I–V characteristic and its fractal dimension for performance’s fault detection

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ABSTRACT
Failures in photovoltaic systems are a major problem since they cause a decrease in the production of electrical energy. It is a challenge for the scientific community to obtain algorithms that adapt to existing systems, reducing the probability density of false positives. This paper solves this problem, presenting two contributions aimed at detecting faults in photovoltaic systems. The first contribution is aimed at a new algorithm based on non-coherent detection. Such algorithm is adaptable to any photovoltaic system and uses the box-counting procedure to estimate the fractal dimension of the normalized signal. The second contribution are to two equations that allow calculating the detection threshold under a failure prediction of such algorithm. The prediction of failures is based on a probability density of false positives set a priori. The algorithm was experimentally validated using 300 signals acquired from a photovoltaic system in series and parallel configurations. The results show that the algorithm had a behaviour, under a probability density of false positives of 2%, higher than those reported in the literature.

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1. Introduction

This paper shows a new algorithm to detect multiple faults of different natures in photovoltaic systems (PVS) and two new equations to calculate the detection threshold under a false positive probability (FPP) set a priori. This algorithm uses the estimation of the fractal dimension (FD) for the feature extraction and a non-coherent approach for the detection of the multiple faults generated (Bollipo et al., 2021). Livera et al. (2019) and Gokdag and Akbaba (2016) suggest that these faults can be generated from an electrical point of view or by environmental factors such as, power loss, aging in the wiring and electrical disconnection, shading effect and dust on the surface. This paper relates to these failures.

At present, there are different sources of renewable energy (Ma & Ma, 2018). Among them, solar energy is one of the most used (Boumaaraf et al., 2020). Kumari and Geethanjali in (2018) suggest that this is due to low costs and the minimum maintenance required for PVS. This interest in PVS has led researchers to develop methods to maximize the use of solar energy and fault detection.

Today there are two paradigms for fault detection. The first paradigm is found in the works documented by Chine et al. (2015), Kaid et al. (2018), Mekki et al. (2016), Prakash et al. (2020) and Yi and Etemadi (2017). Their procedures are based on machine learning, which employ a coherent detection approach. Mellit et al. state in (2018) that the main disadvantage of the procedures developed under this paradigm is that they require very advanced skills to implement them in real time (experimental performance) as well as databases (of different failures) which not always are available. The second paradigm is aimed at a non-learning approach, that is, a non-coherent-detection method, which maximizes its adaptability to any PVS and does not need a large volume of data to know information about the presence of failures in PVS. The procedure developed in this work is based on this paradigm, of which the authors have found the following publications.

Garoudja et al. in (2017) present a model focused on fault detection produced by shadows through the implementation of thresholds and wavelet packets. These researchers present the use of the exponentially weighted moving average (EWMA) to detect incipient changes in PVS. In addition, they explain how they use thresholds for the failure decision process. The main drawback of this work is that the authors do not show the percentage of false alarm rate (FAR, from now on we will call you FPP) produced by their algorithm.
Kumar et al. in (2018) present an algorithm to detect, online, faults produced by partial shadow using wavelet packets. The main drawback of this proposal is that they do not use a mathematical expression to calculate the thresholds for fault detection and not show the FPP that its algorithm presents. Another drawback is that they do not show a procedure for selecting the wavelet function they use.

Mansouri et al. in (2018) present an algorithm based on EWMA, multi-objective optimization (MOO) and wavelet representation. These researchers indicate the use of MOO to solve the problem of selecting the optimal solution for the following two objective functions: (i) missed detection rate (MDR) and (ii) $F_{PP}$. One drawback is that they do not show a procedure for selecting the wavelet function they use.

Fezai et al. in (2019) propose an online reduced kernel generalized likelihood ratio test (OR-KGLRT) technique for improved fault detection in photovoltaic (PV) systems. These authors use the $F_{PP}$ as a performance criterion.

Harrou et al. in (2019) present a robust and flexible strategy for fault detection in grid-connected PVS based on multiscale representation of data using wavelets and EWMA. These authors use the $F_{PP}$ to evaluate the performance of their algorithm. One drawback is that they do not show a procedure for selecting the wavelet function they use.

Zhao et al. in (2020) present a method based on collaborative fault detection in PVS using filtering techniques. These authors use a method to obtain an auto-threshold that allows them to identify the failures caused but does not show $F_{PP}$ produced by their algorithm.

Despite the advances achieved by the scientific community under the second paradigm, the reported works do not take into account non-uniform radiation continuously. They also do not take into account the challenges reported by Mellit et al. (2018) aimed at the development of detection techniques which are characterized by their efficiency, simplicity in terms of implementation, adaptability for different PV technologies and the ability to detect multiple faults as well as new faults. Our research, in addition to taking into account the reported challenges, focuses on minimizing the $F_{PP}$ density. As has been mentioned in the foregoing paragraphs, failure detection in photovoltaic systems can be divided into two categories of prediction:

1. Learning (Supervised or unsupervised approaches) (Abaei & Selamat, 2014).
2. To best of our knowledge, Investigations undertaken during the second category do not yet have the predictive methods by which the probability density of false positives of the failure detection algorithm in PVS is set a priori.

Unlike the articles reported above in this work, the probability density of false positives of the failure detection algorithm is set a priori. Due to this methodological difference the comparison between methods is made using works from the second category as shown in Table 4.

The rest of the manuscript is organized as follows: Section 2 shows the theoretical background used for algorithm design. Section 3 presents the method used for failure detection where emphasis is placed in two equations for the calculation of the threshold predicting failure probability. Section 4 describes the experimental setup. Section 5 shows the validation of the proposed algorithm and section 6 presents the conclusions of the work.

2. Theoretical background

This section describes the theoretical foundations used for the design of the new algorithm, which has as its main objective the detection of multiple failures in PVS.

2.1. Fractal dimension

Wang et al. in (2001) suggest that chaos theory and nonlinear dynamics can be used to describe irregular signals from non-linear dynamical systems. This allows the extraction of descriptive characteristics about the behaviour of the system to be analysed.

The FD is a mathematical tool that allows extracting characteristics of irregular signals coming from non-linear or chaotic systems. The authors of (Han et al., 2019; Rimpaulet et al., 2018; Xing et al., 2019) state that FD allows us to know how the irregularity of a signal (object) fills the space that contains it. Said object has a dimension that is between its topological dimension and the dimension of the container space.

Mallat in (2009); Schwarzenberger and Falconer in (1990) show the procedure to estimate the FD of an object bounded in $R^n$ as the number of squares, $N(\delta)$, of side $\delta$ necessary to cover said object. Equation (3) defines the FD of an object and follows the power law shown in (1).

\[
N(\delta) \sim c\delta^{-s}
\]  

(1)

Applying logarithms to both sides:

\[
\log_{10}N(\delta) \sim \log_{10}c - s\log_{10}\delta
\]  

(2)

Solving for $s$ in Equation (2), we obtain (3):

\[
s = - \lim_{\delta \to 0} \frac{\log_{10}N(\delta)}{\log_{10}\delta}
\]  

(3)
where \( s \) is the dimension of the object, for the case in which \( s \in \mathbb{Z}^+ \) then \( s \) corresponds to the Lebesgue-dimensional measure and \( c \) is a positive proportionality constant. A computational procedure widely used by the scientific community to estimate FD is the counting box method, which has been used in applications reported by (Cimen et al., 2021; Panigrahy et al., 2020) and which will be used in our work.

2.2. Coherent and non-coherent signal detection

Fink in (1975), Sklar in (2001) and Taylor in (2004) argue that signal detection can be done in a coherent or non-coherent way. The coherent approach takes into account previously known characteristics of the acquired signal such as frequency, phase or morphology. In the case of non-coherent detection, there is no prior knowledge about the feature of the signal of interest.

These existing paradigms in detection are based on hypothesis testing where the distribution to which the data fit is previously known as suggested by Sengupta (1988), Dhaene (2001) and Kay (1995) and Trutié-Carrero et al. (2020), see Equation (4).

\[
\begin{align*}
H_0 : z_\gamma(t) &= w(t), \text{ lack of signal}, \\
H_1 : z_\gamma(t) &= x_\gamma(t) + w(t), \text{ presence of signal} 
\end{align*}
\]  

where: \( w(t) \) is additive white Gaussian noise with mean \( \mu \) and standard deviation \( \sigma \), \( H_0 \) and \( H_1 \) are the null hypothesis and alternative hypothesis, respectively, and \( z_\gamma(t) \) is the signal present in each hypothesis.

Knowing about the distribution to which the data fit is of great relevance. This is because this point allows obtaining detection thresholds using the cumulative distribution function, \( \mathbb{P}(\xi) \) (see Equation (6)), and the probability distribution function, \( \zeta(\xi) \) (see Equation (7)), reported by Dhaene (2001).

\[
\mathbb{P}(\xi) : \mathbb{R} \rightarrow [0, 1] 
\]  

For:

\[
\begin{align*}
\Xi(\xi) &= \mathbb{P}(\xi \leq k) \\
\xi(x) &= \mathbb{P}(\xi \geq k') \\
\xi_\omega : \Omega \rightarrow R & \text{ such that } R_\xi = \{ x \in R, \exists \omega \in \Omega : \xi_\omega = x \}
\end{align*}
\]  

where \( \xi_\omega \) is a random variable and \( R_\xi \) is the range of the random variable.

3. Method for detecting faults in photovoltaic systems

3.1. Threshold calculation

In this section, the authors show the second contribution of this work. This is oriented to the calculation of thresholds \( \gamma \) and \( \gamma' \) under a probability of failure determined a priori. The objective of these thresholds is to automate failure detection in PVS. In section 2.2 you can find its basis.

The central limit theorem is widely used to detect flaws in many research areas (Döhler et al., 2016; Trutié-Carrero et al., 2018; Viefhues et al., 2020). Despite its importance in the detection and prediction of failures, its main limitation lies in the need for a large volume of data to be able to work with a normal distribution function and the associated probability calculations. In Equations (9) and (10) what has been stated is exposed in an analytical way

\[
\lim_{n \to \infty} P\left( \frac{\sqrt{n}(\hat{X}_n - \mu)}{\sigma} \leq \gamma \right) = \Phi(\gamma), \quad \forall \gamma \in \mathbb{R} 
\]  

\[
\lim_{n \to \infty} P\left( \frac{\sqrt{n}(\hat{X}_n - \mu)}{\sigma} > \gamma' \right) = \varrho(\gamma'), \quad \forall \gamma' \in \mathbb{R} 
\]

where \( \Phi(\gamma) \) corresponds to the cumulative distribution function and \( \varrho(\gamma') \) corresponds to the probability density function. The main novelty of our work arises from the problem associated with the need to have a large volume of data, which is aimed at obtaining two equations that allow predicting the detection threshold without the need to use the central limit theorem.

For this calculation, the authors used 30 normalized signals corresponding to \( H_0 \), as shown in Equation (11).

\[
H_0 : \beta = FD_{\text{normalized}} \left[ \frac{\chi_{Q-1}^2}{\sup(x_q)_{q=0}^{Q-1}} \right] 
\]

where \( \beta \) is the estimate of the normalized FD and \( \sup(x_q) \) denotes the supreme value of \( x_q \).

After obtaining \( \beta \) for 30 signals, the \( \chi^2 \) goodness of fit test was calculated, showing that the data fit a Gaussian distribution. Taking into account the results presented in Figure 1 as well as Equations (12) and (16) that we will present below, allowed us to obtain new equations that constitute the most important results for the calculation of the \( \gamma \) and \( \gamma' \) values.

Solving from Equation (12) \( \gamma \) to obtain the first new equation.

\[
2F_{pp} = \left[ 1 + \delta \left( \frac{\gamma - \mu}{\sigma \sqrt{2}} \right) \right] 
\]

\[
2F_{pp} - 1 = \delta \left( \frac{\gamma - \mu}{\sigma \sqrt{2}} \right) 
\]
Applying the inverse error function, $\delta^{-1}\left(\frac{\gamma - \mu}{\sigma\sqrt{2}}\right)$, to both sides of Equation (13) we obtain Equation (14):

$$\delta^{-1}(2F_{pp} - 1) = \frac{\gamma - \mu}{\sigma\sqrt{2}}$$

(14)

Finally, we obtain the first new equation (see Equation (15)) for the calculation of $\gamma$ for an $F_{pp}$ a priori:

$$\gamma = \sigma\sqrt{2}\delta^{-1}(2F_{pp} - 1) + \mu$$

(15)

Then to obtain $\gamma'$ the authors start from Equation (16), solving for $\gamma'$ to obtain the second new equation:

$$2F'_{pp} = \eta\left(\frac{\gamma' - \mu}{\sigma\sqrt{2}}\right)$$

(16)

Applying the inverse complementary error function, $\eta^{-1}\left(\frac{\gamma' - \mu}{\sigma\sqrt{2}}\right)$, to both sides of Equation (16) we obtain Equation (17):

$$\eta^{-1}(2F'_{pp}) = \frac{\gamma' - \mu}{\sigma\sqrt{2}}$$

(17)

Finally, we obtain the second new equation (refer to Equation (18)) for the calculation of a-priori $F_{pp}$:

$$\gamma' = \sigma\sqrt{2}\eta^{-1}(2F'_{pp}) + \mu$$

(18)

where $\delta\left(\frac{\gamma - \mu}{\sigma\sqrt{2}}\right)$ is the error function, $\eta\left(\frac{\gamma' - \mu}{\sigma\sqrt{2}}\right)$ is the complementary error function, $\delta^{-1}(2F_{pp} - 1)$ is the inverse error function and $\eta^{-1}(2F'_{pp})$ is the inverse complementary error function according to (Jammalamadaka & Bury, 2000), $\sigma$ denotes the standard deviation and $\mu$ the mean value.

After obtaining the new equations for the calculation of the detection thresholds and having explained the second contribution of this paper, the authors show in Figure 2 the proposed algorithm for the automatic failure detection in PVS.

4. Configuration and experimental condition

To validate the algorithm, 4 PV were used (see Figure 3) ERDM 235TP/6, firstly in serial configuration and then in parallel configuration. Table 1 shows the electrical characteristics of the PV used.
Table 1. Electrical specifications of the ERDM 235TP/6.

| Parameter                      | Value       |
|--------------------------------|-------------|
| Max power output               | 235 W       |
| Open circuit voltage ($V_{oc}$) | 36.57 V     |
| Optimum operating voltage      | 29.04 V     |
| Short circuit current ($I_{sc}$)| 8.69 A      |
| Optimum operating current      | 8.11 A      |

Table 2. SolSensor specifications.

| Parameter                | Value                          |
|--------------------------|-------------------------------|
| Irradiance accuracy      | ±2% typical, 0–1500 W/m²       |
| Tilt accuracy            | ±1 degree typical, 0–90 degree |
| Measurement interval     | Irradiance: 0.1 s              |

Table 3. PVA-1000S analyser specifications.

| Parameter                | Value                          |
|--------------------------|-------------------------------|
| PV voltage range         | 0–1000 V                      |
| Current range            | 0–20 A                        |
| Voltage accuracy         | ±0.5% ± 0.5 V                 |
| Current accuracy         | ±0.5% ±40 mA                  |
| Voltage resolution       | 0.025 V                       |
| Current resolution       | 0.5 mA                        |
| I–V sweep duration       | 80–240 ms                     |

Table 4. Algorithm comparison facing the $F_{pp}$.

| $F_{pp}$ (%) | Algorithms                          | Faults                        |
|--------------|-------------------------------------|-------------------------------|
| 2.258        | WOEWMA                              | Multiple faults (Shadow, Power loss). |
| 12.9630      | OR-KGLRT                            | Multiple failures (Shadow, Power loss). |
| 6.98         | WM-EWMA                             | Shadow.                       |
| 5            | WM-EWMA                             | Open-circuit.                 |
| 2            | Reported in this paper              | Shadow, Dust, Power loss in cables. |
| 0            | Reported in this paper              | Open-circuit.                 |

To acquire the data, the authors used a remote virtual instrument composed of a SolSensor to obtain the radiation intensity (RI) that reaches the PV and a PVA-1000S analyser that allows obtaining the I–V characteristic of the topologies used. Table 2 and Table 3 show the specifications for the SolSensor and the PVA-1000S analyser, respectively.

5. Validation

5.1. Results and discussion of the experimental setup

This subsection is aimed at showing the importance of normalizing the signal to be processed in the algorithm.

5.1.1. Serial topology

For the case of the series topology, the results of the I–V characteristic are shown in Figure 4.

Note in Figure 4 the existence of a variation in short circuit current ($I_{sc}$). This variation is due to the fact that the measurement was carried out under non-uniform radiation, which causes the existence of a variation in RI, as shown in Figure 5. Notice in Figure 6 how, after normalizing the signals, they maintain their morphology.

5.1.2. Parallel topology

Figure 7 shows the I–V characteristic for the parallel topology and Figure 8 shows the RI corresponding to each measurement. Note in Figure 9 how, after normalizing the signals acquired under this topology, they present the same morphology.

As seen in this section, subsection 5.1, normalizing the signal provides invulnerability to data analysis to effects that cause variation in $I_{sc}$ or open-circuit voltage ($V_{oc}$).

5.2. Results and experimental discussion of the algorithm

The first step in the algorithm is wavelet shrinkage noise attenuation, using the SureShrink strategy with a soft threshold rule. This step will allow highlighting the irregularity present in the acquired signal. The mathematical tools and methods described in Sections 2 and 3, respectively, will be used. To carry out this procedure, it is necessary to select a wavelet function that allows highlighting the fractal characteristic present in the signal.

Because the threshold selection process described in section 3 is based on a statistical distribution criterion, the authors analysed the behaviour of the standard deviation, $\sigma_{30}^{\psi_j, \tau}$, and the mean value, $\mu_{30}^{\psi_j, \tau}$, for the 30 signals used in threshold calculation. To select the wavelet function that minimizes $\sigma_{30}^{\psi_j, \tau}$ and $\mu_{30}^{\psi_j, \tau}$, the candidate wavelet families to be studied are: Symlets, Biorthogonal, Coiflets, and Daubechies because they form a dyadic wavelet base, according to studies reported by Goswami and Chan (2011) Figure 10 shows the results obtained for this analysis.

In Figure 10, the wavelet function with the mentioned characteristics is highlighted with a red circle, which corresponds to the Symlet family and more specifically Symlet 4. Once the wavelet function for the algorithm was obtained, the thresholds were calculated with a criterion of $F_{pp} = 2\%$.

5.2.1. Validation for serial topology

Figure 11 shows the results obtained by the algorithm with values of $\gamma = 1.37$ and $\gamma' = 1.55$ which were calculated from Equations (15) and (18), respectively. Figure 12 shows the RI obtained for each signal.

Notice in Figure 11 that the algorithm only showed 4 false positives and 9 false negatives, one of them corresponds to the loss of power in the cables and the rest to partial shade. In Figure 12, it is observed that the eight false negatives correspond to the fact that the RI begins
to be like that produced by the partial shadow effect. The analysis of the eight false negatives allows us to conclude that this problem is normal and indicates that the failure produced by partial shade is not detectable for RI lower than 430 W/m².

5.2.2. Validation for parallel topology

Figures 13–15 show the results obtained by the algorithm and the RI, respectively, where the values obtained for $\gamma = 1.04$ and $\gamma' = 1.08$, which were calculated from Equations (15) and (18), respectively.
**Figure 7.** Parallel topology.

**Figure 8.** RI for the signals shown in Figure 7.

**Figure 9.** Normalized parallel topology.
Notice in Figure 14 that the algorithm only returned four false positives and a single false negative. Table 4 shows the results obtained corresponding to the $F_{PP}$ according to the algorithm reported by Mansouri et al. (2018) which they call WOEWMA, Fezai et al. (2019) OR-KGLRT, Harrou et al. (2019) WM-EWMA and the one reported in this paper. Observe how the algorithm described minimizes the $F_{PP}$ in the detection process, thus showing its advantage over others presented in the literature.

Observe in the results obtained, without the presence of any fault, in this section, for the parallel topology, after evaluating the I–V characteristic using the FD, it tends to its topological dimension, while the series topology
tends to the dimension of the contained space. This result implies that the algorithm does not have a dependence on the configuration where it is used.

It is important to note that in the case of an open circuit, which implies an electrical disconnection, the algorithm created by the authors of this work is capable of detecting this type of failure. As a consequence of this electrical disconnection, a constant signal is generated equal to a straight line that has dimension 1, which corresponds to the topological dimension of the signal. From the results shown in Figures 11 and 14, it is observed that the FPP obtained in both cases is zero percent, showing that our reported algorithm is superior to that shown by Harrou et al. (2019).
6. Conclusion

In this paper, two contributions aimed at the non-coherent detection of failures in photovoltaic systems were presented. The first contribution is an algorithm that detects multiple failures in photovoltaic systems, and adapts, to existing systems, it’s simple concerning implementing and minimizes the probability of failures in the detection.

The second contribution consists of two Equations (15) and (18) that allow threshold detection to be calculated considering a priori probability of algorithm failure.

This fault detection process can be done without using the central limit theorem. This avoids having to use an excessively large volume of data to detect failures. Another present advantage is that the two contributions shown allow for blind detection. This means that it is not necessary to know when the photovoltaic system is facing some type of disturbance that reduces the generation of photovoltaic energy.

The normalization process gives the algorithm invulnerability to non-uniform radiation. Wavelet Symlet 4 is the best candidate for the noise attenuation process. In future studies, the authors will design an algorithm based on multifractal analysis that allows detecting small-magnitude faults.

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