

Review

PV System Predictive Maintenance: Challenges, Current Approaches, and Opportunities

Lisa B. Bosman ^{*}, Walter D. Leon-Salas, William Hutzell and Esteban A. Soto 

Purdue Polytechnic Institute, Purdue University, West Lafayette, IN 47907, USA; wleonsal@purdue.edu (W.D.L.-S.); hutzellw@purdue.edu (W.H.); soto34@purdue.edu (E.A.S.)

* Correspondence: lbosman@purdue.edu; Tel.: +1-765-496-0267

Received: 26 November 2019; Accepted: 6 March 2020; Published: 17 March 2020



Abstract: Within the United States solar energy industry, there is a general motto of “set it and forget it” with solar energy. This notion is derived from much of the research and reliability studies around the photovoltaic (PV) panels themselves, not necessarily the PV system as a whole (including the inverter and other components). This implies that maintenance and regular monitoring is not needed. Yet many things can go wrong to cause the actual performance to deviate from the expected performance. If failures and/or unanticipated degradation issues go undetected, they will lead to reduced energy generation (and associated electricity credits) and/or potential loss of component warranty because of manufacturer turnover. Given the size of the problem and gaps with current solutions, the authors propose that PV system owners need an unbiased third-party off-the-shelf system-level predictive maintenance tool to optimize return-on-investment and minimize time to warranty claim in PV installations. This paper reviews the literature highlighting challenges, current approaches, and opportunities for PV predictive maintenance. The paper concludes with a call to action for establishing a collaborative agenda toward prioritizing PV predictive maintenance.

Keywords: solar energy; system-level; degradation; ROI; quality assurance; responsive; third party evaluation; net-metering; grid-tied; optimization

1. Introduction

1.1. Problem Identification

Within the United States solar energy industry, there is a general motto of “install it and forget it” with solar energy. This notion is derived from much of the research and reliability studies around the photovoltaic (PV) panels or cells themselves, not necessarily the PV system as a whole (including the inverter and other components). This implies that maintenance and regular monitoring is not needed. Yet many things may go wrong to cause the actual system performance to deviate from the expected performance [1–6]. First, design and/or installation could be flawed. PV modules are connected in a series-parallel topology where several panels or cells are connected in series to form a string of modules to obtain an optimal voltage. Strings of modules are then connected in parallel. Thus, any mismatch in the strings can decrease overall system performance. In addition, in many climate zones, the long-term accumulation of dirt and debris on the panels can significantly degrade the solar panel performance [7,8]. Typically, drier climates leave significant deposits of dirt so that mechanical cleaning is necessary to maintain optimal performance. This problem is not as noticeable in regions with significant rainfall because rain tends to clean the solar panels. However, even in the Amazon rainforest, which has abundant rainfall, solar panels can still accumulate dirt and debris if they are not mounted at an angle that allows adequate water runoff. This problem is often exacerbated because the panels are mounted in a difficult-to-access location making routine cleaning more difficult.

Second, the PV array is connected to the inverter, which converts electricity from DC to AC. PV arrays are typically warrantied at 20–25 years and inverters are typically warrantied at 5–10 years. Hence, the inverter needs to be replaced at least once prior to the end of the PV panel life. Also, incorrect sizing of the inverter can result in lower conversion efficiency. In general, going with smaller inverters is cheaper in that if it fails, only one part of the operation is shut down and repair costs are lower; however, smaller inverters have an increased likelihood of failure and are less robust [9].

In summary, it is important for all the PV panels and other components to work together to maximize solar energy generation. Yet, if an individual cell of a single panel is compromised, the power output and efficiency of the entire system is reduced. Unfortunately, without taking performance measurements, it is not possible to identify and assess these issues. Furthermore, considering the turnover of solar energy industry component manufacturers, quickly responding to potential warranty issues is key to optimizing return on investment. If failures and/or unanticipated degradation issues go undetected, this will lead to loss of energy generation (and associated electricity credits) and/or potential loss of component warranty because of manufacturer turnover.

1.2. Options to Mitigate Problem

In response to potential degradation issues, there are three main options for maintaining a PV system. A small percentage of owners decide to pay extra for individual-level component monitoring up front. For example, Enphase Enlighten monitors the output of their microinverters. In addition, SMA Sunny Portal monitors the output of their central inverters and add-on weather sensors (when purchased and installed separately). These online portals allow solar energy system homeowners real-time access to energy production. Another smaller percentage of PV system owners might invest in a maintenance plan [10] or contact an installer as needed if they sense an issue exists. In either case, the installer/electrician will conduct a manual diagnostic on the individual components that costs an average of \$500 per visit. The electrician will likely conduct this data collection and analysis on a sunny, non-cloudy afternoon to avoid drastic changes in incoming solar irradiation (which could further limit the accuracy of the results). Despite the options available for performance monitoring, albeit limited, the large majority of PV system owners do nothing. Deferring maintenance is the default approach taken by many solar installers and researchers because of the perception that a lack of combustion, fuel consumption, or moveable parts should result in minimal maintenance costs [11].

1.3. Gaps to Mitigation Options

Gaps exist in all three cases mentioned above. With respect to individual-level component monitoring, there are three major downfalls. First, monitoring occurs at the individual component level and not at the system level. A typical grid-tied PV system in the United States has several components which have the potential to impact system value and return on investment. These include PV panels, inverter, utility meter, combiner box, and wires to connect everything together. Although, obtaining feedback from one of the components (such as the inverter using Enphase Enlighten or SMA Sunny Portal) is useful, understanding performance from a system level is of much greater value. Using a car as an analogy, the car dashboard is valuable because it provides diagnostics and feedback on just about every component required to make the car run. The second downfall is that the individual component monitoring has limited production outcomes and not necessarily warranty outcomes. This means that the software provides the quantity of electricity generated, not the quantity of electricity that should be generated based on the warranty. As a result, it is up to the PV system owner to do additional calculations to determine if the actual production is in alignment with expected and warrantied production. The final downfall is that there is a potential for an individual component manufacturer to be biased toward the goals and objectives of the component manufacturer, so it is not their priority to notify the PV system owner that there may be a problem with their own components. With respect to installer check-ups, there are also three major downfalls. First, real-time data collection

is lacking. Thus, if the PV system underperforms in between check-ups, there is an opportunity loss due to the electricity that could have been generated during that period, but was not. Second, there is no standard process or quality of care for installer check-ups. Thus, there is no guarantee that an installer will be able to identify an issue. The final downfall is the potential for installers to be biased toward the goals and objectives of their own company, so it is not their priority to notify the PV system owner that there may be a problem with their own installation process and design. Yet, to make matters worse, there is a shortage of skilled manpower to meet maintenance, inspection, and repair needs [12]. With respect to doing nothing, there is only one potential downfall; the PV system may not be operating as intended. By the time the PV system owner figures it out, it could be too late to recoup lost costs. Anecdotal evidence, discovered by the researchers, provides many examples of cases where the “do nothing” approach resulted in big expenses in the long run. An organization (who wishes to remain anonymous) purchased a new 984 kW system in 2010. In 2018, a new employee was hired to focus on innovation efforts within the company. The young engineer was right out of college and just happened to have some knowledge related to PV systems due to a class project. The new employee conducted some basic analysis, estimated the PV system was not working as intended, and proposed hiring an installer to come out and perform an official analysis of the system. Once all the paperwork was submitted, approvals were granted, and the installer was brought on-site in 2019. It was determined that 15 panels (and their individual microinverters) were bad. Unfortunately, the original component manufacturer (a startup solar panel designer, manufacturer, and installer headquartered in Minnesota, USA) had gone bankrupt in 2017, so the warranty claim was no longer an option. The equipment was replaced on the organization’s budget at a cost of about \$50,000. The organization estimated the panels had been bad since 2014, which resulted in another \$5000 in lost electricity credits.

1.4. Summary

Given the size of the problem and gaps with current solutions, the authors propose that PV system owners need a third-party off-the-shelf system-level PV system predictive maintenance tool to optimize their return-on-investment and minimize time-to-warranty claim. The purpose of this article is to provide a brief and easy to understand overview of the literature explaining challenges, current approaches, and opportunities for PV predictive maintenance.

2. Materials and Methods

Given that the purpose of this paper is to provide a brief and easy to understand overview of PV predictive maintenance, the literature review has two key sections. First, Section 2.1 provides a justification of the need for PV predictive maintenance. Second, Section 2.2 provides current approaches and opportunities for PV predictive maintenance categorized as manual diagnostics (Section 2.2.1), failure modes and effects analysis (FMEA) approach (Section 2.2.2), machine learning and forecasting (Section 2.2.3), and real-time sensor analysis (Section 2.2.4).

2.1. Need for PV Predictive Maintenance

A summary of the literature used in this section is provided in Table 1.

Table 1. Summary of the literature (need for predictive maintenance).

Literature which Highlights Need for Solar Energy System Predictive Maintenance
Denio (2012): Aerial solar Thermography and condition monitoring of photovoltaic systems
Grimaccia et al. (2015): Planning for PV plant performance monitoring by means of unmanned aerial systems (UAS)
Ancuta and Cepisca (2011): Fault analysis possibilities for PV panels
Gómez Muñoz et al. (2015): A New Condition Monitoring Approach for Maintenance Management in Concentrate Solar Plants
Díez-Mediavilla et al. (2012): Performance analysis of PV plants: Optimization for improving profitability
Díez-Mediavilla et al. (2014): Performance of grid-tied PV facilities based on real data in Spain: Central inverter versus string system
Mgonja et al. (2017): Effectiveness on Implementation of Maintenance Management System For off-Grid Solar PV Systems In Public Facilities—A Case Study of SSMP1 Project In Tanzania
Jordan et al. (2015): Performance and aging of a 20-year-old silicon PV system

Although much of the literature documents the benefits of PV as it relates to low maintenance costs [11,13–20], anecdotal evidence and recent studies report a different story and the need for maintenance in real-world, non-lab applications. As Denio aptly states: “The demand for cheap renewable energy sources is at its highest that it has ever been. Therefore, solar arrays and installations have been being erected the world over. In this rush for renewable energy there is a growing need for accurate data showing where the solar arrays need maintenance. The difficulty of finding and tracking down problems and potential issues that arise in these installations is monumental” [21]. Grimmacia and colleagues support Denio’s statements and highlight the need for monitoring services by asserting that: “Regarding PV plants’ diffusion, they are going to increase over the coming decades, thus operation and maintenance of PV systems become essential. The highest level of performance will be obtained utilizing reliable and effective monitoring services with reasonable cost” [22]. Indeed, researchers who study PV from a defect perspective are adamant about the need for preventative maintenance and upkeep. Ancuta and Cepisca (2011) state: “Reliable predictive and preventive maintenance techniques are needed to assure lifetime efficiency in service” [6]. In addition, Gómez Muñoz and colleagues reasoned about the benefits of monitoring as follows: “Significant discrepancies between the energy measurements can work as an alarm signal to activate maintenance operations” [23].

Some authors have conducted studies to highlight the problem areas of greatest concern for PV systems. Ancuta and Cepisca (2011) state, “Typical photovoltaic systems suffer from numerous problems that prevent them from realizing their true potential. Many of the present problems stem from power losses—whether due to module mismatch, orientation mismatch, ground faults or partial shading. Other problems come from system design limitations and constraints, lack of monitoring or lack of analysis abilities. In addition, the absence of safety features poses risks to both workers and maintenance personnel [6]”. Yet, unfortunately, data associated with PV system monitoring is limited, as noted by Díez-Mediavilla and colleagues (2012), “But mechanisms have not been implemented which would ensure the quality of installation, neither has optimal plant design and the best conditions for their operation been assured [24]”. Díez-Mediavilla and colleagues (2014) go on to state, “Data from owners or maintenance services are very scarce and real PV systems are not usually monitored. Measurement systems at most facilities only record total production, which is necessary for invoicing the energy that is produced. In some cases, data are recorded in the inverter system after the conversion stage [9]”.

Although rare in the literature, few studies have come forward to provide specific examples of PV systems requiring maintenance issues. Mgonja and colleagues (2017) conducted a study assessing the effectiveness of field maintenance needs and practices in relation to performance of stand-alone solar PV system in public facilities. The study had 54 respondents, applying data collection methods including observations, interviews, and questionnaires. The findings show that more than 40% of the respondents experienced performance issues with the PV system within the past six years [25]. Denio (2012) published a study that assessed the ability for infrared thermography to pinpoint problems in PV arrays using unmanned aerial vehicles (UAVs). As explained by the author, many problems associated with the PV panel specifically has to do with hot spot heating, which can occur because of cell and interconnection failure, partial shading, or mismatched cells [21]. Denio’s work provided examples of several instances where UAVs detected hot spot heating on various PV arrays assessed in the study.

Jordan and colleagues (2015) conducted a long-term performance study of a crystalline silicon PV system over the course of twenty years. Although the panel degradation was found to be typical to historical averages (about 0.8%/year) the primary maintenance issue was related to the inverter, which had to be replaced four times over 20 years [26]. It is important to note that this study occurred in a lab environment with routine data monitoring used to identify performance issues. In one case, the monitoring system detected combiner box arcing, which if it had not been detected, could have result in additional damage to the PV system.

2.2. Current Approaches and Opportunities for PV Predictive Maintenance

Because of increased PV system installations, the demand for testing and validating quality control continues to rise [27]. There are several known approaches for assessing PV systems for potential performance degradation including: (1) visual inspection of the system and individual components, (2) I-V curve and insulation resistance analysis of PV panels, (3) infrared thermography of PV panels, and (4) calculations comparing estimated to actual generation [28]. The first three can be summarized as manual diagnostics (Section 2.2.1). The latter can be broken down into failure modes and effects analysis approach (Section 2.2.2), machine learning and forecasting (Section 2.2.3), and real-time sensor analysis (Section 2.2.4). In addition, Figure 1 provides a summary of the approaches for PV predictive maintenance, containing a comparison of the cost and detection accuracy of each of the four approved approaches. The manual diagnostic is the least expensive but offers the lowest detection accuracy. Machine learning and forecasting and FMEA approach are moderately costly and provide an average amount of detection accuracy. Real-time sensors are the most expensive but offer the highest detection accuracy. A summary of the literature used in this section is provided in Table 2.

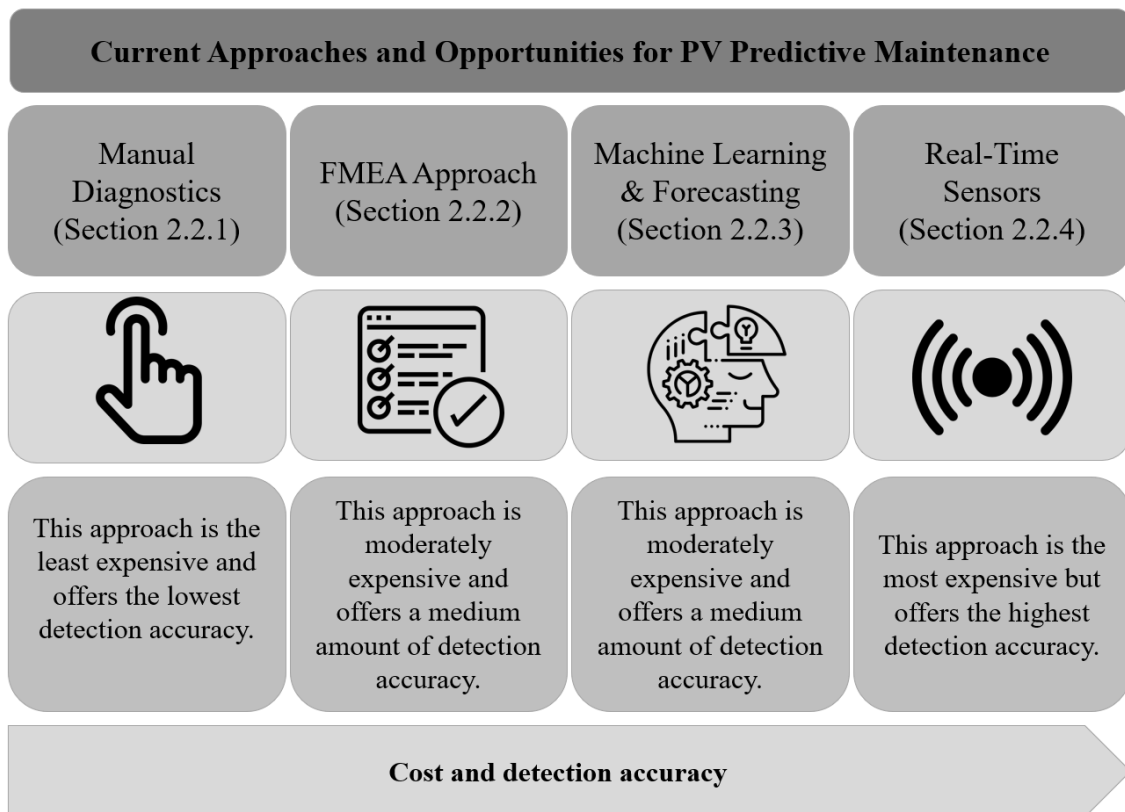


Figure 1. Summary of current approaches for PV predictive maintenance.

Table 2. Summary of Literature (current approaches and opportunities for predictive maintenance).

Literature which Highlights Current Approaches and Opportunities for Solar Energy System Predictive Maintenance	Section 2.2.1: Manual Diagnostics	Section 2.2.2: FMEA Approach	Section 2.2.3: Machine Learning & Forecasting	Section 2.2.4: Real-Time Sensors
Bulanyi and Zhang (2014): Shading analysis and improvement for distributed residential grid-connected photovoltaics systems	X			
Figgis et al. (2016): Review of PV soiling measurement methods	X			
Mundo-Hernández et al. (2014): An overview of solar photovoltaic energy in Mexico and Germany	X			
Gallardo-Saavedra et al. (2018): Technological review of the instrumentation used in aerial thermographic inspection of photovoltaic plants	X			
Quarter et al. (2014): Light Unmanned Aerial Vehicles (UAVs) for cooperative inspection of PV plants	X			
Koch et al. (2016): Outdoor electroluminescence imaging of crystalline photovoltaic modules: comparative study between manual ground-level inspections and drone-based aerial surveys	X			
Buerhop-Lutz and Scheuerpflug (2015): Inspecting PV-plants using aerial, drone-mounted infrared thermography system	X			
Aghaei et al. (2015): IR real-time analyses for PV system monitoring by digital image processing techniques	X			
Solmetric (2014): Solmetric PV Analyzer I-V Curve Tracer with SolSensor TM PVA-1000S, PVA-600 + User's Guide	X			
Dhimish et al. (2018): Novel hot spot mitigation technique to enhance photovoltaic solar panels output power performance	X			
Zhang et al. (2017): Photovoltaic array fault detection by automatic reconfiguration	X			
Kuitche et al. (2014): Investigation of dominant failure mode (s) for field-aged crystalline silicon PV modules under desert climatic conditions			X	
Villarini et al. (2017): Optimization of photovoltaic maintenance plan by means of a FMEA approach based on real data			X	
Cristaldi, Khalil, and Soulatiantork (2017): A root cause analysis and a risk evaluation of PV balance of system failures.			X	
Colli (2015): Failure mode and effect analysis for photovoltaic systems			X	
Shrestha et al. (2014): Determination of dominant failure modes using FMECA on the field deployed c-Si modules under hot-dry desert climate			X	
Catelani et al. (2011): FMECA technique on photovoltaic module			X	
Catelani et al (2013): Electrical performances optimization of Photovoltaic Modules with FMECA approach.			X	
Gallardo-Saavedra and Hernández-Callejo (2019): Quantitative failure rates and modes analysis in photovoltaic plants			X	
Pal et al. (2003): SOFM-MLP: a hybrid neural network for atmospheric temperature prediction				X

Table 2. Cont.

Literature which Highlights Current Approaches and Opportunities for Solar Energy System Predictive Maintenance	Section 2.2.1: Manual Diagnostics	Section 2.2.2: FMEA Approach	Section 2.2.3: Machine Learning & Forecasting	Section 2.2.4: Real-Time Sensors
Krishnamurti et al. (1999): Improved Weather and Seasonal Climate Forecasts from Multimodel Superensemble			X	
Lazos et al. (2015): Development of hybrid numerical and statistical short term horizon weather prediction models for building energy management optimization			X	
Möller and Groß (2016): Probabilistic temperature forecasting based on an ensemble autoregressive modification			X	
Slughter et al. (2013): Probabilistic wind vector forecasting using ensembles and Bayesian model averaging			X	
Marquez and Coimbra (2011): Forecasting of global and direct solar irradiance using stochastic learning methods, ground experiments and the NWS database			X	
Wilson et al. (2004): Predicting housing value: genetic algorithm attribute selection and dependence modelling utilizing the gamma test			X	
Zamora et al. (2005): The accuracy of solar irradiance calculations used in mesoscale numerical weather prediction			X	
Devabhaktuni et al. (2013): Solar energy: Trends and enabling technologies				X
Rivai and Rahim (2013): A low-cost photovoltaic (PV) array monitoring system				X
Chouder et al. (2013): Monitoring, modelling and simulation of PV systems using LabVIEW				X
Anand et al. (2016): Design and analysis of a low-cost PV analyzer using Arduino UNO				X
Silvestre et al. (2013): Automatic fault detection in grid connected PV systems				X
Bayrak and Cebeci (2013): Monitoring a grid connected PV power generation system with labview				X
Guerriero et al. (2015): Monitoring and diagnostics of PV plants by a wireless self-powered sensor for individual panels				X
Prieto et al. (2014): Development of a wireless sensor network for individual monitoring of panels in a photovoltaic plant				X
Xiaoli and Daoe (2011): Remote monitoring and control of photovoltaic system using wireless sensor network				X
Papageorgas et al. (2013): In situ monitoring of photovoltaic panels based on wired and wireless sensor networks				X
Adhya et al. (2016): An IoT based smart solar photovoltaic remote monitoring and control unit				X
Moreno-Garcia et al (2016): Real-time monitoring system for a utility-scale photovoltaic power plant.				X
Shariff, Rahim, and Ping (2013): Photovoltaic remote monitoring system based on GSM				X

2.2.1. Predictive Maintenance Based on Manual Diagnostics

In general, this approach is the least expensive but offers the lowest detection accuracy. This section will cover both qualitative (visual inspection of the system and individual components and infrared thermography of PV panels) and quantitative approaches (I-V curve and insulation resistance analysis of PV panels) to predictive maintenance.

First, visual inspection of the system and individual components can be conducted to determine if there are potential issues. Shade analysis conducted using a tool like the Solmetric Suneye, can identify potential mismatch issues due to new tree growth and/or construction [29]. Visual inspection can also be used to detect soiling (e.g., snow, fallen leaves, bird droppings, dust or other debris) that may have built up on the panels [30]. Yet, there remains challenges and opportunities with visual inspection, one of which includes safety around detection and cleaning.

Second, infrared (IR) thermography can be used to qualitatively assess the quality of PV panels. This approach is often used in combination with unmanned aerial vehicles (UAVs) for large PV plants [22]. Aerial IR thermography is known to be a useful diagnostic technique that can assess performance of PV panels with higher accuracy and more quickly, however, is a bit more costly [31]. Yet, it is important to note that reliable and more cost-efficient methods have been proposed using a combination of both thermal imaging and visual cameras [32]. Thermal imaging is already used by default in most PV panel manufacturing processes to detect a variety of potential issues, thus, leveraging the same qualitative approach in a real-world application has received much praise even though pass/fail criteria are still under debate [33]. Yet, thermal imaging is known to detect fractures in the cell, failures due to soldering, cells which have short-circuited, and substrings being bypassed, to name a few [27]. Thus, cell fracture, soldering failure, short-circuited cells, by-passed substrings, can be distinguished easily using IR-imaging. In some cases, researchers have proposed an automated approach to PV panel monitoring which uses the images to automatically identify defects and failures, and propose actions to remediate the situation [34]. Yet is important to note some challenges and opportunities faced by aerial thermal imaging including image quality, which is highly influenced by the UAV altitude, velocity, and observation angle [27], in addition to the need for better understanding what constitutes a pass/fail from a qualitative, visual perspective.

Finally, from a quantitative perspective, I-V curve and insulation resistance analysis of PV panels can detect potential performance issues within the individual panels. For installers that are experienced and well-trained, they will likely use a tool, such as the Solmetric PVA-1000S PV Analyzer Kit (about \$6000) to analyze the I-V curves of the solar panels, and a variety of other tools (e.g. amp meter, voltage meter, power meter, etc.) to validate the expected values for the other components. The Solmetric analyzer is an easy-to-use portable electronic tool intentionally designed to assess the performance quality of PV panels; it is often used in the installation and commissioning process, and troubleshooting and re-commissioning process [35]. An I-V curve tracer can be used to examine the behavior of the PV panels, taking into consideration solar irradiance and ambient temperature [36]. Using an I-V curve tracer, it is possible to readily identify anomalies caused by short circuit bypass diodes [29] and fault detection [37]. The time to assess PV panel health using an I-V curve tracer is minimal, estimated at less than one minute per panel [37]. Although there are many benefits to using handheld tools to manually assess the performance of the panels, challenges and opportunities remain primarily because of the length of time required to assess an entire array or plant, and the potential for human error during the manual data collection process.

In summary, when all these methods are used together, detection of issues is likely. However, challenges and opportunities remain. These tools are primarily used to assess the performance of the PV panels and fail to consider the PV system as a whole.

2.2.2. Predictive Maintenance Based on FMEA

In general, the failure mode and effects analysis (FMEA) approach is moderately expensive and offers a medium amount of detection accuracy. The analysis of failure modes and effects is a

semi-qualitative method used to prevent failures and analyze the risks of a process by identifying causes and effects on the system to determine the actions that will be used to inhibit failures. This approach has been used in the aerospace, nuclear, automotive, and semiconductor industries to support design fault, safety, logistic support, testability, and other related functions [38]. The FMEA approach has been used in PV systems to identify the components that have the highest risk of failure. While some research has been based on the analysis of historical data to identify the components with a higher probability of failure, others have focused on PV systems exposed to specific climate conditions. The investigations have yielded several results, but all of them have the same objective to reduce the risk of failure and increase the performance of PV systems.

Identifying the failures of components and subcomponents of a system is the first step in establishing a predictive life model of a PV system [39]. The failure of the components in a PV system causes two main consequences: first the damage of the parts and second the loss of energy production [40]. Cristaldi, Khalil, and Soulatiantork [41] used a failure mode effects criticality analysis (FMECA), extension of FMAE, and a Markov process to identify and prioritize the critical components in a PV system. As a result, Cristaldi and colleagues [41] found that the PV inverter has a higher risk priority number (RPN) than the other components, because of which the maintenance activities of the inverter must be prioritized. A similar result was obtained by Colli [38], who applied FMEA using the design of a solar system located in the Brookhaven National Laboratory concluded that the inverter and the ground system has the highest probability of failure in a PV system. Villarini and Cesarotti [40] complemented the FMEA approach with data from real solar plants, weather conditions, and opinions of maintenance technicians; as a result of the study, it was obtained that the highest RPN corresponds to the inverter and ground system. Also, Villarini and Cesarotti [40] found that component failures were an overload of the system and lack of isolation.

Failure mode and effect analysis have also been applied to PV installations under desert climatic conditions. The studies analyze data from plants located in Arizona, where the leading cause of failure was the solder bond fatigue and the discoloration of the encapsulation [39,42]. According to Shrestha and colleagues [42], the degradation of the solder bond could cause failures to the safety of the PV system because it could cause hotspots or back sheet burns.

The failure mode, effects, and criticality analysis methodology seek to reduce the impact of potential failures in photovoltaic systems and thus increase the electrical performance. Other studies carried out with the FMEAC methodology showed that the presence of contamination and dust on the surfaces of the panels generates a decrease in the electrical performance of the solar system [43,44]. After implementing FMEAC, Catelani and Ciani [44] verified the results of FMECA using a correlation between energy reduction and the maximum power point of the PV system. Afterward, the authors were able to optimize the electrical performance of the PV system through a sensitivity analysis of the maximum power point and dust concentration [44].

Gallardo-Saavedra and Hernandez-Callejo [45] performed a quantitative analysis of the failure rates and modes of sixty-three PV plants. The components with the highest probability of failure in PV plants are monitoring systems, communication systems, the inverter, and the grid. In addition, it was found that the failure rate per unit of power is higher in small plants. The annual failure rate is more than double in the PV plants with less than 750 kW installed compared to larger plants. However, the investigation concludes that although the plants have more years of use, proper maintenance can keep the defect rate or even reduce the ratio over time [45]. Taking into account the probabilities of failure of the elements of a PV system is an essential input for the predictive maintenance models. Therefore, a relevant area to improve maintenance models is to consider the risk of failure of the components. In this way, it will be possible to extend the useful life and reduce the probability of failure of the PV systems.

2.2.3. Predictive Maintenance Based on Machine Learning and Forecasting

In general, this approach is moderately expensive and offers a medium amount of detection accuracy. Current research being done on estimating solar energy has explored localized predictions for short-time intervals by using regressive processes and micro-climate parameters, finding parametric factors with greater contribution rate or unveiling temporal patterns in the weather data. Other studies have considered factors such as time of the day, sky-cover, pressure, and wind-speed and employed artificial neural networks, ARIMA (autoregressive integrated moving average) models, etc. to improve prediction accuracy. The relationship between weather station parameters and PV energy impact has also been explored using artificial neural network models to forecast PV energy output. Studies have assessed the value of localization on solar energy prediction by examining effects of data from weather stations and linking the observed variability in irradiance with the NWP forecasts.

- In order to make accurate solar energy predictions, it is important to estimate the weather parameters with absolute precision [1,4,5]. A variety of methods have been developed by researchers, which focus on predicting the weather parameters responsible for solar energy generation. Estimation of weather parameters and subsequently estimating solar energy has led to the emergence of multiple modeling techniques for weather data. Different parameters that affect the amount of solar energy being generated are taken into account when considering solar energy generation and the factors affecting it. These weather parameters include but are not limited to solar irradiance, cloud cover, wind speed, temperature, etc. Various simulation and estimation models have been developed that work on identifying any patterns in the weather data that can help in predicting these weather parameters in advance which can be utilized to estimate the amount of solar energy being generated.
- Solar energy technologies, technically described as photovoltaic technologies, use the natural resource of the sun to generate electricity. The overall performance of solar energy panels is highly attributable to the quantity of incoming solar irradiation (e.g., sunshine). As such, the ability of a solar array to obtain sun light is the largest factor affecting the performance and efficiency of any PV array. Without sunlight, solar energy technologies will not perform. If no sun is available, for example at night, no electricity can be generated. Two other key factors that influence the performance of solar energy technologies include solar panel module temperature and ambient temperature.
- Multiple models have been developed that incorporate historical data and statistical weather prediction frameworks in order to estimate temperature, especially atmospheric temperature in case of solar energy estimation. Pal and colleagues [46] worked on an atmospheric temperature prediction model, utilizing neural networks. This model generated a self-organizing feature map (SOFM) which were used in designing multi-layer perception (MLP) networks also known as SOFM-MLP. This research stated that in order to predict atmospheric parameters more efficiently, selection of features that go into the model is crucial. The feature selection MLP (FSMLP) has been stated to select good features that can be used to tailor efficient models for prediction. It is also suggested further application of this model in predicting other atmospheric parameters.

Another paper written by Krishnamurti and colleagues [47] details the improvements in weather and seasonal climate forecasts by utilizing a multi-model super-ensemble forecast center for weather and seasonal climate forecasts. Recent research done on this topic by Lazos and co-authors [48] developed a hybrid weather-prediction model, which utilized a combination of numerical as well as statistical short-term estimation methods. These papers also included sections where other atmospheric parameter predictions were not as accurate as temperature predictions, showing the need of a universal prediction model which can be trained using historical weather data and include other variables such as global warming and temperature change. Studies on estimating temperature have also worked on ensemble and super-ensemble forecasting methods.

Apart from improving predictions so as to improve model accuracy, prediction accuracy can also be increased by post-processing methods. Moller and Grob [49] published a research paper identifying the potential patterns in forecasting errors, which can be utilized in an autoregressive modification method, generating a model which can distinguish between actual values versus estimated values for future temperature forecasts. Although, the application of this study was specific to temperature, it included the possibility of predicting other weather variables such as wind speed or precipitation, using different predictive distributions e.g., bivariate distributions instead of univariate distributions [50].

Estimation models for predicting solar irradiance data have involved different kinds of models i.e., stochastic learning methods, time series neural networks, numerical weather prediction models, and ARIMA modeling. Research done by Marquez and Coimbra [51] stated that inputs defined by a combination of Gamma test and a genetic algorithm were optimal, inspired by previous research [52], and gave the best performance when fed to a neural network. In this case, this combination resulted in 10–15% improvement in root mean squared error, when compared to the reference models e.g., persistent and Perez's models. They also noticed that in general, their models lost accuracy with increasing forecasting horizon. Although this loss in accuracy was less sharp during the summer due to longer and clearer days as compared to winter months, which usually have hazier days. Another approach to predict solar irradiance utilized the mesoscale numerical weather prediction model, as suggested by a study by Zamora et al. [53], which estimated solar irradiance where the accuracy of the model depended on the aerosol optical depth of the air. Accounting for the effect of aerosols and their assimilation depth measurements can improve the accuracy of solar irradiance forecast models. Thus, another area to work upon when predicting weather parameters used to estimate solar energy is improvement in the understanding of aerosol physics in estimation models.

2.2.4. Predictive Maintenance Using Real-Time Sensors

In general, this approach is the most expensive but offers the highest detection accuracy. It is well-known that sensors have been used for the purpose of tracking, where the PV panel automatically orients according to the sun's direction [54]. However, in some cases, researchers have also used real-time sensors to monitor the PV system to assess for quality control issues. A few researchers have already proposed a low-cost PV monitoring system which uses sensors to measure incoming solar irradiance, ambient and module temperature, open-circuit voltage, short-circuit current, attributes associated with max power, fill factor, and PV panel efficiency [55]. In these cases, the researchers have proposed the hardware application to use of off-the-shelf sensors, such as a pyranometer for solar irradiance, thermocouple to detect temperature, shunt resistor to measure current, and voltage divider to obtain voltage. Software applications have been developed using both Visual Basic [55] and LabVIEW [56,57]. When an Arduino is used as an analyzer and microcontroller [58], results have proven comparable to the commercially available PV analyzers (such as the Solmetric I-V curve tracer). Fault detection algorithms can be used to compare estimated output to actual output given a set of errors thresholds based on fault-free systems [59]; in this manner, both total and partial loss productivity can be identified.

In some studies, wireless sensors have been used for monitoring PV systems [60–63]. Guerriero and his colleagues [60] used a sensor to monitor the voltage and current, the open-circuit voltage and the short-circuit current of the photovoltaic panels. As a result, the ability to detect faults and locate the malfunction of photovoltaic panels was obtained. Using the monitoring sensors allow obtaining a complete view of the PV system and how the inverter interacts in each array in the presence of a shadow. Prieto and his colleagues [61] present a monitoring system based on a network of wireless sensors. The proposed system provides real-time monitoring of a single cell or of the complement system where efficiency, features, failures, and weaknesses are tracked. Using an application developed in MATLAB, the data collected are analyzed. In this way, the PV plants can optimize efficiency and improve energy production [61]. A smart PV system requires power control, monitoring components, and data communication from the sensors to a platform. Monitoring the voltage, current, temperature,

and irradiance with sensors distributed throughout the PV system, Xiao and Daoe [62] demonstrate a low-cost monitoring system using ZigBee network technology. Technology based on an open-source hardware platform, Arduino, and an open-source web platform, Cosm, allows the implementation of a low-cost and scalable model that enables real-time information for monitoring and maintenance of PV systems [63]. Adhya and colleagues [64] based their research on the Internet-of-Things to implement a low-cost platform to monitor PV systems. By installing wireless sensors and sending real-time data to a web platform, preventive maintenance, historical data analysis, and fault detection are facilitated. In another case of real-time monitoring with wired and wireless sensors and using programmable controllers, in this way, it is possible to monitor the performance of all the components of the PV system. The system was designed for a residential scale system but can be scalable for solar plants [65].

Shariff and colleagues [66] carried out the hardware design, using a microcontroller, and software, graphical user interface, for monitoring PV systems using a GSM modem for real-time data transmission. By using GSM, the PV systems can be monitored remotely, increasing efficiency and eliminating the risks of wireless data transmission.

In summary, given the scale of PV system deployment, sophisticated automation and remote monitoring are needed to ensure quality of system operations, yet challenges and opportunities still exist. In particular, these monitoring tools can accurately identify when a PV system is not performing to its full potential, but they typically do not provide specific actionable information that an owner might use to improve solar performance.

3. Discussion

Energy generation, sources and distribution methods have been continuously evolving over the past decade. In 2018, solar-produced energy accounted for 1.6% of the electricity generated in the United States, up from 0.11% in 2012. By 2020, solar-produced energy is forecasted to account for 5% of U.S. generated electricity. With the increased efficiency associated with solar energy production and distribution, prosumers (e.g., producers + consumers) have also assumed the role of energy generators, even getting credit for excess electricity supplied to the grid given the policy around net-metering. However, few resources are dedicated to understanding and optimizing the long-term performance of PV systems. Devising methods and tools that can ensure solar energy systems are working properly will positively impact PV system owners, including utility companies, residential, and non-residential prosumers. Specifically, in this study, the authors provide motivation for an increased priority placed on PV system error detection and preventative maintenance. Ultimately, the authors propose that PV system owners need a third-party (unbiased) off-the-shelf system-level PV system predictive maintenance tool to optimize return-on-investment and minimize time to warranty claim. This tool should be able to monitor incoming solar irradiance and module temperature, for the purpose to determine real-time actual power generation and compare to the manufacturer's warranty. However, there are many other research areas that can and should be targeted. Future research should continue to investigate, assess, and evaluate the long-term quality assurance associated with PV systems. Longitudinal studies should be undertaken to better quantify real-world and long-term quality assurance issues faced by PV systems, allowing researchers to go beyond anecdotal evidence and dispersed studies to establishing long overdue empirical evidence and justification for developing PV system predictive maintenance solutions. In addition, there should be a renewed focus on research and development efforts to optimize return on investment strategies for PV systems, including increasing efficiencies and validating different types of technology (e.g., organic, thin film, perovskite). Given the societal and region-wide impacts presented through solar energy adoption and penetration, government agencies and policies should play a greater role in providing funding to support such research initiatives. As Tom Steyer (American hedge fund manager, philanthropist, and environmentalist) states, "Renewable energy is a clear winner when it comes to boosting the economy and creating jobs".

Author Contributions: Individual author contributions are as follows: conceptualization, L.B.B. and W.D.L.-S.; writing—original draft preparation, L.B.B. and E.A.S.; writing—review and editing, W.D.L.-S. and W.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Bosman, L. A Decision Support System to Analyze, Predict, and Evaluate Solar Energy System Performance: PVSysCO (photovoltaic System Comparison). Ph.D. Thesis, University of Wisconsin-Milwaukee, Milwaukee, WI, USA, 2014.
2. Bosman, L.; Darling, S. Difficulties and recommendations for more accurately predicting the performance of solar energy systems during the snow season. In Proceedings of the 2016 IEEE International Conference on Renewable Energy Research and Applications (ICRERA), Birmingham, UK, 20–23 November 2016; pp. 567–571.
3. Bosman, L.; Darling, S.; Otieno, W. PVSysCo: Solar energy system comparison and evaluation. In Proceedings of the Annual Congress on Environmental Pollution and Sustainable Energy, Melbourne, Australia, 20–22 July 2017.
4. Bosman, L.B.; Darling, S.B. Performance modeling and valuation of snow-covered PV systems: Examination of a simplified approach to decrease forecasting error. *Environ. Sci. Pollut. Res.* **2018**, *25*, 15484–15491. [[CrossRef](#)] [[PubMed](#)]
5. Otieno, W.; Bosman, L. Solar PV Selection Decision Tool: The case of USA Midwest Region. *J. Civ. Eng. Environ. Technol.* **2014**, *1*, 114–120.
6. Ancuta, F.; Cepisca, C. Fault analysis possibilities for PV panels. In Proceedings of the 2011 3rd International Youth Conference on Energetics (IYCE), Leiria, Portugal, 7–9 July 2011; pp. 1–5.
7. Klugmann-Radziemska, E. Degradation of electrical performance of a crystalline photovoltaic module due to dust deposition in northern Poland. *Renew. Energy* **2015**, *78*, 418–426. [[CrossRef](#)]
8. Bouraiou, A.; Hamouda, M.; Chaker, A.; Neçaibia, A.; Mostefaoui, M.; Boutasseta, N.; Ziane, A.; Dabou, R.; Sahouane, N.; Lachtar, S. Experimental investigation of observed defects in crystalline silicon PV modules under outdoor hot dry climatic conditions in Algeria. *Solar Energy* **2018**, *159*, 475–487. [[CrossRef](#)]
9. Díez-Mediavilla, M.; Dieste-Velasco, M.; Rodríguez-Amigo, M.d.C.; García-Calderón, T.; Alonso-Tristán, C. Performance of grid-tied PV facilities based on real data in Spain: Central inverter versus string system. *Energy Convers. Manag.* **2014**, *86*, 1128–1133. [[CrossRef](#)]
10. Cristaldi, L.; Faifer, M.; Rossi, M.; Catelani, M.; Ciani, L.; Dovere, E.; Jerace, S. Economical evaluation of PV system losses due to the dust and pollution. In Proceedings of the 2012 IEEE International Instrumentation and Measurement Technology Conference Proceedings, Graz, Austria, 13–16 May 2012; pp. 614–618.
11. Zareipour, H.; Bhattacharya, K.; Canizares, C. Distributed generation: Current status and challenges. In Proceedings of the 36th Annual North American Power Symposium (NAPS), Chicago, IL, USA, 9 May 2004; pp. 1–8.
12. Kabir, E.; Kumar, P.; Kumar, S.; Adelodun, A.A.; Kim, K.-H. Solar energy: Potential and future prospects. *Renew. Sustain. Energy Rev.* **2018**, *82*, 894–900. [[CrossRef](#)]
13. Obi, M.; Bass, R. Trends and challenges of grid-connected photovoltaic systems—A review. *Renew. Sustain. Energy Rev.* **2016**, *58*, 1082–1094. [[CrossRef](#)]
14. Sampaio, P.G.V.; González, M.O.A. Photovoltaic solar energy: Conceptual framework. *Renew. Sustain. Energy Rev.* **2017**, *74*, 590–601. [[CrossRef](#)]
15. Silveira, J.L.; Tuna, C.E.; de Queiroz Lamas, W. The need of subsidy for the implementation of photovoltaic solar energy as supporting of decentralized electrical power generation in Brazil. *Renew. Sustain. Energy Rev.* **2013**, *20*, 133–141. [[CrossRef](#)]
16. Mundo-Hernández, J.; de Celis Alonso, B.; Hernández-Álvarez, J.; de Celis-Carrillo, B. An overview of solar photovoltaic energy in Mexico and Germany. *Renew. Sustain. Energy Rev.* **2014**, *31*, 639–649. [[CrossRef](#)]
17. Hosenuzzaman, M.; Rahim, N.A.; Selvaraj, J.; Hasanuzzaman, M.; Malek, A.A.; Nahar, A. Global prospects, progress, policies, and environmental impact of solar photovoltaic power generation. *Renew. Sustain. Energy Rev.* **2015**, *41*, 284–297. [[CrossRef](#)]

18. El Chaar, L.; lamont, L.A.; El Zein, N. Review of photovoltaic technologies. *Renew. Sustain. Energy Rev.* **2011**, *15*, 2165–2175. [[CrossRef](#)]
19. Lan, Z.; Li, J. Photovoltaic Technology and Electricity Saving Strategies for Fixed-Velocity-Measuring System. *Indones. J. Electr. Eng. Comput. Sci.* **2014**, *12*, 4416–4419. [[CrossRef](#)]
20. Mekhilef, S.; Safari, A.; Mustafa, W.E.S.; Saidur, R.; Omar, R.; Younis, M.A.A. Solar energy in Malaysia: Current state and prospects. *Renew. Sustain. Energy Rev.* **2012**, *16*, 386–396. [[CrossRef](#)]
21. Denio, H. Aerial solar Thermography and condition monitoring of photovoltaic systems. In Proceedings of the 2012 38th IEEE Photovoltaic Specialists Conference, Austin, TX, USA, 3–8 June 2012; pp. 613–618.
22. Grimaccia, F.; Aghaei, M.; Mussetta, M.; Leva, S.; Quater, P.B. Planning for PV plant performance monitoring by means of unmanned aerial systems (UAS). *Int. J. Energy Environ. Eng.* **2015**, *6*, 47–54. [[CrossRef](#)]
23. Gómez Muñoz, C.Q.; García Marquez, F.P.; Liang, C.; Maria, K.; Abbas, M.; Mayorkinos, P. *A New Condition Monitoring Approach for Maintenance Management in Concentrate Solar Plants*; Springer: Berlin/Heidelberg, Germany; pp. 999–1008.
24. Díez-Mediavilla, M.; Alonso-Tristán, C.; Rodríguez-Amigo, M.C.; García-Calderón, T.; Dieste-Velasco, M.I. Performance analysis of PV plants: Optimization for improving profitability. *Energy Convers. Manag.* **2012**, *54*, 17–23. [[CrossRef](#)]
25. Mgonja, C.T.; Saidi, H. Effectiveness on Implementation of Maintenance Management System For off-Grid Solar PV Systems in Public Facilities—A Case Study of SSMP1 Project In Tanzania. *Int. J. Mech. Eng. Technol.* **2017**, *8*, 869–880.
26. Jordan, D.C.; Sekulic, B.; Marion, B.; Kurtz, S.R. Performance and aging of a 20-year-old silicon PV system. *IEEE J. Photovolt.* **2015**, *5*, 744–751. [[CrossRef](#)]
27. Buerhop-Lutz, C.; Scheuerpflug, H. Inspecting PV-plants using aerial, drone-mounted infrared thermography system. In Proceedings of the 3rd Southern African Solar Energy Conference, Kruger National Park, South Africa, 11–13 May 2015.
28. Fezzani, A.; Mahammed, I.H.; Drid, S.; Zaghba, L.; Bouchakour, A.; Benbitour, M.K. Experimental investigation of effects of partial shading and faults on photovoltaic modules performances. *Leonardo Electron. J. Pract. Technol.* **2017**, *11*, 183–200.
29. Bulanyi, P.; Zhang, R. Shading analysis & improvement for distributed residential grid-connected photovoltaics systems. In Proceedings of the 52nd Annual Conference of the Australian Solar Council, Melbourne, Australia, 8 May 2014.
30. Figgis, B.; Ennaoui, A.; Ahzi, S.; Rémond, Y. Review of PV soiling measurement methods. In Proceedings of the 2016 International Renewable and Sustainable Energy Conference (IRSEC), Marrakech, Morocco, 14–17 November 2016; pp. 176–180.
31. Gallardo-Saavedra, S.; Hernández-Callejo, L.; Duque-Perez, O. Technological review of the instrumentation used in aerial thermographic inspection of photovoltaic plants. *Renew. Sustain. Energy Rev.* **2018**, *93*, 566–579. [[CrossRef](#)]
32. Quater, P.B.; Grimaccia, F.; Leva, S.; Mussetta, M.; Aghaei, M. Light Unmanned Aerial Vehicles (UAVs) for cooperative inspection of PV plants. *IEEE J. Photovolt.* **2014**, *4*, 1107–1113. [[CrossRef](#)]
33. Koch, S.; Weber, T.; Sobottka, C.; Fladung, A.; Clemens, P.; Berghold, J. Outdoor electroluminescence imaging of crystalline photovoltaic modules: Comparative study between manual ground-level inspections and drone-based aerial surveys. In Proceedings of the 32nd European Photovoltaic Solar Energy Conference and Exhibition, Munich, Germany, 21–24 June 2016; pp. 1736–1740.
34. Aghaei, M.; Gandelli, A.; Grimaccia, F.; Leva, S.; Zich, R. IR real-time analyses for PV system monitoring by digital image processing techniques. In Proceedings of the 2015 International Conference on Event-based Control, Communication, and Signal Processing (EBCCSP), Krakow, Poland, 17–19 June 2015; pp. 1–6.
35. Solemetric. Solmetric PV Analyzer I-V Curve Tracer with SolSensor TM PVA-1000S, PVA-600 + User’s Guide. Available online: <http://www.solmetric.net/get/PVA-SolSensor-Users-Guide-Feb19-2014.pdf> (accessed on 13 October 2019).
36. Dhimish, M.; Holmes, V.; Mather, P.; Sibley, M. Novel hot spot mitigation technique to enhance photovoltaic solar panels output power performance. *Sol. Energy Mater. Sol. Cells* **2018**, *179*, 72–79. [[CrossRef](#)]
37. Ji, D.; Zhang, C.; Lv, M.; Ma, Y.; Guan, N. Photovoltaic array fault detection by automatic reconfiguration. *Energies* **2017**, *10*, 699. [[CrossRef](#)]

38. Colli, A. Failure mode and effect analysis for photovoltaic systems. *Renew. Sustain. Energy Rev.* **2015**, *50*, 804–809. [[CrossRef](#)]
39. Kuitche, J.M.; Pan, R.; TamizhMani, G. Investigation of dominant failure mode (s) for field-aged crystalline silicon PV modules under desert climatic conditions. *IEEE J. Photovolt.* **2014**, *4*, 814–826. [[CrossRef](#)]
40. Villarini, M.; Cesarotti, V.; Alfonsi, L.; Introna, V. Optimization of photovoltaic maintenance plan by means of a FMEA approach based on real data. *Energy Convers. Manag.* **2017**, *152*, 1–12. [[CrossRef](#)]
41. Cristaldi, L.; Khalil, M.; Soulatiantork, P. A root cause analysis and a risk evaluation of PV balance of system failures. *Acta Imeko* **2017**, *6*. [[CrossRef](#)]
42. Shrestha, S.M.; Mallineni, J.K.; Yedidi, K.R.; Knisely, B.; Tatapudi, S.; Kuitche, J.; TamizhMani, G. Determination of dominant failure modes using FMECA on the field deployed c-Si modules under hot-dry desert climate. *IEEE J. Photovolt.* **2014**, *5*, 174–182. [[CrossRef](#)]
43. Catelani, M.; Ciani, L.; Cristaldi, L.; Faifer, M.; Lazzaroni, M.; Rinaldi, P. FMECA technique on photovoltaic module. In Proceedings of the 2011 IEEE International Instrumentation and Measurement Technology Conference, Binjiang, China, 10–12 May 2011; pp. 1–6.
44. Catelani, M.; Ciani, L.; Cristaldi, L.; Faifer, M.; Lazzaroni, M. Electrical performances optimization of Photovoltaic Modules with FMECA approach. *Measurement* **2013**, *46*, 3898–3909. [[CrossRef](#)]
45. Gallardo-Saavedra, S.; Hernández-Callejo, L.; Duque-Pérez, O. Quantitative failure rates and modes analysis in photovoltaic plants. *Energy* **2019**, *183*, 825–836. [[CrossRef](#)]
46. Pal, N.R.; Pal, S.; Das, J.; Majumdar, K. SOFM-MLP: A hybrid neural network for atmospheric temperature prediction. *IEEE Trans. Geosci. Remote Sens.* **2003**, *41*, 2783–2791. [[CrossRef](#)]
47. Krishnamurti, T.N.; Kishtawal, C.M.; LaRow, T.E.; Bachiochi, D.R.; Zhang, Z.; Williford, C.E.; Gadgil, S.; Surendran, S. Improved Weather and Seasonal Climate Forecasts from Multimodel Superensemble. *Science* **1999**, *285*, 1548–1550. [[CrossRef](#)] [[PubMed](#)]
48. Lazos, D.; Sproul, A.B.; Kay, M. Development of hybrid numerical and statistical short term horizon weather prediction models for building energy management optimisation. *Build. Environ.* **2015**, *90*, 82–95. [[CrossRef](#)]
49. Möller, A.; Groß, J. Probabilistic temperature forecasting based on an ensemble autoregressive modification. *Q. J. R. Meteorol. Soc.* **2016**, *142*, 1385–1394. [[CrossRef](#)]
50. Sloughter, J.; Gneiting, T.; Raftery, A. Probabilistic Wind Vector Forecasting Using Ensembles and Bayesian Model Averaging. *Mon. Weather Rev.* **2013**, *141*, 2107–2119. [[CrossRef](#)]
51. Marquez, R.; Coimbra, C.F.M. Forecasting of global and direct solar irradiance using stochastic learning methods, ground experiments and the NWS database. *Sol. Energy* **2011**, *85*, 746–756. [[CrossRef](#)]
52. Wilson, I.D.; Jones, A.J.; Jenkins, D.H.; Ware, J.A. Predicting housing value: Genetic algorithm attribute selection and dependence modelling utilising the gamma test. *Adv. Econom.* **2004**, *19*, 243–275.
53. Zamora, R.J.; Dutton, E.G.; Trainer, M.; McKeen, S.A.; Wilczak, J.M.; Hou, Y.-T. The Accuracy of Solar Irradiance Calculations Used in Mesoscale Numerical Weather Prediction. *Mon. Weather Rev.* **2005**, *133*, 783–792. [[CrossRef](#)]
54. Devabhaktuni, V.; Alam, M.; Shekara Sreenadh Reddy Depuru, S.; Green, R.C.; Nims, D.; Near, C. Solar energy: Trends and enabling technologies. *Renew. Sustain. Energy Rev.* **2013**, *19*, 555–564. [[CrossRef](#)]
55. Rivai, A.; Rahim, N.A. A low-cost photovoltaic (PV) array monitoring system. In Proceedings of the 2013 IEEE Conference on Clean Energy and Technology (CEAT), Lankgwawi, Malaysia, 18–20 November 2013; pp. 169–174.
56. Chouder, A.; Silvestre, S.; Taghezouit, B.; Karatepe, E. Monitoring, modelling and simulation of PV systems using LabVIEW. *Sol. Energy* **2013**, *91*, 337–349. [[CrossRef](#)]
57. Bayrak, G.; Cebeci, M. Monitoring a grid connected PV power generation system with labview. In Proceedings of the 2013 International Conference on Renewable Energy Research and Applications (ICRERA), Madrid, Spain, 20–23 October 2013; pp. 562–567.
58. Anand, R.; Pachauri, R.K.; Gupta, A.; Chauhan, Y.K. Design and analysis of a low cost PV analyzer using Arduino UNO. In Proceedings of the 2016 IEEE 1st International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), Delhi, India, 4–6 July 2016; pp. 1–4.
59. Silvestre, S.; Chouder, A.; Karatepe, E. Automatic fault detection in grid connected PV systems. *Sol. energy* **2013**, *94*, 119–127. [[CrossRef](#)]
60. Guerriero, P.; Di Napoli, F.; Vallone, G.; d’Alessandro, V.; Daliento, S. Monitoring and diagnostics of PV plants by a wireless self-powered sensor for individual panels. *IEEE J. Photovolt.* **2015**, *6*, 286–294. [[CrossRef](#)]

61. Prieto, M.J.; Pernía, A.M.; Nuño, F.; Díaz, J.; Villegas, P.J. Development of a wireless sensor network for individual monitoring of panels in a photovoltaic plant. *Sensors* **2014**, *14*, 2379–2396. [[CrossRef](#)] [[PubMed](#)]
62. Xiaoli, X.; Daoc, Q. Remote monitoring and control of photovoltaic system using wireless sensor network. In Proceedings of the 2011 International Conference on Electric Information and Control Engineering, Wuhan, China, 15–17 April 2011; pp. 633–638.
63. Papageorgas, P.; Piromalis, D.; Antonakoglou, K.; Vokas, G.; Tseles, D.; Arvanitis, K. Smart solar panels: In-situ monitoring of photovoltaic panels based on wired and wireless sensor networks. *Energy Procedia* **2013**, *36*, 535–545. [[CrossRef](#)]
64. Adhya, S.; Saha, D.; Das, A.; Jana, J.; Saha, H. An IoT based smart solar photovoltaic remote monitoring and control unit. In Proceedings of the 2016 2nd International Conference on Control, Instrumentation, Energy & Communication (CIEC), Kolkata, India, 28–30 January 2016; pp. 432–436.
65. Moreno-Garcia, I.M.; Palacios-Garcia, E.J.; Pallares-Lopez, V.; Santiago, I.; Gonzalez-Redondo, M.J.; Varo-Martinez, M.; Real-Calvo, R.J. Real-time monitoring system for a utility-scale photovoltaic power plant. *Sensors* **2016**, *16*, 770. [[CrossRef](#)]
66. Shariff, F.; Rahim, N.A.; Ping, H.W. Photovoltaic remote monitoring system based on GSM. In Proceedings of the 2013 IEEE Conference on Clean Energy and Technology (CEAT), Lankgwawi, Malaysia, 18–20 November 2013; pp. 379–383.



© 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).