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Modeling of PV system based on experimental data for fault detection using kNN method

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ABSTRACT

In this paper, a string level fault detection and diagnosis technique for photovoltaic (PV)systems based on k-nearest neighbors (kNN) rule is proposed. It detects and classifies open circuit faults, line-line ($L{-}L$) faults, partial shading with and with-out bypass diode faults and partial shading with inverted bypass diode faults in real time. A detailed modeling of the PV systems based on experimental data is presented that only requires available data from the manufacturer's datasheet reported under standard test conditions (STC) and normal operating cell temperature($NOCT$). This model considers the temperature dependent variables such as junction thermal voltage (V_t), diode quality factor (A) and series resistance(R_s). Simulations of the developed model have been carried out using Matlab/Simulink. A PV analyzer (Solar I-V) of HT instruments is used to measure the $I(V)$characteristics of PV module. The developed model precisely traces the$I(V)$characteristics of PV systems at different irradiance and temperature levels. The simulation results indicate that the error between the measured data and developed model is less than the models available in the literature. The absolute error is confined in the range 0.61 to 6.5%. Finally, the data generated from proposed model and experimental setup are used to validate and test the performance of the proposed fault detection and classification(FDC) technique. It is observed from the results that the average of fault classification gives a high accuracy of 98.70%.

1. Introduction

Photovoltaic (PV) systems provide a promising solution to directly utilizing solar energy and are currently gaining popularity as the technologies are mature and as the material costs are driven down (Mercure and Salas, 2012). Global installed PV capacity at the end of 2016 was reported as 310 GWp (PVPS, IEA, 2015). However, as they are installed in outdoor environment, continuous exposure to harsh climatic conditions (sun beam, rainfall, etc.) may affect the system performance. A monitoring study of PV system is reported in (Firth et al., 2010) and it was reported that the annual power loss due to various faults is about 18.9%. Hence, continuous monitoring along with fault diagnosis techniques is essential to detect the causes affecting the performance of the PV system (Madeti and Singh, 2017). In order to detect and clear the faults present in the system, proper fault classification technique is required. This would enable operator to take corrective measures, which improve the performance of PV system by minimizing the power losses caused by the faults.

Conventional fault detection and protection methods usually add fuses and circuit breakers within PV components to prevent PV components from experiencing large fault current. These devices are also not able to detect various faults unique to the PV system (Zhao et al., 2013). Currently, thermal cameras (Boztepe et al., 2014), earth capacitance measurements (ECMs) (Ding et al., 2012), and time-domain reflectometry (TDR) (Petrone et al., 2007) are the three popular methods for PV fault diagnosis. Thermal cameras are employed to detect the temperature characteristics of a PV array under fault conditions. Thermal images can be also linked to the maximum power point tracking (MPPT) algorithm of a PV controller. In practice, a gradual change in the thermal image of a PV module (e.g., due to device aging)

Abbreviations: AC, alternating current; AI, artificial intelligence; ABC, artificial bee colony; AFSA, artificial fish swarm algorithm; ACMT, adjacent string comparison measurement techniques; ANFIS, adaptive-neuron fuzzy inference systems; CMM, comparison between measured and modeled; CSO, cat swarm optimization; DC, direct current; ECM, earth capacitance measurement; EIM, external injection methods; FDC, fault detection and classification; GCPV, grid connected photovoltaic; HETB, heat exchange and temperature based models; kNN, k-nearest neighbors; L-L, line-line fault; MLT, machine learning techniques; MPPT, maximum power point tracking; NOCT, normal operating cell temperature; NIWE, national institute of wind energy; PC, personal computer; PSO, particle swarm optimization; PLA, power loss analysis; PV, photovoltaic; RES, renewable energy sources; SBDF, shading with faulted bypass diode; SBDI, shading with inverted bypass diode; SBDN, shading with bypass diode normal; STC, standard test conditions; TDR, time-domain reflectometry

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Nomenclature

Symbol	Description, Units
A	diode quality factor, –
G	Measured irradiance, W/m^2
G_d	diffuse solar radiation, kWh/m^2
G_g	global solar radiation, kWh/m^2
G_{ref}	reference irradiance, W/m^2
G_t	tilted solar radiation, kWh/m^2
I	current of module, A
I_0	reverse saturation current, A
I_{arr}	array current, A
I_{bat}	battery current, A
I_{D1}	diode current, A
I_{exp}	experimental model output current, A
I_L	load current, A
$I_{l\text{-}l}$	line to line current, A
I_{mod}	module current, A
I_{model}	mathematical model output current, A
I_{mp}	maximum current, A
I_{mpp}	current at maximum power point, A
I_{ph}	photo-generated current, A
I_{Rsh}	leakage current flowing through the shunt resistor, A
I_{sc}	short circuit current, A
I_{sc}	short-circuit current, A
I_{str}	string current, A
k	Boltzmann's constant, J/K
K_i	temperature co-efficient for short-circuit current, mA/°C
K_v	temperature co-efficient for open-circuit voltage, mV/°C
n_s	number of cells connected in series, –
P_{ac}	output ac power, W
P_{arr}	array power, W
P_{mod}	module power, W
P_{mp}	maximum power, W
P_{str}	string power, W
q	electronic charge, C
R_s	series resistance, Ω
R_{sh}	shunt resistance, Ω
S_w	wind speed, m/s
T	cell temperature, °C
T	cell temperature, K
T_a	ambient temperature, °C
T_{bat}	battery temperature, °C
T_L	load temperature, °C
T_m	module temperature, °C
V	voltage of module, V
V_{arr}	array voltage, V
V_{bat}	battery voltage, V
V_g	grid voltage, V
V_L	load voltage, V
V_{mod}	module voltage, V
V_{mp}	maximum voltage, V
V_{mpp}	voltage at maximum power point, V
V_{oc}	open circuit voltage, V
V_{oc}	open-circuit voltage, V
V_{str}	string voltage, V
V_t	junction thermal voltage, V

poses a technical challenge, and high system costs also limit the wide application of thermal cameras. The ECM can locate the disconnection of PV strings, whereas the TDR technology can predict the degradation of a PV array. Nonetheless, both the ECM and the TDR can only operate offline. In practice, online diagnosis methods are highly desired, which can take measurements while the tested device is in operation.

In (Solórzano and Egido, 2013), to monitor the performance of each PV module the power optimizer is developed, which is connected to each PV module by replacing the traditional solar junction box. The power optimizers increase energy output from PV systems by constantly tracking the maximum power point (MPPT) of each module individually. However, more pieces of equipment must be used causes increase in maintenance and cost of the system. Automatic systems for anomaly detection in the PV systems are thus needed for remote signaling for the detection and classification of the fault. Various methods have been proposed in the past and their characteristics are discussed in Table 1. A comprehensive comparison and analysis of various fault detection techniques has been presented in (Madeti and Singh, 2017).

Due to the non-linear nature of the PV modules, machine learning techniques have been driven more attention over the recent years. Since threshold values are required for the other fault detection techniques which are hard to define for the PV system. From Table 1, it is observed that the machine learning techniques may be the more feasible option for accurate fault detection.

Most of the proposed methods for fault classification categorize the faults in either of the four detectable fault types which are module open circuit, short circuit faults such as Line-Line or Line-Ground faults. The open circuit fault can be related to two subclasses: open circuit PV string and open circuit PV module. The open circuit PV string can be caused by bad connections or aged power cables, while the open circuit PV module can be generated by bad connections or broken cells in hot spot areas. The short circuit fault happens when one or several PV modules in the PV string are short circuited due to bad connections. Some methods however only propose methods to detect the faults and does not propose classification algorithm. And there are others which make an analysis of the classification features of these faults and does not propose or implement a detection means.

Some of the methods (Firth et al., 2010; Drews et al., 2007; Chouder and Silvestre, 2010; Polo et al., 2010), classify the faults in terms of energy losses. The classification is based on the rate of energy loss and not whether the four detectable fault types used for categorization. Their detectable features in addition include component failures, inverter defects, MPP tracking failure etc, but are not able to classify the various faults in DC side of PV systems. A procedure for fault diagnosis in PV systems with distributed MPPT at module level, power optimizers DC-DC or micro-inverters DC-AC, is proposed in (Solórzano and Egido, 2013). It has been shown that the designed procedure can diagnose a large scope of failures including: fixed object shading, localized dirt generalized dirt, hot spots, module degradation and excessive losses in DC cables.

A reliable and accurate PV model is essential for fault detection and classification. It is used for predicting the energy that can be harvested for a PV plant in a specific location. It is also needed to verify the effectiveness of developed fault classification technique, MPPT algorithms and control structures. Moreover, various fault diagnosis techniques are based in the analysis of power losses in the PV system. The losses are calculated by means of comparison between the monitored data with simulation results. When the simulation model of a PV system is not accurate which results in an over/under estimation of the output power in the simulation results. It causes false fault detection.

Various methods have been proposed before for modeling of the PV module from manufacturer's data sheet, but they have certain limitations. The model proposed in this paper builds on these limitations and proposes an improved model. Some of the limitations of the previous models are discussed below.

Di Piazza and Vitale (2013) proposed a new method for *PV* modeling; however, it is able to reproduce the behaviour of a *PV* module and its respective $I(V)$ curve, only under *STC* conditions. This method is