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Statistical fault detection in photovoltaic systems

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A B S T R A C T

Faults in photovoltaic (PV) systems, which can result in energy loss, system shutdown or even serious safety breaches, are often difficult to avoid. Fault detection in such systems is imperative to improve their reliability, productivity, safety and efficiency. Here, an innovative model-based fault-detection approach for early detection of shading of PV modules and faults on the direct current (DC) side of PV systems is proposed. This approach combines the flexibility, and simplicity of a one-diode model with the extended capacity of an exponentially weighted moving average (EWMA) control chart to detect incipient changes in a PV system. The one-diode model, which is easily calibrated due to its limited calibration parameters, is used to predict the healthy PV array's maximum power coordinates of current, voltage and power using measured temperatures and irradiances. Residuals, which capture the difference between the measurements and the predictions of the one-diode model, are generated and used as fault indicators. Then, the EWMA monitoring chart is applied on the uncorrelated residuals obtained from the one-diode model to detect and identify the type of fault. Actual data from the grid-connected PV system installed at the Renewable Energy Development Center, Algeria, are used to assess the performance of the proposed approach. Results show that the proposed approach successfully monitors the DC side of PV systems and detects temporary shading.

1. Introduction

1.1. The state of the art

Traditional sources of energy, such as oil, coal and nuclear energy, have negative effects on human health, biodiversity, ecosystems and climate change. Nonetheless, industrial growth has extensively increased global consumption of fossil fuels, and the concomitant impacts on human health and the environment (Johansson, 1993). Renewable energy sources such as solar, wind and biomass, are promising alternatives to conventional fossil fuels because they are clean, sustainable, safe, and environment-friendly with zero CO_2 emissions (Panwar et al., 2011). One of the most sustainable and economically competitive renewable energy sources is solar photovoltaic (PV) energy (Zhao et al., 2015). Moreover, solar PV energy increases a country's energy security by reducing dependence on fossil fuels.

Under practical conditions, faults are unavoidable in PV systems, particularly on the direct current (DC) side where open circuit faults, short circuits faults, hotspot faults, and total and partial shading faults are possible (Chouder and Silvestre, 2010; Hachana et al., 2016; Silvestre et al., 2015; Yahyaoui and Segatto, 2017). Faults on the DC side of PV systems can result in energy loss, system shutdown and even in serious safety breaches (Brooks, 2011; Alam et al., 2015). For example, two PV facilities in the US (a 383 KWp PV array in Bakersfield, CA and a 1.208 MWp power plant in Mount Holly, NC) burned in 2009 and 2011, respectively (Brooks, 2011). The source for these accidents was a fault on the DC side that was not identified early (Vergura et al., 2009; Hariharan et al., 2016). If such faults in PV systems are not detected promptly, they can affect the system's efficiency and profitability, as well as the health and safety of workers and community members. The detection of faults in PV systems is therefore crucial for maintaining normal operations by providing early fault warnings. Indeed, accurate and early detection of faults in a PV system is critical to avoid the progression of faults and to reduce considerably productivity losses.

Several fault detection techniques for PV systems have been developed. They are two main types of these techniques: process history-based approaches and model-based approaches. Process-history-based methods use implicit empirical models derived from

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analysis of available data and rely on computational intelligence and machine learning methods (Mekki et al., 2016; Shrikhande et al., 2016; Hare et al., 2016; Suganthi et al., 2015; Silvestre et al., 2014; Tadj et al., 2014; Zhao et al., 2013). Mekki et al. (2016) proposed an artificial neural network to evaluate PV system performance under partial shading conditions. Chine et al. (2016) used an artificial neural network to detect short circuits in PV arrays. Tadj et al. (2014) proposed a fault-detection approach based on fuzzy logic to detect possible solar panel abnormalities. Pavan et al. (2013) used a Bayesian neural network and polynomial regression to predict the effect of soiling in large-scale PV system. However, process-history-based methods require the availability of a relevant dataset that describes both healthy and faulty operating conditions in a PV system.

On the other hand, model-based approaches compare analytically computed outputs with measured values and signal an alarm when large differences are detected (Harrou et al., 2014). Several model-based approaches to fault detection in PV systems have been reported in the literature using the one-diode model (Chouder and Silvestre, 2010; Vergura et al., 2009; Chouder and Silvestre, 2009; Chao et al., 2008). In one-diode-based fault detection approaches, model parameters are determined by parameter-extraction methods from weather conditions and the datasheet from the PV module manufacturer (Garoudja et al., 2015; Abou et al., 2015; Chouder and Silvestre, 2010). Both irradiance and solar panel temperature measurements are needed for such approaches to predict the maximum power point (MPP) of the PV system. Kang et al. (2012) used a Kalman filter to predict the power output of a PV system. Johnson et al. (2011) used a Fourier series to detect arc faults in a PV system. Other approaches employed sophisticated tools, such as time-domain reflectometry (TDR) (Munoz et al., 2011) and thermoreflectance imaging (TR) (Hu et al., 2014). The TR method was proposed to detect the appearance of hot spots inside PV systems (Hu et al., 2014). The TDR approach can detect, localize, and diagnose faults in PV systems, but the system must be turned off, which affects system productivity. TDR also requires sophisticated tools to introduce the input signal. Of course, the effectiveness of model-based fault-detection approaches relies on the accuracy of the models used.

1.2. Motivation and contributions

Until recently, statistical process control charts have not been widely used to monitor the performance of PV systems. Zhao et al. (2013) proposed a statistical technique using three outlier rules to classify deviations. Recently, Platon et al. (2015) proposed to use the three-sigma rule for online fault detection in PV systems. However, the three-sigma rule, also known as the Shewhart chart (Montgomery, 2007), loses the ability to detect incipient faults in process data because it makes decisions based only on information about the process in the last observation. Incorporating information about the entire process history, including previous or recent observations, into the decision rule can help to improve sensitivity to small shifts. The exponentially weighted moving average (EWMA) scheme incorporates information from the entire process history, rather than using only the most recent observation. This makes it more sensitive than the Shewhart chart to small anomalies. The main contribution of this work is to exploit the advantages of the exponentially weighted moving average (EWMA) chart and those of one-diode modeling for enhancing detection performances of PV systems, especially for detecting small faults in DC side of PV system and shading fault. Such a choice is mainly motivated by the greater ability of the EWMA metric to detect small fault in process mean, which makes it very attractive as fault detection approach. Note that the main advantage of EWMA chart is that it can be easily implemented in real time because of the low computational cost, which is not the case in a classifiers based methods (the classifier algorithms are performed offline rather than online). A decision can be made for each new sample by comparing the value of the EWMA decision statistic with the value of the threshold. An anomaly is declared if the EWMA statistic exceeds the threshold. To do so, residuals, which are the differences between the measured and predicted MPP for the current, voltage and power, from the PV array simulation model are generated. Under normal operating conditions, the residuals in a PV system are close to zero due to measurement noise and errors, while they significantly deviate from zero when the system is faulty. Residuals are used as fault indicators. Then, an EWMA chart is used to monitor the residuals to reveal abnormalities. Once the fault has been detected, the next step is expected to determine its cause. The proposed approach can also effectively diagnose fault types based on the output DC current and voltage. Indeed, fault diagnosis can help the operators and engineers in the process-monitoring scheme and therefore significantly reduce the risk of safety problems or loss in profitability. The proposed fault detection strategy has been validated using measurements from the 9.54 kWp PV plant at the Renewable Energy Development Center in Algiers, Algeria.

The remainder of this paper is organized as follows. Section 2 gives a brief overview of the grid-connected PV plant that provided data for this study. In Section 3, one-diode model is reviewed. Section 4 introduces the EWMA chart and its use in fault detection. Section 5 applies the proposed fault-detection and diagnosis procedure to the PV plant in Algeria. Finally, Section 6 concludes with a discussion and suggestions for future research directions.

2. The grid-connected PV system in Algiers, Algeria

We assessed our fault detection method using practical data collected from a grid-connected photovoltaic (GCPV) system located at Renewable Energy Development Center (CDER) in Algiers, Algeria. This PV system operates from June 21st, 2004, and the output power by this system is injected directly into the national electric distribution network without any storage device. This 90 module PV system 106 Wp is installed on the roof of the CDER building as shown in Fig. 1. This 9.54 kWp rated system has an output DC voltage of 125–450 V and an output AC voltage of 220 V. It comprises three sub-arrays of 30 modules each. The outputs of these three sub-arrays are connected to a single-phase 2.5 KW PV inverter (IG30 Fronius). Each sub-array consists of 30 Isofoton (106 W-12 V) PV modules, which are grouped into two parallel strings of fifteen PV modules in series. Irradiance measurements are collected with a Kipp & Zonen CM11 thermoelectric pyranometer and the temperature is measured with a K-type thermocouple. An Agilent 34970A data logger acquires the data through a connection to the local grid through an inverter, a safety control box and a meter. When the utility grid is not energized the

Fig. 1. The PV array installed on the roof of the CDER building in Algiers, Algeria (Arab et al., 2005).