

A Critical Review of Fault Detection and Diagnosis in Crystalline Silicon Photovoltaic Systems: From Cell-Level Degradation to Array-Level Failures

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ABSTRACT

The long-term reliability of photovoltaic (PV) systems depends on the timely detection and diagnosis of faults. Crystalline silicon (c-Si) technology dominates the global PV market, and is susceptible to a wide range of degradation modes. This review provides a structured analysis of these faults, categorizing them into material-level intrinsic defects, environmentally-induced extrinsic faults, and system-level interconnection faults. The review details the underlying mechanisms of key degradation modes, including Light- and Elevated Temperature-Induced Degradation (LeTID), Potential Induced Degradation (PID), and micro-crack propagation. A critical evaluation of corresponding Fault Detection and Diagnostic (FDD) methodologies follows. It encompasses laboratory-grade imaging techniques, field-deployable electrical analysis, and emerging data-driven approaches leveraging machine learning and unmanned aerial vehicles (UAVs). This synthesis reveals a fundamental trade-off between diagnostic resolution and operational scalability. To navigate this trade-off, the study analyzes the evolution towards integrated, tiered monitoring strategies and hybrid data-fusion techniques. Furthermore, the review identifies persistent research gaps, such as the need for explainable artificial intelligence (XAI), standardized datasets, robust transfer learning models, and cyber-secure FDD architectures. By bridging the fundamental science of cell degradation with the system-level engineering, this article serves as a roadmap for advancing predictive maintenance and ensuring the sustainability of large-scale PV infrastructure.

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1. INTRODUCTION

The global energy transition toward sustainable power systems has positioned photovoltaic (PV) technology as a cornerstone renewable solution. Crystalline silicon (c-Si) modules dominate more than 95% of the market due to their maturity, efficiency, and declining cost [1]. However, ensuring long-term reliability over operational lifetimes exceeding 25 years remains a critical challenge, as performance degradation directly affects energy yield and the levelized cost of electricity [2].

PV faults arise from intrinsic material defects or extrinsic environmental and operational stresses. Intrinsic mechanisms such as Light-Induced Degradation (LID) and Light- and Elevated Temperature-Induced Degradation (LeTID) cause gradual power loss, while extrinsic faults including Potential-Induced Degradation (PID), corrosion, and delamination can accelerate failure and introduce safety risks. System-level faults at interconnections may also lead to catastrophic events such as arc faults [3].

Detecting these diverse fault modes requires advanced Fault Detection and Diagnosis (FDD) techniques ranging from high-resolution laboratory imaging to field-deployable electrical measurements and data-driven monitoring methods. Although prior reviews have examined individual degradation mechanisms or diagnostic approaches, a unified analysis linking cell-level physics with system-level monitoring strategies remains limited.

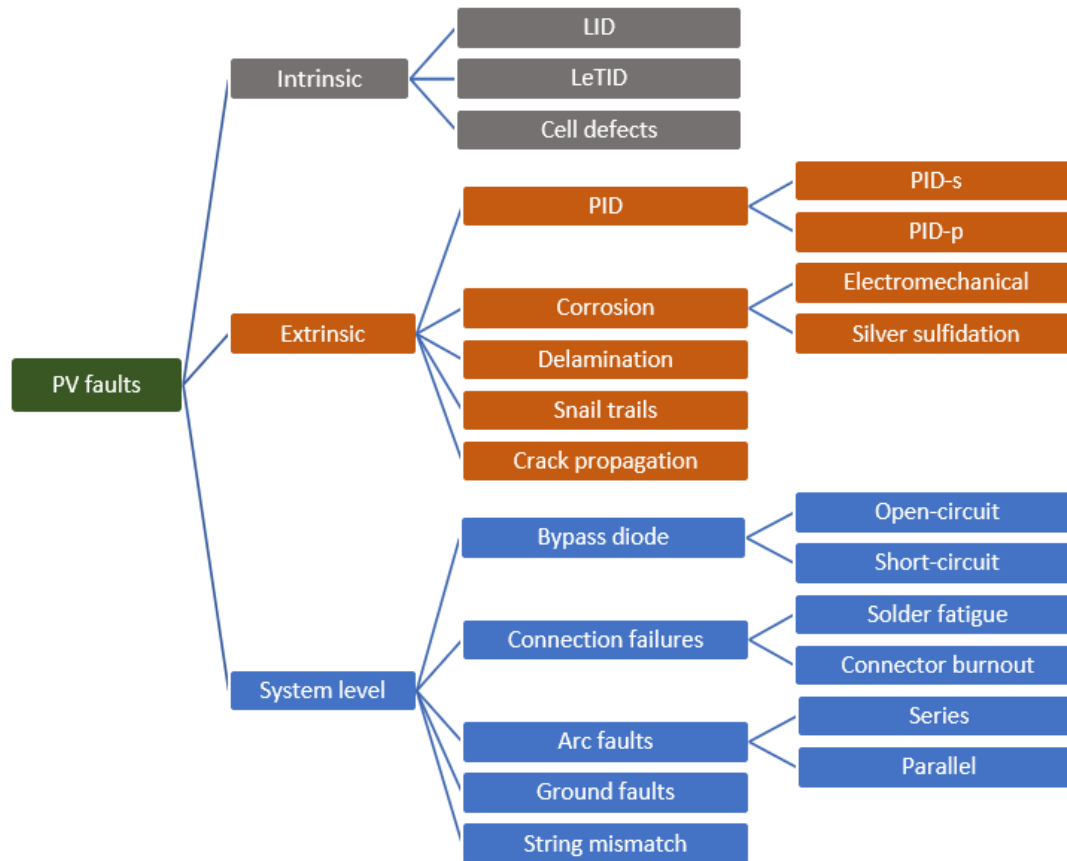


Figure 1. Hierarchical classification of fault and degradation modes in crystalline silicon photovoltaic modules, organized by origin.

This review provides a structured synthesis of fault mechanisms in c-Si PV systems together with a critical evaluation of corresponding FDD methodologies. By integrating material-level degradation science with system-scale diagnostic strategies, the work aims to guide the development of predictive maintenance frameworks for reliable long-term PV operation. A comprehensive taxonomy of these fault modes is detailed in Figure 1, which presents a structural framework for this review.

2. CLASSIFICATION OF FAULTS IN PV SYSTEMS

2.1. Intrinsic (Material & Fabrication) Faults

2.1.1. Light-Induced Degradation (LID)

Light-Induced Degradation is a well-established phenomenon primarily affecting boron-doped p-type Czochralski silicon (Cz-Si), which has been the industry standard for decades. The light-induced degradation (LID) is characterized by a premature and significant loss of solar cell efficiency during the first hours of light exposure with an energy greater than the material bandgap [4]. The formation of boron-oxygen (B-O) complexes within the silicon lattice is the primary mechanism behind LID [5]. These complexes form recombination centers upon initial exposure to light, which reduce the minority carrier lifetime of the silicon bulk.

The resulting power loss typically ranges from 1–3% relative and stabilizes within days. Although limited in magnitude, LID produces a permanent reduction in module performance. Consequently, manufacturers commonly stabilize modules through controlled pre-illumination prior to rating, a practice standardized in qualification protocols such as IEC 61215 [2].

2.1.2. Light- and Elevated Temperature-Induced Degradation (LeTID)

Light- and Elevated Temperature-Induced Degradation (LeTID) is a more severe degradation mode than conventional LID and primarily affects modern high-efficiency architectures such as PERC cells [6]. It occurs under simultaneous carrier injection and elevated temperatures ($\approx 50\text{--}85\text{ }^{\circ}\text{C}$), conditions commonly encountered during field operation [7]. Key distinguishing characteristics between LID and LeTID are summarized in Table 1.

Unlike LID, LeTID exhibits slow kinetics, with degradation developing over months or years before sometimes entering a gradual regeneration phase. Reported power losses typically range from **5–10%**, and can exceed **15%** in severe cases, posing significant risks to energy yield predictions and project economics [8]. Although its mechanism is still under investigation, strong evidence links LeTID to hydrogen introduced during fabrication for defect passivation. Under illumination and heat, hydrogen becomes metastable and forms recombination-active complexes or destabilizes existing passivation, reducing minority carrier lifetime [9].

Because LeTID affects widely deployed PERC modules, it represents a major reliability concern for the current PV fleet. Mitigation strategies include improved material purity, optimized hydrogenation processes, and post-fabrication thermal treatments to stabilize performance [8].

Table 1. Key characteristics of Light-Induced Degradation (LID) and Light- and elevated Temperature-Induced Degradation (LeTID).

Parameter	Light-Induced Degradation (LID)	Light- and elevated Temperature-Induced Degradation (LeTID)
Primary Cause	Formation of boron-oxygen (B-O) complexes	Metastability of hydrogen used for bulk passivation
Main Affected Technology	Boron-doped p-type Czochralski Silicon (Cz-Si)	p-type PERC, other advanced architectures with hydrogenation
Triggering Conditions	Initial light exposure	Light/current injection & elevated temperatures ($50\text{--}85\text{ }^{\circ}\text{C}$)
Typical Power Loss	1 – 3% (relative)	5 – 15% (relative), can be higher
Kinetics	Fast onset (hours/days), saturates quickly	Slow onset (months/years), may exhibit regeneration
Immunity	n-type cells, Ga-doped p-type cells	Varies by technology; often less severe in n-type and Ga-doped p-type

2.1.3. Initial Cell Defects: Micro-Cracks and Shunts

Photovoltaic cells may contain latent defects introduced during wafering, fabrication, or lamination that later propagate under mechanical and thermal stress, reducing performance and reliability [10]. The most critical of these defects are micro-cracks and shunts.

Micro-cracks are microscopic fractures typically caused by wafer slicing, handling, or interconnect soldering [11]. While initially inactive, they can propagate under thermal cycling or mechanical loading, eventually interrupting current paths and creating localized hot spots that accelerate degradation and reduce output power [12]. Electroluminescence (EL) imaging is the most sensitive method for detecting such defects, which appear as dark lines or inactive regions [13].

Shunts are localized low-resistance pathways that divert photocurrent and reduce shunt resistance, fill factor, and open-circuit voltage [14]. They may arise from crystal defects, processing damage, contamination, or inadequate edge isolation. Localized shunts can also initiate hot spots. Detection is typically achieved through lock-in thermography or analysis of dark and illuminated I–V characteristics.

Controlling these defects during manufacturing is essential because they establish the baseline from which subsequent field-induced degradation evolves.

2.2. Extrinsic (Environmental & Operational) Faults

Extrinsic faults are not inherent to the materials or manufacturing but are induced by the system's interaction with its external environment and operational stresses [10]. These include climatic factors, electrical potential, mechanical loads, and biological growth. Such faults are often the primary cause of performance decline and safety hazards in fielded PV systems. The most significant extrinsic degradation modes include Potential Induced Degradation (PID), corrosion, delamination, and snail trails [15]. The most significant extrinsic degradation modes are summarized in Table 2, which outlines their causes, signatures, and detection methods.

2.2.1. Potential Induced Degradation (PID)

Potential Induced Degradation (PID) is a severe performance-loss mechanism occurring when a high voltage difference exists between solar cells and the grounded module frame, most common in high-voltage

strings. The fundamental physics of PID-shunting (PID-s) are governed by the high-voltage stress between the solar cells and the grounded module frame, which drives the migration of mobile sodium ions (Na^+) from the soda-lime glass cover. The chemical kinetics of this degradation follow an Arrhenius-type dependency, where the ion drift velocity (v) is influenced by temperature (T) and relative humidity (RH). As these Na^+ ions traverse the encapsulation and accumulate within the stacking faults and crystal dislocations of the silicon wafer, they create conductive shunting paths that bridge the p-n junction. This migration is a field-driven ion-displacement process; the kinetics are often reversible under a reverse bias, which confirms that the initial failure mode is related to ion concentration gradients rather than permanent lattice rupture [16].

In the dominant PID-s mode affecting p-type PERC cells, mobile sodium ions from the glass migrate through encapsulation toward the cell surface, distorting the junction and creating shunting pathways [17]. This can reduce parallel resistance and power output by more than 30% [18]. A second form, PID-p, mainly affects n-type cells and involves dielectric polarization leading to voltage loss [16]. PID is identifiable in electroluminescence images as dark cells or strings and in infrared imaging as uniform heating [17]. Mitigation strategies include PID-resistant materials, improved encapsulation, optimized grounding, and recovery systems that apply reverse bias during nighttime [19].

2.2.2. Corrosion

Corrosion is the electrochemical degradation of metallic module components such as gridlines, busbars, and interconnect ribbons, typically triggered by moisture ingress and contaminants. In the presence of an electrolyte, dissimilar metals can form galvanic couples, causing oxidation of less noble conductors and increased series resistance, which reduces fill factor and current output [10].

The primary mechanisms are electrochemical Corrosion and silver sulfidation. The first occurs when two dissimilar metals are connected in the presence of an electrolyte, forming a galvanic cell [20]. The second is a severe form of corrosion where silver gridlines react with sulfur compounds to form non-conductive silver sulfide (Ag_2S). This reaction is particularly insidious as it can occur even with minimal moisture ingress and leads to a dramatic increase in series resistance, often rendering the module inoperative [21].

Corrosion is usually visible as discoloration or metallization damage [22] and can be confirmed using electroluminescence imaging, which reveals darkened regions caused by resistive losses. It is a major contributor to long-term degradation, especially in hot and humid environments.

Table 2. Overview of major extrinsic (environmental and operational) PV module faults.

Fault Type	Primary Cause(s)	Visual Signature	Electrical & Performance Signature	Primary Detection Methods
Potential Induced Degradation (PID)	High voltage potential cell-to-frame; ion migration (Na^+)	Dark cells/ strings in EL imaging	Catastrophic drop in shunt resistance (R_{sh}); low fill factor (FF) & power	EL Imaging, I-V Curve (R_{sh}), IR Thermography
Corrosion	Moisture ingress & contaminants; galvanic couples	Discoloration, tarnishing of metallization	Increased series resistance (R_s); reduced FF & I_{sc}	Visual Inspection, EL Imaging, I-V Curve
Delamination	UV/thermal degradation of encapsulant; moisture; poor lamination	Cloudy, bubbled areas at interfaces	Reduced optical coupling; loss of I_{sc} & power	Visual Inspection, EL Imaging
Snail Trails	Silver migration from gridlines via micro-cracks in presence of moisture	Dark, meandering lines on the surface	Underlying micro-crack causes power loss; can increase R_s	Visual Inspection, EL Imaging (for initiating crack)

2.2.3. Delamination

Delamination is the loss of adhesion between laminated module layers, typically between encapsulant and glass, cell, or backsheet. It compromises structural integrity and permits moisture ingress, accelerating secondary degradation such as corrosion [23]. Primary causes include thermo-oxidative polymer degradation from UV exposure and heat, moisture-induced bond hydrolysis, and manufacturing defects such as insufficient curing [24].

The visual signature of delamination is the appearance of cloudy, bubbled, or discolored areas where the layers have separated. Electroluminescence (EL) imaging is highly effective for detecting delamination, as the separated layers cause increased optical scattering and a loss of light-coupling, appearing as dark, often diffuse patches in the image [22]. The primary electrical impact is a reduction in optical transmission to the cells, leading to a loss in short-circuit current (I_{sc}) and overall power. Furthermore, by allowing moisture

ingress, delamination initiates a cascade of other faults, making it a critical failure mode for long-term module durability.

2.2.4. Snail Trails

Snail trails are dark, meandering surface lines caused by chemical reactions involving silver metallization [25]. They typically form when moisture penetrates micro-cracks, enabling silver ion migration and subsequent reactions that deposit dark compounds along crack paths [26].

Although primarily aesthetic, snail trails indicate underlying defects such as micro-cracks, moisture ingress, and metallization corrosion, all of which can degrade performance. Detection is mainly visual, while electroluminescence imaging can reveal initiating cracks before trails become visible [27].

2.2.5. Micro-Crack Propagation

While micro-cracks are often initiated during manufacturing (as discussed in Section 2.1.3), their propagation into larger, electrically significant fractures is predominantly driven by extrinsic operational and environmental stresses in the field. Understanding this progression from latent defect to active failure is crucial for predicting module lifetime.

The first primary driver of micro-crack propagation is thermal cycling, where the repeated expansion and contraction of materials due to daily temperature variations induces cyclic mechanical stress at the crack tips. This stress can cause pre-existing micro-cracks to gradually extend through the silicon wafer [28]. The second is the mechanical loads: static loads from snow accumulation or wind, and dynamic loads from wind gusts, apply bending moments to the module, leading initial cracks to propagate [29]. Other factors like hail can also cause immediate crack initiation and propagation.

As cracks propagate, they may isolate portions of the cell, reducing active area and causing reverse-biased regions that generate localized heating. This leads to fill-factor reduction, power loss, and potential hot-spot damage [30]. Crack growth is therefore a dynamic degradation process governed by environmental exposure and mechanical history.

2.3. System-Level and Interconnection Faults

This category encompasses failures that occur not within the individual module's materials or cells, but in the components and connections that integrate modules into a full system. These faults are critical as they can lead to complete system shutdown, significant energy losses, and pose severe safety hazards, including fire risks. Their characteristics and associated risks are summarized in Table 3.

2.3.1. Bypass Diode Failures

Bypass diodes are connected in parallel with groups of cells (typically 18-24 cells per diode) within a module's junction box. Their function is to provide an alternative current path when a cell or group of cells is shaded or faulty, preventing them from overheating due to reverse bias operation.

Bypass diode failures are categorized into two destructive modes: open-circuit and short-circuit failures. In an open-circuit failure, the protective path is lost, forcing current through shaded cells and triggering rapid hot spot formation, glass breakage, and fire hazards [31]. Conversely, a short-circuit failure bypasses an entire cell group, causing a distinct "step" in the I-V curve and a significant reduction in operating voltage. Both modes pose severe risks to module integrity, often leading to localized overheating and damage to the junction box or encapsulant [32].

2.3.2. Connection Failures

Table 3. Characteristics and impacts of system-level and interconnection faults.

Fault Type	Mechanism	Impact on System	Primary Risks & Hazards
Bypass Diode Failure	Open-Circuit: Diode fails off	No protection for shaded cells; leads to severe hot spots	Fire hazard from localized overheating; glass breakage
	Short-Circuit: Diode fails on	Bypassed cell string; "step" in I-V curve; significant power loss	Thermal damage to junction box; energy yield loss
Connection Failure	Solder/Interconnect: Fatigue from thermal cycling	Increased R_s ; localized heating; power degradation	Hot spots; long-term performance loss
	Connector: Loose/corroded connection	High-resistance point; extreme localized heating ($P = I^2R$)	Fire hazard; melting of components
Arc Fault	Series: Broken conductor	Sustained arc in current-carrying path	Extreme fire hazard (arc temperatures > 3000 °C)
	Parallel: Insulation failure	High-current arc between conductors	Extreme fire hazard; possible electrocution
Ground Fault	Conductor contact with grounded frame	Unintended current path to ground; can trigger PID	Energy loss; electrocution risk; localized heating/fire
String-Level Mismatch	Non-uniform current from shading, soiling, or faulty modules	String current limited by weakest module; cumulative power loss	Significant energy yield loss; not a direct safety hazard

The network of solder bonds, interconnect ribbons, and connectors is susceptible to several failure modes, often acting as “hidden” points of resistance. **Solder bond fatigue and ribbon breakage** is caused by repeated thermal cycling, which induces mechanical stress due to the mismatch in the coefficient of thermal expansion (*CTE*) between the silicon cell, solder, and copper ribbon. This leads to cracked solder joints or broken ribbons, increasing the series resistance (R_s) and localizing heat generation. This is a primary cause of hot spots and long-term power degradation [4]. **Connector burnout** is where loose connections, corrosion, or improper installation at module connectors create a point of high resistance. According to Joule’s law ($P = I^2R$), the power dissipated as heat at this point rises with the square of the current. In high-current strings, this can lead to extreme temperatures, melting the connector plastic, oxidizing the metal contacts, and in severe cases, initiating fires [33].

2.3.3. Arc Faults

Arc faults are a major fire safety hazard in PV systems. They occur when a continuous conductive path is broken, and current bridges the gap through ionized air (an arc). The high temperature of an arc (several thousand degrees Celsius) can easily ignite surrounding materials.

Series arc faults are caused by a break in a current-carrying conductor, such as a broken cable or a loose connection within a connector. They are particularly dangerous because the arc current is limited by the PV array itself, making them difficult for standard overcurrent protection devices to detect [34]. Parallel arc faults: Occur due to insulation failure between conductors of different potentials (e.g., between the positive and negative leads or a conductor and ground). These faults typically involve very high currents and are often, but not always, cleared by string fuses or circuit breakers.

2.3.4. Ground Faults

A ground fault occurs when a current-carrying conductor unintentionally makes contact with a grounded surface, such as the module frame or the racking system. This creates an alternative, unsafe path for current to flow to the ground.

Ground faults can lead to significant energy losses by diverting current away from the inverter. They also pose serious safety hazards by creating electrocution risks for maintenance personnel and present fire risks, particularly if the fault path has high resistance, resulting in persistent, localized heating. Additionally, in certain system configurations, a ground fault can establish the potential difference between the cells and the frame that drives Potential Induced Degradation (PID), further compromising module performance and longevity [35].

2.3.5. String-Level Mismatch

String-level mismatch occurs when the current output of individual modules within a series-connected string is not uniform, forcing the entire string to operate at the current of the weakest module. This results in a cumulative power loss that is greater than the power loss of the underperforming module alone.

The primary causes are partial shading, soiling, and module degradation. **Partial shading** caused by even a small shadow can reduce the cells’ output, creating a significant bottleneck for the entire string. Bypass diodes activate to protect the shaded cells, but the overall string power is still dictated by the shaded module’s reduced current [36]. **Soiling** due to accumulation of dirt, dust, snow, or bird droppings across the array creates a similar effect to partial shading, where the most soiled module limits the string’s current [37]. As for **module degradation**, a single module suffering from a fault will have a different current-voltage characteristic than healthy modules, causing mismatch within the string [38].

The impact of mismatch is a reduction in the overall energy yield of the PV system. It can be identified by comparing the current and power output of different strings. Advanced monitoring at the string or module level is often required to pinpoint the specific underperforming unit causing the mismatch.

Table 4. Mapping of PV defects to corresponding FDD methodologies and diagnostic indicators.

Fault Category	Specific Defect	Primary FDD Technique	Detection Signal/Indicator
Cell-Level	PID / LeTID	Electroluminescence (EL)	Darkening of cell areas
	Micro-cracks	Digital Image Correlation	Surface strain patterns
Module-Level	Hotspots	IR Thermography	Localized temperature rise
	Glass Breakage	Visual Inspection / UAV	Optical surface anomalies
String-Level	Soiling/Shading	I-V Curve Analysis	Fill Factor (FF) reduction
	Bypass Diode	Thermal Imaging / SCADA	ΔT or V_{oc} drops
System-Level	Arc Faults	HF Current Analysis	High-frequency noise
	Inverter Faults	Efficiency Monitoring	P_{ac}/P_{dc} ratio deviation

To provide a concise overview for diagnostic selection, **Table 4** maps the specific physical defects discussed in this section to their most effective corresponding FDD methodologies and primary detection signals.

3. FAULT DETECTION AND DIAGNOSTIC (FDD) METHODOLOGIES

The reliable and efficient operation of photovoltaic (PV) systems is contingent upon the timely identification and diagnosis of faults. A diverse suite of detection methodologies has been developed, ranging from laboratory-grade techniques offering high resolution to field-deployable methods suitable for large-scale, continuous monitoring. These methods can be broadly categorized into visual inspection, electrical characterization, imaging techniques, and advanced data-driven approaches. The selection of an appropriate method involves a critical trade-off between diagnostic resolution, cost, scalability, and the requirement for system downtime. This section provides a detailed review of these techniques, discussing their principles, applications, and limitations.

3.1. Laboratory and Offline Characterization

These methods provide the highest diagnostic accuracy and are predominantly used for root-cause analysis, quality assurance during manufacturing, and certification. A significant drawback is that they typically require disconnecting the module or string from the operational system and are performed under controlled, often stationary, conditions [27].

3.1.1. I-V Curve Tracer Analysis

The current-voltage (I-V) characteristic curve is the fundamental electrical signature of a PV device's health. A controlled measurement of the I-V curve under standard test conditions (STC) or controlled indoor flash testing provides a wealth of quantifiable information. Key performance parameters, including short-circuit current (I_{sc}), open-circuit voltage (V_{oc}), maximum power point (P_{mp}), fill factor (FF), series resistance (R_s), and shunt resistance (R_{sh}), are extracted and compared to rated or baseline values. Specific fault modes create characteristic, identifiable distortions in the I-V curve's shape [39]:

- A reduction in I_{sc} predominantly points to optical losses such as soiling, partial shading, delamination, or encapsulant discoloration.
- A significant drop in V_{oc} can indicate potential-induced degradation (PID), widespread cell degradation, or a high number of shunted cells.
- A low fill factor, particularly when coupled with a measurable decrease in R_{sh} , is a classic signature of shunting faults within the cells.
- A notable increase in R_s suggests resistive losses from issues like contact corrosion, broken or degraded interconnects, or solder bond failure.

While highly informative for assessing overall module health, I-V curve analysis at the module level often lacks the spatial resolution to pinpoint the physical location of a fault within the module. It serves as an excellent first step to identify an anomaly, which can then be investigated with higher-resolution techniques.

3.1.2. Electroluminescence (EL) Imaging

Electroluminescence imaging has become an indispensable, high-resolution tool for fault detection in both laboratory and manufacturing settings. The principle involves placing the PV module in a dark environment, forward-biasing it with an external power source to inject charge carriers, and capturing the near-infrared (NIR) photons emitted due to radiative recombination using a sensitive silicon-charge-coupled device (Si-CCD) camera. Regions with high recombination activity or disrupted current flow appear darker in the resulting image [27].

- **Applications:** EL is exceptionally sensitive for detecting a wide range of defects, including micro-cracks (appearing as sharp, dark lines), shunts (localized dark spots), finger interruptions, material defects (like dislocations and grain boundaries), and PID (manifesting as entirely dark cells or strings).
- **Advantages:** It offers unparalleled spatial resolution for cell-level defects, providing a “map” of the electronic quality of the silicon.
- **Disadvantages:** It requires direct electrical contact and disconnection from the system; imaging large modules can be time-consuming; and performance is assessed at low, non-operational current levels, which may not replicate all failure modes that appear under full sunlight.

3.1.3. Photoluminescence (PL) Imaging

Photoluminescence imaging is a contactless alternative to EL, particularly valuable for characterizing unprocessed wafers and cells without metallization. Instead of electrical injection, the silicon bulk is excited using a monochromatic light source, typically a laser. The luminescence emitted by the

material as excited charge carriers recombine is captured, revealing spatial variations in the minority carrier lifetime [40].

- **Applications:** Similar to EL, PL is effective for detecting cracks, material impurities, and defects in the silicon bulk. It is widely used in production lines for incoming wafer inspection.
- **Advantages:** The contactless nature enables high-throughput, non-destructive characterization. It can probe the bulk material properties independently of the contacts.
- **Disadvantages:** It is generally less sensitive to series resistance-related faults compared to EL, as it does not rely on current injection through the front and rear metallization.

3.1.4. Infrared Thermography (IRT)

Infrared Thermography detects faults by measuring the surface temperature distribution of a PV module. Faults that cause localized power dissipation appear as “hot spots”. It can be performed in two modes [41]:

Active (or Forward-Bias) Thermography: The module is electrically biased, typically at or near its maximum power point current. Defects like shunts, cracked cells with high resistive losses, and faulty solder joints will dissipate power as heat, making them visible to an infrared camera.

Passive (or Outdoor) Thermography: The module operates under natural sunlight. This method can identify hot spots caused by reverse-biased substrings in shaded or faulty cells (activated bypass diodes), as well as poor electrical connections. It is more practical for field inspections but can be influenced by ambient conditions, reflections, and irradiance non-uniformity.

- **Applications:** Highly effective for identifying shunts, hot spots from cracked cells, bypass diode failures (the diode itself may be hot), and poor interconnections.
- **Advantages:** Can be applied in the field without disconnecting the system (in passive mode); provides a direct visualization of thermal anomalies that often correlate with safety hazards.
- **Disadvantages:** Resolution and accuracy are affected by environmental factors (wind, ambient temperature, solar reflection); may not detect early-stage or non-heating faults like minor cracks.

3.2. Online and Field-Deployable Monitoring

These methods are designed for continuous or periodic assessment of PV systems during normal operation, enabling proactive maintenance without necessitating shutdown.

3.2.1. Time-Series Performance Analytics

This approach involves the continuous monitoring of key performance metrics from the inverter or dedicated data loggers.

- **Performance Ratio (PR):** This is a normalized metric that compares the actual energy output to the theoretical output under STC. A declining trend in PR indicates overall system degradation but lacks diagnostic specificity, as many fault types can cause a similar drop [42].
- **Statistical Process Control (SPC):** Control charts (e.g., Shewhart charts) are applied to parameters like string current, voltage, or power. When a parameter deviates significantly from its historical mean or expected range (based on irradiance and temperature), it triggers an alert for further investigation. This is effective for detecting sudden faults like string outages or gradual degradation.

3.2.2. String-Level Inverter Data Analysis

Most commercial inverters provide data on the DC operating parameters of each maximum power point tracker (MPPT) or individual strings. By comparing the current, voltage, and power of parallel strings operating under similar environmental conditions, operators can quickly identify underperforming strings. A string consistently producing lower current may be suffering from soiling, shading, or mismatch, while a string with abnormal voltage could indicate a problem like a shorted bypass diode or PID [43].

3.2.3. Real-Time Electrical Signature Analysis

This involves analyzing the high-frequency components or transient behavior of the electrical signals to detect specific fault types.

- **Arc Fault Circuit Interrupters (AFCIs):** These devices continuously monitor the DC current for the high-frequency noise signature characteristic of an electrical arc. Upon detection, they rapidly de-energize the circuit to prevent fires, as mandated by modern electrical codes like the NEC in the United States [34].
- **Impedance Spectroscopy:** An emerging technique that involves injecting a small, variable-frequency AC signal superimposed on the DC operating point and measuring the system’s impedance response.

Different degradation modes (e.g., corrosion, delamination) can produce distinct impedance spectra, offering a potential tool for incipient fault diagnosis.

3.3. Advanced Data-Driven and Robotic Methods

The scale and complexity of modern photovoltaic installations, particularly utility-scale power plants comprising millions of modules, have rendered purely manual inspection methods economically and logistically infeasible. This challenge has catalyzed the rapid development of advanced, automated methodologies that leverage data analytics, artificial intelligence, and robotics. These approaches are transforming operations and maintenance (O&M) from a reactive, calendar-based model to a proactive, condition-based paradigm.

3.3.1. Machine Learning and Deep Learning for SCADA Data Analysis

Supervisory Control and Data Acquisition (SCADA) systems continuously record vast amounts of operational data, including DC and AC power, voltage, current, irradiance, and module temperature. Machine Learning (ML) and Deep Learning (DL) models are uniquely suited to extract subtle fault signatures from this multivariate, time-series data that may be imperceptible to traditional threshold-based alarms.

- **Supervised Learning for Fault Classification:** Algorithms such as Support Vector Machines (SVM), Random Forests, and Gradient Boosting Machines are trained on historical datasets where periods of normal and faulty operation have been explicitly labeled. These models learn the complex, non-linear relationships between environmental inputs (irradiance, temperature) and electrical outputs (power, voltage, current) to classify the system's state into categories such as "normal," "soiling," "shading," or "degradation" [44]. For instance, a Random Forest can use the relative importance of features like a string's current deviation from its peers under similar irradiance to identify a faulty module.
- **Unsupervised Learning for Anomaly Detection:** A significant limitation of supervised learning is the requirement for labeled fault data, which is often scarce for novel or rare failure modes. Unsupervised learning techniques address this by modeling the system's "normal" operating behavior. Methods like Isolation Forest and Autoencoders are particularly effective. An autoencoder, a type of neural network, is trained to reconstruct its input data (e.g., a day's power profile) after compressing it through a bottleneck layer. During operation, if the reconstruction error for a new data sample exceeds a trained threshold, it is flagged as an anomaly, indicating a potential previously unencountered fault [43].
- **Deep Learning for Sequential Data: Long Short-Term Memory (LSTM)** networks and other recurrent neural networks (RNNs) are specifically designed for time-series data. They can model temporal dependencies, learning how a system's performance evolves over days, weeks, and seasons. This allows them to detect not just sudden faults but also gradual degradation trends, providing early warnings for issues like PID or corrosion before they cause significant energy loss [45].

3.3.2. Computer Vision for Automated Image-Based Diagnosis

The manual analysis of thousands of thermal or EL images from a single drone flight is a major bottleneck. Computer Vision (CV), particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool for automating this process.

- **Architecture and Training:** CNNs are deep learning models whose architecture is inspired by the animal visual cortex. They automatically learn hierarchical features from images, from simple edges in early layers to complex patterns like "hot spot" shapes or "micro-crack" textures in deeper layers. These models are trained on large, curated datasets of images labeled by human experts (e.g., "image contains a hot spot," "image shows snail trails") [46].
- **Applications and Performance:**
 - **Thermal Image Analysis:** CNNs can classify hot spots caused by defective bypass diodes, shunts, or cracked cells with high accuracy (>95%), often surpassing human consistency.
 - **EL Image Analysis:** They are exceptionally proficient at segmenting and classifying defects in EL imagery, identifying micro-cracks, finger interruptions, and areas of low minority-carrier lifetime with a sensitivity that can exceed human capability [47].
 - **Multi-Modal Data Fusion:** The most advanced systems fuse image data with electrical SCADA data. For example, a CNN might identify a potential fault in a thermal image, and an ML model would then correlate it with a specific string's current drop, significantly increasing diagnostic confidence [48].
- **Challenges:** The primary challenge is the "data hunger" of deep learning models. Creating large, diverse, and accurately labeled datasets for every possible fault type is labor-intensive. Techniques

like transfer learning, where a model pre-trained on a generic image dataset is fine-tuned on a smaller set of PV images, are commonly used to mitigate this.

3.3.3. Robotic and UAV-Based Inspection Systems

Robotics provide the physical platform to collect the high-resolution data required for advanced analytics at a scale that is impossible with manual labor.

- **Unmanned Aerial Vehicles (UAVs/Drones):** Modern UAVs are equipped with gimballed, multi-sensor payloads, including high-resolution RGB, radiometric thermal, and sometimes even EL cameras. They can autonomously follow pre-programmed flight paths, capturing geotagged imagery of every module in a multi-megawatt plant in a matter of hours. Post-processing software stitches these images into orthomosaic maps, providing a comprehensive, high-resolution “health map” of the entire facility [49].
- **Data Pipeline and Analytics:** The value of UAVs is realized through the integrated data pipeline. The collected images are automatically uploaded to cloud platforms where computer vision models analyze them. The output is not just a collection of images but a structured report detailing the location, type, and often the severity of detected faults, which is directly integrated with Computerized Maintenance Management Systems (CMMS) to generate work orders.
- **Ground Robots:** For more detailed inspection or tasks beyond imaging, ground-based robots are being developed. These can traverse the space underneath PV arrays, using robotic arms to perform contact-based measurements or cleaning, complementing aerial inspection.

The convergence of these data-driven and robotic methods represents the future of PV O&M. By enabling frequent, comprehensive, and automated asset assessment, they minimize downtime, optimize maintenance resources, and ultimately protect the long-term financial returns of photovoltaic investments.

As the complexity of PV systems increases, the selection of an FDD methodology depends on a trade-off between diagnostic granularity and operational cost. Table 5 provides a comprehensive comparison of common fault types, their detection methods, and their associated costs and detectability stages—ranging from early cell-level defects to advanced system-level failures.

Table 5. Comparative analysis of PV fault types, detection methodologies, and economic deployment factors

Fault Type	Detection Method	Cost	Detectability Stage
PID / LeTID	Electroluminescence (EL)	High (Equip.)	Early (Cell-level)
Micro-cracks	Digital Image Correlation	Moderate	Early (Pre-failure)
Hotspots	IR Thermography (UAV)	Moderate/Low	Intermediate
Soiling / Shading	I-V Curve Analysis	Low	Intermediate
Bypass Diode Failure	Thermal Imaging / SCADA	Low	Advanced (String-level)
Arc Faults	High-Frequency Analysis	Moderate	Advanced (Immediate)

4. COMPARATIVE ANALYSIS AND SYNTHESIS: BRIDGING THE GAP

The extensive taxonomy of PV faults and the diverse portfolio of FDD methodologies presented in the previous sections reveal a critical engineering challenge: no single detection method is universally optimal. The selection of an appropriate FDD strategy is governed by a fundamental trade-off between diagnostic resolution, scalability, and cost that has been documented in the literature [3]. This section provides a detailed comparative analysis to guide this selection, discusses the emergence of hybrid approaches, and synthesizes the interrelationships between fault modes and their detectable signatures based on established research findings.

4.1. The Resolution-Scalability-Cost Trade-off

Table 6 provides a comprehensive comparison of FDD methods, but the underlying trade-offs merit deeper discussion. The relationship between these factors can be visualized conceptually as a spectrum where methods are positioned based on their operational characteristics and limitations.

- **The High-Resolution, Low-Scalability Domain:** Techniques like Electroluminescence (EL) and Photoluminescence (PL) imaging reside in this quadrant. Their supreme resolution for cell-level defects (cracks, shunts, material defects) comes at the cost of requiring system shutdown, controlled conditions, and significant time per module [40]. This makes them ideal for root-cause analysis in laboratories or quality assurance in manufacturing but economically prohibitive for regular field monitoring of large plants, as noted in comprehensive reviews of imaging techniques [27].
- **High-Scalability, Low-Resolution:** At the opposite end lie SCADA-based analytics and Performance Ratio (PR) monitoring. These methods leverage data that is already being collected, enabling continuous, system-wide health assessment at near-zero marginal cost [42]. However, they suffer from low diagnostic specificity, as a drop in string current could indicate soiling, shading, module

degradation, or a combination thereof [43]. They are excellent for anomaly detection but poor for fault identification and localization.

- **The Middle Ground:** Balanced Approaches: Infrared Thermography (IRT) and UAV-based inspections strike a practical balance. IRT can identify thermal anomalies (hot spots, faulty diodes) with good resolution without always requiring shutdown (in passive mode) [41]. When mounted on UAVs, these techniques become scalable for periodic (e.g., quarterly or semi-annual) plant-wide inspections, though the diagnostic outcome remains subject to environmental conditions [49].
- **Data-Driven Methods:** Machine Learning (ML) and computer vision do not represent a single point on this trade-off curve but rather a means of shifting it. By automating analysis, they enhance the diagnostic specificity of scalable methods (e.g., ML on SCADA data) and the scalability of high-resolution methods (e.g., CNNs for EL/IR image analysis) [44] [46].

Table 6. Comprehensive comparison of fault detection and diagnostic methods for PV systems

Method	Diagnostic Resolution	Scalability & Frequency	Relative Cost	Primary Application
EL / PL Imaging	Very High (Cell/Defect)	Very Low (Lab/Offline)	High	Root-cause analysis
I-V Curve Analysis	High (Module)	Low (Periodic, Offline)	Medium	Performance validation, fault confirmation
IR Thermography	Medium-High (Module/String)	Medium (Field, Periodic)	Medium	Hot spot detection, connection faults
UAV-based Inspection	Medium (Module)	High (Plant-wide, Scheduled)	Medium-High	Large-scale thermal/visual survey
SCADA/ML Analytics	Low (String/System)	Very High (Continuous)	Low	Anomaly detection, performance trending

4.2. Synthesis of Fault-Signature Relationships

A critical synthesis of Sections 2 and 3 reveals consistent patterns in how different fault modes manifest across various detection methods. This “fingerprint” of a fault is key to robust diagnosis and has been documented across multiple experimental studies.

- **Dark & Hot Signature:** A combination of a dark region in EL imaging (indicating no current flow or high recombination) and a corresponding hot spot in IR thermography (indicating power dissipation) is a classic signature of severe, active faults. This is observed in shunted cells, where the shunt provides a current path that bypasses the p-n junction, leading to low luminescence and localized resistive heating [12].
- **Electrically Degraded Signature:** Faults that primarily increase series resistance (R_s) or decrease shunt resistance (R_{sh}) leave a distinct mark on the I-V curve but may have no immediate visual or thermal signature in early stages. Corrosion and solder fatigue progressively increase R_s , degrading the fill factor (FF) [50], while PID-s catastrophically reduces R_{sh} , causing a characteristic “slumping” of the I-V curve that serves as a key electrical indicator [18].
- **Optical Loss Signature:** A reduction in short-circuit current (I_{sc}) without a proportional drop in voltage (V_{oc}) is a key indicator of optical losses detectable through I-V curve analysis [39]. This signature is characteristic of delamination and encapsulant discoloration, which scatter and absorb light before it reaches the cell, and soiling, which blocks incident irradiance. While visual inspection can confirm these faults, quantitative I-V analysis is needed to assess their true impact.

4.3. Hybrid and Tiered Monitoring Strategies

Given the complementary strengths and weaknesses of individual methods, the most effective FDD regimes are layered or hybrid. A tiered strategy optimizes resource allocation and has been successfully implemented in large-scale PV plants [49].

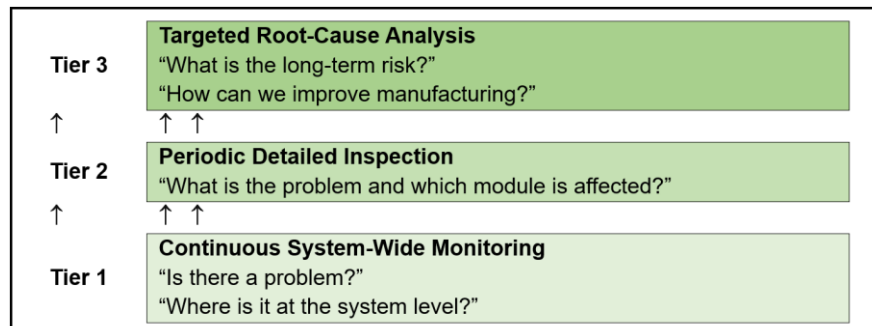


Figure 2. Proposed tiered Fault Detection and Diagnosis (FDD) hierarchy for large-scale PV systems.

The proposed diagnostic framework utilizes a three-tiered approach to balance cost and resolution:

- **Tier 1** provides continuous system-wide monitoring through SCADA-based anomaly detection and performance ratio tracking to identify system-level problems.
- Upon alert, **Tier 2** employs periodic, medium-resolution inspections such as UAV-based infrared thermography to localize faults to specific modules.
- Finally, **Tier 3** involves targeted root-cause analysis using high-resolution tools like electroluminescence imaging and I-V curve tracing on flagged modules to determine the precise physical cause and inform warranty or repair decisions.

This tiered approach ensures that the expensive, high-resolution tools are used only where they are needed most, making comprehensive FDD economically viable for large-scale PV assets [49]. The integration of these tiers through a centralized data platform, where alerts from one tier automatically trigger actions in the next, represents the state-of-the-art in PV asset management.

4.4. Economic Cost-Benefit Analysis: UAV-IRT vs. Manual Inspection

A critical distinction in the operational viability of FDD methodologies lies in the cost-benefit trade-off between Unmanned Aerial Vehicle (UAV)-based Infrared Thermography (IRT) and traditional manual inspection protocols. Traditional methods typically involve maintenance personnel patrolling the PV plant for visual defects or capturing IR/EL images using hand-held cameras or tripod systems. Economically, the annual O&M costs of such traditional inspections are estimated to be approximately 11.30 €/kWp, with roughly 1.50 €/kWp specifically tied to planned monitoring and labor-intensive manual scanning [49].

In contrast, UAV-integrated thermography offers a 10x to 50x increase in inspection speed, providing a reliable, time-saving alternative in the post-incentive era of PV expansion [51]. This methodology allows for a comprehensive plant-wide assessment in a matter of hours, rather than weeks. Although the initial CAPEX for high-resolution thermal sensors and pilot certification is higher, the dramatic reduction in Operational Expenditure (OPEX) and the optimization of the Levelized Cost of Electricity (LCOE) are significant. Empirical results confirm that utilizing light Unmanned Aerial Systems (UAS) for periodic scanning is far more cost-effective than traditional manual monitoring protocols [51].

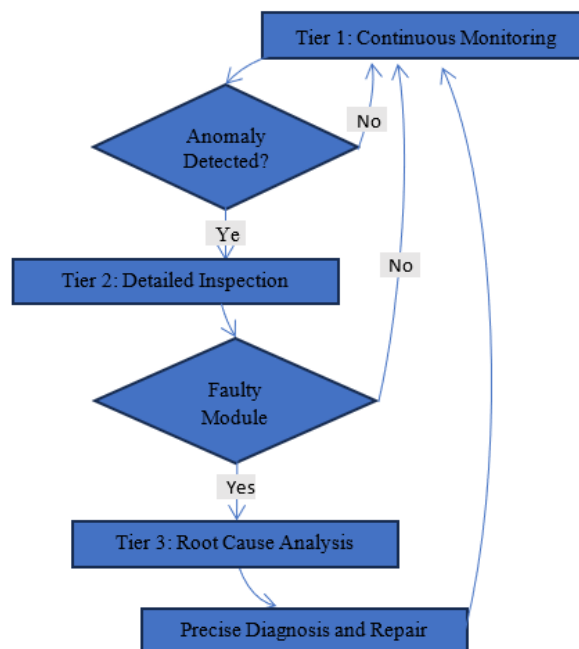
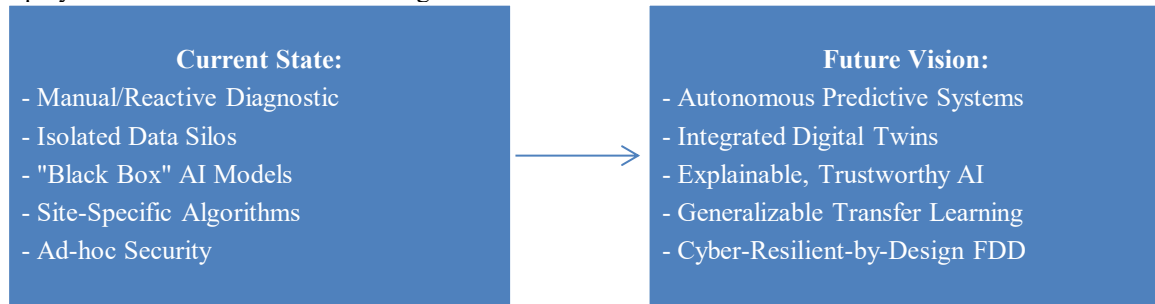


Figure 3. Operational flowchart of the integrated tiered monitoring strategy.

5. RESEARCH GAPS AND FUTURE DIRECTIONS

Despite significant advances in understanding PV degradation and developing FDD methodologies, several critical research frontiers remain. Addressing these gaps is essential for transitioning from reactive

maintenance to truly predictive, autonomous, and robust asset management, particularly as global PV deployment scales into the terawatt range



5.1. The Black Box Problem

The superior accuracy of complex Machine Learning (ML) and Deep Learning (DL) models is often offset by their opacity. In critical infrastructure like PV plants, operators require not just a fault classification but an understandable rationale to justify maintenance actions and investments. Current convolutional neural networks (CNNs) or ensemble models may identify a hot spot with 98% confidence but cannot explain which image features (e.g., specific shape, temperature gradient, location relative to the busbar) led to this diagnosis [52].

Future Direction: Integration of Explainable AI (XAI) techniques, such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations), into PV diagnostics. The goal is to develop models that provide outputs like: Module flagged for potential PID [confidence: 92%] due to: (1) uniform temperature increase of 8°C across all cells, and (2) characteristic 70% reduction in string shunt resistance correlating with negative frame bias. This builds essential trust and enables human-in-the-loop decision-making [47].

5.2. The Data Famine

The performance of data-driven algorithms is intrinsically linked to the quality and quantity of training data. The PV research community suffers from a severe scarcity of large, curated, and publicly available datasets containing labeled faults from diverse climates, technologies, and system configurations [46]. This lack of standardized benchmarks hinders the fair comparison of algorithms, slows progress, and leads to models that are overfitted to specific, often ideal, conditions.

Future Direction: A concerted, collaborative effort to create and maintain open-source data repositories (e.g., "PV-Fault DB"). Such datasets should include synchronized multi-modal data: time-series SCADA (irradiance, temperature, power), high-resolution imagery (EL, IR, visual), and corresponding ground-truth labels verified by physical inspection. This would serve as a universal benchmark, similar to ImageNet in computer vision, dramatically accelerating innovation in algorithmic FDD [53].

5.3. The Generalization Challenge

A model trained to detect cracks in monocrystalline PERC modules in a desert climate may fail dramatically when applied to thin-film modules in a humid coastal environment. This lack of robustness and generalizability is a major barrier to the widespread commercial deployment of AI-driven FDD [44].

Future Direction: Advanced research into domain adaptation and few-shot learning techniques. The objective is to develop base models that can be efficiently fine-tuned with minimal new data from a novel site (different module type, mounting, or climate). Research should focus on learning invariant features that represent fundamental physics of faults (e.g., the thermal signature of a series resistance increase) rather than site-specific characteristics [54].

5.4. Predicting the Inevitable

Most current methods are adept at identifying faults that have already manifested significant electrical or thermal signatures. The next frontier is predictive maintenance, identifying degradation before it causes measurable power loss, and diagnosing intermittent faults that appear only under specific and rare conditions (e.g., a loose connector that arcs only during strong wind gusts) [34].

Future Direction: Development of models sensitive to subtle, early-warning signatures. This includes analyzing the harmonic content or impedance spectroscopy data for early signs of corrosion or delamination, using high-frequency data acquisition (kHz range) to capture transient events indicative of intermittent arcs or connection issues, and applying advanced signal processing to SCADA data to detect minute, sub-annual degradation rates that signal the onset of LeTID or solder fatigue [41].

5.5. The Digital Twin

A Digital Twin is a high-fidelity, physics-based virtual model of a physical PV plant that updates in real-time with operational data, and it holds transformative potential. It serves as a dynamic simulation environment for FDD [55].

Future Direction: A promising future direction lies in the development of integrated PV digital twin platforms that converge multiple modeling paradigms. Such a system would unite precise, parameterized electrical models of cells, modules, and strings and would crucially incorporate dynamic degradation models that simulate the kinetics of faults. This integrated platform would transcend traditional fault detection, enabling the risk-free simulation of future fault progression and virtual testing of mitigation strategies [48].

The strategic transition between these diagnostic levels is conceptualized in Figure 4, which maps the evolution from traditional reactive maintenance to data-driven predictive strategies, and ultimately toward a fully autonomous, self-healing PV management paradigm.

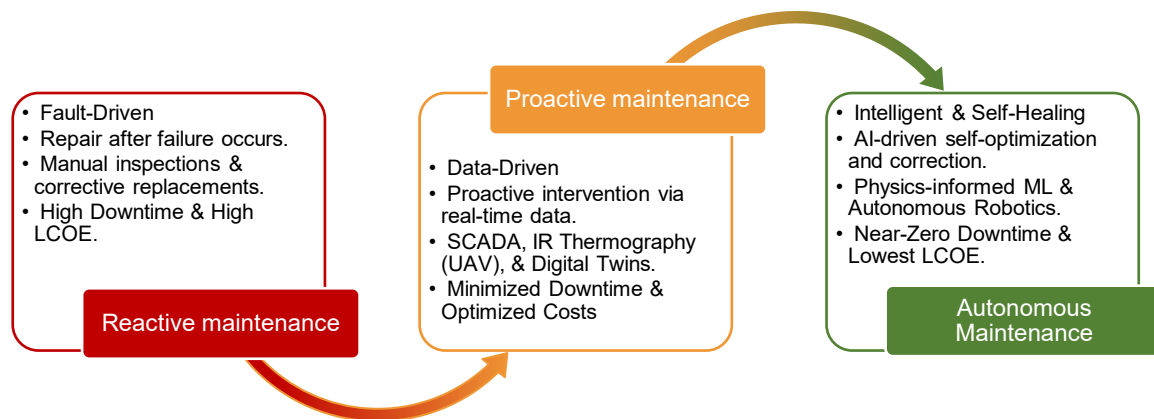


Figure 4. Conceptual evolution of PV maintenance strategies from reactive to autonomous paradigms.

5.6. Cybersecurity of Data-Driven FDD

As PV plants become more connected and reliant on cloud-based analytics and IoT sensors, they expand their attack surface for cyber threats. A malicious actor could manipulate SCADA data to hide faults or, conversely, trigger false alarms to incur unnecessary O&M costs or induce plant shutdowns [56].

Future Direction: Securing the data-driven FDD pipeline necessitates research into cyber-resilient architectures. This includes developing ML-based anomaly detection to flag implausible data patterns indicative of tampering, employing decentralized or edge computing to perform critical diagnostics on-site and reduce transmission vulnerabilities, and implementing blockchain technology to create immutable, distributed audit trails for maintenance actions and fault logs. FDD systems must be designed with security as a foundational principle, not an afterthought [57].

6. CONCLUSION

This review has navigated the complex landscape of photovoltaic reliability, from the microscopic mechanisms of $B-O$ complex formation in LID to the macro-scale challenges of UAV-based plant inspections. As the PV industry shifts toward high-efficiency architectures like PERC and TOPCon, the nature of faults is evolving, requiring a corresponding evolution in diagnostic sophistication. The synthesis of traditional laboratory techniques with modern AI-driven SCADA analysis and robotic imaging offers a tiered, robust framework for ensuring the 25-year-plus lifespan of solar assets. By addressing current gaps in data transparency, model generalization, and cybersecurity, the PV community can secure the financial and environmental promise of the global energy transition.

Beyond technical reliability, the integration of advanced FDD frameworks carries significant economic implications. By transitioning from reactive to predictive maintenance, operators can significantly reduce the Levelized Cost of Electricity and optimize O&M expenditures through the mitigation of catastrophic failures and improved logistics. While high-fidelity tools like Digital Twin architectures require higher initial investment, the long-term reduction in operational expenses and the extension of the asset's productive lifespan ensure a superior return on investment. Ultimately, the digitalization of PV diagnostics serves as a critical driver for the financial viability of large-scale renewable energy infrastructure in competitive markets.

CONFLICT OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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