New four-stage classification method for Fault Detection and Diagnosis applied to photovoltaic power plants

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Topic 5: PV SYSTEM AND STORAGE - MODELLING, DESIGN, OPERATION and PERFORMANCE

Subtopic 5.3: Operation, Performance and Maintenance of PV Systems

New four-stage classification method for Fault Detection and Diagnosis applied to photovoltaic power plants

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Abstract

There is an increasing interest both in academic or industry for health monitoring of photovoltaic (PV) power plants. The main reasons are safety issues and the loss of income due to faults or failures. In a PV power plant, on the DC side, the fault can affect a single cell, a module or a string. The fault effect or signature can be detectable or not, depending on the available information, the fault severity and the fault diagnosis method.

From the abundant literature, there is a diversity of approaches based on different input data (array I-V characteristic, array or string maximum power point, module level power point, infrared images, etc...), different techniques (image processing, neural network, etc...) depending on fault types (mismatch, short-circuit, open-circuit, etc...).

From the application point of view, it is not obvious to identify what would be the most efficient method to implement a condition-based maintenance that is now recognised as the most cost effective method. Therefore, we propose in this work from the analysis of the publications in 2017 to classify the fault detection and diagnosis methods through a framework defined in 4 steps: modelling, pre-processing, features extraction and features analysis.

Keywords: Photovoltaics, Fault Diagnosis

Aim of the work

Several research papers and institutional reports, such as IEA [1], have underlined the low yields of photovoltaic (PV) systems due to faulty components, especially in the DC section. The annual power loss due to various faults in PV power plant can go up to 18.9% [2]. Broadly speaking, faults of PV arrays are categorized as cell cracks, delamination, hot spots, dirt accumulation, modules mismatches, junction box faults, corrosion of the connections,. . .
Today, continuous health monitoring based on Fault Detection and Diagnosis (FDD) techniques is widely accepted as the most efficient approach to address the issue of power production losses in PV power plants. Indeed this approach allows detecting faults at their earliest stage, which helps in lowering cost and time maintenance, but also avoiding energy loss, damage to equipment, and safety hazards.
There is a growing interest to address this issue as it can be noticed in Figure 1 that displays the number of publications on this topic found in $Google\ Scholar$ for the past ten years.
Despite this abundant literature, there is no clear evidence on emerging FDD techniques that could be categorized as the most efficient for PV power plants monitoring.
In this work, we propose to use a new classification method that will help to select the most appropriate techniques of FDD to diagnose PV faults. This methodology will be implemented through the analysis of the literature published in 2017. The FDD methods used for PV fault diagnosis will be classified according to their effectiveness.

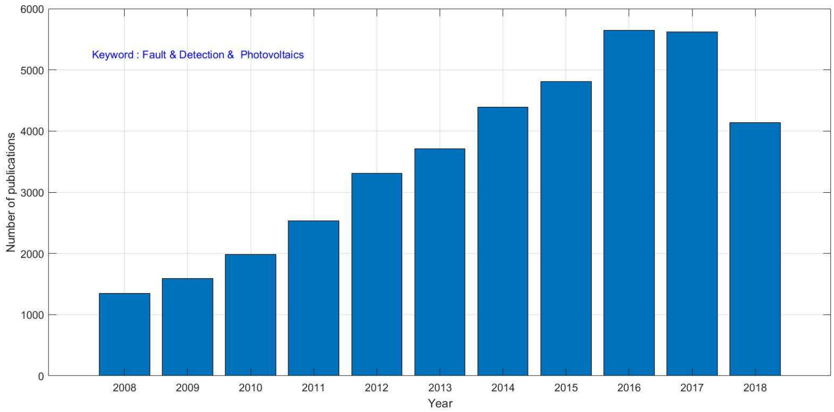


Figure 1: Evolution of the number of publications dealing with "fault detection" and "photovoltaics".

Approach

In this study, only the DC side faults of the installation are considered. The faults under consideration can be for example discoloration, delamination, bubble formation, cracks, micro-cracks, snail tracks, corrosion, PID, bypass diodes, etc. . . They can affect the PV power plant at the cell, module or system level. The faults can lead for example to mismatch, ground-fault (GL), line-to-line fault (LL) and modification of series (R_s) or parallel resistances (R_{sh}), etc. . . The fault occurrence can modify the I-V characteristic, increase the power losses or induce hot-spots, etc. . . .
The starting point for any FDD method is to build the knowledge. This can be done through data-driven models (historical data measurement) or/and physical-based models.
Data-driven models rely on data measurements. The most common sensors are current and voltage at the string level or the inverter input. Other information can be obtained through infrared imaging or electroluminescence for example. The selection of input data depends on the cost and the impact on the PV power plant operation. As an example, btaining the I-V characteristic in old power plants requires an interruption of production, which may be unacceptable for the operator.
The physical-based approach can use either analytical models or empirical ones. Their goals are the description of the PV power plant for all the possible operating conditions. This kind of description is somewhat complex and need to include for example, the aging effects that are not simple to predict.
We propose in the following to do a classification of FDD techniques through the methodology described in [3].

Scientific Innovation and Relevance

There are different ways to classify PV faults and the corresponding FDD methods.

For instance, PV faults can be classified according to:

- The cost effect [4],
- The number of occurrences in a time period [5, 6],
- The number of published studies [7, 8].

And finally, the corresponding FDD methods used to diagnose these faults can be associated.

Madeti [9] and Mellit [10] have proposed to classify the faults according to their consequences (the features) and the associated FDD techniques.

The IEA has proposed to classify FDD methods and then identify the defects that can be diagnosed [1].

A classification can also be done regarding the input data for the FDD techniques, that can be for example:

- String/Module I-V characteristics ($I\,(V)$),
- Module level power measurements ($MLPE$),
- Array/Sting maximum power point (P_{mpp}).

In this work, we propose a new classification method that will help to select the most appropriate techniques of FDD to diagnose PV faults. The methodology is based on the following four steps:

- Modelling or how to build the knowledge,
- Pre-processing that consists in selecting the appropriate information domain and data processing,
- Features selection and extraction,
- Features analysis.

The literature published in 2017 will be analysed in the light of this methodology. For every fault, each of these steps will be described and its relevance analysed.

Preliminary Results

With our specific criteria, we have found 181 journal papers published in in 2017 dealing with the diagnosis of PV faults. Among those, 109 describe or illustrate FDD techniques and 72 focus on a particular PV defect as it can be observed from Figure 2. Therefore in the following, only the 109 papers presenting FDD methods will be considered.

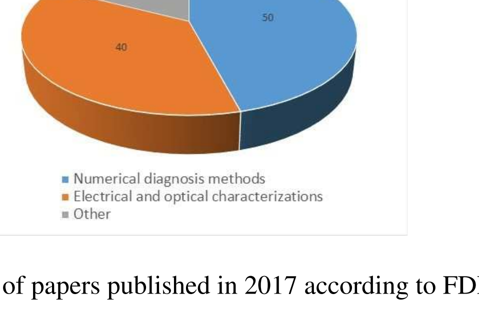
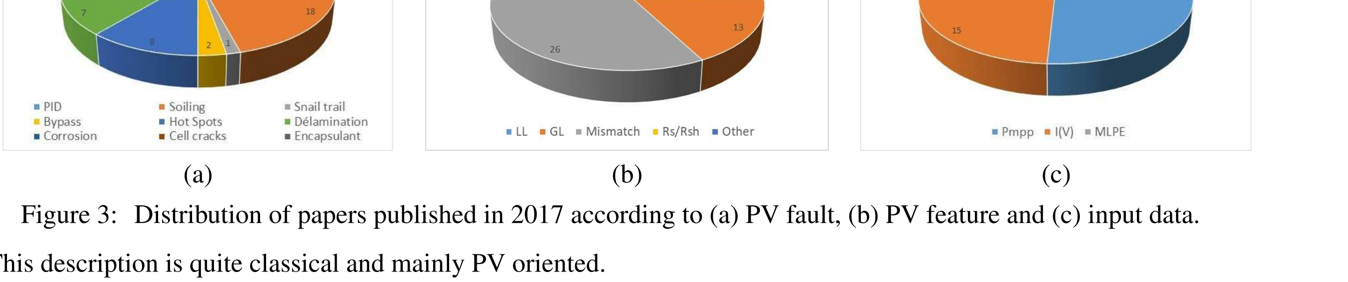


Figure 2: Distribution of papers published in 2017 according to FDD techniques.

Three categories are proposed in the following figures: by type of defect (Figure 3-b), by feature (Figure 3-c) and by type of input data (Figure 3-d).



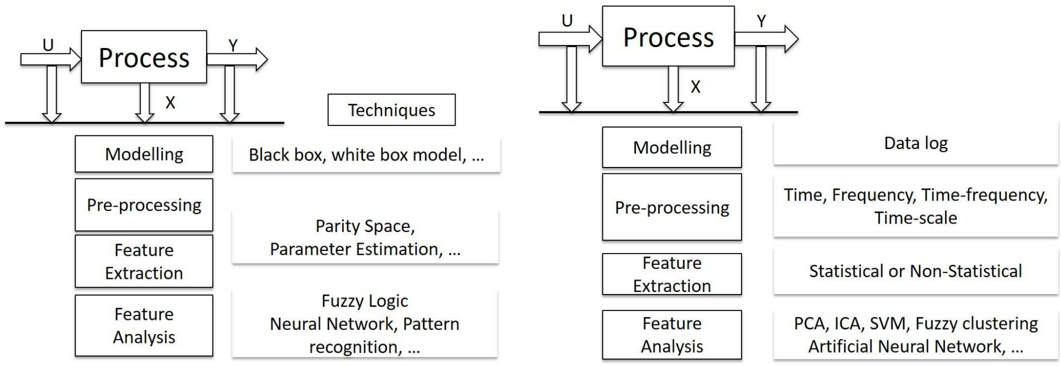
(a) (b) (c)

Figure 3: Distribution of papers published in 2017 according to (a) PV fault, (b) PV feature and (c) input data.

This description is quite classical and mainly PV oriented.

Our proposal consists in using another approach to alternative classification based on the properties of the FDD techniques. The methodology is based on four steps: modelling, pre-processing, features selection and extraction and features analysis to make the decision as displayed in Figure 4.

If a physical model of the PV cell, PV module or PV plant is enough accurate, an analytical model can be derived and state or/and parameter estimation methods can be used for FDD. Artificial intelligence techniques can be used to analyse the residuals or other features extracted with control theory methods.



(a) (b)

Figure 4: (a) Physics-based FDD method and (b) data-driven FDD method.

When the knowledge is based on data as shown in Figure 4 (b), the feature selection is based on data pre-processing. This step is crucial as it determines the information domain and processes useful transformation like filtering or dimension reduction in order to generate relevant features. The data can be processed for example in the time domain or frequency domain depending on the fault signature and the properties of the signals (stationary or non stationary for example).
How to select the appropriate FDD method for one PV fault or several PV faults with different severity levels still remain an issue. Through the framework previously described, we will analyse the performances of the FDD methods published in 2017.

Conclusion

This proposal summarizes an on-going work. The final paper will provide a detailed analysis of the papers published in 2017 on PV fault diagnosis. The analysis will be conducted in a framework defined in four steps: modelling, pre-processing, feature selection and feature analysis. The results will help to select what would be the most efficient FDD methods according to a given PV fault.

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