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Garoudja, E., Harrou, F., Sun, Y., Kara, K., Chouder, A., Silvestre, S.
Statistical fault detection in photovoltaic systems. "Solar energy", 1
Juliol 2017, vol. 150, p. 485-499.

DOI [10.1016/j.solener.2017.04.043](https://doi.org/10.1016/j.solener.2017.04.043)

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1 **Statistical fault detection in photovoltaic systems**

2 Elyes Garoudja ^a, Fouzi Harrou ^b, Ying Sun ^b, Kamel Kara ^a, Aissa Chouder ^c, Santiago Silvestre ^d

3 ^a SET Laboratory, Electronics Department, Blida 1 University, BP 270 Blida, Algeria

4 ^b King Abdullah University of Science and Technology (KAUST), Computer, Electrical and
5 Mathematical Sciences and Engineering (CEMSE) Division, Thuwal 23955-6900, Saudi Arabia

6 ^c Electrical Engineering Laboratory (LGE), University Mohamed Boudiaf of M'sila, BP 166, 28000,
7 Algeria

8 ^d Electronic Engineering Department, Universitat Politècnica de Catalunya, C/ Jordi Girona 1-3,
9 Campus Nord UPC, 08034 Barcelona, Spain

10 **Keywords:** Fault detection;Temporary shading;Photovoltaic systems;One-diode model

11 Statistical monitoring charts

12 **A b s t r a c t**

13 Faults in photovoltaic (PV) systems, which can result in energy loss, system shutdown or even
14 serious safety breaches, are often difficult to avoid. Fault detection in such systems is imperative
15 to improve their reliability, productivity, safety and efficiency. Here, an innovative model-based
16 fault-detection approach for early detection of shading of PV modules and faults on the direct
17 current (DC) side of PV systems is proposed. This approach combines the flexibility, and simplicity
18 of a one-diode model with the extended capacity of an exponentially weighted moving average
19 (EWMA) control chart to detect incipient changes in a PV system. The one-diode model, which is
20 easily calibrated due to its limited calibration parameters, is used to predict the healthy PV array's
21 maximum power coordinates of current, voltage and power using measured temperatures and
22 irradiances. Residuals, which capture the difference between the measurements and the
23 predictions of the one-diode model, are generated and used as fault indicators. Then, the EWMA
24 monitoring chart is applied on the uncorrelated residuals obtained from the one-diode model to
25 detect and identify the type of fault. Actual data from the grid-connected PV system installed at
26 the Renewable Energy Development Center, Algeria, are used to assess the performance of the
27 proposed approach. Results show that the proposed approach successfully monitors the DC side of
28 PV systems and detects temporary shading.

29 **1. Introduction**

30 *1.1. The state of the art*

31 Traditional sources of energy, such as oil, coal and nuclear energy, have negative effects on human
32 health, biodiversity, ecosystems and climate change. Nonetheless, industrial growth has
33 extensively increased global consumption of fossil fuels, and the concomitant impacts on human
34 health and the environment (Johansson, 1993). Renewable energy sources such as solar, wind and

35 biomass, are promising alternatives to conventional fossil fuels because they are clean,
36 sustainable, safe, and environment-friendly with zero CO₂ emissions (Panwar et al., 2011). One of
37 the most sustainable and economically competitive renewable energy sources is solar photovoltaic
38 (PV) energy (Zhao et al., 2015). Moreover, solar PV energy increases a country's energy security by
39 reducing dependence on fossil fuels.

40 Under practical conditions, faults are unavoidable in PV systems, particularly on the direct current
41 (DC) side where open circuit faults, short circuits faults, hotspot faults, and total and partial
42 shading faults are possible (Chouder and Silvestre, 2010; Hachana et al., 2016; Silvestre et al.,
43 2015; Yahyaoui and Segatto, 2017). Faults on the DC side of PV systems can result in energy loss,
44 system shutdown and even in serious safety breaches (Brooks, 2011; Alam et al., 2015). For
45 example, two PV facilities in the US (a 383 KWp PV array in Bakersfield, CA and a 1.208 MWp
46 power plant in Mount Holly, NC) burned in 2009 and 2011, respectively (Brooks, 2011). The source
47 for these accidents was a fault on the DC side that was not identified early (Vergura et al., 2009;
48 Hariharan et al., 2016). If such faults in PV systems are not detected promptly, they can affect the
49 system's efficiency and profitability, as well as the health and safety of workers and community
50 members.

51 The detection of faults in PV systems is therefore crucial for maintaining normal operations by
52 providing early fault warnings. Indeed, accurate and early detection of faults in a PV system is
53 critical to avoid the progression of faults and to reduce considerably productivity losses.

54 Several fault detection techniques for PV systems have been developed. They are two main types
55 of these techniques: process history-based approaches and model-based approaches.

56 Process history-based methods use implicit empirical models derived from analysis of available
57 data and rely on computational intelligence

58 and machine learning methods (Mekki et al., 2016; Shrikhande et al., 2016; Hare et al., 2016;
59 Suganthi et al., 2015; Silvestre et al., 2014; Tadj et al., 2014; Zhao et al., 2013). Mekki et al. (2016)
60 proposed an artificial neural network to evaluate PV system performance under partial shading
61 conditions. Chine et al. (2016) used an artificial neural network to detect short circuits in PV
62 arrays. Tadj et al. (2014) proposed a fault-detection approach based on fuzzy logic to detect
63 possible solar panel abnormalities.

64 Pavan et al. (2013) used a Bayesian neural network and polynomial regression to predict the effect
65 of soiling in large-scale PV system. However, process-history-based methods require the
66 availability of a relevant dataset that describes both healthy and faulty operating conditions in a
67 PV system.

68 On the other hand, model-based approaches compare analytically computed outputs with
69 measured values and signal an alarm when large differences are detected (Harrou et al., 2014).
70 Several model-based approaches to fault detection in PV systems have been reported in the
71 literature using the one-diode model (Chouder and Silvestre, 2010; Vergura et al., 2009; Chouder
72 and Silvestre, 2009; Chao et al., 2008). In one-diode-based fault detection approaches, model

73 parameters are determined by parameter extraction methods from weather conditions and the
74 datasheet from the PV module manufacturer (Garoudja et al., 2015; Abou et al., 2015; Chouder
75 and Silvestre, 2010). Both irradiance and solar panel temperature measurements are needed for
76 such approaches to predict the maximum power point (MPP) of the PV system. Kang et al. (2012)
77 used a Kalman filter to predict the power output of a PV system. Johnson et al. (2011) used a
78 Fourier series to detect arc faults in a PV system. Other approaches employed sophisticated tools,
79 such as time-domain reflectometry (TDR) (Munoz et al.,2011) and thermorefectance imaging (TR)
80 (Hu et al., 2014). The TR method was proposed to detect the appearance of hot spots inside PV
81 systems (Hu et al., 2014). The TDR approach can detect, localize, and diagnose faults in PV systems,
82 but the system must be turned off, which affects system productivity. TDR also requires
83 sophisticated tools to introduce the input signal. Of course, the effectiveness of model-based
84 fault-detection approaches relies on the accuracy of the models used.

85 1.2. Motivation and contributions

86 Until recently, statistical process control charts have not been widely used to monitor the
87 performance of PV systems. Zhao et al. (2013) proposed a statistical technique using three outlier
88 rules to classify deviations. Recently, Platon et al. (2015) proposed to use the three-sigma rule for
89 online fault detection in PV systems.

90 However, the three-sigma rule, also known as the Shewhart chart (Montgomery, 2007), loses the
91 ability to detect incipient faults in process data because it makes decisions based only on
92 information about the process in the last observation. Incorporating information about the entire
93 process history, including previous or recent observations, into the decision rule can help to
94 improve sensitivity to small shifts. The exponentially weighted moving average

95 (EWMA) scheme incorporates information from the entire process history, rather than using only
96 the most recent observation. This makes it more sensitive than the Shewhart chart to small
97 anomalies. The main contribution of this work is to exploit the advantages of the exponentially
98 weighted moving average (EWMA) chart and those of one-diode modeling for enhancing detection
99 performances of PV systems, especially for detecting small faults in DC side of PV system and
100 shading fault. Such a choice is mainly motivated by the greater ability of the EWMA metric to
101 detect small fault in process mean, which makes it very attractive as fault detection approach.
102 Note that the main advantage of EWMA chart is that it can be easily implemented in real time
103 because of the low computational cost, which is not the case in a classifiers based methods (the
104 classifier algorithms are performed offline rather than online). A decision can be made for each
105 new sample by comparing the value of the EWMA decision statistic with the value of the
106 threshold.

107 An anomaly is declared if the EWMA statistic exceeds the threshold. To do so, residuals, which are
108 the differences between the measured and predicted MPP for the current, voltage and power,
109 from the PV array simulation model are generated. Under normal operating conditions, the
110 residuals in a PV system are close to zero due to measurement noise and errors, while they
111 significantly deviate from zero when the system is faulty. Residuals are used as fault indicators.

112 Then, an EWMA chart is used to monitor the residuals to reveal abnormalities. Once the fault has
113 been detected, the next step is expected to determine its cause. The proposed approach can also
114 effectively diagnose fault types based on the output DC current and voltage. Indeed, fault
115 diagnosis can help the operators and engineers in the process-monitoring scheme and therefore
116 significantly reduce the risk of safety problems or loss in profitability. The proposed fault detection
117 strategy has been validated using measurements from the 9.54 kWp PV plant at the Renewable
118 Energy Development Center in Algiers, Algeria. The remainder of this paper is organized as follows.
119 Section 2 gives a brief overview of the grid-connected PV plant that provided data for this study. In
120 Section 3, one-diode model is reviewed. Section 4 introduces the EWMA chart and its use in fault
121 detection. Section 5 applies the proposed fault-detection and diagnosis procedure to the PV plant
122 in Algeria. Finally, Section 6 concludes with a discussion and suggestions for future research
123 directions.

124 **2. The grid-connected PV system in Algiers, Algeria**

125 We assessed our fault detection method using practical data collected from a grid-connected
126 photovoltaic (GCPV) system located at Renewable Energy Development Center (CDER) in Algiers,
127 Algeria. This PV system operates from June 21st, 2004, and the output power by this system is
128 injected directly into the national electric distribution network without any storage device.

129 This 90 module PV system 106 Wp is installed on the roof of the CDER building as shown in Fig. 1.
130 This 9.54 kWp rated system has an output DC voltage of 125–450 V and an output AC voltage of
131 220 V. It comprises three sub-arrays of 30 modules each. The outputs of these three sub-arrays
132 are connected to a single-phase 2.5 KW PV inverter (IG30 Fronius). Each sub-array consists of 30
133 Isofoton (106 W-12 V) PV modules, which are grouped into two parallel strings of fifteen PV
134 modules in series. Irradiance measurements are collected with a Kipp & Zonen CM11
135 thermoelectric pyranometer and the temperature is measured with a K-type thermocouple.

136 An Agilent 34970A data logger acquires the data through a connection to the local grid through an
137 inverter, a safety control box and a meter. When the utility grid is not energized the inverter
138 immediately stops providing power to the grid. The main components of the GCPV system are
139 shown in Fig. 2. The data from only one sub-array are used to simulate both healthy and faulty
140 operating conditions under various meteorological conditions. The electrical characteristics of the
141 Isofoton 106–12 PV module are summarized in Table 1.

142 The standard test conditions for these solar panels were determined at 25 °C and solar irradiance
143 of 1000 W/m². The real measurements (ie., MPP voltage and current) were collected every
144 second.

145 Table 1

146 Electrical characteristics of the Isofoton 106-12 PV module under standard test condition.

147 Electrical characteristics of the solar panels tested in this study Value

148 Peak power (PMPP)	106W
149 Voltage at maximum power point (VMPP)	17.4 V
150 Current at maximum power point (IMPP)	6.10 A

151 Open circuit voltage (V_{oc}) 21.6 V
 152 Short circuit current (I_{sc}) 6.54 A

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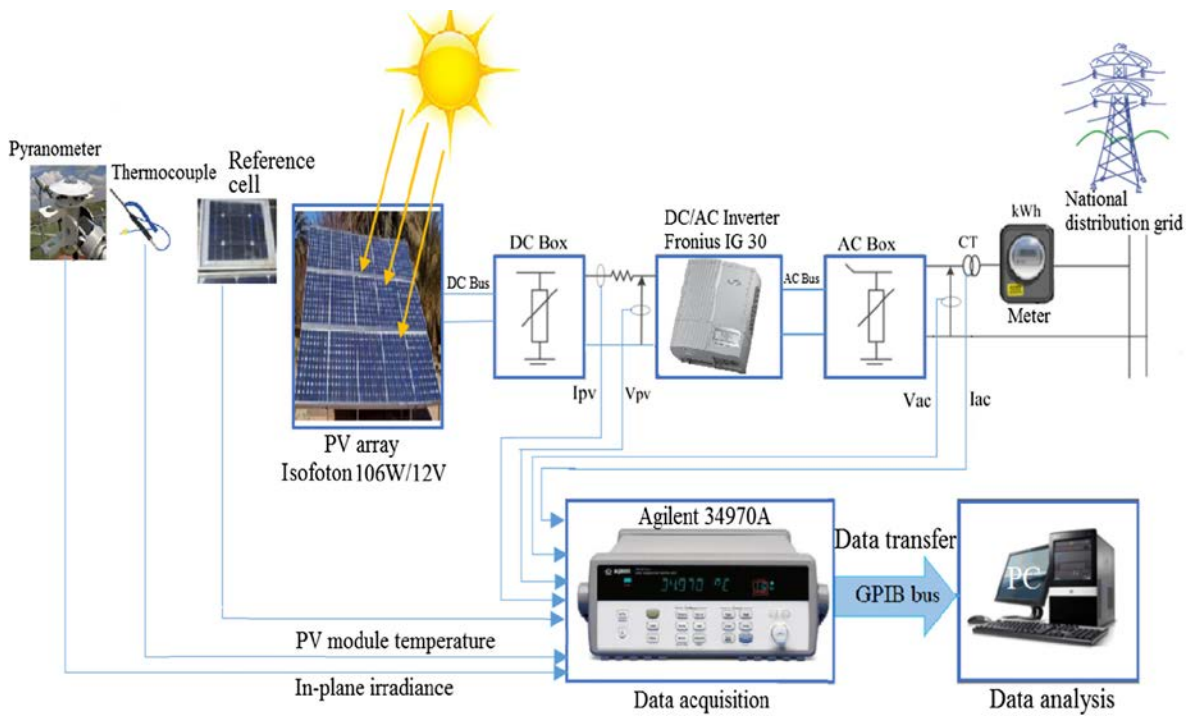
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155 Fig. 1. The PV array installed on the roof of the CDER building in Algiers, Algeria
 156 (Arab et al., 2005).

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163 Fig. 2. The main components of grid-connected PV system used in this study.

164

165 2.1. Typical faults in PV systems

166 Generally, a PV system can be affected by different types of faults that can result in significant loss
167 of power in a PV system.

168 According to the fault duration, two types of faults can be distinguished: temporary and
169 permanent faults. Temporary faults, such as shading, disappear after a certain period of time or
170 after being manually cleared in cases of dust, leaves or bird dropping. The PV system then returns
171 to its normal operating conditions. On the other hand, permanent faults, including short circuits
172 and open circuits are persistent or ongoing. Three well-known faults commonly occurred in the DC
173 side of PV systems (short circuits, open circuits and partial shading) are studied in this paper (see
174 Fig. 3).

175 A short-circuit fault can affect cells, bypass diodes or modules. It is mainly due to the infiltration of
176 water into modules or to bad wiring between the module and the inverter. Additionally, aging of
177 PV modules, which is caused by long-term operation of the PV system, is one of the main sources
178 of short-circuit faults. For example, there is a short-circuit fault at point 'F1' on the second string
179 on thright of the PV array in Fig. 3.

180 An open-circuit fault may occur if any current path that is in series to the load is accidentally
181 removed or opened from a closed circuit. Such a situation mainly occurs due to a break in wires
182 between PV modules or solar cells. An example of an open circuit fault is shown at point at 'F2' in
183 Fig. 3. Open-circuit faults occur when a conductor is accidentally removed from the closed
184 circuit.

185 A partial shading fault occurs when part of the PV array is shaded while the other part is normally
186 exposed to the solar irradiance. This occurs due to several reasons including passage of
187 clouds, dirt on PV modules, snow, or any other light barrier. Nearby obstacles might also interfere
188 and cast shadows, resulting in reduced power output. Even a small amount of shade can
189 dramatically reduce the output amperage of a PV system.

190

191 3. PV module modeling

192 Numerous models have been reported in the literature that model energy production of PV cells.
193 The one-diode model (ODM) is the most common model used to predict energy production
194 from PV cells (Duffie and Beckman, 2013). This model is based on modeling the solar cell as a light-
195 generated current source connected in parallel with a diode with series and parallel resistances
196 accounting for resistive losses (see Fig. 4).

197 ODM determines the resulting current and voltage given the parameters of the solar cell (McEvoy
198 et al., 2012) as follows:

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

199

200 where I and V are the generated current and voltage of the solar cell, respectively. I_{ph}, also called
201 the photogenerated current, corresponds to the amount of current generated by incoming
202 photons; it is proportional to the irradiance and the area of the solar cell. I₀ is the dark saturation
203 current, n is the diode's ideality factor. R_s and R_{sh} are the series and shunt resistances,
204 respectively. k_B is Boltzmann's constant (k_B = 1:38064852 10⁻²³ J K⁻¹). T is the cell's temperature
205 and q is the electronic charge (q = 1:60217662 10⁻¹⁹ C).

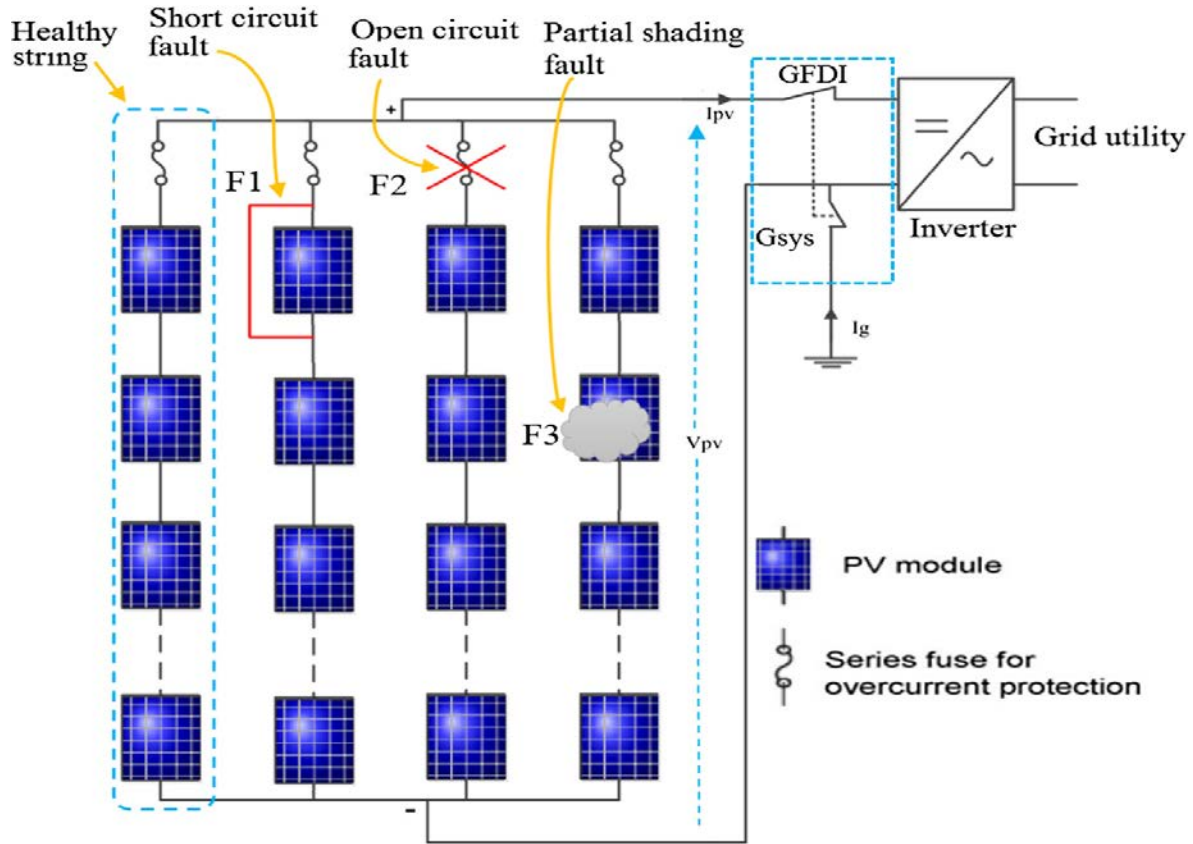
206 The simulation of a PV array is comprised of three stages summarized next.

207

208 Step 1 : Model parameters extraction

209 ODM in Eq. (1) depends on the values of five unknown

210 parameters (I_{ph} ; I_0 ; n , R_s and R_{sh}), which determine the overall performance of a solar cell. These
 211 parameters are not provided in the manufacturer's datasheet. Hence, accurate extraction of these
 212 parameters is a crucial step in PV system modeling. Indeed, solar cell parameters extraction could
 213 be defined as an optimization problem, wherein the cost function to be minimized is defined as
 214 the root mean square error (RMSE) between the measured and the predicted I-V curves by ODM.
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 218 Fig. 3. The faulty operating cases considered in this paper.
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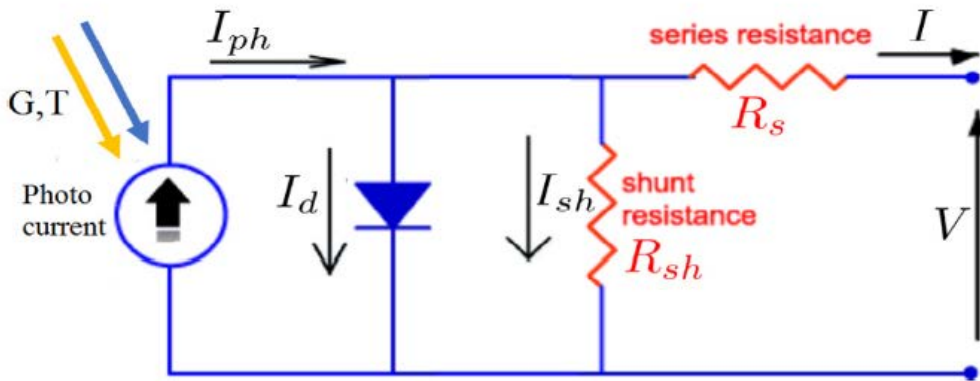
$$RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^m [f_i(I_{meas}, V_{meas}, \theta)]^2}, \quad (2)$$

220 where

$$f(I_{meas}, V_{meas}, \theta) = I_{meas} - \left\{ I_{ph} - I_0 \left[\exp \left(\frac{q(V_{meas} + R_s I_{meas})}{nk_B T} \right) - 1 \right] - \frac{V_{meas} + R_s I_{meas}}{R_{sh}} \right\}, \quad (3)$$

221 I_{meas} and V_{meas} are the measured output current and voltage of
 222 the reference PV module respectively (they define the static
 223

224 I-V curve measurements of the reference PV module), h is the vector of the five unknowns
 225 electrical parameters [I_{ph} ; I_0 ; n , R_s and R_{sh}], m stands for the number of experimental
 226 data used in the parameters extraction process. The static I-V curve of a reference PV module are
 227 measured using an I-V curve tracer when the module is isolated from the inverter.
 228 In practice, I-V curve tracer takes less than one second to measure the current–voltage (I-V)
 229 characteristic of the tested PV module. Of course, the aim of this optimization is to find
 230 the optimal parameters values that minimize the objective function and provides the lowest RMSE
 231 value. In this paper, these five parameters have been extracted using the Artificial Bee Colony
 232 (ABC) algorithm (Garoudja et al., 2015; Abouet al., 2015) on the basis of the real measured static
 233 (I-V) data, the predicted data obtained from the one diode model and the available parameters in
 234 Table 1.



235
 236 Fig. 4. Equivalent circuit of a solar cell based on a current source and a diode, with
 237 losses represented by series and parallel resistance.

238
 239 Step 2 : Model simulation.

240 The identified parameters via ABC algorithm, which are given in Table 2, are used to predict the
 241 MPP coordinates of current, voltage and power of the entire PV array. The
 242 PV array model is simulated using PSIMTM/MatlabTM cosimulation. Using this co-simulation, the
 243 entire PV array is physically constructed (physical PV modules) as two parallel PV string, of fifteen
 244 PV modules each. This model relies on access to both irradiance and solar panel temperature
 245 measurements to predict the MPP coordinates.

246 Step 3 : Model validation

247 Model validation is possibly the most important step in PV array modeling. In this step, the ability
 248 of the simulated model to mimic accurately the real behavior of the monitored
 249 PV plan is evaluated. Specifically, the identified ODM
 250 parameters are used to build the entire PV array cosimulation model, then this later is used to
 251 mimic the real PV array behavior under different meteorological conditions.

252 The input variables of the simulated model consist of real measured meteorological conditions of
 253 temperatures and irradiances. The output variables are the PV array MPP coordinates of current,
 254 voltage and power. The predicted MPP coordinates of voltage and power obtained
 255 from the simulated model are then compared to the real measured MPP coordinates collected
 256 from the real PV array. Here, the co-simulation model is fitted to the fault-free data from the GCPV
 257 system described above. Fig. 5(a) and (b) respectively shows the measured and predicted
 258 DC current and DC power for a cloudy day, June 24, 2008. This figure shows that the model
 259 suitably fits the measured data, thus indicating that the selected parameters are satisfactory. This
 260 figure also shows that after sunset and during periods of negligible irradiances, the system

261 completely shuts down. This is done to reduce power consumption and thereby increase overall
 262 efficiency. Scatter plot of the measured and predicted DC current and DC power are presented in
 263 Fig. 6(a) and (b). These plots indicate that the PV array simulation model predicts the measured
 264 DC current and DC power well.
 265

Table 2
 Extracted PV module parameters.

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

266 In addition, to evaluate the quality of the simulation model with the selected parameters, three
 267 numerical criteria are used: R2, the mean absolute percent error (MAPE) and RMSE. These were
 268 calculated as follows:
 269

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

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

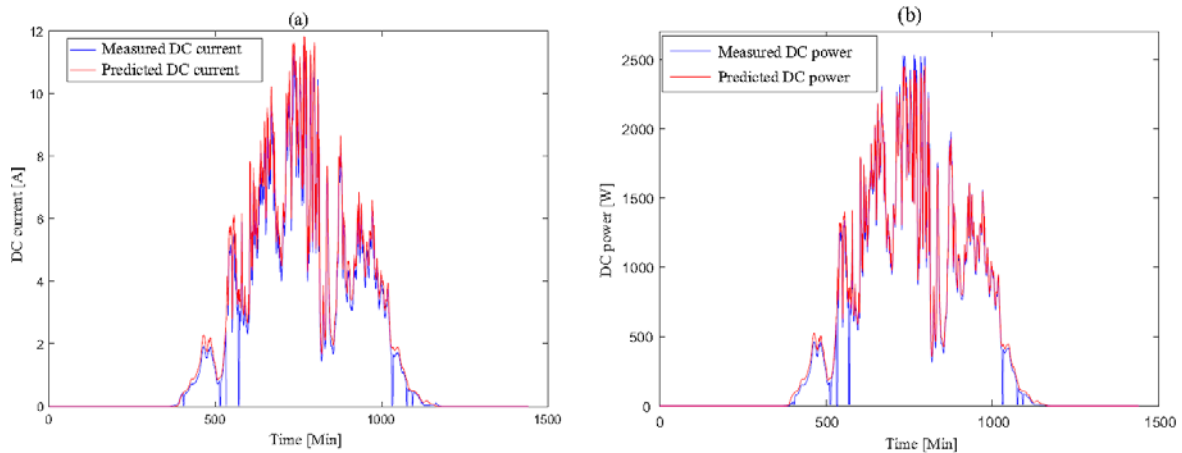
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$$MAPE = 100 \left[\frac{\sum_{t=1}^m \left(\frac{|y_t - \hat{y}_t|}{|y_t|} \right)}{m} \right], \quad (6)$$

271 where y_t are the measured values, \hat{y}_t are the corresponding predicted values by the simulation
 272 model and m is the number of samples.
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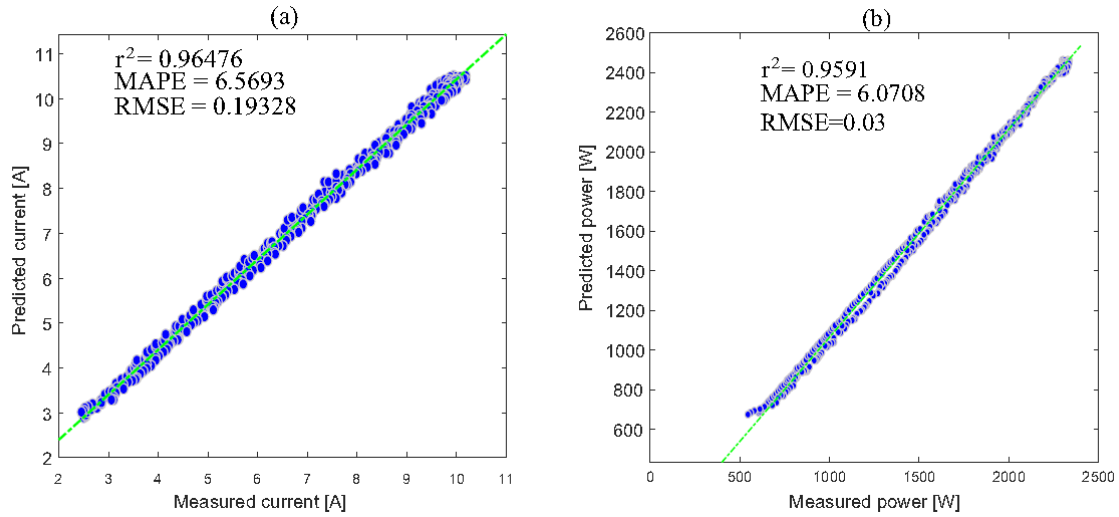
274 Goodness-of-fit results for the three cells studied are presented in Table 3.

275 Results in Table 3 show that the PV array simulation model with the selected parameters captures
 276 the measured DC current and power. The r^2 values above 0.9, the low RMSE of 0.1932 and the
 277 low MAPE of 6.57% demonstrate that ODM provides good predictive quality.
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Fig. 5. Measured and predicted plot of DC current (a) and DC power (b) for June 24, 2008.



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Fig. 6. Scatter plot of the measured and predicted DC current (a) and DC power (b) for June 24, 2008.

Table 3

Statistical validation metrics applied to data in Fig. 6.

	DC current	Power current
r^2	0.96	0.96
RMSE	0.193	0.03
MAPE	6.57	6.07

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4. Fault detection approaches

The overarching goal of this paper is to improve the PV system efficiency by monitoring its DC side in an efficient manner. Traditionally in manufacturing industries, statistical quality control is used for monitoring and controlling product quality. Furthermore, 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 shading faults. These statistical charts include Shewhart, cumulative sum (CUSUM), and EWMA charts. Univariate statistical methods, such as the Shewhart chart and EWMA, have been widely used to monitor industrial processes for many years (Montgomery, 2005). These methods are briefly introduced here.

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4.1. Shewhart monitoring chart

In a Shewhart chart, a sequence of samples (denoted as x_i) is plotted against time (Montgomery, 2005). Upper and lower control limits for the samples are established around the process mean (μ) based on the three-sigma rule, i.e., $UCL/LCL = \mu \pm 3\sigma$, where σ is the standard deviation of the fault-free data computed when the process is running under healthy conditions. Whenever the most recent measured point or a consecutive sequence of points is outside the control limits, an

304 abnormal condition is encountered and attention is focused on diagnosing the source of the
 305 problem.

306 Here, the Shewhart chart is used as a benchmark for fault detection in the DC side of a PV system.
 307 In the next section, EWMA chart and its use in fault detection will be briefly described.

308
 309 4.1.1. EWMA monitoring chart

310 In this section, the basic idea of the EWMA chart and its properties are introduced. For a more
 311 detailed discussion about its design, implementation and properties, refer to (Montgomery,
 312 2005; Reynolds and Stoumbos, 2005; Lucas and Saccucci, 1990; Hunter, 1986). EWMA is
 313 constructed based on exponential weighting of available observations, a design that provides
 314 improved sensitivity to small changes in the mean of a multivariate process.
 315 EWMA charts are able to detect small shifts in the process mean because the EWMA statistic is a
 316 time-weighted average of all previous observations. The EWMA control scheme was first
 317 introduced by Roberts (Hunter, 1986; Lucas and Saccucci, 1990), it has been extensively used in
 318 time series analysis. The EWMA monitoring monitoring chart is an anomaly-detection technique
 319 widely used by scientists and engineers in various disciplines (Kadri et al., 2016; Zerrouki et al.,
 320 2016; Harrou et al., 2015; Harrou and Nounou, 2014; Montgomery, 2005). Assume that $x_1; x_2; \dots$
 321 ; x_n are individual observations collected from a monitored process. The expression
 322 for EWMA is (Montgomery, 2005):

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

323
 324 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
 325 and x_t is the observation from the monitored process at the current time. The forgetting
 326 parameter $\lambda \in [0; 1]$ determines how fast EWMA forgets the data history.
 327 From Eq. (7), it is easy to see that

$$\begin{aligned} z_t &= \lambda x_t + (1 - \lambda) \overbrace{[\lambda x_{t-1} + (1 - \lambda) z_{t-2}]}^{z_{t-1}} \\ &= \lambda x_t + \lambda(1 - \lambda)x_{t-1} + (1 - \lambda)^2 z_{t-2}. \end{aligned}$$

328
 329 Using Eq. (7) recursively, we find that the EWMA is a linear combination of the observations:
 330

$$\begin{aligned} z_n &= \lambda x_n + \lambda(1 - \lambda)x_{n-1} + \lambda(1 - \lambda)^2 x_{n-2} + \dots + \lambda(1 - \lambda)^{n-1} x_1 \\ &\quad + (1 - \lambda)^n \mu_0 \end{aligned} \quad (8)$$

331
 332 Eq. (8) can also be written as:
 333

$$z_t = \lambda \sum_{i=1}^n (1 - \lambda)^{n-i} x_i + (1 - \lambda)^n \mu_0, \quad (9)$$

334
 335 where $\lambda (1 - \lambda)^{1-i}$ is the weight for x_i , which decreases off exponentially for past observations. In
 336 other words, as time passes the smoothed statistic z_t becomes the weighted average of a greater
 337 and greater number of the past observations x_{t-n} , and the weights assigned to previous
 338 observations are in general proportional to the terms of the geometric progression

$$\{\lambda, \lambda(1 - \lambda), \lambda(1 - \lambda)^2, \lambda(1 - \lambda)^3, \dots\}$$

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A geometric progression is the discrete version of an exponential function, so this is where the name for this method originated. The weighting for older data point decrease exponentially, giving much more important to recent observation while still not discarding older observation entirely. It can be seen that if k 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 k 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 (Montgomery, 2005; Kadri et al., 2016). In the special case when $k \approx 1$, EWMA is equal to the most recent observation, x_t , and provides the same results as the Shewhart chart provides. As k approaches zero, EWMA approximates the CUSUM criteria, which give equal weight to historical observations. Under fault-free conditions, the standard deviation of z_t is defined as

$$\sigma_{z_t} = \sigma_0 \sqrt{\frac{\lambda}{(2 - \lambda)} [1 - (1 - \lambda)^{2t}]}, \quad (10)$$

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However, in the presence of a mean shift at the time point,

$$z_t \sim \mathcal{N}\left(\mu_0 + [1 - (1 - \lambda)^{n-\tau+1}](\mu_1 - \mu_0), \sigma_{z_t}^2\right). \quad (11)$$

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It can be seen from Eq. (11) that the mean of the EWMA statistic in the presence of faults is a weighted average of μ_0 and μ_1 , and the weight of μ_1 is larger when n is larger. Therefore, the EWMA statistic, z_t , indeed contains useful information about the mean shift.

The upper and lower control limits of the EWMA chart for detecting a mean shift are

$$UCL/LCL = \mu_0 \pm L\sigma_{z_t},$$

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4.2. ODM-based EWMA for PV monitoring

In general, the model is first built and then fault diagnosis procedures is performed accordingly. The estimation of the residuals, which is crucial in model-based fault detection, depends on the appropriate system modeling. Once ODM is built based on data representing historically normal operations and validated, it can be used to monitor future deviations in the system. Here, the advantages of ODM with those of the EWMA monitoring chart are combined, which should result in an improved fault detection system, especially for detecting small changes. Specifically, in this approach, the EWMA chart is employed for fault detection to indicate how well the measurements conform to the model or how large the deviation from the normal model is. Towards this end, the EWMA chart is applied to monitor residuals obtained from ODM (see Fig. 7). The differences between the real measured and predicted MPP current, MPP voltage and MPP power obtained from the simulated model are the residuals that can be used as indicators to detect a possible fault.

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

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380 where I_t and bI_t are the measured and predicted MPP current, respectively, and V_t and bV_t are
381 the measured and predicted MPP voltage; and P_t and bP_t are the measured and predicted peak
382 power.

383 In this work, the residuals are used as fault indicators. Indeed, under normal operation, the
384 residuals are close to zero due to measurement noise and errors, while they significantly deviate
385 from zero in the presence of abnormal events. The implementation of the developed monitoring
386 methods comprises two stages: off-line modeling and on-line monitoring. In the off-line modeling
387 phase, ODM is used on the normal operating data (training data), enabling us to obtain a
388 reference model. Then, the fault detection procedure is executed by using the reference simulated
389 model with the EWMA chart in the on-line monitoring phase. The ODM-EWMA fault detection
390 algorithm is summarized in Table 4.

391 To improve system operations, we want not only to monitor the system in an efficient manner but
392 also to identify the type of fault that results in any degradation of the PV system, including
393 declines in operation reliability, and profitability, such that we can respond accordingly by making
394 any necessary correction to the system.

395 Towards this end, the EWMA chart is applied based on the residual of output DC power to detect
396 the presence of faults. Then, the type of fault is identified by analyzing the monitoring results of
397 the EWMA chart when it is applied to the residuals of output DC current and voltage. The fault
398 identification procedure is summarized in Fig. 8.

399 The proposed strategy tests at the first stage the peak power to detect a fault. This choice is
400 mainly due to the fact that faults affect inevitably the peak power. Thus, the peak power is used as
401 a fault indicator in the detection phase. On the other hand, both DC output current and voltage
402 are unsuitable to be used as sensitive indicators in this phase. For example, when a short circuit
403 occurs in one PV module from a string, current indicator value will not be significantly changed
404 from its healthy set point. Meanwhile, a substantial change will appear in the power indicator
405 (peak of power).

406 Besides, the same situation occurs when a string is completely disconnected. Indeed, the DC
407 output voltage remains unaltered regarding its healthy status in contrast to the peak power
408 decrease significantly. Moreover, the ranking of the current and voltage indicators is unimportant
409 in the fault diagnosis phase.

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411 **5. Results and discussion**

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413 5.1. Detection results

414 The proposed fault detection scheme is validated using practical data collected from the 9.54 kWp
415 GCPV system installed at CDER in Algeria (see Section 2). In this section, the ability of the EWMA
416 chart to detect the presence of faults in the data and to identify the type of detected fault is
417 assessed. To assess the strength of the EWMA-based monitoring chart, three case studies
418 involving different types of faults were conducted. In the first case study, it is assumed that the PV
419 system contains one or more short-circuited PV module (case A). In the second case study, an
420 open-circuit PV string is considered (case B). In the third case study, the monitored
421 PV system is exposed to temporary shadowing (case C).

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Table 4
EWMA-based fault detection algorithm for PV system monitoring.

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- (1) **Given**
 - Real measurement of irradiance and module temperature
 - Real measurement of maximum power point (MPP) values of current, voltage and power collected from the PV plant under normal operating conditions
 - Module parameters obtained from the PV module datasheet (see Table 1)
 - (2) **Build ODM using the fault-free training data**
 - Extract electrical parameters for the five-parameter model based on the measured cell temperature and irradiance collected from the monitored PV system under normal operating conditions (see Section 2) using the Artificial Bee Colony (ABC) algorithm (Garoudja et al., 2015). The extracted parameters are then used to simulate the PV system
 - 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 for the EWMA chart using Eq. (12)
 - (3) **Test the new data**
 - Generate residual vectors, \tilde{I} , \tilde{V} and \tilde{P} , using the selected five-parameter-based model
 - Compute the EWMA monitoring statistic for the new data using Eq. (7)
 - (4) **Check for faults**
 - Declare a fault when the EWMA decision statistic for the new data exceeds the control limits
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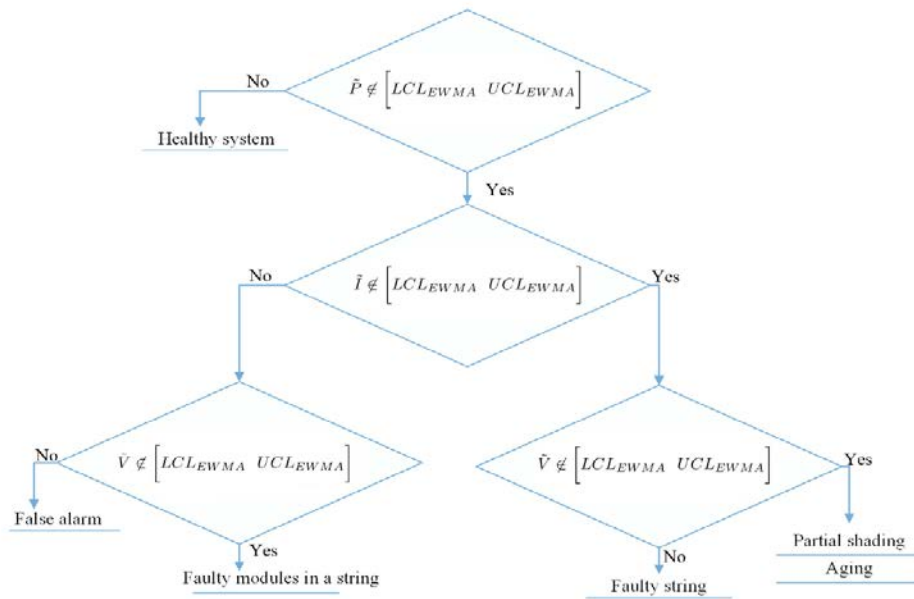


Fig. 8. Fault identification procedure.

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5.1.1. Normal operating conditions

Monitoring results from ODM-based Shewhart chart under normal operating conditions are shown in Fig. 9(a)–(c), monitoring results from the EWMA chart under normal operating conditions are presented in Fig. 10(a)–(c). Since the Shewhart plots for current, voltage and power shown in Fig. 9(a)–(c) are based on normal operating data, we expect that almost all the data will lie within the lower and upper control limits. Similarly, the data points in the EWMA charts are also within the 95% confidence limits (see Fig. 10(a)–(c)). It can be concluded that the ODM model describes the data well when no faults are present.

5.1.2. Case study of open-circuit PV strings

In this case study, the performance of the two monitoring charts when there is an open-circuit fault is investigated. 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 Fig. 11) between sample times 300–500.

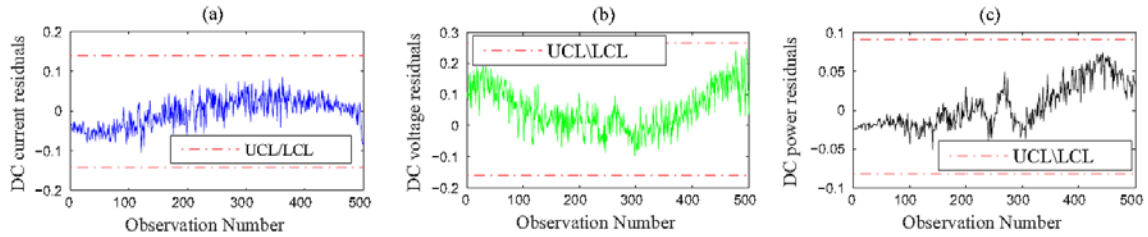


Fig. 9. Monitoring results of a Shewhart chart for DC current (a), DC voltage (b) and DC power (c) under normal operating conditions.

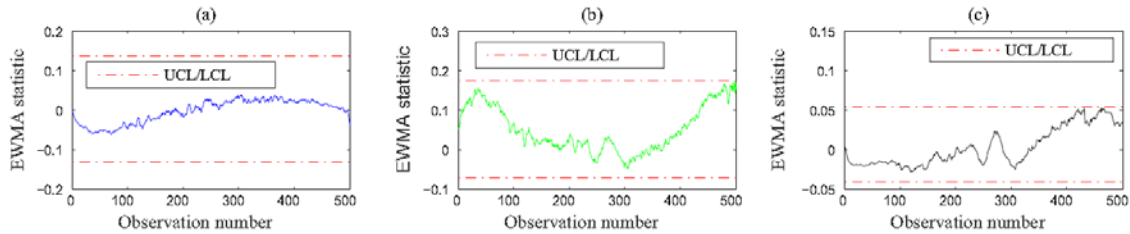


Fig. 10. Monitoring results of EWMA chart for DC current (a), DC voltage (b) and DC power (c) under normal operating conditions.

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442 To monitor the PV system, the residuals (i.e., e_i ; e_v and e_p) are first computed. Then both
 443 monitoring charts, Shewhart and EWMA, are used for fault detection. The Shewhart and EWMA
 444 charts based on the MPP residuals of current, voltage and power are presented in
 445 Figs. 12 and 13, respectively. The shaded area is the region where the fault is introduced. The plots
 446 in Figs. 12(c) and 13(c) indicate that before the occurrence of the fault, both charts are within the
 447 lower and upper control limits. The PV system is thus working normally.
 448 For this case, the two charts can both give fault signals because the introduced fault is quite large.
 449 Figs. 12(c) and 13(c), show that the Shewhart and EWMA charts based on the output
 450 power residuals, e_p , decrease significantly and exceed the lower control limits, indicating that
 451 there is a significant power loss.

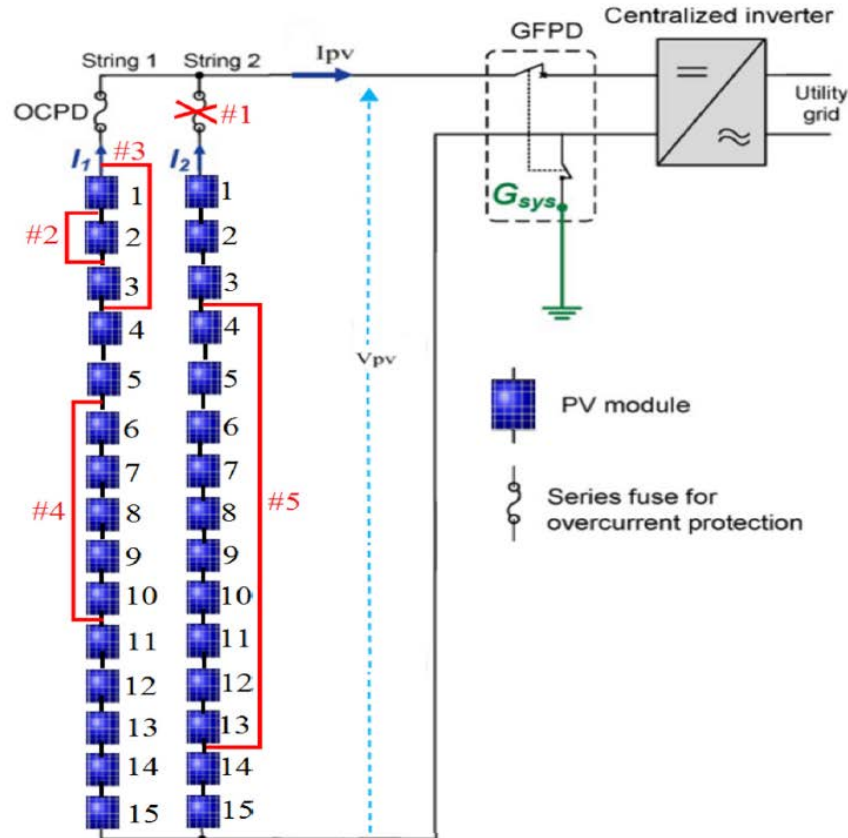


Fig. 11. Open-circuit and short-circuit faults.

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 453 Since one of the two strings of a PV array is disconnected at the fault, a large amount of power
 454 (nearly 50% of the rated power) is lost. After detecting the presence of a fault, the monitoring
 455 results related to the output DC current and voltage are analyzed to identify the type of fault. Both
 456 Figs. 12(b) and 13(b) are within the lower and upper control limits before and after the fault,
 457 which means that the DC voltage is almost the same after the occurrence of this open-circuit fault.
 458 The two monitoring charts based on the current residuals are given in Figs. 12(a) and 13(a). These
 459 charts show that both charts exceed the lower control limits, indicating the presence of a faulty
 460 string (open-circuit fault). Indeed, the current of the faulty string drops to zero when the string is
 461 disconnected from the PV array. As a result, the residuals, which indicate the difference between
 462 the simulated and measured DC current, decrease immediately after the occurrence of the open-
 463 circuit fault. From this case study, it can be seen that the open-circuit fault in a PV array increases
 464 the power loss, reduces the array current and results in almost the same array voltage as the
 465 normal PV array voltage. These results indicate the efficiency of both fault detection
 466 strategies in detecting and diagnosing open-circuit faults in a PV system.

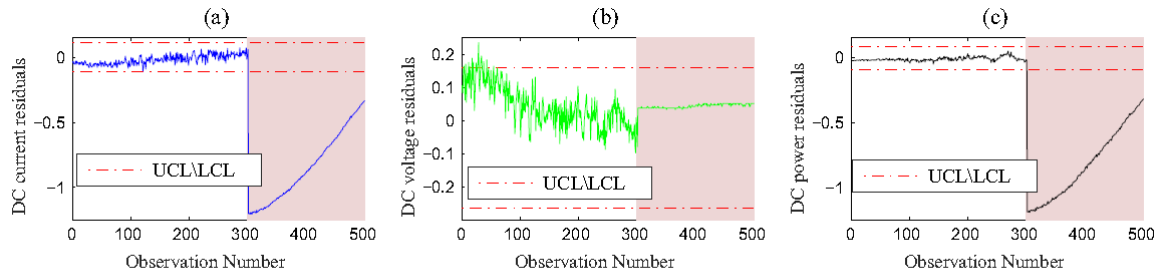


Fig. 12. Monitoring results of a Shewhart chart for DC current (a), DC voltage (b) and DC power (c) in the presence of an open-circuit fault.

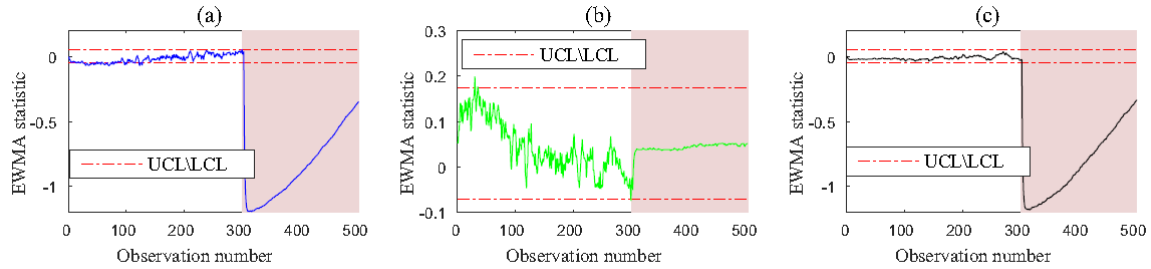


Fig. 13. Monitoring results of an EWMA chart for DC current (a), DC voltage (b) and DC power (c) in the presence of an open-circuit fault.

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5.1.3. Case study of a short circuit in a string of PV modules

470 In this case study, the detection of short-circuited PV modules in the monitored PV system is
 471 investigated. Four examples are given in this case study (see Fig. 11, faults #2–#5).
 472 (1) One short-circuited PV module: In the first example, the second module of the first string is
 473 bypassed from observation number 300 until the end of the testing data (see Fig. 11, fault #2).
 474 The output DC current, voltage and power were monitored using Shewhart and EWMA charts. The
 475 two monitoring charts are shown in Fig. 14(a)–(c) and Fig. 15(a)–(c). Fig. 14 shows that the
 476 Shewhart chart cannot detect this fault. The Shewhart chart is insensitive to this fault because it is
 477 designed to detect relatively moderate and large faults, while the fault in this case is quite small.
 478 This is mainly due to the fact that the Shewhart chart uses only observed data at a particular
 479 instant to make a decision about the process performance and it ignores past data. On the other
 480 hand, the plot in Fig. 15(c) clearly shows the capability of the EWMA monitoring chart in detecting
 481 this small fault. From the plots in Fig. 15(a) and (b), it can be seen that the DC current residuals are
 482 within the control limits, while the DC voltage residuals exceeds the lower control limit. Thus, we
 483 can conclude that the detected fault is related to a faulty module in the string. This case study
 484 clearly shows the superiority of the EWMA over the Shewhart chart in detecting small faults.
 485 (2) Three short-circuited PV modules: In the second example, three modules have been short
 486 circuited in the first string (see Fig. 11, fault #3). The monitoring results of the Shewhart and
 487 EWMA charts are shown in Figs. 16 and 17, respectively. The performance of the Shewhart chart
 488 when it is applied to the output power residuals is presented in Fig. 16(c), which shows that the
 489 Shewhart statistic clearly violates the lower control limit. The Shewhart chart detects this fault
 490 (i.e., a power loss) but it misses some data. On the other hand, the plot in Fig. 17(c) clearly shows
 491 the capability of the EWMA monitoring chart in correctly detecting this moderate fault without
 492 missed data. This short-circuit fault degrades the performance of the monitored systems and leads
 493 to a significant power loss (i.e., approximately 15% power loss).

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After detecting a fault based on the output DC power, the two monitoring charts based on
 residuals of output DC current and voltage, which are shown in Figs. 16(a) and (b) and 17(a) and

497 (b), can provide more information about the type of fault. Both Figs. 16(b) and 17(b) show fault
498 signals because the decrease in output DC voltage in this case is quite large. The output DC current
499 from the array does not change by much. Because the output DC voltage decreases compared to
500 the output DC voltage of the normal array and the output DC current does not change by much,
501 we then conclude that this fault is a short circuit in the PV array.

502 (3) Five short-circuited PV modules: In the third example, five modules in first string are
503 disconnected (Fig. 11, fault #4). This fault leads to a power loss of 30% compared to the healthy PV
504 array. Both monitoring charts can detect this quite large fault as shown in Figs. 18(c) and 19(c).
505 Similar to the cases above, to identify this fault, we look at the monitoring results related to the
506 array voltage and current (see Figs. 18(a) and (b) and 19(a) and (b)). In fact, it is a fault that
507 corresponds to a short-circuited PV module, since both charts based on voltage are below the
508 control limits (see Figs. 18(b) and 19(b)), and the current does not change by much (see Figs. 18
509 (a) and 19(a)). This demonstrates the effectiveness of the proposed strategy in detecting and
510 identifying faults related to shortcircuited modules.

511 (4) Ten short-circuited PV modules: In the fourth example, ten modules in the second string of the
512 monitored PV array were short circuited (see Fig. 11, fault #5). Indeed, the fault resulted in large
513 voltage drops and significant power loss (i.e. nearly 63%). Both monitoring charts can clearly
514 detect and identify this quite large fault (see Figs. 20(a)–(c) and 21(a)–(c)).

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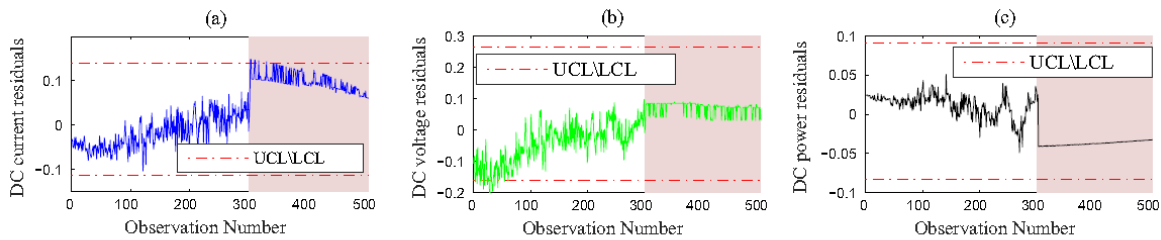


Fig. 14. Monitoring results of a Shewhart chart for DC current (a), DC voltage (b) and DC power (c) in the presence of one short-circuited module.

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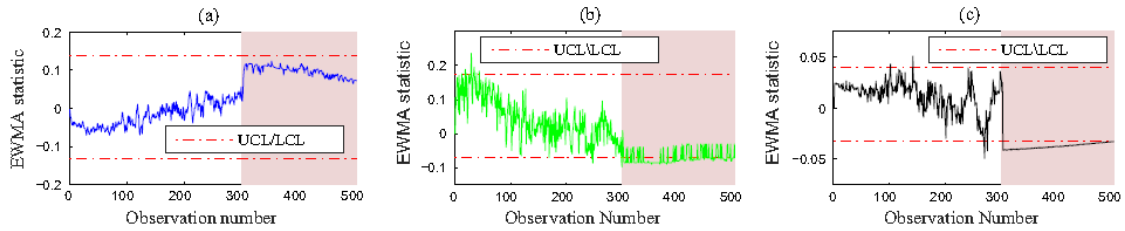


Fig. 15. Monitoring results of an EWMA chart for DC current (a), DC voltage (b) and DC power (c) in the presence of one short-circuited module.

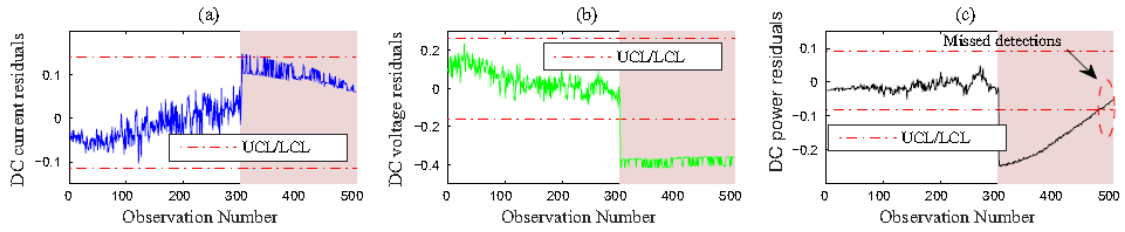


Fig. 16. Monitoring results of a Shewhart chart for DC current (a), DC voltage (b) and DC power (c) in the presence of three short-circuited modules in a PV array.

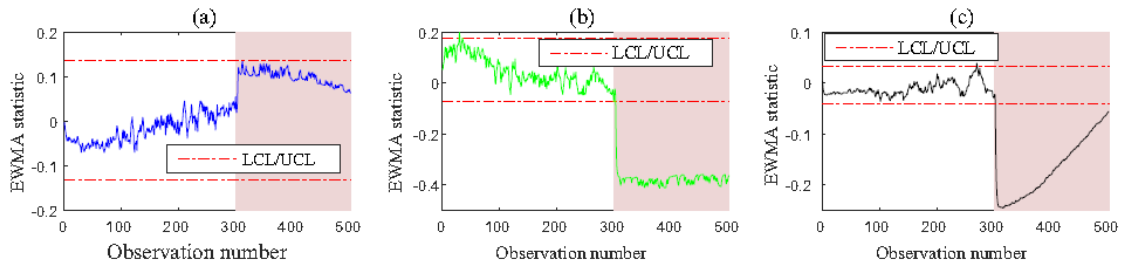


Fig. 17. Monitoring results of an EWMA chart for DC current (a), DC voltage (b) and DC power (c) in the presence of three short-circuited modules in a PV array.

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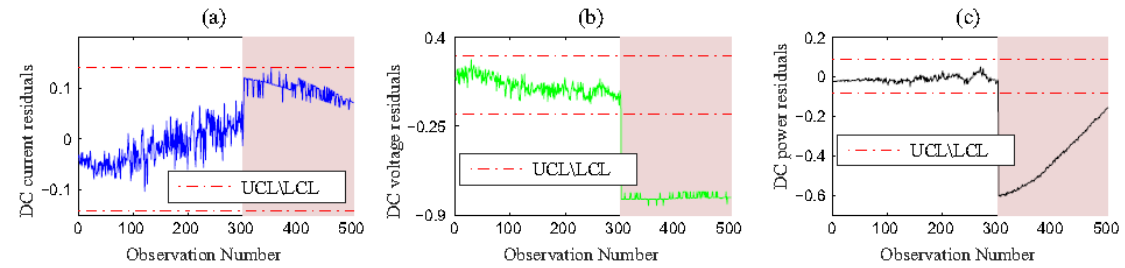


Fig. 18. Monitoring results of a Shewhart chart for DC current (a), DC voltage (b) and DC power (c) in the presence of five short-circuited modules in a PV array.

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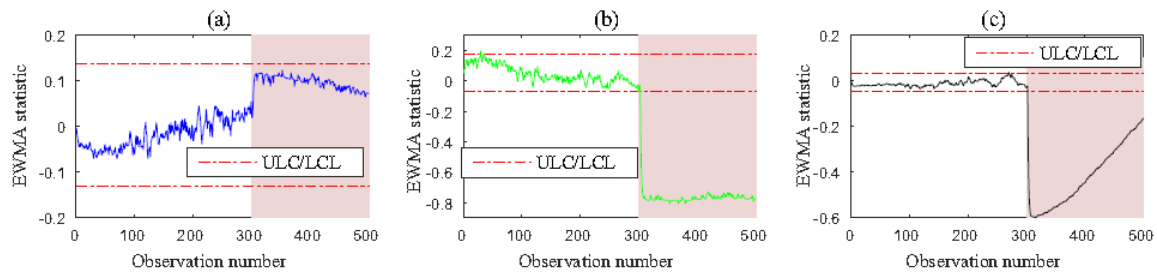


Fig. 19. Monitoring results of an EWMA chart for DC current (a), DC voltage (b) and DC power (c) in the presence of five short-circuited modules in a PV array.

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522 5.1.4. Case study of shading fault

523 The aim of this case study was to assess the potential of the proposed ODM-based EWMA method
524 to detect and identify partial shading faults in a PV system.

525 (1) Temporarily shading of four PV modules: In this example, the first four modules of the PV
526 system were temporarily fully shaded (see Fig. 22, fault #6), between samples 150 and 250. Figs.
527 23 and 24 show that both charts can detect and identify this fault. This type of fault may cause
528 decreases in current and voltage and significant power loss.

529 (2) Fully shading of one PV module: In this example, the module number 14 of the first string of
530 the PV system were temporarily exposed to fully shading (see Fig. 22, fault #7), between samples
531 150 and 250. The shewhart chart fails to detect this fault, as shown in Fig. 25(a)–(c). Fig. 26(c)
532 shows that the EWMA chart is able to detect the fault, but it cannot identify its type (see Fig. 26(b)
533 and (c)).

534
535 5.1.5. Case study of multiple faults

536 To assess the capacity of the proposed method to detect multiple faults, five modules in the PV
537 system were exposed to a partial shading (Fig. 22, fault #6), between samples 150 and 250, and
538 then five modules in one string were short-circuited (Fig. 22, fault #8).

539 Monitoring results of the Shewhart and EWMA charts are illustrated in Figs. 27 and 28,
540 respectively. In this case, both charts can accurately detect and identify these multiple faults.
541 In summary, our ODM-EWMA fault detection scheme provides satisfactory results in detecting and
542 identifying short-circuit faults, open-circuit faults in PV strings and partial shading. In addition, to
543 detect small changes (e.g., one short-circuited module in a string), the EWMA chart is more
544 effective.

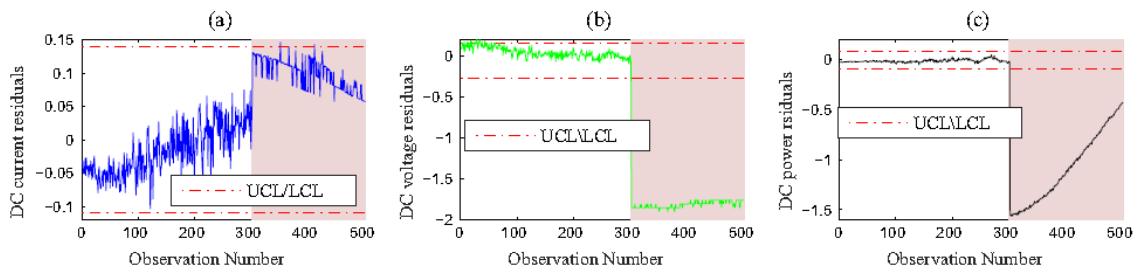


Fig. 20. Monitoring results of a Shewhart chart for DC current (a), DC voltage (b) and DC power (c) in the presence of ten short-circuited modules in a PV array.

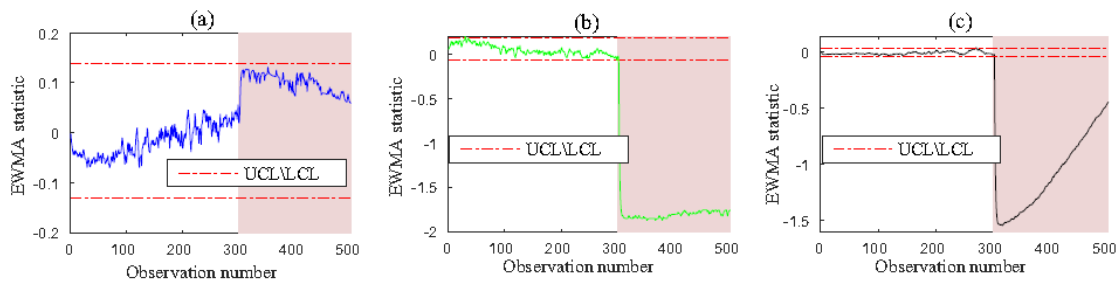


Fig. 21. Monitoring results of an EWMA chart for DC current (a), DC voltage (b) and DC power (c) in the presence of ten short-circuited modules in a PV array.

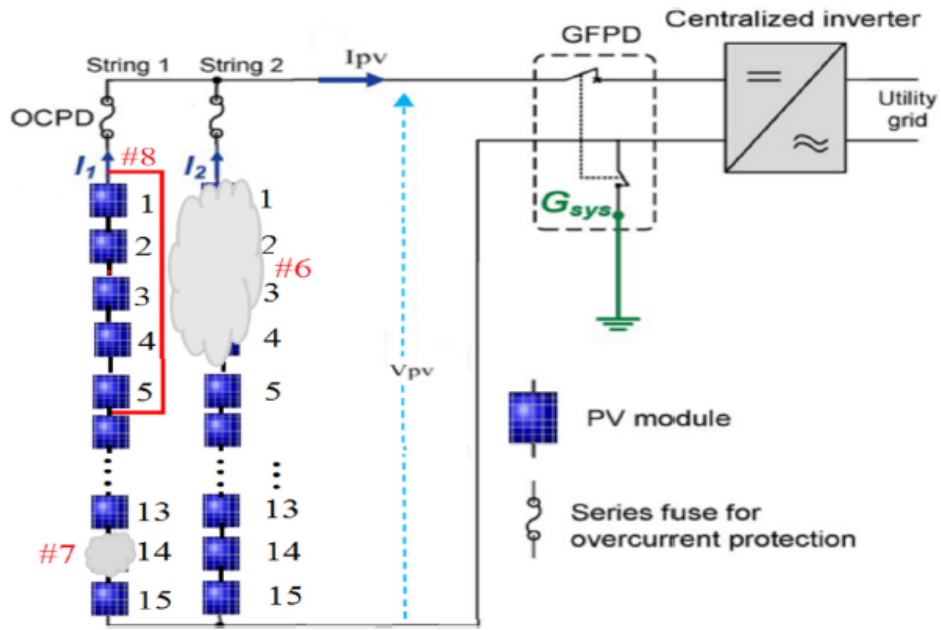


Fig. 22. Typical faults in a PV array: temporarily shading and faulty modules.

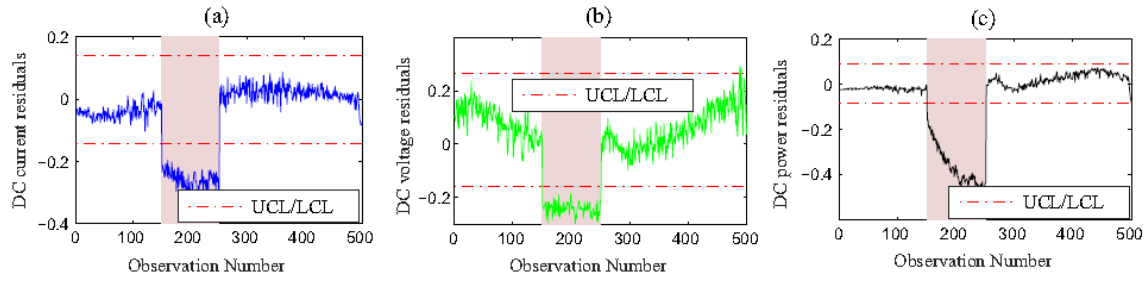


Fig. 23. Monitoring results of Shewhart chart for DC current (a), DC voltage (b) and DC power (c) in the presence of 4 PV modules temporarily shaded in the PV system

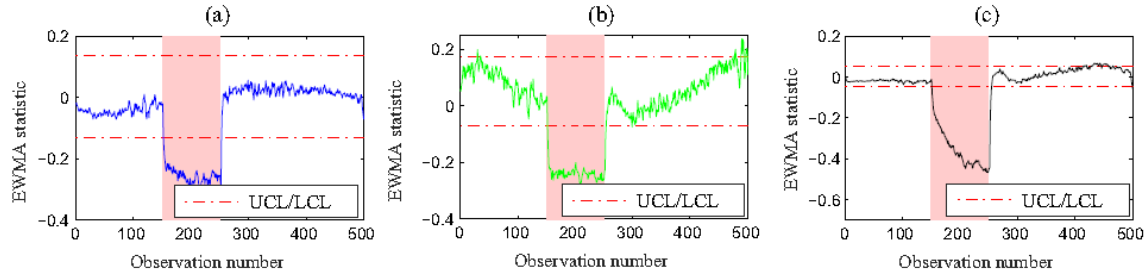


Fig. 24. Monitoring results of EWMA chart for DC current (a), DC voltage (b) and DC power (c) in the presence of 4 PV modules temporarily shaded in the PV system.

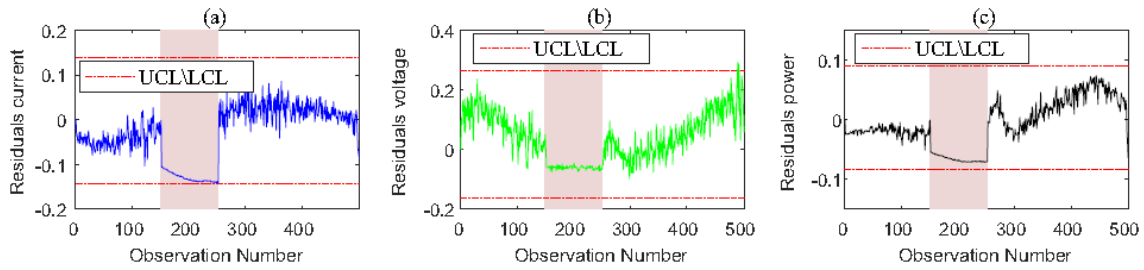


Fig. 25. Monitoring results of Shewhart chart for DC current (a), DC voltage (b) and DC power (c) in the presence of 4 PV modules fully shaded in the PV system.

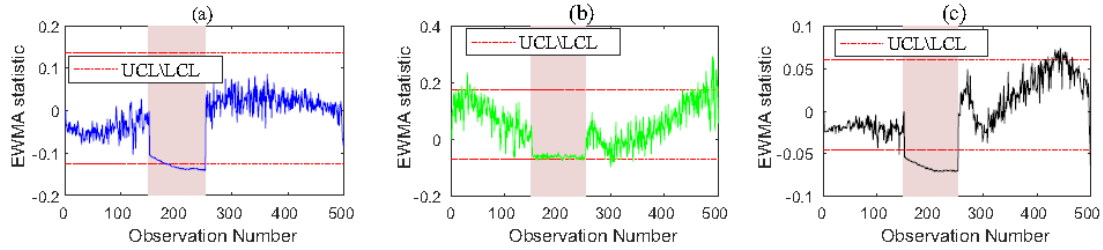


Fig. 26. Monitoring results of EWMA chart for DC current (a), DC voltage (b) and DC power (c) in the presence of one PV module fully shaded in the PV system.

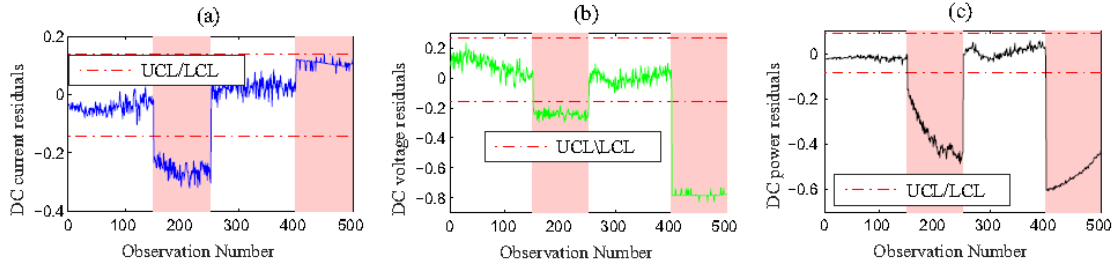


Fig. 27. Monitoring results of a Shewhart chart for DC current (a), DC voltage (b) and DC power (c) in the presence of 4 PV modules that are partially shaded and five short-circuited modules in the PV system.

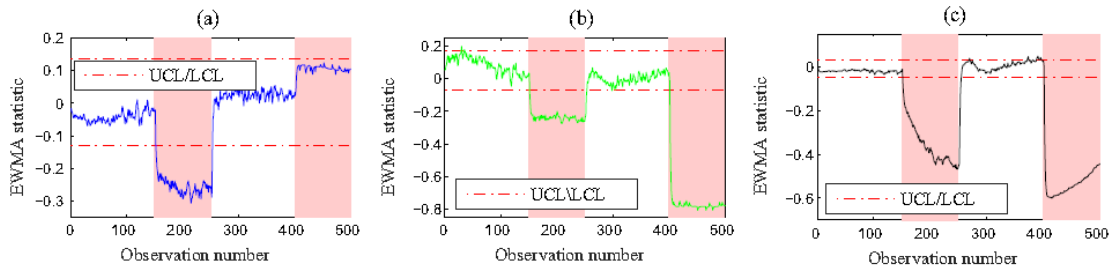


Fig. 28. Monitoring results of an EWMA chart for DC current (a), DC voltage (b) and DC power (c) in the presence of 4 PV modules that are partially shaded and five short-circuited modules in the PV system.

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6. Conclusion

Solar-energy-based photovoltaic (PV) systems are increasingly gaining worldwide attention due to the high electricity consumption in combination with the desired environmental friendly solutions for power production development. Indeed, PV systems are continuously exposed to many factors that significantly degrade their performances and efficiency. Faults such as short-circuit, open circuit and shading in PV systems can reduce solar energy productivity, leading to economic losses. This paper reports the development of a statistical fault detection approach for monitoring the performances of PV systems by detecting faults on the DC side and diagnosing the type of detected fault. This approach uses a simulation model based on the extracted ODM model parameters to predict the maximum current, voltage and power generated from the PV system. Residuals, which are the difference between measured and predicted variables, are used as input for the EWMA chart. Then, the EWMA based on residuals of output DC power is used to identify, in real time, the presence of faults in the monitored system. Voltage and current residuals are used to differentiate between open-circuit faults, short-circuit faults and partial shading in a PV system. Using practical data from a grid connected PV system at CDER in Algeria, the effectiveness of ODM-EWMA to detect and identify faults in an actual PV system has been demonstrated.

567 Despite the promising results for fault detection and diagnosis obtained using the ODM-EWMA
568 approach, the work carried out in this paper raises a number of questions and provides some
569 directions for future works. In particular, the following points merit consideration from
570 researchers.

571

572 Beside fault detection and diagnosis capability, the EWMA chart is able to capture fault severity
573 (amplitude). The larger the fault is, the greater the amplitude of the EWMA statistic compared to
574 its amplitude under healthy conditions. Therefore, this approach can be extended to determine
575 the number of faulty PV strings and/or PV modules.

576

577 Herein, the diagnosis of the fault is done on the basis of only the MPP coordinates of current and
578 voltage to identify the type of fault. In fact, the shading of one PV module or small portion
579 of PV module does not necessarily affect simultaneously current and voltage MPP coordinates.
580 Hence the proposed diagnosis method cannot correctly discriminate this fault. To bypass this
581 shortcoming, we plan to include more input data such as open circuit voltage (V_{oc}), short circuit
582 current (I_{sc}) and fill factor (FF) since they are affected significantly by shading fault.

583

584 The presence of noisy and correlated data makes the fault detection more difficult as the
585 presence of noise degrades fault detection quality and most methods are developed for
586 independent observations. In fact, wavelet-based multiscale representation
587 of data has been shown to provide effective noise-feature separation in the data and to
588 approximately decorrelate the auto-correlated data. As future work, the aim is to develop
589 multiscale EWMA fault detection methods that can provide enhanced performances of this
590 technique, especially when data observed from PV system are noisy and highly autocorrelated.

591

592

593 Acknowledgement

594 We would like to thank the reviewers of this article for their insightful comments, which helped us
595 to greatly improve its quality.

596 This publication is based upon work supported by King Abdullah University of Science and
597 Technology (KAUST), Office of Sponsored Research (OSR) under Award No: OSR-2015-CRG4-
598 2582. The authors (Elyes Garoudja and Kamel Kara) thank the SET Laboratory, Department of
599 Electronics, Faculty of Technology, University of Blida 1, Algeria, for continuous support during the
600 study.

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