Improved Fault Detection, Classification and Protection with Maximum Power Point Tracking (MPPT) Technique

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Abstract—**Fault detection and analysis are important to the efficiency, safety and reliability of solar photovoltaic (PV) systems. The fact is that PV systems have no moving parts and usually require low maintenance, they are still subject to various fault conditions. Especially for PV arrays (dc side), it is difficult to shut down PV modules completely during faults, since they are always energized by sunlight in daytime. Furthermore, conventional series-parallel PV configurations increase voltage and current ratings, leading to higher risk of large fault currents or dc arcs. This paper reviews the challenges and limitations of existing fault detection and protection solutions in solar PV arrays. This paper gives the study of faults under real-working conditions and is capable to identify the blind spots in the conventional protection scheme. It is shown that the line-line fault may not be detectable by traditional overcurrent protection devices (OCPD) under certain conditions. Therefore, the fault may remain in the PV system as a safety concern. To eliminate the detection \blind spot," outlier rules, such as statistical outlier detection rules (ODRs) and local outlier factors (LOFs) are proposed in PV-string monitoring systems. To further identify the fault types (or so-called fault classification), machine learning algorithms are studied in solar PV arrays. To overcome the drawbacks of supervised learning algorithms, a semi-supervised learning algorithm is proposed. The dissertation demonstrates the effectiveness in fault detection and classification in both simulation and experimental results.**

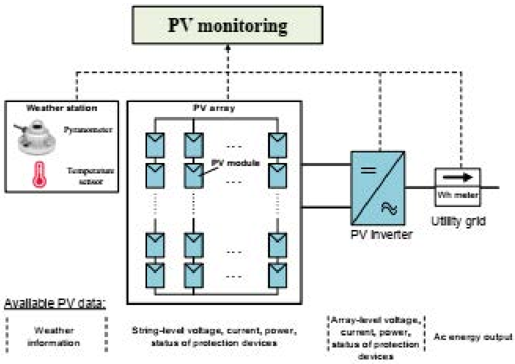
Keywords-Solar Photovoltaic (PV), Overcurrent Protection devices (OCPD), Local Outlier Factors (LOFs),Outlier Detection Rules (ODRs)

I. INTRODUCTION(HEADING 1)

Fault analysis, detection and protection are essential to prevent unexpected events in solar photovoltaic (PV) systems. Despite the fact that solar PV systems have no moving parts and usually require low maintenance, they are still subject to various failures or faults along the PV arrays, power conditioning units, batteries, wiring, and utility interconnections [1, 2]. Especially for PV arrays (dc side), it is difficult to shut down PV modules completely during faults, since they are energized by sunlight in daytime. Furthermore, PV is scalable and modular technology that can build a PV power plant by connecting a large number of PV modules in series and parallel configuration. Once PV modules are electrically connected, any fault among them can affect the entire system performance. This means the PV system is only as robust as its weakest link (e.g., the faulted PV components). In a large PV array, it may become difficult to properly detect or identify a fault, which can remain hidden in the PV system until the whole system breaks down. In addition, conventional series-parallel PV configurations increase voltage and current ratings, leading to higher risk of large fault currents or dc arcs. Due to faults occurring within PV arrays, several fire hazards have been reported in PV installations [3{6]. Fig. 1.1(a) shows the results of a fire hazard in a 383 kW PV array in Bakersfield, California in 2009 [3, 4].

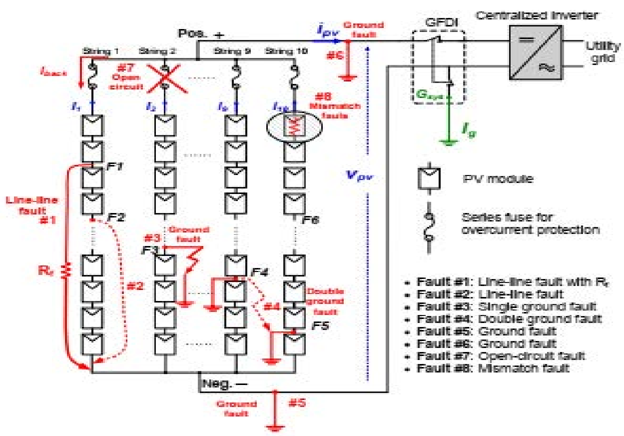
Another fire hazard is illustrated in Fig. 1.1(b), which occurred in a 1 MW PV power plant in Mount Holly, North Carolina, in 2011 [6]. In these cases, the fault remained unnoticed and hidden in the system until the hazard caused catastrophic fire. These fire hazards not only show the weakness in conventional fault detection and protection schemes in PV arrays, but also reveal the urgent need of a better way to prevent such issues.

Nowadays, due to the growing capacity of PV systems, there has been a proliferation of power conversion units, monitoring systems, protection devices and communication equipment being added to PV installations. As a result, excessive PV data becomes available (both instantaneous and historical). For example, as shown in Fig. 1.2 as a typical grid-connected PV system, various PV data are available from the weather station, PV arrays, PV inverters and utility grid. These PV data are mainly used to evaluate the PV system performance and calculate the energy losses over long periods of times. Although fault detection has been developed using historical PV data, it requires a long process time (at least a few hours or days) that may hinder the fault detection response and effectiveness. Hence, it is necessary to develop more responsive fault-detection algorithms that can make better use of these readily available PV data.



II. Problem Statement

Fig. 1.3 demonstrates a typical grid-connected PV system including a PV array with a number of PV modules in series and parallel connection, a central PV inverter with maximum power point tracker (MPPT), overcurrent protection devices (OCPD) and ground fault detection interrupters (GFDI). Several types of fault could happen inside PV arrays, such as line-line faults, ground faults, open-circuit faults, and mismatch faults. Among these faults, line-line faults and ground faults are the most common faults in solar PV arrays, which potentially involve large fault current or dc arcs.



As shown in Fig. 1.3, conventional fault detection and protection methods usually add OCPD (e.g., fuses) and GFDI within PV components [7] to prevent PV components from large fault current. However, it has been shown that certain faults in PV arrays may not be cleared by OCPD or GFDI due to non-linear output characteristics of PV arrays, PV current-limiting nature, high fault impedances, low irradiance conditions, PV grounding schemes, or MPPT of PV inverters [1, 8]. This difficulty brings \blind spots" in the protection schemes, leading to reduced system efficiency, accelerated system aging, dc arcs and similar fire hazards reported previously in [3, 8].

III. Fault Detection Using Outlier Detection Rule

In order to eliminate the previously discussed \blind spots" in overcurrent protection devices (OCPD), outlier detection rules (ODR) are proposed for fault detection in this chapter. By measuring each PV string current, the proposed algorithms can differentiate the faulted string from the normal strings, even under the condition when the faulted string still has the positive current. (Note that the OCPD fails in this case.) Specifically, this chapter of the dissertation demonstrates the following achievements

A. *Features for Fault Detection*

To develop a responsive and reliable fault detection algorithm, the first step is to choose appropriate PV features that are convenient to measure and analyze. Although the previously discussed PV dynamic conductance gpv may be used for fault detection (see (3.2) and Fig. 3.4), it can only be found if the global I-V characteristic of the PV array is scanned when the PV system is off-line. Thus, it is not easy to observe or use gpv directly in real-time operation. Instead of gpv, the following two features are more observable and viable for fault detection amongPV strings.

B. *String Current*

- PV string current is the most convenient feature to detect a fault in a series-parallel connected PV array. Besides, this feature is usually available when a PV string monitoring system is installed. Compared with its neighboring strings, a reduced string current ij on the jth String (j = 1 to N) might indicate a fault.

- A sudden current change at a particular string may indicate an unexpected operating condition. It represents the PV dynamics that are useful for fault detection and fault analysis. String current change rate dij=dt(k) of String #j at the kth sample is defined as dij=dt(k) = ij(k) − ij(k − 1) t(k) − t(k − 1) (4.1) where ij(k) is the kth sample of String #j current and t(k)−t(k−1) is the sampling interval. At the moment of the fault, the faulted string current ij usually reduces and leads to a significant drop of dij=dt, which may be a fault indication. Based on these two features, ODR for fault detection will be introduced as follows, which does not require weather information.

- Do not mix complete spellings and abbreviations of units: “Wb/m2” or “webers per square meter”, not “webers/m2”. Spell out units when they appear in text: “. . . a few henries”, not “. . . a few H”.

- Use a zero before decimal points: “0.25”, not “.25”. Use “cm3”, not “cc”. (bullet list)

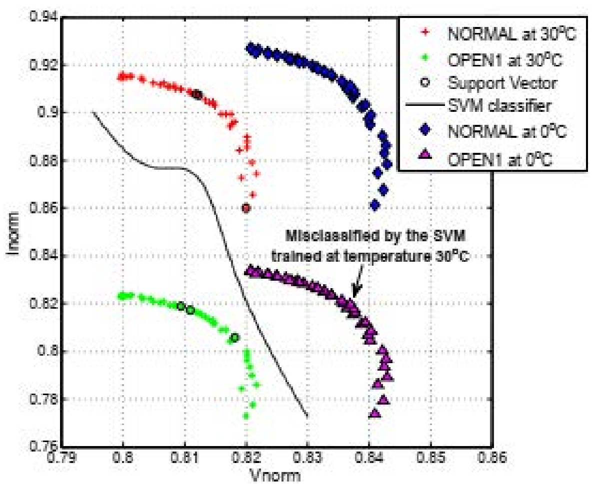
C. Fault Classification UsingMachine-Learning Algorithms

In addition to fault detection (mainly discussed in Chapter 4), this dissertationproposes fault classification as another useful feature in PV systems. Fault classification can indicate the type of fault and further help maintenance people toexpedite the system's recovery. Based on the prior knowledge of the systems, machine learning algorithms are usually used to achieve automatic fault classification.This chapter studies fault classification methods and focuses on graph-based semi-supervised learning (GBSSL) algorithms for PV fault detection and classifications(FDC).

D. Existing Solutions and their limitations

Machine learning techniques have been proposed for both fault detection and classification (FDC) in PV systems [27, 40, 41, 77, 78]. A decision-tree model has beenproposed to detect and classify fault types in PV arrays [40]. A clustering-basedmethod is used for quantifying PV system's effects on utility grids [78]. K-nearestneighbor and support vector machine are used for FDC in solar panels [41].For example, Fig. 5.1 shows a classifier using Support Vector Machine (SVM)model that has been trained to identify the open-circuit fault in one string (\OPEN1")from the normal condition (\NORMAL"). The classification features use VNORMand INORM, which will be explained in the following section. The SVM model istrained using the PV data collected at temperature 30oC in summer. However,Fig. 5.1 shows that the trained model will mistakenly classify \OPEN1 at temperature 0oC" as normal conditions, since the operating points are shifted awayin winter. Because the operating points of solar arrays are dependent on weather,they may change over a year. To solve this problem, the fault detection algorithmneeds to be self-learning and should be updated continuously.

Therefore, these supervised-learning classification models have several drawbacksas:



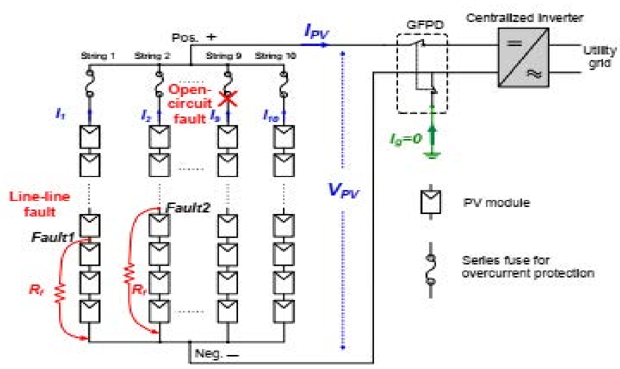
IV. Machine Learning Techniques in PV Systems

The overview of the proposed PV system is shown in Fig. 5.3 schematically, including a typical grid-connected PV system and the proposed machine-learning. The typical PV system includes: a PV array, a PV inverter, utility gridand conventional fault protection devices (i.e. OCPD and GFDI). The PVinverter harvests the maximum output power from the PV array using theMPPT algorithm, and feeds the power into the utility grid. The PV arrayexhibits non-linear current vs. voltage (I-V) curves, whether the PV array isunder normal or fault conditions. The previous chapters in this dissertationhave discussed that when the PV array is faulted, it has a changed configuration, resulting in changed I-V curves and reduced maximum power points(MPP). After that, if the fault is not cleared properly, it is likely that thePV inverter will still work, as long as the PV array can achieve the minimumoperating voltage of the PV inverter [1]. Consequently, the faulted PV arrayis expected to work at a new, but sub-optimal, possibly hazardous MPPalong with its faulted I-V curves. It is worth mentioning that the resultingdeviated PV-array MPPs can provide helpful information for the proposedGBSSL model.

The proposed GBSSL model uses readily available PV data. The GBSSLmodel for FDC measures the instantaneous short-circuit current reference(ISC−REF) and the open-circuit voltage reference (VOC−REF) of the referencemodules (small, lower power), and receives the PV-array current (IMP P) andvoltage (VMP P) at PVs MPP from the inverter. Alternatively, instead ofusing reference modules, it is also possible to obtain ISC−REF and VOC−REFfrom simulation models using instantaneous solar irradiance and solar celltemperature monitored by weather stations that are commonly installed inPV fields. Therefore, the proposed method can take advantage of readilyavailable PV data without adding significant hardware costs.The proposed GBSSL model can be integrated into PV inverters. The GBSSLmodel only monitors the PV array (dc side) at MPP under steady state, soit does not rely on any particular power conversion unit. Thus, anotheradvantage of the proposed method is the ease of integration within a PVinverter of any circuit topology.

Simulation Results

Using the widely used one-diode model [84] for each individual solar module/-panel, this dissertation builds another simulation PV system (17.6kW) in MATLAB/Simulink consisting of 10 × 10 PV modules (monocrystalline silicon) that iscapable of studying faults among modules. Note that this simulation system issmaller than the simulation system presented in Chapter 3 (35kW, 12 × 12 PVmodules). The schematic diagram is shown in Fig. 5.9. The number of series modules per string is NMOD = 10, and the number of parallel strings is NSTR = 10.The main parameters of each PV module at standard test conditions (STC) are asfollows: the maximum power PMP P =176W, the open-circuit voltage VOC=44.4V,the maximum power voltage VMP P =35.7V, the short-circuit current ISC=5.4A,the maximum power current IMP P =4.95A.



As shown in Fig. 5.9, there are two categories of faults in the PV systems: lineline faults (LL) and open-circuit faults (OPEN). The normalized MPPs under avariety of normal and fault conditions have been plotted in Fig. 5.5.

1) Normal condition (NORMAL)
Under a wide range of environmental conditions of changing solar irradianceand temperature, the normalized MPPs have the following operating range:VNORM 2 (0.77, 0.90) and INORM 2 (0.86, 0.91).
2) Line-line fault (LL)
A variety of line-line faults without or with fault resistance (Rf = 0 Ω or 10Ω) are studied. The fault resistance for typical line-line PV faults is consideredas 0Ω at solid faults, or as 10 Ω which may be caused by poor connections ordc arcs [28]. The fault between the fault point Fault1 and negative conductor(Fault1-Neg) in Fig. 5.9 is defined as \30% location mismatch (LL 30%)," since
it involves 3-module mismatch between the fault points in the faulted string(normally 10 modules per string). Similarly, the Fault2-Neg fault is defined as\40% location mismatch (LL 40%)". Compared with NORMAL, INORM underLL is slightly reduced to a range of (0.81, 0.91), but VNORM is significantlydecreased which lies in a wide range of (0.57, 0.78). The reason is that theMPPT tends to reduce VMP P to reach the sub-optimal MPP under LL faults,leading to a reduced VNORM. Meanwhile, INORM may be reduced as well, since the fault tends to reduce IMPP.
3) Open-circuit fault (OPEN)
Open-circuit faults on one string (OPEN1) and two strings (OPEN2) are included in Fig. 5.5. Notice that VNORM of OPEN faults remains the same asthe one in NORMAL conditions. But INORM is reduced proportionally by thenumber of lost strings, due to the parallel connection of PV strings.

CONCLUSION

Some solar PV faults have small fault current so they may not be cleared by overcurrent protection devices (OCPD). Thus, the faults can remain hidden in thePV system, resulting in possible dangers associated with it (sub-optimal performance, dc arcing, fire hazard, etc.). To identify these hidden faults, for the firsttime a graph-based semi-supervised learning (GBSSL) has been propose for faultdetection and classification (FDC) in solar PV arrays. It increases the PV's safetyand reliability by detecting these faults (unnoticeable by OCPD). In addition, theproposed method is able to identify the specific fault type so that PV users canexpedite the system restoration procedure.To better visualize the PV data under normal and faultconditions, this chapterfirst develops new attributes using the normalized voltage and normalized current. Different from previous works, the proposed GBSSL model only requires afew points of the costly labeled data (∼1% of the total data set), while makinguse of inexpensive unlabeled data. The GBSSL algorithm is first analyzed and explained in detail through simulation results. In addition, the self-learning ability ofGBSSL is proved as the label set can be updated over time during weather changesor PV arrays degrade. Furthermore, the proposed method does not depend on anyparticular PV inverter topologies and only uses readily available measurements inexisting PV systems{such as PV-array voltage, array current, operating temperature and irradiance{requiring no additional hardware installations.

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