# Non-coherent detection of dust in photovoltaic systems in series configuration using Lipschitz exponent

**Eduardo Trutié-Carrero [1], Diego Seuret-Jiménez [1,*]**

[1] Universidad Autónoma del Estado de Morelos, Centro de Investigación en Ingeniería y Ciencias Aplicadas; Cuernavaca, Morelos, Mexico; eduardo.trutie@uaem.edu.mx
* Corresponding author: dseuret@uaem.mx

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**Abstract:** Failures in photovoltaic systems are a problem of great importance because they cause a deterioration in the production of electrical energy, among which is the dust on the surface of the photovoltaic system. This paper proposes a method to detect dust on the surface of a photovoltaic system in series configuration. In addition, shows by visual inspection that the IV characteristic of a photovoltaic panel is equal to the IV characteristic of a photovoltaic system. To obtain the results, 120 signals were used, 60 for the design of the method and the rest for the validation of the method. The proposed method only yielded 2 false positives out of 30 signals where there was no fault present.

**Keywords:** Fault detection; photovoltaic system; Lipschitz exponent, Dust detection.

## Introduction

Through the years, energy has been the most important resource for humanity. Because technological development and social welfare demand a higher energy requirement. Caused by population growth, quick urbanization, and industrialization. This growing demand has prompted scientific communities to develop efficient and environmentally friendly energy sources.

(Bhattacharya et al., 2016) state that the United Nations designated the period 2014-2024 as the decade of sustainable energy for all. The main advantage of using clean energy is a reduction in the emission of greenhouse gases, providing a healthier environment. Following the most optimistic scenario developed by the International Energy Agency (IEA) and the report by (Shahbaz et al., 2020), renewable energy in electricity generation will increase to 39% by 2050 causing a reduction of CO2 by 50%.

Solar energy is one of the main sources of environmentally friendly energy, which is acquired through the use of photovoltaic systems (PVS). Despite the benefits that PVS provide to energy sustainability. These are vulnerable to the presence of faults, which makes the energy conversion efficiency not maximum. This has generated great interest for researchers and the photovoltaic (PV) industry in faults detection. (Belboula et al., 2019; Livera et al., 2019; Platon et al., 2012; Takashima et al., 2009; A. Woyte et al., 2013; Achim Woyte et al., 2003) statement that the failures they can occur due to different electrical or environmental factors. Among the environmental factors is dust on the surface of the PVS, which we will address in this investigation.

Nowadays there are two paradigms for the faults detection in PVS. The first paradigm is found in the works reported by (Chaibi et al., 2019; Chouay & Ouassaid, 2018; Das et al., 2018; Dhimish et al., 2017; Fadhel et al., 2020; Hajji et al., 2020; Hu et al., 2017; Kumar et al., 2018; Lu et al., 2019; Mekki et al., 2016; Rouani et al., 2021; Sowthily et al., 2021; Yi & Etemadi, 2017). The procedures reported under this paradigm focus on the use of learning machines (supervised or unsupervised approach), which employ a coherent detection point of view. (Mellit et al., 2018) state that the main drawback in this paradigm is that they require very advanced skills to implement them in real time and databases (of different failures) that are not always available.

The second paradigm presents a non-learning approach, which we call non-coherent detection. Such an approach maximizes its adaptability to any PVS and does not require a large volume of data to learn information about the presence of PVS faults. The procedure developed in this work is based on the second paradigm, where the following publications have been found:

(Garoudja et al., 2017) present a model focused on faults detection produced by shadows through the implementation of thresholds and wavelet packets. These researchers present the use of the exponential weighted moving average

(EWMA) to detect incipient changes in PVS. Besides, they explain how they use thresholds for the faults decision process. The main drawback of the work presented is that the authors do not show the percentage of false alarm rate (FAR, in this work they will be called false positives ($P_{FP}$)) produced by their algorithm.

(Kumar et al., 2018) present an algorithm to detect partial shadow faults online using wavelet packets. The main drawback of this proposal is that they do not use a mathematical method to obtain the fault detection thresholds and they do not show the $P_{FP}$ presented by their algorithm.

(Mansouri et al., 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 from the following two objective functions: (i) miss detection rate (MDR) and (ii) $P_{FP}$.

(Fezai et al., 2019) propose an online reduced kernel generalized likelihood ratio test (OR-KGLRT) technique to improve faults detection in PVS. These authors use the FAR as a performance criterion.

(Harrou et al., 2019) present a robust and flexible strategy for faults detection in PVS connected to the network based on the multi-scale representation of data using Wavelets transform and EWMA. These authors use FAR to evaluate the performance of their algorithm.

(Zhao et al., 2020) present a method based on the collaborative faults detection in PVS using filtering techniques. These authors use a method to obtain an automatic threshold that allows them to identify the failures caused but does not show the FAR produced by their algorithm.

Despite the advances made by the scientific community under the second paradigm, the reported works do not validate their algorithms in the presence of failures with field measurements. They also do not take into account the challenges reported by (Mellit et al., 2018) aimed at the development of detection techniques that are characterized by their efficiency and simplicity in terms of implementation. In addition, the reported works do not develop their procedure for the detection of dust on the surface of a PVS. This investigation makes up for the deficiencies raised earlier. The second contribution of this work shows that the morphology of characteristic IV for a PV panel is the same as for a series panel configuration.

**Materials and Methods**

For data acquisition, the authors used 4 photovoltaic panels (PVP) ERDM 235TP / 6 in series configuration;
Table 1 shows the characteristics of the PVP used. For data acquisition, a remote virtual instrument was used, consisting of a *Solsensor* and a *PVA-1000S* photovoltaic analyzer to obtain information on radiation intensity (RI) and characteristic IV, respectively.
Table 2 and
Table 3 show information for the *Solsensor* and the PV *PVA-1000S*, respectively.

Table 1. ERDM 235TP / 6 specifications.

| Parameter | Value |
|---|---|
| *Maximum power output* | 235 W |
| *Voltage Open Circuit (VOC)* | 36.57 V |
| *Short-circuit current (Icc)* | 8.69 A |

Table 2. SolSensor specifications.

| Parameter | Value |
|---|---|
| *Irradiance accuracy* | $\pm 2$ % typical, 0 to 1500 $W/m^2$ |
| *Tilt accuracy.* | $\pm 1$ degree typical 0 - 90 degree |
| *Measurement interval* | Irradiance: 0.1 s |

Table 3. PVA-1000S specifications.

| Parameter | Value |
|---|---|
| *PV voltaje range* | 0 - 1000 $V$ |
| *Current range* | 0 - 20 $A$ |
| *Voltage accuracy* | $\pm 0.5\ \%\ \pm 0.5\ V$ |
| *Current accuracy* | $\pm 0.5\ \%\ \pm 40\ mA$ |
| *Voltage resolution* | 25 $mV$ |
| *Current resolution* | 500 $\mu A$ |
| *I-V sweep duration* | 80-240 $ms$ |

The IV curve of a PV module is morphologically the same as the IV curve of a PVS in series configuration. This indicates that the resulting characteristic IV and the point of maximum power are represented as the horizontal sum of the individual building blocks, being this the second contribution of our work. By means of this phenomenon, it is observed that the dust signal acquired by PVS presents non-stationary characteristics. Figure 1 and Figure 2 shows the electrical schematic for the serial topology, while Figure 3 shows the expected signal shape in characteristic IV.

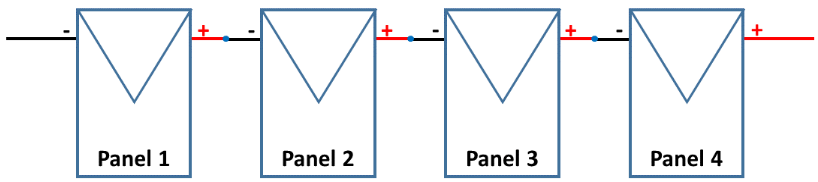


Figure 1. Electrical diagram of the serial configuration.

Figure 2. Experimental installation.

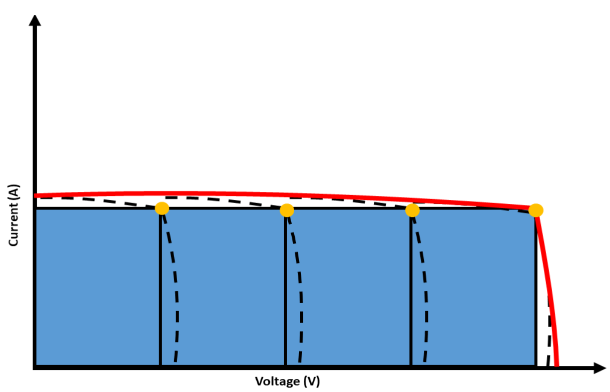


Figure 3. Expected signal serial configuration.

For feature extraction, the authors used equation (1) reported by (Trutié-Carrero et al., 2020).

$$\alpha = -\frac{\log_2\left(\frac{|Wf(k,j)|_{max}}{A}\right)}{j} - \frac{1}{2} \quad \forall\ k,j \in \mathbb{Z}^+ \tag{1}$$

where: $\alpha$ is the Lipschitz exponent, $|Wf(k,j)|_{max}$ is the Wavelet transform of maximum modulus according to (Griffel & Daubechies, 1995; Mallat, 2009), $j$ the jth decomposition level and $A$ is the Lipschitz constant of the analysis function.

**Results and Discussion**

To validate the detection process, the authors used 60 signals divided into two groups. The first group contains 30 signals without fault presence while the second group presents 30 signals with fault presence Notice in Figure 4 how the voltage superposition is fulfilled, in addition to validating the second contribution of the work. On the other hand, Figure 5 shows the existing RI at the time of acquisition.

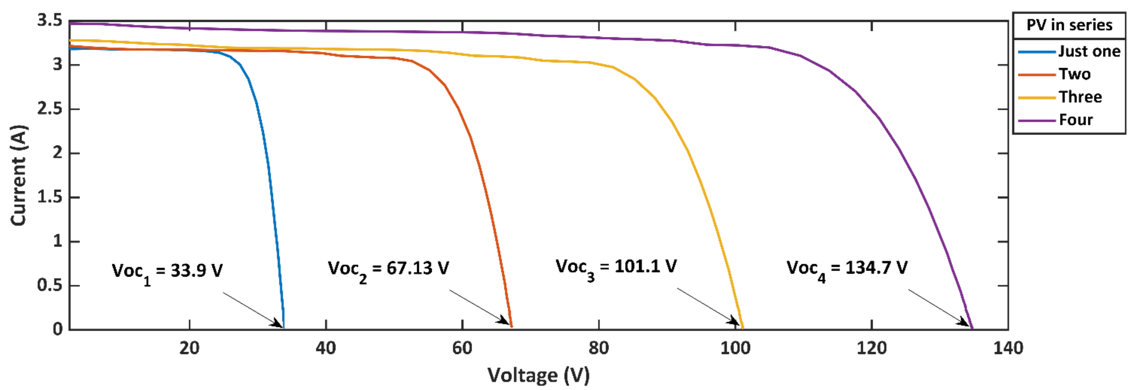


Figure 4. Voltage superposition.

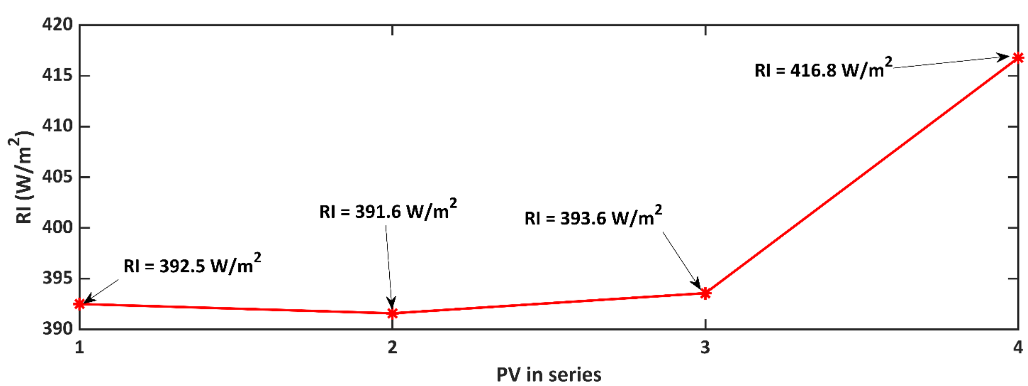


Figure 5. RI existing in the acquisition process.

The variation in Icc seen in Figure 4 is due to the measurement being made under field conditions. In addition, according to the report by (Mrabti et al., 2010; Perraki & Kounavis, 2016; Xiao et al., 2014) suggest that when the RI varies, the Icc does so abruptly.

To carry out the feature extraction process, an important step is to choose the Lipschitz constant and to know what the decomposition level to work at for a given wavelet function. Figure 6 is a figure of merit that allows the selection of the values of A and j for the wavelet function Symlet 4. In this case the authors make a selection for A = 200 and j = 1.

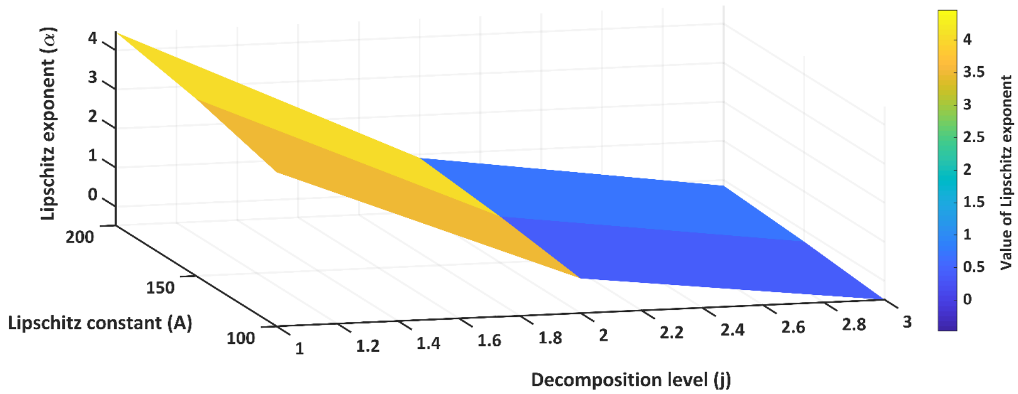


Figure 6. Selection of A and j for the wavelet function Symlet 4.

To automate the detection process, the authors calculated the threshold based on 60 historical data, 30 without the presence of noise and the rest with the presence of signal with noise.

Figure 7 shows in orange the histogram pertaining to the signals under the presence of dust on the surface of the PVS, in blue the histogram pertaining to the signals without fault presence and with dashed lines the threshold selected to automate fault detection. Note in this figure how there is only a small portion of signals without the presence of a fault in the zone where there is a fault.

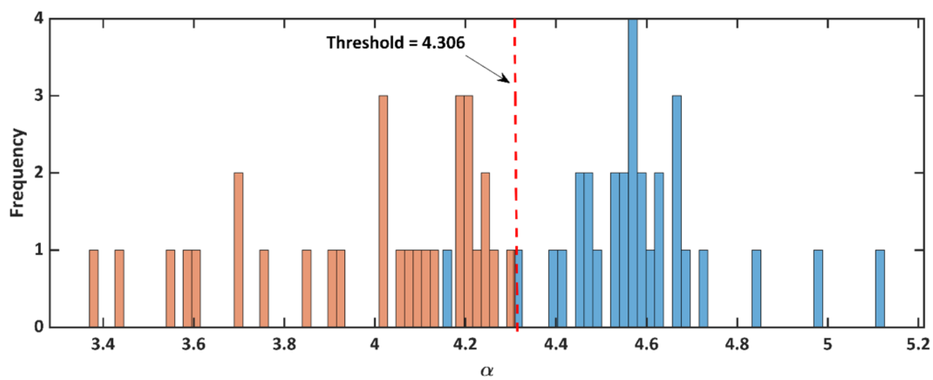


Figure 7. Signals histogram.

Note in Figure 8 how none of the scattered data shown corresponding to signals with fault presence (orange color) are lower than the threshold (dashed line), showing that the proposed method presents a good behavior against the detection of dust showing only 2 false positives.

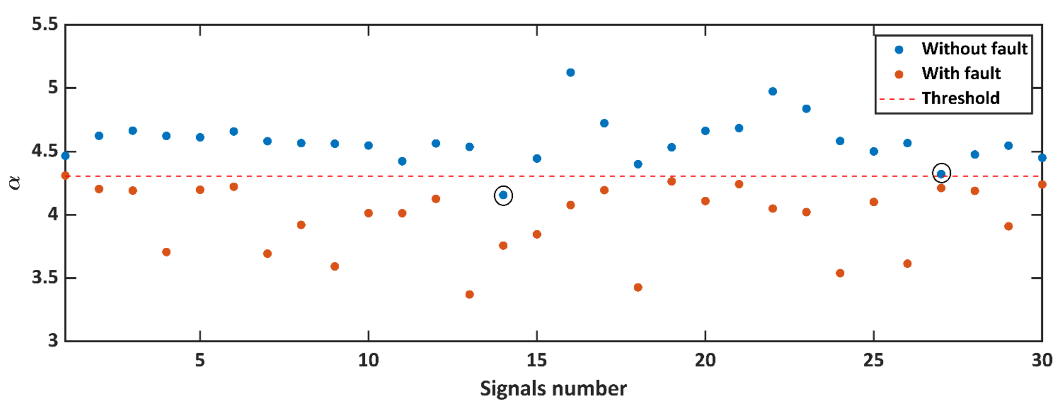


Figure 8. Results obtained by algorithm.

## Conclusions

This paper presented a method based on Lipschitz exponent and a non-coherent detection approach to detect dust on the surface of a photovoltaic system with serial configuration. This method produced only 2 false positives in 30 signals. On the other hand, the morphological behavior of characteristic IV for one, two, three and four photovoltaic panels was evaluated by visual inspection. After completing this evaluation, it was confirmed that the morphology of characteristic IV of a photovoltaic panel is the same as that of characteristic IV of a photovoltaic system in series configuration. In the next studies, a fractal algorithm will be designed to feature extract and maximize accuracy in the morphological evaluation of the signal. In addition, work will be done on optimizing the decision procedure.

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