2$ is irradiance at STC, $T_{ref} = 298.15K$ is the PV cell temperature at STC, μ_I is the temperature coefficient of short-circuit current (A/K) provided by the PV module manufacturer, and $I_{ph,ref}$ is the photocurrent at STC. As reported in [29, 30], solar irradiance has a dominant effect on the current parameters. More specifically, short circuit current (I_{sc}) and maximum power point current (I_{mpp}) of $I-V$ curve, increase linearly with increasing irradiance. On other hand, cell temperature has a significant impact on voltage parameters. Indeed, open circuit voltage (Voc) and maximum power point voltage (V_{mpp}) of $I-V$ curve decrease with increasing temperature value [28].

ODM in Equation (1) also depends on the values of five unknown parameters (I_{ph} , I_0 , n , R_s and R_{sh}), which determine overall performance of solar PV cell. These parameters are not provided in the manufacturer's data sheets. Several approaches for extracting these five unknown parameters have been developed that can be grouped into three main classes: analytical methods, iterative methods, and evolutionary computational methods [31]. Analytical methods are based on analytical model to estimate the unknown electrical parameters [32]. The approaches in this category are simple to implement and computational fast and they are appropriate for solar PV cell or PV module under standard test condition (STC) only. However, these approaches are inefficient in cases with a high variation in the meteorological conditions [32]. Other approaches are based on an iterative parameter extraction to estimate the solar PV cell parameters. However, these methods are complex and suffer from singularity problem in the case of a inappropriate choice of the initial condition of the electrical parameters [32, 31]. On the other hand, evolutionary Computational methods are biological inspired methods, rely on mimetic a biological mechanism in solving an optimization problem. These methods received more attention by researchers because of their capacity to achieve the global solution instead of the local one and their simplicity in term of implementation [32].

Indeed, solar PV cell parameters extraction could be defined as an optimization problem, where the cost function to be minimized is the root mean square error (RMSE) between the real measured $I-V$ curves and the estimated based the identified parameters, defined by Equation (3),

$$RMSE = \sqrt{\frac{1}{L} \sum_{i=1}^L \left[f_i(I_{meas}, V_{meas}, \theta) \right]^2}, \quad (3)$$

where $f(I_{meas}, V_{meas}, \theta) = I_{meas} - \left(I_{ph} - I_0 \left[\exp \left(\frac{q(V_{meas} + R_s I_{meas})}{n k_B T} \right) - 1 \right] - \frac{V_{meas} + R_s I_{meas}}{R_{sh}} \right)$, I_{meas} and V_{meas} are the output current and voltage of a PV module, respectively (obtained from a set of outdoor measurements), θ is the vector of the five unknowns electrical parameters, L stands for the number of experimental data used in the parameters extraction process. Indeed, solar cell parameters extraction is

based on the static $I-V$ (current vs. voltage) curve of a reference PV module, which is measured using an $I-V$ curve tracer when the module is isolated from the inverter. These $I-V$ measurements will be used then in the optimization step to extract the one diode model's unknown electrical parameters. Of course, the aim of this optimization is to find the optimal parameters values that minimize the objective function and provides the lowest RMSE value. In this paper, these five parameters are determined from the Artificial Bee Colony (ABC) algorithm [22, 33] based on the available parameters in Table 1 as shown in Figure 6. More specifically, these five parameters are extracted by minimizing the root mean squared error (RMSE) of the measured current (I) and the predicted current via ABC algorithm. This method relies on access to both irradiance and solar panel temperature measurements to predict the MPP coordinates.

Figure 6: Flowchart of the parameter extraction algorithm.

Table 2: Extracted PV module parameters

PV parameters	$I_{ph}[A]$	$I_0[A]$	n	$R_s[\Omega]$	$R_{sh}[\Omega]$
Value	6.54	1.11e-05	1.66	0.1474	202.6

The extracted parameters in Table 2 are used to estimate $I-V$ curve with the same irradiance and temperatures conditions as the experiments. Figure 7 shows the comparison of the real measured $I-V$ curve and the estimated $I-V$ curve using the identified parameters for the used PV module. It can be seen that the estimated $I-V$ curve with optimized parameters fit well with the experimental $I-V$ curve.

Once the PV module parameters are extracted via ABC algorithm, they are used to predict the MPP coordinates of current, voltage and power of the entire PV array. The PV array model is simulated using

Figure 7: Real measured against estimated $I-V$ curve for ISOFOTON 106-12 PV module.

PSIMTM/MatlabTM co-simulation. Using this co-simulation, the entire PV array is physically constructed (physical PV modules) as two parallel PV string, of fifteen PV modules each. This model relies on access to both irradiance and PV module temperature measurements to predict the MPP coordinates.

In this paper we use testing data from clear sky and cloudy days to assess the accuracy of the simulation model. We validate the constructed model with fault-free data from the GCPV system described by Figure 3, from two days of different conditions: cloudy sky (May 11, 2017) and clear sky (May 06, 2017) days' conditions (see Figures 8 and 9, respectively). Figures 10(a-b) respectively shows the measured and predicted DC current and DC power for a cloudy day, May 11, 2017. This figure shows that the model suitably fits the measured data, thus indicating that the selected parameters are satisfactory. This figure also shows that after sunset and during periods of negligible irradiance, the system completely shuts down. This is done to reduce power consumption and thereby increase overall efficiency. Scatter plot of the measured and predicted DC current and DC power are presented in Figure 11(a-b). These plots indicate that simulated model predicts the measured DC current and DC power well.

Measured versus estimated MPP current and power of the Algerian grid connected PV system under clear sky day condition (May 06, 2017) are shown in Figure 12(a-b). From Figure 12, we can see that the measured MPP current and power are well-adjusted by the simulated model. Furthermore, to illustrate the quality of the simulated model, the scatter plots of the measured and predicted DC current and DC power are presented in Figure 13. It is clear that the measured data are well-fitted by the simulated model.

Figure 8: CDER PV system (a) cloudy day profile of temperature level and (b) cloudy day profile of irradiance level for May 11, 2017.

Figure 9: CDER PV system (a) clear day profile of temperature level and (b) clear day profile of irradiance level for May 06, 2017.

Figure 10: Measured and predicted plot of DC current (a) and DC power (b) for May 11, 2017.

Figure 12: Measured and predicted plot of DC current (a) and DC power (b) for May 06, 2017.

Figure 11: Scatter plot of the measured and predicted DC current (a) and DC power (b) for May 11, 2017.

Figure 13: Scatter plot of the measured and predicted DC current (a) and DC power (b) for May 06, 2017.

In addition, to evaluate the quality of the simulation model with the selected parameters, we used three numerical criteria: R^2 , RMSE, and the mean absolute percent error (MAPE). These were calculated, respectively, by Equations (4-6).

$$R^2 = 1 - \frac{\sum_{t=1}^m (y_t - \hat{y}_t)^2}{\sum_{t=1}^m (y_t - \text{mean}(Y))^2}, \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^m (y_t - \hat{y}_t)^2}{m}}, \quad (5)$$

$$MAPE = 100 \left[\sum_{t=1}^m \left(\frac{|y_t - \hat{y}_t|}{|y_t|} \right) \right] / m, \quad (6)$$

where y_t are the measured current values, $\hat{y}_t$ are the corresponding predicted current values obtained from the simulation model and m is the number of samples. Goodness-of-fit results for the three used metrics of performances are presented in Table 3.

Table 3: Statistical validation metrics applied to data in Figure 11.

	Cloudy day		Clear sky day	
	DC current	Power current	DC current	Power current
r^2	0.98	0.98	0.99	0.99
RMSE	0.14	0.25	0.023	0.04
MAPE	2.83 %	3.55 %	1.05%	1.20%

Results in Table 3 show that the simulation model with the selected parameters captures the measured DC current and power. The r^2 values above 0.9 and the low RMSE of 0.14 and the low MAPE of 2.83% demonstrates that the simulation model provides good predictive quality.

4. Univariate and multivariate EWMA fault detection approaches

Statistical monitoring charts, such as univariate EWMA and its multivariate extension MEWMA, have been widely used to monitor industrial processes for many years [34]. Indeed, statistical process control charts can provide early warnings of abnormal changes in system operations, helping operators to identify the onset of potential faults, such as short circuits, open circuits, sensor bias and partial shading. These methods are briefly introduced here.

4.1. EWMA monitoring chart

EWMA is constructed based on exponential weighting of available observations, a design that provides improved sensitivity to small changes in the process mean. EWMA charts are able to detect small shifts in the process mean because the EWMA statistic is a time-weighted average of all previous observations [35, 36]. The EWMA monitoring chart is an anomaly-detection technique widely used by scientists and engineers in various disciplines [34, 37, 38, 39, 40]. The expression for EWMA is defined by equation (7) [34]:

$$\begin{cases} z_t = \lambda x_t + (1 - \lambda) z_{t-1} & \text{if } t > 0 \\ z_0 = \mu_0, & \text{if } t = 0. \end{cases} \quad (7)$$

The starting value, z_0 , is usually set to be the mean of fault-free data, μ_0 . Z_t is the output of EWMA and x_t is the observation from the monitored process at the current time. The forgetting parameter, $\lambda \in [0, 1]$ determines how fast EWMA forgets the data history. Equation (7) can also be rewritten as in (8),

$$z_t = \lambda \sum_{i=1}^t (1 - \lambda)^{t-i} x_i + (1 - \lambda)^t \mu_0, \quad (8)$$

where $\lambda(1 - \lambda)^{n-t}$ is the weight for x_t , which decreases exponentially for past observations. We can see that if λ is small, more weight is assigned to past observations and the chart is efficient at detecting small changes in the process mean. On the other hand, if λ is large, more weight is assigned to the current observation and less weight is assigned to its previous observations. The chart is thus able to detect large shifts [34, 37]. In the special case when $\lambda = 1$, EWMA is equal to the most recent observation, x_t , and provides the same results as the Shewhart chart provides [34]. As λ approaches zero, EWMA approximates the CUSUM criteria, which gives equal weight to historical observations [34].

Under fault-free (healthy) conditions, the standard deviation of z_t is defined by equation (9),

$$\sigma_{z_t} = \sigma_0 \sqrt{\frac{\lambda}{(2 - \lambda)} [1 - (1 - \lambda)^{2t}]}, \quad (9)$$

where σ_0 is the standard deviation of the fault-free or preliminary data. Therefore, in such cases, $z_t \sim \mathcal{N}(\mu_0, \sigma_{z_t}^2)$. However, in the presence of a mean shift at the time point $1 \leq \tau \leq n$, $z_t \sim \mathcal{N}(\mu_0 + [1 - (1 - \lambda)^{n-\tau+1}](\mu_1 - \mu_0), \sigma_{z_t}^2)$. The upper and lower control limits of the EWMA chart for detecting a mean shift are defined by equation (10).

$$UCL/LCL = \mu_0 \pm L\sigma_{z_t}, \quad (10)$$

where L is a multiplier of the EWMA standard deviation, σ_{z_t} . The parameters L and λ need to be set carefully [34, 37]. L is usually specified in practice to be 3, which corresponds to a false alarm rate of 0.27%. If z_t is within the [LCL UCL] interval, then we conclude that the inspected system is under control up to time point t . Otherwise, the inspected system is considered out of control.

4.2. MEWMA monitoring chart

Unlike the univariate EWMA chart, multivariate EWMA method takes the correlation between variables into account and study many variables simultaneously [41]. The MEWMA chart was first introduced by Lowry et al. in the field of quality control [41, 34]. Let $\mathbf{X}_t = (X_1, X_2, \dots, X_m)^T$ be a dataset obtained from a p -dimensional production process. The MEWMA charting statistic is computed at each observation time point by the recursive formula (11) [41].

$$\begin{cases} \mathbf{Z}_t = \Lambda \mathbf{X}_t + (\mathbf{I}_{m \times m} - \Lambda) \mathbf{Z}_{t-1} & \text{if } t > 0 \\ \mathbf{Z}_0 = \mu_0, & \text{if } t = 0 \end{cases} \quad (11)$$

where $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_m)$ and $\lambda_j \in (0, 1]$ is a smoothing index or weight factor for the j -th component

of $\mathbf{X}$, for $j = 1, 2, \dots, m$, and $\mathbf{I}_{m \times m}$ denotes the identity matrix. We can see that if λ is small, then more weight is assigned to past observations. Thus the chart is tuned to have efficiency for detecting small changes in the process mean. On the other hand, if λ is large, then more weight is assigned to the current observations, and the chart is more suitable for detecting large shifts [34]. The MEWMA monitoring statistic is given by equation (12).

$$\mathbf{V}_t^2 = \mathbf{Z}_t^T \Sigma_{\mathbf{Z}_t}^{-1} \mathbf{Z}_t, \quad (12)$$

where $\Sigma_{\mathbf{Z}_t}$ is the covariance matrix of $\mathbf{Z}_t$. Then, the MEWMA chart with the charting statistic $\mathbf{V}_t^2$ gives a signal of mean shift in cases when $\mathbf{V}_t^2$ exceeds a predefined threshold h . The threshold h can be determined via simulation for a given probability of false alarm [34].

5. PV system Monitoring using EWMA and MEWMA charts

Once the PV module's parameters are accurately identified, and the simulation model of the PV array is successfully validated, we can proceed with fault detection and diagnosis. In this section, we will focus on how to detect and isolate faults in the PV system using univariate and multivariate EWMA control charts. The basic idea of using one-diode model for statistical process monitoring is to build a reference model based on the data when the system is operating at a nominal or normal state. The reference model can then be used to monitor the possible abnormal events in the PV system that may lead the process to depart from its normal state. In this paper, the proposed methodology draws together the advantages of two existing approaches. Specifically, we combine the advantages of ODM modeling with those of the univariate and multivariate EWMA monitoring charts which results in an improved fault detection system, especially for detecting small faults in a PV system. To detect faults in the monitored PV system we apply MEWMA chart to the three uncorrelated residuals of MPP current, voltage and power defined in the reference model. Once an abnormal event is detected in a multivariate EWMA chart, the univariate chart based on the residual of DC current and voltage can be utilized to identify the type of faults (see Figure 14).

Residuals estimation, which is crucial in fault detection and isolation, depends on the appropriate system modeling. The differences between the real measured and predicted MPP current, MPP voltage and MPP power obtained from the simulated model are the residuals, described by equation (13), that can be used as indicators to detect a possible fault.

$$\tilde{I}_t = I_t - \hat{I}_t, \quad \tilde{V}_t = V_t - \hat{V}_t, \quad \tilde{P}_t = P_t - \hat{P}_t, \quad t \in [1, n], \quad (13)$$

Figure 14: A flowchart of the proposed fault detection scheme.

284 where I_t and $\hat{I}_t$ are the measured and predicted MPP current, respectively, and V_t and $\hat{V}_t$ are the measured
 285 and predicted MPP voltage; and P_t and $\hat{P}_t$ are the measured and predicted peak power. In this work, the
 286 residuals are used as fault indicators. Indeed, under normal operation, the residuals are close to zero due
 287 to measurement noise and errors, while they significantly deviate from zero in the presence of abnormal
 288 events. The implementation of the developed monitoring methods comprises two stages: off-line modelling
 289 and on-line monitoring. In the off-line modelling phase, simulation model, which is developed mainly based
 290 on the ODM identified parameters, is used to mimic the PV array operation in healthy (free-fault) status.
 291 Residuals, which are difference of MPP results from reference model and the real MPP measurements, are

292 computed. Then, the fault detection procedure is executed by using the reference model with the MEWMA
 293 chart in the on-line monitoring phase. In this approach, the MEWMA monitoring scheme is applied using
 294 the residuals of current, voltage and power. If the matrix of residuals is defined as

$$X = \begin{bmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \\ \vdots \\ \mathbf{X}_n \end{bmatrix} = \begin{bmatrix} \tilde{I}_1 & \tilde{V}_1 & \tilde{P}_1 \\ \tilde{I}_2 & \tilde{V}_2 & \tilde{P}_2 \\ \vdots & \vdots & \vdots \\ \tilde{I}_n & \tilde{V}_n & \tilde{P}_n \end{bmatrix}$$

295 then the MEWMA function can be computed using the residuals matrix given by equation (14).

$$\mathbf{Z}_t = \lambda \mathbf{X}_t + (1 - \lambda) \mathbf{Z}_{t-1}, \quad t \in [1, n]. \quad (14)$$

296 The MEWMA decision function, $\mathbf{V}_t^2$, can be calculated recursively by the formula (15) [41].

$$\mathbf{V}_t^2 = \mathbf{Z}_t^T \boldsymbol{\Sigma}_{\mathbf{Z}_t}^{-1} \mathbf{Z}_t \quad (15)$$

297 where $\boldsymbol{\Sigma}_{\mathbf{Z}_t}$ is the variance-covariance matrix of $\mathbf{Z}_t$.

298 In this case, since the MEWMA control scheme is applied on the residual data matrix, one MEWMA
 299 decision function will be computed to monitor the process. However, this approach can only detect the
 300 presence of anomalies, i.e., it cannot determine their type. This approach is summarized next.

301 1) **Given:**

- 302 • Real measurement of irradiance and PV module temperature
- 303 • Real measurement of maximum power point (MPP) values of current, voltage and power collected
- 304 from the PV plant under normal operating conditions.
- 305 • Module parameters obtained from the PV module datasheet (see Table 1).

306 2) **Build the reference model using the fault-free training data**

- 307 • Extract electrical parameters for the five-parameter model based on the measured PV cell temper-
- 308 ature and irradiance collected from the monitored PV system under normal operating conditions
- 309 (see Section 2) using the Artificial Bee Colony (ABC) algorithm [22]. The extracted parameters
- 310 are then used to simulate the PV system under healthy operation.

- Compute the residuals between the measured and the predicted DC current, DC voltage and DC power (I_{mpp} , V_{mpp} and P_{mpp}) from the constructed model using fault-free data.

- Compute the control limits of the MEWMA chart.

3) Test the new data

- Generate residual vectors, $\tilde{I}$, $\tilde{V}$ and $\tilde{P}$,
- Compute the MEWMA monitoring statistic for the new data using equation (11).

4) Check for faults

- Declare a fault when the MEWMA decision statistic for the new data exceeds the control limits.

Once the fault has been detected using MEWMA chart, the next step is expected to determine its type. The objective of fault isolation is to determine which system variables have contributed to the observed out-of-control behavior, thereby letting the operators and engineers focus on the subsystem where the fault occurred. In this way, fault isolation can effectively help the operators and engineers in the system monitoring and therefore significantly reduce the risk of safety problems or losses in profitability. To improve system operations, we want not only to monitor the system in an efficient manner but also to identify the type of fault that results in any degradation of the PV system, including declines in operation reliability, and profitability, such that we can respond accordingly by making any necessary correction and maintenance to the system. After an alarm shows up in the MEWMA chart, the univariate EWMA chart can be used to identify the type of fault. Towards this end, we apply the EWMA on the residual of output DC current and voltage. Then, we identify the type of fault by analyzing the monitoring results of the EWMA chart. The fault diagnosis procedure is summarized in Figure 14.

6. Results and discussion

6.1. Detection results

Our fault detection scheme is validated using practical data collected from the 9.6 kWp GCPV system installed at CDER in Algeria (see Section 2). In this section, we assess the ability of both univariate and multivariate EWMA charts to detect the presence of faults in the data and to identify the type of detected fault. To assess the strength of the EWMA-based monitoring chart, three case studies involving different types of faults were conducted. In the first case study, it is assumed that the PV system contains one or

more short-circuited module (case A). In the second case study, an open-circuit PV string is considered (case B). In the third case study, the monitored PV system is exposed to partial shadowing (case C). In the fourth case study, a degradation fault in the monitored PV system is considered (case D).

6.1.1. Normal operating conditions

Monitoring results from MEWMA chart under normal operating conditions are shown in Figure 15. It can be seen that the data points in the MEWMA chart are also within the 95% confidence limits (see Figure 15). We can conclude that the reference model describe the data well when no faults are present.

Figure 15: Monitoring results of MEWMA chart under normal operating conditions.

After a process model has been successfully identified, we can proceed with fault detection and diagnosis. Earlier we have concluded that simulated model based on ODM gives a suitable estimate of MPP current, voltage and power. In this section we will focus on how to detect and identify faults in Algerian PV system using the identified model. Using the simulated model, we introduced faults by using the measured solar radiation and temperature as the input (Figure 16). Residuals, which are the difference between measured and predicted MPP current, MPP voltage and MPP power from the simulated model, are used as the input for the MEWMA scheme to detect potential faults.

6.1.2. Case A - open circuit examples

In this case study, we investigate the performance of the two monitoring charts when there is an open-circuit fault in a PV array. To do so, an open-circuit fault in a PV array is introduced by disconnecting the second string from the monitored PV system (see fault #1 in Figure 17). Fault was introduced between sample times 300-500 of testing data.

To monitor the PV system, we first compute the residuals (i.e., $\tilde{I}$, $\tilde{V}$ and $\tilde{P}$). Then we use MEWMA chart for fault detection and EWMA chart for fault diagnosis. The MEWMA chart based on the residuals of output DC current, voltage and power is presented in Figure 18(a).

Figure 16: (a) Profile irradiation level, and (b) Profile of temperature level.

Figure 17: Open-circuit and short-circuit faults.

The shaded area is the region where the fault is introduced. Figures 18(a) indicates that before the occurrence of the fault, MEWMA statistic is below the decision threshold, which means that the PV system is thus working normally. It can be seen from Figures 18(a) that the MEWMA chart based on the output power residuals, $\tilde{P}$, increase significantly and exceed the decision threshold once the fault has been introduced, indicating that there is a significant power loss. Since one of the two strings of a PV array is disconnected at the fault, a large amount of power (nearly 50% of the rated power) is lost. After an alarm shows up in the MEWMA chart, the univariate EWMA chart can be used to diagnose the type of the fault. Monitoring

results of EWMA chart applied on residuals of current and voltage are shown in Figures 18(b-c). The two dashed lines denotes the upper and lower control limits of the univariate EWMA chart. Figure 18(b) shows the presence of abnormal decrease on the current residuals. It can be seen from Figure 18(c) that the DC voltage is almost the same after the occurrence of this open-circuit fault. From this case study, it can be seen that the open-circuit fault in a PV array decreases the DC power output, reduces the array current and results in almost the same array voltage as the healthy PV array. These results indicate the ability of the proposed strategy in detecting and diagnosing open-circuit faults in a PV system.

Figure 18: Monitoring results of a MEWMA chart (a), monitoring results of an EWMA for DC current (b) and DC voltage (c) in the presence of an open-circuit fault.

6.1.3. Case B - short circuit examples

In this case study, the detection of short-circuited modules in the monitored PV system is investigated. Four different situations are considered (see Figure 17, faults #2-#5).

1) *One short-circuited PV module*: In the first example, the second module of the first string is bypassed from observation number 300 until the end of the testing data (see Figure 17, fault #2). Let us first use the MEWMA chart to simultaneously monitor the output DC current, voltage and power. In the chart, λ is chosen to be 0.25. The chart is presented in Figure 19(a), from which we can see that a signal of a fault is given at the 300th time point. The PV system become out-of-control at the time point 300th. MEWMA can easily detect short-circuit fault. To identify the type of the fault, we apply EWMA chart on the residuals of the DC current and voltage. The monitoring results of univariate EWMA with $\lambda = 0.25$ when it is applied to the residuals of the output DC current and voltage are shown in Figure 19(b-c). In this scenario, the DC current residuals are within control limits as shown in Figure 19(b). Figure 19(c) shows that EWMA

statistic based on the residual of the DC voltage could show up and exceed the lower control limit indicating the occurrence of some abnormalities. Thus, we can conclude that the detected fault is related to a faulty module in the string (short-circuited PV module).

Figure 19: Monitoring results of a MEWMA chart (a), monitoring results of an EWMA for DC current (b) and DC voltage (c) in the presence of one short-circuited module.

2) *Three short-circuited PV modules*: In the second example, three modules have been short circuited in the first string (see Figure 17, fault #3). To monitor the PV system, we first compute MPP residuals. Then we use both univariate and multivariate EWMA charts for fault detection and isolation. The performance of the MEWMA chart when it is applied to the residuals of output DC current, voltage and power is presented in Figure 20(a), which shows that the MEWMA statistic clearly violates the decision threshold. This short-circuit fault degrades the performance of the monitored systems and leads to a significant power loss (i.e., approximately 15% power loss). After alarm shows up in the MEWMA chart, the univariate EWMA chart can be used to isolate the fault. Figure 20(b-c) shows the monitoring results of the EWMA chart when it is applied to residuals of the output DC current and voltage. The output DC current from the array does not change by much (see Figure 20(b)). Figure 20(c) shows fault signals because the decrease in output DC voltage in this case is quite large. Because the output DC voltage decreases compared to the output DC voltage of the healthy PV array and the output DC current does not change by much, we then conclude that this fault is a short circuit in the PV array.

3) *Five short-circuited PV modules*: In the third example, five modules in the first string are disconnected (Figure 17, fault #4). This fault leads to a power loss of 30% compared to the healthy PV array. The MEWMA chart is applied to the residuals of DC power, in which $\lambda = 0.25$ and $\alpha = 0.05$, and thus the

Figure 20: Monitoring results of a MEWMA chart (a), monitoring results of an EWMA for DC current (b) and DC voltage (c) in the presence of three short-circuited modules in a PV array.

406 decision threshold h is 6.46. The MEWMA chart is shown in Figure 21(a). This chart can detect this quite
 407 large fault as shown in Figures 21(a). Similarly to the cases above, to identify this fault, we look at the
 408 monitoring results related to the PV array voltage and current (see Figures 21(b-c)). In fact, it is a fault that
 409 corresponds to a short-circuited PV module, since the current does not change by much (see Figure 21(b)),
 410 and EWMA statistic based of voltage is below the control limit (see Figure 21(c)).

Figure 21: Monitoring results of a MEWMA chart (a), monitoring results of an EWMA for DC current (b) and DC voltage (c) in the presence of five short-circuited modules in a PV array.

411 4) *Ten short-circuited PV modules:* In the fourth example, ten modules in the second string of the

monitored PV array were short circuited (see Figure 17, fault #5). Indeed, the fault resulted in large voltage drops and significant power loss (i.e. nearly 63%). MEWMA and univariate EWMA charts can clearly detect and identify this quite large fault (see Figures 22(a-c)). This demonstrates the effectiveness of the proposed strategy in detecting and identifying faults related to short-circuited modules.

Figure 22: Monitoring results of a MEWMA chart (a), monitoring results of an EWMA for DC current (b) and DC voltage (c) in the presence of ten short-circuited modules in a PV array.

6.1.4. Case C - partial shading example

The aim of this case study was to assess the potential of the proposed method to detect and diagnose partial shading faults in a PV system. Towards this end, the first four modules in the string 2 of the PV system were temporarily exposed to partial shading (see Figure 23, fault #6). This fault was introduced between samples 150 and 250. From Figures 24(a-c) shows that by using both univariate and multivariate charts we can detect and identify this fault. This type of fault may cause decreases in current and voltage and significant power loss.

Figure 23: Typical faults in a PV array: partial shading and faulty modules.

Figure 24: Monitoring results of a MEWMA chart (a), monitoring results of an EWMA for DC current (b) and DC voltage (c) in the presence of 4 PV modules partially shaded in the PV system.

6.1.5. Case D - Degradation fault in a PV array

In this case study, the detection of a degradation fault in a PV array is investigated. Degradation fault occurs due to many factors, such as (i) an increase in the series resistance between the modules due to decreased adherence of contacts or corrosion caused by water vapor, and (ii) front surface soiling (i.e. a dirt spot adheres to module surfaces). For this purpose, a degradation fault has simulated by inserting a resistance of 5Ω to the fifth module in String #1 (see Fault #7 in Figure 23), between samples 200 and 500. Results of the MEWMA chart based on the residuals of output DC current, voltage and power are demonstrated in Figure 25. Figure 25 shows that the MEWMA chart can detect this fault. Therefore, a degradation fault in PV a module can result in degradation of the peak power. Figure 25(b-c) shows that the EWMA chart cannot identify the type of the detected fault.

Figure 25: Monitoring results of a MEWMA chart (a), monitoring results of an EWMA for DC current (b) and DC voltage (c) in the presence of degradation fault in PV module.

When looking at multivariate data (i.e., residuals of MPP current and voltage), univariate EWMA chart will ignore the interaction between the correlated variables and therefore result in a misleading analysis, especially for small faults. Multiple key variables need to be monitored simultaneously. MEWMA chart detected this degradation fault because it takes interaction between the correlated variables and monitor them simultaneously. Also, MEWMA chart has a suitable capacity to detect small faults due to extensive memory of the process.

In summary, our developed fault detection scheme provides satisfactory results in detecting and diagnosing short-circuit faults, open-circuit faults in PV strings, temporary shading and degradation fault in a

PV array.

7. Conclusion

Detecting and identifying faults and failures in time can considerably improve efficiency and reliability in PV systems. Accurate fault detection and diagnosis in PV systems are key enablers for maintenance cost savings and, above all, improving the yield. In this paper, a novel fault detection and identification method in the DC part of the PV system has been proposed. This method can be summarized in three main steps: (i) identify the one-diode model parameters, (ii) simulate the entire PV array and validate it experimentally, and (iii) apply MEWMA chart to detect potential faults and univariate EWMA to identify type of detected faults. To be more explicit, after the simulation model is built, it is used to monitor the abnormal events (faults) in the monitored PV system that may lead the system to depart from its normal state. MEWMA scheme, which is based on a decision statistic that takes into account information from past observations with that of current observations, is used as fault detection scheme, specifically in detecting faults with small magnitudes. Another advantage of this scheme is that it can be easily implemented in real time because of its low computational cost. Here, we applied MEWMA chart to the three residuals of MPP current, voltage and power obtained from the simulated model. Once the fault has been detected, the next step is expected to determine its type by using the univariate EWMA chart. To verify the performance, the proposed method was applied to practical data collected from a grid-connected PV system at CDER in Algeria.

First, this work demonstrated through practical data, the significant advantage of simulated model based on ODM in providing accurate estimation of MPP current, voltage and power. This simulated model can be combined with the well established techniques of monitoring for more accurate detection of faults. Second, this work shows that the EWMA and MEWMA techniques are shown to be complementary approaches for fault detection and diagnosis in PV systems. While MEWMA is concerned with detection a fault in the monitoring system based on , EWMA is concerned with identifying type of detected faults. The experiment results showed that the proposed method could detect and identify faults (i.e., open-circuit, short-circuit, temporary shading and PV module degradation faults) in PV system successfully.

The following important perspectives are obtained through this work.

- Accurately identifying faults, such as degradation and shading of small portions of PV module, cannot be guaranteed by using only MPP coordinates of current and voltage. One direction for future research can, therefore, be to incorporate more data inputs (i.e., indicators), such as open circuit voltage

(Voc), short circuit current (Isc), fill factor (FF), series resistance (Rs), and thermal voltage (Vte) to discriminate temporary shading and degradation faults.

- The proposed procedure depends on the measured MPP current, voltage and power of the GCPV system. Therefore, the quality of the algorithm depends on the quality of the measured data and instrumentation used in the PV plants. Future works will be aimed at more extensively assessing the reliability of the proposed approach in the presence of highly noisy data. Moreover, we plan to develop a robust approach to handle noisy data. To do so, wavelet- based multiscale representation, which is a powerful tool for an effective noise-feature separation in the data, will be integrated with the proposed statistical approach.
- If we already know the fault features or we have enough faulty data for training purposes, it would be a rewarding try for us to use the clustering techniques or pattern recognition techniques jointly with the proposed statistical technique to detect complex faults.

Acknowledgement

This publication is based upon work supported by King Abdullah University of Science and Technology (KAUST), Office of Sponsored Research (OSR) under Award No: OSR-2015-CRG4-2582. We would like to thank the reviewers of this article for their insightful comments, which helped us to greatly improve its quality.

References

- [1] G. Masson, M. Latour, M. Reking, I.-T. Theologitis, and M. Papoutsis, "Global market outlook for photovoltaics 2013-2017," *European Photovoltaic Industry Association*, pp. 12-32, 2013.
- [2] Y. Hu, B. Gao, X. Song, G. Tian, K. Li, and X. He, "Photovoltaic fault detection using a parameter based model," *Solar Energy*, vol. 96, pp. 96-102, 2013.
- [3] B. Marion, R. Schaefer, H. Caine, and G. Sanchez, "Measured and modeled photovoltaic system energy losses from snow for Colorado and Wisconsin locations," *Solar Energy*, vol. 97, pp. 112-121, 2013.
- [4] S. Potnuru, D. Pattabiraman, S. Ganesan, and N. Chilakapati, "Positioning of PV panels for reduction in line losses and mismatch losses in PV array," *Renewable Energy*, vol. 78, pp. 264-275, 2015.
- [5] K. Ishaque and Z. Salam, "A review of maximum power point tracking techniques of PV system for uniform insolation and partial shading condition," *Renewable and Sustainable Energy Reviews*, vol. 19, pp. 475-488, 2013.
- [6] A. Reisi, M. Moradi, and S. Jamasb, "Classification and comparison of maximum power point tracking techniques for photovoltaic system: A review," *Renewable and Sustainable Energy Reviews*, vol. 19, pp. 433-443, 2013.

- [7] O. Perpiñán, J. Marcos, and E. Lorenzo, "Electrical power fluctuations in a network of DC/AC inverters in a large PV plant: Relationship between correlation, distance and time scale," *Solar Energy*, vol. 88, pp. 227–241, 2013.
- [8] B. Brooks, "The bakersfield fire-A lesson in ground-fault protection," *SolarPro Mag*, pp. 62–70, 2011.
- [9] M. Alam, F. Khan, J. Johnson, and J. Flicker, "A comprehensive review of catastrophic faults in PV arrays: Types, detection, and mitigation techniques," *IEEE Journal of Photovoltaics*, vol. 5, no. 3, pp. 982–997, 2015.
- [10] S. Vergura, G. Acciani, V. Amoroso, G. Patrono, and F. Vacca, "Descriptive and inferential statistics for supervising and monitoring the operation of PV plants," *IEEE Transactions on Industrial Electronics*, vol. 56, no. 11, pp. 4456–4464, 2009.
- [11] R. Hariharan, M. Chakkarapani, G. Ilango, and C. Nagamani, "A method to detect photovoltaic array faults and partial shading in PV systems," *IEEE Journal of Photovoltaics*, vol. 6, no. 5, pp. 1278–1285, 2016.
- [12] I. Yahyaoui and M. Segatto, "A practical technique for on-line monitoring of a photovoltaic plant connected to a single-phase grid," *Energy Conversion and Management*, vol. 132, pp. 198–206, 2017.
- [13] H. Mekki, A. Mellit, and H. H. Salhi, "Artificial neural network-based modelling and fault detection of partial shaded photovoltaic modules," *Simulation Modelling Practice and Theory*, vol. 67, pp. 1–13, 2016.
- [14] S. Shrikhande, P. Varde, and D. Datta, "Prognostics and health management: Methodologies & soft computing techniques," in *Current Trends in Reliability, Availability, Maintainability and Safety*. Springer, 2016, pp. 213–227.
- [15] J. Hare, X. Shi, S. Gupta, and A. Bazzi, "Fault diagnostics in smart micro-grids: A survey," *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 1114–1124, 2016.
- [16] L. Suganthi, S. Iniyar, and A. Samuel, "Applications of fuzzy logic in renewable energy systems—a review," *Renewable and Sustainable Energy Reviews*, vol. 48, pp. 585–607, 2015.
- [17] S. Silvestre, M. daSilva, A. Chouder, D. Guasch, and E. Karatepe, "New procedure for fault detection in grid connected PV systems based on the evaluation of current and voltage indicators," *Energy Conversion and Management*, vol. 86, pp. 241–249, 2014.
- [18] M. Tadj, K. Benmouiza, A. Cheknane, and S. Silvestre, "Improving the performance of PV systems by faults detection using GISTEL approach," *Energy conversion and management*, vol. 80, pp. 298–304, 2014.
- [19] W. Chine, A. Mellit, V. Lughi, A. Malek, G. Sulligoi, and A. Pavan, "A novel fault diagnosis technique for photovoltaic systems based on artificial neural networks," *Renewable Energy*, vol. 90, pp. 501–512, 2016.
- [20] A. Pavan, A. Mellit, D. Pieri, and S. Kalogirou, "A comparison between BNN and regression polynomial methods for the evaluation of the effect of soiling in large scale photovoltaic plants," *Applied energy*, vol. 108, pp. 392–401, 2013.
- [21] A. Chouder and S. Silvestre, "Automatic supervision and fault detection of PV systems based on power losses analysis," *Energy Conversion and Management*, vol. 51, no. 10, pp. 1929–1937, 2010.
- [22] E. Garoudja, K. Kara, A. Chouder, and S. Silvestre, "Parameters extraction of photovoltaic module for long-term prediction using artificial bee colony optimization," in *3rd International Conference on Control, Engineering & Information Technology (CEIT)*. IEEE, 2015, pp. 1–6.
- [23] B. Kang, S. Kim, S. Bae, and J. Park, "Diagnosis of output power lowering in a PV array by using the kalman-filter algorithm," *IEEE Transactions on Energy Conversion*, vol. 27, no. 4, pp. 885–894, 2012.
- [24] J. Johnson, S. Kuszmaul, W. Bower, and D. Schoenwald, "Using PV module and line frequency response data to create robust arc fault detectors," in *Proceedings of the 26th European Photovoltaic Solar Energy Conference and Exhibition*, 2011, pp. 05–09.

- [25] Z. Bouzid, N. Ghellai, and T. Mezghiche, "Overview of solar potential, state of the art and future of photovoltaic installations in algeria," *International Journal Of Renewable Energy Research*, vol. 5, no. 2, pp. 427–434, 2015.
- [26] J. Duffie and W. Beckman, *Solar engineering of thermal processes*. Wiley New York, 2013, vol. 3.
- [27] A. McEvoy, L. Castaner, and T. Markvart, *Solar cells: materials, manufacture and operation*. Academic Press, 2012.
- [28] E. Saloux, A. Teyssedou, and M. Sorin, "Explicit model of photovoltaic panels to determine voltages and currents at the maximum power point," *Solar energy*, vol. 85, no. 5, pp. 713–722, 2011.
- [29] I. Karki, "Effect of temperature on the IV characteristics of a polycrystalline solar cell," *Journal of Nepal Physical Society*, vol. 3, no. 1, pp. 35–40, 2016.
- [30] S. Chander, A. Purohit, A. Sharma, S. Nehra, and M. Dhaka, "Impact of temperature on performance of series and parallel connected mono-crystalline silicon solar cells," *Energy Reports*, vol. 1, pp. 175–180, 2015.
- [31] B. Subudhi and R. Pradhan, "Characteristics evaluation and parameter extraction of a solar array based on experimental analysis," in *IEEE Ninth International Conference on Power Electronics and Drive Systems (PEDS)*. IEEE, 2011, pp. 340–344.
- [32] R. Tamrakar and A. Gupta, "A review: extraction of solar cell modelling parameters," *Int. J. Innovative Res. Electr., Electron., Instrum. Control Eng*, vol. 3, no. 1, pp. 55–60, 2015.
- [33] D. Karaboga and B. Basturk, "On the performance of artificial bee colony (abc) algorithm," *Applied soft computing*, vol. 8, no. 1, pp. 687–697, 2008.
- [34] D. C. Montgomery, "Introduction to statistical quality control," *John Wiley& Sons, New York*, 2005.
- [35] J. S. Hunter, "The exponentially weighted moving average," *Journal of Quality Technology*, vol. 18, no. 4, pp. 203–210, 1986.
- [36] J. Lucas and M. Saccucci, "Exponentially weighted moving average control schemes: properties and enhancements," *Technometrics*, vol. 32, no. 1, pp. 1–12, 1990.
- [37] F. Kadri, F. Harrou, S. Chaabane, Y. Sun, and C. Tahon, "Seasonal arma-based spc charts for anomaly detection: Application to emergency department systems," *Neurocomputing*, vol. 173, pp. 2102–2114, 2016.
- [38] N. Zerrouki, F. Harrou, Y. Sun, and A. Houacine, "Accelerometer and camera-based strategy for improved human fall detection," *Journal of medical systems*, vol. 40, no. 12, p. 284, 2016.
- [39] F. Harrou, M. Nounou, H. Nounou, and M. Madakyaru, "PLS-based EWMA fault detection strategy for process monitoring," *Journal of Loss Prevention in the Process Industries*, vol. 36, pp. 108–119, 2015.
- [40] F. Harrou and M. Nounou, "Monitoring linear antenna arrays using an exponentially weighted moving average-based fault detection scheme," *Systems Science & Control Engineering: An Open Access Journal*, vol. 2, no. 1, pp. 433–443, 2014.
- [41] C. Lowry, X. Woodall, C. Champ, and S. Rigdon, "A multivariate exponentially weighted moving average control chart," *Technometrics*, vol. 34, no. 1, pp. 46–53, 1992.

Reliable fault detection and diagnosis of photovoltaic systems based on statistical monitoring approaches

Highlights

- A novel technique for monitoring PV systems is developed.
- EWMA and MEWMA charts are used to monitor the performance of PV systems.
- Practical data from the grid-connected PV system is used for validation.
- This technique successfully monitors the DC side of PV systems and detects partial shading.