# An Algorithm Comparison for Fault Detection in PV arrays

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***Abstract* — In this paper an approach to increase the efficiency of a PV array is proposed. The incorporation of machine learning in the form of a classification algorithm for fault detection and to improve the detection of faults that are usually not detected with other traditional signal processing methods. In addition, a comparison between different algorithms is performed to obtain the best result in different scenarios. This research plans to reduce the mean time taken to repair PV arrays, the cost involved in repairing them and seeks to improve the efficiency of the PV arrays.**

## I. INTRODUCTION

The increasing demand for renewable energy not only for commercial or personal use, but in the creation of large arrays with a high production output is becoming more popular. Nonetheless, the techniques for detecting faults in PV arrays can still be improved by a great amount. The average amount of time it takes to detect and correct a fault is between 3 and 19 days for arrays that only collect data from an inverter. To help overcome these problems a facility has been created by the Sensor signal and information processing center (SENSIP) consisting of an 18 KW array of 104 panels. To aid the process of improving mean repair time, a smart monitoring devices (SMD) shown in Fig 1 is used. The data received from the SMD will help to lower the average time taken to detect and repair an array.

Figure 1: An SMD device setup to its corresponding solar panel.

These devices can monitor each array individually with the help of temperature, voltage, and current sensors. The SMD's is equipped with networking capabilities allowing for wireless communication with servers, data centers and eventually mobile devices. Moreover, all SMD's have relays incorporated into them which will allow for topology reconfigurations (switching from series to parallel or bypass) to produce a better power output for different circumstances. However, owing to human errors, there is a need for automated techniques for fault detection. The information gathered from the SMD's will serve to develop machine learning algorithms that will detect faults in the array in order to take action and correct those faults. In the future, with the implementation of camera hardware, this machine learning algorithm will not only take the information gathered from the SMD; in addition, it will also gather information from cameras to gather weather information and predict the best topological configuration considering these factors [1].

## II. Background Research

There has been a number of machine learning algorithms that have been used in other fields, including decision trees, feature extraction, statistical analysis, and fraud detection as seen in [4]. However, in this research we plan to explore the different clustering methods that exist in order to detect the different faults present in a PV array. These clustering algorithms will be used on an IV Curve where the Maximum Power Point Tracking (MPPT) curve can be found. A different curve that can also be incorporated and used within these models is the Voltage vs. Power curve which can help obtain the maximum power output current, and also help with the identification of faults when irregularities on said graph occur.

In this particular example we will be dealing with Kmeans algorithms, and Support Vector Machines (SVM's), as our main clustering algorithms, as well as Neural Nets as our classification algorithm. We will then compare the results yielded by the algorithms on our generated set of data. Primarily our data consists of two major faults: Arc Faults and Ground Faults. In addition to these faults we included different shading conditions as well for the algorithm to identify them. As mentioned before these algorithms have been proven useful in other fields, therefore their performance here is very promising. All algorithms have been developed on various script programs to compare the results with different methods of the same models on distinct platforms.

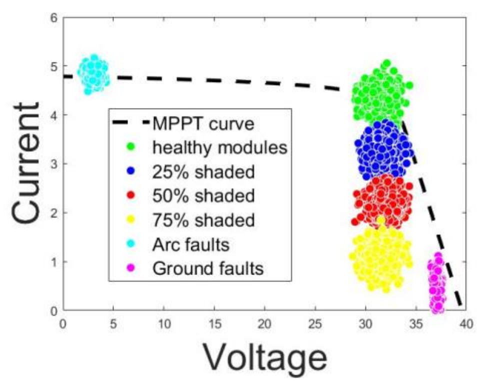


Figure 2: Data Generated by simulation includes ground faults, arc faults, healthy modules, and different grades of shading

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