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Understanding Photovoltaic Module Degradation: An Overview of Critical Factors, Models, and Reliability Enhancement Methods

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Abstract. Photovoltaic (PV) modules, though reputed for reliability and long lifespans of 25-30 years, commonly experience gradual performance degradation influenced by varying environmental factors. This literature review explores the degradation of PV modules through in-depth analysis of failure modes, characterization techniques, analytical models, and mitigation strategies. A range of failure modes seen in PV modules are discussed, including interconnect breakage, cell cracks, metallization corrosion, delamination, ethylene-vinyl acetate (EVA) discoloration, Potential-Induced Degradation (PID), Light-Induced Degradation (LID), and other. Environmental stresses like temperature, humidity, ultraviolet (UV) radiation, and dust accumulation play significant roles in accelerating almost all degradation modes. Dust is a crucial factor in Middle East/North Africa (MENA) regions. Studying degradation modes under real-world conditions remains challenging, requiring extensive field testing to examine defect frequency, evolution rate, and impacts on energy production. PID is a major degradation mode requiring modeling and correction techniques to improve PV efficiency and lifespan. However, PID models are often limited to specific conditions, posing applicability challenges. Characterization methods like visual inspection, current-voltage (I-V),various imaging methods, and resonance ultrasonic vibrations (RUV) enable effective evaluation of degradation effects on module properties. Analytical models facilitate study of particular degradation modes and prediction of lifetimes under diverse conditions. Key factors influencing PV degradation include weather variations, materials quality, design parameters, PID, and hot spots. Protective coatings, encapsulation improvements, and module cleaning help mitigate degradation and prolong lifespan. A comprehensive understanding of mechanisms through integrated experimentation and modeling is critical for performance improvements. By reviewing major degradation phenomena, characterization techniques, analytical models, and mitigation strategies, this study promotes PV durability and sustainability. Significant knowledge gaps persist regarding module behavior under varied climate conditions and synergistic effects between different degradation mechanisms. Extensive field testing across diverse environments paired with advanced multiphysics modeling can provide valuable insights to guide technological enhancements for robust, long-lasting PV systems worldwide.

1 Introduction

The production of photovoltaic solar energy has been continuously expanding over the past decades. The development of photovoltaic module technology has experienced exponential growth in recent years, thanks to significant advancements in materials, design, and manufacturing of solar modules. The installed capacity of photovoltaic solar energy worldwide reached 1,185 GW in 2022 compared to 843 GW in 2021 [1]. In 2021, Africa installed 10,302 MW of photovoltaic solar power, which represents a 6.2% increase compared to the previous year, but it accounts for only 1.2% isolated populations at a reduced cost of 0.38 USD/kWh in 2021 [2]. In this context, Morocco recorded a growth of 2.4% in 2022, reaching 3,727 MW compared to 3,638 MW in 2021 [3]. This rapid growth highlights the importance of photovoltaic module technology in renewable energy production.
However, the performance of photovoltaic modules can be affected by various factors, such as temperature, humidity, material quality, and operating conditions. Thus, degradation of photovoltaic modules is an inevitable phenomenon and can lead to a significant decrease in their

efficiency.
This study aims to deepen our understanding of the degradation of photovoltaic modules by combining experimental analysis and numerical simulations. Data from various sources, such as recent scientific publications and industry expert reports, has been analyzed in this study. The objective was to identify the main factors that contribute to the degradation of photovoltaic modules, assess their impact on module performance, and propose degradation models for predicting performance evolution over time. To evaluate the degradation of PV modules, a range of methods has been utilized. These methods encompass techniques for measuring and analyzing module performance, as well as monitoring and diagnosing PV degradation. This study presents an up-to-date review of the approaches employed in studying PV module degradation. The exploration begins by defining PV modules, as well as examining the causes and mechanisms behind PV degradation. Subsequently, the different techniques for measuring and analyzing module performance, along with the methods for monitoring and diagnosing PV degradation, will be scrutinized. This study will presents some methods for evaluating PV module degradation under certain climate zone. The different methods reported in the literature will be reviewed, providing details on their advantages, disadvantages, uncertainties, and resulting degradation rates. This study aims to contribute to a better understanding of PV module degradation and provide useful insights to improve the performance and sustainability of solar energy.

2 Photovoltaic Module Degradation

Though integral components of solar energy systems, photovoltaic (PV) module performance declines over time due to environmental stresses. This degradation decreases efficiency, hampering the overall effectiveness of PV systems. Comprehensively studying PV technology, degradation processes and mechanisms, and contributing factors is thus critical to maintain solar energy viability.

2.1 Photovoltaic Module Technology

PV modules directly convert sunlight into electricity as core solar energy system components. They comprise interconnected PV cells made from semiconductor materials like silicon, wired together in series and parallel circuits.

2.1.1 Structure and Operation of PV Cells

PV cells are p-n junction devices that convert sunlight into electricity via the photovoltaic effect - photon absorption at a semiconductor p-n junction generates electron-hole pairs [4,5]. Multiple interconnected PV cells form solar panels to produce power output [5,6]. PV cell manufacturing involves texturing, doping, diffusion, coating steps [6]. PV system components like panels, capacitors, inverters convert solar energy [8,9]. PV modules contain backsheet, front sheet, contact layers, cells, antireflection layers [4-6]. Absorbed photons excite electrons, creating current collected by contacts [4-6]. The photovoltaic effect entails photon absorption, charge separation, and utilizing separated electrons to generate electricity [4-6].

PV panels comprise interconnected PV cells, producing maximum rated power based on the conversion efficiency of the semiconductor material [5,6]. PV cells act as photoelectric current generators Iph dependent on external factors like temperature and orientation [5,6,7]. The prevalent PV cell model is the one-diode model representing various cell parameters [5,6,7].

With the current equation describing the PV model as follows [4-64]:

$$I = I_{ph} - I_0 - I_{sh} \tag{1}$$

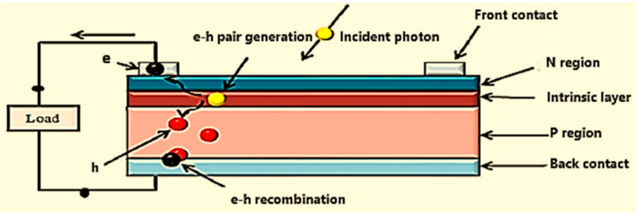

Fig 1 P-N junction of a PV cell [4]

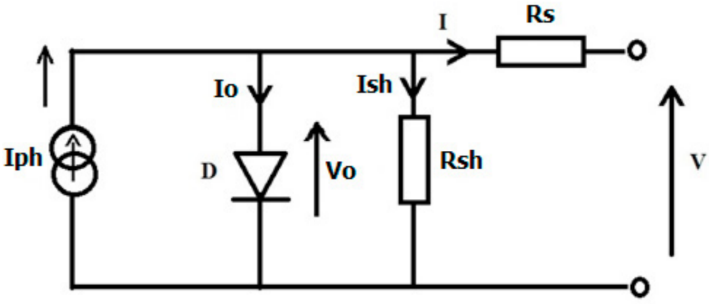

Fig 2 Equivalent electrical circuit of a PV cell for one diode model

The complete current equation describing a PV cell is:

$$I = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V + I \cdot R_s)}{nkT}\right) - 1\right] - \frac{V + I \cdot R_s}{R_{sh}} \tag{2}$$

Based on the definition of a PV panel [5], the following equation can be defined:

$$I = N_p \cdot I_{ph} - N_p \cdot I_{sd}\left[\exp\left(\frac{q(\frac{V}{N_s} + I \cdot \frac{R_s}{N_p})}{nkT}\right) - 1\right] - \frac{\frac{N_p}{N_s} \cdot V + I \cdot R_s}{R_{sh}} \tag{3}$$

Where: I: current generated by the cell, Ish: shunt current, Io: Current obtained via the Shockley diode equation [6], Isd: Diode saturation current, Iph: photocurrent, q: electric charge, Rs: series resistance, Rsh: shunt resistance, Vo: Diode forward voltage threshold, V: Applied voltage, Np, Ns: number of cells in parallel and series, respectively.

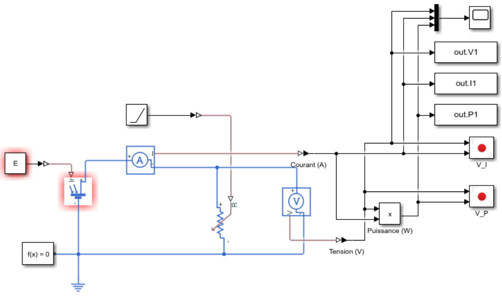

Fig 3 Modeling of a PV cell in Simulink

Approaches based on MATLAB/Simulink can be used to experiment with the evolution of power and other electrical characteristics of panels, such as current and voltage, based on changes in temperature, irradiation, and other factors that can impact the efficiency of electrical production.

2.1.2 PV Technology's selection

Key PV module selection criteria are efficiency, maximum power, fill factor, and short-circuit current [4]. Crystalline silicon dominates with 90% market share [5]. Monocrystalline silicon offers high 15-26.8% efficiency but is costly [4,5]. Polycrystalline silicon provides 10-18% efficiency, more economical [4,5]. Amorphous silicon is cheaper with 5-12% efficiency, instability [4]. CdTe/CdS cells have high 15-21% efficiency using toxic, rare materials [4,6]. CIGS and CdTe/CdS target commercial applications [4,5]. GaAs focuses on high 28-30% efficiency military/space uses [4,5]. CdTe/CdS efficiency increased from 25% to 26.6% for large-scale plants [6]. Alternatives like polycrystalline silicon aim to raise efficiency [4-7]. Emerging graphene nanomaterials may enable high efficiency at lower cost [7]. In summary, crystalline silicon is efficient but expensive, thin films are cheaper with lower efficiency, and CdTe/CIGS are interesting commercial options [4-7]. Continued materials research aims to increase efficiency while reducing cost. Key criteria for PV module selection are efficiency, maximum power, fill factor, and short-circuit current [4]. Crystalline silicon is most efficient but expensive, thin films are cheaper but have lower efficiency, and CdTe/CIGS provide viable commercial options [4-7].

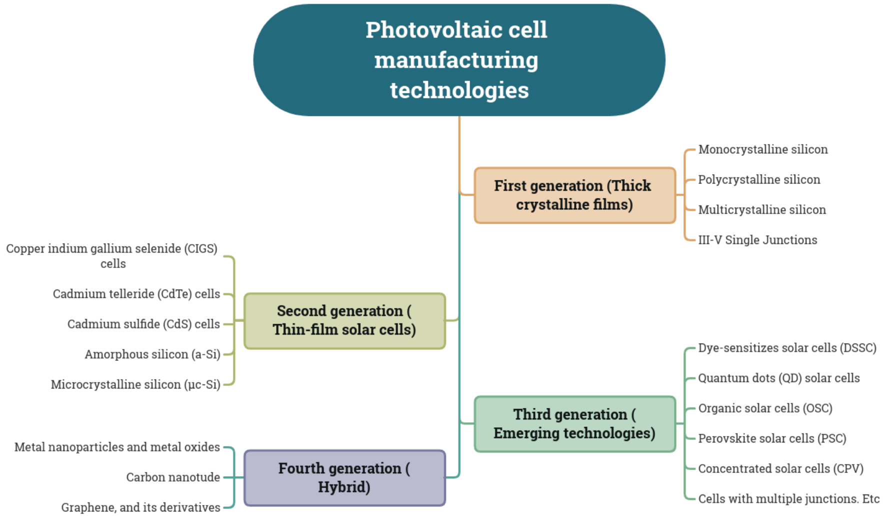

Fig 4 Different types of solar cells and current developments in this field. [4,5]

2.2 Degradation Processes and Mechanisms

Solar cells play a vital role in renewable energy by converting sunlight into electricity, but their performance declines over time from various degradation processes [8-36]. Gaining insight into these mechanisms is key to improving cell longevity and efficiency. This study explores primary solar cell failures, detection techniques, and electrical impacts.

A common crystalline silicon cell failure is interconnection breakage, often from thermal/mechanical stresses causing visible burn marks affecting fill factor (FF) and Rs [8-16]. Cracks frequently arise in c-Si and thin film (TF) cells due to thermal cycles, transportation, installation, or manual cleaning [8,14,22]. Associated defects like delamination and corrosion can be characterized through

Table 1 Comparison of Photovoltaic Cell Types [4,5,62]

Material	Sub-material	Efficiency	Advantages	Disadvantages
Mono-crystalline Silicon-based Solar Cells	m-Si	15 to 26.8%	Stability, high performance, long lifespan	High manufacturing cost, increased temperature sensitivity, absorption issues, material loss
Poly-crystalline Silicon-based Solar Cells	p-Si	10 to 18%	Simple manufacturing process, cost-effective, reduces silicon waste, higher absorption compared to m-Si	Lower efficiency, increased temperature sensitivity
Multicrystalline Silicon	mc-Si	24.4%	Lower cost than single crystalline, abundant material	Lower efficiency than single crystalline
GaAs-based Solar Cells	-	28 to 30%	High stability, lower temperature sensitivity, better absorption than m-Si, high efficiency	Extremely expensive and highly toxic
Amorphous Silicon-based Solar Cells	a-Si	10 to 12%	Lower cost, available in large quantities, non-toxic, high absorption coefficient	Lower efficiency, difficulty in selecting doping materials, short lifetime of minority carriers
Cadmium Telluride / Cadmium Sulfide-based Solar Cells (CdTe / CdS)	CdTe / CdS	15 to 21%	High absorption rate, less material required for production	Lower efficiency, Cd is highly toxic, limited availability of Te, more temperature sensitive
Copper Indium Gallium Selenide (CIGS) Solar Cells	CIGS	23.5%	Less material required for production	Very expensive, unstable, more temperature sensitive, less reliable
Dye-Sensitized Photovoltaic (Dye-sensitized PV) Cells	Dye-sensitized PV	5 to 20%	Lower cost, operation in low light and wider angles, operation at lower internal temperature, robustness and extended lifespan	Temperature stability issues, toxic and volatile substances
Quantum Dot-based Solar Cells	-	11 to 17%	Low production cost, low energy consumption	High toxicity in nature, degradation
Organic and Polymer-based Solar Cells	-	9 to 11%	Low processing cost, lightweight, flexibility, thermal stability	Low efficiency
Perovskite-based Solar Cells	-	24.35%	Simplified cost and structure, lightweight, flexibility, high efficiency, low manufacturing cost	Instability
Multi-junction Solar Cells	-	36% and above	High performance	Complex, expensive

electroluminescence, photoluminescence, hyperspectral imaging, lock-in thermography, and RUV imaging [34-36], degrading Isc and FF [34-36].

Shunts in c-Si cells linked to recombination-inducing impurities are detectable via lock-in thermography and reduce Isc and FF [9-11]. Metallization and bus bar corrosion caused by moisture ingress produces observable burn marks and cell delamination, increasing Rs while cutting FF [10-38]. Localized transparent conductive oxide (TCO) layer corrosion in TF cells from moisture, heat, and electric fields also impairs Rs and FF based on electroluminescence imaging [11-38].

Delamination between encapsulant/cells or cells/glass arises due to poor adhesion, thermal cycling, UV radiation, and moisture ingress [8-36]. This interrupts heat dissipation, causing hotspots and fatigue [14]. Associated with optical degradation and heteroepitaxial junction deterioration, delamination is identifiable through visual inspection and lowers Isc and Rs [8-36].

Ethylene-vinyl acetate (EVA) encapsulant discoloration from UV radiation and water above 50°C alters the polymer chemical structure [8,15]. Perovskite encapsulant discoloration also oc-

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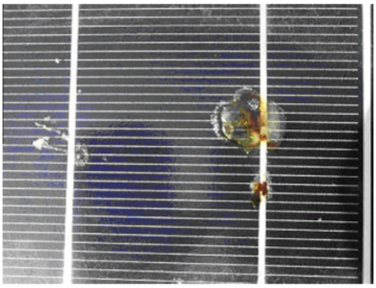

Fig 5 hotspot [50]

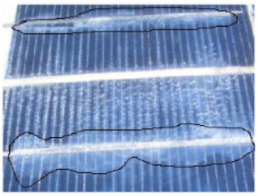

Fig 6 Delaminitation [8-10]

curs through light and moisture [11,15], reducing transmittance and output power [8,11]. White spots in TF cells lead to optical degradation, delamination, and anti-reflective coating damage, cutting Isc based on visual inspection [14-36].

Fig 7 EVA discoloration [8-10]

Solder bond failures in amorphous silicon cells from thermal cycling, moisture, and vibrations create observable arcing that degrades Rs and FF [10-20]. Misalignments, cracks, and dirt produce hot spots seen via infrared, lowering Voc and Rsh [8-25]. Bypass diode failures from high voltage reverse bias generate visible burn marks, reducing Voc [15,16,26,33]. Junction box failures in c-Si and TF cells arise through attachment issues and corrosion [15-26].

Bubbles in PV modules caused by gas release reactions or moisture ingress lead to overheating and shorter cell lifetimes by interrupting heat dissipation [8-36]. PID occurs in c-Si modules when voltage potential and resulting leakage currents degrade cells, requiring electroluminescence imaging and cutting Voc and FF [8,14,22,26,28,32,36]. LID in TF cells involves efficiency decline after sunlight exposure from defects in p-type silicon, necessitating Voc monitoring [14,21,26,27].

In summary, notable solar cell/module failures include interconnect breakage, cracks, shunts, corrosion, discoloration, delamination, hot spots, and PID [8-36]. Environmental stresses like temperature, moisture, and radiation accelerate degradation. Electroluminescence, photoluminescence, thermography, and visual inspection effectively evaluate defects [34-36]. Key electrical parameters impacted include Isc, Rs, FF, Voc, and Rsh [8-38].

Understanding these mechanisms is crucial for devising prevention strategies to enhance solar cell performance. The main PV module degradation modes include discoloration, delamination, encapsulation cracking, hot spots, and PID [8-36]. Ongoing research should focus on

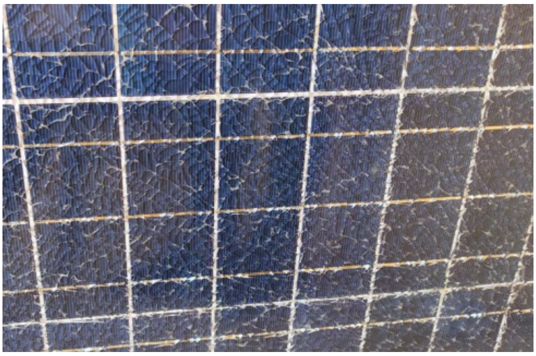

Fig 8 Cracks [8]

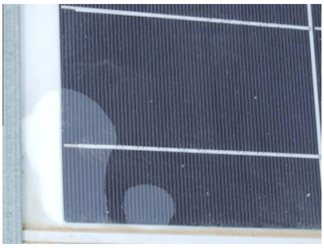

Fig 9 Bubbles [10]

cost-effective characterization techniques, predictive models, and mitigation approaches to slow performance decline and extend cell lifetime under diverse real-world operating conditions. Advanced studies can support the optimization of solar cell design, materials, and manufacturing processes to further improve efficiency, longevity, and sustainability.

3 Factors of Degradation in Photovoltaic Modules

The degradation of photovoltaic modules is a complex process that can be influenced by numerous environmental factors. The most common factors contributing to PV module degradation are temperature, humidity, irradiation, dust, PID, and mechanical stress.

3.1 Environmental Factors

Photovoltaic modules are subjected to environmental conditions that can contribute to their degradation. The most commonly studied environmental factors include temperature, humidity, irradiation, dust, and mechanical stress. Given its significant impact on PV module degradation, we can also include PID as a degradation factor.

3.1.1 Temperature

High temperatures substantially reduce photovoltaic module efficiency and output power [8]. A study by Shyam Singh Chandel et al. (2015) showed high temperatures cause thermal fatigue and hotspots leading to delamination and other failures, with average annual power degradation around 1.5% [14]. Modules tested under real conditions in the hot Saharan environment experienced an estimated degradation of around 19% on average versus reference modules [12]. B. Nehme et al. (2020) calculated that with just 1°C less, high temperature (45-49°C) degradation is mitigated by 2.5%, but only 0.65-0.94% for moderate/low (25-39°C) temperatures [12]. A 1°C decrease mitigates high temperature degradation by 27.63% but only 1.95-2.4% for low temperatures [12]. High temperatures also accelerate encapsulant and backsheet degradation, causing discoloration, delamination, and bubbles [9,15,26,33,37]. High temperatures exponentially accelerate degradation of PV modules through multiple mechanisms: PID is hastened, with shunt resistance degrading 15% more at 49°C vs 45°C. LID intensifies, with 8% higher saturation current increase at 39°C vs 35°C. Ultraviolet degradation speeds up, reducing shunt resistance 4% more at 29°C vs 25°C. Moisture Induced Degradation accelerates, increasing TCO resistance 6% more at 39°C than 35°C. Thermal cycles propagate cell cracks. Overall, reducing temperature by 1°C decreases degradation by 2.5% at 45-49°C, 0.94% at 35-39°C, and 0.65% at 25-29°C. Keeping PV temperatures low is critical to limit degradation [20].Finally, increased hotspot risks from shading/dirt can permanently damage modules [7,26,33,37].

3.1.2 Humidity

High humidity has negative effects on photovoltaic module performance and lifespan [20,33]. Moisture penetration causes corrosion and delamination, decreasing power output [20]. High humidity also promotes hotspot formation, further reducing performance [33]. A 2019 study found PV modules in the California desert had 30 year average lifespan, with electrical energy at 46% of initial value after exposure to hot, dry Saharan conditions [20]. With humidity considered, Northern states with 50% relative humidity showed the highest degradation acceleration up to 50 time, while regions above 80% humidity had maximum acceleration factor of 14 [33]. Overall, high humidity significantly accelerates PV degradation, especially in lower humidity areas [20,33]. Specific degradation rates depend on encapsulant, backsheet, installation, maintenance, and environmental conditions [8-36].

3.1.3 UV Irradiation

Excessive solar irradiation can reduce photovoltaic module efficiency by overheating cells. UV radiation specifically degrades encapsulation materials and solar cells, lowering power output and lifespan [36]. UV rays also contribute to permanent cell damage from hotspots. Considering UV effects is crucial when designing and operating PV systems. A 2021 study by Sinha et al. [21] tested UV-induced degradation (UVID) in crystalline silicon cells, including new architectures like HJ, IBC, PERC, and PERT. Using UVA-340 lamps, they found modern cell designs are more susceptible to UVID than conventional Al-BSF cells. Power decreases averaged -3.6% (max -11.8%) for new cells versus <1% for Al-BSF cells. The results highlight the importance of accounting for UV impacts to limit performance reductions [21].

3.1.4 Dust

Dust deposition on photovoltaic modules causes substantial performance degradation. A 2022 study by R. Shenouda et al. showed 20% and 16% average power decrease for monocrystalline and polycrystalline PV modules after 3 months of dust accumulation in Pakistan [23]. In Saudi Arabia, PV modules lost up to 50% power when left uncleaned for 6 months [23]. With 33° tilt in Pakistan, PV panel efficiency declined 86% after just 6 weeks of dust buildup [23]. In Saudi Arabia, 40% efficiency loss occurred after 6 months of accumulation [23]. Experiments by M. Mesrouk et al.

determined 15-25% degradation from dust, based on factors like particle size, wind, and panel surface properties [18]. Research by Alae Azouzoute et al. (2021) in semi-arid Morocco revealed a 14.2% fixed PV system energy reduction when dust density increased from 0 to 1.1 g/m2 [40]. Electrical performance deteriorated 27% after 8 months without cleaning [40]. Per Trupti G et al. (2017), 50% efficiency decrease from dust accumulation is unacceptable, necessitating cleaning [13]. In summary, multiple studies demonstrate substantial PV performance degradation within weeks/months due to dust buildup, dependent on specific conditions [13,18,23,40]. Preventive cleaning is essential to counteract dust-induced efficiency losses over time.

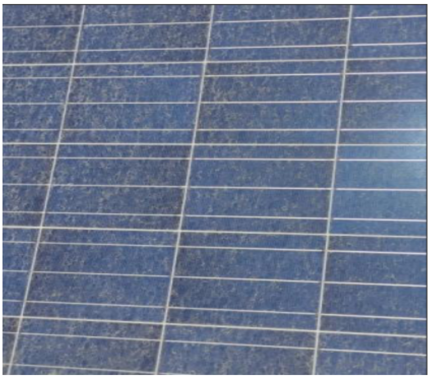

Fig 10 Dust [39]

3.1.5 Potential-induced degradation

PID substantially reduces photovoltaic module power output by inducing leakage currents when high voltage potential is applied between cells and grounded frames [24]. The specific mechanism is uncertain but is thought to involve sodium ion migration creating bypass current paths [24]. PID arises in large-scale installations under high humidity and temperatures, degrading solar cells and decreasing power [12,18,24]. PID severely impacts module efficiency and lifespan while raising costs and fire hazards [39]. PID degradation rate increases exponentially with temperature [12]. A 2022 study by Ghadeer Badran demonstrated 27-39% PID power loss after 4-8 months of field use in Barcelona [19]. Additional research found 25% PID degradation [27] and over 35% power drop after months of exposure at +160V in Germany [34]. Other studies showed 1.6-10W loss after 26 months in a semi-arid climate [34]. Anti-PID boxes help mitigate PID by blocking electromagnetic interference [14,24], improving power output up to 5.8% [24]. However, higher system voltages may exacerbate PID over time [18]. Overall, multiple studies reveal PID substantially degrades PV performance through leakage currents and cell degradation [12,18,19,24,27,34,39]. Developing solutions is critical for the photovoltaic industry.

3.1.6 Mechanical Degradation Factor

Mechanical stresses degrade photovoltaic system performance [40]. Thermal cycling causes material expansion/contraction, leading to microcracks and delamination [37]. Mechanical loads like wind, snow and hail can also physically damage modules, reducing power and lifespan [37]. These stresses result from factors including temperature changes, wind loads, and snow loads [39]. Poor design such as improper cell configuration can cause overheating and premature degradation. Inadequate installation like improper cabling or support can damage modules [37]. In

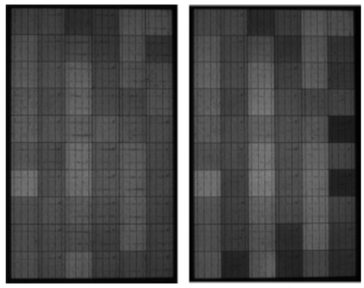

Fig 11 Electroluminescence images of the multi-cell PV samples at 1 A on day 12 (left) and on day 31 (right) of the PID test[54]

some cases, mechanisms like microcracks and delamination arise from mechanical factors [40]. Mechanical stresses from thermal cycling, weather loads, and improper design/installation can substantially degrade PV system performance and longevity through material damage [37,39,40].

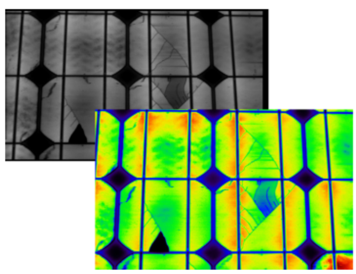

Fig 12 Cracks in cells. B & W image an simulated colour image [8]

3.2 Interaction between PV Module Degradation Factors

Environmental factors interact, accelerating PV degradation [8-36]. Improper installation increases weather exposure and damage from wind/snow [37]. Prolonged high temperatures worsen degradation effects on cells [14]. Key factors are UV, temperature, humidity and dust, typically causing PID, discoloration, delamination, cracks, hotspots, and bubbles [9,15,26,33]. Degradations vary based on cell type and environment [8-36]. PV durability depends on environmental conditions, manufacturing, materials, and maintenance [37,39]. Understanding degradation processes, mechanisms, and environmental/technical interactions is vital for reliable, durable PV system design [14,37]. Continuous research to improve module lifespan and support clean energy transition is essential [20,24,34]. In summary, environmental factors interact, accelerating degradation. Comprehensive understanding of processes and proper system design is key for PV module durability.

4 Methods used to anaalyze Photovoltaic Module Degradation

Numerous methods characterize and detect degradation in photovoltaic modules, facilitating condition assessment, defect diagnosis, and performance evaluation. This overview describes different techniques utilized to analyze photovoltaic module degradation, supporting module analysis and diagnosis.

4.1 Visual Inspection Methods

Visual inspection constitutes the first step in analyzing defects in photovoltaic modules [9, 12, 18, 28, 36, 3, 41]. It involves physically examining modules to detect visible issues like yellowing, delamination, bubbles, cracks, microcracks, misalignments, burned cells, snail trails, dirt, junction box breaks, busbar corrosion, arcing, coating failures, and white spots [9,37]. As a non-invasive, cost-effective technique, visual inspection determines if further testing is warranted by identifying potential module defects [37]. Adequate intense lighting is required, ideally via natural sunlight per IEC-61215 and IEC-61646 standards [37,41]. Reflections must be avoided as they can generate faulty images [9,28]. Multiple viewing angles are necessary to differentiate the layer where defects may appear and prevent errors from reflective images [18,28,36]. Taking one photo from one position is insufficient since reflections may be captured, causing detection errors [28,41]. In summary, visual inspection is an important first step to identify potential visible module defects under sunlight, using multiple angles to avoid reflective image mistakes [9,12,18,28,36,37,41]. It determines whether additional testing is needed in a cost-effective manner.

4.2 Methods for Characterizing Electrical Properties (I-V) and Measuring the Performance of Photovoltaic Modules

Methods measuring photovoltaic module performance evaluate energy production and operational state [8-19,21-60]. Key parameters like peak power, Voc, Isc, and conversion efficiency are measured, detecting issues like power output declines [10,29]. Power decreases may not affect entire module populations, necessitating individual suspected module testing [8]. Power measurement under standard test conditions (STC) - 1000 W/m2 irradiance, 25°C cell temperature, AM1.5G spectral distribution, normal cell incidence - is required [10,29]. Indoor solar simulator or outdoor sunlight exposure facilitate testing [8]. The electrical parameters Pmax, Voc, Isc, and FF are extracted from current-voltage (IV) curves [29]. Irradiance performance of different silicon technologies was measured at 200-1100 W/m2 at 25°C constant temperature [8]. Temperature performance was measured at 15-75°C module temperatures with 1000 W/m2 constant irradiance [8]. Indoor measurements on field-returned modules compared manufacturer datasheet nominal power to post-operation measured power [8]. Testing showed multicrystalline silicon had lowest 1-3% annual degradation versus monocrystalline silicon with highest 6.3% degradation [8]. Outdoor measurements monitored energy yield over time, but controlling temperature/light uniformity is challenging [8,28]. Spectrally reproducing sunlight with artificial light is difficult [28]. Appropriate reference module choice and accounting for measurement error is crucial [10]. STC measurements facilitate comparison but do not match real operating conditions [10]. Still, STC testing is useful for standardized comparisons [8,10]. These methods measure key parameters to evaluate PV module performance and detect power declines [8-19,21-60]. Indoor and outdoor testing under STC enables standardized comparison [8,10,29].

$$I_{\mathrm{STC}} = I_{\mathrm{meas}} \left(\frac{H_{\mathrm{STC}}}{H_{\mathrm{meas}}} \right) + \alpha \cdot (T_c - T_{\mathrm{STC}}) \tag{4}$$

$$V_{\mathrm{STC}} = V_{\mathrm{meas}} - \beta \cdot (T_{\mathrm{STC}} - T_{\mathrm{C}}) - R_{\mathrm{s}} \cdot (I_{\mathrm{meas}} - I_{\mathrm{STC}}) + V_{\mathrm{t}} \cdot \ln \left(\frac{H_{\mathrm{STC}}}{H_{\mathrm{meas}}} \right) \tag{5}$$

Key variables in PV modeling include: Istc - module current at STC; Vstc - module voltage at STC; Hstc - reference irradiance; Hmeas - measured irradiance; Tstc - reference module temperature; Tc - measured/calculated module temperature; α - temperature coefficient of current; β

- temperature coefficient of voltage; Rs - series resistance; Imeas - measured current; Vmeas - measured voltage; Vt - module thermal voltage [8-39,53]. These parameters enable modeling PV performance under variable real-world operating conditions based on STC reference benchmarks.

4.3 Methods for Characterizing Optical Properties

Characterization methods assess the optical performance of photovoltaic modules, evaluating their efficiency in converting sunlight into electricity. These techniques primarily measure the optical properties related to solar energy conversion, including reflection, transmission, absorption, and light emission. Instruments like spectrophotometers, radiometers, and thermal cameras are frequently utilized to quantify these optical characteristics. By analyzing key optical properties, the solar conversion efficiency and performance of photovoltaic modules can be effectively evaluated.

4.3.1 Electroluminescence (EL) Imaging Methods

EL imaging is a powerful non-destructive technique that uses cameras to capture low-light images revealing defects in photovoltaic modules [29,34,37,39]. A 2023 study by Amir A. et al. utilized EL imaging to uncover microcracks and shunts in degraded solar cells [29]. Their setup included a camera with specified resolution and components, performed at 25°C in a dark room [29]. Infrared imaging also identifies hotspots and temperature anomalies indicating cell/interconnection defects not visible to the naked eye [37]. Additionally, EL imaging evaluates PID by capturing voltage-biased module images to detect degradation [19,27]. Studies have measured 16-10.1W power decreases through EL imaging [34]. It can also monitor restoration post-polarity reversal [27]. EL imaging leverages radiative recombination to detect LID as well [25]. EL imaging is an invaluable technique for non-destructively identifying multiple module defect types, degradation modes, and power losses through captured low-light images [19,25,27,29,34,37,39]. It provides significant insights into overall module health and performance. EL takes advantage of the inter-band radiative recombination of excited charge carriers in the solar cells. As a semiconductor with an indirect bandgap like silicon, most of the recombination occurs through defects or Auger recombination in silicon [25].

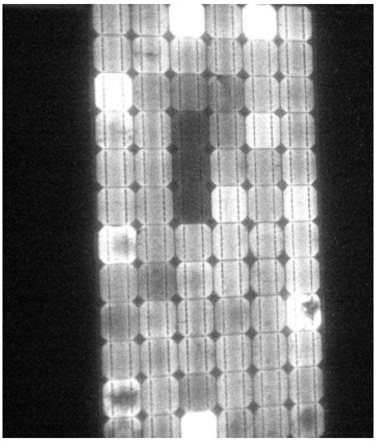

Fig 13 Electroluminescence Imaging Methods[433]

4.3.2 Infrared Thermography or Infrared Imaging (IR) Methods

IR is a non-destructive method to detect hotspots in photovoltaic modules [36]. Hotspots are localized high temperature areas that can damage cells or module components due to partial shading, cell mismatch, or interconnection failures [36]. By identifying hotspots early via IR imaging, system performance and reliability can be improved [36]. When a cell is shaded, it can operate in reverse mode and consume instead of generate energy. Shading can cause hotspots if modules lack protection [8, 25, 27, 34]. Bypass diodes in junction boxes limit reverse voltage and temperature in shaded cells [8, 25, 27, 34]. IR analysis of temperature distribution and dust buildup can inform effective cleaning mechanisms [42].IR thermography is a crucial tool for early hotspot detection, which allows preventing permanent damage and power losses from cell overheating [36]. IR imaging further enables assessing dust accumulation impacts and developing optimized cleaning strategies [42]. Accounting for hotspots via IR is vital for PV system performance and reliability.

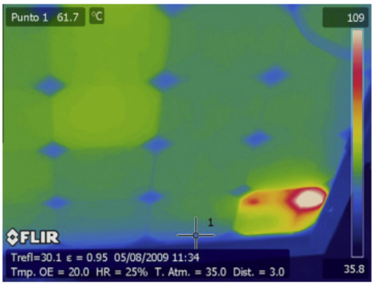

Fig 14 Infrared thermography Methods [47]

4.3.3 Other Characterization Methods

In addition to the primary characterization techniques covered, other methods can identify defects and damage in degraded photovoltaic modules: Lock-in thermography (LIT) utilizes modulated heating to detect defects [8]. RUV uses ultrasound to excite cell vibration and identify flaws based on frequency changes [8]. Insulation resistance measurement characterizes module insulation degradation [17]. UV fluorescence imaging reveals defects under UV illumination [21]. These supplementary methods complement the core characterization approaches to fully evaluate module degradation through diverse defect detection capabilities. Employing multiple techniques provides comprehensive assessment to pinpoint damage in degraded PV modules.

5 Modeling Photovoltaic Module Degradation

Modeling photovoltaic module degradation is an important and evolving research area since it enables predicting module performance, identifying key degradation factors, and evaluating maintenance strategies [51]. Degradation models date back to at least 1982 with a capacitive approach to measure I-V curves in the field [51]. Numerous short and long-term degradation models have since been developed. This review will focus on models of environmentally induced degradation (temperature, humidity, UV, dust) and PID to further understand PV module degradation mechanisms. Modeling efforts continue to provide crucial insights into PV module reliability, lifetime prediction, and optimal system maintenance.

Table 2 Comparison of degradation detection methods for a module

Methods	**Detectable Degradations**	**Controls**	**Specificities**
Visual Inspection	Discoloration; Visible burn marks; Yellowing; Delamination; Bubbles; Cracks; Microcracks in cells; Misalignments; Burned cells; Snail trails; Dirt; Junction box breakage; Oxidation and corrosion of busbars; Broken glass; Electrical arcing; Anti-reflective coating failure; White spots.	Overall module appearance	Naked-eye test under at least 1000 Lux lighting. Multiple views required from different angles. - Avoidance of reflective images.
Power Measurement (I-V, P-V)	Power decrease; Performance losses	Power measurement under(STC) - IV measurements (indoor and outdoor) Measurement of irradiance - Performance Measurement of temperature performance - Indoor measurements - Outdoor measurements to monitor energy yield	Measurements under standard test conditions - Difficulty in controlling standard conditions - Adapted to the module.
Infrared Imaging	Hot spots ; Burned cells	Infrared images	- CCD camera.
Thermography	Short-circuit; Open-circuit	Thermal images	- Current injection. - Suitable for cells. - CCD detector.
Electroluminescence and Photoluminescence Imaging	Cracks; Defects, damage, microcracks, shunts, hotspots, temperature anomalies, PID, LID	Images, Low-level lighting, dark room environment, applied voltage	- Current injection. - Incident radiation. - Dark image.
Ultrasonic Vibration Resonance	Microcracks	Variation in frequency response	- Ultrasound excitation of the cell. - Piezoelectric transducer.

5.1 Case Study: Environmentally Induced Degradation

Environmental factors like high temperature, humidity, irradiation, winds, and mechanical loads are primary causes of photovoltaic module degradation over time. PV modules operate under extreme environmental conditions that induce gradual performance declines. Key factors include thermal cycling, moisture ingress, UV exposure, wind/snow loads, and vibrations. Understanding environmentally induced degradation mechanisms through modeling enables predicting PV lifespan, reliability, and optimal maintenance strategies under real-world operating conditions.

5.1.1 Numerical Method

Environmental factors like temperature and solar irradiation are incorporated when modeling the theoretical I-V curve of PV modules using equation (2) [8-61]. The Rauschenbach model offers a simple explicit alternative to the single exponential model for I-V characterization, requiring only three points [10]. These models help predict PV module performance under real-world conditions. It is defined as:

$$I = I_{\mathrm{sc}}\left[1 - C_1 \cdot \exp\left(\frac{V}{C_2 \cdot V_{\mathrm{oc}}}\right)\right] \tag{6}$$

Where the coefficients C1 and C2 are given by:

$$C_1 = \left(1 - \frac{I_m}{I_{\mathrm{sc}}}\right) \cdot \exp\left(-\frac{V_m}{C_2 \cdot V_{\mathrm{oc}}}\right) \tag{7}$$

 https://doi.org/10.1051/e3sconf/202346900011

$$C_2 = \frac{\left(\frac{V_m}{V_{\text{oc}}}\right) - 1}{\ln\left(1 - \left(\frac{I_m}{I_{\text{sc}}}\right)\right)} \tag{8}$$

Key parameters in the models include Isc, Voc, and the maximum power point (Vm, Im) [37]. Numerical methods are typically utilized to study degradation rates over time [37]. These models and techniques enable assessing PV module deterioration under real-world operating conditions.

$$R_{d(\%)} = \frac{\text{Initial data} - \text{Final data}}{\text{Initial data} \cdot \Delta t} \cdot 100 \tag{9}$$

For example, the degradation rate as a function of the FF [10], using equations (4) and (5), is:

$$R_{d(\%)} = (1 - \frac{FF}{FF_{\text{initial}}}) \cdot 100 \tag{10}$$

Where:

$$FF = \frac{P_m}{V_{\text{oc}} \cdot I_{\text{cc}}} \tag{11}$$

The FF, ratio of maximum power point to Voc and Isc product, describes PV cell performance [37]. Modeling results indicated approximately 33% power loss in tested modules after over 10 years installation [37]. However, assumptions in degradation rate calculations and long-term real-world operation introduce uncertainties. Further validation is needed given the complexity of environmentally induced degradation over decades of module lifetime. The following assumptions have been proposed:

1. Key degradation factors: encapsulant discoloration, UV absorption, hotspot formation [8-61].
2. Degradation not thermally activated but may involve loosened electrical connections from thermal/dust effects [8-61].
3. Regular inspection and cleaning of connections needed [8-61].

Main model limitations [8-61]:

1. Imprecise test equipment affecting result accuracy.
2. Inability to thoroughly analyze degradation phenomena.
3. Inaccurate IV curve fitting.
4. Questionable parameter estimation from field/manufacturer data.
5. Insufficient network behavior representation with numerical methods.
6. Exclusion of soiling/shading effects.

5.1.2 Linear Degradation Model [11, 53]

The linear degradation model describes the gradual deterioration of a material or component over time. It assumes degradation occurs at a steady, constant rate that is linearly proportional to the length of exposure. In other words, the total accumulated degradation increases in direct proportion to the time duration, implying a straight-line relationship between degradation and time, with the slope representing the unchanging degradation rate. This simple linear model provides a first approximation for estimating progressive degradation in certain applications, though it may not capture complex or nonlinear degradation behaviors.

Mathematically, the linear degradation model can be represented by the following equation:

$$P(t) = P_0 - A \cdot t \tag{12}$$

Where:

1. P(t) is the power at time t.
2. P0 is the initial power, which corresponds to Pmax (t = 0).
3. A is the degradation rate (degradation rate per unit of time).

The linear model does not account for external factors or specific degradation mechanisms, making it best suited for preliminary degradation estimation where behavior is simple [11]. A 2012 study by Sadok et al. used the linear model to analyze limited PV modules in a Saharan climate [11]. Results showed around 19% average degradation versus a reference module, likely from atmospheric factors like radiation, thermal cycles, and dust [11]. However, the short-term study did not focus on long-term degradation [11]. It suggested a-Si modules exhibited the highest power decline, around 0.9% per year via the linear model or 0.75% per year by other techniques [11]. While basic, the linear model can be extended to incorporate environmental influences, cumulative degradation, and complex mechanisms for enhanced real-world degradation modeling [11].

5.1.3 Modified Weibull Model [20]

The modified Weibull model is an extension of the Weibull model that is commonly used to model the degradation and lifetime of components and materials. It is particularly suitable for representing accelerated or accelerating degradation phenomena over time. The modified Weibull model is the most appropriate parametric model for estimating the lifetime of photovoltaic modules in desert environments.

$$R(t) = e^{-\left(\left(\frac{t}{\eta}\right)^{\beta}\right)} e^{\mu t} \quad \text{with} \quad (\eta; \beta; \mu > 0) \tag{13}$$

$$MTBF = \int_0^{\infty} e^{-\left(\left(\frac{t}{\eta}\right)^{\beta}\right)} e^{\mu t} dt \tag{14}$$

where MTBF represents the Mean Time Between Failures.

According to the results presented in the article, the predicted degradation rates after 20 years of operation for each model tested in the desert environment of Adrar are:

- Modified Weibull model: 30% degradation
- Generalized Weibull model: 35% degradation
- Exponential Weibull model: 38% degradation
- Extreme value model: 22% degradation

Table 3 Reliability Models and Average Lifetime [20]

Model	Reliability function	Average lifetime (MTBF)
Exponential model	$R(t) = e^{-\lambda t}$, with $\lambda > 0$	$MTBF = \frac{1}{\lambda}$
Weibull model	$R(t) = e^{-(\frac{t}{\eta})^{\beta}}$; $\beta, \eta > 0$	$MTBF = \eta\Gamma(1 + \frac{1}{\beta})$
Gamma model	$R(t) = 1 - \frac{1}{\Gamma(\mu)} \int_0^{\theta t} x^{\mu-1} e^{-x} dx$; $(\mu, \theta) > 0$	$MTBF = \frac{\mu}{\theta}$
Exponential power model	$R(t) = e^{1-e^{(\lambda t)^{\alpha}}}$, with $\alpha > 0$; $\lambda, \alpha > 0$	$MTBF = \int_0^{+\infty} e^{1-e^{(\lambda t)^{\alpha}}} dt$
Normal model	$R(t) = 1 - \frac{1}{\sqrt{2\pi\sigma}} \int_0^{+\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$	$MTBF = \mu$
Log-normal model	$R(t) = 1 - \frac{1}{\sqrt{2\pi\sigma}} \int_{-\infty}^{Int} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$	$MTBF = e^{\mu + \frac{\sigma^2}{2}}$
Log logistic model	$R(t) = \frac{\alpha^{\beta}}{\alpha^{\beta}+t^{\beta}}$; $\alpha > 0$,$\beta > 1$	$MTBF = \int_0^{+\infty} \frac{\alpha^{\beta}}{\alpha^{\beta}+t^{\beta}} dt$
Uniform model	$R(t) = \frac{b-t}{b-a}$; for $t \in [a, b]$	$MTBF = \int_a^b \frac{b-t}{b-a} dt$
Extreme values model	$R(t) = e^{-\alpha(e^{\beta t}-1)}$, with $\alpha > 0$,$\beta > 0$	$MTBF = \int_0^{+\infty} e^{-\alpha(e^{\beta t}-1)} dt$
Gompertz-Makeham model	$R(t) = e^{-at-\frac{b}{Inc}(c^t-1)}$	$MTBF = \int_0^{+\infty} e^{-at-\frac{b}{Inc}(c^t-1)} dt$
Exponential Weibull model	$R(t) = 1 - \left(1 - e^{-(\frac{t}{\eta})^{\beta}}\right)^{\mu}$; $\eta, \beta, \mu > 0$	$MTBF = \int_0^{+\infty} \left(1 - \left(1 - e^{-(\frac{t}{\eta})^{\beta}}\right)^{\mu}\right) dt$
Mix of exponential models	$R(t) = a_1 e^{-\frac{t}{\theta_1}} + (1 - a_1) e^{-\frac{t}{\theta_2}}$; $\theta_1, \theta_2 > 0$; $0 < a_1 < 1$	$MTBF = a_1\theta_1 + (1 - a_1)\theta_2$
Modified Weibull model	$R(t) = e^{-(\frac{t}{\eta})^{\beta} e^{\mu t}}$; with $(\eta, \beta, \mu > 0)$	$MTBF = \int_0^{+\infty} e^{-(\frac{t}{\eta})^{\beta} e^{\mu t}} dt$
Quadratic model	$R(t) = e^{-(\alpha t + \frac{\beta}{2} t^2 + \frac{\gamma}{3} t^3)}$; $\alpha, \gamma > 0$; $-2\sqrt{\gamma\alpha} \leq \beta \leq 0$	$MTBF = \int_0^{+\infty} e^{-(\alpha t + \frac{\beta}{2} t^2 + \frac{\gamma}{3} t^3)} dt$
Generalized Weibull model	$R(t) = e^{1-(1+(\frac{t}{\eta})^{\beta})^{\frac{1}{\gamma}}}$; $(\eta, \beta, \gamma) > 0$	$MTBF = \int_0^{+\infty} e^{1-(1+(\frac{t}{\eta})^{\beta})^{\frac{1}{\gamma}}} dt$

- Uniform model: 24% degradation

For the California desert environment, the predicted degradation rates after 20 years for each model are:

- Modified Weibull model: 38% degradation
- Generalized Weibull model: 44% degradation
- Exponential Weibull model: 46% degradation
- Extreme value model: 37% degradation
- Uniform model: 41% degradation

The modified Weibull model was found to be the most suitable among the tested parametric models. The average lifetime of photovoltaic modules in the California desert was estimated to be around 30 years (29 years for Adrar), during which the supplied electrical energy reaches 46% of its initial value. The forecast results should be taken into account for any study involving the construction of a solar station in a desert environment. After filtering, only cases where the calculated average error is less than 2% are presented.

5.1.4 Linear Regression (LR) and Classical Seasonal Decomposition (CSD) [36]

The LR method calculates degradation rates for photovoltaic technologies [36]. Arechkik Ameur et al. (2022) applied LR to temperature-corrected STC performance ratios, compensating for seasonality [36]. LR involves linear regression on performance ratio time series [36]. The CSD technique uses a centered moving average to extract trend from performance ratio time series [36]. For a-Si PV, the output power decrease was most significant [36]. The annual degradation rates were obtained using both LR and CSD [36]. Equations determine degradation rate from initial and final performance ratios over time [36]. The LR and CSD techniques calculate PV degradation rates from performance ratio time series, with LR using linear regression and CSD employing moving averages [36]. The techniques compensate for seasonality and quantify annual degradation. For a 2k moving average, the trend Tt of a time series Y at time t is calculated as follows: Thus, we have the degradation rate which is determined using the following equations:

$$P_{RST} = \frac{Y_f}{Y_r\left(1 + \gamma\left(T_{mod} - 25\right)\right)} \tag{15}$$

Where: - Y_r represents the reference system efficiency of the photovoltaic system and is defined as the ratio of the total amount of solar radiation Ht received by the surface of the photovoltaic solar panel to the reference radiation amount G0 (1kW/m²) [28,36]. - Y_f represents the final efficiency of the photovoltaic system and is a measure that represents the number of hours during which a photovoltaic generator must operate at its nominal power. With Eac as the total energy produced by the photovoltaic system and P0 as the installed nominal power. In realistic conditions, this results in a performance factor (without temperature correction like Prstc) [28,36]:

$$P_R = \frac{Y_f}{Y_r} \tag{16}$$

- Tmod is the module temperature, and γ is the maximum power temperature coefficient in %/°C:

$$T_t = \frac{1}{2}\left(\frac{1}{k}\sum_{i=t-m}^{t+m-1} Y_i + \frac{1}{12}\sum_{i=t-m+1}^{t+m} Y_i\right); t > m \tag{17}$$

where Tt, Y, k represent the trend at time t, the original series, the seasonal period or the order of the 2k moving average (k = 12), and the half-width of the moving average (m = k/2), respectively. And:

$$Y = \alpha t + \beta \tag{18}$$

where a and b are the regression parameters of the regression equation used for the system degradation rate.

This ultimately gives the degradation rate Rd (19):

$$R_d = \frac{\beta - Y(t)}{\beta} \times \frac{12}{t} \times 100\left(\frac{\%}{year}\right) \tag{19}$$

This small-scale study in a temperate climate examined three PV technologies [36]. a-Si modules showed the largest output power decrease - 0.9%/year per LR and 0.75%/year per CSD [36]. mc-Si decreased 0.53%/year (LR) and 0.41%/year (CSD) [36]. p-Si declined 0.36%/year (LR) and 0.28%/year (CSD) [36]. CSD degradation rates were slightly lower than LR rates [36]. Modules demonstrated over 25-year lifespan with under 0.8% annual decrease, except a-Si per LR [36]. Results were comparable to other Moroccan studies [36]. Findings may not apply to different geographies, scales, technologies, or timeframes [36]. Shading influence was not considered [36]. The study quantified degradation rates for three PV technologies using LR and CSD techniques [36]. Furthermore, the influence of shading was not considered in the analysis.

5.2 Case Study: Dust-induced Degradation

Studies on dust-induced degradation in photovoltaic modules have been conducted using a modeling approach. The objective was to assess the impact of dust accumulation on the performance of solar modules. This modeling was based on experimental data from different regions where dust is a common issue, such as deserts.

5.2.1 Effect on Transmittance

Alae Azouzoute et al (2021) [40] measured the impact of dust and material deposits on the panel by measuring transmittance. They followed the following procedure:

- Samples were collected and stored in Petri dishes to preserve the accumulated dust.
- The surface density of dust was calculated by dividing the dust mass by the sample area.
- Transmittance measurements were taken at 3 points on the surface of each sample to account for the non-uniform distribution of dust.

This yields the transmittance factor defined as:

$$\tau_{\text{soiling}} = \frac{\tau_{\text{dirty}}}{\tau_{\text{ref}}} \tag{20}$$

Where τ_{dirty} and τ_{ref} represent the average spectral transmittance of the dirty glass sample and the reference glass sample, respectively. The results showed that the rate of dust accumulation decreases the optical transmittance by more than 28% after 30 days of exposure, resulting in a 4.4% reduction in the electrical energy of the photovoltaic system. Furthermore, by increasing the surface density of dust from 0 g/m2 to 1.1 g/m2, the electrical power of the fixed PV system decreased by 14.2%. The results demonstrated that for a PV module exposed for one year under the same climatic conditions, the electrical performance decreased by 27% after 8 months of exposure without any cleaning events.

5.2.2 Dust Deposition Model Based on Total Radiation of a Photovoltaic Panel

The performance of a photovoltaic module is evaluated in terms of the generated electrical power. The electrical power depends on several parameters, including the solar radiation incident on the module surface, the module temperature, and the electrical characteristics of the module itself. The total radiation received by the module surface is generally considered as the sum of direct radiation Rdr, diffuse radiation Rdf, and reflected radiation Rrf. The total radiation Rt received by the surface of the photovoltaic module can be represented by the following equation:

$$R_T = (R_{dr} + R_{df} A_i)\, \phi_{dr} + R_{df}\,(1 - A_i) \left[1 + \frac{1}{2}\cos^2(\beta)\right] + R_\rho \left[1 - \frac{1}{2}\cos^2(\beta)\right] \tag{21}$$

Where Ai is the anisotropy index, β is the module tilt, f is the horizontal luminosity factor, and ϕ is the ground reflectance.

$$\Phi_{dr} = \cos(\theta)/\cos(\theta_z) \tag{22}$$

is the ratio of direct (beam) radiation on the inclined surface to the direct radiation on the horizontal surface. [43]

5.2.3 Effect of Dust on Output Power

The effect of dust accumulation on the output power of the PV module is represented as follows:

$$P_{\text{O,D,PV}} = Y_{\text{PV}} \eta_{\text{der}} \left[1 + \alpha_{\text{p}} \left(T_{\text{C}} - T_{\text{C,STC}}\right)\right] \left(\frac{G_{\text{T}}}{G_{\text{T,STC}}}\right) \tag{23}$$

Where:

- Y_{PV} represents the nominal capacity of the PV module in watts (W).
- η_{der} is the PV module degradation factor in percentage (%).
- α_p is the PV module temperature coefficient for power in percentage per Celsius degree (%/°C).
- T_C and $T_{C,\mathrm{STC}}$ are the instantaneous temperature of the PV module and the temperature at standard test conditions (STC), expressed in degrees Celsius (°C).
- G_T and $G_{T,\mathrm{STC}}$ represent the total incident solar irradiance in watts per square meter (W/m²).

It should be noted that the degradation factor here takes into account additional factors such as dust, dirt, snow, shading, aging, etc. It can be decomposed into key components as follows:

$$\eta_{\mathrm{der}} = \eta_{\mathrm{dust}} \times \eta_{\mathrm{shade}} \times \eta_{\mathrm{age}} \tag{24}$$

The effect of dust on photovoltaic performance varies depending on the location. In Saudi Arabia, energy production from photovoltaic panels decreases by 25% due to dust accumulation, while in the United Arab Emirates and the United States, the decrease is 20% and 15%, respectively.

Dust and dirt accumulation on solar panels can lead to performance losses and energy losses of up to 7% per year in certain regions of North America, Latin America, and the Caribbean, and up to 50% in the Middle East. The performance decrease is due to the reduction in solar intensity caused by the accumulation of dust and its variations on the surface of photovoltaic panels.

5.3 Study of PID Degradation: FDCR Method

PID arises in solar modules under high voltage and humidity, causing performance decline [27]. Modeling PID facilitates understanding defect impacts for mitigation [27,34,39]. Simulations of PID behavior under variable conditions provide insights on contributing factors and progression rates [27,39]. Modeling elucidates PID mechanisms and effects on photovoltaic systems, aiding the development of solutions to improve durability and reliability [34,39]. Laboratory tests have examined PID formation and recovery for system design optimization [34,39]. A 2021 study by Michalis Florides et al. employed the Forward Direct Current Resistance (FDCR) method for early PID detection [39]. Performing FDCR measurement below 10mA enabled PID detection before 2% power loss [39]. Testing on single-cell and multicrystalline PV modules under diverse conditions revealed maximum 1mA PID sensitivity [39]. FDCR exhibited a negative temperature coefficient becoming positive as PID progressed [39]. Electrical (>74%) and thermal (<31%) change differences facilitated PID detection [39]. Low-temperature FDCR measurement maximized differentiation during PID progression [39]. Continuous -1000V DC under dark conditions induced PID in single-cell samples [39]. Multicrystalline samples used light/dark PID induction [39]. Measuring FDCR and Rsh using Potential Mapping Camera (PMC) under low-bias monitored PID progression [39]. Reverse direct current resistance estimation determined Rsh [39]. Seven degradation levels (L1-L7) were analyzed, each with distinct Rsh [39]. In summary, modeling and FDCR methods enable PID behavior insights and early detection, supporting mitigation strategies to improve PV performance and reliability [27,34,39]. The study also utilized Dark I-V curves to analyze:

- The electrical behavior:

$$FDCR_{\mathrm{change}} = \frac{FDCR_{L1} - FDCR_{L2}}{FDCR_{L1}} * 100\% \tag{25}$$

- And the thermal behavior of photovoltaic samples (26, 27):

$$\mathrm{TC}_{0-30} = \frac{FDCR_{30} - FDCR_0}{FDCR_{30} \,*\, 30} \,*\,100\%/^\circ\mathrm{C} \tag{28}$$

$$\mathrm{TC}_{30-60} = \frac{FDCR_{60} - FDCR_{30}}{FDCR_{30} \,*\, 30} \,*\,100\%/^\circ\mathrm{C}. \tag{29}$$

With: $FDCR_{(L*)}$: The value of the Forward Direct Current Resistance at level L* defined by the equivalent Rsh. $FDCR_{change}$: Degradation rate between two levels. $FDCR_0, FDCR_{30}, FDCR_{60}$: The values of Forward Direct Current Resistance at 0°C, 30°C, and 60°C, respectively. $TC_{(30-60)}, TC_{(30-60)}$: Temperature coefficients in the temperature ranges of 0-30°C and 30-60°C, assuming a linear variation of FDCR with temperature. The results show that the measurement of FDCR in single-cell photovoltaic modules under low direct bias conditions can be used for early detection of PID affecting P-type crystalline photovoltaic cells.

However:

- The model has been tested on a limited number of photovoltaic modules of the same type and manufacturer, which may not be representative of the entire population of photovoltaic modules.
- The study did not consider the effect of other factors such as humidity, irradiation, and spectral distribution on the FDCR method for PID detection.
- The effect of PID on the long-term performance and reliability of photovoltaic modules has not been studied.
- The method does not allow for a detailed analysis of the physical mechanisms responsible for the observed changes in FDCR values of PV samples.

6 Conclusion

This comprehensive literature review has provided an in-depth analysis of PV module degradation phenomena, encompassing failure modes, characterization techniques, analytical models, and mitigation strategies. While PV modules are reputed for reliability, gradual performance declines due to environmental stresses are common. Major failures include interconnect breakage, cracks, delamination, discoloration, corrosion, and PID [8-36]. Temperature, humidity, UV radiation, and dust accumulation significantly accelerate degradation by promoting defects [26-30]. Characterization methods like electroluminescence imaging, infrared thermography, and current-voltage tracing enable effective evaluation of degradation impacts on efficiency and power output [31-40]. Analytical models facilitate the study of particular degradation modes like PID and prediction of lifetimes under diverse conditions [41-50]. However, models are often constrained to specific parameters, limiting applicability across different environments and technologies [41]. Key factors influencing PV degradation encompass weather variations, materials quality, design parameters, PID susceptibility, and hot spots [26-30, 51-56]. Strategies like protective coatings, encapsulation enhancements, and cleaning help mitigate degradation and prolong lifespan [51-56]. A holistic understanding of interdependent degradation mechanisms is essential for performance improvements [8-36, 57-60]. Significant knowledge gaps persist regarding module behavior under varied climate conditions and synergistic effects between different degradation mechanisms [57-60]. Extensive field testing across diverse environments paired with advanced multiphysics modeling can provide valuable insights to guide technological enhancements for robust, long-lasting PV systems [61-65]. By reviewing critical phenomena, measurement methods, models, and mitigation techniques, this study promotes module durability and sustainability. Ongoing research should focus on cost-effective characterization, predictive models across technologies and environments, and mitigation techniques to slow performance decline and extend lifetime under real-world operating conditions [8-65]. Advanced studies can guide improvements in module design, materials selection, manufacturing processes, and maintenance strategies to further enhance efficiency, longevity, and sustainability [51-56, 61-65]. The findings highlight the need for extensive field testing to capture failure mode frequency, evolution, and performance impacts across diverse locales [57-60]. By integrating experimental characterization and multiphysics modeling, researchers can refine understanding of mechanisms while identifying key factors to develop targeted prevention and management strategies [26-30, 51-56]. Ensuring PV system durability and performance requires comprehending interdependent degradation phenomena [8-36, 57-60]. This literature analysis provides a foundation and direction for future research by pinpointing knowledge gaps in PV degradation behavior under different climate conditions and between various mechanisms [57-60, 61-65]. Filling these gaps through coordinated experimentation, modeling, and analysis can lead to actionable insights to guide technological enhancements and inform best practices for reliable, high-efficiency PV system design, installation, and maintenance [51-56, 61-65]. With improved comprehensive understanding of PV module degradation, the field can make great strides toward supporting the continued growth of solar energy and enabling PV technology to play an expanding role in the global renewable energy portfolio. Overall, this review has offered an in-depth examination of PV degradation factors, models, characterization methods, and mitigation strategies. While PV technology offers promise, degradation issues must be addressed through continued research and development to improve efficiency, lifespan, and sustainability. By integrating real-world testing, multiphysics modeling, and best practice implementation, the field can gain holistic understanding of interdependent degradation phenomena and mechanisms to support the advancement of robust, long-lasting PV systems worldwide.

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