A Review of Photovoltaic DC Systems Prognostics and Health Management: Challenges and Opportunities

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Abstract

The surge in renewable electricity generation using photovoltaic (PV) systems was accompanied by an increased awareness of the fault conditions developing during the operational lifetime. Fault detection, diagnostics, and prognostics are such efforts to detect and classify a fault so the system operational expectations can be managed. Trending of the faults and prognostics also aid to evaluate expected remaining useful life so that mitigation actions can be evaluated and implemented. This paper aims to review the state of the art and practice of prognostics and health management (PHM) for the DC side of PV systems. Following a review of the PV industry current status, the study describes and classifies the different failure modes. Next, it summarizes the PV faults detection, diagnostics and prognostics approaches. A review of the PHM applications for PV systems paves the way to emphasize the key research gaps and challenges in the current practice. The available opportunities are also highlighted through a comprehensive understanding of the PV systems current performance, from where scholars and decision makers can integrate improvement strategies with promising directions for future research and practices.

1. Introduction

The solar energy sector has been growing rapidly over the past decade. In 2015, the U.S. installed 7.6 gigawatts (GW) of solar generation facilities to reach 27.4 GW of total installed capacity, enough to power 5.4 million American homes (Zhou, 2015). As the global energy demand increases, the photovoltaic (PV) industry is expected to continue to grow due to several factors such as the falling prices of PV modules and balance of systems, technological advancements in large scale manufacturing, many governmental incentives, maturation and proliferation of favorable interconnection agreements and continued technological improvement of power converter technologies (Obi & Bass, 2016). While the annual energy losses caused by faults in those PV systems could reach up to 18.9% of their total capacity (Firth, Lomas, & Rees, 2010), emerging technologies and models are driving for greater efficiency to assure the reliability of a product under its actual application conditions.

Fault Detection and Diagnostics (FDD) can help detecting faults in systems and diagnose their reasons. Alongside FDD, failure Prognostics is another area of research to predict the performance over the remaining life and the eventual failure of systems in the future. Together, FDD and failure prognostics methods make up Prognostics and Health Management (PHM) approaches. PHM methods provide numerous advantages, such as: (i) advance time-to-failure prediction; (ii) minimized unscheduled maintenance, extended maintenance cycles, effectiveness through timely repair actions; (iii) reduced life-cycle costs by decreasing downtime, inventory and refurbishment and; (iv) improved qualification and assistance in the design and logistical support of fielded and future systems (Pecht & Jaai, 2010).

A typical grid-connected PV system mainly consists of a PV array, a grid-connected inverter, connection wiring, and protection devices, such as overcurrent protection devices (OCPD) and ground fault protection devices (GFPD). Figure 1 illustrates the setup of a simple PV system. Faults in PV systems damage the PV system components, as well as lead to electrical shock hazards and fire risk. For instance, two fire hazards caused by ground faults and line-line faults, respectively, in PV arrays have been demonstrated in case studies of a large PV power plant in California, US (Collier & Key, 1988). Additionally power inverters are ranked among the most critical components within PV systems whose faults affect the system performance and availability (Kaushik & Golnas, 2011).

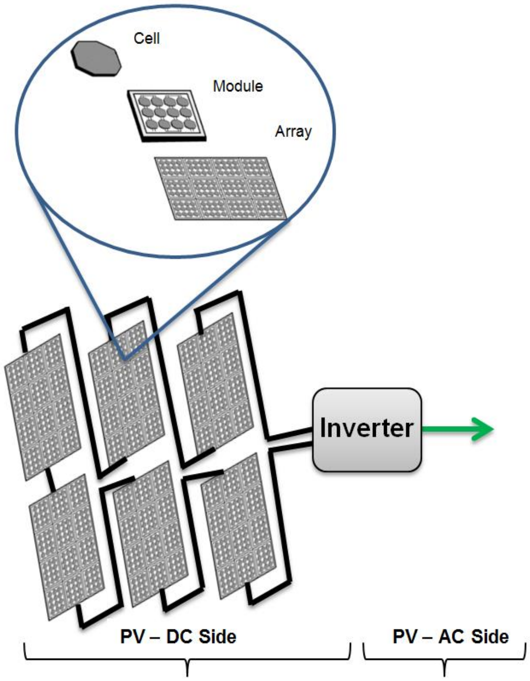

Figure 1. A Solar Photovoltaics system

This paper reviews and discusses the array of PHM methods in the DC side of PV systems. Section 2 presents a comprehensive review of PV DC system failure modes. Such failure modes are also classified based on the system components between modules and cables. Section 3 describes the different physics-based and data-driven models used in the detection and diagnostics of PV DC side's failure. Section 4 presents the prognostics models used to estimate the remaining useful life (RUL) of PV DC systems based on the specific failure mechanisms. Section 5 outlines the key research gaps, challenges in the current practice, as well as the opportunities for future studies. Finally, section 6 summarizes this review of the state of the art in PHM for the DC side of PV systems.

2. FAILURE MODES IN PV SYSTEMS

This section reviews the main failure modes occurring in the PV DC systems for discrete outdoor exposed components such as PV modules and cables. These components are expected to last the lifetime of the system by design. Failure modes for sub-assemblies or sub systems such as inverters or trackers are not covered. A description of the fault mechanism is presented below for PV modules and cables.

2.1. PV Module

Every type of PV module has variable characteristics inevitably caused by process variation; the optimal current and voltage will not be the same for each module in an array at a given point in time. These variations have the effect of reducing the output of the array, since the current and voltage of a module are constrained by the array's electrical configuration (Spertino & Akilimali, 2009). Module mismatch causes each module to operate at a suboptimal point on the Current-Voltage (I-V) curve, reducing the array's power output (Manganiello, Balato, & Vitelli, 2015). I-V mismatches are grouped, according to the causes, as permanent or temporary. Permanent mismatch is due to the effects of changes in one or more parameters of the PV module, such as the value of parallel resistance and/or series resistance (Sharma & Dalal, 2015). In addition to the manufacturing tolerance, module degradation, hot spot, and bubbles mainly cause permanent mismatches. Temporary mismatches are affected by the temporal changes in the irradiance level received by PV modules (Katiraei & Agüero, 2011). Such changes include cloud effects, soiling, snow covering, leaf and bird droppings, and the shading from nearby PV arrays and structures. A review of the failure mechanisms occurring in the module level is presented below.

2.1.1. Degradation

The degradation and aging of a PV module is a continuous process, but several factors can influence its dynamics (Manganiello, Balato, & Vitelli, 2015). In particular, environmental factors such as Sulphur, acidic fumes, or other pollutants can speed up the degradation process (Skoczek, Sample, & Dunlop, 2009). The main degradation types taking place in PV modules are as follows:

- Discoloration: is the browning and yellowing of PV cells, mainly caused by the degradation of the ethylene vinyl acetate (EVA) encapsulant (Kaplani, 2012). The main reasons of EVA degradation are Ultraviolet (UV) rays combined with water under temperatures higher than 50 °C (Oreski & Wallner, 2010). The changes in the color of the encapsulant material produce a variation of the transmittance of the light reaching the solar cells and, as a consequence, a reduction of the power generated (Skoczek, Sample, & Dunlop, 2009; Jeong & Park, 2013).
- Delamination: is defined as the breakdown of the bonds between material layers that constitute a module laminate. Delamination interrupts efficient heat dissipation and increases the possibility of reverse-bias cell heating (Quintana, King, McMahon, & Osterwald, 2002). The main causes of delamination are the movement of cells and cell interconnects due to environmental stresses, the expansion and the contraction of moisture and air that are trapped inside the layers of a PV module, the bond failure due to the combination of moisture and UV radiation, the cell overheating, and the consequent outgassing of the encapsulant (Dumas & Shumka, 1982). In addition, physical aging processes related to the application of high

temperatures could provoke delamination of a PV module (Oreski & Wallner, 2010).

- Cracking: is a common problem encountered in PV modules. It may develop in different stages of the module lifetime; however, it occurs in most of the cases during installation, maintenance, and especially during the transportation of modules to their sites (Wohlgemuth & Kurtz, 2011). In addition, cracking is affected by the high-temperature thermal stresses of a cell and thermal cycling induced thermomechanical stresses (Dumas & Shumka, 1982), mechanical loads due to wind (pressure and vibrations) and snow (pressure) (Cristaldi, Faifer, Lazzaroni, Khalil, Catelani, & Ciani, 2014).
- Corrosion: attacks the metallic connection of PV cells causing a loss of performance by increasing leakage currents. The moisture that enters the module through the laminate edges mainly causes corrosion (Kempe, 2005). The corrosion of the conductive parts of the cells and the interconnections through the encapsulant is responsible for the deterioration of the PV module (Ndiaye, Charki, Kobi, Kébé, Ndiaye, & Sambou, 2013), which results in the increase of the series resistance and the decrease of the parallel resistance of the PV electrical model (Saly, Ruzinsky, Packa, & Redi, 2002).

2.1.2. Hot Spot

The short-circuit current and the open circuit voltage are imposed by the PV cell showing the lowest electrical performance respectively in series and parallel montage. In short circuit conditions, when a PV cell is defective, its voltage is reversed and becomes equal and opposite to the voltage of the other cells in series. This defective cell becomes both a load for other cells and a place of a relatively high thermal dissipation constituting thus a hot spot (Rauschenbach & Maiden, 1972). A hot spot is an area of a PV module that has a very high temperature that could damage a cell or any other element of the module. It occurs in a PV module when the current capability of a particular cell or cells is lower than the operating current of the cell string. Over time, hot spots will permanently degrade the PV panels and decrease the overall performance of the PV plant (Molenbroek, Waddington, & Emery, 1991).

2.1.3. Bubbles

The bubbles are mainly due to the chemical reactions that emit gases trapped in the PV module. They form an air chamber in which the gas temperature is lower than in the adjacent cells. However, the air chamber worsens the heat dissipation capability of the nearby cell so that the latter overheats and therefore exhibits a temperature that is higher than in the adjacent cells (Ndiaye, Charki, K obi, Kébé, Ndiaye, & Sambou, 2013). Moreover, when bubbles appear on the front side, a reduction of the radiation reaching the PV cell occurs, thus creating a decoupling of light and increasing the reflection. Furthermore, bubbles can break, and can damage the back sealing surface that provokes humidity ingress (Kaplani, 2012).

2.1.4. Shading and Soiling

Shading, the total or partial blockage of sunlight from a PV module surface, can bring serious concern in PV arrays (Quaschning & Hanitsch, 1996; Nguyen & Lehman, 2006; Patel & Agarwal, 2008). This blockage can be caused by a number of different reasons, like shade from the building itself, light posts, trees, dirt, snow and other light blocking obstacles (Ancuta & Cepisca, 2011). Shading causes large performance drops and can even damage modules if not properly controlled. Module soiling is the build-up of dirt on the surface of a PV module (Braun, Banavar, & Spanias, 2012). Researchers have found that the effects of soiling are relatively small (2.3% loss of power) for directly incident light but become more significant for larger angles: an 8.1% loss was observed in a soiled module when light is incident from an angle of 56◦ (Hammond, Srinivasan, Harris, Whitfield, & Wohlgemuth, 1997). An experimental investigation on the reduction of PV output efficiency showed that the reduction of efficiency reached up to 11.6% when the dust deposition density was fixed at about 8 g/m2 (Jiang, Lu, & Sun, 2011). In addition, a single dust storm can reduce the output power by 20% and a reduction of 50% could be experienced if no cleaning is performed on modules for long time that exceeds six months (Adinoyi & Said, 2013). The local soil and environmental conditions are key factors for severity impact.

2.2. Cabling

Cables are vital parts of a PV array. Similar to the rest of the PV system, cables are subjected to thermal, mechanical and external loads (Kalogirou & Tripanagnostopoulos, 2007). Though the selection of cables is an important procedure, cable terminations and cables management thereafter can influence how the entire PV system will function. Three major catastrophic failure modes are common in the cabling of PV systems: ground faults, line-line faults, and arc faults.

2.2.1. Ground Faults

A ground failure mode occurs when the circuit develops an unintentional path to ground. This results in lowered output voltage and power, and can be fatal if the leakage currents are running through a person (Braun, Banavar, & Spanias, 2012). If a ground fault remains undetected, it may generate a DC arc within the fault and cause a fire hazard (Alam, Khan, Johnson, & Flicker, 2015). Previous research (Bower & Wiles, 1994; Zhao, Lehman, De Palma, Mosesian, & Lyons, 2011) investigated the potential reasons that can lead to ground faults, and classified them into four categories:

- Cable insulation damage during the installation, due to aging, impact damage, water leakage, and corrosion;

- Ground fault within the PV modules (e.g., degraded sealant and water ingress);
- Insulation damage of cables due to chewing done by rodents and termites; and
- Accidental short circuit inside the PV source circuit combiners, often at the time of maintenance.

2.2.2. Line-Line Faults

A line-to-line failure mode in a PV system is defined as an unintentional connection between two points in a PV panel through a low resistance path (Zhao, Lehman, De Palma, Mosesian, & Lyons, 2011). However, if one of the points is on the Equipment Grounding Conductor (EGC), the line-to-line fault is considered as a ground fault. A line-to-line fault may occur between two points on the same string or between two adjacent strings. The magnitude of the line-to-line fault current depends on the potential difference between the points before the fault occurs. The higher the potential difference, the higher the back feed current results, and the chance of tripping the OCPDs increases (Zhao, Lehman, De Palma, Mosesian, & Lyons, 2011; Johnson, Kuszmaul, Bower, & Schoenwald, 2011). Several studies (Gokmen, Karatepe, Celik, & Silvestre, 2012; Zhao, De Palma, Mosesian, Lyons, & Lehman, 2013) summarize the reasons behind line-to-line faults in PV arrays as follows:

- Insulation failure of cables, i.e. UV degradation, animal chewing through cable insulation;
- Incidental short circuit between current carrying conductors, i.e. a nail driven through unprotected wirings; and
- Line-line faults within the DC junction box, which are caused by mechanical damage, water ingress or corrosion.

2.2.3. Arc Faults

Arc failure mode establishes a current path in the air, and this current path might be established due to any discontinuity in the current carrying conductors or insulation breakdown in adjacent current carrying conductors (Alam, Khan, Johnson, & Flicker, 2013). Any type of arc fault is harmful for the PV system, and may introduce fire that may result in insulation burn-out and fire hazards in presence of any flammable substances in the vicinity of the PV plant (Johnson, Schoenwald, Kuszmaul, Strauch, & Bower, 2011). National Electrical Code® (NEC)-2011 requires a series arc-fault protection device in a PV system if the DC operating voltage is equal to or higher than 80V. These devices are called as arc-fault circuit interrupters (AFCIs) (Schimpf & Norum, 2009). The causes of arc faults depend on their types, whether they are series or parallel. Series arc fault reasons include degradation in solder joints, wiring or connections inside the junction box, loosening of screws, and increased operating temperature that may result in thermal stress, leading to accelerated aging or complete disconnection (Hastings, Juds, Luebke, & Pahl, 2011; Flicker & Johnson, 2013). In addition to series arc-fault reasons, parallel arc faults can result from insulation damage due to mechanical damage, aging, or wildlife (Dini, Brazis, & Yen, 2011).

3. FAULT DETECTION AND DIAGNOSTICS METHODS IN THE DC SIDE OF PV SYSTEMS

This section presents a review of existing fault detection and classification methods in the DC side of PV modules and cables. The findings are presented in table 1, summarizing the fault detection models, measured system parameters, and the techniques used to validate the models. The PV DC side fault detection and classification methods based on the type and method of measurement data can be classified into two main categories: physics-based models and data-driven models. Although most of the presented methods can be used for the different types of faults, some of them are more effective for specific system components.

3.1. Physics-based Models

Physics-based models employ system specific mechanistic knowledge, defect growth formulas, and condition monitoring data to detect and diagnose the faults (Heng, Zhang, Tan, & Mathew, 2009). Five major FDD physics-based approaches for the DC side of PV systems are presented below.

3.1.1. Difference Calculation

This approach quantifies the difference between expected and measured current, voltage, or power. It is based on determining the expected values of PV parameters in varying environmental conditions and comparing real-time measurements with these expected values. This approach usually sets thresholds below or above where any fault signals arise both in modules and cables. For instance, in (Chao, Ho, & Wang, 2008), an extended correlation function is used to identify faults between branches of the PV system. In (Braun, Banavar, & Spanias, 2012), a statistical outlier detection method is employed. In (Gokmen, Karatepe, Celik, & Silvestre, 2012), the expected output voltage value for different MPP is calculated and is used as a reference value for fault detection.

3.1.2. Adjacent Comparison

This approach uses the differences between measurements from adjacent strings as a reference to detect faults in PV cables, including ground, line-line, and arc faults. An example of this method is a study by (Zhao, De Palma, Mosesian, Lyons, & Lehman, 2013), where statistical outlier detection methods such as Hampel Identifier, 3-sigma, and Box plot are used to identify the normal-operating PV strings by comparing all the individual string current measurements.

Table 1. Fault detection models, measured system parameters, and validation techniques in the DC side of PV systems

References	Data-Driven Models									Physics-based Models					Measurement Devices							Validation	
	Regression	Decision Tree	Bayesian Networks	KNN Classification	Artificial Neural Networks	Support Vector Machines	Fuzzy Mathematics	Clustering	Graph based	Difference Calculation	Adjacent Comparison	Energy Loss	Heat Exchange and Temperature	External Devices	Current	Voltage	Irradiance	Temperature	Meteorological	Pulse generator	LCR Meter	Simulated	Experimental
Stellbogen (1993)										x					x	x	x	x				x	
Schirone, Califano, Moschella, and Rocca (1994)														x						x			x
Takashima, Yamaguchi, Otani, Kato, and Ishida (2006)														x						x	x		x
Drews, De Keizer, Beyer, Lorenz, Betcke, Van Sark, et al. (2007)												x			x	x	x	x	x			x	x
Chao, Ho, and Wang (2008)										x					x	x	x	x				x	
Takashima, Yamaguchi, and Ishida (2008a)														x							x		x
Takashima, Yamaguchi, and Ishida (2008b)														x						x			x
Vergura, Acciani, Amoruso, and Patrono (2008)												x			x	x						x	x
Zhiqiang and Li (2009)											x				x	x						x	
Houssein, Heraud, Souleiman, and Pellet (2010)										x					x	x	x	x				x	
Firth, Lomas, and Rees (2010)												x			x	x	x	x					x
Chouder and Silvestre (2010)		x													x	x			x			x	x
Polo, Del Rosario, and García (2010)												x			x	x			x			x	x
Xu, Wang, and Zuo (2011)											x				x	x						x	
Zhao, Lehman, De Palma, Mosesian, and Lyons (2011)										x					x	x						x	x
Syafaruddin and Karatepe (2011)				x											x	x	x	x				x	
Coleman and Zalweski (2011)			x												x	x	x	x				x	
Cheng, Zhong, Li, and Liu (2011)							x								x	x	x	x				x	
Ducange, Fazzolari, Lazzerini, and Marcelloni (2011)							x								x	x	x	x				x	
Lin, Wang, Zhu, Chang, and Pedram (2012)										x					x	x	x	x				x	

Braun, Banavar, and Spanias (2012)										x					x	x						x	
Li, Wang, Zhou, and Wu (2012)													x		x	x		x				x	
Zhao, Yang, Lehman, De Palma, Mosesian, and Lyons (2012)		x													x	x	x	x				x	x
Braun, Buddha, Krishnan, Spanias, Tepedelenlioglu, Yeider et al. (2012)				x	x	x									x	x		x				x	
Zhao, De Palma, Mosesian, Lyons, and Lehman (2013)										x					x							x	x
Gokmen, Karatepe, Silvestre, Celik, and Ortega (2013)										x						x		x				x	x
Hu, Gao, Song, Tian, Li, and He (2013)													x		x	x		x				x	x
Solórzano and Egido (2013)												x			x	x						x	x
Ndiaye, Charki, Kobi, Kébé, Ndiaye, and Sambou (2013)										x					x	x	x	x				x	
Nilsson (2014)								x							x	x						x	x
Phinikarides, Kindyni, Makrides, and Georghiou (2014)	x																						
Cristaldi, Faifer, Lazzaroni, Khalil, Catelani, and Ciani (2014)										x					x	x	x	x				x	
Zhao, Ball, Mosesian, De Palma, and Lehman (2015)									x						x	x	x	x				x	x
Jiang and Maskell (2015)					x												x	x				x	
Hare, Shi, Gupta, & Bazzi (2016)				x	x	x	x			x													

3.1.3. Energy Loss

This approach is based on the energy losses in the PV system. The fault detection and diagnostics are done based on the rate of energy losses in the PV system due to degradation, shading, and soiling. For instance, in (Drews, De Keizer, Beyer, Lorenz, Betcke, Van Sark, et al., 2007), energy loss analysis based on monitored data from grid-connected PV systems and satellite-derived meteorological data is proposed. In (Chouder & Silvestre, 2010) and (Silvestre, Chouder, & Karatepe, 2013), captured losses in a PV system, current, and voltage ratios are used for the fault-detection algorithm.

3.1.4. Heat Exchange and Temperature

Knowing that the PV module temperature changes in case of faults, this approach uses the heat exchange and module temperature during the faulted condition to detect and diagnose the faults, mainly due to hotspots as well as cables failure (Hu, Gao, Song, Tian, Li, & He, 2013). For example, in (Vergura, Acciani, Amoruso, & Patrono, 2008), using finite element methods, the physical defects of different types of PV cells are modeled based on the thermal behavior of the PV cells resulting from electrical faults.

3.1.5. External Devices

This method uses external devices such as signal generators, and LCR [inductance (L), capacitance (C), and resistance (R)] meters for mostfault detection (Takashima, Yamaguchi, Otani, Kato, & Ishida, 2006). The response of the PV system to the injected signals is analyzed to detect and/or classify the type of faults in PV systems.

3.2. Data-Driven Models

This method uses machine-learning methods for fault detection and classification by analyzing the characteristics of streamed data. Machine-learning algorithms are used to learn the relation between some input and output parameters of the PV system and subsequently use the trained models to detect and classify faults.

Therefore, defining an appropriate threshold that is able to detect several types of faults in different conditions is a difficult task. However, training the model with input–output data helps overcoming the limitation of defining thresholds and aids in the detection and classification of faults. Some of the machine-learning techniques used by scholars for the DC side of PV systems are: modified artificial neural networks (ANN) with the extension theory (Chao, 2010), evidence theory and Fuzzy mathematics (Cheng, Zhong, Li, & Liu, 2011), TSK-FRBS Fuzzy estimator (Ducange, Fazzolari, Lazzerini, & Marcelloni, 2011), Bayesian belief networks (Coleman & Zalewski, 2011), three-layered ANN (Katiraei & Agüero, 2011), decision tree-based method (Zhao, Yang, Lehman, De Palma, Mosesian, & Lyons, 2012), and graph-based semi-supervised learning (Zhao, De Palma, Mosesian, Lyons, & Lehman, 2013). Although some techniques are preferred to detect a specific type of fault over the other, research of data-driven models is an ongoing task.

4. PROGNOSTICS METHODS IN THE DC SIDE OF PV SYSTEMS

This section presents a review of prognostics methods in the DC side of PV systems, which are used to estimate the RUL of such systems based on the specific failure mechanisms predominant in the module construction. Knowing that some of these models are stochastic, others are based on assumptions that emphasize a well-determined factor, such as: radiation, temperature, and humidity. Although degradation models of PV systems are still few and further developments are needed, the main approaches found in the literature are summarized below.

4.1. Degradation Models

Several models were developed to estimate the degradation rate of solar modules and therefore their RUL. Vazquez and Ignacio (2008) found the module power P to be an indicator for the performance of the system. Moreover, their study identified the degradation of a PV to be relative to its initial power P_0. Such assumptions recall previous models that were developed to estimate the degradation of PV modules. From one side, some studies (Osterwald, Benner, Pruett, Anderberg, Rummeland, & Ottoson, 2003; Marion & Adelstein, 2003; Raghuraman, Laksman, Kuitche, Shisler, Tamizhani, & Kapoor, 2006) considered P to decrease linearly in time:

$$\mu(t) = P_0 - At$$

where $\mu(t)$ and A are the average power at time t and the annual decrease in power, respectively. From the other side, other studies (Chuang, Ishibashi, Kijima, Nakayama, Ukita, & Taniguchi, 1997; Xie & Pecht, 2003) assumed the degradation rate to be exponential as a function of time:

$$\mu(t) = P_0 e^{-\alpha t}$$

where $\alpha = A/P_0$ is the annual degradation rate. Although these models estimate the PV module degradation over its lifetime, they are limited by many assumptions that do not consider the variation in weather conditions and relevant factors.

Pan, Kuitche, and Tamizhmani (2011) proposed a degradation model of the PV module output power given by:

$$D(t) = 1 - e^{-b.t^a}$$

where a and b are parameters of the degradation model, that can be determined from accelerated testing (Charki, Laronde, & Bigaud, 2013). Knowing that such parameters change according to the studied degradation mode (i.e., discoloration, delamination, corrosion, etc.), the overall degradation of the PV module is estimated as:

$$D_{PVmodule}(t) = 1 - \prod_{i=1}^{n}(1 - D_i(t))$$

where $D_{PVmodule}(t)$ is the overall degradation of the PV module at time t, $D_i(t)$ is the mode i degradation at time t, and n is the number of considered degradation modes. One main limitation presented in this model is the dependency on the accelerated tests to determine a and b. For instance, Wohlgemuth and Kurtz (2011) have determined these parameters from damp heat tests assuming a temperature T of 85 °C and relative humidity RH of 85%. The study found $a_{corrosion} = 3.0868$ and $b_{corrosion} = 5762.10^{-12}$. Knowing that different temperature and humidity can lead to different results, the accuracy of this model is highly related to the test design.

4.2. UV Radiation Model

UV radiation is a major factor for the degradation of PV materials exposed to direct sunlight (Kojima & Yanagisawa, 2004; Oreski & Wallner, 2009; Wohlgemuth & Kurtz, 2011). This is relevant for module constructions using an encapsulant between the glass and the PV cells. This degradation appears in the change of the encapsulating module transmittance that reflects a reduction in the PV module current and voltage. Zimmerman (2008) quantifies the UV degradation of PV module by:

$$D(t) = 1 - b_{cmx}.\ln(1 + a_{cmx}ct)$$

where a_{cmx} and b_{cmx} are parameters of material used for PV cell and $c = \int_{\lambda=0}^{\lambda=400} T_{cmx}(\lambda)P(\lambda)d\lambda$ with $T_{cmx}(\lambda)$ the transmittance of the glass slide of PV cell, $P(\lambda)$ the spectral power density of the sun, and λ the wavelength belonging to the range $[\lambda_{min}, \lambda_{max}]$ in which the spectral response of the PV cell is not zero. Yet, the challenge of this model consists of knowing the materials basic characteristics used in the PV cells, which can vary during the production phase.

4.3. Temperature Based Model

For temperature dependent processes, the Arrhenius law (Laidler, 1984) is one of the most universally used models:

$$K = Ae^{\frac{-E_a}{RT}}$$

Where K is the rate constant of the process, A is an Arrhenius pre-exponential factor, E_a is the apparent activation energy, R is the gas constant, and T is the sample temperature. Cocca, D'Arienzo, and D'Orazio (2011) used that law to develop a temperature based model predict the increase in rate resulting from an increase in temperature in PV modules:

$$AF_T = \frac{K1}{K2} = e^{\frac{E_a}{RT}(\frac{1}{T_2} - \frac{1}{T_1})}$$

where AF_T is the acceleration factor for thermal degradation (ratio of rate constants), K_1 and K_2 are the rate constants of the process at t_1 and t_2 respectively, and T_1 and T_2 are the sample temperatures at t_1 and t_2 respectively. Though this model can be used to quantify the effect of varying temperature and irradiance on the rate of PV module degradation, it does not provide the long-term degradation of PV modules or consider other factors including moisture, time of wetness, airborne pollutants and salinity, and electricity production.

4.4. Temperature And Humidity Based Model

The Peck model defines the acceleration of degradation with the capacity to take into account temperature and relative humidity (Escobar & Meeker, 2006):

$$\tau = A.RH^n.e^{\frac{-E_a}{kT}}$$

where Ea is the effective activation energy of the degradation process; k is the Boltzmann's constant (=8.617.10-5 eV/°K), and A and n are two constants dependent on the failure mode. Later, Charki, Laronde, and Bigaud (2013) developed an equation for acceleration factor for thermal and humidity degradation:

$$AF_{(T,RH)} = e^{n.\ln\left(\frac{RH}{RH0}\right) - \frac{E_a}{k}(\frac{1}{T} - \frac{1}{T0})}$$

where $AF_{(T,RH)}$ is the acceleration factor for thermal and humidity degradation and RH_0 and T_0 are the relative humidity and temperature in the reference conditions. Although that model takes into account the effect of temperature and humidity on the degradation of PV module, its parameters are dependent on the design of the accelerated test. Defining the reference conditions for the temperature and relative humidity present some limits for the model.

5. RESEARCH GAPS AND CHALLENGES

While research in PHM for the DC side of PV systems active is ongoing, most of the previous work investigated the FDD in these systems. However, the endeavor to design and properly control a PV system to ensure it lifetime and reliability underline several challenges and technical gaps.

Although some of the reviewed FDD models are effective and reliable, almost all of them require the installation of external sensors to collect data. Further research is needed to determine the sensitivity, resolution, frequency and location of these sensors that might impose additional cost. Uncertainty in the collected data highly affects the uncertainty of FDD models. Studies investigating the sources of uncertainties and their propagations through the whole system are needed. Moreover, the literature reveals a limited number of studies applying data-driven models. Future research can incorporate such models with the physics-based models to develop hybrid models.

A review of the literature shows the prognostics models of PV systems to be poorly studied by scholars and researchers. The reviewed models have solely studied the degradation of the PV modules. While additional studies and research are needed, cabling termination and connector degradation models are equally important and crucial. Moreover, different types of materials in PV systems require different studies. Another challenge for the development of PHM models is their verification and validation using experimental data. Knowing that the design life of PV systems is usually more than 30 years, the availability of experience feedback and real performance data over long periods highlights the opportunity to test such models in the future. Such data is also generally not publicly available and solutions to address gaps for shared and clean data streams are also needed.

Solar technologies are still evolving and new materials are being discovered to produce reliable and efficient systems. The surge of such technologies continues to challenge the researchers in developing new models and integrating them with operations and management planning and control. Accordingly, future studies can benefit from PHM models by developing online frameworks and algorithms to automatically detect and diagnose a fault and also predict the system RUL.

The importance and usefulness of PHM to inform decision-makers within time and different operational limitations requires an assessment for Return on Investment (ROI) of PHM activities. A major gap that exists in the literature is a comprehensive assessment of the additional costs that can be associated with the PHM models integration. Moreover, future studies that can support the decision-makers in selecting between different types of PHM and determining whether to adopt PHM versus more traditional maintenance approaches are crucial.

6. CONCLUSIONS

PHM applications are essential for the reliability of PV systems by facilitating condition based maintenance and minimization of cascading failures. This paper provided an overview of the different types of failure modes in the DC side of PV system. Next, it summarized the PV fault detection, diagnostics and prognostics approaches. The presented methods presented showed the different approaches documented in literature to address the faults in the DC side of PV systems. However, depending on the monitoring technology, communication infrastructure, availability of physical models, and measured data, some solution approaches may perform better than the others due to the difference in the problem formulation. Through the integration of fault detection, diagnostics, and prognostics, future PV systems will possess the ability to sustain the power generation while increasing the reliability and resiliency of the system itself. A review of the PHM applications for PV systems paved the way to emphasize the key research gaps and challenges in the current practice as well as the available opportunities. Future studies are invited to fill the identified gaps by: (1) determining the parameters, location, resolution and precision of required sensors in the PV systems; (2) developing and testing new data-driven models; (3) generating new prognostics models for the different parts and materials of PV systems; (4) verifying and validating the developed models using experimental data; (5) designing online frameworks and algorithms to implement the PHM models; and (6) assisting the decision-makers in their investigation of the ROI for PHM activities.

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