Fault Detection in PV Arrays using Machine Learning Methods

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Abstract – An increase in grid-connected photovoltaic arrays creates a need for efficient and reliable fault detection. In this study, machine learning strategies for fault detection are presented. An unsupervised approach was successfully implemented using the k-means clustering algorithm to detect arc and ground faults. To distinguish and localize additional faults such as shading and soiling, a supervised approach is adopted using a Radial Basis Function Network. A solar array dataset with voltage, current, temperature, and irradiance was examined. This dataset had labeled data with normal conditions and faults due to soiling and shading. The direction for this study is to apply machine learning strategies to household-scale PV arrays within a zip code. Unlike the utility-scale arrays, aggregate data is used in rooftop installations, meaning that statistical methods will be examined alongside the fault detection.

Index terms – solar energy, machine learning, fault detection, radial basis networks, k-means.

I. Introduction

Consumer interest and deployment of rooftop solar energy systems require effective and implementable fault detection strategies. Fault detection and shading effects have been previously studied for utility-scale photovoltaic (PV) arrays using various machine learning methods [1,2,3,4]. In addition to faults, the increase of household-scale Grid-Connected Photovoltaic Systems (GCPVS) has been found to create fluctuations and imbalances in voltage [5,6] on the grid. It is critical to have effective and implementable fault detection strategies in place to ensure a steady power output for any grid-connected array.

The Sensor Signal and Information Processing (SenSIP) Center at ASU [7] developed an experimental facility consisting of an 18kW array of 104 panels. Each panel is equipped with a Smart-Monitoring Device (SMD) in which current, voltage, and irradiance sensors are integrated. This allows for connection topology reconfiguration through relay switches, since each SMD is connected to its neighboring SMD through a switching matrix, or by bypassing the underperforming panel all together [2].

Realistic synthetic data was created from a Simulink model of this array which can then be used in various machine learning techniques. An example is shown in Figure 1, where the *k*-means algorithm can accurately identify arc and ground faults by forming clusters and comparing them to a normal I-V curve. The algorithm is unsupervised and relies heavily on finding patterns in I-V characteristics, so it cannot distinguish between faults if their features are too similar. In this case, faults due to soiling and shading will only show decreased irradiance, making them unidentifiable within the Maximum Power Point (MPP) cluster. To detect a wider range of faults a labeled dataset and a supervised learning technique is required.

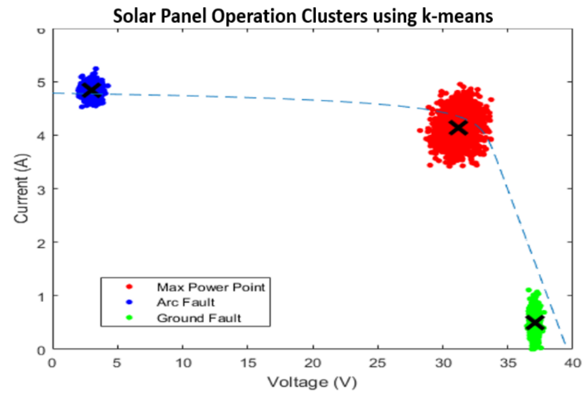

Fig. 1 – Preliminary results using *k*-means clustering.

In contrast to utility-scale arrays, rooftop installations lack hardware like the SMD so detection methods must be employed from an aggregate of data. Along with other factors not available in the data such as panel orientation, tilt, and weather [6], faults in rooftop PV systems are challenging to detect and localize. Therefore, statistical matrix analysis methods will be examined alongside machine learning for fault detection in rooftop installations.

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