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Review

Solar Photovoltaic Modules' Performance Reliability and Degradation Analysis—A Review

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Abstract: The current geometric increase in the global deployment of solar photovoltaic (PV) modules, both at utility-scale and residential roof-top systems, is majorly attributed to its affordability, scalability, long-term warranty and, most importantly, the continuous reduction in the levelized cost of electricity (LCOE) of solar PV in numerous countries. In addition, PV deployment is expected to continue this growth trend as energy portfolio globally shifts towards cleaner energy technologies. However, irrespective of the PV module type/material and component technology, the modules are exposed to a wide range of environmental conditions during outdoor deployment. Oftentimes, these environmental conditions are extreme for the modules and subject them to harsh chemical, photo-chemical and thermo-mechanical stress. Asides from manufacturing defects, these conditions contribute immensely to PV module's aging rate, defects and degradation. Therefore, in recent times, there has been various investigations into PV reliability and degradation mechanisms. These studies do not only provide insight on how PV module's performance degrades over time, but more importantly, they serve as meaningful input information for future developments in PV technologies, as well as performance prediction for better financial modelling. In view of this, prompt and efficient detection and classification of degradation modes and mechanisms due to manufacturing imperfections and field conditions are of great importance towards minimizing potential failure and associated risks. In the literature, several methods, ranging from visual inspection, electrical parameter measurements (EPM), imaging methods, and most recently data-driven techniques have been proposed and utilized to measure or characterize PV module degradation signatures and mechanisms/pathways. In this paper, we present a critical review of recent studies whereby solar PV systems performance reliability and degradation were analyzed. The aim is to make cogent contributions to the state-of-the-art, identify various critical issues and propose thoughtful ideas for future studies particularly in the area of data-driven analytics. In contrast with statistical and visual inspection approaches that tend to be time consuming and require huge human expertise, data-driven analytic methods including machine learning (ML) and deep learning (DL) models have impressive computational capacities to process voluminous data, with vast features, with reduced computation time. Thus, they can be deployed for assessing module performance in laboratories, manufacturing, and field deployments. With the huge size of PV modules' installations especially in utility scale systems, coupled with the voluminous datasets generated in terms of EPM and imaging data features, ML and DL can learn irregular patterns and make conclusions in the prediction, diagnosis and classification of PV degradation signatures, with reduced computation time. Analysis and comparison of different models proposed for solar PV degradation are critically reviewed, in terms of the methodologies, characterization techniques, datasets, feature extraction mechanisms, accelerated testing procedures and classification procedures. Finally, we briefly highlight research gaps and summarize some recommendations for the future studies.

Keywords: photovoltaics; degradation; characterization; data-driven analytics; machine learning

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1. Introduction

Recognized as a cheap and sustainable option, renewables including solar and wind energy technologies provide clean energy options that contribute heavily to the reduction of ecological problems globally, particularly CO_2 emission [1–5]. Solar as well as wind technologies are projected to be the major energy source by the year 2025, with solar energy production contributing 60% of the capacity additions [6,7]. This projection is highly feasible provided that the reliability, accessibility, and performance issues are continuously monitored and resolved. In recent years, the installation of solar photovoltaic (PV) modules, both at utility-scale and residential roof-top systems, has increased geometrically majorly due to factors which include their well-known affordability, scalability and long-term warranty, and most importantly, the continuous reduction in the levelized cost of electricity (LCOE) of solar PVs worldwide [8–11]. On the LCOE basis, nuclear technology, coal, natural gas, etc. are more expensive compared to solar and wind systems. For the calculation of LCOE, the fuel cost for solar and wind generation is zero, when compared to other technologies. According to a LCOE estimate analysis for various energy generation technologies [12], the cost of solar and wind have consistently dropped compared to other conventional technologies which include gas, nuclear, coal etc. While it took nearly six decades to realize 100 GW of solar energy generation by 2012, National Renewable Energy Laboratory (NREL) reported that 939 GW mark has been reached as at 2021 [13,14]. Thus, making PV energy generation the fastest growing energy source globally. Figure 1 presents the global cumulative PV installed capacity-GigaWatts peak (GWp) over the past decade.

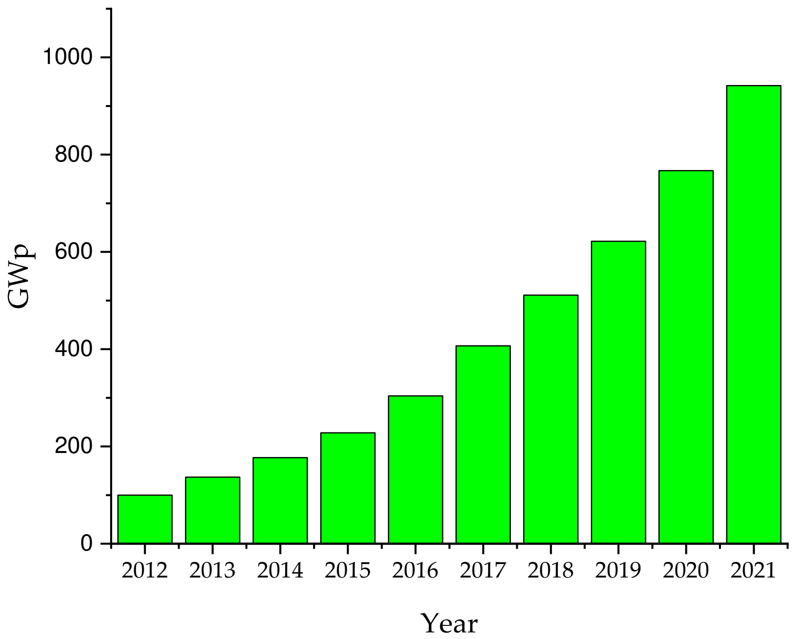

Figure 1. Evolution of PV installations over the past decade [14–16].

As described in [17], one of the macrotrends that have increased the global ascendency of the PV industry in recent times is that, improved designs boast of increased performance. Newer PV modules are projected to operate effectively for 30 years [18–20]. However, irrespective of the PV module type/material technology, the modules are exposed to a wide range of environmental conditions during outdoor deployment [21–23]. Oftentimes, these outdoor environmental conditions are extreme for the modules and subject them to harsh chemical, photo-chemical and thermo-mechanical stress. Asides from manufacturing defects, these conditions contribute immensely to PV module's aging rate, defects and degradation. Historically, when PV solar power was initially developed at the Flat-Plate Solar Array Block Program in the 1970s, the goal was to provide a sustainable energy alternative. While the developments paved the way for the development of some silicon PV power plants in the early 1980s, there was little consideration of the potential degradation and reliability challenges that come with aging of the PV modules [24]. In fact, some of the power plants had an annual power degradation rate of approximately 10%/year, far beyond currently designed modules with a rate of <1%/year. Advancement in technology in recent times have revolutionized PV technology industry with the creation of newer technologies in module designs, with lower cost materials and better degradation rates. Newer module designs boast of other features which include half-cut cells to reduce series resistance, bifacial modules that allows capturing light reflections from both sides, glass to glass constructions, etc. Thus, modules warranties have advanced positively from the 5 years in the 80s, to an average of 10/20 years in the 90s, compared to the current possibility of 80% optimal performance for an average 30 years [25].

However, despite the huge progress in PV technologies in recent years, the issue of PV cell, module and system reliability and degradation mechanisms that affect their efficiency, stability, and operating lifetime are major concerns globally [26–28]. The authors in [29] explained that although, PV systems are becoming increasingly affordable, the extended lifetime reliability of the systems is still a major concern as they are hugely vulnerable to various forms of faults as well as degradations. Hence, various research and investigations have shifted towards PV reliability and degradation mechanisms in recent times. These studies provide insight on how PV module's performance degrades over time, especially under field conditions [18]. More importantly, the studies serve as meaningful input information for future developments in PV technologies, as well as performance prediction for better financial modelling. Various governmental parastatals and research institutions are working assiduously towards prolonging the 80% minimum performance warranty on PV modules from 25 years to 50 years. A major way to achieve this is by investigating the various degradation mechanisms. Generally, factors such as the material and technology type, field environment deployed determine the PV systems' aging and degradation process/patterns. Module components such as the encapsulant, backsheet, glass, etc. are susceptible to degradation and failures. Figure 2 presents the degradation analysis result involving 1.9 million modules across 197 installations in different climes [30]. Due to aging from field exposure ranging from 0–25 years with an average age of 3.4 years for all 197 installations, the result showed that 43 out of the total installations have experienced extensive degradation and defects which are classified as cell defects (corrosion, snail trails), encapsulant defects (discoloration and delamination) and backsheet defects (front and airside delamination, yellowing, cracking, peeling, and localized burning) [30].

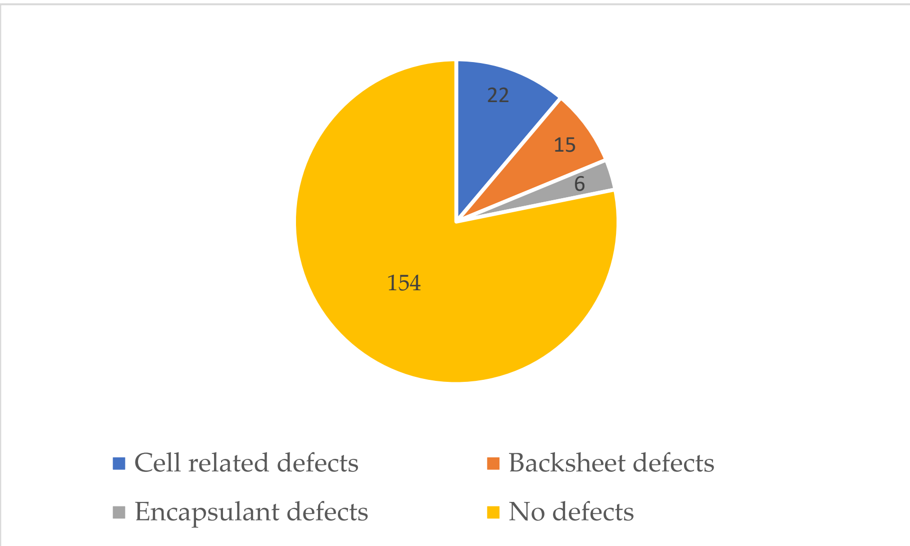

Figure 2. Degradation analysis result involving 1.9 million modules across 197 installations [30].

With regards to degradation mechanisms, moisture ingress is adjudged as a major concern that causes degradation. Moisture in EVA encapsulant can lead to metal grids corrosion, delamination and discoloration of encapsulants, potential induced degradation, etc. Figure 3 presents typical degradation modes and signatures that are usually associated with moisture ingress degradation mechanism.

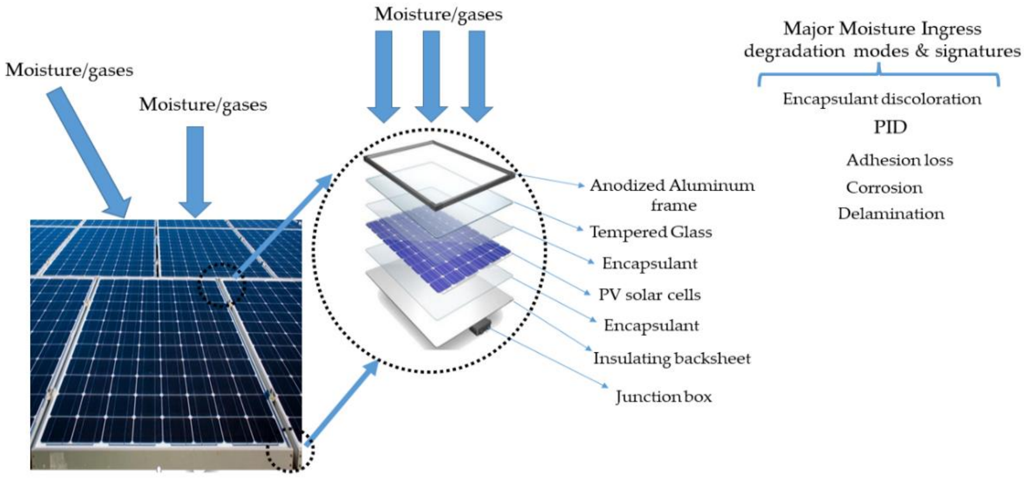

Figure 3. Typical degradation modes and signatures associated with moisture ingress [31].

In view of the degradation menace, the prompt and efficient prediction, detection and classification of degradation modes and mechanisms due to manufacturing imperfections and prolonged outdoor conditions are of great importance towards minimizing potential failure and associated risks. In the literature, several methods, ranging from visual inspection, electrical parameter measurements (EPM), imaging methods, and most recently data-driven analytic models have been proposed and utilized for measuring or characterizing PV module degradation mechanisms/pathways. In this work, we present a critical review of recent research works whereby solar PV systems performance reliability and degradation were analyzed. The paper aims to offer ideas for future studies particularly in the area of data-driven analytics modelling for PV degradation analysis. Data-driven analytic methods including machine learning (ML) and deep learning (DL) have better computational capability with regards to the handling of voluminous data, with high number of features, with reduced computation time. In addition, they provide a simple option for easy automation of the laboratory-based techniques for real time analysis. Thus, they can be applicable for the performance and degradation assessment of PV modules in the laboratory, during the manufacturing process, and during outdoor deployments. With the huge size of PV modules' installations especially in utility scale systems, coupled with the voluminous data generated in terms of EPM and imaging data features, it is paramount to deploy advanced models such as ML and DL techniques that can learn and discover irregular patterns and reach meaningful conclusions in the diagnosis and classifications of PV degradations, with reduced computation time. PV performance forecasting and degradation are currently receiving huge attention with regards to ML and DL applications. Realistically, ML and DL models are not currently considered as definitive solutions to PV degradation challenges. However, these models present powerful set of tools that justify thoughtful considerations in the analysis of PV performance and degradation. Traditionally, based on the learning strategy, ML models can be categorized into supervised, semi-supervised, unsupervised learning and reinforcement learning. Supervised learning model learns the correlations between training set features, so as to create a prediction model which has the capability of inferring annotations for another set of datasets with unknown annotations [32,33]. Unsupervised learning models do not require labelled data. Semi-supervised models use both labelled and unlabeled datasets for training [34]. For reinforcement learning models, the learning agents observe and interact with the system environment, alter the state of the environment by taking some control actions. Afterwards, they observe the effects of the actions in order to maximize the notion of cumulative reward [35]. Supervised learning models are perhaps the most prominent learning approach for PV performance and degradation analysis. As demonstrated in numerous works in the literature, researchers use the EPM and imaging data features as training datasets, for inferring models for predicting, diagnosing and classifying feature annotations in validation or testing sets.

Several articles in the literature have surveyed PV performance and reliability degradation from different viewpoints. Phinikarides et al. [36] reviewed the various methods for measuring the degradation rates of various PV technologies. The authors in [37] reviewed several statistical and analytical PV degradation models. In [38], the authors reviewed the popular practice of using infrared (IR) and electroluminescence (EL) imaging techniques for identifying degradation modes of PV modules, both from the perspective of environmental and device requirements as well as the interpretation of sampled abnormal patterns. Bouraioua et al. [39] surveyed the various detectable failures of monocrystalline as well as polycrystalline silicon PV modules that are exposed to outdoor Saharan medium fields. In the study, the authors focused on the inspection and assessment of PV module defects in fielded modules in a desert location. Using several degradation modes as criteria, the authors in [29] reviewed defects and degradations in traditional screen-printed metallization and soldered interconnects. In the study, the authors investigated underlying defect mechanisms attributed to electrical loss modes as well as their sensitivity to parameters ranging from positioning to defects by electrical stimulation using various characterization techniques. Similarly, the authors in [40] reviewed different characterization methods and their application in PV degradation studies. Focusing on a key component of PV modules, the authors in [41] reviewed the degradation mechanisms of ethylene-vinyl-acetate (EVA) encapsulant, due to exposures to climate-induced stress factors such as ultra violet (UV) irradiance, humidity, etc. Similarly, Gupta [42] reviewed hailstorm impacts on PV system performances in terms of output power and lifetime reductions. In another related work, the authors in [43] reviewed PV performance degradation focusing on different weather climates. In the work, the authors also did a comparative analysis on economic and environmental impact of different PV technologies at different climes.

Contrary to other review studies in the literature, in this work, we comprehensively review, analyze and compare different models for solar PV performance reliability and degradation in terms of the methodologies, characterization techniques, datasets, feature extraction (FE) mechanisms, accelerated testing procedures and classification procedures, particularly in the area of data-driven analytics approaches. This study aims to contribute to the state-of-the-art, identify critical issues as well as propose thoughtful ideas for future research works especially with regards to ML and DL applications to PV degradation analysis. The intention is to provide an extensive summary of recent research trends in the area of PV performance degradation and reliability analysis. Finally, we highlight several recommendations for future research studies.

The remainder of the paper is structured as follows. In Section 2, we briefly describe technical defects and degradation issues in current PV technologies. In the section, five prominent PV degradation modes and signatures that dominates recent PV reliability and degradations investigations are briefly discussed. Section 3 presents an overview of PV degradation mode measurement and characterization techniques that dominate recent PV reliability and degradations analysis. In Section 4, we discuss several prominent data-driven analytics methodologies for PV performance degradation and reliability. In the section, the analysis and comparison of the processes involved in using ML and DL algorithms for PV performance degradation and reliability assessment, especially in terms of characterization techniques, dataset generation process, FE and other data preprocessing mechanisms and classification procedures is given. Section 5 presents the summary of some suggestions and recommendations for future studies. Lastly, Section 6 concludes the paper.

2. Technical Defects and Degradation Issues in Current PV Technologies

The LCOE of solar energy can be reduced significantly by lessening the manufacturing and installation costs, improving PV systems' efficiencies and reliability [44,45]. Hence, the ability to extend the lifetime and improve the performance reliability of PV modules is crucial at both grid-connected and residential roof-top systems [46]. Ensuring that solar PV systems operate effectively and efficiently without failure or reduced performance below the specified warranty years especially after it has been exposed to a variety of climatic stress factors such as intense UV irradiance, relative humidity, temperature, etc., during outdoor deployment is a major challenge to stakeholders such as residential owners, utility operators, manufacturers, investors, research institutions and laboratories such as NREL and Fort Hare Institute of Technology [19]. The authors in [25] explained that PV manufacturers tend to provide assurance to buyers by providing warranties. Usually, these warranties are of the range: 90–95% optimal performance for the first 5–10 years and afterwards, 80–87% of optimal performance for as long as 25–30 years of operation. Recent degradation studies have shown that the current PV technologies undergo various degradation scenarios that play vital roles in their degradation rates. Various factors such as cell chemistry and environmental factors (available solar irradiance, ambient temperature, humidity, wind speed and direction, etc.) can contribute significantly to the PV module aging and degradation rates [47]. As reported by NREL, module degradation rates can be as extreme as 4%/year, while the median and average degradation rates are estimated at 0.5%/year and 0.8%/year, respectively [48]. Typically, modules perform better in Mediterranean climes when compared to temperate climes while the degradation rate is higher for modules operated at hot climes as compared to other climes. The annual average degradation rate for crystalline silicon modules is estimated at about 1.2% in hot arid climes, 1.06% in hot humid climes, 0.72% in cold arid climes and 0.15% in temperate climes [43]. In various PV performance reliability studies, degradation rate estimations were calculated using various statistical and analytical models which include linear regression, classical seasonal decomposition, holt-winters exponential smoothing, seasonal and trend decomposition using LOESS (locally weighted smoothing), and autoregressive integrated moving average models [37,49–51]. Each of these statistical methods yield different results with varying uncertainty depending on factors ranging from measuring equipment, the data qualification, performance metrics, etc. This imposes the risk of overestimating or underestimating the true degradation rates [36]. Furthermore, important parameters such as the fill factor determines the efficiency of typical PV modules. Fill factor reduces as PV module degradation increases [52]. Considering that short-circuit current (I_{SC}) and the open-circuit voltage (V_{OC}) are the solar cell's maximum current and voltage, respectively, the fill factor in conjunction with I_{SC} and V_{OC} determines the maximum power (P_{MP}). The fill factor is defined in (1) [52] as:

$$Fill\ factor = \frac{P_{MP}}{V_{OC} \times I_{SC}} \tag{1}$$

In terms of the voltage and current at maximum power, V_{MP} and I_{MP}, respectively, the fill factor is defined in (2) [52] as:

$$Fill\ factor = \frac{V_{MP} \times I_{MP}}{V_{OC} \times I_{SC}} \tag{2}$$

The solar cell efficiency (η) is described in terms of the energy input and energy output from the cells, as defined in (3) [52];

$$\eta = \frac{V_{OC} \times I_{SC} \times FF}{P_{in}} \tag{3}$$

where P_{in} is the input power and FF is the fill factor.

Over the years, the numerous innovations and advancements in the PV industry have resulted in new solar cell technologies including the second-generation thin film PV technologies—Amorphous silicon (a-Si), Cadmium telluride (CdTe), and Copper Indium Gallium Diselenide Solar Cells (CIGS) and third generation standards—polymer based cells, organic, nano-crystalline and dye-sensitized solar cells, etc., with various distinctive characteristics [53]. While the first-generation crystalline cells are made from single and multiple crystalline silicon, the non-crystalline amorphous silicon cells are synthesized by depositing thin film on flexible substrate. Amorphous silicon thin film modules are generally known to be highly prone to light induced degradation (LID) owing to Staebler Wronski effect [54,55]. The CdTe cells are well recognized for their relatively low manufacturing cost and relatively high laboratory efficacy [56,57]. Despite the numerous PV innovations, various reports and experimentations have revealed that all PV systems globally are facing defects and degradation challenges [58]. For analysis, several authors subject PV modules to various accelerated life testing procedure such as damp heat (DH), thermal cycling (TC), UV irradiance, dynamic mechanical loading, etc., in an effort to study degradation and failures. Gebhardt et al. [59] explained that accelerated tests which are defined in the certification standards IEC 61730 and IEC 61215 are typically used for evaluating module reliability. While the standard IEC 61730 focus is on electrical safety, the standard IEC 61215 focus is on performance and quality. Figure 4 presents typical PV module degradation signatures. Encapsulant discoloration, corrosion, cracks and breakages, potential induced degradation (PID) and LID/LeTID are five of the prominent PV degradations modes and signatures that are heavily investigated and analyzed in the literature in recent years.

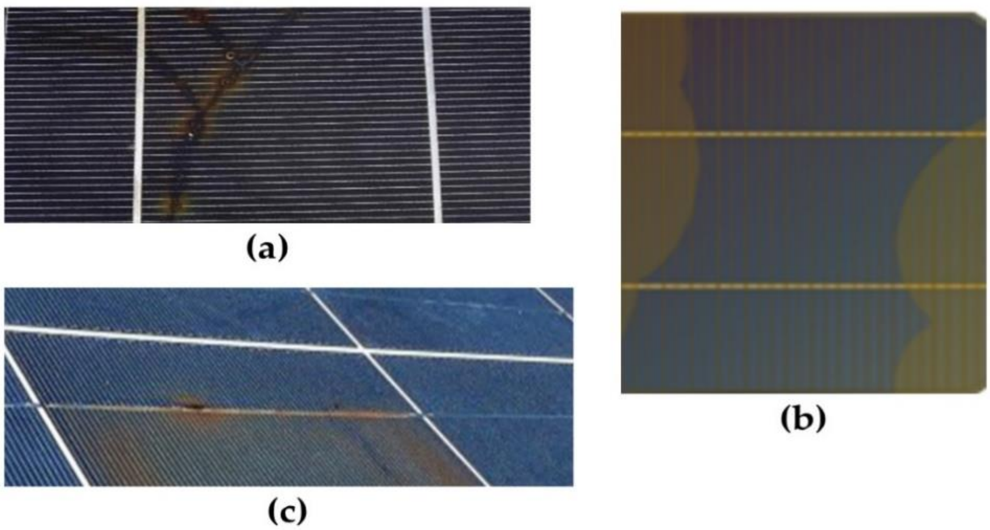

Figure 4. Typical PV module degradation signatures (**a**) cracked cell sample, (**b**) discolored encapsulant sample, (**c**) corroded sample.

2.1. Encapsulant Discoloration

Encapsulant discoloration is among the most reported and investigated degradation issues that affect PV modules performances as they reduce the sunlight approaching the PV panels [60]. The encapsulant is an integral component of PV module, that protects the cells from harsh external stresses [61]. Encapsulant parameters such as inadequate bond between glass and module cells, soiling and moist ingress from edge seals, environmental factors such as high operating temperature, high UV radiation intensity, and ambient humidity, etc. are some of the factors that can contribute to encapsulant discoloration patterns and rates [61,62]. Discolorations are easily noticeable by visual inspection only after the color becomes darker. Discolorations are of two types: browning and yellowing of modules surface and fingers discoloration. For the last few decades, EVA has consistently been used as encapsulants for crystalline silicon modules owing to its relatively low cost, high transmittance, adhesion to glass and resistance to UV radiation and adverse weather [41,63]. The authors in [60,64–66] explained that EVA discoloration occurs as the transparency of the EVA changes from clear to yellow and then to brownish, due to extended exposure to intense UV radiation and high temperature. Polyvinyl butyral, ionomer, thermoplastic polyurethane silicone, and polyolefin elastomers are some of the popular substitute encapsulants to EVA [67]. Encapsulant discoloration has been widely analyzed in the literature as it can cause pronounced decrease in I_{SC} among other things [68,69]. While analyzing defects and degradation on some aged outdoor deployed crystalline silicon PV modules, the authors in [39,70] discovered that EVA discoloration is a major PV module degradation menace. In a degradation analysis study [65], involving 30-year-old PV modules in Northern Califonia, USA, experimentation analysis showed that encapsulant discoloration contributed significantly to power degradation rates. Similarly, the authors in [64] presented a detailed analysis on discoloration of encapsulants using various characterization tools which include quantum efficiency (QE) measurement, energy dispersive spectroscopy (EDS), Fourier transform infrared (FTIR) spectroscopy, X-ray diffraction (XRD), and scanning electron microscopy (SEM) on some crystalline silicon PV modules. Owing to the severity of the menace, especially on silicon PV modules, the mitigation of encapsulant discoloration has continued to receive massive attention in solar PV degradation research.

2.2. Corrosion

Corrosive degradation is arguably the most frequent menace PV modules encountered during outdoor deployment [71,72]. Corrosion detections are quite challenging. Corrosion is initiated and the rate is accelerated by varieties of factors such as the deterioration of the PV-module components such as backsheets, insufficient lamination, encapsulants and environmental factors. Corrosion basically permits the infiltration of water molecules and oxygen into the cells. Hamdi et al. [73] explained that the condensation of water in the air on the solar cell wall causes a viscous surface that facilitates the capture of dust and dirt particles. Electrolytes, oxidizing agents, metals (busbar, fingers, etc.), interconnects (tabs and strings) play vital roles in the corrosion process. The authors in [72,74,75] explained that EVA deteriorates when the delaminated EVA forms acetic acid (HAc) via hydrolysis (chemical breakdown of a material usually from moisture and high-temperature exposure [41]), which accelerates metal corrosion. The HAc generated in encapsulant increase the series resistance. PV modules corrosion is a major threat particularly to PV modules installed in humid climates. As a major PV system reliability and degradation challenge, module corrosion has been widely analyzed in the literature. Various researchers in the literature have deployed several material characterization techniques such as SEM, EDS, and top-down high-resolution X-ray photoelectron spectroscopy (XPS) analytical processes and imaging techniques on cored samples to analyze corrosion [40,76–79]. In [78,80], the authors used EL imaging as characterization method to analyze degradation signatures including corrosions in both multicrystalline and monocrystalline silicon cells. The authors in [78] used ac impedance spectroscopy to analyze degradation in crystalline silicon modules that are exposed to HAc vapor. Kumar et al. [77] analyzed the effect of moist induced degradation in modules that underwent DH test using SEM and EDS micro-structural characterization and imaging techniques.

2.3. Cracks and Breakages

Similar to corrosion, cracks is among the commonly observed degradations especially in Silicon PV modules [21,81–83]. Thus, over the last decade, scientific research has been focusing heavily on cracks in silicon cells and wafers. Cracks are usually initiated as a result of mechanical and thermo-mechanical stresses at different stages of PV module lifetime. During the manufacturing stage, cracks can occur whereby the soldering induces high stresses into PV cells. During transportation and installation, cracks can occur during the process of transporting modules from manufacturing/retailers' site to installation site, as well as during installation whereby insouciant handling can create cracks or equally expand them [83]. In addition, during extended outdoor deployment whereby environmental stress due to strong winds and hailstorms, etc. can influence the creation of cracks on module surfaces. Owing to the remarkable technological progress at PV module material level, the size and dimension of the solar cells have been reduced immensely over the last two decades. For example, cell thicknesses have been reduced significantly from 300 µm to less than 150 µm on production lines. The various remarkable changes in cell structure and architecture have rendered the solar cells to be significantly brittle and vulnerable to fractures, cracks and breakages during the process of lamination, transportation and installation of the module. The primary effect of cracks is that they can cause the disconnection of cell parts and, therefore reduced maximum power output. Cracks can also cause mismatch in electrical parameters, which can then create a situation of non-uniform temperature distribution in PV modules [21]. In the literature, various approaches have been deployed in the analysis of cracks. In several research works, cracks are introduced by diverse methods which include the mechanical load test—IEC 61215 10.16 standard test [81]. In [84,85], the authors used imaging methods for the analysis of cracks in crystalline silicon modules. Using a different approach, the authors in [81] used T-Test as well as F-test statistical method for identifying significant impact of cracks on PV power output. In the study, the authors used Labview to predict theoretical power output performance based on the I-V, P-V curve analysis, while analyzing 45 polycrystalline silicon PV modules. Similarly, the authors in [86] investigated degradation impacts due to cracks and bubble formation using 12 PV systems that are made up of 4 different module technologies, crystalline silicon, amorphous silicon, CIGS as well as organic perovskites.

2.4. Potential Induced Degradation (PID)

Potential-induced degradation (PID) is arguably the most severe degradation mechanisms in modern modules as it has the potential to cause catastrophic module failures [87–89]. According to the authors in [90,91], PID is initiated as follows: when PV modules (especially grid connected ones) are connected in series (to build up volt output), the module frames are grounded for safety and support reasons. Depending on inverter type and operating conditions such as moisture ingress and persistent shading, a huge potential difference between the solar cells and the module frame may be induced in modules at either end of long sets of modules connected in series (string). The electric potential difference causes leakage currents to flow from the module frame to the solar cells (or vice versa, depending on the module position in a module string), and this process results in PID. PID is known to be prevailing as the module ages due to outdoor deployments. In addition, other PV degradation modes, including cracks, failure in the bypass diodes, encapsulant and coating challenges, shading, etc., have been identified as modes that accelerate PID. In order to mitigate PID, operators typically install anti-PID box between the strings and the inverter. PID has received considerable attention in recent years due to its detrimental impact on both crystalline silicon (PID-shunting) and thin-film PV module performance under field conditions [92]. The authors in [19] investigated the correlation between power losses and the performance ratio of modules that are having PID challenges. In the study, the authors experimented on 28 PID infested modules. Using IEC 61215 standard test on the PID affected samples, experimentation showed that the average power loss is 25%, while 60% of the experimented modules failed the reliability test. Lee et al. [91] investigated PID in CIGS technological standards at cell level using various tests and analysis tools which include PID and recovery tests, Light current–voltage (I-V), dark I-V, QE, etc. As the PV industry is tending towards increasing the maximum system voltage output, as a cost saving means, PID is envisaged to be more severe in the future [90].

2.5. Light-Induced Degradation (LID) and Light and Elevated Temperature Induced Degradation (LeTID)

Similar to corrosion, LID and LeTID have continued to receive special attention lately, due to their frequency and contribution to global PV degradation rates [7]. LID is characterized by a premature and significant loss of cell efficiency during the first hours of light exposure with an energy greater than the material bandgap [93,94]. The authors in [95–97] explained that, considering the numerous advantages of the Boron-doped Czochralski Silicon (Cz-Si) solar cell technology which include low cost, huge efficacy, etc., the technology suffer mostly from LID challenge that is due to Boron-Oxygen complexes formation and it restricts their development. LID significantly reduce power generation. Furthermore, the LID mechanisms vary according to the cell, material, and manufacturing process. On the other hand, LeTID is relatively temperature dependent and it is most significant in multicrystalline Silicon Passivated Emitter and Rear Contact (PERC) cells [98–100]. LeTID is quite different from the conventional LID, as it is a degradation process that is triggered by extended exposure to light and intense temperature. The hydrogen in bulk silicon is recognized to be responsible for the LeTID defects in multicrystalline silicon cells [99]. De Guzman et al. [100] explained that LeTID typically takes months/years to produce a degradation rate of about 2–5%. Considering the devastating consequences of LID and LeTID, extensive studies are being carried out to discuss the general mechanisms and mitigation of the menaces. Rabelo et al. [7] analyzed several PV modules degradation and failure modes with special emphasis on corrosion, LID and LeTID. In the work, the authors discussed some variants of LID and LeTID, as well as the mechanisms responsible for recombination defects. Using PVsyst tool, Kumar et al. [101] analyzed the significant implications of LID in terms of performance, power loss as well as degradation rates using a 200-kW crystalline PV system installed in the Northern part of India. Modanese et al. [98] analyzed how copper doping on Cz-Si PERC cells influence LID. In the study, the authors doped Cz-substrates of varying quality with different quantities of copper and process the substrates into complete industrial Cz-Si PERC cells. Experimentation results showed that the copper contamination level as well as Cz crystal quality are prominent factors that affect the level of Cu-LID. With regards to LeTID, research works are yet to be advanced on the mechanisms surrounding LeTID, especially in terms of the correlation between the amounts of impurities present in the silicon and the rate of LeTID. Fokuhl et al. [93] investigated the effects of BO-LID and LETID defects on silicon PV modules. The analysis was carried out using experimental data from 12 mono-crystalline and 2 poly-crystalline PERC modules, that are exposed to a detailed experiment which include 5 indoor tests as well as an outdoor test. Similarly, Repins et al. [18] analyzed the effects of BO-LID and LeTID in silicon modules during standard IEC 61215 accelerated test conditions.

Other notable PV degradation modes and signatures include junction box failure, soldier bond failure, snail trails, hotspots, etc.

3. PV Degradation Measurement and Characterization Methodologies

To enhance the marketability of solar PV systems as well as the proceeds on investment, it is vital to improve the reliability of PV systems' performances. As explained by Kumar [1], reliability and degradation investigation are vital for the prediction of the generated power over time. In addition, it plays a major role in minimizing potential failure risks for cell and module technologies. PV module reliability can be analyzed by understanding the degradation modes and mechanisms, especially during outdoor operations [67,102]. Some degradation signatures if they are not spotted and isolated early and promptly, they can cause devastating failures. Thus, the operation and maintenance encourage the condition monitoring of solar modules, the early detection, replacement or repair of defective units in order to ensure maximum efficiency up to the designed warranty years of solar power plants [103–105]. There are varieties of ways to analyze, measure and characterize PV degradation qualitatively and quantitatively. In the literature, popular methods include visual inspection, EPM, imaging and data-driven analytics techniques.

3.1. Visual Inspection

Visual inspections present the swiftest and the first option of identifying PV modules degradation modes and signatures that are visible to human eyes [78,79,106,107]. Visual inspection of PV modules is typically performed before and after the modules have been subjected to environmental, electrical, or various laboratory stress tests. Visual inspection easily allows the identification of damages inflicted on panels during installation, or either by environmental influences, or due to aging. Visual inspection focuses majorly on "symptoms" such as discoloration, haziness, texture changes, damage to backsheets, breakages, bubbles, etc., rather than "diagnoses" (e.g., hot-spots, PID, etc.). Bouraioua et al. [39] analyzed the relationship between the use of visual inspection and electrical test result of 608 degraded modules operated at hot dry climes in Algeria. Similarly, the authors in [108] used visual inspection method for the detection of several degradation signatures which include generation of snail trails, cell browning and junction box failure on outdoor deployed silicon PV modules. However, visual inspection results are typically observational in nature, and they do not provide qualitative explanations into module's degradation causes as they can only reveal obvious damages [79]. Aside from obvious glass cracks, discoloration and corrosion, many defects that reduce the efficiency of a PV module such as microcracks (during manufacturing or installation) and other structural defects are not visible. In addition, visual inspection method for degradation mode and signature detection is labor intensive, time consuming and generally ineffective, especially with regards to large scale PV plants.

3.2. Electrical Parameter Measurement

The current–voltage (I-V) characteristics and Suns-Voc (quasi-steady-state open-circuit voltage) contain a lot of information about the health of the modules. Thus, EPM methods provide quick and reliable in-depth details about the real time monitoring and performance evaluation of PV modules and traditional string inverter systems in terms of their electrical properties. EPM methods are mostly used alongside other techniques when fault localization is required. I-V and P-V curve tracing method provides a detailed information on the electrical properties including short circuit to open circuit condition [109,110]. The ideal shape of a typical I-V and P-V curve of a solar cell, highlighting important parameters such as I_{SC}, V_{OC}, P_{MP}, I_{MP}, P_{MP} is presented in Figure 5. The authors in [109] explained that Suns-Voc tracer assist in measuring the cell V_{OC} at varying illumination levels [109,111–113]. The authors in [39] used MP-160-I-V tracer to measure the I-V characteristics of degraded modules at standard test conditions. Bouaichi et al. [70] used PVPM1000X I-V tracer to measure the drop in electrical performances of several outdoor deployed modules (due to degradation) and compared the values with the initial parameters provided by manufacturers. The authors in [65] used ESL Solar 500 tracer for measuring the I-V curves of degraded modules in ambient conditions with different irradiance and temperature. In a similar study in [114], Whitaker et al. used a Spire 4600 SLP Flash Tester as well as I-V curve tracer at 1 sun illumination to measure I-V parameters in a degradation analysis of cell cracks. Parameters measured include time-series maximum power, voltage, and current, etc. In addition, in a degradation analysis study, the authors in [115] used MPPT3000 tracer to measure the same set of parameters at every 5 min between February 2014 and July 2018. Despite the vital information provided by EMP, the EPM are poor gauge of PV module's mechanistic behavior. Thus, PV module degradation classification using EPM tools have limited capacity for identifying the various degradation mode causes. In addition, EPM methods do not provide information regarding the precise defective regions of the module such as the corroded regions, regions with cracks and glass breakages, delaminated regions, etc. [105].

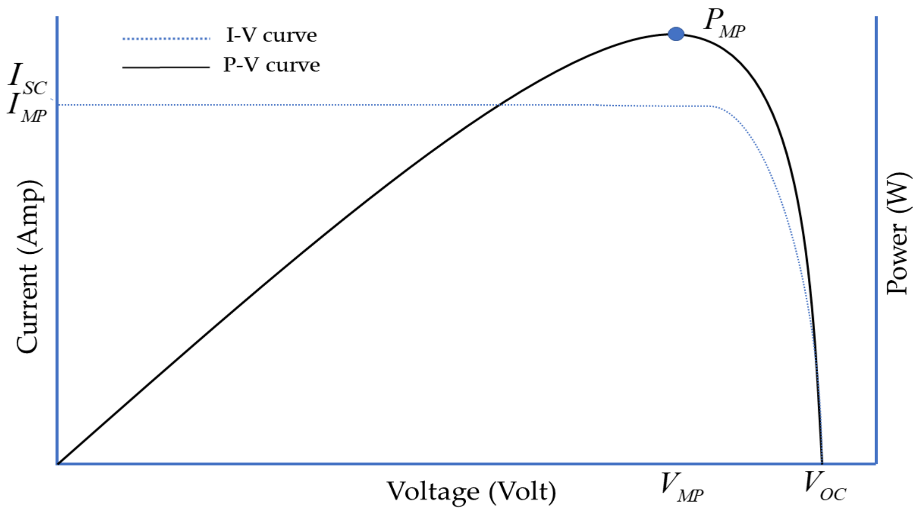

Figure 5. Ideal shape of solar cell I-V and P-V characteristic curves [116].

3.3. Imaging

PV modules are susceptible to defects and degradation modes either during the manufacturing process, installation process or due to aging during field deployment. Several defects and degradation modes can be fixed if they are detected and classified in time. In recent literatures, imaging techniques such as photoluminescence (PL), EL, and UV fluorescence imaging techniques are popular imaging characterization techniques that are used for PV module degradation analysis. These imaging characterization techniques have the capability to identify various degradations modes that are undetectable by visual inspections, that can cause a severe drop in PV modules performance and sometimes safety issues [103,104].

3.3.1. EL Imaging

In the literature, EL imaging is arguably the most popular non-destructive analyzing techniques for characterizing the health of PV cells in recent years [117–120]. EL imaging for PV degradation characterization is a process whereby forward bias current is applied to modules, and the radiative recombination result emits IR light (spectral range for silicon), which are captured using a camera with silicon Charge-coupled Device (CCD) sensor features [78]. Each individual pixel denotes a spatially resolvable datapoint of local photon emission registered on the CCD sensor [121]. The grayscale images captured will present thick darkened parts which reflects defective areas that contribute to module power loss (i.e., the part of the cell that is defective will appear darker as disconnected parts will not irradiate) [117]. Figure 6 presents typical EL images of solar wafers [122]. As shown in Figure 6a, the emission of light from the cells is not limited by any error. Thus, the wafer is degradation-free. However, the image presented in Figure 6b shows that the wafer has been extensively degraded by microcracks as well as the degradation of cell interconnects. The dark grey and black marks show the degraded parts where the cells are electrically separated. Experimentally, the captured EL images can be analyzed to extract the features that provide detailed information about specific degradation mechanisms and signatures as well as overall module performance and specific degradation mechanisms. Islam et al. [123] analyzed the degradation behavior due to PID, using EL imaging, light I-V and dark I-V measurement methodologies. From the experimentation, the captured EL images of the modules present details about signatures and modes which include localized shunting, cracks, etc. Similarly, Kumar et al. [77] analyzed moisture induced degradation in crystalline silicon modules that underwent DH test using EL and dark lock-in-thermography (DLIT) imaging. In addition, the authors in [10] used EL imaging for characterizing defects which include browning and encapsulant delamination on crystalline silicon modules caused by aging from 15 years outdoor exposure in Brazil. In another related work, the authors in [124] used EL as part of the characterization techniques for analyzing brownish and milky patterns as well as the oxidation of the metallization grid on aged modules that underwent outdoor exposure of 22 years in Seville, Spain.

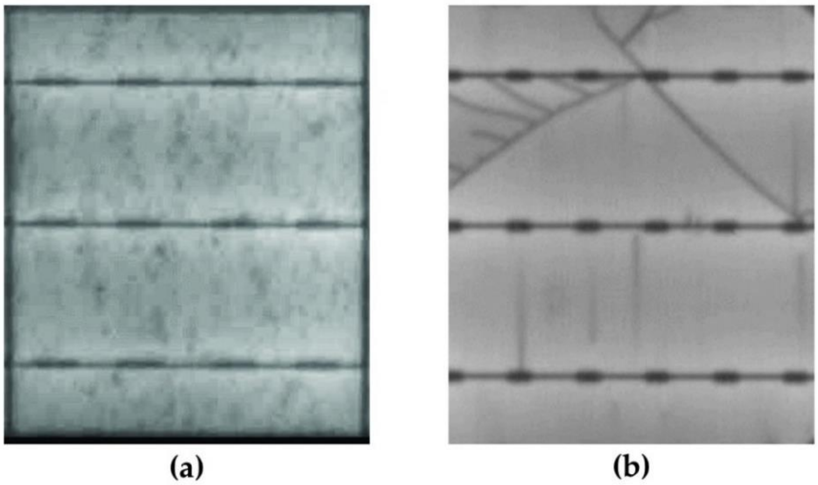

Figure 6. Typical grayscale EL images of a solar wafer. (**a**) degradation-free, (**b**) degraded [122].

3.3.2. PL Imaging

Similar to EL imaging, PL imaging is a popular contactless characterization technique, for analyzing PV module statuses by providing information in terms of determining spatially resolved quality, performance, and defects [125–129]. While explaining the difference between PL and EL, Koester et al. [103] described both PL and EL imaging as techniques that are based on the collection of a luminescence signal emitted by solar cell material, and the difference between them is the way the signals are created. While EL can detect various degradation modes which include cell cracks, PID, electrical mismatches etc., PL can detect minority carrier lifetime and series resistance in addition to majority of the modes that EL can detect. In addition, in contrast with EL, PL can be effectively carried out without electrical connections to the solar cells/wafers, nor require any change in the wiring [105]. PL can be described as the radiative signals that are emitted from cell materials when charge carriers recombine from being excited by irradiation [117]. Similar to EL images, bright areas from the images gives an indication of well-performing cells, while darker regions of weak band-to-band light emission indicate defective regions. In recent literature, various authors have deployed PL as a methodological tool for analyzing numerous degradation modes and signatures. The authors in [104,128] used PL imaging technique for analyzing PV modules performance. Vaqueiro-Contreras et al. [94] utilized PL and deep level transient spectroscopy for the analysis of LID in Silicon PV modules. Using the sun as the excitation source, Bhoopathy et al. [105] used PL imaging to analyze modules with series resistance as well as open circuit bypass diode failures. Considering that PL is relatively less sensitive to shunting as well as high series resistance when compared to EL, the authors in [129] used PL imaging to characterize degradation as well as identifying degraded regions in an analysis involving CdTe modules. In the study, the authors used time-of-flight secondary ion mass spectrometry for measuring copper depth profiles in relation to the degradation rates using PL imaging. Germain et al. [130] used PL imaging for studying heat stress impacts on CIGS modules. Results achieved from the PL images provided insight on the degradation causes.

3.3.3. UV Fluorescence Imaging

In recent years, UV fluorescence imaging have continued to offer a promising, fast and nondestructive option for the analysis and characterization of PV defects and degradation especially with regards to encapsulant discoloration [68]. UV fluorescence imaging technique can be used as an alternative or as a complement to EL, PL imaging. The tool which is based on UV fluorescence measurements have received a lot of interest lately. The method involves UV fluorescence spectrum analysis using spectrometers as well as the UV fluorescence imaging tools. The UV fluorescence imaging methods bank on the excitation of fluorophores that are present in module encapsulants. Typically, a bandwidth-limited light emitting diodes are deployed as UV radiation sources due to their easiness of adaptation and affordability when compared with other sources such as lasers [131]. The fluorophores are formed in the encapsulant material over time, depending on the rate of exposure of the module to light and temperature. The emission can then be detected typically using complementary metal-oxide-semiconductor (CMOS) or CCD sensors, which are available in typical modern day digital cameras, equipped with filters that eliminate the reflected excitation UV light. Figure 7a,b presents typical UV fluorescence images of PV module using CMOS and CCD camera, respectively. In recent literatures, various authors have deployed UV Fluorescence imaging especially for the assessment of EVA discoloration and cracks in PV modules. Even though UV fluorescence imaging technique can be deployed for identifying cracks, it is mostly effective when there is limited time exposure in the field. The authors in [132] investigated the various defects and degradation modes that were observed in some PV modules that have been installed for 5 years at United Arab Emirates using UV Fluorescence, EL, microscopic visual inspection (MVI) and illuminated I-V analysis. Using UV fluorescence imaging, MVI and QE, the authors in [133] investigated the optical defect degradations in encapsulant and glass layer. For the characterization of the degradation behavior of EVA samples that have been exposed to varieties of accelerated aging tests as well as aged outdoor modules, Kim et al. [63] used a Zeiss LSM510 Meta laser scanning confocal microscope for performing morphological and fluorescence imaging. Lyu et al. [134] investigated degradation depth-profiles of the glass/EVA/backsheet laminates using UV Flourescence imaging and micro-UV/VIS spectroscopy, atomic force microscopy-based quantitative nanomechanical mapping after exposing PV cell samples to accelerated test. The authors also used Zeiss LSM510 Meta laser scanning confocal microscope for conducting morphology and fluorescence imaging. Li et al. [68] investigated the discoloration patterns of 10 modules deployed in two different climes of varying field years using UV fluorescence imaging characterization tool. The author used 2 UV flashlight LED arrays with wavelength spectrum of the range 350 and 450 nm (dominant wavelength of 395 nm) for the UV Fluorescence image capturing. In addition, they used other cameras that are equipped with long-pass filter (Schott RG850) to reduce the reflective excitation UV lights. The authors performed the experiment in a dark room at room temperature. Similarly, the authors in [135] used UV Fluorescence imaging technique for characterizing material yellowing in three 3 EVA materials from two different manufacturers. In the study, the authors captured the fluorescence images using devices consisting of a digital camera as well as 2 UV LED arrays with a spectral wavelength signal between 450 nm and 750 nm for the UV Fluorescence image acquisition. Dolia et al. [61] used UV fluorescence imaging, yellowness index (YI), and I-V measurements for the detection of EVA discoloration in an experiment involving indoor accelerated testing of eight laboratory fabricated mini-modules. Gopalakrishna et al. [69] deployed UV fluorescence imaging, YI, cell-level short circuit current measurements and reflectance measurements for evaluating EVA encapsulant browning and delamination menace in an experiment involving six mini-modules that were exposed to an accelerated UV testing at different temperatures.

Another notable imaging technique is the thermal IR imaging which is also a contactless and non-destructive method whose technology is based on measuring the module's electrical and thermal failures under steady state conditions. The thermal IR imaging methods use typical IR cameras that are sensitive to black body emission in the range of 3.6–5 µm range. By exposing PV panels to thermal or IR imaging, shunted or defective cells will appear as bright hotspots when compared to other cell parts due to heat dissipation. Furthermore, it should be noted that several research works are focusing on relatively newer characterization methods which include signal transmission methods, impedance spectroscopy, etc. [136–138].

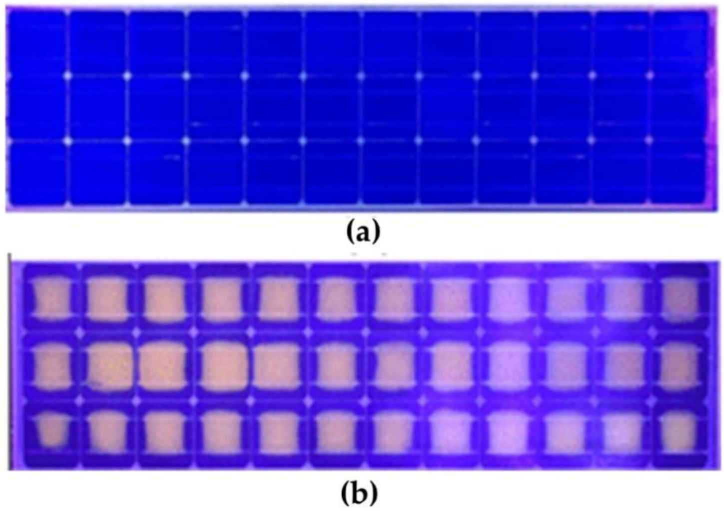

Figure 7. Typical UV fluorescence images of a PV module (**a**) unexposed using CMOS camera, (**b**) Grayscaled image using CCD camera [40].

4. Data-Driven Analytics Models for PV Performance and Reliability Analysis

As it is becoming increasingly challenging to analyze and classify the various degradation and defect modes and signatures via conventional methods of visual inspection methods by skilled personnel, proper and accurate PV degradation and failure diagnosis and classification models are required to promptly and accurately identify and classify degradation and defects modes and signatures, in order to considerably improve the PV system performances such as the power capacity and lifespan of the modules, reliability as well as the safe operation of the overall systems. Apart from the requirement of human expertise for computation and analysis, the other draw-back of conventional methods includes non-linearity and computational complexity, high error rates, non–feasibility in large PV installations as well as excessive manpower requirements [139–141]. Hence, there is a huge need for advanced and effective PV degradation diagnosis models. The main objective of effective diagnostic models is to identify and categorize the degradation modes such that the proper preemptive measures can be promptly arranged [142]. Data-driven analytic methods such as ML and DL models are continuously proving to be feasible options based on their performance and efficiency (high computing capacity with reduced computation time compared with other methods). In addition, ML and DL models can be helpful for the prediction of the future state of events that occurs in systems. Thus, in recent years, ML and DL methods have drawn the attention of many PV degradation and reliability analysis stakeholders, as they can be applicable for the performance and degradation assessment of PV modules in the laboratory, during the manufacturing process, and during outdoor deployments. Hence, the models are widely being proposed in recent literatures for monitoring, predicting, detecting and classifying various PV degradation menaces. With the huge size of PV modules' installations especially in utility scale systems, coupled with the voluminous datasets, ML and DL models can learn and discover irregular patterns and make meaningful inferences in the prediction, detection and classification of PV degradations features, with reduced computation time. Conventionally, DL and ML models for PV degradation analysis studies in recent literature are generally a three-phase process: dataset generation, preprocessing (feature engineering) and evaluation/classification. Several research works deployed various feature optimization models and multiple ML and DL models to boost the classification performances.

4.1. Dataset Generation Phase

Owing to the advancements in technology, authors in recent literature deploy non-destructive imaging techniques such as I-V, EL, PL, UV fluorescence imaging tools as well as/or EPM tools to generate datasets for analysis. The images and/or electrical parameter measurements (containing features such as I_{SC}, V_{OC}, I_{MP}, P_{MP}, V_{MP}) are typically used as classifier input to predict, detect and classify PV degradation menaces [143]. Generally, compromised/defective PV module components such as the encapsulants, the cell and interconnects etc. typically have footprint (no matter how marginal), that the various imaging techniques can pick up or result in electrical parameter measurements' variations from the measurements indicated in the PV module manufacturers' datasheets. Conventional PV reliability and degradation analysis using ML and DL involves the use of these dataset(s) that contains both normal and defective data, as they contain adequate features and information that can be extracted, to build a training and testing datasets.

In a PV fault diagnosis analysis, the authors in [143] generated I-V curve datasets from a field operated 960 W PV systems located at RELab Jijel university Algeria. Similarly, Chen et al. [144] used I-V curve datasets measured at different operating conditions for analysis. Garoudja et al. [145] used meteorological data and maximum power point current and voltage datasets generated from a grid-connected PV systems installed in Algiers, as input data for the classification algorithm. As alternatives to the use of ordinary EPM, which is generally believed to only offer in-depth assessments of PV modules in terms of their electrical properties without providing analytical details of individual module components, several authors in recent literature opted for the use of imaging tools for the generation of input datasets for their classification model. In a PID and LeTID degradation study, Bordihn et al. [141] deployed EL images captured from field modules, as input dataset for classification and analysis. In another PV degradation analysis that focus mainly on cracking and corrosion, Karimi et al. [110] generated datasets using EL images captured from three different 60 cell modules that overwent DH accelerated test. Using another form of imaging technique different from EL, Kurukuru et al. [146] used Fluke TiS45 thermal imager to capture thermal images of one normal and seven faulty module panels at different solar irradiance as well as temperature conditions, located at India. For experimentation, each thermal image captured were split into subwindows during preprocessing. Similarly, Ali et al. [147] used a dataset that was generated using infrared thermography technique in a PV degradation analysis involving the detection and classification of hotspots. For the dataset generation, FLIR VUE-Pro 640 camera was used to capture 315 thermal images of PV panels of 3 classes (i.e., healthy, non-faulty hotspot as well as faulty), at solar irradiance above 700 W/M2 and temperature condition between 32 and 40 degrees, in Pakistan. In another related study involving different modes and signatures which include delamination, glass breakage and discoloration, etc., the authors in [142] used an unmanned aerial vehicle to capture RGB images which are used as input dataset for PV degradation mode classification.

In addition, various authors in recent studies used both imaging and EPM as input datasets for classification, in order to qualitatively and quantitively analyze various PV degradation signatures. Karimi et al. [148] generated both I-V curve and EL image datasets from PV modules that underwent several accelerated tests such as DH, TC, UV exposure, and dynamic mechanical loading tests. In the study, the authors analyzed various degradation modes which include busbar corrosion, cracks, etc. In a related study, the authors in [121] generated I-V curve and EL image datasets from experimentation involving the study of busbar corrosion in 30 monocrystalline silicon and multicrystalline silicon PV modules that underwent DH and TC accelerated tests. With regards to the generated image dataset from the study, approximately 200 pairs of EL images as well as I-V curve were generated and analyzed, resulting in a total of almost 12,000 cell images. As alternative to real case scenarios involving experimentation with real PV systems, several authors make use of publicly accessible dataset which include CWRU SDLE EL dataset [149] and SDLE SunFarm I-V Curve Data [150]. Furthermore, several authors in recent literature have modelled PV systems using various simulation tools for the generation of experimental datasets. Da Costa et al. [151] used MATLAB Simulink and PSIM as simulation tools for generating analysis datasets for classification. Similarly, the authors in [139] designed a PV system using MATLAB Simulink and real time irradiance and temperature dataset which are captured from grid-connected PV System of National Institute of Technology Agartala for PV degradation analysis.

4.2. Feature Engineering/Optimization Phase

Ideally, the large dimension feature datasets (captured imaging and EPM) generated are not suitable to be used as input for the classifier(s), as they contain redundant features that will significantly increase classifier's computational time and reduce classification results [79]. Hence, for efficient classification and prediction, there is usually a need to preprocess the datasets. To enhance the PV degradation modes prediction and classification performances, various authors in recent literatures proposed several feature engineering techniques for the dataset(s) preprocessing phase. Some of these feature engineering techniques ranges from feature selection/reduction to optimization techniques, with the aims of reducing feature vector dimensions, cleaning and eliminating irrelevant features and for optimizing the classifiers' performance. Furthermore, some of these preprocessing techniques can assist in organizing the datasets into suitable formats, for effective training as well as testing. Kurukuru et al. [146] used the popular 2nd-order statistical texture analysis model, Grey Level Co-occurrence Matrixes (GLCM) to extract relevant texture features of the thermal images captured for classification. In a related work, Karimi et al. [148] used median filter and Principal Component Analysis (PCA) to filter relevant EL image features. Similarly, for the reduction of noise as well as the removal of barrel distortion and redundant background data, the authors in [121] used filtering and thresholding methods for the preprocessing of captured EL images. Considering the effect of irrelevant features and the effect of local information in the captured EL images, Bordihn et al. [141] used PCA and Gaussian blurring process as data preprocessing tools to remove redundant features. In [79], Pierce et al. used ORB, Daisy, KAZE, and FAST algorithms for extracting dominant features in the captured EL images. For the processing of raw EL images to planar indexed module and single cell images, the authors in [110] preprocessed the captured images using lens distortion correction, filtering, thresholding, convex hull, regression fitting, and perspective transformation.

4.3. Classification/Detection/Prediction Phase

The ability of data-driven analytic models to autonomously learn, adapt to variations and act without being pre-programmed/re-programmed have continued to enhance their status as feasible methodologies for effective PV degradation and defect detection and classification tools in recent times. In recent literature, numerous ML and DL models such as Support Vector Machine (SVM) [147,148,152], Decision Tree (DT) [143,151,153], K-nearest neighbors (KNN) [141,142,151–153], Random Forest (RF) [143,152], Naïve Bayes (NB) [152], Neural Networks [110,121,145,146,148,151], have been employed in PV degradation and defect detection and classification analysis. Prominent supervised learning algorithms: SVM, DT and NB are simple and memory efficient models that are widely used for classification tasks. However, with regards to image classification tasks, SVM typically performs better, compared to DT. Another popular supervised learning algorithm that is typically considered for image classification is the RF. RF is an ensemble algorithm that is made up of multiple iterations of DTs. Nevertheless, in spite of the many varieties of classifiers proposed for PV degradation and defect detection and classification, KNN, shallow and deep neural networks are the most widely deployed, due to some specific attributes that makes them suitable for the tasks. Generally, neural networks are series of computer algorithms that are based on a collection of connected nodes in arbitrary number of layers, whereby the nodes endeavor to recognize patterns and underlying relationships in dataset through a process that is similar to the way the human brain works. Learnable parameters: weights and biases are important factors that determines the performance of neural networks. In addition, activation functions play major roles in how neural networks learn complex patterns in datasets. Typical activation functions which are used in studies include the sigmoid, rectified linear unit and hyperbolic tangent function (tanh) functions which are defined in (4)–(6), respectively [154].

$$f_{(x)} = \frac{1}{1 + e^{-x}} \tag{4}$$

$$f_{(x)} = \begin{cases} 0 & for\,x \prec 0 \\ x & for\,x \geq 0 \end{cases} \tag{5}$$

$$f_{(x)} = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{6}$$

Garoudja et al. [145] explained that Probabilistic neural networks (PNN) are efficient, computing algorithms for pattern recognition that have the advantage of training process simplicity as they do not require weights adaptation and also, they can classify new data without extensively repeating the entire training procedure. In addition, KNN is a simple, easy-to-implement supervised ML algorithm that operates on the assumption that similar things exist in close proximity. Thus, they perform classification tasks by analyzing the distances between datapoints. In contrast with the various shallow neural networks (PNN, back propagation neural network, etc.) with only one hidden layer, deep neural networks have multiple hidden layers, which makes them better suited for classification tasks, especially when deployed on voluminous datasets. Convolutional Neural Networks (CNN) is one of the most widely deployed deep neural networks algorithms for image classification assignments as they utilize the local spatial coherence in the input (images), which allow them to have fewer weights, as several important parameters are shared in form of convolution, which makes them highly suitable to the task of extracting relevant information at much lower computation cost. Various authors in the literature have used CNN in several PV degradation tasks, most especially for analyzing captured PV module images. The authors in [142] used CNN to extract the captured images features, before feature selection using J48 DT and lastly, they used KNN, locally weighted learning and K-star algorithm for classification. Similarly, Bordihn et al. [141] used KNN for the classification of PID and LeTID in captured EL images. Kurukuru et al. [146] successfully used Neural Network for training extracted features from captured thermal images in the classification of PV module faults. In a comparative study [153], the authors compared the results of DT, SVM, KNN discriminant classifier (DC) for the diagnosis of early-stage PV hotspots. Experimental results showed that DC presented the best accuracy from the four algorithms, while DT presented the least detection accuracy. Similarly, the authors in [151] experimented using KNN, DT, SVM and Neural network algorithms for classifying various defects and faults in PV systems. The authors achieved the best result from neural network algorithm, although the issue of neural network training time was raised by the authors. To improve the speed, minimize training error and overall performance of classification, the authors in [144] exploited the admirable regression capability of extreme learning machine for the analysis and classification of I-V measurement datasets. In another related work, the authors in [110] compared the result of SVM, RF, and CNN for classifying EL images. Using key performance metrics, the result from the experiment demonstrated that CNN presented the best results in terms of classifying EL images into good, corroded as well as cracked classes.

In Table 1, we summarized and compared some recent works that focused on the use of data-driven analytic models for the detection and classification of PV module degradations and defects. The dataset generation method, the preprocessing methods in terms of feature engineering method and ML/DL model(s) adopted are presented. As depicted in Table 1, the ideas of ML and DL approaches to PV module degradations analysis have been immensely successful. In addition, from Table 1, the various forms of NN have been the most adopted models as they guarantee effectiveness and high accuracy especially with images classifications. It can be observed that data preprocessing has good effect on model performances.

Table 1. Comparison of recently proposed data-driven analytics-based models for the analysis, detection and classification of PV module degradations and defects.

Ref.	Data Generation Process	Preprocessing Techniques	PV Degradation and Defects Analyzed	ML/DL Used and Performance Rating	Brief Description
[146]	Thermal images of normal as well as potentially faulty modules were acquired from a grid connected rooftop PV system using Fluke TiS45 imager.	Texture FE using GLCM. Scaled conjugate gradient back propagation for adjusting weight and bias during training process	Faulty PV panels	ANN 93.4% Training efficiency and 91.7% testing efficiency	Thermal images of 8 PV panels are classified using ANN. The thermal images are split into subwindows to improve classification efficiency and the subwindows are subjected to GLCM for texture FE before the classification using ANN
[151]	MATLAB Simulink and PSIM for simulating PV module system	-	Short circuit (SC), MPPT, open circuit (OC) faults, partial shading, disconnected string	KNN, DT, SVM, ANN. Best accuracy result achieved from ANN. SVM presented the fastest computational result	Comparison of different ML algorithms for detecting various simulated PV module faults. Metrics used for assessing the performance of the ML is the accuracy and computational complexity.
[153]	I-V curve data retrieved from PV modules focusing on hotspots	Min-max normalization	Hotspots	Comparison of DT, SVM, KNN and DC. DC presented the best result while DT presented the worst detection result	Classification using 4 ML models for diagnosis of early-stage hotspots in PV modules
[145]	PV design simulation using PSIM and MATLAB. Agilent 34,970 datalogger for acquiring data from 9.54 kWp Algerian grid connected PV system	Canonical Artificial Bee Colony algorithm for extracting the one diode model parameters	PV faults	PNN, Feed forward back propagation NN. PNN with 82.34% detection efficiency and 98.19% diagnosis efficiency	PNN model developed for fault detection and diagnosis in the direct current side of PV system.
[143]	I-V curve data retrieved using Prova 210 IV tracer, on 960 W PV array from RELab JiJel university, Algeria.	FE of I_{SC}, V_{OC}, P_{MP}, I_{MP}, P_{MP}, FF. dimensionality reduction using PCA and normalization	Partial shading, line to line degradation, dust accumulation	NB, KNN, SVM, LR, DT, RF, NN. Hist gradient Boosting, Extra Trees, AdaBoost, Gradient Boosting	Modelling of several single and ensemble ML algorithms for detection and classification of varieties of PV faults
[144]	I-V curve data retrieved from different operating conditions of 6 PV modules from NREL	V-I grid based method for resampling and feature reduction. Slope change to exclude abnormal data features. Irradiance temperature grid-based method to downsample data.	-	Extreme learning machine optimizing single hidden layer feedforward NN (SLFN). Result compared with SVM, etc.	Modelling of SLFN trained by extreme learning machine for characterizing I-V data multicrystalline PV modules at different operating conditions from NREL.
[139]	I-V data. PV system design using MATLAB Simulink. Real time irradiance and temperature data from grid connected PV system at Agartala	Array capture loss was used for training ML algorithm	Common faults including Line to Ground, Line to line, OC, arc, shading faults, and degradation	CatBoost, Light gradient boosting machine (LGBM), XGBoost. LGBM performed best, followed by CatBoost	PV system was modelled using Simulink and real time data to analyze and diagnose common faults. 3 ML algorithms were compared in terms of accuracy and computational time.
[147]	IR thermal images captured using FLIP VUE-Pro 640.8 PV strings' modules at Lahore Pakistan	Data fusion approach for FE of RGB texture, histogram of oriented gradient and local binary pattern, Noise filtering.	Hotspots	SVM. 96.8% training accuracy and 92% testing accuracy	SVM model to classify PV panels thermal images into healthy, non-faulty hotspot and faulty hotspots. 5-fold cross validation method for algorithm training and testing

Table 1. *Cont.*

Ref.	Data Generation Process	Preprocessing Techniques	PV Degradation and Defects Analyzed	ML/DL Used and Performance Rating	Brief Description
[148]	I-V curve and EL images captured during accelerated tests including DH, TC, PID +1000 V, PID −1000 V, UV irradiance and dynamic mechanical load test	Image correction, coplanar indexing to align images. PCA for FE	Busbar corrosion, cracking, wafer edge darkening, between busbar darkspots	CNN, SVM. Accuracy of 98.95% and 98.24% from SVM and CNN, respectively	CNN and SVM models were developed for PV degradation analysis. Several accelerated tests were conducted on PV modules to generate I-V curve and EL images. 5-fold cross-validation approach to verify algorithm robustness.
[152]	I-V data. PV system design using MATLAB Simulink. PV array model of 6 Wittec 62391-50W Sc-Si modules	Data were corrected and resampled. Fault FE using Gramian angular field. PCA for feature reduction	Several faults including partial shading, SC fault, OC fault, Rs degradation and Rsh degradation	SVM, DT, NN, RF, KNN, NB. ANN presented the best result.	Several ML models were developed for PV degradation analysis. I-V curve data from simulations and real l = time datasets were used for experimentation.
[141]	EL images captured from outdoor deployed PV modules	Gaussian blurring for image processing	PID and LeTID	PCA and KNN. 89% accuracy using KNN	Modelling PCA-KNN algorithm for predicting PID and LeTID. Field-installed modules were used for acquiring the EL images. 5-fold cross-validation was used for algorithm robustness validation.
[121]	EL images (using Sensovation coolSamBa camera) and I-V curve data (using Spire 4600SLPflash), captured from modules that underwent DH and TC tests	Filtering and thresholding to remove barrel distortion, noise and redundant data. Convex hull algorithm to preprocess image into binary array. Perspective transformation applied to uniformly orientate and planarize images	Busbar corrosion	CNN. 95% Accuracy	Modelling CNN for classification of corrosion. Preprocessed EL and I-V curve data captured from 5 brands of PV modules (including 3 silicon modules) that underwent DH and TC tests.

5. Research Gaps and Suggestions for Future Research Works

Despite the astonishing accomplishments that are being achieved from PV degradation and reliability analysis studies, especially in terms of data-driven analytic modelling approaches, there are still several pending challenges as well as suggestions and recommendations for future works. The performance of ML/DL classification, detection or prediction models depend heavily on the qualitative and quantitative characteristics of the datasets/the dataset generation processes. The acquisition of sufficient and adequate datasets has continued to be an issue as evidently, most of the recent research works used small quantity of data while others turned to the use of open-source datasets, data augmentation as well as simulated datasets in order to have adequate datasets for classifications. The use of simulated datasets by scholars and researchers typically shows inconsistency in prediction and classification [35]. In addition, as field deployed PV modules' performance depends majorly on the geographical clime at which they are being used, the use of open-source datasets (some of which were acquired from fielded modules in a different clime), will not provide a contextual evaluation of the specific PV modules' performance. Future research works should focus on implementation and verification of these models for real-time applications using real time datasets of PV module experiencing degradations. In addition, for the imaging techniques, factors such as the type of camera used for the dataset acquisition, the image capturing process (orientation of the camera, proper capturing of the modules), the image processing such as the texture feature extraction, etc. are important factors that determine the quality of the acquired datasets. More importantly, these factors have significant impact on the classification performances of the ML and DL algorithms as well as the degradation analysis process. Furthermore, as the performances in terms of accuracy, precision, sensitivity, etc. of the classification models depend heavily on the dataset preprocessing steps (they assist in improving the quality of the input features for the classifiers), the parameter tuning such as the weight and bias tuning, and feature engineering technique (image processing, image segmentation, feature extraction such as Gaussian blurring), etc. that are currently being proposed in recent works are cumbersome and require some expertise, and they are deemed to be computationally expensive. Thus, future works should focus on faster and better preprocessing and parameter tuning models for PV image segmentation and feature extraction.

6. Conclusions

Degradation and defects due to aging and exposure to wide range of environmental conditions during field deployment is a major issue system for PV module manufacturers, owners, installers, researchers, etc. Irrespective of the PV module type/material and component technology, the harsh chemical, photo-chemical and thermo-mechanical stress that the modules are exposed to contribute massively to the degradation and effectiveness of PV modules. Thus, in recent times, there has been various investigations into PV reliability and degradation mechanisms. These studies provide insight on PV module's performance degrades over time, especially under field conditions. In this paper, we present a critical review of recent research works whereby solar PV systems performance reliability and degradation were analyzed, particularly in the area of data-driven analytics. Majority of the research works in recent literature focused on monocrystalline and poly-crystalline silicon PV panels as they currently dominate the global market. Thus, this research work concentrates majorly on crystalline silicon modules. Various technical defects and degradation issues, characterization techniques that are being deployed in recent literature are extensively reviewed. I-V curve and Sun-Voc tracing methods, imaging techniques which include EL, PL, UV fluorescence techniques are current degradation measurements and characterization techniques that are popularly used for the analysis of key degradation modes in recent literatures. These techniques were broadly discussed and compared in the paper. While the EPM methods provide details about the electrical properties with less information on the defective components, the visual inspection and especially the imaging techniques provide qualitative details on the classification of degradation modes and signatures. Compared to the other imaging types that are popularly used, the image quality of EL images is usually acknowledged to considerably higher. In contrast with conventional methods that require huge computational needs in analyzing and categorizing the various degradation mechanisms and modes, ML and DL models are proving to be feasible autonomous options based on their high efficiency and computational capacity, especially with regards to large scale installations. Through extensive research and analysis, the paper addressed and compared the methodologies applied in using ML and DL models for PV systems performance reliability and degradation analysis, in terms of the methodologies, characterization techniques, datasets, feature extraction mechanisms, accelerated testing procedures and classification procedures. Using acquired imaging and/or EPM datasets from modules that were degraded due to being subjected to accelerated test(s) or due to their exposed to wide range of environmental conditions during outdoor deployment, findings showed that KNN, shallow and deep neural networks are the most widely deployed algorithms for classifying the various degradation modes and signatures, in recent studies. In addition, findings showed that ML and DL models. Furthermore, research gaps and recommendations for future research works were presented.

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Abbreviations

LCOE	Levelized cost of electricity
EPM	Electrical parameter measurements
EL	Electroluminescence
FE	Feature Extraction
PL	Photoluminescence
EVA	Ethylene-vinyl-acetate
PID	Potential-induced degradation
PERC	Passivated emitter and rear contact
CCD	Charge-coupled device
YI	Yellowness index
DH	damp heat
I_{SC}	short-circuit current
V_{OC}	open-circuit voltage
P_{MP}	maximum power
FF	Fill factor
TC	thermal cycling
SDLE	Solar Durability and Lifetime Extension Center
LOESS	locally weighted smoothing
LID	Light-induced degradation
LeTID	Light and elevated temperature induced degradation

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